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

Francesco Andreoli† Eugenio Peluso‡

October 2018

Abstract

This paper contributes to the literature on neighborhood inequality along both theoretical and empirical lines. We introduce a new neighborhood inequality index to measure income inequality within individual neighborhoods of varying sizes, and study its normative and statistical properties. The neighborhood inequality 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 neighborhood inequality 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, census, ACS, intergenerational mobility, divided city, mixed city.


*We are grateful to Rolf Aaberge, Nathaniel Baum-Snow, Alberto Bisin, Martina Menon, Patrick Moyes, John Östh, Iñaki Permanyer, Alain Trannoy, Claudio Zoli and seminar participants at the Aix-Marseille University, Catholic University of Milan, Statale University of Milan, LISER, the 2017 Canazei Winter School, the RES Meeting (Bristol, 2017), The Spatial Dimension of Labor Market workshop (Mannheim, 2017), EMUEA (Copenhagen, 2017), the LAGV Conference (Aix-en-Provence, 2017), the ECINEQ Conference (NYC, 2017), EEA/ESEM (Lisbon, 2017) for valuable comments on a preliminary draft. Proofs, data description and additional results are collected in an online appendix, accessible from the authors’ webpages. This paper forms part of the research projects The Measurement of Ordinal and Multidimensional Inequalities (grant ANR-16-CE41-0005-01) of the French National Agency for Research and the NORFACE project IMCHILD: The impact of childhood circumstances on individual outcomes over the life-course (grant INTER/NORFACE/16/11333934/IMCHILD) of the Luxembourg National Research Fund (FNR), whose respective financial support is gratefully acknowledged. Eugenio Peluso thankfully acknowledges hospitality from LISER.

†(Corresponding author) Luxembourg Institute of Socio-Economic Research, LISER. MSH, 11 Porte des Sciences, L-4366 Esch-sur-Alzette/Belval Campus, Luxembourg. E-mail: francesco.andreoli@liser.lu.

‡DSE, University of Verona. Via Cantarane 24, 37129 Verona, Italy. E-mail: eugenio.peluso@univr.it.
1 Introduction

American cities are not all alike when it comes to income inequality (Watson 2009). In some cities, income inequality has skyrocketed over 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 heterogeneous 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), gentrification (Christafore and Leguizamon 2018) and the behavioral responses to other households’ location decisions (Schelling 1969, Parea 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 significant consequences both on objective dimensions of residents’ 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), the consequences of raising neighborhood inequality on children future opportunities and intergenerational mobility remain unexplored.

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, introducing bias due to the Modifiable Areal Units Problem (see Openshaw 1983, Wong 2009). We study neighborhood inequality developing instead upon 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. 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.

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 and the Community Survey publicly available data to obtain a rich, georeferenced, 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 neighborhoods have become increasingly representative of the income distribution in the city. An exhaustive description of main findings is in Section 3.

1Hardman 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.

2An 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.
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 a positive spillover effect 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. 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.

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

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 \( i = 1, \ldots, n \). Let \( y_i \in \mathbb{R}_+ \) be the income of individual \( i \) and \( y = (y_1, y_2, \ldots, y_n) \) 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 \( d \). 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

\footnote{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).}
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). 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 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:

$$\Delta_i(y, d) = \frac{1}{\mu_{id}} \sum_{j \in d_i} \frac{|y_i - y_j|}{n_{id}}.$$  \hfill (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 $\Delta_i$ across the whole population of the city:

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

---

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

8
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 $y$ and $d$. Moreover, $NI(y, d) = 0$ 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 $NI(y, \infty) = G(y)$. Otherwise, when $d$ approaches zero, one expect individual neighborhoods to be singletons and $NI(y, 0) = 0$. 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 flat when the individual neighborhood size is big compared to the geographic scale of the city.

