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So close yet so unequal: Neighborhood inequality in American cities*

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Abstract

This paper contributes to the literature on neighborhood inequality along both theoretical and empirical lines. We introduce a new neighborhood inequality index (NI) to measure income inequality within individual neighborhoods of varying sizes, and study its normative and statistical properties. The NI index is used in combination with a large database of income distributions defined on a fine-grained geographic scale to study neighborhood inequality in American cities over the last 35 years. Inequality within small individual neighborhoods is found to grow steadily over the period, albeit heterogeneously across cities. We investigate the intergenerational consequences of a rising NI index, exploiting labor market responses to minimum wage regulation as a source of identification. We find that lower neighborhood inequality during childhood makes income mobility for children with a disadvantaged parental background more likely.

Keywords: income inequality, individual neighborhood, geostatistics, census, ACS, intergenerational mobility, divided city, mixed city.

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

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1 Introduction

American cities are not all alike when it comes to income inequality (Watson 2009). In some cities, income inequality has skyrocketed in the last decades, while in others inequality has stagnated and even decreased. For instance, the Gini index of equivalent household income in New York City in 2014 is above 0.5, while it is below 0.4 in other major cities such as Washington, DC. Differences in income inequality across cities can be explained by the uneven distribution of skills and human capital across labor markets, the presence of environmental amenities and the city size and density (Glaeser, Resseger and Tobio 2009, Moretti 2013, Baum-Snow and Pavan 2013). These differences have important consequences for local policies, for targeting program participation based on the location of the treated, and for designing federal redistribution schemes (Sampson 2008, Reardon and Bischoff 2011).

Not all neighborhoods of the city are made equally unequal, though. Income stratification *across* neighborhoods is pervasive in large American metro areas, and associated with problems of poverty concentration (Massey and Eggers 1990, Jargowsky 1996, Iceland and Hernandez 2017) and income segregation (Reardon and Bischoff 2011). While inequalities between neighborhoods have received substantial attention in the literature, far less is known about the patterns of inequality *within* the neighborhood. This aspect of inequality is related to both the features of the urban income distribution and to the motives for low, middle and high income households to sort across space and form heterogenous communities. Factors such as preferences for local composition of the neighborhood (Brueckner, Thisse and Zenou 1999, Bayer and Timmins 2005), commuting costs (Bayer and McMillan 2012), housing tenure (Hardman and Ioannides 2004) and the presence of public housing developments (Baum-Snow and Marion 2009), local fiscal competition (de Bartolome and Ross 2003) and the behavioral responses to other households' location decisions (Schelling 1969, Pancs and Vriend 2007) are found to affect both stratification and the income mix in the neighborhood.

Other things being equal, the degree of income inequality experienced within the neighborhood bears consequences both on objective dimensions of residents's well-being

(Durlauf 2004, Ludwig et al. 2012), as well as on their ambitions (Ellen et al. 2013) and sense of deprivation (Luttmer 2005). Evidence from the Moving to Opportunity experiment highlights that the implications of neighborhood inequality extend as well across generations (Ludwig et al. 2013, Chetty et al. 2016). The neighborhood may hence have a mediating role in converting inequality in parental income into larger intergenerational income persistence (Bénabou 1996, Durlauf 1996, Durlauf and Seshadri 2018), a relation that is well pictured (in cross-country studies) by the "Great Gatsby curve" (Corak 2013). While there is increasing evidence that children economic opportunities greatly vary across North American counties and cities (Chetty, Hendren, Kline and Saez 2014, Corak 2017), little is known about the way intergenerational mobility is affected by neighborhood inequality.

This paper adds to this debate. We make use of a large income database alongside new methodology, to investigate patterns and trends of neighborhood inequality in American metro areas. We then relate observed strong heterogeneity of neighborhood inequality to the intergenerational income opportunities of the children exposed to it during youth. Our contribution develops along three lines.

The first contribution is on the methodology side. It is standard in the literature to use linearly decomposable inequality measures in order to isolate within and between neighborhood inequality components (Shorrocks and Wan 2005, Dawkins 2007, Wheeler and La Jeunesse 2008). Empirical research shows that the proportion of citywide inequality explained by the within neighborhood component is large and highly heterogeneous across American cities. These findings are based on methods that have drawbacks. First, the within neighborhood inequality component of total inequality is not directly comparable across cities or time, but only relative to total inequality. Second, the decomposition puts the emphasis on the administrative neighborhood as the unit of analysis, potentially introducing bias due to the Modifiable Areal Units Problem (see Openshaw 1983, Wong 2009). We rely instead on the notion of "individual neighborhood" (Galster 2001, Clark et al. 2015, Marcon and Puech 2017), defined as a set of neighbors located within a certain distance range from any given individual. We first measure income inequality within *each* individual neighborhood, and then we aggregate linearly these inequalities across individuals to obtain a *neighborhood inequality NI* index for the city. This new index maps the spatial distribution of incomes into a level of income inequality, irrespectively of the administrative division of the urban territory. The implied level of neighborhood inequality is measured on a scale comparable to that of the Gini coefficient for the citywide income distribution. An approach to neighborhood inequality related to ours is that of Hardman and Ioannides (2004), who investigate income heterogeneity within housing clusters.[1] The NI index has comparative advantages over this approach. First, the NI index applies to a broad spectrum of spatial data and has additional degrees of freedom in the way the size of the individual neighborhoods is selected. Second, the NI index estimates are representative at the city level and are related to citywide inequality. Third, it has desirable statistical and normative properties, which we derive in Section 2. Furthermore, the NI index captures features of the spatial income distribution that are conceptually different from income segregation.[2]

The second contribution is descriptive. We analyze patterns and trends of neighborhood inequality in American metro areas over the last 35 year. To do so, we explore American Census an the Community Survey publicly available data to obtain a rich, georeferened, income database that is representative at the block group level. Data show that neighborhood inequality has substantially increased over the period 1980-2014, with patterns that are highly heterogenous across American cities. Over the same period, income inequality in individual neighborhoods that are a fraction of a mile in size has been growing faster than the expansion of citywide inequality. As a consequence, individual

[1] Hardman and Ioannides (2004) measure income inequality with the coefficient of variation and using income information from households clusters sampled from the American Housing Survey. These households are selected within a distance range comparable to that of a block group, implying that their index is representative for a specific location (the cluster) and it cannot be meaningfully aggregated across locations to estimates neighborhood inequality at the city level, nor related to citywide inequality.

[2] An income segregation index captures the degree at which low and high income households sort unevenly across the cells of an administrative partition of the city. Reardon and Bischoff (2011) focus on the degree of disproportionality in the shares of low and high income households population across the neighborhoods. Kim and Jargowsky (2009) suggest instead to assess spatial segregation as the share of citywide inequality that is explained by the between neighborhood inequality component. In both cases, inequalities (in incomes or income groups' proportions) across neighborhoods are normalized by the population distribution to attain comparability.

neighborhoods have become increasingly representative of the income distribution in the city. An exhaustive description of findings is in Section 3.

The third contribution investigates the welfare implications of rising neighborhood inequality. The standard normative view about income inequality (Atkinson 1970) would regard increasing neighborhood inequality as welfare reducing. This view can be questioned insofar the sorting of households across the urban space is driven by preferences, rather than needs. Furthermore, larger income mix in the neighborhood may have positive spillovers on socio-economic outcomes of the residents (Manley, van Ham and Doherty 2012). Modern theories of (re)distributive justice (Fleurbaey 2008, Roemer and Trannoy 2016, Andreoli et al. 2019), targeting equality of opportunity rather than equality of outcomes as the relevant social justice criterion, take on a different perspective. These theories advocate for compensating neighborhood inequality if it bears consequences on the economic opportunities of children exposed to it. Following these lines, we investigate if neighborhood inequality is transmitted across generations, thus fostering spirals of growing intergenerational income persistence (Lee and Solon 2009, Chetty et al. 2017). Chetty and Hendren (2018) identify and estimate the causal effects of the neighborhood of residence, experienced by kids with poor parental background, on their income when adult.[3] They find strong geographic heterogeneity in the distribution of these effects. In Section 4, we combine their estimates at city level with our neighborhood inequality measures. We exploit decennial changes in minimum wage coverage at industry and State level as identifying information, to show that an exogenous increase in neighborhood inequality yields a significant drop in income opportunities for the treated children. A Great Gatsby curve relation, linking rising parental income inequality to lower intergenerational mobility, is shown to hold as well at the individual neighborhood scale.

A discussion of potential implications is given in the concluding Section 5. Proofs of the propositions and additional material are collected in an online appendix.

[3] This can be seen a measure of upward relative income mobility (Jäntti and Jenkins 2015).

2 The measurement of neighborhood inequality

In this section we introduce a new measure of neighborhood inequality. We study its properties from two different angles. We first investigate its main statistical properties, establishing new links between spatial inequality measurement and geostatistics. We then highlight some difficulties of the standard axiomatic approach when dealing with neighborhood inequality and conclude by identifying a suitable inequality-reducing redistributive scheme.

2.1 The neighborhood inequality index

Consider a population of $n \geq 3$ individuals, indexed by $i = 1, ..., n$. 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 $\mu > 0$. 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. 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.[4] 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 $\mu_{id} = \frac{\sum_{j \in d_i} y_j}{n_{id}}$.

We introduce the Neighborhood Inequality (NI) index, which measures the average degree of relative income inequality within individual neighborhoods of a given size. The construction of the NI index is inspired by the probabilistic interpretation of the Gini index of inequality proposed by Pyatt (1976).[5] The Gini index can be seen as the relative 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. Income comparisons are now supposed to be restricted to people residing within each individual neighborhood of size d. For each individual i, we first compute

[4] We use the Euclidian distance to determine the extent of the neighborhood, for a discussion of the use of multidimensional notions of distance, see Conley and Topa (2002).

[5] The Gini coefficient, the most popular measure of income inequality for an income distribution $\mathbf{y}$, is defined as $G(\mathbf{y}) = \frac{1}{2n(n-1)\mu} \sum_i \sum_j |y_j - y_i|$.

the average difference between i's income and the income of her neighbors. Then, this quantity is scaled by the neighborhood average income. This gives:

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

There are $1/n_{id}$ chances of drawing a neighbor from d_i with whom i can compare her income with. This probability changes across individuals, reflecting differences in the population density across individual neighborhoods. The NI index is the average of the normalized mean income gaps Δ_i across the whole population of the city:

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

The NI index captures the degree of inequality that would be observed if income comparisons were limited only to neighbors located at a distance smaller than d from the average person in the city. The distance range d is a parameter that is chosen by the researcher.

For a large population, the index is bounded in the unitary interval for any $\mathbf{y}$ and d. Moreover, $NI(\mathbf{y}, d) = 0$ if and only if all incomes within individual neighborhoods of size d are equal. When d reaches the size of the city, each individual neighborhood spans the whole city and neighborhood inequality converges to citywide inequality, that is $NI(\mathbf{y}, \infty) = G(\mathbf{y})$.[6] Otherwise, when d approaches zero, one expect individual neighborhoods to be singletons and $NI(\mathbf{y}, 0) = 0$. The in-between pattern is described by the *neighborhood inequality curve*, which is obtained by plotting the NI index values against d (on the horizontal axis). The curve can locally decrease or increase in d according to the spatial distribution of incomes. Close to the origin, the curve is expected to be steep and increasing when individual neighborhood size grows, because the individual neighborhood distribution tend to converge to the citywide distribution. The curve is expected to be

[6]Despite its clear connection with the Gini index, $NI(\mathbf{y}, d)$ can take values that are either larger or smaller than $G(\mathbf{y})$. 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, neighborhood inequality is maximal (i.e., $NI(., d) = 1$ for d small) and larger than citywide inequality.

flat when the individual neighborhood size is big compared to the geographic scale of the city.[7]

Neighborhood inequality rankings of cities across space or time can be accomplished by comparing neighborhood inequality curves. At any distance threshold d, cities can be ranked according to the level of neighborhood inequality implied by $NI(.,d)$. These rankings may contradict each others if evaluated at different distance cutoff. Comparisons of neighborhood inequality that are robust to the choice of the size of the individual neighborhood can be carried out by looking at the ranking of cities implied by non-intersecting neighborhood inequality curves. The statistical and normative foundations of this approach are now discussed.

2.2 Statistical properties of the NI index

The NI index is tightly related to the degree of dispersion and of spatial association displayed by the urban distribution of incomes. Let $\{Y_s : s = 1, \ldots, n\}$ with $s \in \mathcal{S}$ denote an income process distributed over the random field $\mathcal{S}$, which serves as a model for the relevant urban space. Incomes are jointly distributed as $\mathcal{F}_{\mathcal{S}}$. An empirical spatial income distribution can be seen as a draw from this model. The NI index in (2) is hence the sample counterpart of the neighborhood inequality index $NI(\mathcal{F}_{\mathcal{S}}, d)$ that applies to the underlying income process.

