Understanding trends and drivers of urban poverty in American cities.[*]

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Abstract

Urban poverty arises from the uneven distribution of poor population across neighborhoods of a city. We study the trend and drivers of urban poverty across American cities over the last 40 years. To do so, we resort to a family of urban poverty indices that account for features of incidence, distribution, and segregation of poverty across census tracts. Compared to the universally-adopted concentrated poverty index, these measures have a solid normative background. We use tract-level data to assess the extent to which demographics, housing, education, employment, and income distribution affect levels and changes in urban poverty. A decomposition study allows to single out the effect of changes in the distribution of these variables across cities from changes in their correlation with urban poverty. We find that demographics and income distribution have a substantial role in explaining urban poverty patterns, whereas the same effects remarkably differ when using the concentrated poverty indices.

Keywords: Concentrated poverty, Gini index, Oaxaca-Blinder decomposition, Census, American Community Survey, Spatial inequality.
JEL codes: C34, D31, H24, P25.

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1 Introduction

The extent of concentration of poor people in some neighborhoods of a city is found to have medium- and long-term adverse effects on health outcomes (Ludwig et al. 2011, Ludwig et al. 2013), job opportunities (Conley and Topa 2002) and well-being (Ludwig et al. 2012) for those exposed to it. The level of poverty concentration in a city is measured by the concentrated poverty index (Wilson 1987, Jargowsky and Bane 1991). This index indicates the share of poor population in a city who lives in neighborhoods with a poverty incidence greater than or equal to a certain threshold (e.g., 20% is used for identifying high-poverty neighborhoods, whereas 40% is set for identifying extreme-poverty neighborhoods). Several studies examine the trends and drivers of concentrated poverty across American metropolitan areas. Massey, Gross and Eggers (1991) finds that residential segregation is the main driver of spatial concentration of poverty in American urban areas. Quillian (2012) investigates changes in concentrated poverty in American metro areas by developing a model which incorporates variations in residential segregation. Iceland and Hernandez (2017) analyze the trends in concentrated poverty in American metropolitan areas over the 1980-2014 period and identify the variation in the segregation of poor people as a key driver of the change in concentrated poverty.

Albeit widely used in the empirical literature, the concentrated poverty index does not fulfill some desirable properties. Andreoli et al. (2021) have axiomatically derived a family of urban poverty indices which overcome some drawbacks of the concentrated poverty index. In particular, these indices produce evaluations of urban poverty that take into account (and make explicit the relation between) aspects of incidence of poverty in the city, the distribution of poverty across high-poverty neighborhoods, and the extent of segregation of poor and non-poor residents between high- and low-poverty neighborhoods.

In this paper, we study the drivers of levels and changes in urban poverty across American metropolitan statistical areas (MSAs) between 1980 and 2014. To do so, we consider measuring urban poverty with selected indices belonging to the family characterized in Andreoli et al. (2021). Two indices within this family are the adjusted concentrated poverty index and the urban poverty index, which are calculated by setting a poverty incidence threshold for identify-

ing high-poverty (or extreme-poverty) neighborhoods. A further index belonging to this family of urban poverty measures is the Gini index of inequality in neighborhood poverty incidence, which is obtained by considering all neighborhoods in a city, including medium- and low-poverty neighborhoods (i.e., setting a tolerance level to poverty incidence equal to 0% instead of 20% or 40%). Since the Gini index can be broken down into a neighborhood and a non-neighborhood component (Rey and Smith 2013), the degree of spatial clustering of poverty across neighborhoods can be assessed directly within the urban poverty measurement framework. Furthermore, the change in the Gini index can be split into different components measuring the convergence and re-ranking of neighborhoods in terms of poverty incidence (Andreoli et al. 2021), adding information to the analysis of trends in urban poverty.

The aforementioned indices constitute the measurement apparatus that we use to assess urban poverty for a panel of MSAs over the 1980-2014 period, built by exploiting rich data from the Census and the American Community Survey (hereafter, ACS). We produce a comparative analysis of the potential drivers of concentrated poverty and urban poverty. The partial effects of poverty drivers are obtained from pooled OLS regressions of the various indices of urban poverty concentration on a set of explanatory variables controlling for year, state, and region fixed effects. We also examine the roles of the same explanatory variables in driving the changes in urban poverty concentration by running OLS regressions on the pooled period-to-period changes in the indices of concentrated poverty and urban poverty. A covariate describing gentrification at the census tract level is added in the regression analysis, as gentrification may cause changes in the composition of the population living in historically high-poverty neighborhoods of a city (Christafore and Leguizamon 2019).

We further analyze the contribution of changes in the distribution of explanatory variables on urban poverty, net of the effect of changes in the correlation between these variables and urban poverty. To do so, we resort on a Oaxaca-Blinder decomposition (Blinder 1973, Oaxaca 1973), which separates the difference between the estimated average levels of urban poverty concentration in 1980 and 2014 into three different components. We find that American MSAs display substantial heterogeneity in urban poverty patterns and that both the re-ranking and

convergence components of urban poverty changes are substantial across MSAs. The spatial component of urban poverty is negligible for the large majority of MSAs but very significant in the largest MSAs, where the clustering of high-poverty census tracts seems to be an issue. Demographic variables, income distribution, and the distribution of housing values within a MSA are major drivers of urban poverty concentration in American MSAs over the period considered.

The reminder of the paper is organized as follows: Section 2 outlines relevant literature on consequences and drivers of neighborhood poverty and concentrated poverty, highlights critics to the latter measure and presents the urban poverty index. Section 3 describes data and the covariates entered in regressions. Results are shown and discussed in Section 4. Section 5 concludes.

2 Urban poverty and concentrated poverty

2.1 Poverty in the city: relevant literature

The empirical literature has brought about evidence that growing up or living in poor neighborhoods is detrimental for a wide set of individuals' lifetime outcomes. From a short-term perspective place matters for the cognitive development of children, as children living in high-poverty neighborhood tend to have worse performances in math and reading test scores (Pearman 2019, Sharkey and Elwert 2011, Vinopal and Morrissey 2020, Wolf et al. 2017) and lower verbal abilities (Sampson, Sharkey and Raudenbush 2008) than their peer from other neighborhoods. When the focus is on the long-term outcomes, Chetty, Hendren and Katz (2016) and Chetty and Hendren (2018) show that a longer exposure to high-poverty neighborhood during childhood has causal negative consequences on the economic opportunities of future generations, as it reduces college attendance and earnings and increases single parenthood rates, whereas Conley and Topa (2002) and Ludwig et al. (2012) find an adverse effect on job opportunities and well-being respectively. The estimated effects can be explained by the fact that residents in poor neighborhoods tend to be more isolated from the middle-class environment, having a bad connection to the labor market and access to low-quality schools and other public amenities (Jargowsky 2013, Wang et al. 2018). In addition, there is also evidence that living in poor places is associated with poor

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heath outcomes (Ludwig et al. 2011, Ludwig et al. 2013, Thierry 2020) and increased drug use (Boardman et al. 2001, Nandi et al. 2010). Residents in poor neighborhoods, indeed, are exposed to stressful circumstances which have a negative impact on some biomarkers of biological aging (Lei et al. 2018, Smith et al. 2017, Thierry 2020) as well as to more environmental pollution due to the high density of industrial facilities which reduces air quality (Ard and Smiley 2021). Besides the deleterious impact on this wide range of individual outcomes, poor places act as a barrier reducing the likelihood of moving towards better neighborhoods and hence towards more opportunities for residents and their offspring (Alvarado and Cooperstock 2021, Huang et al. 2021), contributing to the perpetuation of poverty and inequality of opportunities across generations.

The aforementioned literature suggests that cities that differ in the way poverty concentrate across neighborhoods may differ as well in terms of long run wellbeing. Assessing the extent at which poverty is distributed *within* a city is hence key for performing poverty comparisons *across* cities. In order to be able to perform meaningful comparisons, two fundamental issues need to be addressed: i) identify high- or extreme-poor neighborhoods and aggregate information about the distribution of poverty in those places, and ii) uncover the drivers and determinants of the implied level of urban poverty.

Comparisons of poverty distribution across cities can be carried over by aggregating evaluations of the distribution of poverty across neighborhoods of a city through an index, which is a function mapping information (specific to a city and period) about the distribution of poor and non-poor people across the city neighborhoods into a number, regarded to as the level of urban poverty of that city. When we make use of the term "city", we refer to a specific MSA, as defined by the American Census Bureau, observed in a given year. Each city is partitioned into n non-overlapping *census tracts*, which are the smallest available statistical units for which a broad set of characteristics are observable from available census data. It is standard to use census tracts partition to define neighborhoods. For every census tract $i \in \{1, \ldots, n\}$, we observe the demographic size of the tract, denoted by $N_i \in \mathbb{R}_+$, with $N = \sum_{i=1}^{n} N_i$ being the overall population in the MSA, and the size of the group of individuals that are poor and reside

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therein, denoted by P_i, with $P = \sum_{i=1}^{n} P_i$ being the total number of poor in the MSA.

