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Theory and evidence from American cities

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Urban poverty:
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Abstract

The concentrated poverty index, i.e. the proportion of a metro area's poor population living in extreme-poverty neighborhoods, is widely adopted as a policy-relevant measure of urban poverty. We challenge this view and develop a family of new indices of urban poverty that, differently from concentrated poverty measures, i) capture aspects of the incidence and distribution of poverty across neighborhoods and ii) are grounded on empirical evidence that living in a high-poverty neighborhood is detrimental for many dimensions of residents's well-being. We demonstrate that a parsimonious axiomatic model that incorporates these two aspects characterizes exactly one urban poverty index. We show that changes of this urban poverty index within the same city are additively decomposable into the contribution of demographic, convergence, re-ranking and spatial effects. We collect new evidence of heterogeneous patterns and trends of urban poverty across American metro areas over the last 35 years and use city characteristics to identify relevant drivers.

Keywords: Concentrated poverty, axiomatic, decomposition, census, ACS, spatial.
JEL codes: I32, D31, P25.

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1 Introduction

Cities are the most unequal places in America (Moretti 2013, Baum-Snow and Pavan 2013). Over the last three decades, income inequality has increased substantially in most of American metro areas (Watson 2009), albeit with heterogenous trends. Inequality within and across neighborhoods is also substantial (Wheeler and La Jeunesse 2008) and increasingly related to the patterns and trends of inequalities in the city as a whole, with low and high income households increasingly living in close spatial proximity (Andreoli and Peluso 2018).

Poverty in American cities has evolved accordingly. The urban poor population, i.e. the individuals living in families with aggregate income below the federal poverty line and living in urbanized areas, has increased from 25.4 mln in 1980 to 31.1 mln in 2000 and up to 43.7 mln in the 2012-2016 period (estimates based on Census and American Community Survey data), which corresponds to about 11% of the population before 2000, rapidly increasing to 14.9% after the Great Recession. The geography of poverty has also evolved over the period. The number of census tracts displaying extreme poverty (where at least 40% of the population is poor) has almost doubled since 2000 (2,510 to 4,412 in 2013), offsetting demographic growth (the overall number of census tracts increased by 11% during the same period). The growth of poverty is concentrated in some neighborhoods of the city. In fact, the population living in high-poverty neighborhoods nearly doubled since 2000, the increase being underway before the Great Recession. Most of these changes have occurred in metro areas of population size smaller than 1 million (Jargowsky 1997, Jargowsky 2015).

These trends have contributed to the re-emergence of *concentrated poverty*. First proposed by Wilson (1987), concentrated poverty is defined as the share of a metro area's poor population that lives in high or extreme poverty neighborhoods. Jargowsky and Bane (1991), Jargowsky (1997), Kneebone (2016) and Iceland and Hernandez (2017) have documented the dynamic and drivers of concentrated poverty across American metro areas. After declining in the 1990s, concentrated poverty has increased in the last two decades from about 11% to 14.1% in the largest 100 metro areas. Patterns are heterogenous across metro areas and depend on differences in the size, geographic location, income inequality alongside the degree of income and ethnic

segregation in the city (Massey, Gross and Eggers 1991, Iceland and Hernandez 2017).

The degree of concentrated poverty is supposed to measure the proportion of the poor population that likely suffers an additional burden from poverty (besides being poor), which can be traced down to the high concentration of poor residents in the neighborhood where they live. Empirical works provide estimates of this double burden of concentrated poverty on many relevant outcomes (see also Oreopoulos 2003). Living in extreme poverty neighborhoods has causal negative consequences on health outcomes (Ludwig et al. 2011, Ludwig et al. 2013), on labor market attachment (Conley and Topa 2002), on individual well-being (Ludwig et al. 2012) and on the economic opportunities of future generations (Chetty, Hendren and Katz 2016, Chetty and Hendren 2018).

From a normative perspective, it is reasonable to require that any measure of urban poverty must increase (i.e. measure more urban poverty) when the share of poor population living in extreme poverty neighborhoods rises, even if this increment originates from a reduction of the incidence of poverty in neighborhoods where poverty is less extreme. This requirement is consistent with a social welfare representation where individual well-being depends on household characteristics (such as poverty status) alongside the proportion of poor in the neighborhood (as in Bayer and Timmins 2005), and well-being is decreasing in this proportion. The larger the share of population exposed to high-poverty neighborhoods, the stronger the welfare effect, implying rising urban poverty. We provide counterexamples showing that the concentrated poverty index does not obey this intuitive principle (see also Massey and Eggers 1990, Jargowsky 1996), rising concerns about its relevance for welfare analysis.

This paper addresses these concerns and contributes with a new framework for urban poverty measurement that is inspired by inequality analysis and is consistent with the intuitive requirement outlined above. As a starting point, we introduce a parsimonious axiomatic model that incorporates relevant normative properties for the analysis of urban poverty. We develop an ordinal approach (as in Sen 1976) for urban poverty measurement to demonstrate that the axiomatic model we propose characterizes a unique urban poverty index, which aggregates information about the incidence, intensity and distribution of poverty across the city neighborhoods. When

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evaluations of urban poverty are required to be sensitive even to low poverty concentration (and not only to extreme concentration), the urban poverty index is shown to coincide with the Gini inequality index for the distribution of poor population shares across the city neighborhoods. We conclude that urban poverty is maximal when there are neighborhoods displaying a very high proportion of population that is poor and neighborhoods that are virtually poverty-free. Urban poverty is zero when poverty is evenly distributed across the city neighborhoods. In this case, there is no welfare gain in moving a poor person out of an extreme poverty neighborhood, since poverty is evenly concentrated everywhere across the city.

We show that the urban poverty index is additively and non-parametrically decomposable along different dimensions, notably space and time. In this way, we can assess whether urban poverty is mostly driven by neighborhoods that are spatially clustered, unveiling local poverty traps that can potentially reinforce the double burden effects of poverty concentration, distinguishing from the case where urban poverty is idiosyncratic to the neighborhoods characteristics. Moreover, we can linearly decompose changes in urban poverty across time within the same city into the contributions of citywide poverty incidence, of changes in population density across neighborhoods, of convergence of poverty incidence across neighborhoods, and of re-ranking of neighborhoods ordered by the incidence of poverty therein.

We use our measurement apparatus to assess the dynamics of poverty across all American metro areas over the last 35 years exploiting rich data from the Census and the American Community Survey. Our main findings are that: i) American MSA display strong heterogeneity in urban poverty patterns; ii) urban poverty has not evolved significantly over the 35 years and has been hardly affected by the Great Recession burst, contrary to the rising trends of concentrated poverty; iii) Both re-ranking and convergence components of urban poverty changes are substantial across MSA, indicating the role of changes in neighborhood poverty composition; iv) the spatial component of urban poverty is negligible for the large majority of cities, but very significant in largest MSA where clustering of high-poverty neighborhoods seems to be an issue; v) ethnic segregation, the distribution of income and of housing values within the city (jointly defining the degree of affordability of a given neighborhood) are major drivers of urban poverty.

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The paper is organized as follows. In Section 2 we propose our normative model and provide the main results. The decomposition of the urban poverty index is analyzed in Section 3. Section 4 reports results from our study of urban poverty in American metro areas. Section 5 concludes with a discussion.

2 Measuring urban poverty

2.1 Setting

We consider a partition of the urban space into n neighborhoods. In empirical analysis, neighborhoods can coincide with an administrative division of the territory, such as the partition of American cities into census tracts. We take the partition into neighborhoods as given, and we study the distribution of poor and non-poor people therein.

Let $i \in \{1, \ldots, n\}$ indicate a neighborhood. There are N_i individuals in neighborhood i and $N = \sum_{i=1}^{n} N_i$ individuals in the city. An individual is poor when living in a household whose total disposable income is lower than an exogenous poverty line (such as the federal poverty threshold provided by the American Census Bureau), calculated in a given year for that specific type of family. The analysis of urban poverty is hence conditional on the definition of poverty status, which we take as given (based on 100% federal poverty line). We use P_i to denote the number of individuals that are poor and live in neighborhood i, while $P = \sum_{i=1}^{n} P_i$ denotes the total number of poor in the city. The *urban poverty configuration*, denoted $\mathcal{A}$, $\mathcal{B}$,..., is a collection of counts of poor and non-poor individuals distributed across neighborhoods and it is denoted $\mathcal{A} = \{P_i^{\mathcal{A}}, N_i^{\mathcal{A}}\}_{i=1}^{n}$. In what follows, a configuration always represents a city in a given year, and we use superscripts to indicate a specific urban poverty configuration only when disambiguation is needed.

The ratio $\frac{P_i}{N_i}$ measures the incidence of poverty in neighborhood i. The ratio $\frac{P}{N}$ measures instead the incidence of poverty in the city, and is equivalent to the average of poverty incidences across neighborhoods, weighted by population density, i.e. $\frac{P}{N} = \sum_{i=1}^{n} \frac{N_i}{N} \frac{P_i}{N_i}$. The number $\frac{P}{N}$ defines an interesting cutoff point, discriminating between neighborhoods where the poor are over-represented, and neighborhoods where the poor are under-represented compared to

the relative incidence of poverty in the city. In a more general setting, we use $\zeta \in [0,1]$ to define a *urban poverty line*, i.e. a cutoff point identifying those neighborhoods where poverty is over-concentrated. The urban poverty line incorporates normative judgement about tolerance to poverty concentration, with $\zeta \approx 0$ (respectively, $\zeta \approx 1$) indicating high (low) priority to neighborhoods displaying some poverty therein. If $\frac{P_i}{N_i} \geq \zeta$, then i is addressed to as a high concentrated poverty neighborhood, where the proportion of residents in that neighborhood that are poor is larger than the threshold ζ.

For a given urban poverty line ζ, neighborhoods can be ranked according to the incidence of poverty therein:

$$\frac{P_1}{N_1} \geq \frac{P_2}{N_2} \geq \ldots \geq \frac{P_z}{N_z} \geq \zeta \geq \ldots \frac{P_n}{N_n}.$$

For simplicity, the labels $1, 2, \ldots, n$ are assumed to coincide with the rank of the neighborhoods, ordered by decreasing magnitude of poverty incidence. Among all neighborhoods in the metro area, we identify with z the neighborhood where poverty incidence coincides (or is approximately as large as) the urban poverty line. This neighborhood z will serve as a benchmark: the poor are over-represented in neighborhood i if and only if $i \leq z$.

2.2 A relative urban poverty line

The choice of the cutoff poverty line ζ may be consistent with absolute or relative notions of urban poverty. Poverty literature (Ravallion 2008, Ravallion and Chen 2011, Marx, Nolan and Olivera 2015) strongly advocate for relative concepts of poverty lines. We endorse this view as well in the analysis of urban poverty, so that differences in poverty incidence accross metro areas can be controlled for in cross-city comparisons. The urban poverty cutoff ζ is assumed to be proportional to the citywide poverty incidence, $\frac{P}{N}$, scaled by a positive real coefficient α, so that

$$\zeta = \alpha \frac{P}{N}. \tag{1}$$

The coefficient α expresses a normative view about sensitivity of urban poverty to the incidence of poverty in the city. Larger values of α imply that urban poverty evaluations should focus on

Figure 1: Urban poverty curve and concentrated poverty

(a) Concentrated poverty

(b) A measurement issue
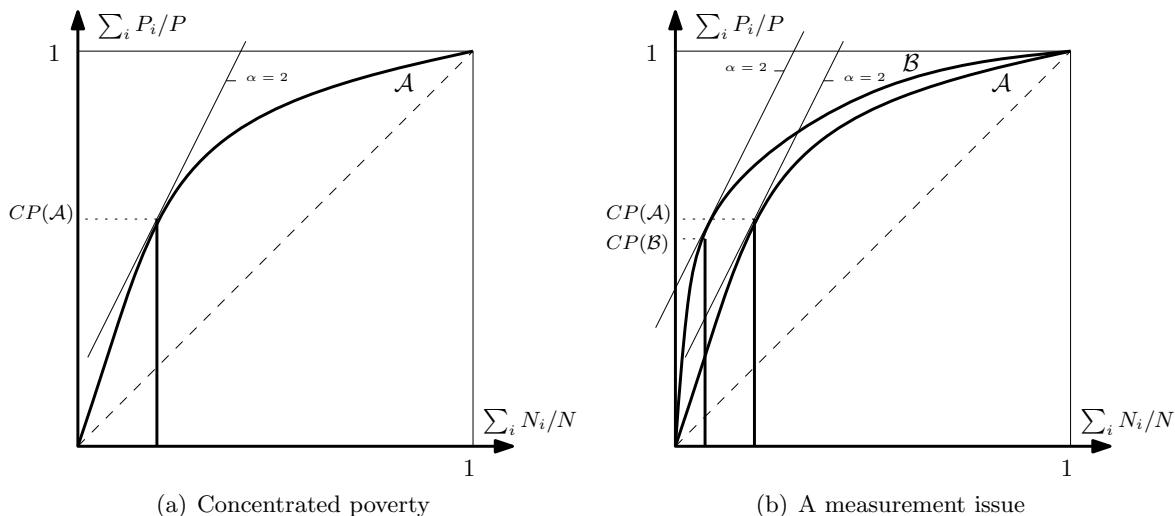
Note: CP index values (vertical black solid lines) for two configurations $\mathcal{A}$ and $\mathcal{B}$.

neighborhoods where poverty is highly concentrated. For instance, poverty incidence among the poorest American cities is approximatively 20%. By setting $\alpha = 2$, the focus is on urban poverty originating from those neighborhoods where more than 40% of the residents are poor. Conversely, small values of α put the emphasis on the distribution of poverty across the neighborhoods. Comparisons of urban poverty across cities are conditional on the relative poverty threshold α, which is held constant across cities.

2.3 Concentrated poverty and its critical aspects

A convenient way to represent the distribution of the poor population in the city is to plot the cumulative proportion of the poor against the proportion of the overall population living in the neighborhoods displaying higher incidence of poverty, i.e. ranked by decreasing $\frac{P_i}{N_i}$. The cumulative proportion of poor people in neighborhood j is given by $\sum_{i=1}^{j} \frac{P_i}{P}$ and the cumulative proportion of residents therein is $\sum_{i=1}^{j} \frac{N_i}{N}$. Consider plotting the points with coordinates $\left(\sum_{i=1}^{j} \frac{N_i}{N}, \sum_{i=1}^{j} \frac{P_i}{P} \right)$ with $j = 1, \ldots, n$ on a graph. The curve starting from the origin and interpolating these points is the *urban poverty curve*. The urban poverty curve of an hypothetical configuration $\mathcal{A}$ is reported in panel (a) of Figure 1. Its graph is concave and always lies above

the unit square diagonal, implying that in configuration $\mathcal{A}$ there are neighborhoods with poverty incidence smaller than $\frac{P}{N}$ and other neighborhoods with poverty incidence greater than $\frac{P}{N}$.[1]

The lack of intersections of urban poverty curve is a natural criterion to rank distributions by the degree of urban poverty they display. If the urban poverty curve of configuration $\mathcal{B}$ lies nowhere below and somewhere above that of $\mathcal{A}$, then any proportion of the population living in high-poverty neighborhoods in $\mathcal{B}$ displays systematically larger incidence of poverty than the corresponding proportion in $\mathcal{A}$.

We can relate this curve to the measurement of urban poverty in a city. Literature has focused on a particular aspect of urban poverty, denoted *concentrated poverty*. It is measured by the index $CP := \sum_{i=1}^{z} \frac{P_i}{P}$ where $\frac{P_z}{N_z} \approx \zeta$, which is the proportion of poor people who live in high-poverty neighborhoods. According to the American census, concentrated poverty corresponds to the proportion of poor residents that live in census tracts where at least 40% of inhabitants fall below the poverty line (i.e., $\zeta = 0.4$).

The index CP can be related to the urban poverty curve: it is, in fact, the level of the curve corresponding to the proportion $\sum_{i=1}^{z} \frac{N_i}{N}$ of the city population living in neighborhoods where at least 40% of residents are income-poor. The index CP is calculated on the basis of an absolute urban poverty line. A relative version of the index, denoted $CP(\mathcal{A}; \alpha)$, can be constructed in a similar way and employed to compare cities that differ in poverty incidence. In this case, the urban poverty line is $\alpha \frac{P^{\mathcal{A}}}{N^{\mathcal{A}}}$ for a city with a configuration of urban poverty $\mathcal{A}$, and it changes across configurations depending on poverty incidence in the city. Consider now a city where $\frac{P^{\mathcal{A}}}{N^{\mathcal{A}}} = 0.2$ and $\alpha = 2$, which gives $\zeta = 0.4$ from (1) (implying that concentrated poverty calculations based on an absolute or a relative urban poverty threshold coincide). The coefficient α gives the slope of a line tangent to the urban poverty curve, as in Figure 1, panel a). The tangent point identifies the neighborhood z displaying poverty incidence of about $\alpha \frac{P^{\mathcal{A}}}{N^{\mathcal{A}}}$, the relative urban poverty threshold. The length of the vertical line segment on the same figure

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[1]This curve can be interpreted as the Lorenz curve of the distribution of poor population proportions $\frac{P_i}{N_i}$ across the city neighborhoods, each weighted by $\frac{N_i}{N}$. The curve of a configuration in which poor people are evenly spread across neighborhoods of the city, that is $\frac{P_i}{N_i} = \frac{P}{N}$ for every neighborhood i, coincides with the unit square diagonal. For simplicity, we assume that the city has many neighborhoods that differ in terms of poverty shares, so that the urban poverty curve appears smooth.

corresponds to the concentrated poverty index.

The concentrated poverty index might miss important aspects of the distribution of poverty across the city neighborhoods and, as a consequence, it may rank cities inconsistently with non-intersecting urban poverty curves. Panel b) of Figure 1 draws an example. In the figure we consider two configurations $\mathcal{A}$ and $\mathcal{B}$ where $\frac{P^{\mathcal{B}}}{N^{\mathcal{B}}} = \frac{P^{\mathcal{A}}}{N^{\mathcal{A}}}$. The distribution of poverty across the neighborhoods of city $\mathcal{B}$ is more uneven than in city $\mathcal{A}$, in the sense that in $\mathcal{B}$ a larger fraction of the poor population is concentrated in high poverty neighborhoods, compared to $\mathcal{A}$. As a consequence, the urban poverty curve of the former lies always above that of the latter. Nonetheless, $CP(\mathcal{B}, \alpha) < CP(\mathcal{A}, \alpha)$ as shown in the figure for $\alpha = 2$.

The example above highlights a weakness of concentrated poverty, already identified by Massey and Eggers (1990) who suggest valuing the intensity *and* the distribution of poverty in the city. The approach they propose, based on mixtures of dissimilarity and interaction indices, is interesting and related to the urban poverty curve ordering, but not clearly connected with the underling principle that urban poverty induces a double welfare burden on people exposed to poverty concentration.

The approach to urban poverty measurement we propose in this paper is inspired by social welfare and inequality analysis, and is based on the *Gini coefficient* $G(.; \alpha)$ of the distribution of poverty proportions $\frac{P_1}{N_1}, \ldots, \frac{P_z}{N_z}$ across neighborhoods of the city, where neighborhood z is such that $\frac{P_z}{N_z} \approx \alpha \frac{P}{N}$. For a given configuration, the index writes:

$$G(.; \alpha) \quad := \quad \frac{1}{2 \sum_{i=1}^{z} P_i / \sum_{i=1}^{z} N_i} \sum_{i=1}^{z} \sum_{j=1}^{z} \frac{N_i N_j}{\left(\sum_{i=1}^{z} N_i\right)^2} \left| \frac{P_i}{N_i} - \frac{P_j}{N_j} \right|. \qquad (2)$$

The index $G(.; \alpha)$ is related to the area comprised between the urban poverty curve and the unit square diagonal, up to a proportion $\sum_{i=1}^{z} \frac{N_i}{N}$ of the overall population. In what follows, we provide an axiomatic model for urban poverty that explicitly incorporates normative judgments about the welfare implications of concentrated poverty. Our main result states that the *unique* index of urban poverty consistent with the setting is the index $G(\mathcal{A}) := G(\mathcal{A}; 0)$

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2.4 Characterization of a family of urban poverty measures

A urban poverty index is a function $UP : \mathcal{P} \to \mathbb{R}_+$ (with $\mathcal{P}$ the set of urban configurations) assigning to each configuration a number, interpreted as the level of urban poverty in that configuration. We write $UP(\mathcal{A}; \alpha)$ to explicitly recall that evaluations of urban poverty are conditional on a relative urban poverty line. Every urban poverty index should obey a simple monotonicity principle:

Axiom *A1 (Monotonicity)* *An increase of the proportion of poor people in a neighborhood i where poverty is highly concentrated (i.e., $i \leq z$) cannot reduce urban poverty.*

As illustrated in figure 1, the concentrated poverty index may violate the monotonicity axiom.[2] A convenient way to incorporate the implications of this axiom on urban poverty measurement is to focus on urban poverty indices that explicitly depend on the *urban poverty shortfall* $\frac{P_i/N_i}{P_z/N_z} - 1$, with z being the neighborhood identified by the urban poverty threshold α. The shortfall is positive in those neighborhoods where poverty is mostly concentrated, and increases if the proportion of the poor $\frac{P_i}{N_i}$ grows in some of the neighborhoods with $i \leq z$. The next axiom emphasizes that urban poverty indices should be written as normalized (weighted) averages of urban poverty shortfalls.

Axiom *A2 (Urban Poverty)* *The urban poverty index for configuration $\mathcal{A}$ at relative urban poverty threshold α is:*

$$UP(\mathcal{A}; \alpha) \; := \; A(\mathcal{A}, \alpha) \; \sum_{i=1}^{z} \frac{N_i}{N} \left(\frac{P_i/N_i}{P_z/N_z} - 1 \right) \; w_i(\mathcal{A}, \alpha), \tag{3}$$

with $A(\mathcal{A}, \alpha)$ a normalization factor and $w_i(\mathcal{A}, \alpha)$ are normative weights attached to the neighborhoods (and distinct from the population weights $\frac{N_i}{N}$).

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[2]For instance, a movement of a proportion of poor people from low poverty neighborhoods towards extreme poverty neighborhoods can reduce concentrated poverty, albeit this movement always implies an upward shift of the urban poverty curve. Consider a city with $n = 3$ neighborhoods, $(N_1, N_2, N_3) = (10, 10, 10)$ and $(P_1, P_2, P3) = (6, 6, 3)$, implying $P/N = 15/30 = 0.5$ and $z = 2$. For $\alpha \frac{P}{N} = 0.4$ we find that $CP = 12/15$. Consider now the effect of moving poor residents towards neighborhood 1 (compensated by movements of non-poor residents), to obtain $(P'_1, P'_2, P'_3) = (10, 3, 2)$ and $N'_i = N_i$, implying $P'/N = 15/30 = 0.5$ and $z = 1$. Now we find $CP' = 10/15 < CP$, despite a strong dominance in urban poverty curves: $(10, 13, 15) \geq (6, 12, 15)$.

Figure 2: Urban poverty curve and corrected concentrated poverty

(a) Corrected concentrated poverty

(b) A measurement issue
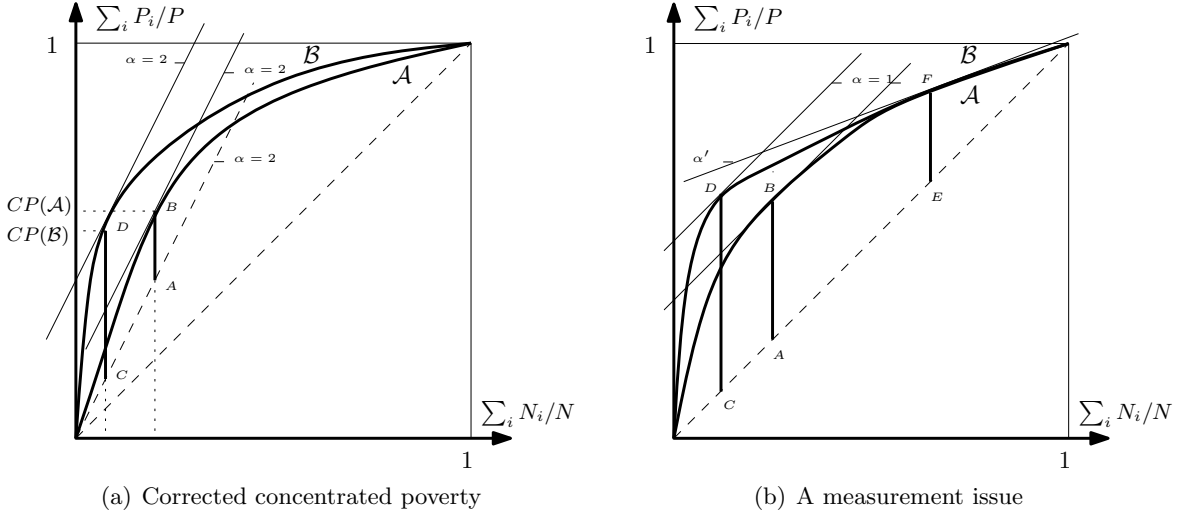
Note: The corrected concentrated poverty index CP^* corresponds to the vertical black solid line segments marked in the figure. In panel (a), the index is computed for both configurations $\mathcal{A}$ (line segment AB) and $\mathcal{B}$ (line segment CD) also reported in Figure 1 for $\alpha = 2$. In panel (b), the urban poverty curve of the hypothetical configuration $\mathcal{B}$ lies nowhere below and somewhere above the curve of the hypothetical configuration $\mathcal{A}$. The corresponding CP^* indices at different poverty thresholds $\alpha = 1$ and $\alpha' < \alpha$ are also provided.

Different urban poverty indicators can be obtained for specific choices of the normalization and weighting parameters. Let consider the case of $A(\mathcal{A}, \alpha) = \alpha$ and $w_i(\mathcal{A}, \alpha) = 1$ for every neighborhood i. The urban poverty index that stems from this choices of the parameters expresses exclusively concerns for the incidence of concentrated poverty, but not for the distribution of poor individuals across neighborhoods where poverty is more concentrated. Under these circumstances we have that

$$
\begin{aligned}
UP(\mathcal{A}; \alpha) &= \alpha \sum_{i=1}^{z} \frac{N_i}{N} \left(\frac{P_i/N_i}{P_z/N_z} - 1 \right) \\
&= CP(\mathcal{A}; \alpha) - \alpha \sum_{i=1}^{z} \frac{N_i}{N} =: CP^*(\mathcal{A}; \alpha).
\end{aligned}
$$

The result, which follows from (1), shows that the index $CP(.; \alpha)$ is consistent with Axioms A1 and A2 only up to a correction factor $\alpha \sum_{i=1}^{z} \frac{N_i}{N}$, measuring the expected degree of concentrated poverty among the z neighborhoods, calculated under the assumption that the poor population is evenly spread out across the city neighborhoods. In panel (a) of Figure 2 we show the same

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urban poverty curves as in Figure 1, and we denote with bold solid lines the corrected concentrated poverty indices $CP^*(\mathcal{A}, \alpha)$ (segment AB) and $CP^*(\mathcal{B}, \alpha)$ (segment CD). The corrected concentrated poverty index ranks $CP^*(\mathcal{B}; \alpha) > CP^*(\mathcal{A}; \alpha)$, coherently with the ordering of configurations induced by the urban poverty curves. Since every urban poverty curve is concave and lies above the diagonal, the index $CP^*(.; \alpha)$ is always positive and bounded above by $CP(.; \alpha)$.