Under fairly standard assumptions about the characteristics of the spatial income process[8], the NI index can be explicitly related to the *variogram* function $\gamma(d)$ (introduced in geostatistics literature by Matheron 1963), a non-parametric statistics that measures the effect of spatial association of incomes on income variability across locations at distance d one from the other. When incomes are spatially uncorrelated, $\gamma(d)$ converges to the variance, implying that the individual neighborhood income distribution is representative

[7]When the role played by space is negligible, i.e. the neighborhood 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.

[8]We assume that the process satisfies *intrinsic stationarity*, i.e. its second order moments are identified on the basis of distance between locations, which are assumed to occur on the transect (see Cressie and Hawkins 1980, Chilès and Delfiner 2012). See the online appendix for a detailed discussion.

of the citywide income distribution.

Proposition 1 *If $\mathcal{F}_{\mathcal{S}}$ displays intrinsic stationarity and Y_s is gaussian with mean μ $\forall s$, then $NI(\mathcal{F}_{\mathcal{S}}, d) = \sum_{b=1}^{B_d} w_b \frac{\sqrt{\gamma(b)/\pi}}{\mu}$, where the distance spectrum $[0, d]$ is partitioned into B_d ordered intervals of fixed size d/B_d and w_b is a demographic weight of locations on $\mathcal{S}$.*

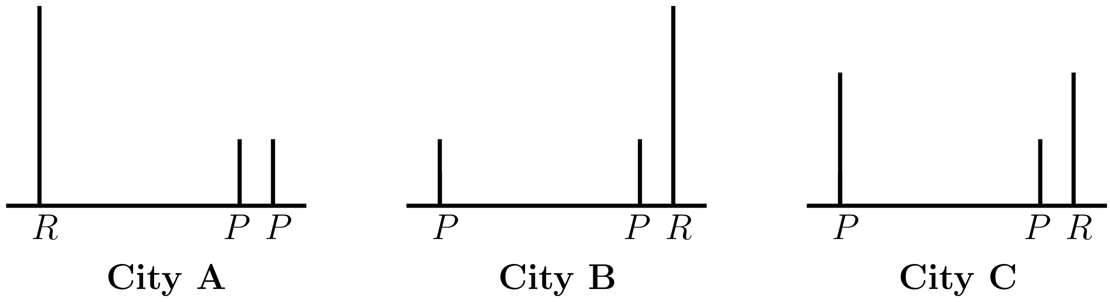
The proposition has several consequences. First, it shows that the NI index can be interpreted as an average of coefficients of variation (the terms $\sqrt{\gamma(b)}/\mu$) taken over the distance domain d. The degree of population density is accounted for by the weighting component, which in high density cities attributes relatively larger weight to income observations in close proximity. Second, the proposition allows to connect the NI index to the growing demand for spatial heterogeneity indicators that develop over the continuous space (Duranton and Overman 2008). The NI index relies on individual neighborhoods and is then not affected by the MAUP. Third, the proposition allows to conclude that the NI index captures aspects of income variability in space that are logically different from attraction and repulsion between locations, commonly used in the analysis of spatial concentration (for a review, see Marcon and Puech 2017) and from income stratification, which relates instead to differences across locations. Finally, the proposition serves as a basis to draw inference for the NI index (Andreoli 2018).

2.3 Normative properties of the NI index

The inequality literature agrees that relative inequality indices should satisfy at least four properties that have normative relevance: (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 (PD) principle, implying that every rich-to-poor income transfer should not increase inequality. The NI index satisfies properties (i) and (ii), which have desirable implications for the measurement of neighborhood inequality.[9] Furthermore, the NI index is linear in normalized mean income gaps Δ_i. As a consequence, the NI index can be directly applied to

[9]Direct implications of these properties are that populations of different sizes 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 neighborhood inequality es-

Figure 1: Distributions of income (vertical spikes) in three linear cities.



population subgroups, identified for instance by the income, the administrative jurisdiction or the schooling district of residence, as well as by other characteristics of the city residents. These estimates of neighborhood inequality are comparable across subgroups and with the degree of neighborhood inequality in the population.[10]

Anonymity strongly conflicts with the idea that location matters in spatial inequality evaluations. In fact, while income permutations are irrelevant for citywide inequality, they affect heavily neighborhood inequality. This point is illustrated in Figure 1. Consider two stylized linear cities *City A* and *City B*, each inhabited by two poor (P) and one rich (R). The length of the spikes indicate the incomes of these persons. The two cities display the same citywide inequality, but differ in the way rich and poor people sort in space. Arguably, City B displays more neighborhood inequality than City A, at least when evaluations are made considering individual neighborhoods of sufficiently small size (so that, for instance, in City A the person R has no neighbor while P has only P as neighbor). Nonetheless, one city is obtained from another only by permuting the location of the residents. Dropping anonymity also undermines the normative validity of the PD transfer, as shown by the example of *City C* in Figure 1.[11] City C can be obtained from

timates. Both properties are satisfied through standardization of the income gaps in (2) by individual neighborhood-specific population counts and average incomes.

[10]This is different to requiring decomposability into within and between components of neighborhood inequality, a property not satisfied by the NI index. In fact, interaction terms appear because individual neighborhoods are expected to contain people from different subgroups, and individual neighborhoods largely overlap across individuals.

[11]Notice that Anonymity (also called symmetry) is a necessary condition for Schur-convexity, a mathematical property satisfied by all inequality indices consistent with the PD transfer principle (see Marshall and Olkin 1979, p.54).

either City A or City B by leveling income disparities between a P person and the R person through a PD transfer. While this operation undisputedly reduces inequality in the city, it rises neighborhood inequality if the distribution of departure is that of City A.

The examples show that both relocation policies switching the position of poor and rich people across the city (without affecting citywide inequality) and rich-to-poor income transfers (reducing overall inequality) may give rise to unpredictable implications for neighborhood inequality. These ambiguous effects might likely be amplified by the behavioral responses of people whose sorting across space depends on the income dimension (Durlauf 2004).

To overcome the inadequacy of standard redistributive principles when dealing with neighborhood inequality, we consider *redistribution schemes* that apply to all income recipients in the city, and we study their properties. A redistributive tax-benefit scheme is a function $f : \mathbb{R}_+ \to \mathbb{R}_+$ that associates a post-redistribution income $f(y)$ to any pre-redistribution income y. We focus on rank-preserving redistributive schemes, meaning that f is non-decreasing (Le Breton, Moyes and Trannoy 1996).

There are many of such schemes f that reduce citywide income inequality. Nor all schemes, however, have clear implications for NI. We require that the redistributive scheme reduces inequality irrespectively of the geography of incomes, that is NI must decrease for any possible income distribution and any spatial arrangement. To gain in robustness, we focus on those schemes that reduce NI at *any* distance threshold. The following proposition substantially restricts the class of admissible redistribution schemes.

Proposition 2 *The post-redistribution income distribution* $\mathbf{f} = (f(y_1), \ldots, f(y_n))$ *is such that* $NI(\mathbf{f}, d) \leq NI(\mathbf{y}, d)$ $\forall d$ *for any* $\mathbf{y} \in \mathbb{R}^n_+$ *and for any location of the* n *individuals if and only if* f *is a basic income flat tax scheme.*

The basic income flat tax scheme (BIFT) is a well-known example of redistributive linear income taxation: tax revenues are collected through a flat tax $1 - \beta$ and equally redistributed among all individuals as a basic income $\alpha > 0$ so that $f(y) = \beta y + \alpha$. All individuals with pre-tax income below the average receive a net benefit from redistribution, while the rest is a net contributor (for a review, see Atkinson 1996). Proposition

2 demonstrates that the BIFT scheme is the unique scheme f that relies exclusively on information about pre-redistribution *individual* incomes y (that is, f does not depend on the shape and geography of the income distribution) to produces post-redistribution incomes $f(y)$ that are less unequally distributed than $\mathbf{y}$, both at the city as well as at the individual neighborhood level.

This result is relevant for policy purposes, for instance, for a federal government targeting income inequality reduction across and within jurisdictions. The only tax instruments that guarantee to achieve the goal for all possible locations and income distributions across jurisdictions, as well as for every possible design of jurisdictions, should be based on a federal BIFT scheme. This result is also relevant for providing normative content to the analysis of neighborhood inequality changes, that we carry out in the next section.

3 Neighborhood inequality in American cities: 1980-2014

We make use of the NI index to investigate neighborhood inequality in the largest 50 American metro areas. In this way, we are able to understand underlying patterns and rank cities by the neighborhood inequality they display. Then, we provide stylized evidence on spatial inequality for all American cities for which reliable information is available. We use these estimates to study how neighborhood inequality is related to the features of the citywide income distribution.

3.1 Data

Our income database for years 1980, 1990 and 2000 is constructed from the US census data. 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. Due to anonimization issues, the STF 3A only reports summary tables of demographics and income distribution aggregates that are 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). 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, and income heterogeneity at the block group scale is widely unexplored.

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: aggregate income and households counts per income interval. 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. Estimates of incomes and household frequencies vary across block groups, implying strong heterogeneity within the city in block-group specific household gross income distributions.[12]

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 equivalent 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 years. All block groups are geocoded, and measures of distance between the block groups centroids can therefore be constructed. All income observations within the same block group are

[12]We refer to the online appendix for further details on the data and the estimation.

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 Statistical Area (MSA) provided in 2015. For each city-year we obtain an income database consisting of strings of incomes and frequency weights at each geocoded location on the map. Thus, weighted variants of the NI index estimators can be produced and neighborhood inequality can be meaningfully assessed in 381 MSA.

3.2 Patterns and trends of neighborhood inequality in the largest 50 MSA

We construct now neighborhood inequality curves for the 50 largest MSA in the US for the Census years 1980, 1990, 2000 and for the ACS module 2010/2014.[13] These are displayed in figure 2. At any given abscissa, heterogeneity in neighborhood inequality curves reflects differences in NI index across cities for neighborhood of comparable size. Trends of neighborhood inequality emerge when comparing the four panels in the figure.

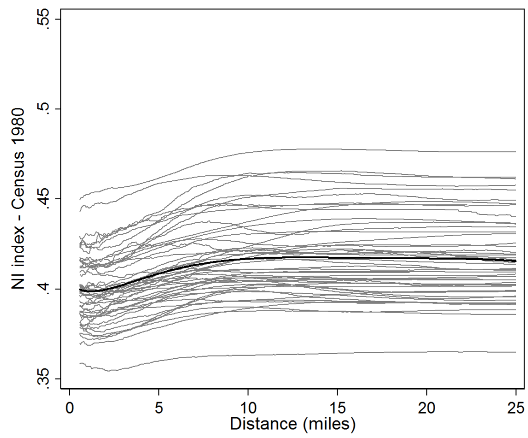
We highlight three stylized facts: First, neighborhood inequality is high (generally above 0.35 on a scale comparable to that of the Gini index) even when computed on individual neighborhoods of small size, below one mile diameter. This pattern is consistent over time, suggesting that income inequality within individual neighborhoods of small size closely matches the degree of dispersion in the income distribution at the city level.

Second, neighborhood inequality estimates display strong heterogeneity across the 50 largest US cities that persists over the four decades. Interestingly, heterogeneity has a predominant intercept effects on the neighborhood inequality curves, while the shape of the curves is only marginally affected. Data reveal mixed evidence of rank reversal of cities in terms of neighborhood inequality when the individual neighborhood size increases.

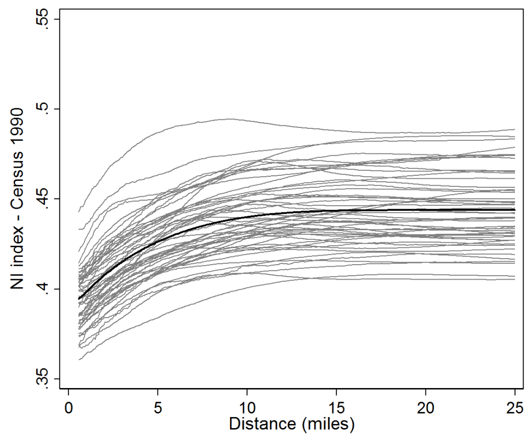
Third, neighborhood inequality has been constantly on the rise over the period 1980 to 2014, irrespectively of the size of individual neighborhoods. A fifth degree polynomial fit of the relation between NI measure and distance, whose predictions are represented by the black curves in the figures, portraits this general trend.

[13]The list of cities, ordered by their size, can be found in the online appendix, Section D.