Neighborhood inequality rankings of cities across space or time can be accomplished by comparing neighborhood inequality curves. At any distance threshold $d$, cities can

---

6Despite its clear connection with the Gini index, $NI(y, d)$ can take values that are either larger or smaller than $G(y)$. 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., $NI(\cdot, d) = 1$ for $d$ small) and larger than citywide inequality.

7When 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.
be ranked according to the level of neighborhood inequality implied by $NI(\cdot,d)$. These rankings may contradict each other 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 $s \in S$ denote an income process distributed over the random field $S$, which serves as a model for the relevant urban space. Incomes are jointly distributed as $\mathcal{F}_S$. 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 $NI(\mathcal{F}_S,d)$ that applies to the underlying income process.

Under fairly standard assumptions about the characteristics of the spatial income process, 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

---

8We 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, Chiles and Delfiner 2012). See the online appendix for a detailed discussion.
of the citywide income distribution.

**Proposition 1** If \( \mathcal{F}_S \) displays intrinsic stationarity and \( Y_s \) is gaussian with mean \( \mu \forall s \), then \( NI(\mathcal{F}_S, d) = \sum_{b=1}^{B_d} w_b \sqrt{\gamma(b)/\mu} \), 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 \( S \).

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. Furthermore, the NI index is linear in normalized mean income gaps $\Delta_i$. As a consequence, the NI index can be directly applied to 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.

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

---

9Direct 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 estimates. Both properties are satisfied through standardization of the income gaps in (2) by individual neighborhood-specific population counts and average incomes.

10This 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.
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. City C can be obtained from 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

\[\text{\textsuperscript{11}}\text{Notice that Anonymity (also called symmetry) is a necessary condition for Schur-convexity, a mathematical property satisfied by all inequality indices consistent with the PD transfer principle (see Marshall and Olkin 1979, p.54).}\]
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 \( f = (f(y_1), \ldots, f(y_n)) \) is such that \( NI(f, d) \leq NI(y, d) \) \( \forall d \) for any \( y \in \mathbb{R}^n_+ \) 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 \( y \), 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

¹²We refer to the online appendix for further details on the data and the estimation.
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 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. These are displayed in figure 2. At any given abscissa, heterogeneity in neighborhood inequality

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.

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.

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 $G(\mu_d)$ applied to the distribution $\mu_d = (\mu_{1d}, \ldots, \mu_{nd})$ of average incomes estimated at the individual neighborhood level$^{14}$ Differently from the 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

---

$^{14}$The inequality index $G(\mu_d)$ takes values on the $[0, 1]$ interval for any $y$ and $d$. The index is equal to $G(y)$ when $d \approx 0$. It converges to zero when $d$ approaches the size of the city. When plotted against $d$, the values of the index can be represented by a curve which is downward sloping, because neighborhood affluence $\mu_{id}$ tend to converge to $\mu$ as the neighborhood size $d$ increases.
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 $G(y, d)$ 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.

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 $G(\mu_d)$ 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 $G(\mu_d)$ index defines ‘divided cities’, where inequality is substantial and spatial sorting patterns of low and high income families tend to separate
the two groups across the urban space. 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 $G(\mu_d)$ 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.

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

\[\text{The image of a “divided city” provided in the Habitat 2016 “World cities report” (chapter 4) is also discussed in van Kempen (2007)}\]

\[\text{Duclos, Esteban and Ray (2004) describe polarization through the concept of alienation between groups. Alienation is stronger when groups are more homogeneous and cohesive (i.e., the lowest is inequality within neighborhoods) and more diverse (i.e., the highest degree is inequality between neighborhoods).}\]
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 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 $G(\mu_d)$ index (right panel), estimated from a polynomial interpolation of the neighborhood inequality curves and of the $G(\mu_d)$ 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 skilled people from suburbia to inner city (the “Great Inversion” hypothesis proposed
Figure 4: Neighborhood inequality (fitted curves), 1980, 1990, 2000 and ACS 2010/14, all US MSAs

![Graph showing neighborhood inequality](attachment://graph.png)

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

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). 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

---

17In 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.
Figure 5: Neighborhood inequality changes, all US MSA

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.