The corrected concentrated poverty index $CP^*(.; \alpha)$ might be regarded to as a natural reference measure for urban poverty assessments. It combines three aspects of poverty: a normative view about the identification of concentrated poverty (α), which reflects a policy target; the incidence of the burden of concentrated poverty across the population (denoted by the index H, the share of the population living in high concentrated poverty neighborhoods); the intensity of poverty in the neighborhoods where poverty is concentrated (denoted by I, the neighborhood poverty gap). In fact, the index can be written as follows:

$$
\begin{aligned}
CP^*(\mathcal{A}; \alpha) &= \alpha \left(\sum_{i=1}^{z} \frac{N_i}{N} \right) \sum_{i=1}^{z} \frac{N_i/N}{\sum_{i=1}^{z} N_i/N} \left(\frac{P_i/N_i}{P_z/N_z} - 1 \right) \\
&= \alpha \, H \, I.
\end{aligned}
$$

The index $CP^*(.; \alpha)$ is, nonetheless, far from being an ideal measure of urban poverty, for at least two reasons. First, the index measures the degree of concentration of poverty by focusing on a particular point of the urban poverty curve. Hence, there are cases in which the index may not be able to rank configurations even if they are unambiguously ordered by the urban poverty curves. Panel (b) in Figure 2 reports one of such cases.[3]

The second critical aspect of $CP^*(.; \alpha)$ is that the index does not value heterogeneity in the concentration of poor individuals across the city's neighborhoods. There are two potential sources of heterogeneity. First, heterogeneity in $\frac{P_i}{N_i}$ ratios for neighborhoods $i \leq z$. When these ratios are homogenous across neighborhoods where poverty is concentrated, i.e., $\frac{P_1}{N_1} = \ldots = \frac{P_z}{N_z} \leq \alpha \frac{P}{N}$, the $CP^*(.; \alpha)$ index is a sufficient statistic for urban poverty. If they are not, the index $CP^*(.; \alpha)$ might rank as indifferent configurations that can be unambiguously ranked

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[3]The curve of configuration $\mathcal{B}$ lies above that of $\mathcal{A}$ almost everywhere. For $\alpha = 1$, $CP^*(\mathcal{B}; 1) > CP^*(\mathcal{A}; 1)$. For α' small enough, however, $CP^*(\mathcal{B}; \alpha') = CP^*(\mathcal{A}; \alpha')$ and the two configurations become indistinguishable despite a larger fraction of the poor population of $\mathcal{B}$ is concentrated in poor neighborhoods compared to $\mathcal{A}$.

Figure 3: Corrected concentrated poverty and neighborhood structure heterogeneity

(a) In neighborhood composition   (b) In neighborhood size
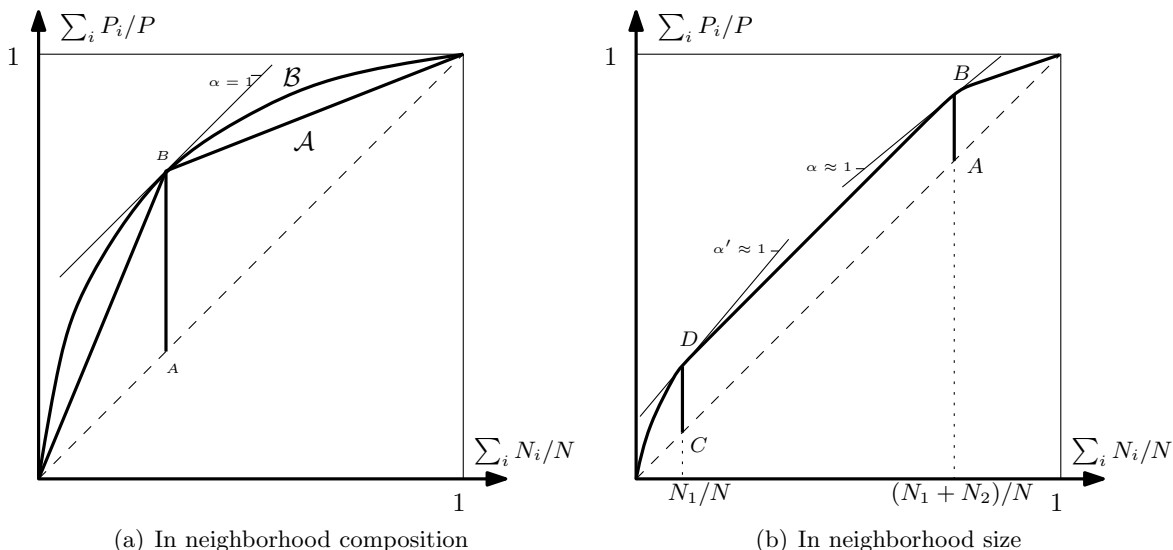
Note: Corrected concentrated poverty measures at poverty thresholds $\alpha = 1$ are given by solid line segments AB in both graphs.

according to the urban poverty curve. The graph in panel (a), Figure 3, provides an example where urban poverty is unambiguously larger in configuration $\mathcal{B}$ than in configuration $\mathcal{A}$ for $\alpha = 1$, but $CP^*(\mathcal{B}; 1) = CP^*(\mathcal{A}; 1)$.

Another source of heterogeneity is the demographic size of the neighborhoods, $\frac{N_i}{N}$. The index $CP^*(.; \alpha)$ is insensitive to marginal changes in the poverty threshold that are due to changes in the demographic size of the neighborhoods. Panel (b) of Figure 3 reports an example of a city with many small neighborhoods, with an aggregate population share of N_1/N, and one large neighborhood of size N_2/N with a proportion of poor people equal to that in the population as a whole. The corrected concentrated poverty measure is unaffected by small changes in the poverty threshold from α to α'. While this property of CP^* is appealing in some cases, it also implies that concentrated poverty evaluations neglect the size effects of the population that is actually exposed to poverty in the neighborhood of residence. In the figure, a large proportion of the population $((N_1 + N_2)/N)$ is concerned with concentrated poverty when the poverty threshold is α, while when the poverty threshold marginally reduces to α', only a minor share of the population seems to be exposed to poverty in the neighborhood.[4]

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[4]For a poverty threshold α (marginally larger than 1) the corrected concentrated poverty index is the segment

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We require that the urban poverty index coincides with CP^* when the neighborhoods where poverty is highly concentrated have homogeneous size and poverty is evenly distributed therein. This is formalized with a normalization axiom for the urban poverty index.

Axiom A3 (Normalization) *For any configuration $\mathcal{A}$ where $\frac{P_i}{N_i} = \frac{P^*}{N^*}$ and $\frac{N_i}{N} = \frac{N^*}{N}$ for all neighborhoods $i \leq z$ and P^* and N^* are constant, urban poverty is normalized to $UP(\mathcal{A}; \alpha) = CP^*(\mathcal{A}; \alpha) = \alpha HI$.*

The next axiom introduces social-welfare concerns in urban poverty measurement. Consistently with empirical findings, we requires that social welfare in a neighborhood i experiencing high poverty concentration has to be smaller than welfare in any other neighborhood j with a smaller proportion of residents that are poor, all else equal. Let denote $W(., \frac{P_i}{N_i})$ the social welfare in neighborhood i, which depends on the share of poor individuals therein. The next axiom conveys the idea that the concentration of poverty in the neighborhood produces negative externalities on individual welfare, often addressed to as the *double burden* of concentrated poverty.

Axiom A4 (Double burden of poverty on welfare) *If $\frac{P_i}{N_i} \geq \frac{P_j}{N_j}$ then $W(., \frac{P_i}{N_i}) \leq W(., \frac{P_j}{N_j})$ for any admissible social welfare function W.*

A natural way to relate the measurement of urban poverty in Axiom A2 to Axiom A4 is to assume that neighborhoods where poverty is more concentrated also receive the largest weights in urban poverty assessments. There are many weighting functions $w(.; \alpha)$ in (3) that respect this view. We restrict the focus on those weights that depend exclusively on information about the position that each neighborhood occupies in the ranking of neighborhoods ordered by the degree of poverty concentration therein.

Axiom A5 (Rank weights) *The weight $w_i(., \alpha)$ of neighborhood i in (3) is given by i's position in the ranking of neighborhoods ordered by their contribution to social welfare.*

Welfare is assumed monotonic in the proportion of poor in the neighborhood, implying

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AB. When the poverty threshold slightly changes to α' (marginally smaller than 1) the corrected concentrated poverty index, now identified by the segment CD, does not change.

that all individuals in the same neighborhood share the same proportion of concentrated poor and their rank is constant within the neighborhood. In any neighborhood $i \leq z$ there are N_i individuals, each weighted $1/N$, sharing the same position in the welfare ranking. According to axioms A4 and A5, we can express the weight of neighborhood i as follows:

$$w_i(.,\alpha) \;\; = \;\; \sum_{j=1}^{z} \frac{N_j}{N} - \sum_{j=1}^{i} \frac{N_j}{N} + \frac{N_i}{N} \tag{4}$$

There is only one urban poverty index that is consistent with axioms A1 and A2, that converges to $CP^*(.;\alpha)$ in specific cases and that accounts for heterogeneity in the distribution of concentrated poverty in a way that is consistent with the implications of concentrated poverty on individual welfare. The functional form characterized in the next lemma shows that the urban poverty index only depends on the relative urban poverty threshold and the data.

Lemma 1 *For any configuration $\mathcal{A}$ with a large number of neighborhoods, the unique urban poverty index that satisfies axioms A1-A5 is given by:*

$$UP(\mathcal{A},\alpha) \;\; = \;\; \frac{\alpha z}{(z+1)} H \left[I \;+\; (I+1)G(\mathcal{A};\alpha) \;-1+\; \frac{2}{H^2} \sum_{i=1}^{z} \frac{N_i}{N} \sum_{j=1}^{i-1} \frac{N_j}{N} \right], \tag{5}$$

where $G(\mathcal{A};\alpha)$ is as in (2).

Proof. See supplemental appendix. ∎

The urban poverty index reflects the implication of three aspects of the distribution of poverty across the city neighborhoods: the incidence, H, the intensity, I, and the degree of inequality in the distribution of poor people in those neighborhoods that display higher levels of concentrated poverty, $G(.;\alpha)$. Which aspect of urban poverty prevails depends on the full distribution of poverty across the neighborhoods where poverty is more concentrated.

The index $UP(.;\alpha)$ characterized in Lemma 1, however, has only an ordinal interpretation since its scale depends on the chosen relative urban poverty threshold and on the number and size of neighborhoods. Furthermore, the urban poverty index does not account for the distribution

of poverty in neighborhoods where the incidence of poverty is smaller than that implied by the urban poverty line.

Next, we propose axioms that overcome these limitations.

2.5   Main result: A unique urban poverty index

In empirical analysis of urban poverty it is desirable to use indices that have the form of (5) and that satisfy a minimum degree of cardinal comparability across configurations, that might differ, for instance, in the number of neighborhoods. Comparability is achieved by scaling the $UP(.; \alpha)$ index characterized in Lemma 1 by a factor that depends upon the poverty threshold α and on z.

Axiom *A6* (Cardinality) *Urban poverty evaluations do not depend on the number of neighborhoods. The urban poverty index $UP(.; \alpha)$ should be hence scaled by the factor $\frac{z+1}{z\alpha}$.*

The size of the neighborhoods also affects urban poverty evaluations. We introduce a new operation, denoted the *neighborhood splitting*, which reshapes the demographic size and geographic boundaries of any neighborhood i by splitting i into two new neighborhoods i' and i'' of smaller geographic and demographic size, but such that $\frac{P_i}{N_i} = \frac{P_{i'}}{N_{i'}} = \frac{P_{i''}}{N_{i''}}$ and $N_i = N_{i'} + N_{i''}$. Any sequence of splits of neighborhoods increases the number of neighborhoods and reshapes their size, but does not affect the relative incidence of poverty in the population of the new neighborhoods (thus preserving the urban poverty curve). We postulate invariance of the urban poverty index to any sequences of neighborhood splitting. This postulate owes its normative appeal to replication invariance properties formulated in inequality (Atkinson 1970, Cowell 2000) and segregation analysis (Hutchens 1991, Frankel and Volij 2011, Andreoli and Zoli 2014).

Axiom *A7* (Invariance to neighborhood splitting) *The $UP(.; \alpha)$ index is invariant to any sequence of neighborhood splitting operations.*

Lastly, we retain the idea that urban poverty evaluations should be concerned with the distribution of poor people across all neighborhoods of the city, rather than being focused on the subset of neighborhoods of the city where poverty is more concentrated. By doing so, we ex-

plicitly consider that rising poverty in those neighborhoods where poverty is more concentrated prevents other people living in neighborhoods where the poor are under-represented to be exposed to the double burden of poverty. We take a normative stance on this aspect by requiring that $z = n$, a result which can be achieved by setting $\zeta = 0$.

Axiom A8 (Focus on citywide urban poverty) $\alpha \rightarrow 0_+$.

Theorem 1 *The urban poverty index $U(.; \alpha)$ satisfies Axioms A1-A8 if and only if it is the Gini index $G(.)$.*

Proof. See supplemental appendix. ■

Theorem 1 contributes in four ways to the measurement of concentrated poverty. First, it shows that the simple, normatively appealing axiomatic model A1-A8 characterizes exactly one measure of urban poverty, which does not depend on a urban poverty line (i.e., $UP(\mathcal{A}, 0) := UP(\mathcal{A})$), and which takes the specific functional form of the Gini inequality coefficient of the distribution of poverty shares across the city neighborhoods (i.e., $UP(\mathcal{A}) = G(\mathcal{A})$).

Second, the theorem highlights that urban poverty arises when the proportion of poor people in the neighborhood, $\frac{P_i}{N_i}$, is different from the proportion of poor people in the city, $\frac{P}{N}$. Coherently with the intuitions in Massey and Eggers (1990), urban poverty includes aspects of the segregation of poverty across the neighborhoods of a city.

Third, the urban poverty index accounts for the distribution of poverty throughout the city and is normalized by the incidence of poverty. Comparisons based on the $UP(.)$ index always agree with the ranking of configurations produced by non-intersecting urban poverty curves.

Fourth, the urban poverty index $UP(.)$ can be conveniently factorized to assess the contribution of time variations in neighborhood poverty concentration in a longitudinal dimension. This aspect is relevant for the American case, where poverty concentration within the same census tract can be followed through time and its contribution to urban poverty at the level of the city can be then isolated. The next section investigates temporal and spatial decompositions of $UP(.)$.

3 Addressing changes in urban poverty

3.1 Decomposing changes in urban poverty

We focus now on changes in urban poverty between two periods t and t' within the same metro area. We are interested in the difference

$$\Delta UP = UP(\mathcal{A}') - UP(\mathcal{A}) = G(\mathcal{A}') - G(\mathcal{A}).$$

and on its components. Referring more explicitly to the American case, we consider a partition of the urban space into *census tracts*, each corresponding to a neighborhood. The number of census tracts and the territory spanned by each tract are fixed across time for a given city, but change across cities. For each tract i we observe P_i and N_i in both t and t'. We exploit the longitudinal component of our data to decompose ΔUP into four components.

The first component captures the dynamic effect of changes in the *demographic weights* of the census tracts on urban poverty, and is denoted by W. In empirical applications, it is generally the case that $\frac{N_i^{\mathcal{A}}}{N^{\mathcal{A}}} \neq \frac{N_i^{\mathcal{A}'}}{N^{\mathcal{A}'}}$ for some tracts. The variability in the demographic weight of the census tract may have non-trivial effects on urban poverty changes. The demographic component contributes positively to changes in urban poverty ($W > 0$) if the demographic weight of those tracts that are more dissimilar in terms of poverty composition grows relative to the average. Conversely, if the demographic growth is concentrated in those tracts displaying a more proportionate distribution of the poor in relative terms (i.e., where $\frac{P_i}{N_i} \approx \frac{P}{N}$), then urban poverty decreases ($W < 0$). The element W captures the interplay between growth in proportions of poverty and the change in absolute poverty. It allows to factor out the effect of population change from changes related to the distribution of poverty across the city's census tracts.

The second component of changes in urban poverty captures the effect of *changes in incidence of poverty* in the city. This component is denoted by C, which is a function of the growth rate

c of the incidence of poverty in the city, defined as:

$$c := \left(\frac{P^{\mathcal{A}'}}{N^{\mathcal{A}'}} - \frac{P^{\mathcal{A}}}{N^{\mathcal{A}}} \right) / \frac{P^{\mathcal{A}}}{N^{\mathcal{A}}}.$$

The component C measures the implication of a citywide expansion of poverty incidence on urban poverty, thus allowing to disentangle the consequences of proportional growth in concentrated poverty across all neighborhoods (i.e. proportional to the growth rate of citywide poverty incidence P/N, which means $\frac{P_i^{\mathcal{A}'}}{N_i^{\mathcal{A}'}} = (1+c)\frac{P_i^{\mathcal{A}}}{N_i^{\mathcal{A}}}$ for every i) from the neighborhood-specific growth rates of poverty incidence (heterogeneous across the city's neighborhoods). By factoring out C, we can isolate the component of urban poverty change that is related to changes of poverty incidence in the city from other components that are related to the way poverty is distributed across census tracts.

The last component captures the effect of disproportionate changes in tract poverty rates on the change in urban poverty. Poverty rates can converge or diverge over time across tracts. They diverge between t and t' when poverty rates of tracts with high (low) poverty concentration in t increase (decrease) faster than poverty rates in low (high) poverty tracts. As a consequence, urban poverty increases. Tract poverty rates instead converge if poverty rates increase (decrease) faster in those tracts where poverty is lower (higher) in t.

The implications of convergence of concentrated poverty on changes in urban poverty can be ambiguous. If convergence is limited, urban poverty decreases. This happens when poverty incidence in each neighborhood is closer to the poverty incidence in the city in t' than it was in t. If, however, there is a strong convergence that induces a re-ranking of neighborhoods in terms of poverty incidence, then urban poverty may not diminish to the same extent. Borrowing the terminology from the analysis of panel income growth (Jenkins and Van Kerm 2016), we propose to isolate two components of convergence in poverty incidence across census tracts. The first component, denoted by R, captures the effect on urban poverty of re-ranking of census tracts, and is relevant to detect situations where at least two census tracts swap their positions in the ranking of tracts but the overall distribution of tract poverty rates after the re-ranking remains the same. The second component, denoted by E, captures instead the extent of convergence

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(divergence) in the neighborhood incidence of poverty. It does so by comparing the disparities between the tract poverty rates in t and those in t', while holding the ranking of tracts as constant.

3.2 Result and discussion

Our first result is that the changes in urban poverty can be linearly decomposed into the four components illustrated above.

Corollary 1 *The change in urban poverty ΔUP from configuration $\mathcal{A}$ in time t to $\mathcal{A}'$ in time t' for a urban poverty index satisfying axioms A1-A8 can be decomposed as follows:*

$$\Delta UP = G(\mathcal{A}') - G(\mathcal{A}) = W \ + \ R \ + \ C \cdot E,$$

where $C = 1/(1 + c)$.

Proof. See supplemental appendix. ∎

The interesting elements of the decomposition are E and R. The term $R + C \cdot E$ measures the degree of convergence or divergence in poverty incidence across neighborhoods once changes in population composition have been factored out. The component E is negative in case of convergence and positive in case of divergence of poverty rates across census tracts. The component R, instead, is always non-negative: this term offsets, at least partly, the implications of strong forms of convergence (implying $E < 0$) that simply induce a reversal in the ranks of the census tracts where convergence occurs.

The component R captures the intensity of swaps in the ranking of census tracts, ordered by increasing magnitude of P_i/N_i. The component E is computed under the assumption that the ranking of tracts remains constant over time to that observed in t, and by comparing the inequality in poverty incidence in t to that in t' for every pair of tracts. While the components R and C measure respectively the effects of re-ranking and change in citywide poverty incidence on urban poverty, the component E isolates the convergence component of the change in urban poverty, all else equal. $E < 0$ indicates a convergence in poverty incidence between the census

tracts from t to t', whereas $E > 0$ when poverty incidence diverges across census tracts. The effect of E can be either inflated or mitigated by C, since the latter component reflects the change in citywide poverty incidence. For instance, the potential effect of a convergence in poverty incidence among census tracts ($E < 0$) is reduced when changes in tract poverty rates lead to increasing citywide poverty incidence ($C < 1$).

The result in Corollary 1 is useful for decomposing additively the contribution of poverty incidence and demographic changes at neighborhood and city level on the dynamics of urban poverty. The decomposition displays advantages over other methods. First, these components can be identified from available census data tables such as those in the American Census and Community Survey. Second, the decomposition allows to factor out the effect of demographic changes (W) on urban poverty, thus disentangling the effect of changes in poverty from the effect of demographic shifts and growth across census tracts. Third, the components R and $C \cdot E$ allow pick up specific aspects of changes in poverty concentration that cannot be inferred from the knowledge of ΔUP alone. For instance, consider two cities $\mathcal{A}$ and $\mathcal{B}$ displaying no decennial changes in urban poverty ($\Delta UP^{\mathcal{A}} = \Delta UP^{\mathcal{B}} = 0$), with $R^{\mathcal{A}} = C^{\mathcal{A}} \cdot E^{\mathcal{A}} = 0$ for the first city while $R^{\mathcal{B}} = -C^{\mathcal{B}} \cdot E^{\mathcal{A}} > 0$ for the second. While the poor population is immobile in the first city $\mathcal{A}$, poverty concentration varies substantially in the second city $\mathcal{B}$, despite the change does not imply a neat form of convergence in the degree of poverty concentration, but rather a shift of poverty across the census tracts of the city (large $R^{\mathcal{B}}$). Another interesting example could be that in which urban poverty grows in both cities, although in one city urban poverty grows because the number of poor households grows faster in places that are historically poor, implying a divergence in poverty concentration across the census tracts of the city. The component R would be small in this case. In the other case, instead, the map of poverty might be substantially re-designed, with traditionally poor census tracts experiencing substantial reductions in the share of poor residents, and middle- and lower-class tracts having a growth in concentrated poverty that is even more intense than the average. The component R and $C \cdot E$ would be both large in this case.

3.3 Spatial components of urban poverty

The urban poverty levels UP, variations ΔUP and components W, R and E can be further decomposed into spatial components, accounting for the proximity of the census tracts where changes in poverty occur. Following Rey and Smith (2013), we consider two components: the "neighborhood component" measures distributional changes in concentrated poverty originating from neighboring census tracts; the "non-neighborhood component" measures instead the contribution to urban poverty of tracts that are not in close spatial proximity. The spatial decomposition we study is conditional on the knowledge of the proximity matrix $\mathbf{N}$, its generic binary element $n_{ij} \in [0, 1]$ indicating whether census tracts i and j are neighbors according to a given criterion. For simplicity, we assume that n_{ij} is equal to 1 if census tracts i and j are neighbors, and to 0 otherwise, so that the non-zero elements of row i in $\mathbf{N}$ indicate the census tracts neighboring tract i. The matrix $\mathbf{N}$ can be constructed from the data and is assumed fixed throughout the comparisons, but is specific to the metro area. Spatial dependence of concentrated poverty is accounted for by looking at the spatial proximity of the census tracts.

The decomposition derived in Corollary 1 is preserved even when changes in urban poverty and its components are further decomposed into changes occurring among neighboring census tracts (denoted with a "N" subscript) and non-neighboring tracts (denoted with a "nN" subscript). Besides, the levels of urban poverty can be decomposed spatially, as we show in the next corollary.

Corollary 2 *The change in urban poverty ΔUP from configuration $\mathcal{A}$ in time t to $\mathcal{A}'$ in time t' for a urban poverty index satisfying axioms A1-A8 can be decomposed as follows:*

$$
\begin{aligned}
\Delta UP = G(\mathcal{A}') - G(\mathcal{A}) &= \big(G_N(\mathcal{A}') + G_{nN}(\mathcal{A}')\big) - \big(G_N(\mathcal{A}) + G_{nN}(\mathcal{A})\big) \\
&= (W_N + W_{nN}) + (R_N + R_{nN}) + C(E_N + E_{nN}).
\end{aligned}
$$

Proof. See supplemental appendix. ∎

The corollary delivers two important results. The first result is that the urban poverty index characterized in the main theorem can be exactly and linearly decomposed into N and nN

components. When G_N is large relative to G_{nN}, most of the heterogeneity in urban poverty occurs in census tracts that are located in close proximity on the city map. In this case, high and low poverty intensity census tracts tend to be located in close proximity on the city map. Conversely, when G_N is small, neighboring census tracts display similar levels of concentrated poverty, thus providing evidence of spatial *clustering* of the poor. In this case, there is positive spatial autocorrelation in the distribution of poverty among the census tracts in the city. When neighborhood and non-neighborhood components coincide, then high poverty tend to be randomly distributed across the urban space. The clustering dimension of urban poverty is relevant for policy analysis for at least two reasons. First, spatial clustering of high poverty tracts may decrease the likelihood of access to transportation, to the job market, to high-quality supply of public goods and definitely to economic and social opportunities for the residents, thus amplifying the double burden from poverty these people already experience. Second, when clusters of high poverty neighborhood overlap with administrative divisions of the territory, such as counties or school districts, more economically vulnerable residents might face poverty traps that extend their effects both on long-term poverty status of the residents as well as on inter-generational mobility prospects of the children living therein.

The second important result of the corollary is that changes over time in urban poverty can be also decomposed along the spatial dimension. In this way, we can disentangle the contribution of changes in poverty within the cluster from changes across clusters, which are more relevant for understanding spatial drivers of urban poverty. We explore these decomposition results to describe patterns and trends of urban poverty in American cities.