We represent a city by the corresponding *urban poverty configuration*, denoted by $\mathcal{A}$, which is a collection of counts of poor and non-poor individuals distributed across tracts of the MSA, so that $\mathcal{A} = \{P_i^{\mathcal{A}}, N_i^{\mathcal{A}}\}_{i=1}^{n}$. In what follows, we use superscripts to indicate a specific urban poverty configuration only when disambiguation is needed. The analysis of urban poverty that we make is conditional exclusively on the distribution of poor and non-poor individuals in space that is provided by a urban poverty configuration. The ratios $\frac{P_i}{N_i}$ and $\frac{P}{N}$ measure the incidence of poverty in tract i in the MSA, respectively. In this paper, the poor are always exogenously identified (for instance by a federal poverty line for equivalent household income) and the focus is on how poor and non-poor individuals are distributed across census tracts. A urban poverty line $\zeta \in [0, 1)$ can be used to identify tracts where poverty is over-concentrated. A tract i is a high-poverty tract when $\frac{P_i}{N_i} \geq \zeta$. According to the Census Bureau, for instance, $\zeta = 0.2$ and $\zeta = 0.4$ identify high-poverty and extreme-poverty census tracts (ghettos) respectively, i.e. places where poor individuals count for above 20% or 40% of the resident populations. For a given urban poverty line ζ, there are $z \geq 1$ tracts where poverty is highly concentrated and $n - z \geq 0$ where poverty is not concentrated. Assume that tracts are ordered by decreasing magnitude of poverty incidence, so that $\frac{P_i}{N_i} \geq \frac{P_{i+1}}{N_{i+1}}$, we can hence denote $\overline{P}_z = \sum_{i=1}^{z} P_i$ and $\overline{N}_z = \sum_{i=1}^{z} N_i$.

The most widely used measure for urban poverty analysis is the *concentrated poverty* index (hereafter, CP) (Wilson 1987, Jargowsky and Bane 1991, Iceland and Hernandez 2017). It measures the proportion of poor people who live in high-poverty census tracts as identified by urban poverty line ζ. Formally:

$$CP(\mathcal{A}, \zeta) = \frac{\overline{P}_z}{P}.$$

The index produces an aggregate evaluation of poverty that is meant to correlate with the incidence of the "double burden" of poverty, arising from the fact that poverty tends to concentrate in neighborhoods where poverty incidence is high, thus producing the external effects highlighted above. Understanding how concentrated poverty evolves over time and to what are the determinants of these changes is a fundamental concern even from the policy-

maker's perspective.

Several studies analyzing recent trends of concentrated poverty across MSAs document that concentrated poverty displays substantial heterogeneity across cities and over time, reflecting socio-economic transformation occurred in the US over the last decades. More specifically, after a growth of the share of the poor living in high-poverty neighborhoods occurred during the 1980s, the next decade has been characterized by a sharp decline in concentrated poverty. However, this trend has again reversed in the 2000s, when the Great Recession completely wiped the progress of the previous decade (Jargowsky 1997, Jargowsky 2015, Kneebone et al. 2011, Kneebone 2014), the trend being similar in rural and metro areas (Thiede, Kim and Valasik 2018). Different drivers are found to be responsible of these trends. Massey et al. (1991), Massey and Denton (1993) and Massey, Gross and Shibuya (1994) find that residential segregation is the main driver of spatial concentration of poverty in American urban areas. On the same line, Quillian (2012) investigates changes in concentrated poverty in American metro areas by developing a model which incorporates variations in residential segregation, yielding similar effects. Racial segregation is found to explain only a small share of variations in trends of concentrated poverty across American cities (Iceland and Hernandez 2017), whereas income segregation[1] and the extent of segregation of the poor is found to be positively and robustly associated with concentrated poverty (Dwyer 2012, Bischoff and Reardon 2014, Wilson 1987). Overall, the worsening of the economic circumstances, exacerbated by the Great Recession, substantially contributed to increase the incidence of poverty, which has been found to be one of the drivers of the recent re-emergence of concentrated poverty (Iceland and Hernandez 2017).

Poverty incidence and the segregation of the poor are important dimensions of urban poverty that fail to be addressed by (but are correlated with) the concentrated poverty index. Andreoli et al. (2021) have highlighted some additional drawbacks of the concentrated poverty index, which have to do with the normative justification of the index. In particular, counterexamples can be constructed in which a movement of poor people from a low-poverty neighborhood towards a high-poverty neighborhood, i.e. a shift which unambiguously increases poverty con-

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[1]Income segregation refers to the to the extent at which different income groups (poor, middle class, rich, for instance) are under- or over-represented in some neighborhoods compared to the city as whole. Measures of income segregation are conceptually different from concentrated poverty measures.

centration, can in fact reduce concentrated poverty as measured by CP. Andreoli et al. (2021) characterize a *urban poverty* index consistent with the implications of such transfer. We describe the index and its decomposition properties in the following section. The empirical analysis highlights trends and drivers of levels and changes in the urban poverty index across MSAs between 1980 and 2014.

2.2 Urban poverty measurement

The *urban poverty* index (hereafter, UP) combines aspects of incidence and distribution of poverty and it is defined as follows (Andreoli et al. 2021):

$$UP(\mathcal{A};\zeta) := \beta \left(\frac{\overline{P}_z - \zeta \overline{N}_z}{P}\right) + \gamma \left(\frac{\overline{N}_z}{N}\right) \left(\frac{\overline{P}_z}{P}\right) G(\mathcal{A},\zeta) + \gamma \left(\frac{N - \overline{N}_z}{N}\right) \left(\frac{\overline{P}_z - \zeta \overline{N}_z}{P}\right), \quad (1)$$

where $\zeta \in [0,1)$, $\beta, \gamma \geq 0$ and $z \geq 1$. The index value is bounded below by zero, since when $z = 0$ then $UP(\mathcal{A}, \zeta) = 0$. The level of urban poverty measured by UP depends on its parametrization. The parameters β and γ have a normative interpretation. The parameter γ is the weight of the distributional component of urban poverty, which compounds information about the distribution of poverty across high-poverty neighborhoods $i = 1, \ldots, z$ measured by the Gini index $G(\mathcal{A}, \zeta)$, alongside information about the distribution of poverty across high- and low-poverty incidence neighborhoods. The parameter β is, instead, the weight of poverty incidence. A convenient weighting scheme assigns equal weight to both components, implying $\beta = \gamma = \frac{1}{2}$. Conversely, by setting $\gamma = 0$ and $\beta = 1$, we identify a specific measure of urban poverty, denoted the *adjusted concentrated poverty* index CP^* (hereafter CP^*). It is defined as follows:

$$CP^*(\mathcal{A}, \zeta) := \frac{\overline{P}_z - \zeta \overline{N}_z}{P} = CP(\mathcal{A}, \zeta) - \zeta \left(\frac{\overline{N}_z}{P}\right). \quad (2)$$

The index provides an adjustment of CP by a counterfactual level of poverty concentration in high-poverty tracts that can be tolerated according to the normative view expressed by the urban poverty line ζ.

Lastly, the UP index also depends on the threshold ζ. An interesting case is when $\zeta = 0$,

indicating that distributional concerns about poverty are extended to all neighborhoods of the city. By setting $\gamma = 1$ and $\beta = 0$, and noticing that when $\zeta = 0$ then $z = n$ and $\overline{P}_z = P$, it can be shown that the relevant urban poverty index converges to the Gini index of poverty incidence at the tract level, which can be written as

$$UP(\mathcal{A}, 0) = G(\mathcal{A}) := \frac{1}{2P/N} \sum_{i=1}^{n} \sum_{j=1}^{n} \left[\left(\frac{N_i N_j}{N^2} \right) \left| \frac{P_i}{N_i} - \frac{P_j}{N_j} \right| \right]. \tag{3}$$

The index has interesting decomposition properties which turn out to be useful for the analysis of urban poverty distribution. As shown in Rey and Smith (2013), the Gini index can be additively decomposed into a neighborhood and a non-neighborhood component. This spatial decomposition of the Gini index relies on the specification of a binary spatial weights matrix quantifying the spatial relationship between any two census tracts i and j within a MSA. More specifically, the ij-th element of the binary spatial weights matrix is equal to 1 if tracts i and j are considered close according to a given criterion,[2] and to 0 otherwise. Once a binary spatial weights matrix has been created, the Gini index can be split into a neighborhood component, which measures inequality among census tracts that are in spatial proximity, and a non-neighborhood component measuring inequality among non-neighboring census tracts. MSAs characterized by a positive spatial autocorrelation in poverty incidence tend to display little heterogeneity among neighboring tracts, and hence a neighborhood component which is relatively small compared to the non-neighborhood component of urban poverty. Conversely, a negative spatial autocorrelation in poverty incidence implies a large heterogeneity in neighboring tracts, hence a higher level of the neighborhood component (relative to the non-neighborhood component).

A further advantage of the index in equation 3 is that the year-to-year change in urban poverty from $\mathcal{A}_t$ to $\mathcal{A}_{t+1}$ can be broken down into components measuring different contributions. The quantity $\Delta G = G(\mathcal{A}_{t+1}) - G(\mathcal{A}_t)$ measures the change in urban poverty from time t to $t+1$. However, some aspects that are relevant for assessing the change in urban poverty may

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[2]There are various criteria to establish whether two spatial units are close or not; among them, a main distinction can be made between the contiguity-based criteria (e.g., two spatial units are close if they share a common border) and the distance-based ones (e.g., two spatial units are close if the distance between their centroids is less than or equal to a chosen distance).

be neglected just by observing the variation in the index. Changes in the distribution of poor and non-poor people across census tracts may modify not only the relative difference in poverty incidence between tracts i and j in equation 3 but also the relative weight of that difference, which depends on tract population sizes.[3] To separate the roles of changes in tract population sizes and changes in tract poverty incidences when assessing urban poverty variations, Andreoli et al. (2021) broke down the change in urban poverty into three components, $\Delta G := W + R + D$. In the decomposition, W is the demographic component measuring the change in urban poverty due to changes in tract population sizes, while tract poverty incidences are kept fixed at time $t+1$. A positive (negative) value of W means that the relative weights of more unequal pairs of tracts have increased (decreased) from t to $t+1$. Component D measures the change in urban poverty owing to the changes in relative disparities between tract poverty incidences from t to $t+1$, while the ranking of tracts by poverty incidence is kept fixed at time t. A negative (positive) value of D indicates that the relative disparities in poverty incidence between initially high-poverty and low-poverty tracts have become smaller (greater) in $t+1$. As D measures the extent to which the poverty incidences of initially high-poverty and low-poverty tracts have changed disproportionately, this component can be seen as a measure of convergence ($D < 0$) or divergence ($D > 0$) in poverty incidence across tracts.[4] When tract poverty incidences vary disproportionately, a re-ranking of tracts can occur as the poverty incidence of an initially lower-poverty tract can become greater than that of an initially higher-poverty tract. Component R measures the change in urban poverty due to the re-ranking of tracts from t to $t+1$. Since the re-ranking component is always non-negative ($R \geq 0$) (Jenkins and Van Kerm 2016), the re-ranking component contrasts the effect of convergence ($D < 0$) whereas reinforces the divergence effect ($D > 0$) (O'Neill and Van Kerm 2008).