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 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
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) and 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 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
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

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

1990 and 2014. 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 $\sum_i \frac{1}{P} \tau_i \Delta_i(y, d)$, where $\Delta_i$ is as in \([1]\), $\tau_i = 1$ if the representative equivalent household income observed in location $i$ is below the poverty threshold $\tau$ 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 $\pi_s$), so that $\tau = \sum_s \frac{t_s}{\sqrt{s}} \pi_s$. 

---

27
such as the degree of poverty concentration therein (Iceland and Hernandez 2017). Never-
theless, 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 they address specifically the income opportunities of the children raised in poor families (at the bottom quartile of the parental national income distribution).\(^\text{19}\)

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,\(^\text{19}\))

\(^{19}\)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 \(\text{causal}_{p25\_czkr26}\)) available on the authors’ webpage.
We pair intergenerational mobility gains estimates at CZ level for children who are 26 or above in 2006-2014 with the corresponding level of neighborhood inequality experienced during youth, about year 2000.\textsuperscript{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

\textsuperscript{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.
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. 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 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

---

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.
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 use the Common Core of Data and the Private School Survey\textsuperscript{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

\textsuperscript{22}The \textit{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 \textit{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.

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>NIindex 2000</td>
<td>-0.044** (0.01)</td>
<td>-0.034** (0.01)</td>
</tr>
<tr>
<td>Controls:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A) Demographics</td>
<td>- y y y y y y y</td>
<td></td>
</tr>
<tr>
<td>B) Local finance</td>
<td>- - y y y y y y y y</td>
<td></td>
</tr>
<tr>
<td>C) Education</td>
<td>- - y y y y y y y y</td>
<td></td>
</tr>
<tr>
<td>D) Distribution</td>
<td>- - y y y y y y y y</td>
<td></td>
</tr>
<tr>
<td>E) Regional fe</td>
<td>- - - y y y y y y y</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.048 0.128 0.148 0.227 0.331</td>
<td>. .</td>
</tr>
<tr>
<td>MSA</td>
<td>449 449 449 318 262 244</td>
<td>244 244</td>
</tr>
<tr>
<td>Root MSE</td>
<td>0.182 0.175 0.174 0.194 0.182</td>
<td>0.249 0.268</td>
</tr>
<tr>
<td>First stage</td>
<td>- - - - 6.743** -2.476*</td>
<td>(3.12) (1.37)</td>
</tr>
<tr>
<td>R-squared</td>
<td>- - - - 0.717 0.718</td>
<td></td>
</tr>
</tbody>
</table>

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%.
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.\footnote{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.} We also include controls for the presence and intensity of
crime events in the city, an important measure of quality of life conditions in the most
distressed areas of the city.

Model (5) 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 in-
come 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. Fur-

\footnote{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.}
thermore, 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\textsuperscript{24}. Let this share be $MW_{ij}$. The regional 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\textsuperscript{26}. Predicted minimum wage coverage at the CZ level in year 2000, denoted $MW_{i2000}$, 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 $MW_{i2000} = 1 - \sum_j MW_{ij} \cdot (1 + g_{j80/00})$.

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

\textsuperscript{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.

\textsuperscript{25}We consider U.S. regions as defined in the CPS: Northeast, Midwest, West and South Regions.

\textsuperscript{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: $FMW_i = \ln(3.10/5.15) \cdot MW_{i2000}$. The second specification further exploits changes in minimum wage regula-
tions 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: $RMW_i = 
\ln(smw_{i1980}/smw_{i2000}) \cdot MW_{i2000}$.

Identification rests on geographical variation in the instrument, and on the assump-
tion that minimum wage regulation does not reflect patterns of wage inequality within
one specific city. One potential drawback of the instrument is that in the period consid-
ered 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 ef-
fects. 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 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. 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 (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. Or equivalently, a 1.5% income growth,

\(^{27}\) 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.

\(^{28}\) 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
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 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 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).
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.
References