4 Patterns, trends and drivers of urban poverty in American cities: 1980-2014

4.1 Data

We use data from the U.S. Census Bureau. Data for 1980, 1990 and 2000 are from the decennial census Summary Tape File 3A. Due to anonymization issues, the STF 3A data are given in

the form of statistical tables representative at the census tract level. After 2000, the STF 3A files have been replaced with survey-based estimates of the income tables from the American Community Survey (ACS), which runs annually since 2001 on representative samples of the U.S. resident population. We focus on three waves of the 5-years module of ACS (estimates based on about 2% of resident population): 2006-2010, 2010-2014 and 2012-2016. We interpret estimates from the ACS modules as representative for the mid-interval year, i.e. 2008, 2012 and 2014 respectively. These years roughly correspond to the onset, the striking and the early aftermath of the Great Recession period (Jenkins, Brandolini, Micklewright and Nolan 2013, Thompson and Smeeding 2013).

The census and ACS report, consistently across years, information about poverty incidence at the census tract level. Poverty incidence is measured by the number of individuals in families with total income below the poverty threshold, which varies by family size, number of children, and age of the family householder or unrelated individual. Poverty status is determined for all families (and, by implication, all family members). Poverty status is also determined for persons not in families, except for inmates of institutions, members of the Armed Forces living in barracks, college students living in dormitories, and unrelated individuals under 15 years old.[5] The census reports poverty counts at census tract level for various poverty thresholds. In this paper, we consider as poor the households with income below the 100% federal poverty line.

Poverty counts are estimated separately for each census tract in America. Following Andreoli and Peluso (2018), we consider the 2016 Census Bureau definition of American Metropolitan Statistical Areas (MSA) to group census tracts into cities. The number and geographic size of the census tracts varies substantially across time within the same MSA. Some census tracts increase in population and are split into smaller tracts. Some other census tracts are consolidated to account for demographic shifts. While raw data allow to estimate urban poverty at the

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[5]Both Census 1990 and 2000 and ACS determine a family poverty threshold by multiplying the base-year poverty thresholds (1982) by the average of the monthly inflation factors for the 12 months preceding the data collection. The poverty thresholds in 1982, by size of family and number of related children under 18 years can be found on the Census Bureau web-site: *https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html*. For a four persons household with two underage children, the 1982 threshold is \$9,783. Using the inflation factor of 2.35795 gives a poverty threshold for this family in 2013 of \$23,067. If the disposable household income is below this threshold, then all four members of the household are recorded as poor in the census tract of residence, and included in the 2014 wave of ACS.

city level, they cannot be used to perform the decomposition exercise, insofar the definition of neighborhood is not constant over time. We resort on the Longitudinal Tract Data Base (LTDB), which provides crosswalk files to create estimates within 2010 tract boundaries for any tract-level data that are available for prior years as well as in ACS following years (Logan, Xu and Stults 2014). These files make use of reweighting methods to assign each census and ACS year population to the exact census tract boundary defined in 2010 census. In this way we can construct a balanced longitudinal dataset of census tracts for 395 American Metropolitan Areas (those with at least 10 census tracts according to 2010 census) for years 1980, 1990, 2000, 2008, 2012 and 2014. We calculate poverty incidence in each census tract/year and then construct measures of urban poverty and concentrated poverty in high (i.e. where poverty incidence is above 20% of the resident population) and extreme (i.e. where poverty incidence is above 40% of the resident population) poverty neighborhoods.

On average, the selected group of MSAs display 107.8 inhabited census tracts in 1980, rising to 152.2 in 2014. More than 93% of these MSA display at least one census tract with more than 20% poverty incidence, the citywide incidence being always below 16% on average on the sample we consider. The average number of census tracts by MSA that display more than 20% (40%) poverty incidence has more than doubles over 35 years, from 21.6 (5.4) in 1980 to 45.2 (10.8) in 2014. The balanced panel allows to further decompose changes in urban poverty in its underlying components and to study convergence/divergence in urban poverty incidence at neighborhood level. Census tracts are also geolocalized, implying that measures of proximity of these tracts can be further produced to disentangle neighborhood and non-neighborhood components of urban poverty and test their significance across all years and all MSA. A description of the data and covariates is reported in the appendix.

4.2 Patterns and trends of urban poverty

Panel a) of Figure 4 describes the levels and trends of urban poverty and concentrated poverty of 395 largest American MSA over the 35 years we consider. In line with the literature, we find that concentrated poverty is high in American cities. More than 40% of the poor population

Figure 4: Urban poverty distribution among American MSA, 1980 to 2014
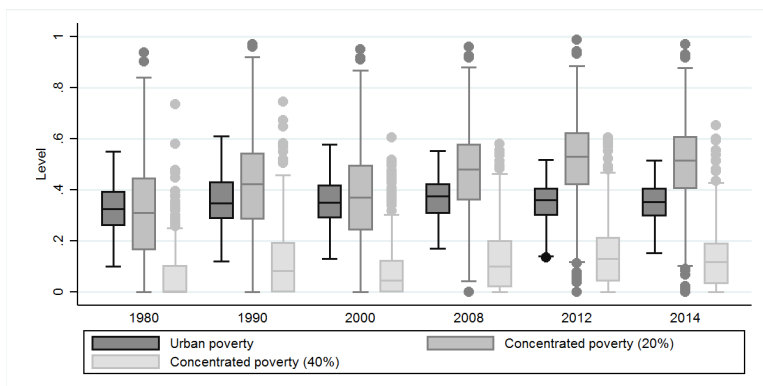
(a) UP and CP, by year
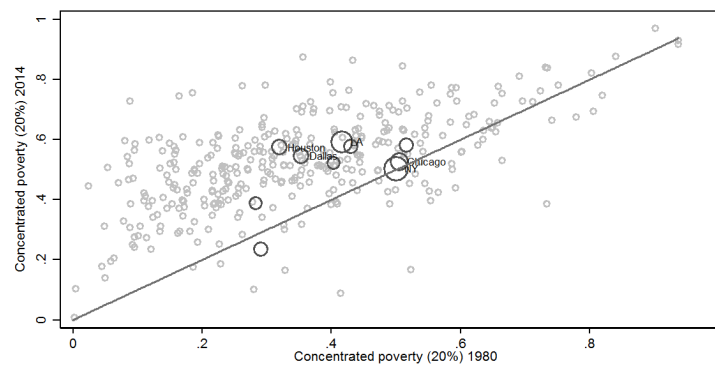
(b) Variation in Concentrated Poverty
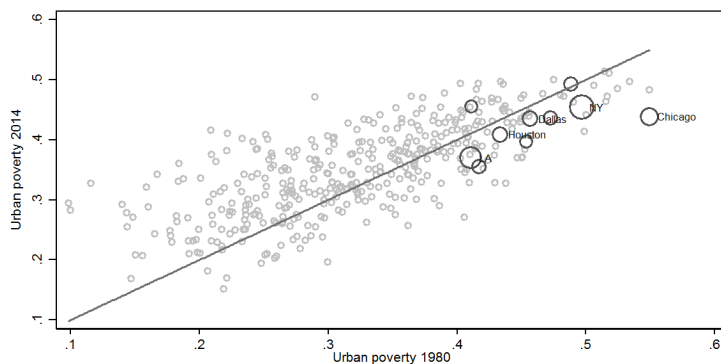
(c) Variation in Urban Poverty
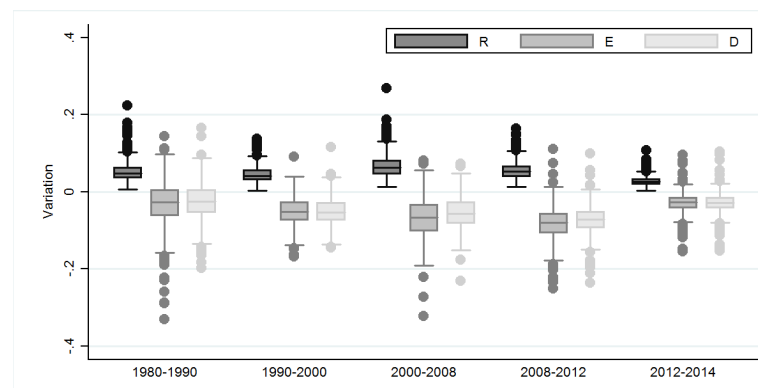
(d) ΔUP components

Note: Levels of urban poverty and concentrated poverty (concentration of poverty at neighborhood level at 20% and 40%), and of urban poverty components (R, E and $D = C \cdot E$), 1980-2014. Data for 395 selected MSA. Solid line represent no changes in concentrated poverty or in urban poverty.

lives in neighborhoods where poverty incidence is at least of 20% for the large majority of the MSA we consider. Concentrated poverty has uniformly increased by about 10 percentage points since the onset of the Great Recession, and it has remained stable in the aftermath. Conversely, we find that urban poverty as measured by the Gini index has been substantially stable over the 35 years we consider. Differently from concentrated poverty estimates, urban poverty estimates for the 395 MSAs we consider are relatively less spread out around the median level.

Panel b) and c) displays heterogeneity in the distribution of concentrated poverty and urban poverty over the whole period considered. Overall, concentrated poverty has grown on a large majority of MSAs in 1980-2014, with most of the growth concentrated in MSA that displayed relatively low concentrated poverty in 1980. The trends of urban poverty are less clear-cut. In fact, we observe both positive and negative changes in urban poverty across the whole sample of MSA. Interestingly, the 10 largest MSA tend to display very high and stable levels of urban poverty over the period, despite rising concentrated poverty. Panel d) of figure 4 breaks down heterogeneity of year-to-year variation in urban poverty into its components, computed separately for each MSA. The re-ranking component is small (and always positive as expected), although the dynamics of urban poverty seems to be effectively driven by the D component, which is negative for a majority of MSA albeit more heterogeneously distributed than R. These findings indicate systematic convergence in poverty concentration across neighborhoods for these cities. The weighting component W does not contribute significantly to change in urban poverty. Overall, year-to-year comparisons in heterogeneity of re-ranking and convergence components do not reveal detectable patters.

This last piece of evidence, alongside evidence on increasing poverty concentration, reflects a major trend of convergence in poverty across American MSA neighborhoods, with poverty growing everywhere in cities after the Great Recession, but less so in high-poverty neighborhoods, while concentrating into historically middle-class, low-poverty neighborhoods. Table 1 adds a piece of evidence to the picture. The table reports correlations between year-to-year urban poverty changes and its components (by row) and MSA-specific measures of β-convergence in poverty incidence across neighborhoods.[6] We find this correlation to be mild, about 0.5 across

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[6]To obtain the year-MSA specific measure of β-convergence, we regress the year-to-year log-change in poverty

	1980-1990	1990-2000	2000-2008	2008-2012	2012-2014
	(1)	(2)	(3)	(4)	(5)
ΔUP	0.576***	0.543***	0.437***	0.483***	0.638***
ΔUP_N	0.441***	0.355***	0.381***	0.400***	0.571***
ΔUP_{nN}	0.387***	0.463***	0.298***	0.414***	0.509***
R	-0.317***	-0.362***	-0.408***	-0.507***	-0.416***
E	0.680***	0.675***	0.681***	0.700***	0.751***
$C \cdot E$	0.722***	0.704***	0.723***	0.725***	0.750***
MSA	395	395	395	395	395

*** $p < 0.01$

Table 1: Correlations of β-convergence (log-log specification) in concentrated poverty across cities census tracts and with ΔUP and its components, by year-to-year changes.

the years, yet strongly significant. Evidence is robust across years, indicating that changes in urban poverty capture distributional aspects of the geography of changes in poverty that are different from what convergence regressions measure. The linearity of ΔUP decomposition allows break down these correlations into the independent contribution of components R and $D = C \cdot E$ (being the correlation between components R and D negligible, as Figure 6 in the appendix shows). The component $C \cdot E$ is highly correlated with β-convergence estimates, indicating that cities where poverty growth is clustered in low-poverty tracts on average (more β-convergence) also have consequences on the whole distribution of poverty across neighborhoods of the city, so that urban poverty is reduced. The component R is negatively and significantly related to the extent of β-convergence. Cities where poverty growth is clustered in low-poverty tracts also display major changes in the map of poverty, with poverty growing proportionally much less, or even decreasing, in high-poverty neighborhoods compared to the growth observed in low-poverty neighborhoods. This combination of changes induces substantial re-ranking across neighborhoods.

We investigate the spatial components of urban poverty. For the large majority of the MSAs we consider, neighborhood and non-neighborhood components of urban poverty are found to coincide in levels with urban poverty estimates. This evidence is robust across years (see

incidence P_i/N_i registered in each neighborhood i of a given MSA on the initial period log-level of poverty incidence. We estimate coefficients via OLS for each MSA and each year-to-year change and collect these estimates, which we use to compute correlations in table 1. The estimated coefficients are negative (see data appendix) implying that poverty incidence grows less in neighborhoods where poverty is highly concentrated.

	Spatial independence, 1980			Spatial independence, 2014			Population (mln)	CT
	Reject 1%	Reject 10%	Accept	Reject 1%	Reject 10%	Accept		
Q1	0.08	0.17	0.83	0.05	0.18	0.82	0.08	19
Q2	0.11	0.23	0.77	0.16	0.39	0.61	0.15	36
Q3	0.24	0.43	0.57	0.37	0.56	0.44	0.33	74
Q4	0.69	0.80	0.20	0.79	0.82	0.18	2.02	455
All	0.28	0.41	0.59	0.34	0.48	0.52	0.64	145

Table 2: Proportion of acceptances (p-values> 10%) and weak (p-values < 10%) and strong (p-values < 1%) rejections of spatial independence assumption, based on Moran-I tests with order-1 nearest neighborhood spatial weighting matrices.

Appendix B, Figure 7). Raw estimates seems to suggest that, for a large number of MSA, urban poverty measured across neighboring census tracts reflects the degree of urban poverty in the city, implying absence of positive spatial association of in poverty incidence. We put this evidence under the test.

We estimate Moran-I statistics to test for spatial dependence (putting spatial independence at the null against positive spatial correlation at the alternative) and register for each MSA the p-values of the tests, computed separately in 1980 and 2014. In Table 2 we report proportions of cases of weak (at 10% significance level) and strong (at 1% significance level) rejections of the null hypothesis, alongside the proportion of acceptances (with p-value larger than 10%). The Moran-I statistics captures the degree of positive spatial association in poverty incidence among neighboring census tracts. The statistics can be highly influenced by the population size of the city and the number of neighborhoods. We hence report rejections and acceptance rates by quartiles of MSA ranked by population size.

In large MSA (about 2mln residents on average) data weakly reject the null hypothesis in about 80% of the cases (in both years alike). In these cities, poverty tend to be spatially concentrated in neighboring census tracts, thus rising the risk of presence of spatial poverty traps, as our spatial decomposition is able to detect. Based on this evidence, we separately analyze the patterns of urban poverty in the largest five American MSA in Figure 5, and further decompose the changes of urban poverty into neighborhood and non-neighborhoods components. Overall, we find that urban poverty has increased from 1980 to 1990, with largest MSA displaying significantly more urban poverty than the rest. Urban poverty in largest cites has declined after

Figure 5: Urban poverty across American MSA, 1980 to 2014
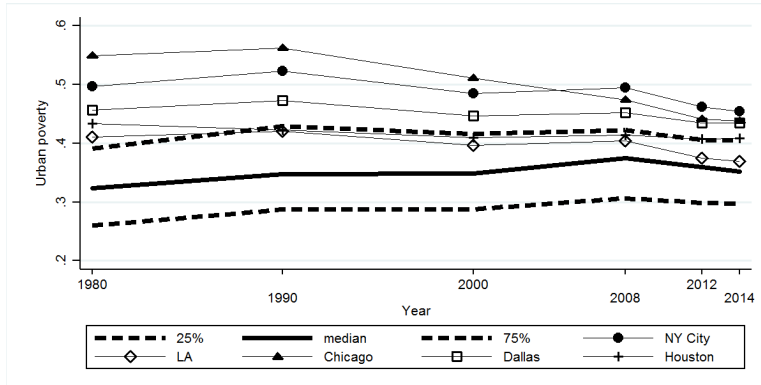
(a) UP by year
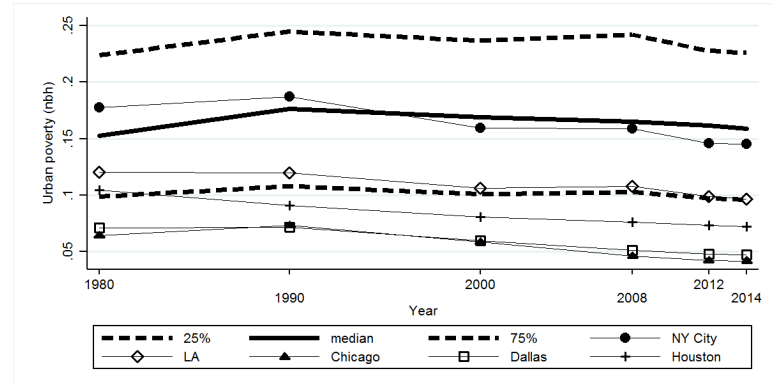
(b) Neighborhood component
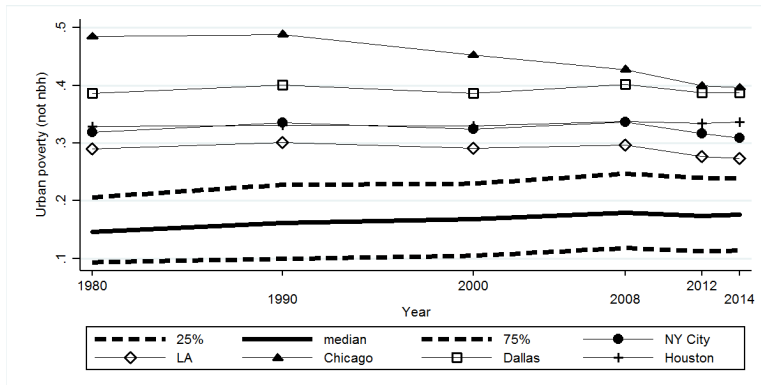
(c) Non-neighborhood component
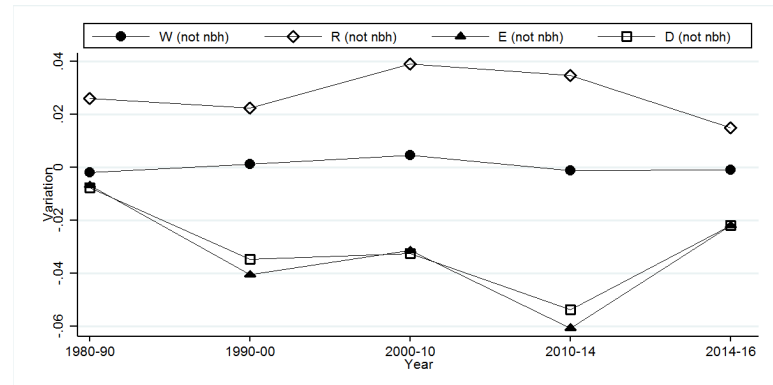
(d) Components of UP changes (non-neighborhood) in NY City

Note: Urban poverty levels and components of changes in urban poverty (R, E and $D = C \cdot E$) for median, top and bottom quartile cities in the sample, 1980-2014. Data for 395 selected MSA and five selected MSA (with largest population as of 2012-2016 ACS module): New York-Newark-Jersey City, NY-NJ-PA (NY City); Los Angeles-Long Beach-Anaheim, CA (LA); Chicago-Naperville-Elgin, IL-IN-WI (Chicago); Dallas-Fort Worth-Arlington, TX (Dallas); Houston-The Woodlands-Sugar Land, TX (Houston).

2000, slowly converging towards the rest of the MSAs we consider. This change is mostly driven by non-neighborhood components of urban poverty (panel c) of the figure), which is generally high in these cities and matches the aggregate level of urban poverty. In large MSA, urban poverty estimates are driven by changes in non-neighboring components among clusters of census tracts, that form areas of attraction or repulsion for poverty. Large MSA also display small and decreasing neighborhood components of urban poverty (panel b)). As a case study, we report in panel d) of figure 5 trends of components of variations in non-neighborhood urban poverty in NY City. We find evidence of convergence in poverty incidence across non-neighboring census tracts ($D < 0$), albeit re-ranking.

The spatial decomposition reveals that urban poverty is mostly driven by the patterns in poverty concentration across clusters of census tracts. The dynamics of urban poverty across these clusters (and not within) drives convergence in urban poverty across larger cities. As Table 2 shows, patterns of acceptance of positive spatial association in poverty incidence are less clear-cut in smaller cities (Q1-Q3). In 44% (57%) of mid-size cities (on average 0.3 mln residents) in 2014 (1980) we cannot reject spatial independence, while strong rejections are only observed in 37% (24%) of the cases. Spatial independence cannot be rejected in more than 80% of the smaller cities.

Overall, we conclude that there is little evidence about significant changes in urban poverty in the average American MSA over the lat 35 years, albeit cities are heterogeneous in patterns of urban poverty they display. This evidence suggests that characteristics of the cities (rather than of the neighborhoods), may be key drivers of urban poverty. Nonetheless, the apparent steadiness of urban poverty masks substantial changes in the geography of poverty concentration within these cities. We find evidence consistent with poverty deconcentrating from traditionally high-poverty neighborhoods towards more mixed census tracts. When the focus is on large MSA, we find significant evidence of spatial clustering of poverty across neighboring census tracts, implying that the distribution across neighborhoods of potential drivers of urban poverty, such as housing values and income, may also matter in explaining levels and trends of urban poverty. We now investigate the separate role of these drivers on urban poverty levels and changes using

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cross-cities regressions.

4.3 Drivers of urban poverty

The bulk of this section is to identify potential drivers of cross-sectional variation of urban poverty and of its year-to-year changes. A detailed description of the drivers we consider can be found in Appendix B. Iceland and Hernandez (2017) have shown that the incidence and segregation of poverty, the degree of ethnic segregation, the composition of the population in terms of education, labor market attachment and age structure are important predictors of concentrated poverty in high poverty neighborhoods (more than 20% poverty incidence). Our best estimates, reported in appendix B (tables 6 and 7), confirm previous findings and additionally suggest that MSA with larger share of high educated population, holding managerial positions and sprawling into suburbia (hence increasing time to destination to work) display less poverty concentration. The average income at the city level is a significant driver of concentrated poverty, although the effect is minor compared to that of ethnic segregation. Ethnic composition of the city (in particular black, white and asian groups), alongside ethnic segregation, are the stronger drivers of concentrated poverty in extreme poverty neighborhoods (more than 40% poverty incidence). Interestingly, the distribution of housing prices and income across the census tracts do not significantly affect poverty concentration.

Urban poverty estimates correlate with different drivers. Our preferred pooled and panels models in Table 3 agree that the characteristics of the urban income distribution and the implied incidence and distribution of poverty are key drivers of urban poverty. Poverty incidence has a negative effect on urban poverty, highlighting that the unequal incidence of poverty across neighborhoods becomes less likely in MSA where a large fraction of the population is poor. Richer cities tend to display less urban poverty.

The distribution of income across census tracts, as well as the features of the housing market, have important implications for urban poverty. This evidence can be reconciled with the implications of affordability of the neighborhood on the geography of poverty. Cities with higher median income across census tracts (controlling for average household income) display more income mix

Dependent Variable	UP				ΔUP	
	Pool		Panel FE		Pool	
	1980-2014		1980-2014		1980-2014	
	(1)		(2)		(3)	
A) % Black	0.032*	(0.02)	0.023	(0.05)	0.081**	(0.04)
A) % Hispanic	0.014	(0.02)	0.003	(0.05)	0.067*	(0.04)
A) % Asian	-0.003	(0.02)	-0.012	(0.05)	0.047	(0.04)
A) % White	-0.014	(0.02)	-0.028	(0.05)	0.116**	(0.04)
A) Population size (ln)	0.018**	(0.01)	0.017**	(0.00)	0.006	(0.01)
A) % 65 plus yrs old	0.051*	(0.03)	0.064**	(0.01)	0.136**	(0.06)
A) % 2564 yrs old	0.035	(0.02)	0.039	(0.03)	0.005	(0.05)
A) % Foreign	-0.056**	(0.02)	-0.068**	(0.01)	-0.059	(0.04)
A) Moved from outside of state	0.008	(0.01)	0.015	(0.01)	-0.070**	(0.02)
B) % New Houses (10 less yrs old)	-0.053**	(0.02)	-0.060**	(0.02)	-0.042	(0.03)
B) % Old houses (20 plus yrs old)	-0.028**	(0.01)	-0.030*	(0.01)	-0.074**	(0.02)
B) % Owner occupied	0.066**	(0.03)	0.093**	(0.02)	0.149**	(0.07)
B) % Vacant	-0.014	(0.01)	-0.014	(0.01)	-0.003	(0.02)
B) % Rented	0.044	(0.03)	0.059*	(0.03)	0.249**	(0.07)
B) Avg. value house (ln)	0.006**	(0.00)	0.007	(0.00)	0.001	(0.01)
B) Median value house by CT (ln)	0.008**	(0.00)	0.009**	(0.00)	0.008	(0.01)
B) p25% value house by CT (ln)	-0.005*	(0.00)	-0.006	(0.00)	-0.011**	(0.01)
B) S.d. value house by CT (ln)	-0.006**	(0.00)	-0.007*	(0.00)	-0.006	(0.00)
B) Avg. rent (ln)	-0.010**	(0.00)	-0.009	(0.00)	-0.002	(0.01)
B) Median rent by CT (ln)	0.004	(0.01)	0.006	(0.01)	0.000	(0.02)
B) p25% rent by CT (ln)	-0.002	(0.01)	-0.003	(0.01)	0.020	(0.02)
B) S.d. rent by CT (ln)	-0.000	(0.00)	-0.001	(0.00)	0.005	(0.00)
C) College Town	-0.002*	(0.00)	-0.002**	(0.00)	0.003	(0.00)
C) Student Town	-0.007**	(0.00)	-0.006**	(0.00)	-0.005	(0.00)
C) % less than high school	-0.002	(0.03)	0.001	(0.03)	-0.074	(0.06)
C) % with high school	-0.018	(0.02)	-0.020	(0.03)	0.092*	(0.05)
C) % with college	-0.024*	(0.01)	-0.022*	(0.01)	0.016	(0.03)
C) % enrolment (any)	0.041**	(0.02)	0.047	(0.03)	0.187**	(0.04)
D) % Managerial position	0.040**	(0.01)	0.040**	(0.01)	0.036	(0.03)
D) % Timework	0.025**	(0.01)	0.031**	(0.01)	0.094**	(0.03)
E) Avg hh income (ln)	0.011**	(0.01)	0.009*	(0.00)	0.032**	(0.01)
E) Median hh income by CT (ln)	-0.071**	(0.01)	-0.073**	(0.02)	0.038	(0.02)
E) p25% hh income by CT (ln)	0.046**	(0.01)	0.046**	(0.01)	-0.037**	(0.01)
E) S.d. hh income by CT (ln)	0.028**	(0.00)	0.029**	(0.00)	0.002	(0.01)
E) % of poor	-0.388**	(0.02)	-0.388**	(0.01)	0.160**	(0.05)
E) Dissimilarity poor	1.017**	(0.01)	1.020**	(0.01)	-0.338**	(0.02)
E) Dissimilarity whiteblack	-0.025**	(0.01)	-0.029*	(0.01)	-0.053*	(0.03)
E) Dissimilarity black	0.028**	(0.01)	0.030*	(0.01)	0.035	(0.03)
E) Dissimilarity hispanic	0.005	(0.01)	0.005*	(0.00)	0.025**	(0.01)
E) Dissimilarity asian	0.010**	(0.00)	0.012*	(0.01)	0.020*	(0.01)
E) Dissimilarity white	-0.056**	(0.02)	-0.059**	(0.02)	0.109**	(0.04)
Greatrecession	-0.030	(0.02)			0.000	(0.00)
Regional fe	y		y		y	
Year fe	y		y		y	
N. of obs.	2342		2202		1947	
MSA	367		367		367	
N. of years	6		6		-	
N. of year-to-year intervals	-		-		5	
R-squared	0.966		0.964		0.377	
Root MSE	0.016		0.016		0.031	

Table 3: Drivers of urban poverty.