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[3] The relative weight of the difference in poverty incidence for the pair of tracts i and j in t, $N_i^{\mathcal{A}_t} N_j^{\mathcal{A}_t} / \left(N^{\mathcal{A}_t}\right)^2$, may differ from that in $t+1$, $N_i^{\mathcal{A}_{t+1}} N_j^{\mathcal{A}_{t+1}} / \left(N^{\mathcal{A}_{t+1}}\right)^2$, for effect of changes in the relative distribution of population across census tracts.

[4] The interpretation of D is consistent with the approach suggested by O'Neill and Van Kerm (2008) to examine income convergence across countries. O'Neill and Van Kerm (2008) broke down the change in the Gini index, obtaining a two-term decomposition where a component assesses to what extent the incomes of poorer countries, initially at the bottom of the distribution, have grown proportionally more than those of richer countries at the top of the initial distribution. Such a component is therefore considered as a measure of β-convergence in income across countries (O'Neill and Van Kerm 2008).

Exploiting the linear aggregation features of the Gini index, Andreoli et al. (2021) showed that the three-term decomposition of the change in urban poverty can be further decomposed to separate the contribution of a change in poverty incidence at the MSA level, which otherwise remains incorporated in D.[5] Component D can be factored as the product of two terms, $D = C \cdot E$. Component E is a measure of convergence (or divergence) in poverty incidence between tracts, just like component D, with the difference that E is calculated by assuming that the poverty incidence of the whole MSA is unchanged from t to $t+1$. Component E is therefore a "pure" measure of convergence in poverty incidence across tracts. C is a scaling factor, expressed as a function of the relative variation in the poverty incidence of the whole MSA from t to $t+1$.[6] A value of C smaller (greater) than 1 indicates that overall poverty incidence has increased (decreased) over time. The decomposition of the change in urban poverty becomes

$$\Delta G := W + R + C \cdot E. \tag{4}$$

As shown in Andreoli et al. (2021), ΔG and each of its components, except C being a scaling factor, can be split into a neighborhood and a non-neighborhood component:

$$\Delta G_N + \Delta G_{nN} := W_N + W_{nN} + R_N + R_{nN} + C \cdot (E_N + E_{nN}). \tag{5}$$

In equation 5, ΔG_N is the change in the neighborhood component of the index, and is given by the sum of the neighborhood components of W, R and E (scaled by C), $\Delta G_N := W_N + R_N + C \cdot E_N$; the same holds for the change in the non-neighborhood component of the index, $\Delta G_{nN} := W_{nN} + R_{nN} + C \cdot E_{nN}$.

In the rest of the paper, we study the metro-level drivers of the indices $CP(.,\zeta)$, $CP^*(.,\zeta)$, $UP(.,\zeta)$, by setting the urban poverty threshold $\zeta = 0.2$ or $\zeta = 0.4$, and of G, corresponding to the case in which $\zeta = 0$.

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[5]The overall poverty incidence, P/N, changes also when all tract poverty incidences vary in the same proportion, while both D and R are equal to 0 in that case.

[6]c being the relative variation in overall poverty incidence, C is equal to $1/(1+c)$ and ranges between 0 and $+\infty$.

3 Data

We use data produced by 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 ACS, which runs annually since 2001 on representative samples of the US 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 et al. 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 (each family member is assigned with the same status). 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 of age.[7] 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 MSA to aggregate census tracts into cities. The number and geographic size of the census tracts vary substantially over time within the same MSA. Some census tracts increase in population and are split into smaller

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[7]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.

tracts. Some other tracts may be consolidated to account for demographic shifts. While raw data allow to estimate urban poverty at the MSA 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 of census tables based on the 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 re-weighting methods to assign the population in each census and ACS year to the exact census tract boundary defined in the 2010 census. In this way, we can construct a balanced longitudinal database of census tracts for 395 MSAs (those with at least 10 census tracts according to the 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 tracts.

The incidence of poverty at the MSA level is always below 16% on average in the sample under consideration. More than 93% of these MSAs display at least one census tract with a poverty incidence grater than 20%. 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 the tract level. Census tracts are also geolocalized, implying that measures of proximity of these tracts can be further produced to separate the neighborhood and non-neighborhood components of urban poverty.

3.1 Poverty

In this study, the dependent variables are the measures of concentrated poverty (CP), urban poverty (CP^*, UP and G) and the components of the change in the urban poverty Gini index (G). These measures are constructed from the observed poverty incidence P_i/N_i in census tract

Variable	Statistics	1980-1990	1990-2000	2000-2008	2008-2012	2012-2014
$\Delta CP(.,0.2)$	mean	.0958	-.0474	.104	.0491	-.0153
	pc(25)	.0089	-.1	.0305	-.0028	-.0487
	pc(75)	.1722	.0105	.1697	.0997	.0123
$\Delta CP(.,0.4)$	mean	.0578	-.0393	.0461	.021	-.0118
	pc(25)	0	-.0736	0	-.0013	-.0325
	pc(75)	.0954	0	.0841	.0535	.0055
$\Delta CP^*(.,0.2)$	mean	.0498	-.0259	0	.0664	-.0104
	pc(25)	.0134	-.0537	0	.0326	-.0234
	pc(75)	.0833	-.0003	0	.096	.0032
$\Delta CP^*(.,0.4)$	mean	.013	-.0082	.01	.0032	-.002
	pc(25)	0	-.0122	0	-.0015	-.0062
	pc(75)	.0191	0	.0163	.009	.0014
$\Delta UP(.,0.2)$	mean	.0447	-.0226	0	.0571	-.0087
	pc(25)	.0126	-.0467	0	.0286	-.0198
	pc(75)	.0753	0	0	.0831	.0029
$\Delta UP(.,0.4)$	mean	.0124	-.0078	.0096	.003	-.0019
	pc(25)	0	-.0121	0	-.0014	-.0059
	pc(75)	.0188	0	.016	.0088	.0014
$\Delta G(.)$	mean	.0314	-.0038	.0153	-.016	-.0016
	pc(25)	.0026	-.0258	-.0109	-.0337	-.0135
	pc(75)	.0592	.015	.0401	.0009	.0097
$\Delta G(.)$ (not-nbh)	mean	.0151	.0015	.0121	-.0077	-.0001
	pc(25)	-.0042	-.0097	-.001	-.0181	-.0054
	pc(75)	.0305	.0106	.0247	.0011	.0051
$\Delta G(.)$ (nbh)	mean	.0163	-.0053	.0032	-.0083	-.0014
	pc(25)	-.0029	-.0206	-.0122	-.0164	-.0076
	pc(75)	.0355	.0069	.0169	.002	.0048
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
$D = C \cdot E$	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 1: Summary statistics of changes in urban poverty concentration, all 395 American MSA.

i, which is calculated by making use of the count of equivalent individuals that are poor in the tract, relative to the demographic size of the tract. When calculating CP and UP, the reference urban poverty thresholds provided by the Census Bureau are used to define high-poverty tracts

(if the local poverty incidence is greater than 20%) and extreme-poverty tracts (if the local poverty incidence is greater than 40%). The Gini index of tract poverty incidence is obtained by setting the poverty threshold equal to $\zeta = 0$, implying that all census tracts of a MSA are considered when measuring urban poverty in the MSA. Table 1 provides descriptive statistics (mean, 25th percentile and 75th percentile) of the distributions of the changes in CP, UP and G in five sub-periods of the 1980-2014 period. We also report the components of the change in G in Table 1. While ΔCP, ΔCP^*, ΔUP and ΔG are overall measures of the change in urban poverty concentration, the various components of ΔG (C, D, E, R and W) measure the effects of specific distributional changes in the distribution of poverty within a MSA.

We also consider a measure of convergence that is alternative to D and E. Such a measure is obtained by regressing the year-to-year log-change in poverty incidence P_i/N_i of each tract i of a given MSA on the log-level of tract poverty incidence in the initial period, getting a year-MSA specific measure of β-convergence. β-convergence occurs when the partial correlation between the log-change in tract poverty incidence and the initial log-level of tract poverty incidence is negative (Barro and Sala-i-Martin 1992). We estimate the partial correlation coefficient via OLS for each MSA and each year-to-year change. The descriptive statistics for the distribution of the partial correlation coefficients estimated for the 395 MSAs in each sub-period are reported in the last row of Table 1, denoted by β(log-log).[8] These descriptive statistics are negative for each sub-period, suggesting that poverty incidence grew less in census tracts where poverty was already highly concentrated in the initial period.