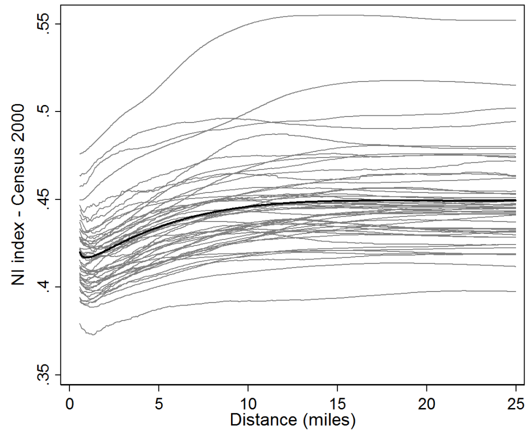
Figure 2: Neighborhood inequality (NI) index for 50 largest US MSAs



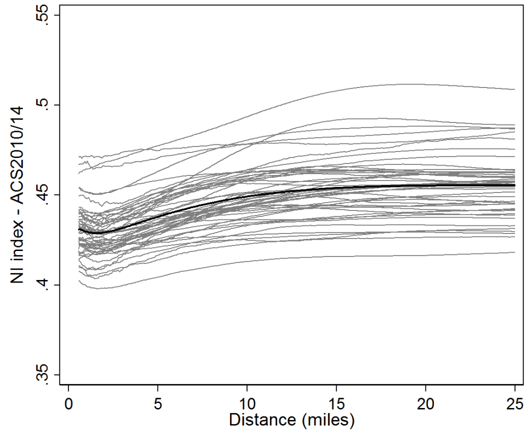
(a) Census 1980



(b) Census 1990



(c) Census 2000



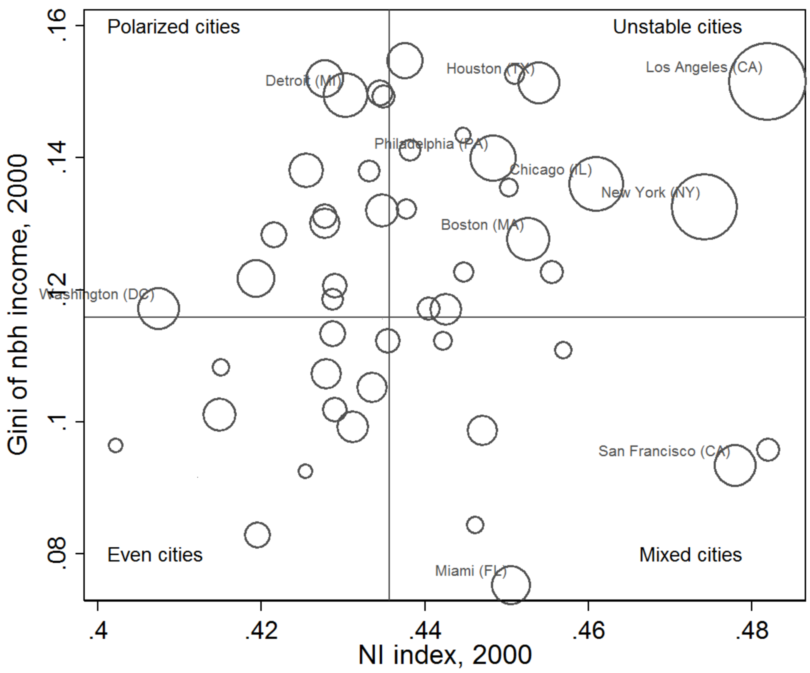
(d) ACS 2010/2014

Note: Authors analysis of US Census and ACS data.

The NI index is a relative inequality index, obtained by normalizing income heterogeneity at the individual neighborhood level by the average income therein. High and growing values of the NI index can provide a misleading picture of spatial inequality if, for instance, high income heterogeneity is paralleled by spatial stratification of high- and low-income households. Consistently with our approach, we propose to measure stratification by the Gini inequality index $G(\boldsymbol{\mu}_d)$ applied to the distribution $\boldsymbol{\mu}_d = (\mu_{1d}, \ldots, \mu_{nd})$ of average incomes estimated at the individual neighborhood level.[14] Differently from the

[14]The inequality index $G(\boldsymbol{\mu}_d)$ takes values on the $[0, 1]$ interval for any $\mathbf{y}$ and d. The index is equal to $G(\mathbf{y})$ when $d \approx 0$. It converges to zero when d approaches the size of the city. When plotted against d,

Figure 3: Taxonomy of the largest 50 US metro areas, Census 2000



Note: Authors analysis of 2000 US Census data. Estimates of NI and of the Gini index $G(\mathbf{y}, d)$ 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. High/low values of the indices are computed with respect to the a polynomial fitting of NI and the Gini index values across 50 largest US metro areas.

NI index, this Gini index relates closely to income segregation, summarizing the heterogeneity of average incomes across individual neighborhoods.

Patterns of inequality between neighborhood average incomes in the 50 largest US cities are detailed in the online appendix. The interesting finding is in the trends: while stratification has increased over the 1980s, it has substantially stabilized after 1990, differently from the NI index, always growing over this period.

Figure 3 shows that the NI and the $G(\boldsymbol{\mu}_d)$ indices capture different, and potentially unrelated, features of cross sectional neighborhood inequality over the 50 largest MSA in America. Based on the figure, we distinguish a taxonomy of four models for the spatial income distribution, generated by low/high levels of the NI and Gini indices in year 2000. Moving along the vertical axis, the $G(\boldsymbol{\mu}_d)$ index defines 'divided cities', where inequality is

the values of the index can be represented by a curve which is downward sloping, because neighborhood affluence μ_{id} tend to converge to μ as the neighborhood size d increases.

substantial and spatial sorting patterns of low and high income families tend to separate the two groups across the urban space.[15] The growing neighborhood inequality along the horizontal axis indicates "income mixed" neighborhoods. Four models of spatial inequality obtain by crossing the two dimensions.

The first model, illustrated by the example of Detroit, MI, is that of a "polarized city" where high values of the $G(\boldsymbol{\mu}_d)$ index are paired with low levels of neighborhood inequality. This model is characterized by high segregation of high and low income families in different areas of the city.[16]

Los Angeles, CA, New York City and Chicago, IL belong to the "unstable cities" model, displaying high levels of income segregation across neighborhoods and high neighborhood inequality. According to this model, the spatial income distribution is characterized by high variability of average incomes across individual neighborhoods altogether with high income heterogeneity within individual 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) and amplify the effects of income inequality.

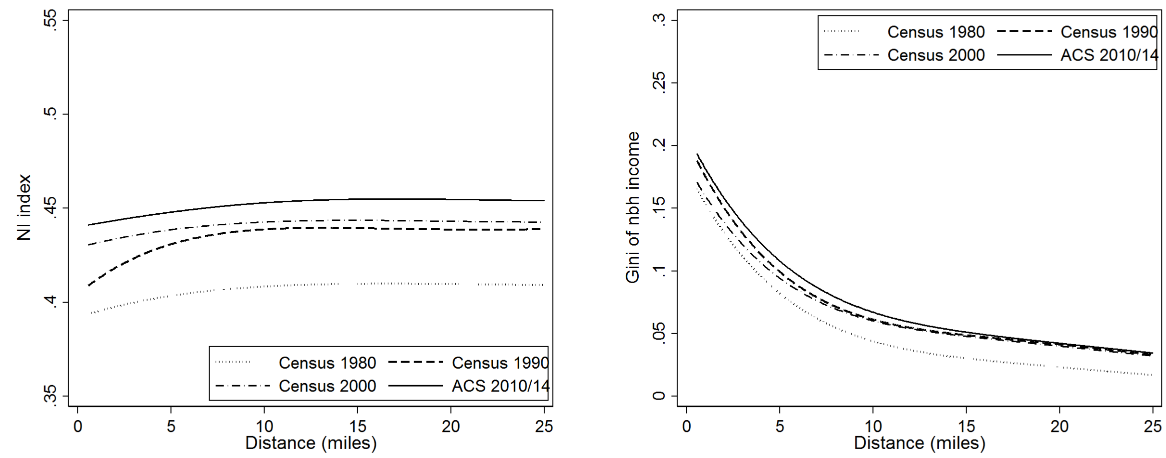
Among the largest cities, San Francisco, CA and Miami, FL belong to the "mixed cities" model, characterized by relatively similar individual neighborhoods across the urban space, implying low income segregation, which are highly heterogeneous in terms of local income distribution. The role of neighborhood inequality is prevailing in these cities. 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 et al. 2012).

None of the spatial income distributions in the 10 largest U.S. cities fits the "even city" model, where low levels of the Gini and the NI indices imply that inequality within

[15]The image of a "divided city" provided in the Habitat (2016) report (chapter 4) is discussed in van Kempen (2007)

[16]Duclos, Esteban and Ray (2004) describe polarization through the concept of alienation between groups. Alienation is stronger when groups are more homogeneous and cohesive (i.e., the lowest is inequality within neighborhoods) and more diverse (i.e., the highest degree is inequality between neighborhoods).

Figure 4: Neighborhood inequality (fitted curves), 1980, 1990, 2000 and ACS 2010/14, all US MSAs



(a) (b)

Note: Authors analysis of US census and ACS data. The curves report year-specific fifth degree polynomial fittings of NI and $G(\boldsymbol{\mu}_d)$ curves across all US metro areas.

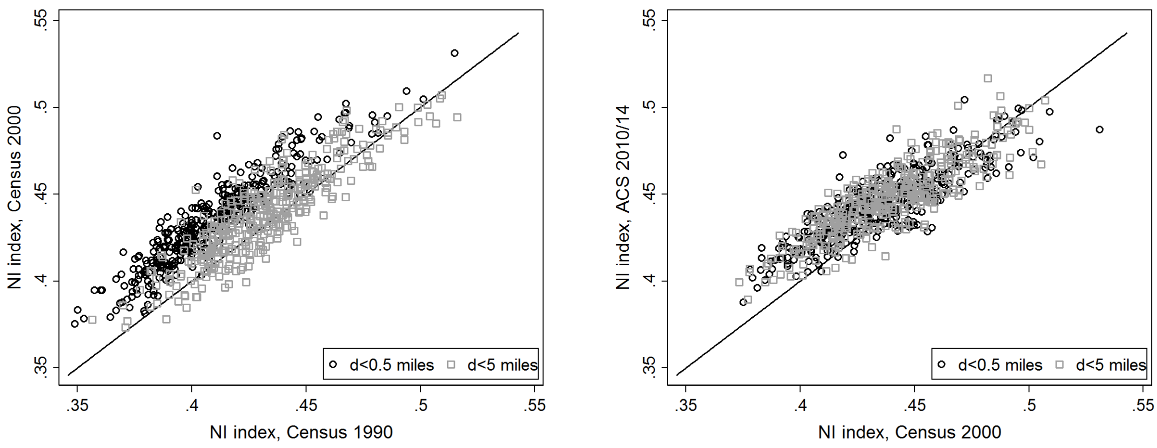
individual neighborhoods is low and neighborhoods resemble each other in terms of income composition (for a discussion of the *Just City*, see Fainstein 2010).

3.3 Neighborhood inequality across all American MSA

The patterns highlighted so far generalize to the rest of American MSAs. Figure 4 reports the predicted patterns of the NI index (left panel) and of the $G(\boldsymbol{\mu}_d)$ index (right panel), estimated from a polynomial interpolation of the neighborhood inequality curves and of the $G(\boldsymbol{\mu}_d)$ curves of the 381 American metropolitan areas. Trends illustrated in the first panel of the figure confirm the evidence so far. The raise in neighborhood inequality over 1980 to 1990 is contextual to the rise in inequality between neighborhood average incomes, as displayed in panel b) of figure 4.

In the following years (1990 to the ACS 2010/2014 coverage years), income inequality between individual neighborhoods has stabilized, while neighborhood inequality has been growing constantly. These trends might mirror the joint consequences of the changes in the income distribution and the effects of a recent wave of gentrification of wealthy and

Figure 5: Neighborhood inequality changes, all US MSA



(a) (b)

Note: Authors analysis of U.S. Census and ACS data. The solid line separates MSAs that have experienced positive (above the line) and negative (below the line) changes in NI. Estimates of the index are reported for individual neighborhoods of size smaller than 0.5 miles and 5 miles respectively.

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). High income households move closer to the middle class households, pricing out poor households from neighborhoods where urban poverty has been historically concentrated.

Trends of neighborhood inequality are highly heterogeneous across the 381 MSA. Figure 5 shows changes in neighborhood inequality from 1990 to 2000 Census Years (left panel) and from 2000 to ACS 2010/2014 (right panel).[17] Both panels of the figure highlight substantial heterogeneity in NI levels and changes. For small-sized individual neighborhood (of size $d < 0.5$ miles), the NI index has increased for all MSAs between 1990 and 2000, while in the following period it has also increased for the vast majority of the cities. Changes in NI are heterogenous, albeit strongly associated with NI level, implying only some reversals in the neighborhood inequality ranking of cities across the census and ACS waves. Heterogeneity in NI index levels and changes persists when neighborhood

[17]In what follows, we always differentiate between neighborhood inequality based on individual neighborhoods of maximum size 0.2 miles radius (in black) and 5 miles radius (in gray). Above 10 miles, the NI index always converges to citywide inequality.

inequality is estimated on individual neighborhoods of larger size (of size $d < 5$ miles). Interestingly, neighborhood inequality estimates in ACS 2010/14 coincide across distance ranges, bringing further evidence of convergence in distributional features of the income distribution observed in small individual neighborhoods towards the citywide distribution. It is hence likely that the trends of the NI index are driven by the implications of changing features of the household income distribution in the city, and only to a minor extent by changing patterns of income sorting across the city. This result places particular emphasis on the role that changes in citywide income distribution have in shaping the patterns and the trends of neighborhood inequality after 1990. The next section investigates this point more in detail.