Note: Dependent variable is the UP index by MSA and year (models (1) and (2)) and changes in urban poverty ΔUP calculated on a year-to-year basis by MSA. Model (1) and (3) are pooled OLS regression controlling for years fixed effects and Great Recession (2008-2012) fixed effects. Model (2) is a FE estimator for the balanced panel of MSA (367). All models controls for regional FE. Significance levels: $^{*} = 10\%$ and $^{**} = 5\%$. Standard errors in parenthesis.

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at the neighborhood level and less inequality across neighborhoods (as the median converges to the average, held fixed). This pattern of income sorting may indicate more widespread access to urban amenities and localized public goods, and hence lower incentives for high and low income families to sort unevenly across census tracts. The partial effect of median household income by census tract on urban poverty is in fact negative. Additional features of the distribution of income across census tracts, such as the income dispersion and the bottom income quartile across census tracts, tend to counteract this effect by rising urban poverty as an effect of sorting.

The distribution of housing value/prices across census tracts has opposite implications for urban poverty compared to the effects related to the distribution of income across census tracts. Cities with increasing average housing values tend to display more urban poverty, the effect being stronger when median housing prices across census tract rise. These two variables hints on the possibility that widespread affordability constraints contribute to the process of clustering of poor individuals into specific areas of the city, thus rising urban poverty. The effect is attenuated in presence of large variability of housing values across the city neighborhoods, with the standard deviation and the bottom quartile of housing values distribution contributing to rising urban poverty. While widespread ownership increases urban poverty, improving new housing infrastructure seem to counteract the implications of affordability for urban poverty. Ceteris paribus, cities with large proportion of older (and cheaper) accommodation also display lower urban poverty.

The drivers we consider explain about 97% of variability in urban poverty across American MSA. The same drivers are less informative about urban poverty changes. Model (3) in Table 3 reports effects of demographic, housing, educational, labor market and distributional drivers on year-to-year changes in urban poverty. Our estimates confirm that demographics, labor market characteristics and features of the housing stock are relevant drivers of urban poverty changes, with the expected signs. The distribution of housing values and income within and across census tracts does not have a significant impact on urban poverty changes. Nonetheless, increments in income and housing prices in low income/housing value neighborhoods (bottom quartile) are associated with smaller increments in urban poverty. We find similar effects when we correlated

the urban poverty drivers to re-ranking and convergence components of urban poverty (see Appendix B).

5 Conclusions

This paper introduces a parsimonious axiomatic model that identifies one specific urban poverty measure, related to the Gini inequality index. The model incorporates the idea that concentration of poverty across neighborhoods can produce welfare losses for those exposed to it. The concentrated poverty index, the official measure of urban poverty adopted by the Census Bureau to assess urban poverty, may fail to satisfy this basic requirement.

The paper highlights patterns, trends and drivers of urban poverty using census and American Community Survey data for the largest 395 American MSA over the last 35 years. While there is evidence that concentrated poverty has increased after the onset of the Great Recession, we find no systematic trends in the evolution of urban poverty. This apparent steadiness masks the implications of ongoing changes in the geography of poverty within MSAs, with poverty rising and falling across census tracts. The data we use do not allow to distinguish whether trends in urban poverty are driven by relocation of chronically poor individual across census tracts, or rather by the fact that the likelihood of occurrence of poverty spells is unevenly distributed across census tracts, possibly affected by unobservable factors that are also relevant for the way rich and poor households sort in space. Distinguishing the two effects would require knowledge of individual-level incidence of poverty spells alongside residential decisions.

The analysis of drivers of urban poverty reveals, nonetheless, that the distribution of income ad housing values across census tracts are strongly associated with urban poverty, but not with concentrated poverty. Urban poverty is larger in cities with more similarly distributed housing values (i.e. the distribution of prices within each tract resemble that of the city, with median tract housing values closer to the average city housing values) and more unequally distributed income across census tracts, while it is smaller in cities with census tracts displaying more similar levels of inequality and where housing values are more unequally distributed across neighborhoods. These findings are consistent with the premises of the *Great Inversion* hypothesis

(Ehrenhalt 2012), which predicts that gentrification induced by the inflow of young, middle class cohorts into the most affordable, historically extreme-poverty neighborhoods located at the core of the American cities tend to displace poor residents towards traditionally middle class, low-poverty neighborhoods, which become more mixed. As a consequence of displacement, most affordable neighborhoods tend to attract disproportionally more poor than other neighborhoods (rising poverty concentration), although overall the redistribution of poverty from inner cities towards more marginal neighborhoods makes the distribution of poverty more widespread across neighborhoods, thus explaining the relatively steady trends of urban poverty we measure (which is declining in largest American MSA), albeit sizable re-ranking and convergence components underlying these trends. Evidence from cross-cities regressions reveal that the major drivers of urban poverty, namely the large shares of old (more than 20 year) and new (less than 10 year) housing constructions, alongside variation in housing values across census tracts, are associated with reducing urban poverty. The presence of census tracts with old and low-value buildings, alongside the unequal distribution of housing values across neighborhoods, have been found to drive gentrification phenomena (Freeman 2005, Freeman 2009), which in turn triggers renovation and increase in supply of new residential units. The framework we provide seems an appropriate starting point for analyzing the premises of gentrification on urban poverty and for testing the Great Inversion hypothesis.

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Supplemental Appendix
For online publication only

A   Proofs

A.1   Proof of Lemma 1

For any configuration $\mathcal{A}$ with a large number of neighborhoods, the unique urban poverty index that satisfies axioms A1-A5 is given by:

$$UP(\mathcal{A}, \alpha) \;=\; \frac{\alpha z}{(z+1)} H \left[I \;+\; (I+1)G(\mathcal{A}; \alpha) \;-1+\; \frac{2}{H^2} \sum_{i=1}^{z} \frac{N_i}{N} \sum_{j=1}^{i-1} \frac{N_j}{N} \right], \tag{6}$$

where $G(\mathcal{A}; \alpha)$ is as in (2).

Proof. Consider first the case in which $\frac{P_1}{N_1} = \ldots = \frac{P_z}{N_z} = \frac{P^*}{N^*}$ and $N_1 = \ldots = N_z = N^*$ with P^* and N^* two natural numbers such that $\frac{P^*}{N^*} \leq \zeta$. Under axioms A1 and A2 we write:

$$
\begin{aligned}
UP(.; \alpha) \;&=\; A(.; \alpha) \sum_{i=1}^{z} \frac{N^*}{N} \left(\frac{P^*/N^*}{\zeta} - 1 \right) w_i(.; \alpha) \\
&=\; A(.; \alpha) \frac{N^*}{N} \left(\frac{P^*/N^*}{\zeta} - 1 \right) \sum_{i=1}^{z} w_i(.; \alpha).
\end{aligned}
\tag{7}
$$

Axioms A4 and A5 imply that (7) can be written as follows:

$$
\begin{aligned}
UP(.; \alpha) \;&=\; A(.; \alpha) \frac{N^*}{N} \left(\frac{P^*/N^*}{\zeta} - 1 \right) \sum_{i=1}^{z} \left(\sum_{j=1}^{z} \frac{N^*}{N} - \sum_{j=1}^{i} \frac{N^*}{N} + \frac{N^*}{N} \right) \\
&=\; A(.; \alpha) \frac{N^*}{N} \left(\frac{P^*/N^*}{\zeta} - 1 \right) \frac{N^*}{N} \sum_{i=1}^{z} (z - i + 1) \\
&=\; A(.; \alpha) \frac{N^*}{N} \left(\frac{P^*/N^*}{\zeta} - 1 \right) \frac{N^*}{N} \frac{z(z+1)}{2}.
\end{aligned}
\tag{8}
$$

According to axiom A3, the index $UP(.; \alpha)$ can be also written as follows:

$$
\begin{aligned}
UP(.; \alpha) \;&=\; \alpha H I = \alpha \sum_{i}^{z} \frac{N^*}{N} \left(\frac{P^*/N^*}{\zeta} - 1 \right) \\
&=\; \alpha \frac{N^*}{N} \left(\frac{P^*/N^*}{\zeta} - 1 \right) z.
\end{aligned}
\tag{9}
$$

Equating (8) to (9) and solving for $A(.; \alpha)$ we obtain the following specification for the scaling

coefficient:

$$
\begin{aligned}
A(.;\alpha) &= \frac{2\alpha}{z+1}\frac{N}{N^*} \\
&= \frac{2\alpha z}{z+1}\frac{1}{H},
\end{aligned}
\tag{10}
$$

where (10) follows from the fact that $N^* = \sum_{i=1}^{z}\frac{N_i}{z}$ and from the definition of H.

Using the definition of rank-dependent weights consistent with axioms A4 and A5, and substituting for (10), we can write:

$$
\begin{aligned}
UP(.;\alpha) &= \frac{2\alpha z}{z+1}\frac{1}{H}\sum_{i=1}^{z}\frac{N_i}{N}\left(\frac{P_i/N_i}{\zeta}-1\right)\left(\sum_{j=1}^{z}\frac{N_j}{N}-\sum_{j=1}^{i}\frac{N_j}{N}+\frac{N_i}{N}\right) \\
&= \frac{2\alpha z}{z+1}\frac{1}{H}\left[\frac{1}{\zeta}\sum_{i=1}^{z}\frac{N_i}{N}\frac{P_i}{N_i}\left(\sum_{j=1}^{z}\frac{N_j}{N}-\sum_{j=1}^{i}\frac{N_j}{N}+\frac{N_i}{N}\right)-\sum_{i=1}^{z}\frac{N_i}{N}\left(\sum_{j=1}^{z}\frac{N_j}{N}-\sum_{j=1}^{i}\frac{N_j}{N}+\frac{N_i}{N}\right)\right]
\end{aligned}
\tag{11}
$$

We show now that the first term within square brackets in (11) can be expressed as a function of known elements and of the Gini index $G(.;\alpha)$, measuring the unequal distribution of poverty shares (P_i/N_i) across the neighborhood where poor people are mostly concentrated.

Let m_α denote the average incidence of poverty among the neighborhoods in which poverty is more concentrated for a given poverty threshold defined by α, so that

$$
m_\alpha = \sum_{i=1}^{z}\frac{1}{\sum_{i=1}^{z}N_i/N}\frac{N_i}{N}\frac{P_i}{N_i}.
\tag{12}
$$

The Gini index $G(.;\alpha)$ can be written as follows:

$$
\begin{aligned}
G(.;\alpha) &= \frac{1}{2m_\alpha\left(\sum_{i=1}^{z}N_j/N\right)^2}\sum_{i=1}^{z}\sum_{j=1}^{z}\frac{N_i}{N}\frac{N_j}{N}\left|\frac{P_i}{N_i}-\frac{P_j}{N_j}\right| \\
&= \frac{1}{2m_\alpha\left(\sum_{i=1}^{z}N_j/N\right)^2}\sum_{i=1}^{z}\sum_{j=1}^{z}\frac{N_i}{N}\frac{N_j}{N}\left[2\max\left\{\frac{P_i}{N_i},\frac{P_j}{N_j}\right\}-\frac{P_i}{N_i}-\frac{P_j}{N_j}\right] \\
&= \frac{1}{2m_\alpha\left(\sum_{i=1}^{z}N_j/N\right)^2}\left[\sum_{i=1}^{z}\sum_{j=1}^{z}\frac{N_i}{N}\frac{N_j}{N}2\max\left\{\frac{P_i}{N_i},\frac{P_j}{N_j}\right\}-2\sum_{i=1}^{z}\frac{N_i}{N}\sum_{i=1}^{z}\frac{N_i}{N}\frac{P_i}{N_i}\right]
\end{aligned}
\tag{13}
$$

We now develop the first term appearing in squared brackets in (13), denoted max in short-hand notation, to show that it can written as a function of the rank weights. First, let develop the

double summations term as follows:

$$
\begin{aligned}
max &= \sum_{i=1}^{z}\sum_{j=1}^{z} \frac{N_i}{N}\frac{N_j}{N}\max\left\{\frac{P_i}{N_i},\frac{P_j}{N_j}\right\}\\[2mm]
&= \frac{N_1}{N}\frac{N_1}{N}\frac{P_1}{N_1} + \left(\frac{N_1}{N}\frac{N_2}{N}\frac{P_1}{N_1}+\ldots+\frac{N_1}{N}\frac{N_z}{N}\frac{P_1}{N_1}\right)+\\[2mm]
&\quad +\frac{N_2}{N}\frac{N_1}{N}\frac{P_1}{N_1}+\frac{N_2}{N}\frac{N_2}{N}\frac{P_2}{N_2}+\left(\frac{N_2}{N}\frac{N_3}{N}\frac{P_2}{N_2}+\ldots+\frac{N_2}{N}\frac{N_z}{N}\frac{P_2}{N_2}\right)+\\[2mm]
&\quad +\frac{N_3}{N}\frac{N_1}{N}\frac{P_1}{N_1}+\frac{N_3}{N}\frac{N_2}{N}\frac{P_2}{N_2}+\frac{N_3}{N}\frac{N_3}{N}\frac{P_3}{N_3}+\left(\frac{N_2}{N}\frac{N_4}{N}\frac{P_3}{N_3}+\ldots+\frac{N_3}{N}\frac{N_z}{N}\frac{P_3}{N_3}\right)+\\[2mm]
&\quad \ldots+\frac{N_{z-1}}{N}\frac{N_1}{N}\frac{P_1}{N_1}+\ldots+\frac{N_{z-1}}{N}\frac{N_{z-1}}{N}\frac{P_{z-1}}{N_{z-1}}+\frac{N_{z-1}}{N}\frac{N_z}{N}\frac{P_{z-1}}{N_{z-1}}+\\[2mm]
&\quad +\frac{N_z}{N}\frac{N_1}{N}\frac{P_1}{N_1}+\ldots+\frac{N_z}{N}\frac{N_z}{N}\frac{P_z}{N_z}.
\end{aligned}
$$

Rearranging the terms in the summation, this quantity can be equivalently written as:

$$
\begin{aligned}
max &= \frac{N_1}{N}\frac{P_1}{N_1}\left(\sum_{j=1}^{z}\frac{N_j}{N}+\sum_{j=2}^{z}\frac{N_j}{N}\right)+\frac{N_2}{N}\frac{P_2}{N_2}\left(\sum_{j=2}^{z}\frac{N_j}{N}+\sum_{j=3}^{z}\frac{N_j}{N}\right)+\\[2mm]
&\quad \ldots+\frac{N_{z-1}}{N}\frac{P_{z-1}}{N_{z-1}}\left(\sum_{j=z-1}^{z}\frac{N_j}{N}+\frac{N_z}{N}\right)+\frac{N_z}{N}\frac{P_z}{N_z}\frac{N_z}{N}\\[2mm]
&= \sum_{i=1}^{z}\frac{N_i}{N}\frac{P_i}{N_i}\left(\frac{N_i}{N}+2\sum_{j=i+1}^{z}\frac{N_j}{N}\right)
\end{aligned}
\tag{14}
$$

After adding and subtracting the quantity $\sum_{i=1}^{z}\frac{N_i}{N}\frac{P_i}{N_i}\frac{N_i}{N}$, we obtain:

$$
\begin{aligned}
max &= \sum_{i=1}^{z}\frac{N_i}{N}\frac{P_i}{N_i}\left(2\frac{N_i}{N}+2\sum_{j=i+1}^{z}\frac{N_j}{N}\right)-\sum_{i=1}^{z}\frac{N_i}{N}\frac{P_i}{N_i}\frac{N_i}{N}\\[2mm]
&= \sum_{i=1}^{z}\frac{N_i}{N}\frac{P_i}{N_i}\left(2\frac{N_i}{N}+2\left(\sum_{j=1}^{z}\frac{N_j}{N}-\sum_{j=1}^{i}\frac{N_j}{N}\right)\right)-\sum_{i=1}^{z}\frac{N_i}{N}\frac{P_i}{N_i}\frac{N_i}{N}\\[2mm]
&= 2\sum_{i=1}^{z}\frac{N_i}{N}\frac{P_i}{N_i}\left(\sum_{j=1}^{z}\frac{N_j}{N}-\sum_{j=1}^{i}\frac{N_j}{N}+\frac{N_i}{N}\right)-\sum_{i=1}^{z}\frac{N_i}{N}\frac{P_i}{N_i}\frac{N_i}{N},
\end{aligned}
\tag{15}
$$

where the term in parenthesis in (15) coincide with the rank weights identified by axioms A4 and A5. We can now substitute the term max in (13) with (15). Using the explicit formula for

m_α, we obtain:

$$
\begin{aligned}
G(.;\alpha) &= \frac{1}{\left(\sum_{i=1}^z N_j/N\right)^2 \sum_{i=1}^z \frac{1}{\sum_{i=1}^z N_i/N}\frac{N_i}{N}\frac{P_i}{N_i}} \left[2\sum_{i=1}^z \frac{N_i}{N}\frac{P_i}{N_i}\left(\sum_{j=1}^z \frac{N_j}{N} - \sum_{j=1}^i \frac{N_j}{N} + \frac{N_i}{N}\right) - \sum_{i=1}^z \frac{N_i}{N}\frac{P_i}{N_i}\frac{N_i}{N}\right] - \\
&\quad - \frac{1}{\left(\sum_{i=1}^z N_j/N\right)^2 \sum_{i=1}^z \frac{1}{\sum_{i=1}^z N_i/N}\frac{N_i}{N}\frac{P_i}{N_i}} 2\left(\sum_{i=1}^z \frac{N_i}{N}\sum_{i=1}^z \frac{N_i}{N}\frac{P_i}{N_i}\right) \\
&= \frac{2}{\sum_{i=1}^z \frac{N_i}{N}\sum_{i=1}^z \frac{N_i}{N}\frac{P_i}{N_i}}\sum_{i=1}^z \frac{N_i}{N}\frac{P_i}{N_i}\left(\sum_{j=1}^z \frac{N_j}{N} - \sum_{j=1}^i \frac{N_j}{N} + \frac{N_i}{N}\right) - \\
&\quad - \frac{1}{\sum_{i=1}^z \frac{N_i}{N}\sum_{i=1}^z \frac{N_i}{N}\frac{P_i}{N_i}}\sum_{i=1}^z \frac{N_i}{N}\frac{N_i}{N}\frac{P_i}{N_i} - 1
\end{aligned}
\tag{16}
$$

The second term of (16) is a function of z. If the number of neighborhood is large enough, and the neighborhoods are small enough in size, this term converges to zero at a rate that is quadratic in the demographic size of the neighborhood. Hereafter we maintain that the number of neighborhoods is large, so that the rank weights in (16) can be approximated as follows:

$$
\sum_{i=1}^z \frac{N_i}{N}\frac{P_i}{N_i}\left(\sum_{j=1}^z \frac{N_j}{N} - \sum_{j=1}^i \frac{N_j}{N} + \frac{N_i}{N}\right) \approx \frac{1}{2}(G(.;\alpha)+1)\sum_{i=1}^z \frac{N_i}{N}\sum_{i=1}^z \frac{N_i}{N}\frac{P_i}{N_i}.
\tag{17}
$$

Substituting (17) into (11) and using the fact that

$$
\begin{aligned}
\sum_{i=1}^z \frac{N_i}{N}\left(\sum_{j=1}^z \frac{N_j}{N} - \sum_{j=1}^i \frac{N_j}{N} + \frac{N_i}{N}\right) &= \sum_{i=1}^z \frac{N_i}{N}\left(\sum_{j=1}^z \frac{N_j}{N} - \sum_{j=1}^{i-1} \frac{N_j}{N}\right) \\
&= H^2 - \sum_{i=1}^z \frac{N_i}{N}\sum_{j=1}^{i-1} \frac{N_j}{N},
\end{aligned}
$$

we get:

$$
UP(.;\alpha) = \frac{2\alpha z}{z+1}\frac{1}{H}\left[\frac{1}{2}(G(.;\alpha)+1)\sum_{i=1}^z \frac{N_i}{N}\frac{1}{\zeta}\sum_{i=1}^z \frac{N_i}{N}\frac{P_i}{N_i} - H^2 + \sum_{i=1}^z \frac{N_i}{N}\sum_{j=1}^{i-1} \frac{N_j}{N}\right].
\tag{18}
$$

Adding and subtracting the term $\frac{1}{2}(G_\alpha+1)\left(\sum_{i=1}^z N_i/N\right)^2$ within square brackets in (18) we

obtain:

$$
\begin{aligned}
UP(.;\alpha) &= \frac{2\alpha z}{z+1}\frac{1}{H}\left[\frac{1}{2}(G(.;\alpha)+1)H^2 I + \frac{1}{2}(G(.;\alpha)+1)H^2 - H^2 + \sum_{i=1}^{z}\frac{N_i}{N}\sum_{j=1}^{i-1}\frac{N_j}{N}\right] \\
&= \frac{\alpha z}{z+1}\frac{1}{H}\left[(G(.;\alpha)+1)H^2 I + \frac{1}{2}(G(.;\alpha)+1)H^2 - 2H^2 + 2\sum_{i=1}^{z}\frac{N_i}{N}\sum_{j=1}^{i-1}\frac{N_j}{N}\right] \\
&= \frac{\alpha z}{z+1}H\left[I + (I+1)G(.;\alpha) - 1 + \frac{2}{H^2}\sum_{i=1}^{z}\frac{N_i}{N}\sum_{j=1}^{i-1}\frac{N_j}{N}\right],
\end{aligned}
$$

which concludes the proof. ∎

A.2 Proof of Theorem 1

The urban poverty index $U(.;\alpha)$ satisfies Axioms A1-A8 if and only if it is the Gini index $G(.)$.

Proof. Axioms A1-A5 are equivalent to (6). For any given configuration $\mathcal{A}$ with n neighborhoods, consider now an alternative configuration $\mathcal{A}'$ with $n' > n$ neighborhoods obtained from $\mathcal{A}$ by operations of splitting of neighborhoods, so that $\left(\frac{N_1^{\mathcal{A}}}{N},\ldots,\frac{N_n^{\mathcal{A}}}{N}\right) \to \left(\frac{N_1^{\mathcal{A}'}}{N},\ldots,\frac{N_{n'}^{\mathcal{A}'}}{N}\right)$ and $\frac{N_i^{\mathcal{A}'}}{N} = \frac{1}{n'}$ for any $i = 1,\ldots,n'$. Let z' be the poverty line defined by α and by the fact that $\frac{P^{\mathcal{A}'}}{N^{\mathcal{A}'}} = \frac{P^{\mathcal{A}'}}{N^{\mathcal{A}'}}$. We can hence write the residual term $2\sum_{i=1}^{z}\frac{N_i}{N}\sum_{j=1}^{i-1}\frac{N_j}{N}$ for $UP(\mathcal{A}';\alpha)$ as follows:

$$
\begin{aligned}
2\sum_{i=1}^{z'}\frac{N_i^{\mathcal{A}'}}{N^{\mathcal{A}'}}\sum_{j=1}^{i-1}\frac{N_j^{\mathcal{A}'}}{N^{\mathcal{A}'}} &= 2\sum_{i=1}^{z'}\frac{1}{n'}\sum_{j=1}^{i-1}\frac{1}{n'} = \frac{2}{n'^2}\sum_{i=1}^{n'}(i-1) \\
&= \frac{2}{n'^2}\left(\frac{n'(n'+1)}{2} - n'\right) = \frac{n'-1}{n'} \approx 1, \quad (19)
\end{aligned}
$$

when the number of neighborhood n' is large. From Axiom A8 it follows that $z \to n$ and $H \to 1$. Axiom A7 along with the fact that n is large imply that there always exists a neighborhood z such that $\frac{P_z}{N_z} \approx \alpha\frac{P}{N}$. Axiom A8 would then give:

$$
\lim_{n\to\infty} I = \lim_{n\to\infty}\sum_{i=1}^{z}\frac{N_i/N}{\sum_{i=1}^{z}N_i/N}\left(\frac{P_i/N_i}{P_z/N_z} - 1\right) = \frac{1}{\alpha}\sum_{i=1}^{n}\frac{N_i}{N}\frac{P_i/N_i}{P/N} - 1 = 0.
$$

Axiom A6, along with the result in (19) and the fact that $H = 1$ and $I = 0$ under axioms A7 and A8, give that $UP(\mathcal{A},\alpha) = G(\mathcal{A})$. ∎

A.3 Proof of Corollary 1

The change in urban poverty ΔUP from configuration $\mathcal{A}$ in time t to $\mathcal{A}'$ in time t' for a urban poverty index satisfying axioms A1-A8 can be decomposed as follows:

$$\Delta UP = G(\mathcal{A}') - G(\mathcal{A}) = W \ + \ R \ + \ C \cdot E,$$

where $C = 1/\left(1+c\right)$.