3.2   Covariates

Explanatory variables are also drawn from STF3A Census files and from ACS. We identify two categories of covariates. For non-monetary characteristics, Census and ACS report information about the number of individuals reporting one specific attribute and living in a given census tract. We aggregate information at the MSA level and then standardize population counts by the appropriate population, so that all variables can be interpreted as population shares ranging between 0 and 1. For monetary variables, the Census and ACS report information about the total

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[8]β here indicates the type of convergence and should not be confused with parameter β in equation 1.

aggregate value in current dollars of that variable at census tract level. We aggregate measures at the MSA level and compute per capita or per census tract values. Monetary variables always appear in logs after being actualized at the 2010 prices by using the CPI seasonally adjusted estimates for all US urban consumers (obtained from the Bureau of Labor Statistics).

Census and ACS data come in the forms of tabulations by census tract level. 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 MSAs (those with at least 10 census tracts according to 2010 census) for the years considered in this study. The sample of MSAs we consider is grouped by region: Northeast (12.66%), Midwest (27.34%), South (39.75%) and West (20.25%). Table 2 reports unweighted means and standard deviations of the variables observed in the sample of MSAs that we use to perform regression analysis.

The covariates 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 MSAs. We consider the shares of new and old houses aged less than 10 years (*New Houses (10 less yrs old)*) or more than 20 years (*Old houses (20 plus yrs old)*) respectively. These variables capture 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

	(1)		(2)		(3)		(4)		(5)		(6)	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
$CP(.,0.2)$	0.32	0.20	0.41	0.20	0.37	0.20	0.47	0.17	0.52	0.17	0.50	0.17
$CP(.,0.4)$	0.06	0.10	0.12	0.14	0.08	0.11	0.13	0.12	0.15	0.13	0.14	0.13
$CP^*(.,0.2)$	0.10	0.09	0.15	0.10	0.12	0.09	0.12	0.09	0.19	0.09	0.18	0.09
$CP^*(.,0.4)$	0.01	0.02	0.02	0.03	0.01	0.03	0.02	0.03	0.03	0.03	0.03	0.03
$UP(.,0.2)$	0.09	0.07	0.14	0.09	0.11	0.08	0.11	0.08	0.17	0.07	0.16	0.08
$UP(.,0.4)$	0.01	0.02	0.02	0.03	0.01	0.02	0.02	0.03	0.03	0.03	0.02	0.03
$G(.)$	0.33	0.09	0.36	0.09	0.35	0.09	0.37	0.08	0.35	0.07	0.35	0.07
$G(.)$ (nbh)	0.16	0.08	0.18	0.09	0.18	0.09	0.18	0.09	0.17	0.09	0.17	0.09
$G(.)$ (no-nbh)	0.16	0.09	0.18	0.10	0.18	0.10	0.19	0.10	0.18	0.10	0.18	0.10
A) % 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
A) % 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
A) % 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
A) % 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
A) 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
A) % 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
A) % 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
A) % 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
A) 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
B) % 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
B) % 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
B) % 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
B) % 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
B) % 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
B) 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
B) 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
B) 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
B) 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
B) 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
B) 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
B) 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
B) 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
C) 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
C) 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
C) % less than high school	10.49	3.63	6.38	2.70	99.35	2.22	3.73	2.17	3.46	2.11	3.28	2.04
C) % 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
C) % with college	9.15	3.18	15.37	4.13	41.70	5.69	31.64	5.63	38.28	5.63	39.23	5.67
C) % enrollment (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
D) % 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
D) % Timework	34.33	5.00	34.53	4.29	32.84	4.97	33.24	5.16	32.12	5.24	32.32	5.29
E) 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
E) 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
E) 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
E) 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
E) % 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
E) 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
E) Dissimilarity whiteblack	0.59	0.13	0.56	0.12	0.52	0.12	0.53	0.10	0.52	0.10	0.51	0.10
E) 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
E) 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
E) 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
E) 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
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
Observations	395		367		395		395		395		395	

Table 2: Descriptive statistics of regressors.

distinguish the situations 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 the situations where 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)*), first quartile 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 values are expressed in log terms.

The third group of covariates that we examine reports information about education and human capital (C). We separately consider three dimensions of education. First, we consider the proportion of the resident population aged 25 or above in a given MSA that has low education (*Less than high school*), some qualification at high school level (*With high school*) and tertiary education or above (*With college*). These variables are meant to measure the human capital composition of a MSA, which reflects both historical trends and residential choices of low and high educated people on the basis of specific characteristics of the labor market and the supply of services and amenities produced at the census tract and MSA level. Second, we consider the share of population that is actually enrolled in any form of education (*Enrollment (any)*), as a measure of the demand for consumption of education services in the MSA. Third, we introduce indicators for whether the MSA is a college town and student town. The former (*College Town*) identifies MSAs where most selective American colleges are located. The selectivity level is measured according to the college tier description used by the Department of Education (DOE) IPEDS database. We consider as college town those MSAs 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.[9]

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. The distribution of income across census tracts signals the 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 tracts (*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 MSA 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*).[10] Finally, we measure the ethnic dimension of segregation across the MSA census tracts by using standard measures of segregation (dissimilarity index) for the Whites, Blacks, Hispanics and Asians with respect to the overall population, as well as a traditional measures of black and white segregation (*Dissimilarity white-black*).

A related aspect to the quality and the affordability of tracts is the gentrification, which appears as both the cause and the consequence of the level of urban poverty. Gentrification, which is induced by the inflow of young, middle class cohorts into the most affordable and historically high-poverty tracts located in inner cities, displaces poor residents towards traditionally middle class and low-poverty neighborhoods which become more mixed. As a consequence of such a displacement, most non-gentrifying tracts tend to attract disproportionately more poor

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[9]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/`.

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

	(1)		(2)		(3)		(4)		(5)	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
F) % gentrified CT (BSM def.)	0.30	0.04	0.31	0.02	0.28	0.06	0.26	0.09	0.27	0.07
F) % stable CT (BSM def.)	0.35	0.04	0.35	0.02	0.36	0.07	0.37	0.09	0.37	0.08
F) % declining CT (BSM def.)	0.35	0.05	0.34	0.02	0.36	0.07	0.37	0.08	0.36	0.05
Observations	391		392		394		394		393	

Table 3: Descriptive statistics of gentrification.

Note: Gentrification is defined according to Baum-Snow and Marion (2009). Gentrified census tracts are those located in the top tercile of the distribution of housing value appreciation between year t and $t + 1$. Census tract in the middle and bottom tercile are considered as stable and declining respectively.

than other tracts (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. In this paper, we follow Baum-Snow and Marion (2009) and consider the housing value variations at census tract level to measure gentrification.[11] More specifically, for each census tract we compute the variation in the housing average value between years t and $t + 1$ and consider the distribution of these variations at the MSA level. Then, in each period and in each MSA, gentrified census tracts are those located in the top tercile of the distribution of housing value appreciation. Tracts in the middle and bottom tercile are defined as stable and declining tracts respectively. Table 3 reports the gentrification indicators for the 1980-2014 period.

4 Results

4.1 Trends in urban poverty

In the last decades, there has been evidence 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. Poverty has been increasingly concentrating into historically middle-class, low poverty neighborhoods. The set of measures of urban poverty described in previous sections are capable of capturing some relevant features of this secular trend. More specifically, we consider the trends in CP and UP for urban poverty lines at 20% (i.e., $\zeta = 0.2$) and 40% (i.e., $\zeta = 0.4$), and the trends in CP^* and G, which are obtained in correspondence

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[11]See Christafore and Leguizamon (2019) for alternative definitions of gentrification.

	1980-1990	1990-2000	2000-2008	2008-2012	2012-2014
	(1)	(2)	(3)	(4)	(5)
$\Delta CP(.,0.2)$	0.130**	0.164**	0.151**	0.112**	0.172**
$\Delta CP(.,0.4)$	0.163**	0.034	0.266**	0.101**	0.150**
$\Delta CP^*(.,0.2)$	0.207**	0.097*	0.000	0.209**	0.320**
$\Delta CP^*(.,0.4)$	0.160**	0.026	0.257**	0.142**	0.139**
$\Delta UP(.,0.2)$	0.225**	0.112**	0.000	0.186**	0.325**
$\Delta UP(.,0.4)$	0.170**	0.033	0.259**	0.141**	0.137**
$\Delta G(.)$	0.576**	0.543**	0.437**	0.483**	0.638**
$\Delta G(.)$ (nbh)	0.441**	0.355**	0.381**	0.400**	0.571**
$\Delta G(.)$ (no-nbh)	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

Note: Significance levels: $^* = 10\%$, $^{**} = 5\%$, and $^{***} = 1\%$.

Table 4: Correlations of β-convergence (log-log specification) and measures of urban poverty concentration, by year-to-year changes.

of a specific choice of the parameters β, γ and ζ in the general formula of UP (i.e., $\beta = 1$ and $\gamma = 0$ for CP^*, and $\beta = 0$, $\gamma = 1$ and $\zeta = 0$ for G). We then calculate the correlations between the year-to-year changes in these measures and the MSA-specific measure of β-convergence in poverty incidence across tracts (see table 1).

Table 4 shows that correlations are all statistically significant in the last two sub-periods considered, suggesting that all measures of urban poverty agree on convergence of tracts within MSAs in terms of poverty incidence. However, these correlations are different in terms of magnitude, with mild levels for the general measures of urban poverty concentration (CP, UP and CP^*) and higher levels for the components of the change in Gini index, especially E and consequently $D = C \cdot E$. Component E is highly and positively correlated with β-convergence estimates, indicating that MSAs where poverty growth is clustered in low-poverty tracts on average (higher levels of β-convergence), also display relatively low urban poverty. Component R is negatively and significantly related to the extent of β-convergence. MSAs 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 tracts compared to the growth observed in low-poverty ones. This combination of changes induces a substantial re-ranking of tracts.