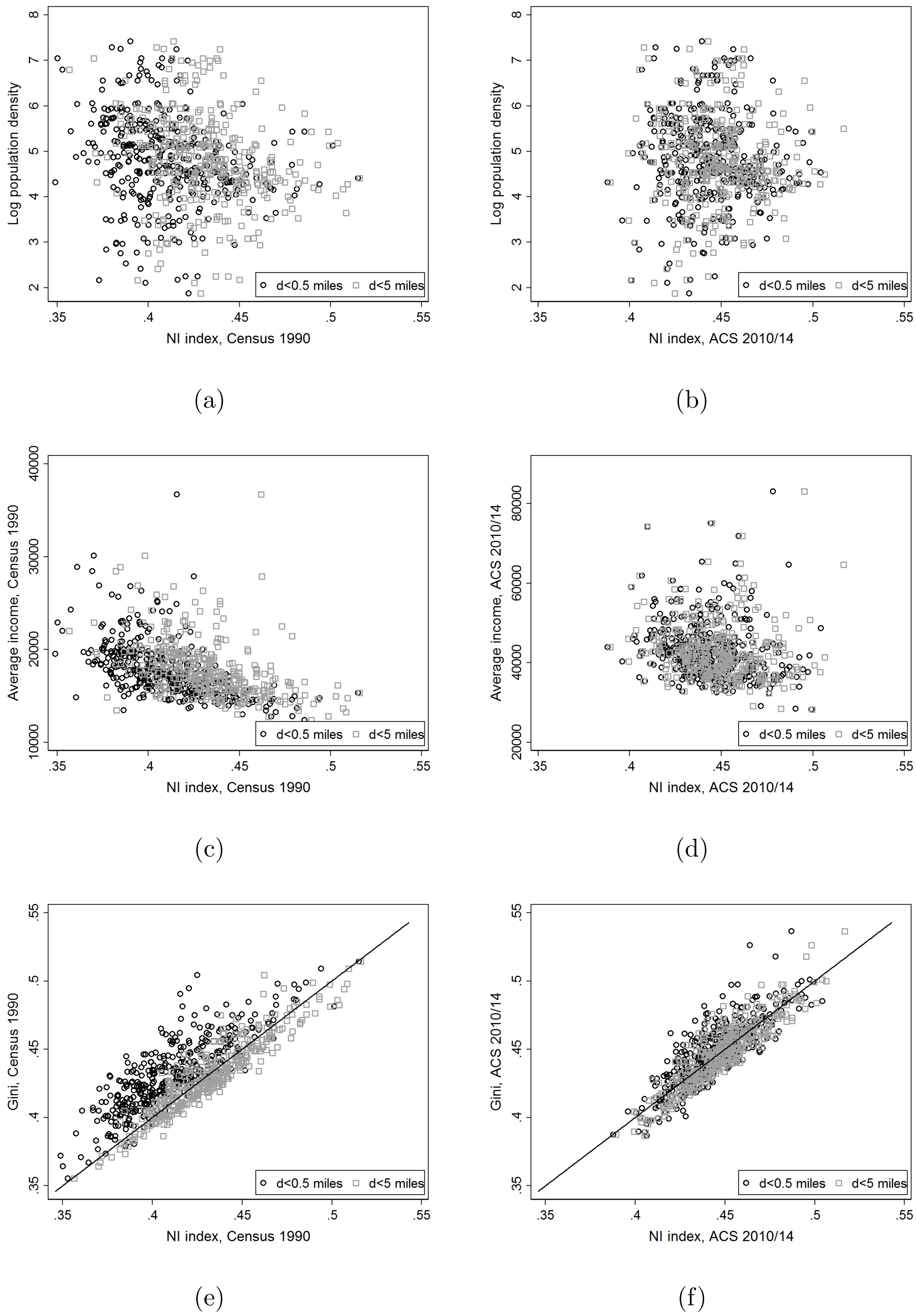
3.4 Neighborhood inequality and the urban income distribution

We use Census and ACS data to estimate moments of the citywide income distribution and investigate how these correlate with neighborhood inequality. In figure 6 we display results for the 381 MSAs to uncover relevant heterogeneity.

We focus first on aspects of the size of the citywide distribution, such as the population density (which relates to the way land is used) and the average equivalent household income at the MSA level. Both dimensions are not associated with heterogeneity in neighborhood inequality. Evidence is robust to the choice of the period (Census 1990 in panels a) an c) versus AS 2010/14 in panels b) and d)), as well as to the size of the individual neighborhood considered. Second, we relate the NI index estimates to income inequality (Gini index) in the city. The data reveal that neighborhood inequality is increasingly representative of citywide inequality. While panels e) and f) of figure 6 show that NI estimates based on small individual neighborhoods are positively but imperfectly associated with citywide inequality in census year 1990, the association becomes more precise in ACS.

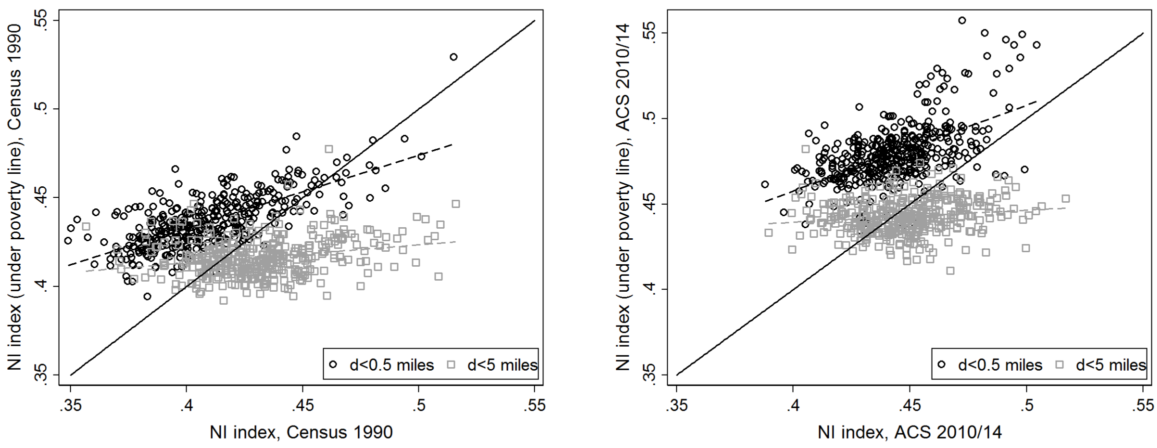
In presence of income stratification, neighborhood inequality estimates may differ along the income dimension. We compute the level of neighborhood inequality experienced by low and high income households separately. These indices are directly comparable with

Figure 6: Neighborhood inequality and the urban income distribution



Note: Authors analysis of US Census and ACS data. Estimates of MSA size were available only in census year 2000. The solid lines in panels e) and f) denote equality in NI and Gini of the urban income distribution.

Figure 7: Neighborhood inequality in the population and among the low-income households



(a) (b)

Note: Authors analysis of U.S. Census and ACS data. The solid line denotes equality in NI indices. The dashed lines are fitted.

the NI index baseline estimates. We focus first on neighborhood inequality experienced by poor households, with gross income below the need-adjusted federal poverty line in 1990 and 2014.[18] Figure 7 displays heterogeneity of MSA along the lines of the NI index for the subgroup of poor households and our baseline estimates. When estimated from individual neighborhoods of small size, the two indices display sizable (rank) cross-sectional correlation, in the range of 70% (65.8%) in 1990 and 55% (51%) in ACS. The correlation is slightly lower when considering NI index estimates based on individual neighborhoods of size less than 5 miles.

Households below the federal poverty line experience levels of neighborhood inequality that differ slightly from those of the average household of the city (baseline estimates), reflecting idiosyncratic characteristics of the neighborhoods where these household live,

[18]The neighborhood inequality experienced by this subgroup of household has been estimated as $\sum_i \frac{1}{P}\tau_i \Delta_i(\mathbf{y}, d)$, where Δ_i is as in (1), $\tau_i = 1$ if the representative equivalent household income observed in location i is below the poverty threshold τ and $P = \sum_i \tau_i$. The time series for the historical federal poverty thresholds by family size and number of children are from the US Census Bureau. To obtain poverty thresholds expressed in equivalent income units, actual poverty thresholds t_s have been equivalized by household size $s = 1, \ldots, 9$ weighted according to the demographic composition at the block group level (denoted π_s), so that $\tau = \sum_s \frac{t_s}{\sqrt{s}} \pi_s$.

such as the degree of poverty concentration therein (Iceland and Hernandez 2017). Nevertheless, the two indices largely agree on the *relative* magnitude of neighborhood inequality across cities. The federal poverty line defines a strong criterion to delimit the group of households in poverty, insofar the size and the relative economic condition of this group varies substantially across cities. In the online appendix we replicate the correlations in Figure 7 defining groups on the basis of the citywide income distribution. We find that the correlation between baseline NI estimates and levels of NI index for the group of individuals below the bottom quintile and the median, as well as above the median, are always above 90%, indicating that neighborhood inequality is relatively constant along the income distribution.

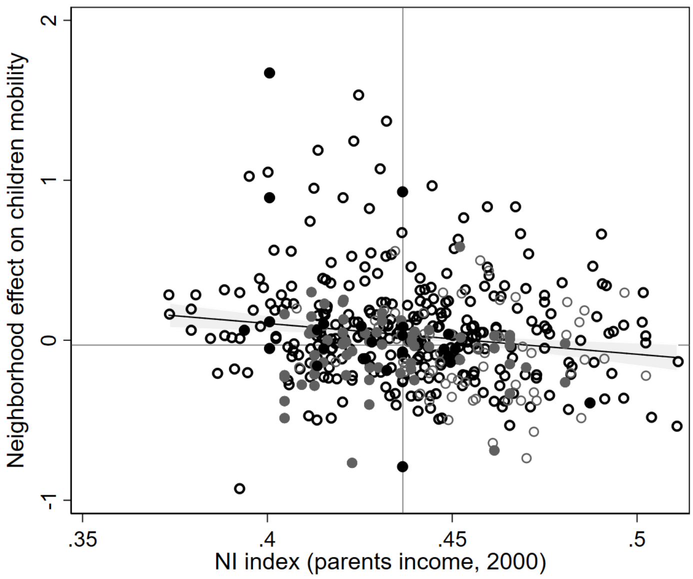
City-specific drivers of income inequality (related, for instance, to the features of the local labor market) have hence a prominent role in explaining the patterns of neighborhood inequality, as compared to city-specific neighborhood idiosyncracies. Findings that these correlations persist over time provides additional arguments in support of this conjecture. We rely on this evidence and propose to use cross-sectional heterogeneity of NI estimates across cities to identify the long terms consequences of rising neighborhood inequality. We do so in the next section.

4 Neighborhood inequality and intergenerational mobility

We investigate the consequences of rising neighborhood inequality in the *parents'* generation on the income opportunities of their *children* when adult.

Our first concern is to single out the causal effect of the place experienced during youth on income opportunities. This point is addressed in Chetty and Hendren (2018). They exploit quasi-experimental approximations and tax records data to identify the exposure effect to the place of residence during youth, estimated in terms of changes in percent rank occupied in the national household income distribution at age 26. We refer to these effects, available at Commuting Zone (CZ) level, as *intergenerational mobility gains*, since

Figure 8: Long run implications of neighborhood inequality on intergenerational mobility



Note: Data at Commuting Zone level are from Chetty and Hendren (2018). Neighborhood inequality estimates at distance range of two miles are based on the census 2000. The vertical gray lines correspond to average levels of NI index in 2000, while black (resp., gray) circles refer to cities with levels of inequality between average neighborhood incomes below (resp., above) the sample average for 2000 (see reading note Figure 4). The shaded area indicates the 95% confidence bounds of regression predictions.

they address specifically the income opportunities of the children raised in poor families (at the bottom quartile of the parental national income distribution).[19]

Estimates of mobility gains are based on children who moved across CZ during youth. Estimates are on the range of -1% to 2% (in percentile ranks) per year of exposure to the new environment. The overall effect, cumulated over the years of exposure, reflects the differences in earnings in the CZ of destination with respect to that of departure that a child expects to attain by moving in early age. Identification of these effects relies on the fact that the timing of the move is an exogenous treatment to the children, although potential for place effects vanishes after children reach their late teens (for further details, see Chetty and Hendren 2018).

We pair intergenerational mobility gains estimates at CZ level for children who are

[19]Formally, the effects estimated in Chetty and Hendren (2018) can be interpreted as the impact of spending one additional year of childhood in a CZ where children of permanent residents have 1% higher income ranks on the national household income distribution at age 24. These effects are collected in the Online Data Table 3 (variable *causal_p25_czkr26*) available on the authors' webpage.