Proof. Let neighborhood i be the neighborhood having rank i when neighborhoods are sorted in decreasing order of neighborhood poverty incidence. To simplify notation, let $p_i = \frac{P_i}{N_i}$ and $s_i = \frac{N_i}{N}$ denote the poverty incidence and population share of neighborhood i, respectively. Let $\mathbf{p} = (p_1, \ldots, p_n)^T$ be the $n \times 1$ vector of neighborhood poverty incidences sorted in decreasing order and $\mathbf{s} = (s_1, \ldots, s_n)^T$ be the $n \times 1$ vector of the corresponding population shares. A configuration is fully identified by the pair $(\mathbf{s}, \mathbf{p})$, and is used interchangeably. Let $\mathbf{1}_n$ being the $n \times 1$ vector with each element equal to 1, $\mathbf{P}$ is the $n \times n$ skew-symmetric matrix:

$$\mathbf{P} = \frac{1}{\bar{p}}\left(\mathbf{1}_n\mathbf{p}^T - \mathbf{p}\mathbf{1}_n^T\right) = \begin{bmatrix} \frac{p_1-p_1}{\bar{p}} & \cdots & \frac{p_n-p_1}{\bar{p}} \\ \vdots & \ddots & \vdots \\ \frac{p_1-p_n}{\bar{p}} & \cdots & \frac{p_n-p_n}{\bar{p}} \end{bmatrix}, \tag{20}$$

where $\bar{p}$ is the overall poverty incidence in the city. The elements of $\mathbf{P}$ are the n^2 relative pairwise differences between the neighborhood poverty incidences as ordered in $\mathbf{p}$. Let $\mathbf{S} = diag\left\{\mathbf{s}\right\}$ be the $n \times n$ diagonal matrix with diagonal elements equal to the population shares in $\mathbf{s}$, and $\mathbf{G}$ be a $n \times n$ G-matrix (a skew-symmetric matrix whose diagonal elements are equal to 0, with upper diagonal elements equal to -1 and lower diagonal elements equal to 1) (Silber 1989). The Gini index of urban poverty is expressed in matrix form:

$$G\left(\mathbf{s}, \mathbf{p}\right) = \frac{1}{2}tr\left(\tilde{\mathbf{G}}\mathbf{P}^T\right), \tag{21}$$

where the matrix $\tilde{\mathbf{G}} = \mathbf{SGS}$ is the weighting G-matrix, a generalization of the G-matrix introduced by Mussini and Grossi (2015) to add weights in the calculation of the Gini index. Suppose that neighborhood poverty incidences and population shares are observed in times t and t'. Let $\mathbf{p}_t$ be the $n \times 1$ vector of the t poverty incidences sorted in decreasing order and $\mathbf{s}_t$ be the $n \times 1$ vector of the corresponding population shares. Let $\mathbf{p}_{t'}$ be the $n \times 1$ vector of the t' poverty incidences sorted in decreasing order and $\mathbf{s}_{t'}$ be the $n \times 1$ vector of the corresponding population shares. The change in urban poverty concentration from t to t' is measured by the difference between the Gini index in t' and the Gini index in t:

$$\Delta UP = G\left(\mathbf{s}_{t'}, \mathbf{p}_{t'}\right) - G\left(\mathbf{s}_t, \mathbf{p}_t\right) = \frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t'}\mathbf{P}_{t'}^T\right) - \frac{1}{2}tr\left(\tilde{\mathbf{G}}_t\mathbf{P}_t^T\right). \tag{22}$$

Equation (22) can be broken down into three components by applying the matrix approach used in Mussini and Grossi (2015) and in Mussini (2017). The three components separate the contributions of changes in neighborhood population shares, ranking of neighborhoods and disparity of neighborhood poverty incidences. Let $\mathbf{s}_{t|t'}$ stand for the $n \times 1$ vector of the t population shares arranged by the decreasing order of the corresponding t' poverty incidences.

Let $\lambda = \bar{p}_{t'}/\bar{p}_{t'|t}$ be the ratio of the actual t' overall poverty incidence to the fictitious t' overall poverty incidence which is the weighted average of t' poverty incidences where the weights are the corresponding population shares in t. After defining $\mathbf{S}_{t|t'} = diag\left\{\mathbf{s}_{t|t'}\right\}$, the Gini index of t' neighborhood poverty incidences calculated by using the t neighborhood population shares is

$$
\begin{aligned}
G\left(\mathbf{s}_{t|t'}, \mathbf{p}_{t'}\right) &= \frac{1}{2}tr\left(\mathbf{S}_{t|t'}\,\mathbf{G}\mathbf{S}_{t|t'}\,\lambda\mathbf{P}_{t'}^{T}\right) \\
&= \frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t|t'}\,\lambda\mathbf{P}_{t'}^{T}\right)
\end{aligned}
\tag{23}
$$

where $\tilde{\mathbf{G}}_{t|t'} = \mathbf{S}_{t|t'}\,\mathbf{G}\mathbf{S}_{t|t'}$ is the weighting G-matrix obtained by using the neighborhood population shares in t instead of those in t'. In equation (23), the multiplication of $\mathbf{P}_{t'}^{T}$ by λ ensures that the pairwise differences between the t' neighborhood poverty incidences are divided by $\bar{p}_{t'|t}$ instead of $\bar{p}_{t'}$. By adding and subtracting $G\left(\mathbf{s}_{t|t'}, \mathbf{p}_{t'}\right)$ in equation (22), the contribution to ΔUP due to changes in neighborhood population shares can be separated from that attributable to changes in disparities between neighborhood poverty incidences:

$$
\begin{aligned}
\Delta UP &= \left[\frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t'}\mathbf{P}_{t'}^{T}\right) - \frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t|t'}\,\lambda\mathbf{P}_{t'}^{T}\right)\right] + \left[\frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t|t'}\,\lambda\mathbf{P}_{t'}^{T}\right) - \frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t}\mathbf{P}_{t}^{T}\right)\right] \\
&= \frac{1}{2}tr\left(\mathbf{W}\mathbf{P}_{t'}^{T}\right) + \left[\frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t|t'}\,\lambda\mathbf{P}_{t'}^{T}\right) - \frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t}\mathbf{P}_{t}^{T}\right)\right] \\
&= W + \left[\frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t|t'}\,\lambda\mathbf{P}_{t'}^{T}\right) - \frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t}\mathbf{P}_{t}^{T}\right)\right],
\end{aligned}
\tag{24}
$$

where $\mathbf{W} = \tilde{\mathbf{G}}_{t'} - \lambda\tilde{\mathbf{G}}_{t|t'}$. Component W measures the effect of changes in neighborhood population shares. A positive value of W indicates that the weights assigned to more unequal pairs of neighborhoods are larger in t' than in t, increasing urban poverty concentration from t to t'. A negative value of W indicates that the weights assigned to more unequal pairs of neighborhoods are smaller in t' than in t, reducing urban poverty concentration from t to t'.

The difference enclosed within square brackets on the right-hand side of equation (24) can be additively split into two components: one component measuring the re-ranking of neighborhoods, a second component measuring the change in disparity of neighborhood poverty incidences. Let $\mathbf{p}_{t'|t}$ be the $n \times 1$ vector of t' neighborhood poverty incidences sorted in decreasing order of the respective t neighborhood poverty incidences, and $\mathbf{B}$ be the $n \times n$ permutation matrix re-arranging the elements of $\mathbf{p}_{t'}$ to obtain $\mathbf{p}_{t'|t}$, that is $\mathbf{p}_{t'|t} = \mathbf{B}\mathbf{p}_{t'}$. Matrix $\mathbf{P}_{t'|t} = \left(1/\bar{p}_{t'|t}\right)\left(\mathbf{1}_{n}\mathbf{p}_{t'|t}^{T} - \mathbf{p}_{t'|t}\mathbf{1}_{n}^{T}\right)$ contains the n^{2} relative pairwise differences between the neighborhood poverty incidences as arranged in $\mathbf{p}_{t'|t}$. The concentration index of the t' poverty incidences sorted by the t poverty incidences, calculated by using the t population shares, is defined as follows:

$$
C\left(\mathbf{s}_{t}, \mathbf{p}_{t'|t}\right) = \frac{1}{2}tr\left(\tilde{\mathbf{G}}_{t}\mathbf{P}_{t'|t}^{T}\right).
\tag{25}
$$

By using permutation matrix $\mathbf{B}$, the concentration index $C\left(\mathbf{s}_{t}, \mathbf{p}_{t'|t}\right)$ can be re-written as a function of $\mathbf{P}_{t'}$ instead of $\mathbf{P}_{t'|t}$. Since $\mathbf{P}_{t'|t} = \mathbf{B}\lambda\mathbf{P}_{t'}\mathbf{B}^{T}$, the concentration index $C\left(\mathbf{s}_{t}, \mathbf{p}_{t'|t}\right)$

expressed as a function of $\mathbf{P}_{t'}$ becomes

$$
\begin{aligned}
C\left(\mathbf{s}_t, \mathbf{p}_{t'|t}\right) &= \frac{1}{2} tr\left(\tilde{\mathbf{G}}_t \mathbf{B} \lambda \mathbf{P}_{t'}^T \mathbf{B}^T\right) \\
&= \frac{1}{2} tr\left(\mathbf{B}^T \tilde{\mathbf{G}}_t \mathbf{B} \lambda \mathbf{P}_{t'}^T\right).
\end{aligned}
\tag{26}
$$

By adding $C\left(\mathbf{s}_t, \mathbf{p}_{t'|t}\right)$ as expressed in (25) and subtracting it as expressed in (26) to the difference enclosed within square brackets on the right-hand side of equation (24), we obtain

$$
\begin{aligned}
\frac{1}{2} tr\left(\tilde{\mathbf{G}}_{t|t'} \lambda \mathbf{P}_{t'}^T\right) - \frac{1}{2} tr\left(\tilde{\mathbf{G}}_t \mathbf{P}_t^T\right) &= \left[\frac{1}{2} tr\left(\tilde{\mathbf{G}}_{t|t'} \lambda \mathbf{P}_{t'}^T\right) - \frac{1}{2} tr\left(\mathbf{B}^T \tilde{\mathbf{G}}_t \mathbf{B} \lambda \mathbf{P}_{t'}^T\right)\right] \\
&\quad + \left[\frac{1}{2} tr\left(\tilde{\mathbf{G}}_t \mathbf{P}_{t'|t}^T\right) - \frac{1}{2} tr\left(\tilde{\mathbf{G}}_t \mathbf{P}_t^T\right)\right] \\
&= \frac{1}{2} tr\left[\left(\tilde{\mathbf{G}}_{t|t'} - \mathbf{B}^T \tilde{\mathbf{G}}_t \mathbf{B}\right) \lambda \mathbf{P}_{t'}^T\right] \\
&\quad + \frac{1}{2} tr\left[\tilde{\mathbf{G}}_t \left(\mathbf{P}_{t'|t}^T - \mathbf{P}_t^T\right)\right] \\
&= \frac{1}{2} tr\left(\mathbf{R} \lambda \mathbf{P}_{t'}^T\right) + \frac{1}{2} tr\left(\tilde{\mathbf{G}}_t \mathbf{D}^T\right) \\
&= R + D,
\end{aligned}
\tag{27}
$$

where $\mathbf{R} = \tilde{\mathbf{G}}_{t|t'} - \mathbf{B}^T \tilde{\mathbf{G}}_t \mathbf{B}$ and $\mathbf{D} = \mathbf{P}_{t'|t} - \mathbf{P}_t$. Component R measures the effect of re-ranking of neighborhoods from t to t' and its contribution to the change in urban poverty concentration is always non-negative. The nonzero elements of $\mathbf{R}$ indicate the pairs of neighborhoods which have re-ranked from t to t'.

Component D measures the effect of disproportionate change between neighborhood poverty incidences. The generic (i,j)-th element of $\mathbf{D}$ compares the relative difference between the t poverty incidences of the neighborhoods in positions j and i in $\mathbf{p}_t$ with the relative difference between the t' poverty rates of the same two neighborhoods in $\mathbf{p}_{t'|t}$. A negative value of D means that relative disparities in neighborhood poverty incidences have overall decreased from t to t', reducing urban poverty concentration. A positive value of D indicates that relative disparities in neighborhood poverty incidences have overall increased from t to t', increasing urban poverty concentration. If all neighborhood poverty incidences have changed by the same proportion from t to t', then $D = 0$.

Given equations (24) and (27), a three-term decomposition of ΔUP is obtained:

$$
\Delta UP = \frac{1}{2} tr\left(\mathbf{W} \mathbf{P}_{t'}^T\right) + \frac{1}{2} tr\left(\mathbf{R} \lambda \mathbf{P}_{t'}^T\right) + \frac{1}{2} tr\left(\tilde{\mathbf{G}}_t \mathbf{D}^T\right) = W + R + D.
\tag{28}
$$

Since component D would not reveal changes in neighborhood poverty incidences if all neighborhood poverty incidences changed by the same proportion, this component is split into two further terms: one measuring the change in overall poverty incidence, the second measuring the changes in disparities between neighborhood poverty incidences by assuming that overall poverty incidence remains the same from t to t'. Let c stand for the change in overall poverty

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incidence by assuming that neighborhood population shares are unchanged from t to t':

$$c = \frac{\bar{p}_{t'|t} - \bar{p}_t}{\bar{p}_t}. \tag{29}$$

Let $\mathbf{p}^c_{t'|t} = \mathbf{p}_t + c\mathbf{p}_t$ be the vector of neighborhood poverty incidences we would observe in t' if every neighborhood poverty incidence changed by proportion c. This implies that $\bar{p}^c_{t'|t} = \bar{p}_{t'|t}$. Vector $\mathbf{p}_{t'|t}$ can be expressed as

$$\mathbf{p}_{t'|t} = \mathbf{p}^c_{t'|t} + \mathbf{p}^\delta_{t'|t},$$

where the elements of vector $\mathbf{p}^\delta_{t'|t}$ are the element-by-element differences between vectors $\mathbf{p}_{t'|t}$ and $\mathbf{p}^c_{t'|t}$. Since $\mathbf{p}^c_{t'|t} = \mathbf{p}_t + c\mathbf{p}_t$, $\mathbf{p}_{t'|t}$ can be re-written as

$$\mathbf{p}_{t'|t} = \underbrace{\mathbf{p}_t + \mathbf{p}^\delta_{t'|t}}_{\mathbf{p}^e_{t'|t}} + c\mathbf{p}_t \tag{30}$$

$$= \mathbf{p}^e_{t'|t} + c\mathbf{p}_t,$$

where the elements of $\mathbf{p}^e_{t'|t}$ account for disproportionate changes in neighborhood poverty incidences from t to t', as $\mathbf{p}^e_{t'|t}$ would equal $\mathbf{p}_t$ if there were no disproportionate changes in neighborhood poverty incidences. Given equations (29) and (31), matrix $\mathbf{P}_{t'|t}$ can be written as

$$\mathbf{P}_{t'|t} = \left(1/\bar{p}_{t'|t}\right)\left(\mathbf{1}_n \mathbf{p}^T_{t'|t} - \mathbf{p}_{t'|t}\mathbf{1}^T_n\right) \tag{31}$$

$$= \frac{1}{1+c}\begin{bmatrix} \frac{p^e_{1,t'|t} - p^e_{1,t'|t}}{\bar{p}_t} & \cdots & \frac{p^e_{n,t'|t} - p^e_{1,t'|t}}{\bar{p}_t} \\ \vdots & \ddots & \vdots \\ \frac{p^e_{1,t'|t} - p^e_{n,t'|t}}{\bar{p}_t} & \cdots & \frac{p^e_{n,t'|t} - p^e_{n,t'|t}}{\bar{p}_t} \end{bmatrix} + \frac{c}{1+c}\begin{bmatrix} \frac{p_{1,t} - p_{1,t}}{\bar{p}_t} & \cdots & \frac{p_{n,t} - p_{1,t}}{\bar{p}_t} \\ \vdots & \ddots & \vdots \\ \frac{p_{1,t} - p_{n,t}}{\bar{p}_t} & \cdots & \frac{p_{n,t} - p_{n,t}}{\bar{p}_t} \end{bmatrix}$$

$$= \frac{1}{1+c}\mathbf{P}^e_{t'|t} + \frac{c}{1+c}\mathbf{P}_t.$$

Since matrix $\mathbf{D}$ in equation (28) is obtained by subtracting $\mathbf{P}_t$ from $\mathbf{P}_{t'|t}$, $\mathbf{D}$ can be re-written as

$$\mathbf{D} = \mathbf{P}_{t'|t} - \mathbf{P}_t \tag{32}$$

$$= \frac{1}{1+c}\mathbf{P}^e_{t'|t} + \frac{c}{1+c}\mathbf{P}_t - \mathbf{P}_t$$

$$= \underbrace{\left(\frac{1}{1+c}\right)}_{C}\underbrace{\left(\mathbf{P}^e_{t'|t} - \mathbf{P}_t\right)}_{\mathbf{E}}$$

$$= C\mathbf{E}$$

By replacing $\mathbf{D}$ in equation (28) with its expression in equation (32), the decomposition of the change in urban poverty concentration becomes

$$\Delta UP = \frac{1}{2}tr\left(\mathbf{W}\mathbf{P}^T_{t'}\right) + \frac{1}{2}tr\left(\mathbf{R}\lambda\mathbf{P}^T_{t'}\right) + C\frac{1}{2}tr\left(\tilde{\mathbf{G}}_t\mathbf{E}^T\right) = W + R + CE. \tag{33}$$

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■

A.4   Proof of Corollary 2

The change in urban poverty ΔUP from configuration $\mathcal{A}$ in time t to $\mathcal{A}'$ in time t' for a urban poverty index satisfying axioms A1-A8 can be decomposed as follows:

$$\Delta UP = G(\mathcal{A}') - G(\mathcal{A}) = \big(G_N(\mathcal{A}') + G_N(\mathcal{A}')\big) - \big(G_{nN}(\mathcal{A}) + G_{nN}(\mathcal{A})\big)$$
$$= (W_N + W_{nN}) + (R_N + R_{nN}) + C(E_N + E_{nN}).$$

Proof. Let $\mathbf{N}_t$ be the $n \times n$ spatial weights matrix having its (i,j)-th entry equal to 1 if and only if the (i,j)-th element of $\mathbf{P}_t$ is the relative difference between the poverty incidences of two neighboring neighborhoods, otherwise the (i,j)-th element of $\mathbf{N}_t$ is 0. Using the Hadamard product,[7] the relative pairwise differences between the poverty incidences of neighboring neighborhoods can be selected from $\mathbf{P}_t$:

$$\mathbf{P}_{N,t} = \mathbf{N}_t \odot \mathbf{P}_t. \tag{34}$$

For each pair of neighborhoods, the relative difference between the t' poverty incidences of two neighborhoods in $\mathbf{P}^e_{t'|t}$ has the same position as the relative difference between their t poverty incidences in $\mathbf{P}_t$. Thus, $\mathbf{N}_t$ also selects the relative pairwise differences between neighboring neighborhoods from $\mathbf{P}^e_{t'|t}$:

$$\mathbf{P}^e_{N,t'|t} = \mathbf{N}_t \odot \mathbf{P}^e_{t'|t}. \tag{35}$$

Since $\mathbf{E} = \mathbf{P}^e_{t'|t} - \mathbf{P}_t$, the Hadamard product between $\mathbf{N}_t$ and $\mathbf{E}$ is a matrix with nonzero elements equal to the elements of $\mathbf{E}$ pertaining to neighboring neighborhoods:

$$\mathbf{E}_N = \mathbf{P}^e_{N,t'|t} - \mathbf{P}_{N,t} = \mathbf{N}_t \odot \left(\mathbf{P}^e_{t'|t} - \mathbf{P}_t\right) = \mathbf{N}_t \odot \mathbf{E}. \tag{36}$$

Let $\mathbf{N}_{t'}$ be the $n \times n$ spatial weights matrix having its (i,j)-th entry equal to 1 if and only if the (i,j)-th element of $\mathbf{P}_{t'}$ is the relative difference between the poverty incidences of two neighboring neighborhoods, otherwise the (i,j)-th element of $\mathbf{N}_{t'}$ is 0. The Hadamard product of $\mathbf{N}_{t'}$ and $\mathbf{P}_{t'}$ is the matrix

$$\mathbf{P}_{N,t'} = \mathbf{N}_{t'} \odot \mathbf{P}_{t'}. \tag{37}$$

The nonzero elements of $\mathbf{P}_{N,t'}$ are the relative pairwise differences between the t' poverty incidences of neighboring neighborhoods.

The decomposition of the change in the neighbor component of urban poverty concentration is obtained by replacing $\mathbf{P}_{t'}$ and $\mathbf{E}$ in equation (33) with $\mathbf{P}_{N,t'}$ and $\mathbf{E}_N$ respectively:

$$\Delta UP_N = \frac{1}{2}tr\left(\mathbf{WP}^T_{N,t'}\right) + \frac{1}{2}tr\left(\mathbf{R}\lambda\mathbf{P}^T_{N,t'}\right) + C\frac{1}{2}tr\left(\tilde{\mathbf{G}}_t\mathbf{E}^T_N\right) = W_N + R_N + CE_N. \tag{38}$$

Let $\mathbf{J}_n$ be the matrix with diagonal elements equal to 0 and extra-diagonal elements equal to 1, the matrix with nonzero elements equal to the relative pairwise differences between the t'

---

[7]Let $\mathbf{X}$ and $\mathbf{Y}$ be $k \times k$ matrices. The Hadamard product $\mathbf{X} \odot \mathbf{Y}$ is defined as the $k \times k$ matrix with the (i,j)-th element equal to $x_{ij}y_{ij}$.

poverty incidences of non-neighboring neighborhoods is

$$\mathbf{P}_{nN,t'} = (\mathbf{J}_n - \mathbf{N}_{t'}) \odot \mathbf{P}_{t'}. \tag{39}$$

The matrix selecting the elements of $\mathbf{E}$ pertaining to the pairs of non-neighboring neighborhoods is

$$\mathbf{E}_{nN} = (\mathbf{J}_n - \mathbf{N}_t) \odot \mathbf{E}. \tag{40}$$

The decomposition of the change in the non-neighbor component of urban poverty concentration is obtained by replacing $\mathbf{P}_{t'}$ and $\mathbf{E}$ in equation (33) with $\mathbf{P}_{nN,t'}$ and $\mathbf{E}_{nN}$, respectively:

$$\Delta UP_{nN} = \frac{1}{2}tr\left(\mathbf{W}\mathbf{P}_{nN,t'}^T\right) + \frac{1}{2}tr\left(\mathbf{R}\lambda\mathbf{P}_{nN,t'}^T\right) + C\frac{1}{2}tr\left(\tilde{\mathbf{G}}_t\mathbf{E}_{nN}^T\right) = W_{nN} + R_{nN} + CE_{nN}. \tag{41}$$

Given equations (41) and (38), the spatial decomposition of the change in urban poverty concentration is

$$\Delta UP = W_N + W_{nN} + R_N + R_{nN} + C\left(E_N + E_{nN}\right). \tag{42}$$

■

B Additional results

In this section we report additional evidence on trends and patterns of urban poverty levels and changes. We also describe the urban poverty drivers and provide additional regression analysis of drivers of concentrated poverty as well as of components of urban poverty changes. The data we use, alongside the replication code, are available upon request.

B.1 Urban poverty trends and components

variable	statistics	1980-1990	1990-2000	2000-2008	2008-2012	2012-2014
ΔUP	mean	.0314	-.0038	.0153	-.016	-.0016
	pc(25)	.0026	-.0258	-.0109	-.0337	-.0135
	pc(75)	.0592	.015	.0401	.0009	.0097
$\Delta CP(20)$	mean	.0958	-.0474	.104	.0491	-.0153
	pc(25)	.0089	-.1	.0305	-.0028	-.0487
	pc(75)	.1722	.0105	.1697	.0997	.0123
$\Delta CP(40)$	mean	.0578	-.0393	.0461	.021	-.0118
	pc(25)	0	-.0736	0	-.0013	-.0325
	pc(75)	.0954	0	.0841	.0535	.0055
W	mean	.0041	.0008	.003	.0006	.0004
	pc(25)	-.0043	-.005	-.0018	-.0015	-.0007
	pc(75)	.0138	.0062	.0069	.0028	.0016
R	mean	.0525	.0462	.0664	.0556	.0277
	pc(25)	.0357	.0318	.0463	.0391	.0192
	pc(75)	.0628	.0567	.0808	.0663	.0325
E	mean	-.0328	-.0507	-.0682	-.082	-.0291
	pc(25)	-.0612	-.0733	-.1017	-.107	-.0411
	pc(75)	.0046	-.0275	-.034	-.0562	-.0157
C	mean	.8869	1.044	.8257	.8923	1.0289
	pc(25)	.7709	.9462	.7387	.8437	.9955
	pc(75)	1.0091	1.1325	.9054	.9308	1.0556
D	mean	-.0252	-.0508	-.054	-.0722	-.0297
	pc(25)	-.0527	-.0727	-.0808	-.0925	-.0419
	pc(75)	.0042	-.028	-.0276	-.0515	-.016
β (log-log)	mean	-.1306	-.1935	-.1694	-.2666	-.1228
	pc(25)	-.2477	-.2679	-.2492	-.3386	-.1712
	pc(75)	-.0247	-.1094	-.0802	-.1892	-.067

Table 4: Summary statistics of changes in urban poverty concentration, all 395 American MSA.