An advantage of using the Gini index to measure urban poverty is that each component of the change in urban poverty can be split into neighborhood and non-neighborhood components.[12] Figure 1 shows the box-plots of the distributions of the spatial components of ΔG, R, D and E. From figure 1, we see that convergence in tract poverty incidence occurs both among neighboring census tracts and among non-neighboring census tracts, as the values of E_N and E_{nN} are mainly negative. However, the re-ranking effect mitigates the convergence process both among neighboring census tracts and among non-neighboring census tracts.

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[12] A spatial weights matrix representing the spatial relationships between census tracts in a MSA is needed to obtain the spatial decomposition. We specify a binary spatial weights matrix, the ij-th element of which equals 1 if tracts i and j are neighboring and 0 otherwise. A distance-based criterion is used to establish whether two tracts are neighboring (Andreoli et al. 2021). More specifically, two tracts are considered close if the distance between their centroids is less than or equal to a cut-off distance, which is set equal to the minimum distance for which every tract in a MSA has at least one neighbor.
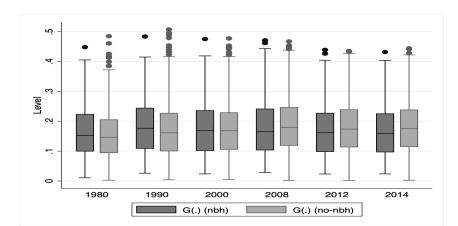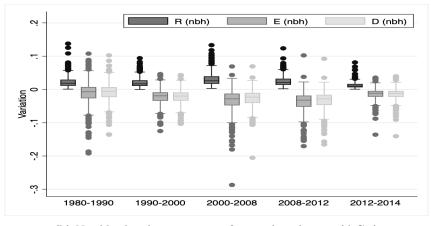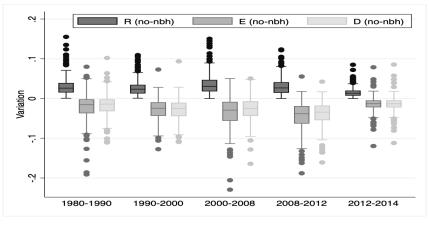
Figure 1: Neighborhood and non-neighborhood components of urban poverty levels and year-to-year changes.

(a) G levels components

(b) Neighborhood components of inequality changes (ΔG_N)

(c) Non-neighborhood components of inequality changes (ΔG_{nN})

Note: Inequality changes and its components (R, E and $D = C \cdot E$), 1980-2014. Data for 395 MSAs.

4.2 Drivers of concentrated poverty and urban poverty: Levels

We produce comparative evidence about potential drivers of concentrated poverty and urban poverty, and study the partial associations of these variables with the levels and changes in urban poverty across American MSAs. Table 5 reports estimates of the effects of the relevant drivers. Values of these indicators are obtained for each MSA and year. The partial correlations of urban poverty with the relevant drivers are obtained from pooled OLS regressions controlling for year, state and region fixed effects and including a binary indicator for the Great Recession (years 2008 to 2012).

Regression results show that the demographic composition in terms of origin group is correlated with CP^* and UP calculated for both high (20%) and extreme (40%) poverty thresholds. The population distribution by age is correlated with CP^* and UP when the focus is on extreme poverty. Lower levels of urban poverty are associated with a larger share of population aged 25 or above. This may be explained by the fact that people aged 25-64 are more likely to be employed while those aged 65 or above are mainly retired. The education and employment composition, strongly associated with opportunities offered by the labor market, correlate with CP, CP^* and UP for both of the poverty thresholds that we consider. That is, MSAs with higher poverty concentration are characterized by lower shares of high educated population and living in proximity of the workplace. MSAs with higher shares of workers holding a managerial position tend to have higher levels of urban poverty, except when $CP(.,0.2)$ is considered.

The distribution of income across census tracts, as well as the features of the housing market, have important implications for $UP(.,0.2)$, $CP^*(.,0.2)$ and G. This evidence can be reconciled with the implications of neighborhood affordability on the geography of poverty. MSAs with a higher median income across census tracts (holding average household income as fixed) display more income mix at the tract level and less inequality across tracts (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.

All estimated models agree that the poverty incidence in the whole MSA and the degree of

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Table 5: Drivers of concentrated poverty and urban poverty levels, pooled sample.

	CP(.,0.2) (1)		CP(.,0.4) (2)		CP*(.,0.2) (3)		CP*(.,0.4) (4)		UP(.,0.2) (5)		UP(.,0.4) (6)		G(.) (7)	
A) % Black	-0.062	(0.12)	0.120	(0.08)	-0.004	(0.06)	0.007	(0.02)	-0.045	(0.05)	0.007	(0.02)	0.026	(0.04)
A) % Hispanic	0.038	(0.11)	-0.060	(0.09)	-0.061	(0.04)	-0.044**	(0.02)	-0.091**	(0.03)	-0.041**	(0.02)	0.001	(0.03)
A) % Asian	-0.057	(0.15)	0.030	(0.09)	-0.146**	(0.06)	0.015	(0.03)	-0.154**	(0.05)	0.014	(0.03)	-0.025	(0.04)
A) % White	-0.094	(0.14)	0.039	(0.09)	-0.068	(0.06)	-0.017	(0.03)	-0.076	(0.05)	-0.014	(0.02)	-0.035	(0.04)
A) Population size (ln)	-0.018	(0.04)	0.017	(0.03)	-0.001	(0.01)	-0.012	(0.01)	-0.003	(0.01)	-0.011	(0.01)	0.020**	(0.01)
A) % 65 plus yrs old	0.387**	(0.16)	-0.025	(0.17)	0.010	(0.10)	-0.144**	(0.05)	0.001	(0.09)	-0.132**	(0.05)	0.053	(0.04)
A) % 25-64 yrs old	0.399**	(0.16)	-0.269	(0.19)	-0.149	(0.09)	-0.203**	(0.04)	-0.129	(0.08)	-0.191**	(0.04)	0.034	(0.04)
A) % Foreign	-0.027	(0.11)	-0.105	(0.10)	-0.028	(0.06)	0.014	(0.03)	-0.039	(0.05)	0.010	(0.03)	-0.068**	(0.03)
A) Moved from outside of state	0.170**	(0.07)	0.021	(0.06)	0.035	(0.03)	-0.008	(0.02)	0.048	(0.03)	-0.005	(0.02)	0.014	(0.02)
B) % New Houses (10 less yrs old)	-0.090	(0.09)	0.089	(0.07)	0.039	(0.04)	0.004	(0.02)	0.020	(0.03)	0.002	(0.02)	-0.049**	(0.02)
B) % Old houses (20 plus yrs old)	0.039	(0.06)	-0.116**	(0.05)	-0.012	(0.03)	-0.027	(0.02)	-0.008	(0.02)	-0.026	(0.02)	-0.025**	(0.01)
B) % Owner occupied	-0.114	(0.22)	0.343	(0.25)	0.155*	(0.08)	0.002	(0.07)	0.100	(0.07)	-0.002	(0.06)	0.080*	(0.04)
B) % Vacant	-0.047	(0.08)	-0.035	(0.06)	-0.005	(0.02)	-0.005	(0.01)	-0.007	(0.02)	-0.005	(0.01)	-0.014	(0.02)
B) % Rented	0.016	(0.19)	0.307	(0.27)	0.201**	(0.08)	0.010	(0.07)	0.180**	(0.07)	0.011	(0.07)	0.050	(0.05)
B) Avg. value house (ln)	-0.001	(0.02)	-0.003	(0.01)	0.001	(0.01)	-0.001	(0.00)	-0.001	(0.00)	-0.001	(0.00)	0.007**	(0.00)
B) Median value house by CT (ln)	-0.015	(0.02)	0.023*	(0.01)	0.006	(0.01)	0.004	(0.00)	0.003	(0.01)	0.004	(0.00)	0.010**	(0.00)
B) p25% value house by CT (ln)	-0.008	(0.01)	-0.008	(0.02)	-0.001	(0.01)	0.001	(0.00)	-0.002	(0.00)	0.001	(0.00)	-0.007	(0.00)
B) S.d. value house by CT (ln)	-0.005	(0.01)	0.005	(0.01)	0.003	(0.00)	0.004	(0.00)	0.003	(0.00)	0.004	(0.00)	-0.005**	(0.00)
B) Avg. rent (ln)	0.022	(0.04)	-0.025	(0.03)	-0.002	(0.01)	0.009	(0.01)	0.001	(0.01)	0.008	(0.01)	-0.012	(0.01)
B) Median rent by CT (ln)	-0.018	(0.07)	0.147**	(0.05)	0.038	(0.03)	0.017	(0.01)	0.033	(0.02)	0.016	(0.01)	0.005	(0.03)
B) p25% rent by CT (ln)	-0.009	(0.03)	-0.075**	(0.03)	-0.025	(0.02)	-0.011	(0.01)	-0.024	(0.02)	-0.011	(0.01)	-0.008	(0.02)
B) S.d. rent by CT (ln)	0.004	(0.01)	-0.016*	(0.01)	-0.006	(0.00)	-0.004	(0.00)	-0.007	(0.00)	-0.004*	(0.00)	0.000	(0.00)
C) College Town	0.002	(0.01)	0.005	(0.01)	0.003	(0.00)	0.001	(0.00)	0.002	(0.00)	0.001	(0.00)	-0.003*	(0.00)
C) Student Town	0.003	(0.01)	-0.003	(0.01)	0.002	(0.01)	-0.002	(0.00)	0.002	(0.01)	-0.002	(0.00)	-0.007	(0.00)
C) % less than high school	-0.003*	(0.00)	-0.000	(0.00)	-0.001	(0.01)	0.001	(0.00)	-0.001	(0.00)	0.001	(0.00)	-0.000	(0.00)
C) % with high school	-0.359**	(0.18)	0.109	(0.18)	-0.076	(0.07)	0.076*	(0.04)	-0.084	(0.06)	0.065	(0.04)	-0.029	(0.03)
C) % with college	-0.002*	(0.00)	-0.000	(0.00)	-0.000	(0.00)	0.000**	(0.00)	-0.000	(0.00)	0.000*	(0.00)	-0.000*	(0.00)
C) % enrollment (any)	0.167	(0.12)	0.210**	(0.09)	0.060	(0.04)	-0.050*	(0.03)	0.030	(0.03)	-0.050*	(0.03)	0.036	(0.03)
D) % Managerial position	-0.255**	(0.10)	0.280**	(0.07)	0.097**	(0.04)	0.124**	(0.02)	0.078**	(0.04)	0.116**	(0.02)	0.034	(0.03)
D) % Timework	-0.002*	(0.00)	0.001*	(0.00)	-0.000	(0.00)	0.000*	(0.00)	-0.000	(0.00)	0.000*	(0.00)	0.000**	(0.00)
E) Avg hh income (ln)	0.007	(0.03)	0.004	(0.03)	-0.005	(0.01)	-0.011	(0.01)	-0.003	(0.01)	-0.010	(0.01)	0.012*	(0.01)
E) Median hh income by CT (ln)	-0.078	(0.07)	-0.017	(0.07)	-0.066**	(0.03)	-0.006	(0.02)	-0.087**	(0.02)	-0.009	(0.02)	-0.066**	(0.02)
E) p25% hh income by CT (ln)	0.066**	(0.03)	0.008	(0.03)	0.022	(0.02)	0.015	(0.01)	0.028**	(0.01)	0.016	(0.01)	0.045**	(0.01)
E) S.d. hh income by CT (ln)	0.026*	(0.02)	-0.011	(0.01)	0.007	(0.01)	-0.000	(0.00)	0.012**	(0.00)	0.000	(0.00)	0.025**	(0.00)
E) % of poor	3.268**	(0.20)	2.083**	(0.21)	1.464**	(0.07)	0.456**	(0.03)	1.067**	(0.06)	0.411**	(0.03)	-0.369**	(0.04)
E) Dissimilarity poor	1.296**	(0.05)	0.825**	(0.08)	0.654**	(0.02)	0.172**	(0.02)	0.625**	(0.02)	0.167**	(0.02)	1.014**	(0.01)
E) Dissimilarity whiteblack	0.102	(0.08)	-0.090	(0.09)	-0.015	(0.05)	-0.019	(0.03)	0.008	(0.05)	-0.017	(0.03)	-0.024	(0.03)
E) Dissimilarity black	-0.141*	(0.08)	0.162	(0.10)	0.044	(0.05)	0.040	(0.03)	0.007	(0.04)	0.036	(0.03)	0.027	(0.03)
E) Dissimilarity hispanic	0.061	(0.04)	-0.021	(0.03)	-0.001	(0.01)	-0.012	(0.01)	-0.001	(0.01)	-0.012	(0.01)	0.007	(0.01)
E) Dissimilarity asian	0.013	(0.03)	0.040	(0.03)	0.007	(0.01)	0.021**	(0.01)	0.012	(0.01)	0.021**	(0.01)	0.008	(0.01)
E) Dissimilarity white	-0.320**	(0.14)	0.110	(0.11)	0.042	(0.06)	-0.013	(0.04)	0.033	(0.05)	-0.010	(0.03)	-0.071*	(0.04)
Great Recession	0.020	(0.18)	0.110	(0.12)	0.006	(0.05)	-0.013	(0.03)	0.016	(0.05)	-0.013	(0.03)	-0.048	(0.04)
State fe	y		y		y		y		y		y		y	
Regional fe	y		y		y		y		y		y		y	
Year fe	y		y		y		y		y		y		y	
N. of obs.	2342		2342		2342		2342		2342		2342		2342	
MSA	395		395		395		395		395		395		395	
N. of years	6		6		6		6		6		6		6	
R-squared	0.898		0.770		0.928		0.711		0.917		0.709		0.969	
Root MSE	0.065		0.062		0.026		0.016		0.024		0.015		0.015	