26 or above in 2006-2014 with the corresponding level of neighborhood inequality experienced during youth, about year 2000.[20] We exploit heterogeneity in both mobility gains and NI index estimates across American cities to conclude that rising neighborhood inequality during childhood has a significant and negative effect on intergenerational mobility gains, as shown in figure 8. The figure is suggestive about the existence of a "Great Gatsby curve" relation between inequality and mobility that holds at the very low scale of the individual neighborhood. If causal, the implied correlation would be alarming in a context of rising neighborhood inequality. Nevertheless, mechanisms related to social interactions among neighbors or environmental and institutional factors (see for instance Leventhal and Brooks-Gunn (2000) and Ch. 12 in Shonkoff and Phillips (2000)) can provide explanations for this correlation beyond the effect of exogenously rising neighborhood inequality *per se*.

Our second concern is then to produce reliable estimates of the effect of rising NI index that do not reflect the implications of confounders and of potential simultaneity bias. In the rest of the section, we implement different strategies to cope with these issues.

4.1 Main effects

To measure the desired effects we rely on cross-sectional evidence from 450 CZ for which intergenerational mobility gains are available. We assign to each CZ the corresponding level of neighborhood inequality, estimated at the MSA level using 2000 U.S. Census data. CZ are aggregates of counties and it is frequent that largest MSA display several CZ.[21] The NI index has been normalized to have standard deviation equal to one across CZ in the full sample. The coefficients estimates from a linear regression model, reported in table 1, can hence be interpreted as the effect of one standard deviation increase in the NI index (approximatively 0.025 points) on the intergenerational mobility gains. These

[20]Mobility gains estimates refer to children born 1980-88 whose parents moved to another CZ in 1996-2012, i.e., when the children was nine or older. Neighborhood 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. An accurate description of data and sources is in the appendix.

[21]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 CZ based on the cross walk files.

regressions are based on the full cross-section of American CZ weighted by population size in year 2000, and can be interpreted under the (somehow stringent) hypothesis of homogeneity of the effect across American cities.

As expected, the raw effect (model (1) in table 1) is negative and significant. It reflects in size and sign the slope of the regression line in figure 8. We estimate that across American cities, a unit standard deviation increase in the neighborhood inequality index is associated with a significant decrease of 0.044 percent points of intergenerational 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 (as highlighted in Deaton and Lubotsky 2003). In model (2) we control for demographic factors such as population density, racial composition and racial segregation (measured by the dissimilarity index) at the CZ level. We do not detect relevant changes in 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).

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 CZ. These factors neglect the role of the urban income distribution at the moment that educational choices are made. 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 where public schools display large heterogeneity in quality, implying substantial effects on future intergenerational mobility patterns of students. We

	OLS					IV	
						FMW	RMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NIindex 2000	-0.044**	-0.034**	-0.029**	-0.046**	-0.040**	-0.382*	-0.431*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.20)	(0.26)
Controls:							
A) Demographics	-	y	y	y	y	y	y
B) Local finance	-	-	y	y	y	y	y
C) Education	-	-	-	y	y	y	y
D) Distribution	-	-	-	-	y	y	y
E) Regional fe	-	-	-	-	-	y	y
R-squared	0.048	0.128	0.148	0.227	0.331	.	.
MSA	449	449	449	318	262	244	244
Root MSE	0.182	0.175	0.174	0.194	0.182	0.249	0.268
First stage	-	-	-	-	-	6.743**	-2.476*
						(3.12)	(1.37)
R-squared	-	-	-	-	-	0.717	0.718

Table 1: Neighborhood inequality effects on intergenerational mobility gains.
Note: Based on authors' analysis of US Census 2000, CCD, PSS, CPS March Supplement and Chetty and Hendren (2018). The dependent variable is defined as in Figure 8. The NI index in 2000 is normalized by the cross-sectional standard deviation. Individual neighborhoods based on less than two miles radius. Significance levels: * = 10% and ** = 5%.

use the Common Core of Data and the Private School Survey[22] to gather information about 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. Since people can vote with their feet, variability in schooling inputs across neighborhoods may result from unobserved differences in wealth. Additionally, 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 effects making use of median rent values.[23] 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.

[22]The *Common Core of Data (CCD) Public Elementary/Secondary School Universe Survey* 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. The *Private School Universe Survey* (PSS) survey covers private schools in the U.S. that meet the NCES definition, and it is similar in content and structure to CCD. Due to data availability, we use CCD 2000/2001 and PSS 2003/2004 waves.

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

Model (5) includes the controls listed above. The estimated coefficient does not vary in size and significance from previous estimates. However, the effects of neighborhood inequality on intergenerational mobility gains can still suffer a simultaneity bias due to the way neighborhood inequality and mobility gains are jointly determined. Coefficients are expected to be biased towards zero. This may occur, for instance, if places with larger intergenerational mobility gains also offer greater access to high quality public services (such as education and health) have historical traditions and political support towards income redistribution. In this case, we expect to observe smaller citywide and neighborhood inequality. Intergenerational mobility gains may also be imperfectly measured, resulting in estimates of the parameter of interest of smaller magnitude. Our identification strategy relies on an instrumental variable strategy based on changes in minimum wage coverage across industries and cities. We propose a shift-share instrument which produce income shocks affecting the bottom of the income distribution. The instrument should produce shocks that are exogenous and relevant for the neighborhood income distribution. Furthermore, the instrument we consider is unlikely to correlate with behavioral responses if low-income households have reduced opportunity for sorting within and across cities.

4.2 IV estimates

Following Bartik (1991) and Blanchard and Katz (1992), we isolate shifts in local labor share coverage of minimum wage policies that come from national shocks on growth rates of industry-specific employment (for a review see Baum-Snow and Ferreira 2015). Minimum wage regulation affects the bottom of the income distribution and the intensity of its effect 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-specific employment. Identification leverages on the fact that these changes are exogenous to unobservable confounders correlated with inequality at the neighborhood level 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 by industry (as of 1980) in the city, under the assumption that coverage in 1980 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 CZ is captured by the percent share of workers in each CZ 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.[24] Let this share be MW_{ij}. The regional[25] 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, thus capturing the joint effect of changes labor supply skills and equilibrium wage adjustments.[26] Predicted minimum wage coverage at the CZ level in year 2000, denoted MW_i^{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, which gives $MW_i^{2000} = 1 - \sum_j MW_{ij} \cdot (1 + g_{j80/00})$.

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 CZ-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 in federal

[24]We use federal minimum wage to exclude correlations in minimum wage State regulation with unobservable characteristics of the CZ which may endogenously affect sorting behavior, hence invalidate the instrument. Historical Federal and State minimum wage regulation is from the US Bureau of Labor Statistics.

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

[26]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 distribution changes 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 (induced by $g_{j80/00} < 0$) on the predicted number of employees with an hourly pay below the minimum wage.

minimum wage over 1980 to 2000 (which increased nationwide 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: $RMW_i = ln(smw_{i1980}/smw_{i2000}) \cdot MW_i^{2000}$.

Identification rests on geographical variation in the instrument, and on the assumption that minimum wage regulation does not reflet patterns of wage inequality within one specific city. One potential drawback of the instrument is that in the period considered firms can adopt opportunistic behaviors by relocating labor-intensive productions in places with less tight minimum wage regulation. This behavior is likely related to poverty status of minimum wage recipients, as well as with the dynamics of regional labor market. Both dimensions contribute to define parental background circumstances and shape the local income distribution in 2000. We strengthen the exclusion restriction by controlling for poverty and income inequality within the city, and by introducing regional fixed effects. We also control for income segregation at MSA level, which is informative of the distribution of poor and rich people across the city neighborhoods.

Columns (6) and (7) of table 1 report the effect of one standard deviation increase in NI index in 2000 on intergenerational mobility gains after instrumenting neighborhood inequality with the FMW and the RMW instruments. In both cases, estimated effects are negative and significant (with p-values slightly larger than 5%), but larger in magnitude than previous estimates in models (1)-(5). The first stage coefficient of the FMW instrument in model (6) is positive, implying that a larger predicted minimum wage coverage increases neighborhood inequality.[27] These estimates are preferred to model (7), 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

[27]The positive sign of the coefficient is due to the the choice of standardizing the minimum wage coverage growth rate by the relative size of 1980 nominal federal minimum wage to 2000 nominal federal minimum wage, which is negative.

(hence explaining the negative first stage coefficient of RMW).

Our estimates show that an exogenous standard deviation increase in neighborhood inequality within a narrow individual neighborhood reduces by 0.38 percentage points the intergenerational mobility gains (measured in percentage ranks) of American children raised in poor families. We provide robustness checks in the Appendix, where we show that the effect is stable, although less significant, even when the notion of individual neighborhood is relaxed to include all neighbors within a range of six miles.

The effect expresses the consequences of reducing exposure to neighborhood inequality for just one year during childhood, as measured in terms of household income today. These effects cumulate over long periods of exposure and can produce substantial income gains. Consider, for instance, those exposed to neighborhood inequality in New York City during their childhood, about year 2000. Back then, the NI index was 0.435 Gini points. The effect of reducing the NI index by one standard deviation over five years of exposure would have cumulated into an expected \$770 (2015 prices) increase in gross household income for the "median" children when adult.[28] Or equivalently, a 1.5% income growth, comparable in magnitude to the intergenerational earnings effect of increasing the EITC coverage for low-income parents (Bastian and Michelmore 2018).

5 Concluding remarks

We make use of a rich and publicly accessible income database from the Census and the ACS to study patterns and trends of inequality among neighbors in American cities. Overall, we find that neighborhood inequality has been on the rise over Census 1990 to ACS 2010/14 for the vast majority of American MSA. Changes are strongly heterogeneous across cities but have similar directions. Across the years, individual neighborhoods of small size are replicating patterns of changes in neighborhood inequality estimates based

[28] The estimated effect of reducing the NI index by one standard deviation (approximately 0.025 points, or 5.7%) is 0.234 percentage points ($0.382 - 0.148$, the mobility gain for New York City), which cumulates to 1.17 points on the percentile rank scale in the national household income distribution after 5 years of exposure. The incomes for the median (\$52,102) and $51,17$ percentile (\$52,872) of the deflated household income distribution are from the 2012 CPS March supplement data (61,173 observations).

on larger size neighborhoods. The pattern of expansion of neighborhood inequality seems to have little to do with the size of the urban income distribution (based on density estimates and average incomes at MSA level) but are increasingly related to the structure of inequality in the city, which in ACS 2010/14 is well replicated even in individual neighborhoods of very small size.

Evidence from regression analysis suggests that a marginal increase in neighborhood inequality is detrimental for intergenerational mobility gains associated to the place of birth. The result provide evidence about a "Great Gatsby curve" type of relationship between inequality and intergenerational mobility at the level of the individual neighborhood. This result offers an argument leveraging on intergenerational fairness concerns in favor of urban redistribution policies that can help reducing neighborhood inequality and, indirectly, to promote opportunities for less advantaged children.

The analysis of this paper could be extended along several lines. For instance, the NI index allows to assess inequality in individual neighborhoods in dimensions other than income, such as ethnic origin, cultural affiliation and human capital attainment of the residents. An appropriate variant of the NI index can be then constructed to assess spatial segregation (see Mele 2013) or separation across these groups. Furthermore, the fact that the NI index can be computed and compared across population subgroups can be explored to infer the contribution of individual traits and of the geographic administrative partition on patterns and trends of neighborhood inequality. While drawing representative subgroups by socio-economic characteristics of the residents requires rich data with individual observations, Census and ACS data tables allow to produce neighborhood inequality estimates by school catchment areas, electoral districts or by fiscal jurisdictions. For instance, the territory of many MSA spans over two or more States and many counties. Differences in regulation and policies across administrative geographic units can provide valuable identifying information, which can be used to disentangle the contribution of different mechanisms on neighborhood inequality within the city, as well as to estimate its long-run consequences. These lines of research are left for further investigations.

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Supplemental Appendix
For Online Publication Only

So close yet so unequal: Neighborhood inequality in American cities

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Contents

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A Proofs and empirical properties

A.1 Proof of Proposition 1

Proposition 1 *If $\mathcal{F}_{\mathcal{S}}$ displays intrinsic stationarity and Y_s is gaussian with mean μ $\forall s$, then $NI(\mathcal{F}_{\mathcal{S}}, d) = \sum_{b=1}^{B_d} w_b \frac{\sqrt{\gamma(b)/\pi}}{\mu}$, where the distance spectrum $[0, d]$ is partitioned into B_d ordered intervals of fixed size d/B_d and w_b is a demographic weight of locations on $\mathcal{S}$.*

The proof is by construction. 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 $\mathcal{F}_{\mathcal{S}}$. 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 $\mathcal{F}_{\mathcal{S}}$, 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.

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 $\mathcal{F}_{\mathcal{S}}$ is said to display *intrinsic (second-order) stationarity* (see Chilès and Delfiner 2012) 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 (Matheron 1963). The function $2\gamma(h)$ 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.