Figure 6: Components of changes in urban poverty: re-ranking (R) and convergence/divergence (D) of poverty incidence across American MSA, 1980 to 2014
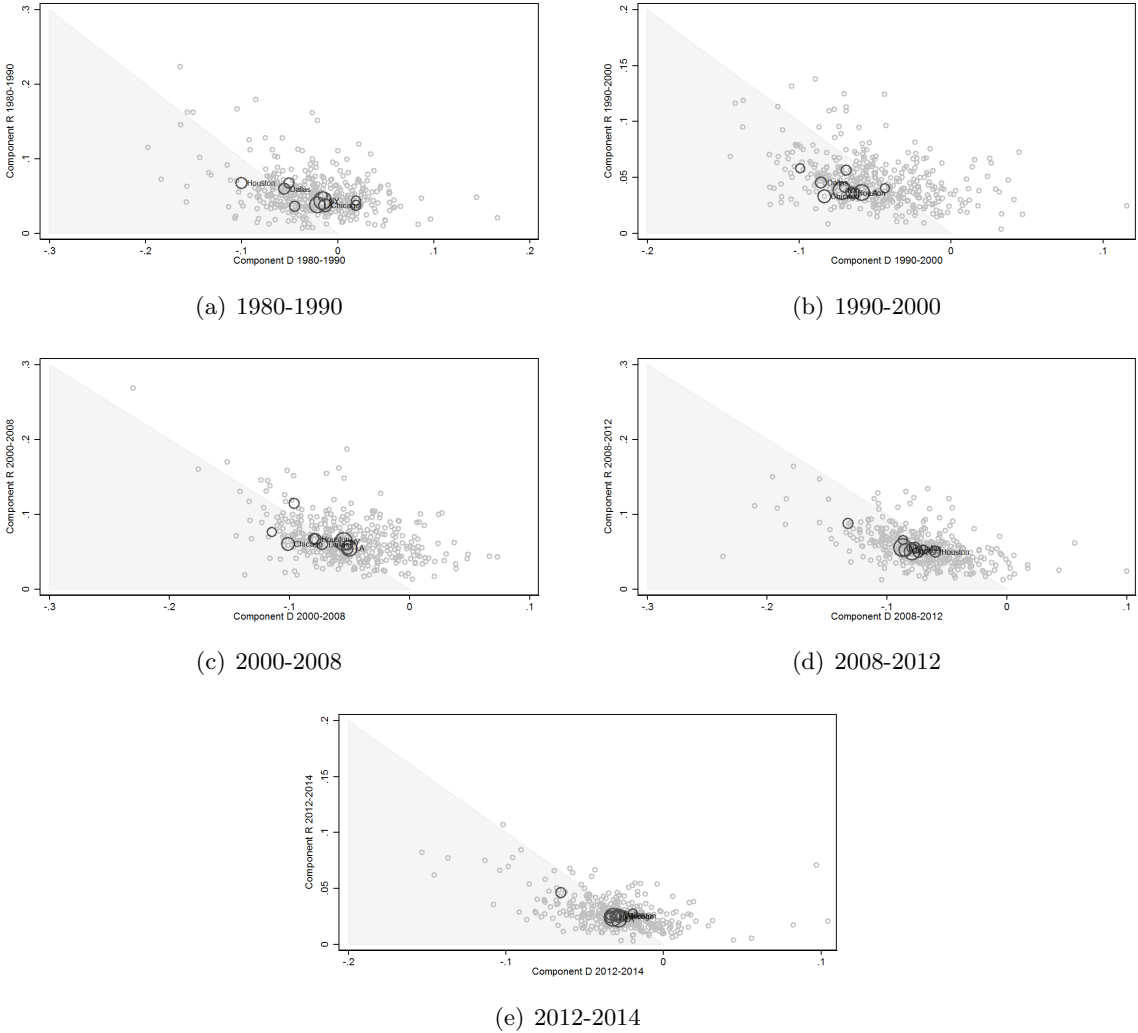
(a) 1980-1990

(b) 1990-2000

(c) 2000-2008

(d) 2008-2012

(e) 2012-2014

Note: Levels of urban poverty and concentrated poverty (concentration of poverty at neighborhood level at 20%), in 1980 and 2014. Data for 395 selected MSA.

Figure 7: Neighborhood and non-neighborhood components of urban poverty levels and year-to-year changes.
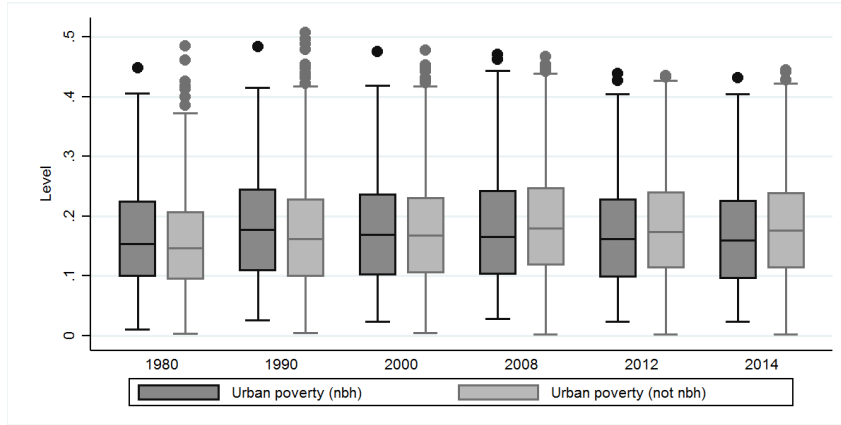
(a) UP levels components
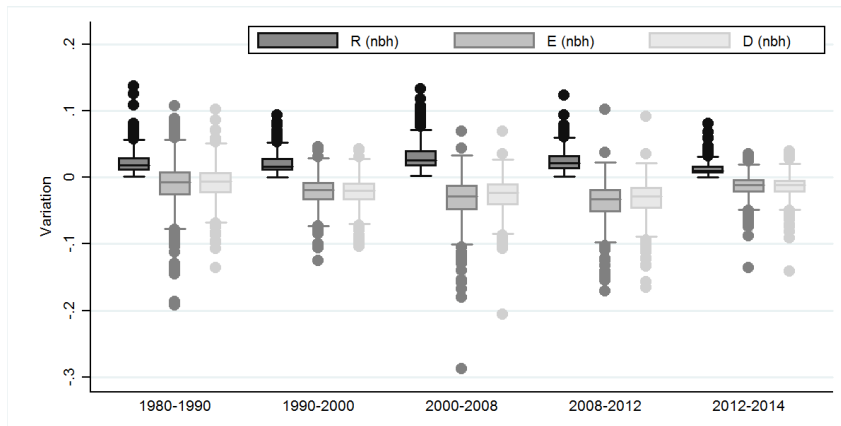
(b) Neighborhood components of urban poverty changes (ΔUP_N)
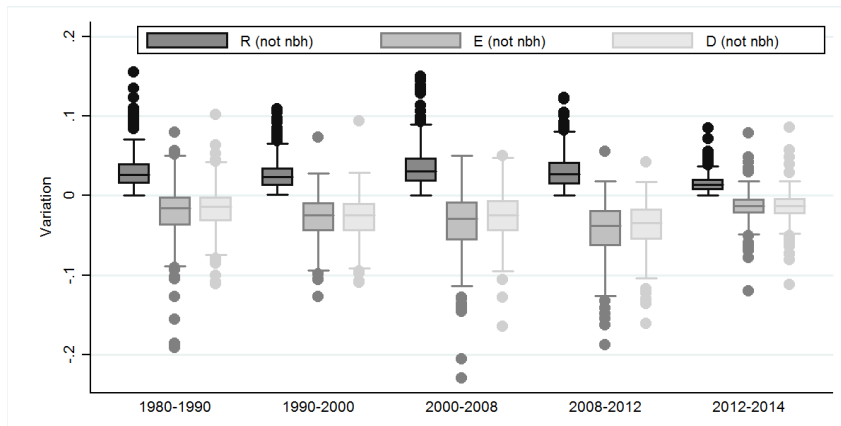
(c) Non-neighborhood components of urban poverty changes (ΔUP_{nN})

Note: Urban Poverty changes and is components (R, E and $D = C \cdot E$), 1980-2014. Data for 395 selected MSA.

B.2 Descriptive statistics

Metro area characteristics	(1980)		(1990)		(2000)		(2008)		(2012)		(2014)	
	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.
Concentrated Poverty (20%)	0.32	0.20	0.41	0.20	0.37	0.20	0.47	0.17	0.52	0.17	0.50	0.17
Concentrated Poverty (40%)	0.06	0.10	0.12	0.14	0.08	0.11	0.13	0.12	0.15	0.13	0.14	0.13
Urban Poverty	0.33	0.09	0.36	0.09	0.35	0.09	0.37	0.08	0.35	0.07	0.35	0.07
Demographics												
Black	0.09	0.10	0.10	0.11	0.10	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Hispanic	0.05	0.10	0.06	0.12	0.09	0.14	0.12	0.15	0.13	0.16	0.13	0.16
Asian	0.03	0.07	0.02	0.06	0.02	0.05	0.03	0.05	0.03	0.05	0.03	0.05
White	0.82	0.16	0.82	0.16	0.77	0.17	0.74	0.18	0.72	0.19	0.72	0.19
Population size (ln)	12.43	1.05	12.30	1.13	12.40	1.14	12.47	1.16	12.50	1.17	12.51	1.18
65 plus yrs old	0.11	0.03	0.13	0.03	0.13	0.03	0.14	0.03	0.15	0.03	0.16	0.03
25-64 yrs old	0.48	0.03	0.50	0.03	0.51	0.03	0.54	0.03	0.53	0.03	0.53	0.02
Foreign	0.04	0.04	0.04	0.04	0.06	0.06	0.05	0.04	0.05	0.04	0.04	0.04
Moved from outside of state	0.11	0.07	0.10	0.05	0.43	0.06	0.03	0.02	0.03	0.01	0.03	0.01
Housing												
New Houses (10 less yrs old)	0.14	0.05	0.21	0.09	0.18	0.07	0.13	0.06	0.16	0.07	0.17	0.07
Old houses (20 plus yrs old)	0.77	0.06	0.56	0.13	0.67	0.12	0.73	0.10	0.70	0.11	0.69	0.11
Owner occupied	0.72	0.06	0.70	0.06	0.71	0.06	0.71	0.06	0.68	0.06	0.67	0.06
Vacant	0.03	0.02	0.10	0.06	0.09	0.05	0.12	0.05	0.12	0.06	0.12	0.06
Rented	0.32	0.06	0.33	0.06	0.32	0.06	0.32	0.06	0.34	0.06	0.34	0.06
Avg. value house (ln)	4.26	0.40	11.05	0.38	11.30	0.36	11.03	0.49	10.94	0.46	10.94	0.50
Median value house by CT (ln)	10.10	0.40	11.68	0.40	11.84	0.38	12.80	0.49	12.67	0.42	12.67	0.43
p25% value house by CT (ln)	9.40	0.54	11.35	0.40	11.53	0.38	11.73	0.49	11.62	0.43	11.61	0.45
S.d. value house by CT (ln)	9.66	0.43	10.74	0.56	10.81	0.56	11.03	0.58	10.98	0.54	11.00	0.58
Avg. rent (ln)	17.36	1.27	17.84	1.28	17.79	1.31	17.97	1.33	18.05	1.33	18.06	1.34
Median rent by CT (ln)	8.79	0.16	6.56	0.22	6.41	0.27	6.48	0.29	6.53	0.28	6.53	0.28
p25% rent by CT (ln)	8.61	0.17	6.39	0.22	6.22	0.26	6.29	0.28	6.35	0.27	6.35	0.27
S.d. rent by CT (ln)	7.35	0.39	5.19	0.47	5.01	0.52	5.11	0.50	5.12	0.49	5.12	0.50
Education												
College Town	0.10	0.31	0.11	0.31	0.10	0.31	0.10	0.31	0.10	0.31	0.10	0.31
Student Town	0.05	0.22	0.05	0.22	0.05	0.22	0.05	0.22	0.05	0.22	0.05	0.22
Less than high school	0.10	0.04	0.06	0.03	0.99	0.02	0.04	0.02	0.03	0.02	0.03	0.02
With high school	0.30	0.04	0.32	0.04	0.02	0.01	0.27	0.05	0.21	0.05	0.21	0.05
With college	0.09	0.03	0.15	0.04	0.42	0.06	0.32	0.06	0.38	0.06	0.39	0.06
Enrolment (any)	0.23	0.02	0.27	0.04	0.15	0.02	0.14	0.02	0.14	0.02	0.13	0.02
Employment												
Managerial position	0.22	0.04	0.24	0.04	0.31	0.05	0.32	0.05	0.33	0.05	0.34	0.06
Timework	0.34	0.05	0.35	0.04	0.33	0.05	0.33	0.05	0.32	0.05	0.32	0.05
Distributive aspects												
Median income (pop)	16166.76	2648.83	26991.94	5374.54	38801.79	7309.99	48003.64	9396.44	49490.55	9798.25	51113.42	10364.36
Avg hh income (ln)	10.39	0.33	11.03	0.16	11.14	0.16	11.04	0.18	11.03	0.18	11.03	0.19
Median hh income by CT (ln)	10.75	0.15	10.82	0.19	10.90	0.18	10.88	0.18	10.86	0.19	10.85	0.19
p25% hh income by CT (ln)	10.51	0.18	10.53	0.22	10.64	0.19	10.59	0.20	10.56	0.21	10.55	0.21
S.d. hh income by CT (ln)	9.57	0.34	9.78	0.35	9.76	0.37	9.81	0.33	9.80	0.34	9.78	0.34
Fraction of poor	0.12	0.04	0.13	0.05	0.12	0.04	0.15	0.04	0.16	0.04	0.16	0.04
Dissimilarity poor	0.27	0.08	0.31	0.08	0.30	0.08	0.32	0.07	0.31	0.07	0.31	0.07
Dissimilarity white-black	0.59	0.13	0.56	0.12	0.52	0.12	0.53	0.10	0.52	0.10	0.51	0.10
Dissimilarity black	0.54	0.13	0.50	0.12	0.46	0.12	0.46	0.11	0.44	0.11	0.44	0.10
Dissimilarity hispanic	0.34	0.10	0.35	0.10	0.33	0.10	0.35	0.10	0.33	0.10	0.32	0.09
Dissimilarity asian	0.42	0.11	0.47	0.11	0.43	0.09	0.48	0.10	0.47	0.10	0.46	0.10
Dissimilarity white	0.08	0.07	0.09	0.07	0.10	0.08	0.11	0.08	0.12	0.08	0.12	0.08
MSA	395		367		395		395		395		395	
Share of MSAs with 20% CT poor	0.93	0.25	0.97	0.18	0.95	0.21	0.99	0.09	1.00	0.05	0.99	0.07
N. of CT	107.88	288.90	125.77	318.49	135.38	332.47	152.15	357.96	152.23	358.31	152.19	358.29
N. of CT with 20% of poor	21.60	66.25	30.89	75.88	29.37	86.32	39.04	89.18	46.93	106.39	45.25	103.88
N. of CT with 40% of poor	5.43	22.78	10.90	30.42	6.64	22.97	9.52	21.14	12.07	27.12	10.86	24.62

Table 5: Descriptive statistics of regressors

Table 5 reports unweighted means and standard deviations of the variables we include in the regression analysis. Variables have been constructed from STF3A Census files for years 1980, 1990 and 2000 and from ACS modules 2006-2010, 2010-2014 and 2012-2016. Census and ACS data come in the forms of tabulations by census tract level. MSAs display on average 107 census tracts in 1980 up to more than 150 in 2014. We extrapolate information from these tables and aggregate at the level of the MSA to produce relevant control variables. We construct a dataset of census tracts characteristics for 395 American Metropolitan Areas (those with at least 10 census tracts according to 2010 census) for the years considered in this study. The sample of

MSA we consider is grouped by region: Northeast (12.66%), Midwest (27.34%), South (39.75%) and West (20.25%).

Our dependent variables are measures of concentrated poverty (CP index for urban poverty lines at 20% and 40%), urban poverty (index UP) and the components of urban poverty variation. Explanatory variables can be grouped into two categories. For non-monetary characteristics, Census and ACS report information about the number of individuals reporting one specific attribute and living in one given census tract. We aggregate information at the MSA level and then standardize population counts by the appropriate reference population, so that all variables can be interpreted as population shares bonded between 0 and 1. For monetary dimensions, the Census and ACS report information about the total aggregate value in dollars of that dimension at census tract level. We aggregate measures at MSA levels and compute per capita or per census tract values. Monetary variables always appear in logs after being actualized at 2010 prices using CPI seasonally adjusted estimates for all US urban consumers (obtained from the Bureau of Labor Statistics).

The covariates we use can be grouped in five dimensions: demographics, housing, education, employment and distributive aspects. Demographics (A) includes the total size of the population (expressed in log) and its composition in terms of both racial/ethnic, age and origin groups (*Foreign* captures the proportion of non-US citizens and *Moved from outside of state* the proportion of those who declared to have moved from another US State to the MSA in previous years), which are expressed in terms of shares with respect to the entire population of the MSA.

The second group of control variables gathers housing characteristics (B) of the metro areas. We consider the shares of new and old houses with less than 10 years (*New Houses (10 less yrs old)*) or more than 20 years (*Old houses (20 plus yrs old)*) respectively. These variables are likely to measure the aggregate quality of the MSA housing market. We further distinguish houses according to the occupant subject, by considering the share of houses which are rented (*Rented*) or vacant (*Vacant*) with respect to the total number of houses. The variable *Owner occupied* refers instead to the share of houses that are occupied by the owner. The tenure status of the houses is a strong predictor of housing opportunities for low-income, renting households. Lastly, we include variables for the value of owner occupied houses and for value of rents that are averaged across households (*Avg. value house (ln)* and *Avg. rent (ln)*). We also consider the distributions of owner occupied housing values and of rents across neighborhoods. This information allows to distinguish cases in which low-rent/low-value houses are equally represented across all neighborhood of the city (in which case the median rent by census tracts would coincide across census tracts) from situation where the the rents/values are highly heterogeneous across neighborhoods (in which case we would expect large variance in median values and rents by census tracts, with some census tracts being more affordable than others). Starting from the observation of the median value/rent at the census tract level, we aggregate distributional features of median housing values/rents across census tracts into median (*Median value house by CT (ln)* and *Median rent by CT (ln)*), lower quantile of the housing value and rent distribution (*p25% value house by CT (ln)* and *p25% rent by CT (ln)*) and dispersion (*S.d. value house by CT (ln)* and *S.d. rent by CT (ln)*). All these variables are expressed in log.

The third group of covariates we examine reports information about education (C). We separately consider three dimensions of education. First, we consider the proportion of the resident population aged 25 and above in a given city that has low education (*Less than high school*), some qualification at high school level (*With high school*) and tertiary education and above (*With college*). These variables are meant to measure the human capital composition of a

city, which reflect both historical trends and residential choices of low and high educated people on the basis of specificities of the labor market and the supply of services and amenities produced at the city level. Second, we consider the share of population that is actually enrolled in any form of education (*Enrolment (any)*), as a measure of the demand for consumption of education services in the city. Third, we introduce indicators for whether the city is a college town and student town. The former (*College Town*) identifies MSA where most selective American colleges are located. The selectivity level is measured according to the college tier description used by the Department of Education´s (DOE) IPEDS database. We consider as college town those MSA hosting colleges of tier levels equal to 1 or 2, which are associated respectively with Ivy League colleges plus Stanford, Chicago, Duke, MIT alongside other elite schools (both public and private) with a Barron´s 2009 selectivity index of 1. The second indicator (*Student Town*) identifies the top 20 MSA with the highest number of students enrolled in any college. The number of students refers to the number of IPEDS enrollment (full time and part time) in fall 2013 semester.[8]

The employment structure (D) of the MSA is described by the share of workers occupied with managerial positions (*Managerial Position*) and by the share of workers less than half an hour away from the workplace (*Timework*). Both shares are computed with respect to the total population.

Lastly, to take into account the distributive aspects (E) of income, poverty and ethnicity within MSA. We control for average household income in the city (*Avg hh income (ln)*) as an objective measure of well-being. How income is distributed across census tracts signals quality of the tracts and their affordability. We use measures in the census and ACS about median income in the census tract and compute measures of the distribution of incomes across census tracts considering the median affluence of the neighborhoods (*Median hh income by CT (ln)*), the household income for poorest 25% of the census tracts (*p25% hh income by CT (ln)*) and a measure of dispersion of income across census tracts (*S.d. hh income by CT (ln)*). We also consider information about the poverty incidence in the city as a whole (*Fraction of poor*) and the way poor and non-poor people (according to the 100% federal poverty line) are unevenly represented across the census tracts (*Dissimilarity poor*).[9] Finally, we measure the ethnic dimension of segregation across the city neighborhoods by using standard measures of segregation (dissimilarity index) for white, black, hispanics, asians, with respect to the overall population, as well as a traditional measures of black and white segregation (*Dissimilarity white-black*).

B.3 Additional results

This section reports additional results about the effects of demographic, housing, education, employment and distributional factors on concentrated poverty and on the components of urban poverty changes.

Regression tables 6 and 7 highlight the drivers of poverty concentration across census tracts displaying high (20%) and extreme (40%) poverty intensity. Tables 6 and 7 report results by year,

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[8]For a detailed description of the variables used to construct our indicators, see Chetty, Friedman, Saez, Turner and Yagan (2017) and Table 6 and Table 10 at `https://opportunityinsights.org/data/`.

[9]The unevenness dimension is captured by the dissimilarity index, measuring the proportion of poor individuals that should move to restore proportionality across the city neighborhoods (about 30% on average across all MSA), see Andreoli and Zoli (2014).

for a pooled model with year fixed effects and for a FE longitudinal analysis. Our results confirm findings in Iceland and Hernandez (2017). Demographics play the lion share in driving poverty concentration in high and extreme concentration neighborhoods. The share of poor residents and the degree of segregation of poor people strongly positively correlate with poverty concentration. Pooled regression reveals that concentrated poverty can be explained as well by sorting on the basis of ethnicity. While income and housing value size and distribution have little explanatory power, the education and employment composition, as well as the demographic features of the urban population, strongly associated with opportunities offered by the labor market, correlate with concentrated poverty (more than 20% poverty incidence). That is, MSA with larger poverty concentration are characterized by low shares of high educated population, holding managerial position and less than half an hour away from the workplace. Racial factors only play a significant role in determining poverty concentration in extreme poverty neighborhoods (more than 40% poverty incidence), while the proportion of people moving from outside state (which are likely non-poor and who tend to distribute more randomly across the city neighborhoods than long-term residents) negatively (positively)contributes to the incidence of concentrated poverty in extreme (high) poverty neighborhoods.

Tables 8 and 9 replicate estimates in Table 3, alongside year-specific estimates. Tables 10 and 11 investigate components of the changes in urban poverty on a year-to-year basis (models (1)-(5)), as well as on the basis of a pooled regression with year fixed effects. When we correlate the urban poverty drivers to the re-ranking component (Table 10), pooled regression models show that the incidence and segregation of poverty has a negative impact on the changes in this urban poverty component. In addition, we find that the features of the housing stock correlate with the re-ranking component. While a larger proportion of old dwellings is associated with lower changes in the re-ranking component, the proportion of owner occupied, vacant and rented houses explain positive variations of that component. Lastly, among the demographics drivers only the share of black and old population seem to be significative. Table 11 reports drivers of the convergence component of urban poverty. Our estimates reveal that the drivers we consider are less informative about the convergence component than the re-ranking one. In addition, the pooled regression model shows that the incidence and the segregation of poverty have respectively a positive and a negative on the convergence component. Demographic, housing, education and labor market (except for the population share sprawling into suburbia) drivers tend to have no effect on the convergence components. Only the levels of average income across census tracts and income dispersion across neighborhoods are positively correlated with the convergence component.