Note: pooled OLS regression controlling for years fixed effects and Great Recession (2008-2012) fixed effects. All models controls for state and regional FE (Regions: Northeast, Midwest, South, West). Standard errors, clustered at state level, are in parenthesis. Significance levels: * = 10% and ** = 5%.

dissimilarity in the distribution of poor within the MSA are important drivers of urban poverty. While the dissimilarity in the distribution of poor is strongly positively correlated with every measure of poverty concentration, poverty incidence has a positive impact on all measures except from G. This is a consequence of the fact that the index G focuses on the inequality in poverty incidence across tracts and such an inequality is less emphasized in MSAs where a large fraction of the population is poor. While the impacts of dissimilarity in the distribution of poor and poverty incidence in the MSA on urban poverty are not unexpected, they may be relevant to anti-poverty policy making when the effects of the remaining explanatory variables are controlled for. Regression results suggest that the tendency of poor people to distribute unevenly across census tracts in a MSA is influenced only to a small extent by the explanatory variables that can be controlled, like the employment composition or the quality of house market.

Table 6 reports estimates of the marginal effects of interest that are based on a FE model. The incidence of poverty at the MSA level plays a major role in explaining urban poverty concentration, irrespective of the measure we use. Variables linked to income distribution mainly affect $UP(., 0.2)$ and G but seem uncorrelated with other measures of urban poverty concentration. Overall, the FE estimates support the findings of the cross-sectional models.

4.3 Drivers of concentrated poverty and urban poverty: Changes

We examine the effects of the same covariates considered in section 4.2 on the pooled period-to-period changes in the measures of concentrated poverty and urban poverty. We expand the model by including controls for gentrification at the census tract level. Table 7 presents the effects of demographics, education, housing, labor market, and income distribution on the relevant urban poverty changes. Overall, we find that demographics, education, and housing are the most relevant (and significant) drivers of changes in concentrated and urban poverty. An increment in the proportion of non-US citizens increases $CP^*(., 0.2)$ and $UP(., 0.2)$, while the effect is statistically insignificant for the other indicators. Meanwhile, a high mobility of citizens from other US states is associated with a lower change in urban poverty. These findings suggest an asymmetry in the residential choice of natives and immigrants that move into a MSA. Ethnic