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 $Cov[(Y_{s+h_1} - Y_s), (Y_{v+h_2} - Y_v)] = \gamma(s+h_1-v) + \gamma(s-(v+h_2)) - \gamma(s-v) - \gamma(s+h_1-(v+h_2))$ as in Cressie and Hawkins (1980) and Cressie (1991). Let first assume that the spatial data occur on a transect. Denote by s and v the position on the transect, and consider $s - v = h \geq 0$ where h indicates that the random variables are located within distance range h. The transect can be directional, implying that negative and positive distances carry relevant information when aggregated. Let $\delta_p = 1$ whenever $h_p > 0$ and $\delta_p = -1$ whenever $h_p < 0$, $p = 1, 2$. Under these circumstances: $Cov[(Y_{s+h_1} - Y_s), (Y_{v+h_2} - Y_v)] = \gamma(|h+\delta_1 h_1|) + \gamma(|h-\delta_2 h_2|) - \gamma(|h|) - \gamma(|h+\delta_1 h_1 - \delta_2 h_2|)$. If we further abandon directional information by assuming that locations are arranges so that $h_1 > 0$ and $h_2 > 0$ and adopt the convention that $\gamma(-h) = \gamma(h)$ (i.e. only the order but not the direction on the transect matters), covariance is identified as $Cov[(Y_{s+h_1} - Y_s), (Y_{v+h_2} - Y_v)] = \gamma(h + h_1) + \gamma(h - h_2) - \gamma(h) - \gamma(h + h_1 - h_2)$

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 $Var[|Y_{s+h} - Y_s|] = (1 - 2/\pi)2\gamma(h)$.

The NI index of the spatial process $F_{\mathcal{S}}$ can be written in terms of first order moments of the random variables Y_s as follows:[1]

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

The degree of spatial dependence represented by $F_{\mathcal{S}}$ enters in the NI formula through the expectation terms conditional on $\mathcal{S}$. We maintain the assumption that the spatial

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

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 ordered 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 listed assumptions (data are distributed on the transect, intrinsic stationarity of $F_{\mathcal{S}}$ and normality), the NI index rewrites:

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

which concludes the proof.

A.2 Proof of Proposition 2

Proposition 2 *i) The post-redistribution income distribution* $\mathbf{f} = (f(y_1), \ldots, f(y_n))$ *is such that* $NI(\mathbf{f}, d) \leq NI(\mathbf{y}, d)$ $\forall d$ *for any* $\mathbf{y} \in \mathbb{R}^n_+$ *and for any location of the* n *individuals if and only if ii)* f *is a basic income flat tax scheme.*

i)⇒ii). Since i) holds for any distribution $\mathbf{y}$, let consider the distribution with $n = 4$ individuals with incomes $y < \overline{y} < y + h$, $\mu = \overline{y} = \frac{y+y+h}{2}$ with $y, h > 0$ and $y_1 = y$, $y_2 = y_3 = \overline{y}$ and $y_4 = y + h$. Two individuals have income $\overline{y}$ and are located on the same point on the map, which is distant from the point where are located the other two individuals with incomes y and $y + h$. Consider neighborhoods of sufficient small size d so that $\Delta_2(\mathbf{y}, d) = \Delta_3(\mathbf{y}, d) = 0$ and $\Delta_1(\mathbf{y}, d) = \Delta_4(\mathbf{y}, d) = \frac{y+h-y}{y+h+y}$. To reduce the NI index after applying the redistributive scheme f we need $\frac{f(y+h)-f(y)}{f(y+h)+f(y)} < \frac{h}{2y+h}$. By taking the limit for $h \to 0$, we get $f'(y) < \frac{f(y)}{y}$ (i.e. f is starshaped from above, see Bruckner and Orstrow 1962), which is an equivalent condition to $\frac{f(y)}{y}$ being decreasing (i.e. the scheme is progressive, see Lambert 2001). Furthermore, since budget balance is required and the distribution $\mathbf{y}$ is symmetric, we have that $\sum_i f(y_i) = n\mu$ and $f(\overline{y}) = \mu$. It follows that $\frac{f(y)+f(y+h)}{2} = \mu = f(\overline{y}) = f(\frac{y+y+h}{2})$. This is the Jensen's functional equation, that is well-known to admit only affine solutions (see Theorem 1, p.43 in Aczel 1966). Hence $f(y) = \beta y + \alpha$. The scheme f is starshaped if and only if $\beta/\alpha > 0$, and hence BIFT.

ii)⇒i). Consider the difference

$$NI(\mathbf{f}, d) - NI(\mathbf{y}, d) = \sum_i \frac{1}{n} \sum_{j \in d_i} \left(\frac{|f(y_i) - f(y_j)|}{\sum_{j \in d_i} f(y_j)} - \frac{|y_i - y_j|}{\sum_{j \in d_i} y_j} \right)$$

for every d. The BIFT scheme is such that $f(y) = \beta y + \alpha$. Substituting above and collecting terms gives:

$$NI(\mathbf{f}, d) - NI(\mathbf{y}, d) = \sum_i \frac{1}{n} \sum_{j \in d_i} \left(\frac{\beta}{\beta \sum_j y_j + n_{d_i} \alpha} - \frac{1}{\sum_{j \in d_i} y_j} \right) \frac{|y_i - y_j|}{\sum_{j \in d_i} y_j}.$$

The fact that $\alpha > 0$ is sufficient to guarantee that the term in parenthesis is negative, which implies $NI(\mathbf{f}, d) \leq NI(\mathbf{y}, d)$ for every d irrespectively of the distribution $\mathbf{y}$ and the location of individuals.

A.3 Implementation of the NI index

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 size d, denoted 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 NI index, denoted $\hat{NI}(\mathbf{y}, d)$, 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

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

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

The estimation 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 the empirical applications, we estimate as many values of d as there are pairs of observations in distinct locations on the maps. For computational reasons, the NI index is 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 NI index converges to the Gini index. 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 $(d_k, \hat{NI}(\mathbf{y}, d_k))$ 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 neighborhood inequality curves.

B NI index trends and patterns: Additional results

B.1 Estimating the income distribution at block group level

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.

Data in the Census 1980, 1990 and 2000 are reported as population counts per income interval at the block group level. 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. There are 17 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. Information on population and total income at the block group level are also reported.

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. 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 should coincide with the observed average income observed in the data. Estimated medians for top income intervals are used as reference income levels, and empirical population counts as income weights. For robustness purposes, we estimate block-group level incomes using different methods, including GMM (preferred), quantile estimation as in Quandt (1966) or exploiting 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

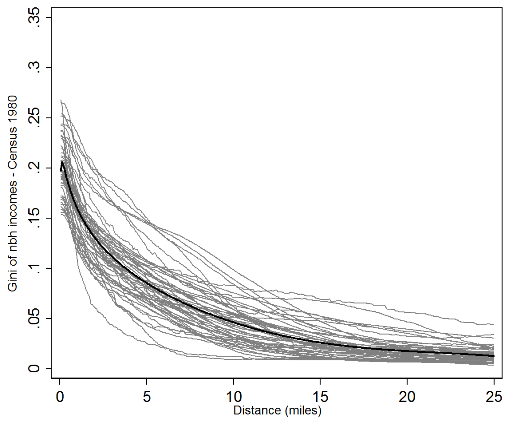
95.2% with quantile fitting income estimates (MSA-years population weighted correlations range between $min = 76\%$ and $max = 98.9\%$ across all MSA, with 95% of the correlations larger than 89.3%), and 90.4% average correlation with log-normal fitting income estimates at the block group level (MSA-years population weighted correlations range between $min = 45.6\%$ and $max = 97.1\%$ across all MSA, with 95% of the correlations larger than 85.1%). Estimates of incomes and household frequencies vary across block groups, implying strong heterogeneity within the city in block-group specific household gross income distributions.

B.2 Evidence on between neighborhood inequality patterns across the largest 50 US MSAs

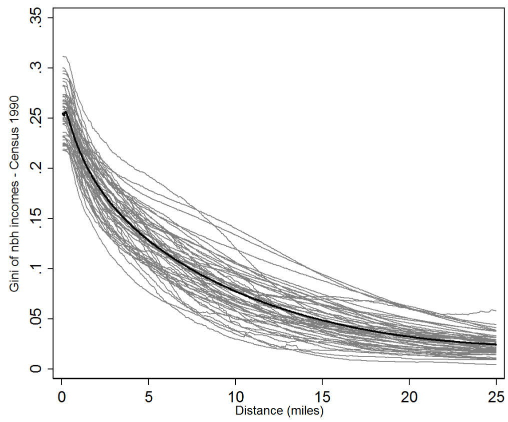
To understand the role of neighborhood affluence on neighborhood inequality, we compute the Gini inequality index for the average incomes estimated at the individual neighborhood level, denoted $\boldsymbol{\mu}_d = (\mu_{1d}, \ldots, \mu_{nd})$. This index is denoted $G(\boldsymbol{\mu}_d)$, and takes values on the $[0, 1]$ interval for any $\mathbf{y}$ and d. Formally, $G(\boldsymbol{\mu}_d) := \frac{1}{2n(n-1)\mu_d} \sum_i \sum_j |\mu_{id} - \mu_{jd}|$. The spatial component enters the problem in a non-trivial way. 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 place in the city, 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. Inequality between individual neighborhoods can be studied by plotting the values of $G(\boldsymbol{\mu}_d)$ corresponding to predefined levels of d.

Patterns of inequality between neighborhood incomes for each Census year for the 50 largest US cities are displayed in figure 1. We observe that, on the one hand, all panels confirm that inequalities between neighborhood incomes do not match citywide income inequality when evaluations are based on individual neighborhoods of very small size. The values of the Gini index for individual neighborhoods of size below one mile is virtually

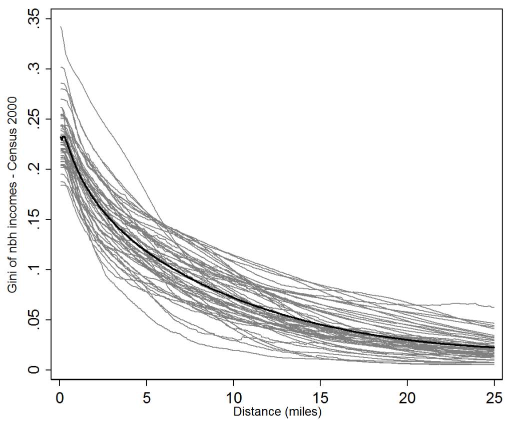
Figure 1: Inequality (Gini) of individual neighborhoods average incomes for 50 largest US MSAs



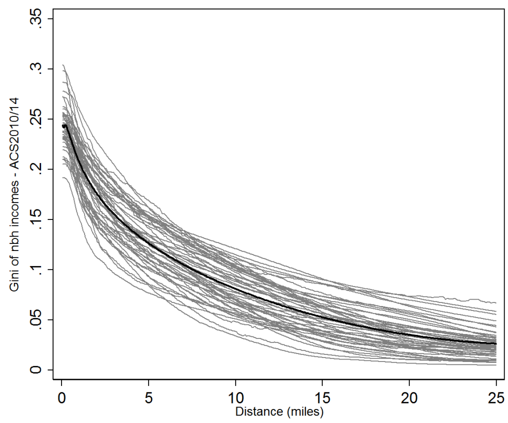
(a) Census 1980



(b) Census 1990



(c) Census 2000



(d) ACS 2010/2014

Note: Authors analysis of US Census and ACS data.

never above 0.3, far below the actual value of the Gini index in the 50 cities. This evidence is consistent with the presence of income segregation, despite only about half of the value expected in presence of strong income segregation across the cities block groups. On the other hand, the degree of inequality between neighborhoods income tend to persist when the neighborhood size increases, even above 5 miles radius. While we observe very similar patterns for all 50 largest US cities in all Census years, an in-depth scrutiny of the panels in figure 1 reveals that the index $G(\boldsymbol{\mu}_d)$ has substantially raised over the period 1980 to

1990, and has stagnated afterwards. These results are in line with Reardon and Bischoff (2011), who document the trends of income segregation across families grouped by their income levels (see Figure 3, p.16).

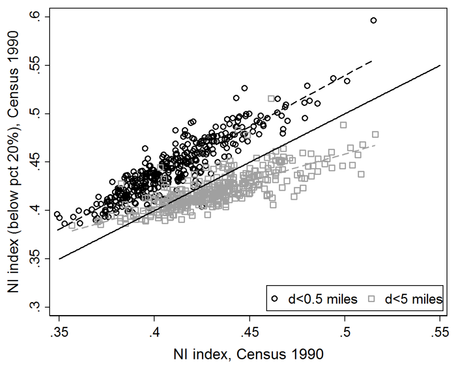
B.3 NI index for selected income groups

In figure 2 we plot the NI index computed for the whole population (our baseline estimates) and for selected subgroups of the households population. The subgroups are defined by income quintile of the citywide distribution of gross equivalent household income. We focus on three groups: households with income below the first quintile, denoted p20%, households with income below the median and households with income above the median.[2] In all cases, the income quintile that we use to define the groups refers to the equivalent household income distribution in the city. Differently from results that we report on the main paper, based on federal poverty lines, findings in figure 2 are hence relative to the income distribution observed in the city.