	OLS 1980 (1)		1990 (2)		2000 (3)		2008 (4)		2012 (5)		2014 (6)		Pool 1980-2014 (7)		Panel FE 1980-2014 (8)	
A) % Black	-0.050	(0.26)	0.524**	(0.23)	0.211	(0.18)	-0.319**	(0.15)	-0.185	(0.15)	-0.243	(0.15)	-0.061	(0.07)	-0.020	(0.12)
A) % Hispanic	-0.157	(0.24)	0.686**	(0.22)	0.311*	(0.17)	-0.152	(0.15)	-0.044	(0.15)	-0.165	(0.14)	0.090	(0.07)	0.128	(0.12)
A) % Asian	-0.282	(0.24)	0.855**	(0.24)	0.339*	(0.19)	-0.093	(0.15)	-0.048	(0.17)	-0.166	(0.16)	0.048	(0.07)	0.097	(0.15)
A) % White	-0.296	(0.25)	0.564**	(0.24)	0.145	(0.19)	-0.088	(0.16)	0.109	(0.17)	-0.203	(0.16)	-0.039	(0.07)	0.016	(0.12)
A) Population size (ln)	0.032	(0.05)	-0.067	(0.08)	-0.045	(0.07)	-0.026	(0.06)	-0.028	(0.08)	0.064	(0.07)	-0.015	(0.02)	-0.014	(0.02)
A) % 65 plus yrs old	-0.163	(0.42)	0.043	(0.47)	-0.091	(0.34)	0.603*	(0.36)	0.333	(0.54)	1.328**	(0.55)	0.330**	(0.12)	0.294	(0.17)
A) % 2564 yrs old	0.034	(0.35)	-0.110	(0.49)	0.144	(0.34)	0.733**	(0.30)	0.266	(0.49)	1.125**	(0.49)	0.385**	(0.10)	0.325	(0.17)
A) % Foreign	0.202	(0.22)	-0.401	(0.25)	-0.234	(0.18)	-0.291	(0.22)	-0.107	(0.26)	0.484*	(0.26)	-0.057	(0.07)	-0.117	(0.06)
A) Moved from outside of state	-0.141	(0.11)	0.118	(0.15)	0.373*	(0.20)	0.222	(0.27)	0.357	(0.32)	0.053	(0.32)	0.145**	(0.05)	0.170**	(0.04)
B) % New Houses (10 less yrs old)	0.014	(0.28)	-0.146	(0.19)	-0.058	(0.16)	0.012	(0.21)	-0.402*	(0.22)	-0.205	(0.21)	-0.115*	(0.07)	-0.157**	(0.05)
B) % Old houses (20 plus yrs old)	-0.169	(0.23)	0.041	(0.14)	0.126	(0.12)	0.016	(0.12)	-0.204	(0.14)	-0.065	(0.14)	0.006	(0.04)	-0.020	(0.04)
B) % Owner occupied	-0.064	(0.38)	-0.558	(0.39)	-0.300	(0.38)	0.448	(0.37)	0.542	(0.38)	0.252	(0.37)	-0.137	(0.14)	-0.047	(0.22)
B) % Vacant	0.425	(0.35)	-0.124	(0.12)	-0.114	(0.11)	-0.181*	(0.11)	-0.225*	(0.12)	-0.355**	(0.12)	-0.045	(0.04)	-0.039	(0.03)
B) % Rented	-0.308	(0.38)	-0.474	(0.39)	-0.294	(0.39)	0.369	(0.39)	0.613	(0.40)	0.398	(0.39)	-0.040	(0.14)	-0.002	(0.18)
B) Avg. value house (ln)	-0.144**	(0.06)	-0.064	(0.06)	-0.054	(0.05)	0.005	(0.02)	0.030	(0.02)	0.015	(0.02)	-0.002	(0.01)	-0.004	(0.02)
B) Median value house by CT (ln)	0.031	(0.06)	0.001	(0.11)	0.126	(0.10)	0.041	(0.03)	0.000	(0.03)	0.019	(0.03)	-0.016	(0.01)	-0.015	(0.02)
B) p25% value house by CT (ln)	0.031	(0.02)	-0.048	(0.07)	-0.090	(0.06)	-0.043	(0.03)	-0.048	(0.03)	-0.018	(0.03)	-0.001	(0.01)	-0.004	(0.02)
B) S.d. value house by CT (ln)	-0.013	(0.03)	0.006	(0.03)	-0.034	(0.03)	-0.011	(0.02)	-0.008	(0.02)	-0.018	(0.02)	0.000	(0.01)	0.001	(0.01)
B) Avg. rent (ln)	-0.026	(0.05)	0.073	(0.08)	0.043	(0.07)	0.033	(0.06)	0.036	(0.08)	-0.060	(0.07)	0.019	(0.02)	0.019	(0.01)
B) Median rent by CT (ln)	0.228*	(0.13)	0.027	(0.14)	-0.361**	(0.13)	-0.324**	(0.12)	0.079	(0.15)	0.361**	(0.14)	-0.039	(0.05)	-0.026	(0.10)
B) p25% rent by CT (ln)	-0.149	(0.09)	0.082	(0.08)	0.233**	(0.09)	0.240**	(0.09)	-0.050	(0.10)	-0.259**	(0.11)	0.005	(0.03)	0.005	(0.07)
B) S.d. rent by CT (ln)	-0.028	(0.02)	0.006	(0.02)	0.069**	(0.02)	0.045**	(0.02)	-0.011	(0.02)	-0.034*	(0.02)	0.005	(0.01)	0.001	(0.01)
C) College Town	0.003	(0.01)	0.003	(0.02)	0.006	(0.01)	-0.004	(0.01)	0.004	(0.01)	0.008	(0.01)	0.002	(0.01)	0.004	(0.00)
C) Student Town	-0.002	(0.02)	0.022	(0.02)	0.001	(0.02)	0.017	(0.02)	-0.003	(0.02)	-0.004	(0.02)	0.001	(0.01)	0.004	(0.01)
C) % less than high school	0.182	(0.43)	0.175	(0.60)	0.002	(0.25)	1.033*	(0.58)	1.739**	(0.83)	-0.801	(0.83)	-0.267**	(0.12)	-0.122	(0.08)
C) % with high school	-0.153	(0.39)	-0.131	(0.46)	0.939	(0.68)	-0.130	(0.31)	0.163	(0.55)	-1.054*	(0.55)	-0.322**	(0.10)	-0.248	(0.13)
C) % with college	-0.225	(0.49)	-0.297	(0.45)	-0.003	(0.30)	0.045	(0.32)	0.494	(0.50)	-0.677	(0.51)	-0.154**	(0.06)	-0.124**	(0.04)
C) % enrolment (any)	-0.463	(0.41)	0.046	(0.37)	-0.075	(0.52)	0.551	(0.48)	1.264**	(0.51)	0.905*	(0.51)	0.181**	(0.09)	0.191	(0.12)
D) % Managerial position	0.087	(0.30)	0.118	(0.31)	-0.130	(0.22)	-0.237	(0.17)	-0.173	(0.17)	0.020	(0.17)	-0.232**	(0.06)	-0.229**	(0.06)
D) % Timework	0.034	(0.12)	-0.180	(0.18)	-0.251*	(0.14)	0.040	(0.12)	0.003	(0.13)	0.025	(0.12)	-0.170**	(0.05)	-0.145**	(0.05)
E) Avg hh income (ln)	0.128*	(0.07)	0.191	(0.14)	0.018	(0.13)	-0.158*	(0.09)	-0.319**	(0.09)	-0.329**	(0.09)	-0.001	(0.02)	0.008	(0.03)
E) Median hh income by CT (ln)	-0.164	(0.13)	-0.274*	(0.16)	-0.079	(0.14)	0.041	(0.12)	0.095	(0.13)	0.129	(0.13)	-0.120**	(0.05)	-0.128**	(0.04)
E) p25% hh income by CT (ln)	0.064	(0.07)	0.104	(0.07)	0.107	(0.07)	0.048	(0.06)	0.052	(0.06)	-0.009	(0.06)	0.074**	(0.02)	0.080**	(0.02)
E) S.d. hh income by CT (ln)	0.020	(0.03)	0.031	(0.04)	0.025	(0.03)	0.078**	(0.03)	0.044	(0.04)	-0.004	(0.04)	0.031**	(0.01)	0.031**	(0.01)
E) % of poor	3.165**	(0.29)	3.220**	(0.31)	3.614**	(0.28)	3.721**	(0.26)	3.203**	(0.26)	2.918**	(0.26)	3.206**	(0.10)	3.215**	(0.13)
E) Dissimilarity poor	1.416**	(0.10)	1.325**	(0.11)	1.533**	(0.09)	1.209**	(0.09)	1.179**	(0.10)	1.120**	(0.10)	1.335**	(0.04)	1.352**	(0.06)
E) Dissimilarity whiteblack	-0.136	(0.17)	0.060	(0.17)	0.054	(0.15)	0.236**	(0.12)	0.217*	(0.13)	0.225*	(0.12)	0.128**	(0.05)	0.104*	(0.05)
E) Dissimilarity black	0.127	(0.17)	-0.194	(0.18)	0.029	(0.15)	-0.398**	(0.12)	-0.394**	(0.13)	-0.253**	(0.12)	-0.182**	(0.05)	-0.180**	(0.06)
E) Dissimilarity hispanic	0.040	(0.06)	0.050	(0.06)	-0.052	(0.06)	-0.012	(0.06)	0.023	(0.06)	0.134**	(0.06)	0.053**	(0.02)	0.051*	(0.02)
E) Dissimilarity asian	0.072	(0.06)	0.071	(0.06)	-0.068	(0.06)	-0.013	(0.04)	0.052	(0.05)	0.006	(0.05)	0.022	(0.02)	0.025*	(0.01)
E) Dissimilarity white	-0.229	(0.22)	-0.443*	(0.24)	-0.214	(0.19)	-0.086	(0.16)	-0.046	(0.18)	-0.342*	(0.18)	-0.255**	(0.07)	-0.212**	(0.05)
Greatrecession													0.001	(0.09)		
Regional fe	y		y		y		y		y		y		y		y	
Year fe	-		-		-		-		-		-		y		y	
N. of obs.	395		367		395		395		395		395		2342		2202	
MSA	395		367		395		395		395		395		367		367	
N. of years	1		1		1		1		1		1		6		6	
R-squared	0.897		0.885		0.910		0.902		0.882		0.890		0.893		0.874	
Root MSE	0.069		0.073		0.063		0.057		0.061		0.060		0.066		0.066	

Table 6: Drivers of concentrated poverty (poverty incidence threshold at 20%).

Note: Dependent variable is the *CP* index by MSA and year. Models (1)-(6) report year specific effects of controls. Model (7) is a pooled OLS regression controlling for years fixed effects and Great Recession (2008-2012) fixed effects. Model (8) is a FE estimator for the balanced panel of MSA (367). All models controls for regional FE (Regions: Northeast, Midwest, South, West). Significance levels: * = 10% and ** = 5%.

	OLS												Pool		Panel FE	
	1980		1990		2000		2008		2012		2014		1980-2014		1980-2014	
	1		2		3		4		5		6		7		8	
A) % Black	-0.781**	(0.22)	0.161	(0.19)	0.221	(0.16)	0.391**	(0.16)	0.342**	(0.15)	0.346**	(0.15)	0.279**	(0.07)	0.280*	(0.13)
A) % Hispanic	-0.870**	(0.21)	-0.200	(0.19)	0.128	(0.14)	0.322**	(0.15)	0.183	(0.15)	0.217	(0.14)	0.041	(0.07)	0.024	(0.15)
A) % Asian	-0.853**	(0.21)	-0.149	(0.21)	0.177	(0.16)	0.350**	(0.16)	0.204	(0.16)	0.207	(0.16)	0.173**	(0.07)	0.150	(0.15)
A) % White	-0.497**	(0.21)	-0.039	(0.21)	0.324**	(0.16)	0.296*	(0.16)	0.064	(0.16)	0.055	(0.16)	0.166**	(0.07)	0.132	(0.13)
A) Population size (ln)	0.052	(0.05)	-0.015	(0.07)	-0.028	(0.06)	0.023	(0.07)	-0.064	(0.07)	-0.084	(0.07)	0.016	(0.02)	0.010	(0.02)
A) % 65 plus yrs old	0.277	(0.35)	-0.215	(0.41)	-0.494*	(0.29)	0.016	(0.37)	-1.808**	(0.53)	-1.681**	(0.55)	-0.084	(0.11)	-0.049	(0.12)
A) % 2564 yrs old	-0.304	(0.30)	-0.861**	(0.42)	-0.500*	(0.29)	-0.028	(0.31)	-1.667**	(0.47)	-1.362**	(0.49)	-0.402**	(0.10)	-0.361**	(0.09)
A) % Foreign	-0.220	(0.18)	-0.120	(0.21)	-0.073	(0.15)	0.116	(0.23)	-0.392	(0.25)	-0.008	(0.26)	-0.096	(0.07)	-0.063	(0.06)
A) Moved from outside of state	0.014	(0.09)	-0.165	(0.13)	-0.562**	(0.17)	-0.436	(0.28)	-0.661**	(0.31)	-0.521	(0.32)	-0.078*	(0.05)	-0.065**	(0.02)
B) % New Houses (10 less yrs old)	0.097	(0.24)	0.212	(0.16)	-0.146	(0.14)	-0.566**	(0.22)	-0.194	(0.21)	-0.267	(0.21)	0.086	(0.06)	0.069	(0.12)
B) % Old houses (20 plus yrs old)	-0.147	(0.19)	-0.068	(0.12)	-0.367**	(0.10)	-0.398**	(0.13)	-0.167	(0.14)	-0.201	(0.14)	-0.100**	(0.04)	-0.108*	(0.05)
B) % Owner occupied	0.298	(0.33)	-0.118	(0.34)	-0.595*	(0.33)	0.241	(0.38)	-0.052	(0.37)	-0.070	(0.37)	0.209	(0.13)	0.244	(0.14)
B) % Vacant	0.298	(0.30)	-0.143	(0.10)	-0.019	(0.10)	0.132	(0.11)	0.265**	(0.12)	0.384**	(0.12)	-0.058	(0.04)	-0.056*	(0.03)
B) % Rented	0.553*	(0.33)	-0.316	(0.34)	-0.436	(0.34)	0.158	(0.40)	-0.038	(0.39)	-0.183	(0.39)	0.216	(0.13)	0.258	(0.17)
B) Avg. value house (ln)	0.091*	(0.05)	-0.045	(0.05)	0.029	(0.05)	-0.013	(0.02)	0.027	(0.02)	-0.004	(0.02)	0.001	(0.01)	-0.001	(0.01)
B) Median value house by CT (ln)	-0.138**	(0.05)	0.202**	(0.10)	-0.168**	(0.08)	-0.006	(0.03)	0.056**	(0.03)	0.007	(0.03)	0.019*	(0.01)	0.019	(0.01)
B) p25% value house by CT (ln)	0.048**	(0.02)	-0.091	(0.06)	0.115**	(0.05)	0.062*	(0.04)	-0.052	(0.03)	0.013	(0.03)	-0.009	(0.01)	-0.006	(0.01)
B) S.d. value house by CT (ln)	0.069**	(0.02)	-0.054**	(0.03)	0.028	(0.02)	-0.003	(0.02)	-0.032*	(0.02)	-0.008	(0.02)	0.001	(0.01)	-0.001	(0.01)
B) Avg. rent (ln)	-0.048	(0.05)	0.013	(0.07)	0.015	(0.06)	-0.037	(0.07)	0.063	(0.07)	0.080	(0.07)	-0.023	(0.02)	-0.018	(0.02)
B) Median rent by CT (ln)	0.005	(0.11)	0.223*	(0.12)	0.369**	(0.11)	0.144	(0.12)	0.018	(0.14)	-0.375**	(0.14)	0.146**	(0.05)	0.123*	(0.06)
B) p25% rent by CT (ln)	0.046	(0.08)	-0.165**	(0.06)	-0.213**	(0.08)	-0.079	(0.09)	-0.035	(0.10)	0.212**	(0.11)	-0.050	(0.05)	-0.043	(0.05)
B) S.d. rent by CT (ln)	0.009	(0.02)	-0.017	(0.02)	-0.072**	(0.02)	-0.002	(0.02)	-0.009	(0.02)	0.045**	(0.02)	-0.021**	(0.01)	-0.019	(0.02)
C) College Town	0.017	(0.01)	0.010	(0.01)	0.009	(0.01)	0.013	(0.01)	0.001	(0.01)	-0.011	(0.01)	0.007	(0.01)	0.006	(0.00)
C) Student Town	-0.023	(0.02)	-0.003	(0.02)	-0.020	(0.02)	0.001	(0.02)	0.004	(0.02)	-0.005	(0.02)	-0.004	(0.01)	-0.001	(0.01)
C) % less than high school	0.142	(0.37)	0.059	(0.52)	-0.124	(0.22)	-1.951**	(0.60)	1.452*	(0.81)	0.493	(0.83)	0.049	(0.11)	0.014	(0.10)
C) % with high school	0.243	(0.33)	0.167	(0.40)	-0.606	(0.58)	-0.263	(0.32)	1.825**	(0.53)	1.415**	(0.55)	0.260**	(0.10)	0.186	(0.15)
C) % with college	0.290	(0.41)	0.466	(0.39)	-0.386	(0.25)	-0.467	(0.33)	1.355**	(0.49)	0.957*	(0.52)	-0.001	(0.06)	-0.017	(0.04)
C) % enrolment (any)	0.593*	(0.35)	0.335	(0.31)	-1.340**	(0.44)	-0.140	(0.50)	0.084	(0.50)	-0.423	(0.52)	0.185**	(0.08)	0.192	(0.15)
D) % Managerial position	-0.044	(0.26)	-0.288	(0.27)	-0.000	(0.19)	0.167	(0.17)	0.050	(0.16)	-0.130	(0.17)	0.257**	(0.06)	0.249**	(0.05)
D) % Timework	0.009	(0.11)	0.048	(0.15)	0.052	(0.12)	0.069	(0.12)	-0.010	(0.12)	-0.220*	(0.12)	0.065	(0.05)	0.045	(0.04)
E) Avg hh income (ln)	-0.036	(0.06)	0.120	(0.12)	-0.001	(0.11)	0.214**	(0.10)	0.255**	(0.09)	0.398**	(0.09)	0.007	(0.02)	-0.005	(0.02)
E) Median hh income by CT (ln)	0.099	(0.11)	-0.179	(0.14)	-0.033	(0.12)	-0.296**	(0.12)	-0.250**	(0.12)	-0.260**	(0.13)	0.001	(0.05)	0.007	(0.04)
E) p25% hh income by CT (ln)	0.005	(0.06)	0.059	(0.06)	0.031	(0.06)	-0.022	(0.06)	0.097	(0.06)	0.080	(0.06)	0.016	(0.02)	0.009	(0.01)
E) S.d. hh income by CT (ln)	-0.040	(0.03)	0.014	(0.03)	0.007	(0.03)	-0.003	(0.03)	0.007	(0.03)	-0.002	(0.03)	-0.015	(0.01)	-0.015	(0.01)
E) % of poor	1.820**	(0.25)	1.747**	(0.26)	1.846**	(0.24)	1.791**	(0.27)	2.532**	(0.25)	2.306**	(0.26)	2.095**	(0.09)	2.031**	(0.08)
E) Dissimilarity poor	0.438**	(0.08)	0.849**	(0.09)	0.757**	(0.08)	1.011**	(0.09)	1.153**	(0.09)	1.242**	(0.10)	0.865**	(0.03)	0.872**	(0.10)
E) Dissimilarity whiteblack	-0.073	(0.14)	-0.410**	(0.15)	0.148	(0.13)	-0.073	(0.12)	-0.214*	(0.13)	-0.200	(0.12)	-0.184**	(0.05)	-0.199**	(0.06)
E) Dissimilarity black	0.127	(0.15)	0.533**	(0.15)	-0.036	(0.13)	0.179	(0.13)	0.306**	(0.13)	0.290**	(0.12)	0.274**	(0.05)	0.308**	(0.06)
E) Dissimilarity hispanic	0.006	(0.05)	-0.009	(0.05)	-0.072	(0.05)	0.004	(0.06)	0.026	(0.06)	0.018	(0.06)	-0.018	(0.02)	-0.016	(0.02)
E) Dissimilarity asian	-0.045	(0.05)	0.059	(0.06)	0.081*	(0.05)	0.021	(0.04)	0.006	(0.05)	-0.023	(0.05)	0.033*	(0.02)	0.024	(0.02)
E) Dissimilarity white	0.838**	(0.19)	0.405*	(0.21)	0.103	(0.16)	0.118	(0.17)	-0.131	(0.18)	-0.216	(0.18)	0.120*	(0.07)	0.094	(0.08)
Greatrecession													0.161*	(0.09)		
Regional fe	y		y		y		y		y		y		y		y	
Year fe	-		-		-		-		-		-		y		y	
N. of obs.	395		367		395		395		395		395		2342		2202	
MSA	395		367		395		395		395		395		367		367	
N. of years	1		1		1		1		1		1		6		6	
R-squared	0.707		0.818		0.784		0.792		0.820		0.798		0.750		0.738	
Root MSE	0.058		0.063		0.055		0.059		0.059		0.060		0.064		0.063	

Table 7: Drivers of concentrated poverty (poverty incidence threshold at 40%).

Note: Dependent variable is the *CP* index by MSA and year. Models (1)-(6) report year specific effects of controls. Model (7) is a pooled OLS regression controlling for years fixed effects and Great Recession (2008-2012) fixed effects. Model (8) is a FE estimator for the balanced panel of MSA (367). All models controls for regional FE (Regions: Northeast, Midwest, South, West). Significance levels: * = 10% and ** = 5%.

	OLS												Pool 1980-2014		Panel FE 1980-2014	
	1980		1990		2000		2008		2012		2014					
	1		2		3		4		5		6		7		8	
A) % Black	-0.285**	(0.07)	0.140**	(0.06)	0.117**	(0.04)	0.036	(0.04)	0.051	(0.03)	0.056*	(0.03)	0.032*	(0.02)	0.023	(0.05)
A) % Hispanic	-0.273**	(0.06)	0.100*	(0.06)	0.086**	(0.04)	0.027	(0.03)	0.013	(0.03)	0.033	(0.03)	0.014	(0.02)	0.003	(0.05)
A) % Asian	-0.289**	(0.06)	0.085	(0.06)	0.080*	(0.05)	0.038	(0.04)	0.018	(0.04)	0.036	(0.03)	-0.003	(0.02)	-0.012	(0.05)
A) % White	-0.329**	(0.06)	0.065	(0.06)	0.093**	(0.05)	0.036	(0.04)	0.036	(0.04)	0.037	(0.03)	-0.014	(0.02)	-0.028	(0.05)
A) Population size (ln)	0.011	(0.01)	0.019	(0.02)	0.043**	(0.02)	0.019	(0.01)	0.042**	(0.02)	0.026	(0.02)	0.018**	(0.01)	0.017**	(0.00)
A) % 65 plus yrs old	0.079	(0.11)	-0.119	(0.12)	0.065	(0.08)	0.115	(0.08)	0.018	(0.12)	0.068	(0.12)	0.051*	(0.03)	0.064**	(0.01)
A) % 2564 yrs old	-0.014	(0.09)	-0.372**	(0.12)	-0.020	(0.08)	0.126*	(0.07)	-0.042	(0.11)	0.076	(0.11)	0.035	(0.02)	0.039	(0.03)
A) % Foreign	-0.114**	(0.06)	-0.148**	(0.06)	-0.026	(0.04)	-0.039	(0.05)	-0.088	(0.06)	-0.030	(0.06)	-0.056**	(0.02)	-0.068**	(0.01)
A) Moved from outside of state	-0.016	(0.03)	-0.038	(0.04)	0.015	(0.05)	-0.053	(0.06)	-0.040	(0.07)	-0.028	(0.07)	0.008	(0.01)	0.015	(0.01)
B) % New Houses (10 less yrs old)	-0.173**	(0.07)	-0.039	(0.05)	-0.004	(0.04)	-0.110**	(0.05)	-0.094**	(0.05)	-0.049	(0.05)	-0.053**	(0.02)	-0.060**	(0.02)
B) % Old houses (20 plus yrs old)	-0.180**	(0.06)	-0.039	(0.03)	-0.013	(0.03)	-0.078**	(0.03)	-0.056*	(0.03)	-0.013	(0.03)	-0.028**	(0.01)	-0.030*	(0.01)
B) % Owner occupied	-0.054	(0.10)	0.081	(0.10)	0.107	(0.09)	0.153*	(0.09)	0.087	(0.08)	0.026	(0.08)	0.066**	(0.03)	0.093**	(0.02)
B) % Vacant	-0.157*	(0.09)	-0.018	(0.03)	-0.057**	(0.03)	0.006	(0.02)	-0.008	(0.03)	0.021	(0.03)	-0.014	(0.01)	-0.014	(0.01)
B) % Rented	-0.069	(0.10)	0.118	(0.10)	0.110	(0.10)	0.146	(0.09)	0.096	(0.09)	-0.001	(0.08)	0.044	(0.03)	0.059*	(0.03)
B) Avg. value house (ln)	0.010	(0.01)	0.022	(0.01)	-0.014	(0.01)	-0.006	(0.01)	0.007	(0.00)	0.012**	(0.00)	0.006**	(0.00)	0.007	(0.00)
B) Median value house by CT (ln)	-0.034**	(0.02)	-0.006	(0.03)	-0.018	(0.02)	0.001	(0.01)	0.009*	(0.01)	0.012**	(0.01)	0.008**	(0.00)	0.009**	(0.00)
B) p25% value house by CT (ln)	0.005	(0.01)	-0.016	(0.02)	0.011	(0.01)	0.006	(0.01)	-0.009	(0.01)	-0.012*	(0.01)	-0.005*	(0.00)	-0.006	(0.00)
B) S.d. value house by CT (ln)	0.011*	(0.01)	-0.015**	(0.01)	0.004	(0.01)	-0.004	(0.00)	-0.006	(0.00)	-0.014**	(0.00)	-0.006**	(0.00)	-0.007*	(0.00)
B) Avg. rent (ln)	0.001	(0.01)	-0.009	(0.02)	-0.036**	(0.02)	-0.015	(0.01)	-0.037**	(0.02)	-0.019	(0.02)	-0.010**	(0.00)	-0.009	(0.00)
B) Median rent by CT (ln)	0.033	(0.03)	0.014	(0.04)	0.016	(0.03)	-0.017	(0.03)	0.027	(0.03)	0.002	(0.03)	0.004	(0.01)	0.006	(0.01)
B) p25% rent by CT (ln)	-0.027	(0.02)	0.001	(0.02)	0.016	(0.02)	0.027	(0.02)	0.009	(0.02)	0.014	(0.02)	-0.002	(0.01)	-0.003	(0.01)
B) S.d. rent by CT (ln)	-0.008	(0.01)	-0.006	(0.01)	0.003	(0.01)	0.008*	(0.00)	0.001	(0.00)	0.001	(0.00)	-0.000	(0.00)	-0.001	(0.00)
C) College Town	-0.002	(0.00)	-0.002	(0.00)	-0.002	(0.00)	-0.002	(0.00)	-0.004	(0.00)	-0.003	(0.00)	-0.002*	(0.00)	-0.002**	(0.00)
C) Student Town	-0.012**	(0.01)	0.002	(0.01)	-0.009*	(0.00)	-0.005	(0.00)	-0.005	(0.00)	-0.007*	(0.00)	-0.007**	(0.00)	-0.006**	(0.00)
C) % less than high school	-0.035	(0.11)	0.258*	(0.15)	0.094	(0.06)	0.009	(0.13)	0.222	(0.18)	0.001	(0.18)	-0.002	(0.03)	0.001	(0.03)
C) % with high school	-0.020	(0.10)	0.076	(0.12)	0.199	(0.17)	-0.041	(0.07)	0.101	(0.12)	-0.054	(0.12)	-0.018	(0.02)	-0.020	(0.03)
C) % with college	0.170	(0.13)	0.183	(0.11)	0.044	(0.07)	-0.033	(0.07)	0.087	(0.11)	-0.050	(0.11)	-0.024*	(0.01)	-0.022*	(0.01)
C) % enrolment (any)	0.041	(0.11)	-0.223**	(0.09)	0.260**	(0.13)	0.226**	(0.11)	0.162	(0.11)	0.148	(0.11)	0.041**	(0.02)	0.047	(0.03)
D) % Managerial position	-0.054	(0.08)	0.080	(0.08)	0.123**	(0.05)	0.052	(0.04)	0.042	(0.04)	0.057	(0.04)	0.040**	(0.01)	0.040**	(0.01)
D) % Timework	0.040	(0.03)	0.004	(0.05)	0.025	(0.04)	0.026	(0.03)	0.034	(0.03)	0.035	(0.03)	0.025**	(0.01)	0.031**	(0.01)
E) Avg hh income (ln)	0.011	(0.02)	0.055	(0.04)	0.025	(0.03)	0.028	(0.02)	0.002	(0.02)	-0.004	(0.02)	0.011**	(0.01)	0.009*	(0.00)
E) Median hh income by CT (ln)	-0.061*	(0.03)	-0.053	(0.04)	-0.064*	(0.03)	-0.148**	(0.03)	-0.086**	(0.03)	-0.088**	(0.03)	-0.071**	(0.01)	-0.073**	(0.02)
E) p25% hh income by CT (ln)	0.026	(0.02)	0.016	(0.02)	0.051**	(0.02)	0.081**	(0.01)	0.059**	(0.01)	0.060**	(0.01)	0.046**	(0.01)	0.046**	(0.01)
E) S.d. hh income by CT (ln)	0.021**	(0.01)	0.031**	(0.01)	0.027**	(0.01)	0.045**	(0.01)	0.045**	(0.01)	0.048**	(0.01)	0.028**	(0.00)	0.029**	(0.00)
E) % of poor	-0.401**	(0.08)	-0.384**	(0.08)	-0.332**	(0.07)	-0.414**	(0.06)	-0.386**	(0.06)	-0.387**	(0.06)	-0.388**	(0.02)	-0.388**	(0.01)
E) Dissimilarity poor	1.011**	(0.03)	1.029**	(0.03)	1.034**	(0.02)	1.015**	(0.02)	0.963**	(0.02)	0.964**	(0.02)	1.017**	(0.01)	1.020**	(0.01)
E) Dissimilarity whiteblack	-0.013	(0.04)	-0.105**	(0.04)	-0.040	(0.04)	0.000	(0.03)	-0.048*	(0.03)	-0.034	(0.03)	-0.025**	(0.01)	-0.029*	(0.01)
E) Dissimilarity black	0.021	(0.04)	0.087*	(0.04)	0.044	(0.04)	0.001	(0.03)	0.042	(0.03)	0.032	(0.03)	0.028**	(0.01)	0.030*	(0.01)
E) Dissimilarity hispanic	-0.017	(0.02)	0.004	(0.02)	0.001	(0.01)	0.004	(0.01)	-0.005	(0.01)	0.002	(0.01)	0.005	(0.01)	0.005*	(0.00)
E) Dissimilarity asian	0.046**	(0.02)	0.005	(0.02)	0.007	(0.01)	-0.000	(0.01)	0.018	(0.01)	0.001	(0.01)	0.010**	(0.00)	0.012*	(0.01)
E) Dissimilarity white	-0.070	(0.06)	-0.082	(0.06)	-0.049	(0.05)	-0.005	(0.04)	0.003	(0.04)	-0.029	(0.04)	-0.056**	(0.02)	-0.059**	(0.02)
Greatrecession													-0.030	(0.02)		
Regional fe	y		y		y		y		y		y		y		y	
Year fe	-		-		-		-		-		-		y		y	
N. of obs.	395		367		395		395		395		395		2342		2202	
MSA	395		367		395		395		395		395		367		367	
N. of years	1		1		1		1		1		1		6		6	
R-squared	0.964		0.965		0.973		0.976		0.973		0.973		0.966		0.964	
Root MSE	0.018		0.019		0.016		0.013		0.013		0.013		0.016		0.016	

Table 8: Drivers of urban poverty.