	CP(.,0.2) (1)		CP(.,0.4) (2)		CP*(.,0.2) (3)		CP*(.,0.4) (4)		UP(.,0.2) (5)		UP(.,0.4) (6)		G(.) (7)	
A) % Black	0.021	(0.10)	0.095	(0.07)	-0.001	(0.06)	0.005	(0.02)	-0.040	(0.05)	0.005	(0.02)	0.029	(0.04)
A) % Hispanic	0.102	(0.08)	-0.091	(0.07)	-0.076*	(0.04)	-0.046**	(0.02)	-0.100**	(0.04)	-0.042**	(0.02)	-0.002	(0.04)
A) % Asian	0.047	(0.15)	-0.043	(0.10)	-0.126**	(0.06)	0.014	(0.04)	-0.131**	(0.05)	0.016	(0.04)	-0.027	(0.04)
A) % White	0.019	(0.12)	-0.033	(0.09)	-0.079	(0.06)	-0.023	(0.03)	-0.077	(0.05)	-0.018	(0.03)	-0.038	(0.04)
A) Population size (ln)	-0.011	(0.04)	0.007	(0.03)	-0.004	(0.01)	-0.016	(0.01)	-0.006	(0.01)	-0.015	(0.01)	0.020**	(0.01)
A) % 65 plus yrs old	0.321*	(0.17)	0.074	(0.17)	0.028	(0.09)	-0.139**	(0.05)	0.011	(0.09)	-0.129**	(0.05)	0.070*	(0.04)
A) % 25-64 yrs old	0.305*	(0.17)	-0.159	(0.18)	-0.167*	(0.10)	-0.187**	(0.04)	-0.147*	(0.08)	-0.176**	(0.04)	0.043	(0.05)
A) % Foreign	-0.029	(0.12)	-0.103	(0.11)	-0.000	(0.05)	0.017	(0.04)	-0.020	(0.05)	0.013	(0.03)	-0.078**	(0.03)
A) Moved from outside of state	0.164**	(0.07)	0.053	(0.06)	0.037	(0.03)	0.002	(0.02)	0.051*	(0.03)	0.004	(0.01)	0.019	(0.02)
B) % New Houses (10 less yrs old)	-0.135	(0.08)	0.079	(0.07)	0.013	(0.03)	0.001	(0.02)	-0.006	(0.03)	-0.001	(0.02)	-0.053**	(0.02)
B) % Old houses (20 plus yrs old)	0.025	(0.06)	-0.133**	(0.05)	-0.021	(0.03)	-0.030	(0.02)	-0.018	(0.03)	-0.029	(0.02)	-0.028**	(0.01)
B) % Owner occupied	-0.107	(0.22)	0.406	(0.25)	0.192**	(0.09)	0.010	(0.07)	0.136*	(0.07)	0.007	(0.06)	0.098**	(0.04)
B) % Vacant	-0.047	(0.08)	-0.031	(0.06)	0.000	(0.02)	-0.005	(0.01)	-0.004	(0.02)	-0.006	(0.01)	-0.015	(0.02)
B) % Rented	-0.013	(0.19)	0.385	(0.29)	0.217**	(0.09)	0.015	(0.08)	0.193**	(0.08)	0.015	(0.07)	0.057	(0.05)
B) Avg. value house (ln)	0.001	(0.02)	-0.005	(0.01)	0.001	(0.01)	-0.002	(0.00)	-0.001	(0.00)	-0.002	(0.00)	0.009**	(0.00)
B) Median value house by CT (ln)	-0.011	(0.02)	0.023	(0.01)	0.004	(0.01)	0.004	(0.00)	0.002	(0.01)	0.004	(0.00)	0.012**	(0.00)
B) p25% value house by CT (ln)	-0.009	(0.01)	-0.006	(0.02)	-0.000	(0.01)	0.002	(0.00)	-0.001	(0.01)	0.001	(0.00)	-0.007	(0.00)
B) S.d. value house by CT (ln)	-0.006	(0.01)	0.004	(0.01)	0.002	(0.00)	0.003	(0.00)	0.002	(0.00)	0.003	(0.00)	-0.006**	(0.00)
B) Avg. rent (ln)	0.017	(0.04)	-0.017	(0.03)	0.001	(0.01)	0.014	(0.01)	0.004	(0.01)	0.013	(0.01)	-0.012	(0.01)
B) Median rent by CT (ln)	0.014	(0.07)	0.100**	(0.05)	0.040	(0.03)	0.004	(0.01)	0.038	(0.02)	0.005	(0.01)	0.006	(0.03)
B) p25% rent by CT (ln)	-0.014	(0.03)	-0.063*	(0.04)	-0.024	(0.02)	-0.008	(0.01)	-0.025	(0.02)	-0.008	(0.01)	-0.009	(0.02)
B) S.d. rent by CT (ln)	0.001	(0.01)	-0.011	(0.01)	-0.007	(0.00)	-0.003	(0.00)	-0.008*	(0.00)	-0.003	(0.00)	0.000	(0.00)
C) College Town	0.001	(0.01)	0.007	(0.01)	0.002	(0.00)	0.001	(0.00)	0.001	(0.00)	0.001	(0.00)	-0.003*	(0.00)
C) Student Town	0.005	(0.01)	0.001	(0.01)	0.003	(0.01)	-0.001	(0.01)	0.003	(0.01)	-0.001	(0.00)	-0.005	(0.01)
C) % less than high school	-0.001	(0.00)	-0.001	(0.00)	-0.001	(0.00)	0.001	(0.00)	-0.001	(0.00)	0.000	(0.00)	-0.000	(0.00)
C) % with high school	-0.217	(0.17)	-0.062	(0.12)	-0.061	(0.07)	0.049	(0.04)	-0.063	(0.06)	0.041	(0.04)	-0.037	(0.03)
C) % with college	-0.001	(0.00)	-0.001	(0.00)	-0.000	(0.00)	-0.000	(0.00)	-0.000	(0.00)	0.000	(0.00)	-0.000*	(0.00)
C) % enrollment (any)	0.183	(0.12)	0.208**	(0.09)	0.059	(0.04)	-0.051*	(0.03)	0.031	(0.03)	-0.051*	(0.03)	0.041	(0.03)
D) % Managerial position	-0.244**	(0.10)	0.260**	(0.08)	0.114**	(0.04)	0.117**	(0.02)	0.091**	(0.04)	0.109**	(0.02)	0.032	(0.03)
D) % Timework	-0.002	(0.00)	0.001	(0.00)	0.000	(0.00)	0.000	(0.00)	-0.000	(0.00)	0.000	(0.00)	0.000*	(0.00)
E) Avg lhh income (ln)	0.012	(0.04)	-0.009	(0.03)	-0.009	(0.01)	-0.016	(0.01)	-0.007	(0.01)	-0.015	(0.01)	0.009	(0.01)
E) Median lhh income by CT (ln)	-0.088	(0.07)	-0.010	(0.07)	-0.072**	(0.03)	-0.004	(0.02)	-0.092**	(0.03)	-0.008	(0.02)	-0.068**	(0.02)
E) p25% lhh income by CT (ln)	0.070**	(0.03)	-0.001	(0.04)	0.028*	(0.02)	0.015	(0.01)	0.033**	(0.01)	0.016	(0.01)	0.046**	(0.01)
E) S.d. lhh income by CT (ln)	0.027	(0.02)	-0.013	(0.02)	0.008	(0.01)	-0.001	(0.00)	0.013**	(0.01)	-0.000	(0.00)	0.026**	(0.00)
E) % of poor	3.287**	(0.20)	1.995**	(0.20)	1.463**	(0.07)	0.451**	(0.04)	1.073**	(0.06)	0.406**	(0.03)	-0.363**	(0.04)
E) Dissimilarity poor	1.294**	(0.06)	0.847**	(0.08)	0.652**	(0.02)	0.178**	(0.02)	0.623**	(0.03)	0.172**	(0.02)	1.014**	(0.01)
E) Dissimilarity whiteblack	0.066	(0.08)	-0.099	(0.09)	-0.023	(0.06)	-0.015	(0.03)	-0.000	(0.05)	-0.013	(0.03)	-0.029	(0.03)
E) Dissimilarity black	-0.130	(0.08)	0.191*	(0.10)	0.055	(0.05)	0.039	(0.03)	0.016	(0.05)	0.034	(0.03)	0.030	(0.03)
E) Dissimilarity hispanic	0.060	(0.04)	-0.020	(0.03)	0.003	(0.01)	-0.011	(0.01)	0.002	(0.01)	-0.011	(0.01)	0.008	(0.01)
E) Dissimilarity asian	0.021	(0.03)	0.029	(0.02)	0.009	(0.01)	0.021**	(0.01)	0.015	(0.01)	0.021**	(0.01)	0.010	(0.01)
E) Dissimilarity white	-0.255*	(0.14)	0.067	(0.13)	0.042	(0.07)	-0.018	(0.04)	0.039	(0.06)	-0.014	(0.04)	-0.071*	(0.04)
State fe	y		y		y		y		y		y		y	
Regional fe	y		y		y		y		y		y		y	
Year fe	y		y		y		y		y		y		y	
N. of obs.	2202		2202		2202		2202		2202		2202		2202	
MSA	367		367		367		367		367		367		367	
N. of years	6		6		6		6		6		6		6	
R-squared	0.897		0.776		0.928		0.716		0.918		0.713		0.968	
Root MSE	0.065		0.061		0.026		0.016		0.024		0.015		0.015	

Table 6: Drivers of concentrated poverty and urban poverty levels, FE estimator.

Note: FE estimators for the balanced panel of MSA (367). All models controls for state and regional FE (Regions: Northeast, Midwest, South, West). Standard errors, clustered at state level, are in parenthesis. Significance levels: * = 10% and ** = 5%.

Table 7: Drivers of changes in concentrated poverty and urban poverty.