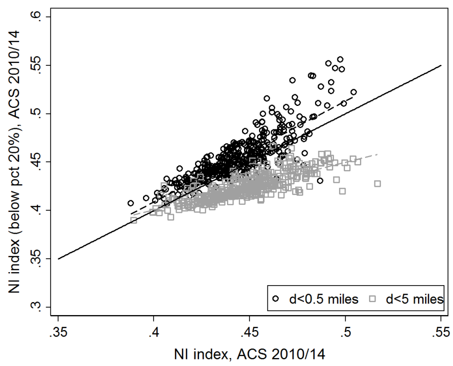
In panel (a) and (b) we study the relation between the NI index for the group of households with income below the city bottom quintile and the NI index baseline estimates. We find that the NI index estimates for this group is highly linearly associated to our baseline estimates, with (rank) correlation on the range of 91% (88%) in 1990 and 82% (82%) in the ACS module, for neighborhoods of size smaller than half a mile. Correlations are on the same range when neighborhood inequality is estimated on individual neighborhoods of larger size. The scatter plots in figure 2 confirm that baseline neighborhood inequality estimates are not affected by the degree of income heterogeneity observed in the neighborhoods where low-income households live, which tend to face the same level of neighborhood inequality as the average household in the city. The correlation we find is higher than those estimated when using the federal poverty line to define the low-income households group. In most affluent and less affordable cities, in fact, the federal poverty line may identify only the group of very deprived households, which might display a very

[2] The neighborhood inequality experienced by each subgroup of households is estimated as $\sum_i \frac{1}{T}\tau_i\Delta_i(\mathbf{y}, d)$, where Δ_i is as in Section 2 of the article, $\tau_i = 1$ if the representative equivalent household income observed in location i belongs to a specific income group, while $T = \sum_i \tau_i$.

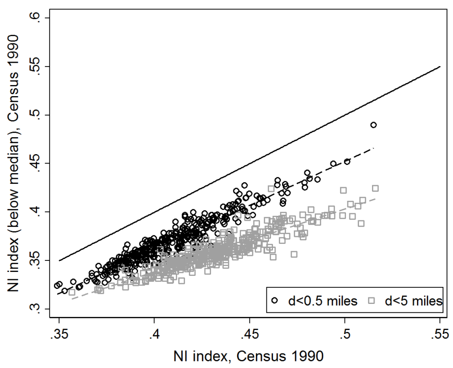
Figure 2: Neighborhood inequality in the population and among selected groups of households by gross equivalent income



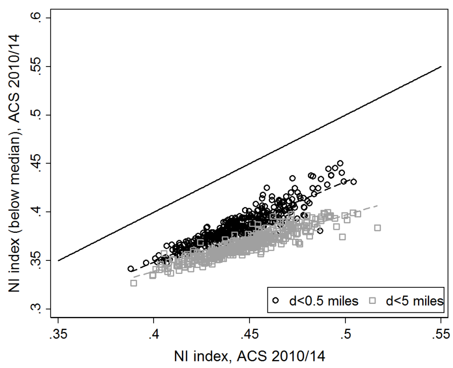
(a) Below p20%, 1990



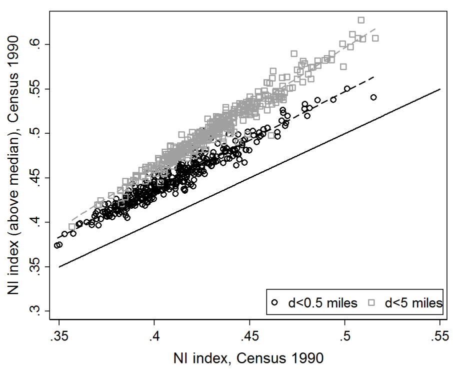
(b) Below p20%, 2010/2014



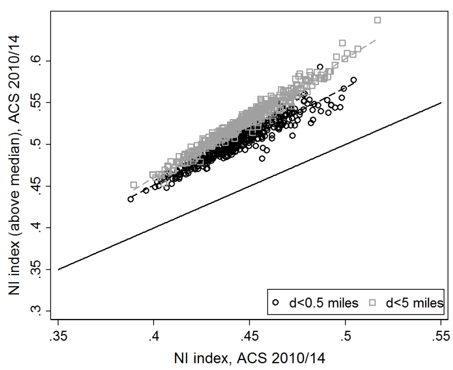
(c) Below median, 1990



(d) Below median, 2010/2014



(e) Above median, 1990



(f) Above median, 2010/2014

Note: Authors analysis of U.S. Census and ACS data. The solid line denotes equality in NI indices. The dashed lines are fitted. Bottom quintiles and median incomes are estimated for each MSA separately.

specific pattern of location dictated by housing affordability and proximity to labor market, rather than to sorting. Correlation estimates reported in the paper have hence to be interpreted as lower bounds for the group of low-income households. Conversely, using city-specific quantiles to define groups of households, we are able to design groups of low-income households relative to the income distribution observed in the same city. Finding that correlations are rising when using this group provides supports for the validity of our baseline estimates.

We replicate the exercise above focussing on the groups of household with income either below the citywide median (panels (c) and (d)) or above the citywide median (panels (e) and (f)). In both cases, correlations between baseline estimates of the NI index and estimates of the NI index conditional on the income subgroups are well above 90%. NI index estimates for the group of households with income below the median are smaller than the baseline estimates. Conversely, NI index estimates for the group of households with income above the median are larger than the baseline estimates. This evidence can be explained by fact that the equivalent household income distributions we consider are heavily right-skewed, implying that income heterogeneity above the median tend to be larger then income heterogeneity below the median. Individual neighborhoods based on income observations above the median tend to display larger income gaps compared to income observations below the median, and the difference is not offset by the average income registered in these individual neighborhoods, implying the patterns of NI we describe. In both cases, indices rank cities consistently.

Overall, we find evidence that NI levels differ slightly across income groups, although NI indices for these groups largely agree with our baseline estimates on the ranking of cities. In our evaluation of the effect of neighborhood inequality on intergenerational mobility, we rely on these findings and adopt our baseline estimates to infer neighborhood inequality experienced by children raised in low-income families, and explore variability across cities to identify the desired effects.

C 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 and rank mobility of long-term residents) have been made available in Chetty and Hendren (2018). 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). 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.[3]

The *intergenerational mobility gains* are taken from Chetty and Hendren (2018) (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 (2018) (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

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

	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 1: 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 (2018) and Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016). Controls are grouped by (A) Demographics, (B) Local finance, (C) Education, (D) Distribution and (F) Health indicators.

and have been raised from parents at the bottom income quartile of their respective income distribution. Across American CZ, rank mobility varies approximatively between 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 below 50%, the expected rank in the national income distribution in the absence of intergenerational transmission.

The treatment variable is spatial inequality measured by the NI index based on 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 NI 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 characteristics of the CZ. Summary statistics for controls used in our regression models are reported in Table 1. *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 (2018).

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 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 Distribution (panel D) controls allow to partial out observable determinants of distribution of households within the CZ. There are two groups of controls. The first group of controls is associated with distribution 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.[4] 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 possibly correlates 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 quality of life offered across neighborhoods. We use information on the distribution of income 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

[4]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).

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 (2018).

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 et al. (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. 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.* 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 4 of the main paper are reported hereafter. Table 2 is an extended version of regression results about mobility perspectives reported in the main text. Table 3 reproduces estimates in models (1)-(8) in Table 2 while using as treatment the NI index in 2000 (normalized by the full sample standard deviation) computed on individual neighborhoods of distance range smaller than six miles. Overall, sign and size of the coefficients in Table 3 are comparable to those reported in the main text. Tables 4 and Table 5 apply the same specifications of models (1)-(8) in Tables 2 and 3, 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 neighborhood inequality has weak effects for intergenerational rank mobility of long term residents after controlling for sorting.

	OLS					IV	
						FMW	RMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NIindex 2000	-0.044**	-0.034**	-0.029**	-0.046**	-0.040**	-0.382*	-0.431*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.20)	(0.26)
A) Pct black		-0.329**	-0.309**	-0.222	0.747	0.104	0.049
		(0.12)	(0.12)	(0.16)	(0.50)	(0.86)	(0.94)
A) Racial segregation		-0.196	-0.258*	0.141	-0.270	-0.413	-0.440
		(0.14)	(0.14)	(0.22)	(0.33)	(0.47)	(0.51)
A) Pop density (log)		0.010	-0.013	-0.056**	-0.052	-0.026	-0.018
		(0.01)	(0.02)	(0.02)	(0.03)	(0.07)	(0.07)
A) Pct foreign born		-0.442**	-0.473**	0.210	-0.777	-2.848*	-3.189*
		(0.10)	(0.14)	(0.23)	(0.54)	(1.58)	(1.94)
A) Migration flow		-1.684*	-2.086**	-4.672**	-0.707	-2.135	-2.373
		(0.90)	(0.93)	(1.31)	(2.65)	(4.11)	(4.47)
B) Avg tax rate			0.705	-0.213	-24.728**	-21.875	-21.431
			(3.73)	(5.09)	(12.13)	(16.53)	(17.71)
B) Fiscal revenues pc			0.113	0.135	0.931**	1.276**	1.322**
			(0.08)	(0.12)	(0.37)	(0.58)	(0.64)
B) Expenditure pc			0.000	0.000	-0.000	-0.000	-0.000
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B) Avg EITC exposure			0.001	-0.002	-0.002	0.002	0.002
			(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
C) Pub. school budget				0.000	0.014	-0.005	-0.007
				(0.02)	(0.02)	(0.04)	(0.05)
C) Students/teachers (pub.)				0.004	0.015	0.033	0.033
				(0.01)	(0.01)	(0.02)	(0.02)
C) Avg pub. school score				-0.000	0.000	-0.004	-0.004
				(0.00)	(0.00)	(0.01)	(0.01)
C) Avg dropout rate (pub.)				-2.386**	-0.957	0.838	1.019
				(0.86)	(1.05)	(1.50)	(1.68)
C) Pub. schoold pc				6.194**	6.055**	6.677	6.832
				(2.67)	(2.94)	(4.31)	(4.54)
C) Avg tuition				-0.000**	-0.000**	-0.000**	-0.000*
				(0.00)	(0.00)	(0.00)	(0.00)
C) Kindergartens(pub.)				0.238	0.061	0.149	0.160
				(0.19)	(0.21)	(0.29)	(0.32)
C) Students/teachers (priv.)				0.007	0.016	-0.004	-0.007
				(0.01)	(0.01)	(0.02)	(0.02)
D)Sd of students/teachers (priv.)					-0.011	-0.009	-0.008
					(0.01)	(0.01)	(0.01)
D) Sd of students/teachers (pub.)					0.009	0.021*	0.023
					(0.01)	(0.01)	(0.01)
D) Pct black students (pub.)					-0.821**	-0.776*	-0.787
					(0.32)	(0.46)	(0.50)
D) Pct violent crime					28.706	96.413*	106.716*
					(26.31)	(53.44)	(63.53)
D) Crimes pc					-14.359	-29.267*	-31.724*
					(8.71)	(15.17)	(17.45)
D) Median rent					-0.001	-0.001	-0.002
					(0.00)	(0.00)	(0.00)
D) Pct poors					1.684*	6.138*	6.802*
					(0.95)	(3.17)	(3.90)
D) Income segregation					2.683**	1.881	1.735
					(0.87)	(1.40)	(1.54)
D) Avg income					-0.000	-0.000	-0.000
					(0.00)	(0.00)	(0.00)
D) Gini index					-0.523	1.558	1.874
					(0.40)	(1.33)	(1.63)
$_{c}ons$	-0.035**	0.085	0.108	-0.016	0.386	-0.574	-0.709
	(0.01)	(0.06)	(0.09)	(0.22)	(0.50)	(0.91)	(1.05)
E) Regional fe	-	-	-	-	-	y	y
R-squared	0.048	0.128	0.148	0.227	0.331	.	.
MSA	449	449	449	318	262	244	244
Root MSE	0.182	0.175	0.174	0.194	0.182	0.249	0.268