Note: Dependent variable is the UP index by MSA and year. Models (1)-(6) report year specific effects of controls. Model (7) is a pooled OLS regression controlling for years fixed effects and Great Recession (2008-2012) fixed effects. Model (8) is a FE estimator for the balanced panel of MSA (367). All models controls for regional FE. Significance levels: * = 10% and ** = 5%. Standard errors in parenthesis.

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	OLS					Pool
	1980-1990	1990-2000	2000-2008	2008-2012	2012-2014	1980-2014
	1	2	3	4	5	6
A) % Black	0.158 (0.14)	0.126 (0.09)	0.142 (0.09)	-0.065 (0.08)	0.051 (0.06)	0.081** (0.04)
A) % Hispanic	0.030 (0.13)	0.088 (0.09)	0.156* (0.08)	-0.103 (0.07)	0.066 (0.06)	0.067* (0.04)
A) % Asian	0.094 (0.13)	0.006 (0.09)	0.137 (0.09)	-0.166** (0.08)	0.063 (0.06)	0.047 (0.04)
A) % White	0.191 (0.14)	0.094 (0.09)	0.097 (0.09)	-0.029 (0.08)	0.109* (0.06)	0.116** (0.04)
A) Population size (ln)	0.009 (0.03)	-0.007 (0.03)	0.014 (0.03)	0.019 (0.03)	0.018 (0.03)	0.006 (0.01)
A) % 65 plus yrs old	0.594** (0.23)	-0.003 (0.18)	-0.322** (0.16)	0.140 (0.18)	-0.187 (0.21)	0.136** (0.06)
A) % 2564 yrs old	0.267 (0.19)	-0.194 (0.19)	-0.113 (0.16)	-0.054 (0.15)	-0.077 (0.19)	0.005 (0.05)
A) % Foreign	-0.241** (0.12)	-0.190** (0.10)	-0.061 (0.08)	0.046 (0.11)	-0.049 (0.10)	-0.059 (0.04)
A) Moved from outside of state	-0.080 (0.06)	0.014 (0.06)	-0.022 (0.10)	-0.011 (0.14)	-0.351** (0.12)	-0.070** (0.02)
B) % New Houses (10 less yrs old)	-0.048 (0.15)	0.008 (0.07)	-0.033 (0.08)	-0.131 (0.11)	0.028 (0.08)	-0.042 (0.03)
B) % Old houses (20 plus yrs old)	-0.203 (0.12)	-0.042 (0.05)	-0.023 (0.06)	-0.116* (0.06)	-0.010 (0.05)	-0.074** (0.02)
B) % Owner occupied	0.049 (0.21)	0.115 (0.15)	0.225 (0.18)	0.182 (0.19)	-0.007 (0.14)	0.149** (0.07)
B) % Vacant	0.095 (0.19)	-0.013 (0.05)	0.054 (0.05)	-0.035 (0.05)	0.026 (0.05)	-0.003 (0.02)
B) % Rented	0.241 (0.21)	0.196 (0.15)	0.186 (0.19)	0.302 (0.19)	0.028 (0.15)	0.249** (0.07)
B) Avg. value house (ln)	0.008 (0.03)	0.038* (0.02)	0.017 (0.03)	0.022* (0.01)	0.010 (0.01)	0.001 (0.01)
B) Median value house by CT (ln)	-0.013 (0.03)	0.019 (0.04)	-0.061 (0.05)	0.019 (0.01)	0.017* (0.01)	0.008 (0.01)
B) p25% value house by CT (ln)	0.015 (0.01)	-0.025 (0.03)	0.008 (0.03)	-0.064** (0.02)	-0.028** (0.01)	-0.011** (0.01)
B) S.d. value house by CT (ln)	0.002 (0.01)	-0.012 (0.01)	0.022* (0.01)	-0.013 (0.01)	0.001 (0.01)	-0.006 (0.00)
B) Avg. rent (ln)	0.001 (0.03)	0.014 (0.03)	-0.016 (0.03)	-0.017 (0.03)	-0.019 (0.03)	-0.002 (0.01)
B) Median rent by CT (ln)	-0.086 (0.07)	0.047 (0.06)	0.004 (0.06)	0.001 (0.06)	0.084 (0.06)	0.000 (0.02)
B) p25% rent by CT (ln)	0.074 (0.05)	-0.039 (0.03)	0.021 (0.04)	0.063 (0.04)	-0.075* (0.04)	0.020 (0.02)
B) S.d. rent by CT (ln)	0.010 (0.01)	0.006 (0.01)	0.013 (0.01)	0.010 (0.01)	-0.003 (0.01)	0.005 (0.00)
C) College Town	0.007 (0.01)	-0.000 (0.01)	-0.001 (0.01)	0.008 (0.01)	0.002 (0.00)	0.003 (0.00)
C) Student Town	-0.007 (0.01)	-0.008 (0.01)	-0.005 (0.01)	0.000 (0.01)	-0.001 (0.01)	-0.005 (0.00)
C) % less than high school	-0.258 (0.23)	0.101 (0.23)	0.158 (0.12)	-0.093 (0.29)	-0.061 (0.32)	-0.074 (0.06)
C) % with high school	-0.253 (0.21)	0.269 (0.18)	0.434 (0.33)	0.057 (0.16)	0.019 (0.21)	0.092* (0.05)
C) % with college	-0.144 (0.26)	0.149 (0.17)	0.062 (0.14)	-0.115 (0.16)	0.112 (0.19)	0.016 (0.03)
C) % enrolment (any)	0.375* (0.22)	0.408** (0.14)	-0.655** (0.25)	-0.333 (0.24)	-0.134 (0.19)	0.187** (0.04)
D) % Managerial position	0.152 (0.16)	-0.140 (0.12)	0.027 (0.11)	0.050 (0.08)	-0.018 (0.06)	0.036 (0.03)
D) % Timework	0.184** (0.07)	-0.076 (0.07)	0.092 (0.07)	0.092 (0.06)	0.021 (0.05)	0.094** (0.03)
E) Avg hh income (ln)	0.011 (0.04)	-0.014 (0.06)	0.077 (0.06)	0.017 (0.05)	0.040 (0.04)	0.032** (0.01)
E) Median hh income by CT (ln)	-0.001 (0.07)	0.069 (0.06)	0.154** (0.07)	0.087 (0.06)	0.016 (0.05)	0.038 (0.02)
E) p25% hh income by CT (ln)	0.009 (0.04)	-0.026 (0.03)	-0.106** (0.03)	-0.043 (0.03)	-0.019 (0.02)	-0.037** (0.01)
E) S.d. hh income by CT (ln)	0.015 (0.02)	-0.013 (0.02)	-0.027* (0.01)	-0.011 (0.02)	-0.005 (0.01)	0.002 (0.01)
E) % of poor	0.151 (0.16)	0.181 (0.12)	0.291** (0.13)	0.138 (0.13)	0.168* (0.10)	0.160** (0.05)
E) Dissimilarity poor	-0.453** (0.05)	-0.281** (0.04)	-0.402** (0.05)	-0.322** (0.04)	-0.213** (0.04)	-0.338** (0.02)
E) Dissimilarity whiteblack	-0.118 (0.09)	-0.086 (0.07)	0.002 (0.07)	-0.085 (0.06)	-0.010 (0.05)	-0.053* (0.03)
E) Dissimilarity black	0.105 (0.09)	0.105 (0.07)	0.014 (0.07)	0.080 (0.06)	0.005 (0.05)	0.035 (0.03)
E) Dissimilarity hispanic	0.081** (0.03)	0.041* (0.02)	0.034 (0.03)	0.007 (0.03)	-0.005 (0.02)	0.025** (0.01)
E) Dissimilarity asian	-0.037 (0.03)	0.025 (0.02)	-0.010 (0.03)	0.003 (0.02)	-0.028 (0.02)	0.020* (0.01)
E) Dissimilarity white	0.377** (0.12)	-0.023 (0.09)	-0.097 (0.09)	0.169** (0.08)	0.070 (0.07)	0.109** (0.04)
Greatrecession						0.005 (0.05)
Regional fe	y	y	y	y	y	y
Year fe	-	-	-	-	-	y
N. of obs.	395	367	395	395	395	1947
MSA	395	367	395	395	395	367
N. of years interval	1	1	1	1	1	5
R-squared	0.445	0.374	0.398	0.289	0.193	0.377
Root MSE	0.037	0.029	0.031	0.028	0.023	0.031

Table 9: Drivers of urban poverty changes.

Note: Dependent variable is the change in urban poverty ΔUP calculated on a year-to-year basis, by MSA. Models (1)-(5) report year specific effects of controls, all measured at the base year. Model (6) is a pooled OLS regression of year-to-year changes controlling for years fixed effects and Great Recession (2008-2012) fixed effects. All models controls for regional FE. Significance levels: * = 10% and ** = 5%. Standard errors in parenthesis.

	OLS										Pool	
	1980-1990		1990-2000		2000-2008		2008-2012		2012-2014		1980-2014	
	1		2		3		4		5		6	
A) % Black	0.066	(0.09)	0.040	(0.05)	-0.005	(0.06)	0.044	(0.05)	0.053**	(0.03)	0.046*	(0.02)
A) % Hispanic	0.055	(0.08)	0.022	(0.05)	-0.028	(0.06)	0.059	(0.05)	0.055**	(0.03)	0.025	(0.02)
A) % Asian	0.030	(0.08)	-0.038	(0.06)	-0.046	(0.07)	0.001	(0.05)	0.057**	(0.03)	0.015	(0.02)
A) % White	0.046	(0.08)	-0.012	(0.06)	-0.037	(0.07)	0.030	(0.05)	0.023	(0.03)	0.014	(0.02)
A) Population size (ln)	0.011	(0.02)	0.009	(0.02)	-0.055**	(0.02)	0.008	(0.02)	0.004	(0.01)	0.015**	(0.01)
A) % 65 plus yrs old	0.182	(0.14)	0.010	(0.11)	-0.291**	(0.12)	-0.123	(0.12)	0.015	(0.09)	0.065*	(0.04)
A) % 2564 yrs old	0.069	(0.12)	-0.193*	(0.11)	-0.325**	(0.12)	-0.152	(0.10)	0.024	(0.08)	-0.004	(0.03)
A) % Foreign	0.036	(0.07)	0.028	(0.06)	0.083	(0.06)	-0.123*	(0.07)	-0.072	(0.04)	0.007	(0.02)
A) Moved from outside of state	0.020	(0.04)	0.002	(0.04)	-0.095	(0.07)	0.073	(0.09)	0.180**	(0.05)	0.015	(0.01)
B) % New Houses (10 less yrs old)	0.165*	(0.10)	0.023	(0.04)	0.041	(0.05)	-0.133*	(0.07)	-0.083**	(0.04)	-0.023	(0.02)
B) % Old houses (20 plus yrs old)	0.032	(0.08)	-0.013	(0.03)	-0.022	(0.04)	-0.083**	(0.04)	-0.050**	(0.02)	-0.039**	(0.01)
B) % Owner occupied	0.058	(0.13)	0.033	(0.09)	0.157	(0.13)	0.171	(0.12)	0.066	(0.06)	0.133**	(0.04)
B) % Vacant	0.112	(0.12)	-0.022	(0.03)	0.118**	(0.04)	0.071**	(0.04)	0.024	(0.02)	0.049**	(0.01)
B) % Rented	0.137	(0.13)	-0.007	(0.09)	0.152	(0.14)	0.159	(0.13)	0.058	(0.07)	0.122**	(0.04)
B) Avg. value house (ln)	0.038**	(0.02)	-0.001	(0.01)	0.002	(0.02)	-0.008	(0.01)	-0.003	(0.00)	-0.000	(0.00)
B) Median value house by CT (ln)	0.015	(0.02)	0.009	(0.03)	-0.013	(0.03)	-0.005	(0.01)	0.005	(0.00)	0.008**	(0.00)
B) p25% value house by CT (ln)	-0.005	(0.01)	0.001	(0.02)	0.024	(0.02)	0.004	(0.01)	-0.004	(0.01)	-0.001	(0.00)
B) S.d. value house by CT (ln)	-0.010	(0.01)	0.005	(0.01)	0.013	(0.01)	0.004	(0.01)	0.001	(0.00)	-0.000	(0.00)
B) Avg. rent (ln)	-0.011	(0.02)	-0.005	(0.02)	0.055**	(0.02)	-0.011	(0.02)	-0.004	(0.01)	-0.014**	(0.01)
B) Median rent by CT (ln)	-0.055	(0.04)	0.003	(0.03)	-0.041	(0.05)	0.078**	(0.04)	-0.033	(0.03)	0.012	(0.02)
B) p25% rent by CT (ln)	0.002	(0.03)	-0.014	(0.02)	0.001	(0.03)	-0.030	(0.03)	0.042**	(0.02)	-0.002	(0.01)
B) S.d. rent by CT (ln)	0.008	(0.01)	-0.003	(0.01)	0.012*	(0.01)	-0.006	(0.01)	0.002	(0.00)	0.004	(0.00)
C) College Town	0.002	(0.00)	-0.005	(0.00)	-0.000	(0.00)	0.002	(0.00)	-0.001	(0.00)	-0.000	(0.00)
C) Student Town	0.001	(0.01)	-0.016**	(0.01)	0.005	(0.01)	0.002	(0.01)	-0.003	(0.00)	-0.002	(0.00)
C) % less than high school	-0.050	(0.15)	0.060	(0.14)	-0.038	(0.09)	0.230	(0.19)	0.063	(0.14)	0.033	(0.04)
C) % with high school	-0.170	(0.13)	0.011	(0.11)	0.370	(0.24)	0.218**	(0.10)	-0.057	(0.09)	0.022	(0.03)
C) % with college	-0.337**	(0.16)	0.041	(0.11)	0.316**	(0.10)	0.125	(0.10)	-0.055	(0.09)	0.008	(0.02)
C) % enrolment (any)	0.022	(0.14)	0.012	(0.09)	0.262	(0.18)	0.167	(0.16)	-0.055	(0.09)	0.100**	(0.03)
D) % Managerial position	0.258**	(0.10)	-0.002	(0.07)	0.125	(0.08)	-0.033	(0.05)	0.011	(0.03)	-0.017	(0.02)
D) % Timework	0.064	(0.04)	0.014	(0.04)	0.053	(0.05)	-0.045	(0.04)	-0.014	(0.02)	0.022	(0.02)
E) Avg hh income (ln)	-0.028	(0.02)	0.037	(0.03)	-0.023	(0.05)	0.009	(0.03)	-0.003	(0.02)	0.006	(0.01)
E) Median hh income by CT (ln)	0.109**	(0.04)	0.035	(0.04)	0.055	(0.05)	0.013	(0.04)	0.025	(0.02)	0.044**	(0.02)
E) p25% hh income by CT (ln)	-0.023	(0.02)	-0.012	(0.02)	-0.025	(0.02)	0.034*	(0.02)	-0.006	(0.01)	-0.006	(0.01)
E) S.d. hh income by CT (ln)	-0.031**	(0.01)	-0.011	(0.01)	-0.025**	(0.01)	0.003	(0.01)	-0.014**	(0.01)	-0.015**	(0.00)
E) % of poor	-0.186*	(0.10)	-0.140*	(0.07)	-0.288**	(0.10)	-0.055	(0.08)	-0.158**	(0.04)	-0.117**	(0.03)
E) Dissimilarity poor	-0.136**	(0.03)	-0.113**	(0.03)	-0.138**	(0.03)	-0.108**	(0.03)	-0.041**	(0.02)	-0.109**	(0.01)
E) Dissimilarity whiteblack	0.065	(0.06)	-0.008	(0.04)	-0.025	(0.05)	0.019	(0.04)	0.017	(0.02)	0.001	(0.02)
E) Dissimilarity black	-0.049	(0.06)	0.013	(0.04)	0.055	(0.05)	-0.015	(0.04)	0.002	(0.02)	0.014	(0.02)
E) Dissimilarity hispanic	0.028	(0.02)	0.002	(0.01)	-0.030	(0.02)	0.023	(0.02)	-0.000	(0.01)	0.004	(0.01)
E) Dissimilarity asian	-0.026	(0.02)	0.015	(0.02)	0.003	(0.02)	-0.005	(0.01)	0.001	(0.01)	0.001	(0.01)
E) Dissimilarity white	-0.012	(0.08)	-0.044	(0.06)	0.005	(0.07)	-0.031	(0.05)	-0.014	(0.03)	-0.008	(0.02)
Greatrecession											0.036	(0.03)
Regional fe	y		y		y		y		y		y	
Year fe	-		-		-		-		-		y	
N. of obs.	395		367		395		395		395		1947	
MSA	395		367		395		395		395		367	
N. of years interval	1		1		1		1		1		5	
R-squared	0.376		0.417		0.493		0.453		0.478		0.489	
Root MSE	0.023		0.017		0.022		0.019		0.010		0.020	

Table 10: Drivers of re-ranking component of urban poverty changes.

Note: Dependent variable is the component R of year-to-year variation in urban poverty, by MSA. Models (1)-(5) report year specific effects of controls, all measured at the base year. Model (6) is a pooled OLS regression of year-to-year changes controlling for years fixed effects and Great Recession (2008-2012) fixed effects. All models controls for regional FE (Regions: Northeast, Midwest, South, West). Significance levels: * = 10% and ** = 5%.

	OLS										Pool	
	1980-1990		1990-2000		2000-2008		2008-2012		2012-2014		1980-2014	
	1		2		3		4		5		6	
A) % Black	-0.094	(0.15)	0.070	(0.10)	0.119	(0.10)	-0.109	(0.09)	0.008	(0.06)	0.013	(0.04)
A) % Hispanic	-0.208	(0.14)	0.022	(0.09)	0.145	(0.09)	-0.176**	(0.08)	0.015	(0.06)	0.004	(0.04)
A) % Asian	-0.063	(0.14)	0.022	(0.09)	0.163	(0.10)	-0.176**	(0.09)	0.011	(0.07)	0.015	(0.04)
A) % White	0.003	(0.14)	0.082	(0.10)	0.136	(0.10)	-0.065	(0.09)	0.085	(0.07)	0.082*	(0.04)
A) Population size (ln)	-0.004	(0.03)	-0.019	(0.04)	0.085**	(0.04)	0.007	(0.04)	0.011	(0.03)	-0.002	(0.01)
A) % 65 plus yrs old	0.485**	(0.24)	-0.076	(0.20)	-0.013	(0.18)	0.283	(0.20)	-0.188	(0.23)	0.061	(0.06)
A) % 2564 yrs old	0.320	(0.20)	-0.006	(0.21)	0.186	(0.19)	0.103	(0.17)	-0.081	(0.20)	-0.002	(0.06)
A) % Foreign	-0.199	(0.12)	-0.161	(0.10)	-0.136	(0.10)	0.208*	(0.12)	0.034	(0.11)	-0.036	(0.04)
A) Moved from outside of state	-0.025	(0.06)	0.026	(0.06)	0.080	(0.11)	-0.062	(0.15)	-0.510**	(0.13)	-0.055**	(0.03)
B) % New Houses (10 less yrs old)	-0.201	(0.16)	-0.002	(0.08)	-0.098	(0.09)	0.018	(0.12)	0.095	(0.09)	-0.020	(0.04)
B) % Old houses (20 plus yrs old)	-0.249*	(0.13)	-0.013	(0.06)	-0.008	(0.06)	-0.020	(0.07)	0.034	(0.06)	-0.030	(0.02)
B) % Owner occupied	-0.006	(0.22)	-0.029	(0.17)	0.013	(0.21)	0.042	(0.21)	-0.064	(0.16)	-0.032	(0.08)
B) % Vacant	-0.149	(0.20)	-0.006	(0.05)	-0.075	(0.06)	-0.099	(0.06)	0.002	(0.05)	-0.055**	(0.02)
B) % Rented	0.093	(0.22)	0.069	(0.17)	-0.047	(0.22)	0.175	(0.22)	-0.019	(0.17)	0.061	(0.08)
B) Avg. value house (ln)	-0.009	(0.03)	0.038	(0.03)	0.015	(0.03)	0.031**	(0.01)	0.014	(0.01)	-0.000	(0.01)
B) Median value house by CT (ln)	-0.056	(0.04)	0.037	(0.05)	-0.043	(0.05)	0.025*	(0.02)	0.014	(0.01)	-0.002	(0.01)
B) p25% value house by CT (ln)	0.024**	(0.01)	-0.041	(0.03)	-0.016	(0.03)	-0.068**	(0.02)	-0.025*	(0.01)	-0.009	(0.01)
B) S.d. value house by CT (ln)	0.016	(0.01)	-0.017	(0.01)	0.007	(0.01)	-0.017*	(0.01)	0.000	(0.01)	-0.005	(0.00)
B) Avg. rent (ln)	0.012	(0.03)	0.019	(0.04)	-0.087**	(0.04)	-0.002	(0.04)	-0.011	(0.03)	0.005	(0.01)
B) Median rent by CT (ln)	-0.033	(0.08)	0.009	(0.06)	0.065	(0.07)	-0.093	(0.07)	0.122**	(0.06)	-0.005	(0.03)
B) p25% rent by CT (ln)	0.073	(0.05)	-0.006	(0.03)	0.023	(0.05)	0.103**	(0.05)	-0.121**	(0.04)	0.026	(0.02)
B) S.d. rent by CT (ln)	-0.004	(0.01)	0.009	(0.01)	0.001	(0.01)	0.018*	(0.01)	-0.007	(0.01)	-0.000	(0.00)
C) College Town	0.004	(0.01)	0.005	(0.01)	0.003	(0.01)	0.006	(0.01)	0.003	(0.01)	0.003	(0.00)
C) Student Town	-0.009	(0.01)	0.006	(0.01)	-0.009	(0.01)	-0.003	(0.01)	0.002	(0.01)	-0.003	(0.00)
C) % less than high school	-0.170	(0.25)	0.081	(0.25)	0.225	(0.14)	-0.375	(0.32)	-0.144	(0.35)	-0.061	(0.06)
C) % with high school	-0.078	(0.22)	0.260	(0.20)	-0.009	(0.37)	-0.166	(0.18)	0.071	(0.23)	0.079	(0.05)
C) % with college	0.075	(0.28)	0.195	(0.19)	-0.296*	(0.16)	-0.257	(0.18)	0.143	(0.21)	0.028	(0.03)
C) % enrolment (any)	0.339	(0.23)	0.369**	(0.16)	-1.017**	(0.28)	-0.484*	(0.27)	-0.055	(0.21)	0.072	(0.05)
D) % Managerial position	-0.057	(0.17)	-0.151	(0.13)	-0.132	(0.12)	0.078	(0.09)	-0.023	(0.07)	0.054	(0.03)
D) % Timework	0.109	(0.07)	-0.135*	(0.08)	0.055	(0.08)	0.119*	(0.07)	0.033	(0.05)	0.061**	(0.03)
E) Avg hh income (ln)	0.031	(0.04)	-0.062	(0.06)	0.134*	(0.07)	0.016	(0.05)	0.039	(0.04)	0.035**	(0.01)
E) Median hh income by CT (ln)	-0.093	(0.07)	-0.002	(0.07)	0.021	(0.08)	0.075	(0.07)	-0.009	(0.05)	-0.031	(0.03)
E) p25% hh income by CT (ln)	0.045	(0.04)	0.006	(0.03)	-0.050	(0.04)	-0.078**	(0.03)	-0.013	(0.03)	-0.019	(0.01)
E) S.d. hh income by CT (ln)	0.045**	(0.02)	0.006	(0.02)	-0.000	(0.02)	-0.016	(0.02)	0.008	(0.01)	0.020**	(0.01)
E) % of poor	0.426**	(0.17)	0.263**	(0.13)	0.573**	(0.15)	0.204	(0.15)	0.321**	(0.11)	0.257**	(0.06)
E) Dissimilarity poor	-0.255**	(0.06)	-0.166**	(0.05)	-0.267**	(0.05)	-0.214**	(0.05)	-0.167**	(0.04)	-0.214**	(0.02)
E) Dissimilarity whiteblack	-0.146	(0.09)	-0.102	(0.07)	0.033	(0.08)	-0.115*	(0.07)	-0.030	(0.05)	-0.059*	(0.03)
E) Dissimilarity black	0.114	(0.10)	0.121	(0.07)	-0.045	(0.08)	0.104	(0.07)	0.007	(0.05)	0.027	(0.03)
E) Dissimilarity hispanic	0.040	(0.04)	0.033	(0.03)	0.054*	(0.03)	-0.018	(0.03)	-0.006	(0.02)	0.014	(0.01)
E) Dissimilarity asian	0.004	(0.04)	-0.004	(0.03)	-0.023	(0.03)	0.007	(0.02)	-0.028	(0.02)	0.018	(0.01)
E) Dissimilarity white	0.409**	(0.13)	0.031	(0.10)	-0.045	(0.10)	0.207**	(0.09)	0.068	(0.08)	0.130**	(0.04)
Greatrecession											0.002	(0.05)
Regional fe	y		y		y		y		y		y	
Year fe	-		-		-		-		-		y	
N. of obs.	395		367		395		395		395		1947	
MSA	395		367		395		395		395		367	
N. of years interval	1		1		1		1		1		5	
R-squared	0.348		0.299		0.314		0.348		0.258		0.328	
Root MSE	0.039		0.031		0.035		0.032		0.025		0.034	

Table 11: Drivers of convergence component of urban poverty changes.

Note: Dependent variable is the component $D = C \cdot E$ of year-to-year variation in urban poverty, by MSA. Models (1)-(5) report year specific effects of controls, all measured at the base year. Model (6) is a pooled OLS regression of year-to-year changes controlling for years fixed effects and Great Recession (2008-2012) fixed effects. All models controls for regional FE (Regions: Northeast, Midwest, South, West). Significance levels: * = 10% and ** = 5%.

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