Table 2: Neighborhood inequality 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 (2018). The dependent variable is defined as in the main text. $GINI_W$ 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	
						FMW	RMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NI index, 2000	-0.039**	-0.036**	-0.029**	-0.045**	-0.034	-0.599	-0.694
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.40)	(0.53)
A) Pct black		-0.316**	-0.303**	-0.201	0.761	-1.067	-1.321
		(0.12)	(0.12)	(0.16)	(0.50)	(1.62)	(2.01)
A) Racial segregation		-0.224*	-0.280**	0.079	-0.273	-0.395	-0.428
		(0.14)	(0.14)	(0.22)	(0.33)	(0.57)	(0.64)
A) Pop density (log)		0.009	-0.013	-0.055**	-0.054	0.028	0.047
		(0.01)	(0.02)	(0.02)	(0.03)	(0.10)	(0.13)
A) Pct foreign born		-0.472**	-0.512**	0.119	-0.781	-5.224	-6.024
		(0.10)	(0.14)	(0.22)	(0.55)	(3.53)	(4.65)
A) Migration flow		-1.727*	-2.111**	-4.615**	-0.584	-3.760	-4.315
		(0.90)	(0.93)	(1.31)	(2.66)	(5.33)	(6.16)
B) Avg tax rate			0.325	-0.191	-25.185**	-26.493	-26.732
			(3.73)	(5.12)	(12.15)	(18.84)	(20.96)
B) Fiscal revenues pc			0.115	0.129	0.924**	1.613**	1.726*
			(0.08)	(0.12)	(0.37)	(0.74)	(0.90)
B) Expenditure pc			0.000	0.000	-0.000	-0.000	-0.000
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B) Avg EITC exposure			0.001	-0.003	-0.002	-0.004	-0.004
			(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
C) Pub. school budget				0.003	0.016	-0.032	-0.039
				(0.02)	(0.02)	(0.06)	(0.07)
C) Students/teachers (pub.)				0.003	0.014	0.017	0.014
				(0.01)	(0.01)	(0.03)	(0.03)
C) Avg pub. school score				-0.001	-0.000	-0.005	-0.006
				(0.00)	(0.00)	(0.01)	(0.01)
C) Avg dropout rate (pub.)				-2.486**	-1.089	-0.318	-0.273
				(0.86)	(1.06)	(1.79)	(2.02)
C) Pub. schoold pc				6.146**	5.933**	6.292	6.409
				(2.68)	(2.95)	(5.21)	(5.73)
C) Avg tuition				-0.000*	-0.000**	-0.000	-0.000
				(0.00)	(0.00)	(0.00)	(0.00)
C) Kindergartens(pub.)				0.256	0.068	0.374	0.423
				(0.19)	(0.21)	(0.42)	(0.49)
C) Students/teachers (priv.)				0.007	0.016*	-0.011	-0.015
				(0.01)	(0.01)	(0.02)	(0.03)
D)Sd of students/teachers (priv.)					-0.011	0.001	0.003
					(0.01)	(0.02)	(0.02)
D) Sd of students/teachers (pub.)					0.009	0.032	0.036
					(0.01)	(0.02)	(0.03)
D) Pct black students (pub.)					-0.810**	-0.147	-0.060
					(0.33)	(0.80)	(0.96)
D) Pct violent crime					26.797	144.580	164.910
					(26.46)	(95.07)	(122.23)
D) Crimes pc					-13.590	-36.193	-40.331
					(8.73)	(22.14)	(27.37)
D) Median rent					-0.001	-0.002	-0.002
					(0.00)	(0.00)	(0.00)
D) Pct poors					1.705*	11.619	13.299
					(1.00)	(7.42)	(9.78)
D) Income segregation					2.535**	-1.246	-1.916
					(0.89)	(3.16)	(4.02)
D) Avg income					-0.000	-0.000	-0.000
					(0.00)	(0.00)	(0.00)
D) Gini index					-0.599	1.689	2.095
					(0.39)	(1.82)	(2.37)
$_cons$	-0.038**	0.099*	0.119	-0.025	0.397	-1.351	-1.637
	(0.01)	(0.06)	(0.09)	(0.22)	(0.50)	(1.53)	(1.92)
E) Regional fe	-	-	-	-	-	y	y
R-squared	0.033	0.128	0.146	0.224	0.327	.	.
MSA	450	450	450	319	263	245	245
Root MSE	0.184	0.175	0.174	0.195	0.182	0.316	0.354

Table 3: Neighborhood inequality 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 (2018). The dependent variable is defined as in the main text. $GINI_W$ 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	RMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$NIindex$ 2000	-0.576**	-0.356**	-0.235**	-0.502**	-0.272	-4.304*	-5.502*
	(0.14)	(0.10)	(0.09)	(0.12)	(0.18)	(2.41)	(3.34)
A) Pct black		-17.935**	-16.553**	-14.080**	-23.823**	-24.346**	-25.711**
		(1.27)	(1.17)	(1.44)	(4.35)	(9.49)	(11.68)
A) Racial segregation		-11.133**	-10.253**	-5.713**	-2.825	-3.498	-4.152
		(1.44)	(1.37)	(1.97)	(2.89)	(4.37)	(5.37)
A) Pop density (log)		0.474**	-0.397**	-1.077**	-1.329**	-1.525**	-1.335*
		(0.12)	(0.15)	(0.21)	(0.29)	(0.63)	(0.81)
A) Pct foreign born		4.726**	7.552**	12.109**	17.929**	-2.053	-10.396
		(1.03)	(1.40)	(2.08)	(4.68)	(18.20)	(24.86)
A) Migration flow		-44.760**	-49.751**	-64.235**	-14.063	-59.139	-64.942
		(9.59)	(9.09)	(11.79)	(23.18)	(43.12)	(51.46)
B) Avg tax rate			-140.775**	-92.025**	-358.698**	-191.832	-180.965
			(36.56)	(45.93)	(106.10)	(175.28)	(210.92)
B) Fiscal revenues pc			5.450**	4.249**	14.155**	12.871**	13.989*
			(0.82)	(1.08)	(3.20)	(6.05)	(7.54)
B) Expenditure pc			-0.001**	-0.001**	-0.001**	-0.001	-0.001
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B) Avg EITC exposure			0.159**	0.047	0.056	0.132**	0.137*
			(0.03)	(0.03)	(0.04)	(0.06)	(0.07)
C) Pub. school budget				0.110	0.037	-0.499	-0.557
				(0.16)	(0.20)	(0.43)	(0.52)
C) Students/teachers (pub.)				0.207**	0.392**	0.674**	0.658**
				(0.08)	(0.11)	(0.22)	(0.27)
C) Avg pub. school score				0.037	0.016	-0.009	-0.019
				(0.03)	(0.04)	(0.07)	(0.08)
C) Avg dropout rate (pub.)				-27.049**	-11.977	17.172	21.602
				(7.77)	(9.22)	(17.40)	(21.44)
C) Pub. schoold pc				27.912	20.361	49.903	53.680
				(23.07)	(25.72)	(37.56)	(44.86)
C) Avg tuition				0.000	-0.000	-0.000	-0.000
				(0.00)	(0.00)	(0.00)	(0.00)
C) Kindergartens(pub.)				-1.820	-3.257*	-2.671	-2.420
				(1.74)	(1.85)	(3.13)	(3.79)
C) Students/teachers (priv.)				0.390**	0.287**	0.195	0.138
				(0.06)	(0.08)	(0.18)	(0.24)
D)Sd of students/teachers (priv.)					0.121	0.083	0.101
					(0.07)	(0.10)	(0.13)
D) Sd of students/teachers (pub.)					-0.050	0.065	0.109
					(0.07)	(0.13)	(0.17)
D) Pct black students (pub.)					7.518**	2.779	2.505
					(2.84)	(5.27)	(6.36)
D) Pct violent crime					432.081*	1,234.632**	1,486.381*
					(230.25)	(628.24)	(831.07)
D) Crimes pc					-217.917**	-410.357**	-470.396**
					(76.26)	(164.87)	(213.12)
D) Median rent					-0.014**	-0.015	-0.018
					(0.00)	(0.01)	(0.01)
D) Pct poors					-10.006	42.281	58.504
					(8.31)	(36.90)	(50.59)
D) Income segregation					20.155**	8.225	4.670
					(7.60)	(14.47)	(17.89)
D) Avg income					-0.000*	-0.000	-0.000
					(0.00)	(0.00)	(0.00)
D) Gini index					-7.631**	15.864	23.574
					(3.46)	(16.01)	(21.77)
$_cons$	43.391**	45.708**	50.175**	44.797**	59.841**	44.976**	41.682**
	(0.14)	(0.61)	(0.93)	(1.94)	(4.39)	(10.31)	(13.36)
E) Regional fe	-	-	-	-	-	y	y
R-squared	0.034	0.592	0.661	0.720	0.787	0.336	0.014
MSA	450	450	450	319	262	244	244
Root MSE	2.853	1.863	1.707	1.755	1.589	2.541	3.097

Table 4: Neighborhood inequality 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 (2018). 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	
						FMW	RMW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NI index, 2000	-0.666**	-0.400**	-0.217**	-0.439**	-0.153	-7.313	-9.569
	(0.16)	(0.10)	(0.10)	(0.13)	(0.20)	(5.01)	(7.45)
A) Pct black		-17.737**	-16.524**	-13.860**	-23.158**	-39.144*	-45.209
		(1.27)	(1.18)	(1.47)	(4.39)	(20.56)	(28.63)
A) Racial segregation		-11.470**	-10.477**	-6.544**	-3.078	-3.836	-4.616
		(1.43)	(1.37)	(1.97)	(2.89)	(6.33)	(8.16)
A) Pop density (log)		0.464**	-0.386**	-1.024**	-1.278**	-0.696	-0.245
		(0.12)	(0.15)	(0.21)	(0.29)	(1.18)	(1.68)
A) Pct foreign born		4.401**	7.131**	10.692**	18.156**	-34.303	-53.396
		(1.02)	(1.37)	(2.03)	(4.86)	(43.86)	(64.87)
A) Migration flow		-45.857**	-50.279**	-65.107**	-13.483	-81.719	-94.977
		(9.58)	(9.10)	(11.86)	(23.25)	(59.39)	(77.78)
B) Avg tax rate			-143.127**	-91.740**	-363.581**	-252.841	-258.544
			(36.51)	(46.57)	(106.40)	(220.90)	(278.23)
B) Fiscal revenues pc			5.449**	4.270**	14.191**	17.810**	20.506*
			(0.83)	(1.10)	(3.21)	(8.72)	(12.05)
B) Expenditure pc			-0.001**	-0.001**	-0.001*	-0.001	-0.001
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B) Avg EITC exposure			0.158**	0.044	0.054	0.066	0.050
			(0.03)	(0.03)	(0.04)	(0.09)	(0.12)
C) Pub. school budget				0.093	0.026	-0.865	-1.040
				(0.16)	(0.20)	(0.66)	(0.88)
C) Students/teachers (pub.)				0.206**	0.389**	0.496	0.421
				(0.08)	(0.11)	(0.33)	(0.44)
C) Avg pub. school score				0.039	0.019	-0.026	-0.042
				(0.03)	(0.04)	(0.10)	(0.13)
C) Avg dropout rate (pub.)				-28.133**	-12.443	5.072	6.153
				(7.83)	(9.24)	(22.51)	(28.53)
C) Pub. schoold pc				27.853	19.395	44.647	47.441
				(23.28)	(25.80)	(56.02)	(70.81)
C) Avg tuition				0.000	-0.000	-0.000	-0.000
				(0.00)	(0.00)	(0.00)	(0.00)
C) Kindergartens(pub.)				-1.398	-3.115*	0.329	1.507
				(1.75)	(1.86)	(4.86)	(6.49)
C) Students/teachers (priv.)				0.391**	0.282**	0.073	-0.025
				(0.06)	(0.08)	(0.27)	(0.39)
D)Sd of students/teachers (priv.)					0.129*	0.214	0.272
					(0.07)	(0.18)	(0.25)
D) Sd of students/teachers (pub.)					-0.053	0.205	0.296
					(0.07)	(0.26)	(0.36)
D) Pct black students (pub.)					7.395**	10.485	12.544
					(2.86)	(10.49)	(14.05)
D) Pct violent crime					401.856*	1,907.674	2,392.916
					(231.70)	(1,183.21)	(1,709.60)
D) Crimes pc					-211.861**	-516.502*	-615.274
					(76.40)	(268.87)	(375.05)
D) Median rent					-0.014**	-0.020	-0.024
					(0.00)	(0.01)	(0.02)
D) Pct poors					-10.965	113.896	153.986
					(8.74)	(92.15)	(136.37)
D) Income segregation					19.747**	-30.596	-46.569
					(7.75)	(38.16)	(54.92)
D) Avg income					-0.000*	0.000	0.000
					(0.00)	(0.00)	(0.00)
D) Gini index					-8.758**	19.449	29.139
					(3.42)	(22.85)	(33.30)
$_{c}ons$	43.321**	45.851**	50.189**	44.524**	60.377**	34.869*	28.051
	(0.14)	(0.61)	(0.93)	(1.96)	(4.42)	(19.05)	(27.00)
E) Regional fe	-	-	-	-	-	y	y
R-squared	0.039	0.594	0.660	0.715	0.785	.	.
MSA	451	451	451	320	263	245	245
Root MSE	2.844	1.860	1.710	1.771	1.596	3.649	4.655

Table 5: Neighborhood inequality 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 (2018). 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 $^{**} = 5\%$.

D Statistics for 50 largest US MSAs

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 7: 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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