	Δ CP(.,0.2) (1)	Δ CP(.,0.4) (2)	Δ CP*(.,0.2) (3)	Δ CP*(.,0.4) (4)	Δ UP(.,0.2) (5)	Δ UP(.,0.4) (6)	Δ G(.) (7)
A) % Black	0.109 (0.11)	0.289** (0.08)	0.108** (0.04)	0.047** (0.02)	0.093** (0.04)	0.041** (0.02)	0.016 (0.03)
A) % Hispanic	0.006 (0.09)	0.210** (0.04)	0.062** (0.03)	0.033** (0.01)	0.055** (0.02)	0.029** (0.01)	0.018 (0.03)
A) % Asian	0.207** (0.10)	0.389** (0.18)	0.299** (0.09)	0.050 (0.05)	0.231** (0.07)	0.040 (0.04)	-0.054 (0.09)
A) % White	-0.077 (0.09)	0.185** (0.06)	0.091* (0.05)	0.038** (0.02)	0.077** (0.04)	0.033** (0.01)	0.069 (0.05)
A) Population size (ln)	-0.203** (0.04)	-0.101** (0.03)	-0.064** (0.02)	-0.022** (0.01)	-0.054** (0.01)	-0.021** (0.01)	0.002 (0.01)
A) % 65 plus yrs old	-0.189 (0.17)	-0.200 (0.14)	0.052 (0.07)	-0.036 (0.03)	0.046 (0.06)	-0.036 (0.03)	0.156* (0.08)
A) % 25-64 yrs old	-0.637** (0.17)	-0.107 (0.24)	0.024 (0.09)	-0.057 (0.04)	0.022 (0.07)	-0.055* (0.03)	0.036 (0.06)
A) % Foreign	0.136 (0.15)	0.025 (0.09)	0.136** (0.04)	-0.016 (0.02)	0.117** (0.04)	-0.014 (0.02)	-0.056 (0.05)
A) Moved from outside of state	-0.263** (0.13)	-0.079 (0.08)	-0.126** (0.04)	-0.011 (0.02)	-0.109** (0.04)	-0.010 (0.02)	-0.070** (0.03)
B) % New Houses (10 less yrs old)	0.306** (0.10)	0.057 (0.12)	-0.035 (0.04)	0.003 (0.02)	-0.027 (0.03)	0.005 (0.02)	-0.038 (0.04)
B) % Old houses (20 plus yrs old)	0.080 (0.08)	0.051 (0.08)	-0.079** (0.03)	0.006 (0.01)	-0.068** (0.03)	0.007 (0.01)	-0.080** (0.03)
B) % Owner occupied	-0.049 (0.21)	0.166 (0.23)	-0.026 (0.11)	0.060 (0.04)	-0.009 (0.09)	0.055 (0.04)	0.111 (0.11)
B) % Vacant	-0.037 (0.07)	-0.006 (0.04)	-0.007 (0.02)	-0.006 (0.01)	-0.010 (0.02)	-0.006 (0.01)	-0.008 (0.02)
B) % Rented	0.159 (0.24)	0.224 (0.22)	-0.004 (0.12)	0.077* (0.04)	-0.002 (0.10)	0.071* (0.04)	0.252** (0.11)
B) Avg. value house (ln)	0.038* (0.02)	0.010 (0.01)	0.006 (0.01)	0.000 (0.00)	0.005 (0.01)	0.000 (0.00)	0.000 (0.01)
B) Median value house by CT (ln)	0.066** (0.02)	-0.005 (0.02)	0.015* (0.01)	0.003 (0.00)	0.014* (0.01)	0.003 (0.00)	0.002 (0.01)
B) p25% value house by CT (ln)	-0.010 (0.02)	-0.005 (0.02)	-0.008 (0.01)	-0.002 (0.00)	-0.007 (0.01)	-0.001 (0.00)	-0.012** (0.01)
B) S.d. value house by CT (ln)	-0.032** (0.01)	0.001 (0.01)	-0.008* (0.00)	-0.000 (0.00)	-0.007* (0.00)	-0.000 (0.00)	-0.005 (0.00)
B) Avg. rent (ln)	0.201** (0.04)	0.096** (0.03)	0.064** (0.02)	0.021** (0.01)	0.054** (0.02)	0.020** (0.01)	0.006 (0.01)
B) Median rent by CT (ln)	-0.390** (0.08)	-0.080 (0.07)	-0.100** (0.03)	-0.006 (0.02)	-0.079** (0.03)	-0.007 (0.02)	0.008 (0.03)
B) p25% rent by CT (ln)	0.136** (0.05)	-0.022 (0.05)	0.019 (0.02)	-0.016 (0.01)	0.016 (0.02)	-0.014 (0.01)	0.013 (0.02)
B) S.d. rent by CT (ln)	0.019 (0.02)	0.011 (0.01)	0.004 (0.00)	-0.000 (0.00)	0.004 (0.00)	-0.000 (0.00)	0.004 (0.01)
C) College Town	-0.003 (0.01)	-0.006 (0.01)	-0.003 (0.00)	-0.000 (0.00)	-0.003 (0.00)	-0.000 (0.00)	0.003 (0.00)
C) Student Town	-0.015 (0.01)	-0.006 (0.00)	-0.012** (0.00)	0.000 (0.00)	-0.009** (0.00)	-0.000 (0.00)	-0.009* (0.00)
C) % less than high school	0.003 (0.00)	0.001 (0.00)	-0.002** (0.00)	-0.000 (0.00)	-0.002** (0.00)	-0.001 (0.00)	-0.001 (0.00)
C) % with high school	0.028 (0.18)	-0.037 (0.18)	-0.087 (0.08)	-0.045 (0.04)	-0.066 (0.06)	-0.042 (0.03)	0.085 (0.06)
C) % with college	0.001 (0.00)	0.001* (0.00)	-0.001** (0.00)	-0.000 (0.00)	-0.001* (0.00)	-0.000 (0.00)	0.000 (0.00)
C) % enrollment (any)	-0.038 (0.14)	-0.278* (0.14)	-0.070 (0.07)	-0.077* (0.04)	-0.035 (0.06)	-0.068* (0.04)	0.195** (0.04)
D) % Managerial position	-0.109 (0.10)	-0.170 (0.10)	-0.089* (0.05)	-0.010 (0.02)	-0.074** (0.04)	-0.008 (0.02)	0.056 (0.02)
D) % Timework	-0.001 (0.00)	-0.000 (0.00)	0.000 (0.00)	-0.000 (0.00)	0.000 (0.00)	-0.000 (0.00)	0.001** (0.00)
E) Avg hh income (ln)	-0.241** (0.04)	-0.064* (0.04)	-0.058** (0.02)	-0.013* (0.01)	-0.049** (0.02)	-0.013* (0.01)	0.031** (0.01)
E) Median lh income by CT (ln)	0.217** (0.10)	0.024 (0.10)	0.032 (0.04)	0.001 (0.01)	0.023 (0.03)	0.001 (0.01)	0.037 (0.03)
E) p25% lh income by CT (ln)	-0.142** (0.04)	-0.003 (0.04)	-0.014 (0.01)	0.003 (0.00)	-0.010 (0.01)	0.002 (0.01)	-0.040** (0.01)
E) S.d. lh income by CT (ln)	-0.016 (0.02)	0.011 (0.02)	0.006 (0.01)	0.002 (0.00)	0.006 (0.01)	0.002 (0.00)	0.005 (0.01)
E) % of poor	-1.209** (0.26)	-0.201 (0.16)	-0.146** (0.07)	-0.039 (0.03)	-0.103** (0.06)	-0.038 (0.03)	0.183** (0.08)
E) Dissimilarity poor	-0.280** (0.08)	-0.067 (0.05)	-0.034 (0.03)	-0.005 (0.01)	-0.039 (0.03)	-0.006 (0.01)	-0.395** (0.03)
E) Dissimilarity whiteblack	-0.055 (0.10)	-0.183** (0.07)	-0.050 (0.04)	-0.033** (0.02)	-0.042 (0.03)	-0.029** (0.01)	-0.015 (0.03)
E) Dissimilarity black	0.101 (0.11)	0.183** (0.07)	0.055 (0.04)	0.032* (0.02)	0.045 (0.03)	0.028* (0.01)	0.003 (0.02)
E) Dissimilarity hispanic	0.082** (0.04)	0.030 (0.02)	0.031** (0.01)	-0.003 (0.01)	0.029** (0.01)	-0.002 (0.01)	0.020 (0.02)
E) Dissimilarity asian	-0.097** (0.05)	-0.067 (0.04)	-0.043** (0.02)	-0.013 (0.01)	-0.031** (0.01)	-0.010 (0.01)	0.017 (0.01)
E) Dissimilarity white	0.049 (0.13)	0.043 (0.10)	0.043 (0.05)	0.031 (0.03)	0.027 (0.05)	0.026 (0.02)	0.120** (0.07)
F) % gentrified CT (BSM def.)	0.041 (0.08)	0.004 (0.04)	-0.024 (0.03)	0.007 (0.01)	-0.025 (0.02)	0.006 (0.01)	-0.061** (0.02)
Great Recession	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
State fe	y	y	y	y	y	y	y
Regional fe	y	y	y	y	y	y	y
Year fe	y	y	y	y	y	y	y
N. of obs.	1936	1936	1936	1936	1936	1936	1936
MSA	395	395	395	395	395	395	395
N. of years	5	5	5	5	5	5	5
R-squared	0.376	0.254	0.547	0.255	0.545	0.258	0.413
Root MSE	0.096	0.073	0.036	0.016	0.031	0.015	0.031

Note: Dependent variables are measured in terms of period-to-period variations (1980-1990, 1990-2000, 2000-2008, 2008-2012, 2012-2014). Pooled OLS regression controlling for years fixed effects and Great Recession (2008-2012) fixed effects. All models controls for state and regional FE (Regions: Northeast, Midwest, South, West). Standard errors, clustered at state level, are in parenthesis. Significance levels: * = 10% and ** = 5%.

density and segregation play a pivotal role in the changes of the indices. The segregation of Blacks and Hispanics is positively associated with the variations in the indices. Conversely, this finding does not apply to segregation of Asians, which is negatively associated with changes in $CP(., 0.2)$, $CP^*(., 0.2)$ and $UP(., 0.2)$.

An increment of housing value tends to increase urban and concentrated poverty. Higher housing cost might force poor individuals to concentrate in some areas, creating distinct rich and poor census tracts. Similarly, the greater the average rent at the MSA level, the higher the concentrated and urban poverty indices, while an increase in median rent by CT implies a decrease in the indices. Finally, the population size, the incidence of poverty, and the fact that a significant share of the population has managerial positions reduce concentrated and urban poverty indices.

Andreoli et al. (2021) tested the null hypothesis of spatial independence in the distribution of poverty incidence across census tracts of American MSAs in 1980 and 2014, rejecting the null hypothesis for the large majority of MSAs with a population larger than 300,000 residents for both years. The presence of positive spatial autocorrelation in poverty incidence across tracts, however, is not informative about its implications in terms of uneven distribution of poor people across the tracts. The Gini index decomposition into neighborhood and non-neighborhood components allows to separate the contributions of neighboring and non-neighboring tracts to overall urban poverty.

The effects of the drivers of urban poverty on the levels and changes of the two spatial components of the Gini index are in Table 8, models (1)-(4). Few covariates have a significant and stable effect on the levels and changes of the neighborhood and non-neighborhood components of the Gini index. The segregation of the poor has a positive effect on the levels of both the spatial components of the Gini index. This means that a greater degree of segregation of the poor does not generally yield a greater tendency of tracts with similar levels of poverty incidence to cluster. The incidence of poor people is negatively associated with the neighborhood component, suggesting that high-poverty tracts have a greater tendency to cluster in MSAs with higher levels of poverty incidence. Demographic variables, like population composition by origin group

and total population size, are positively correlated with the change in the non-neighborhood component, suggesting that a more heterogeneous population composition tends to increase disparities in poverty incidence between non-neighboring tracts within larger MSAs. Other controls, including housing and education, never yield significant effects.

Columns (5) and (6) of Table 8 investigate the re-ranking and convergence components of the changes in urban poverty based on a pooled regression with year fixed effects. When considering the re-ranking component R (see column (5)), the pooled regression model shows that the incidence and segregation of poverty has a negative impact on R, suggesting that a re-ranking of tracts is less likely to occur in the MSAs with higher levels of incidence and segregation of poverty. Besides, 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 a lower re-ranking component, the proportions of owner-occupied and vacant houses have a positive impact on that component. Finally, demographic variables do not seem to play a significant role in the re-ranking of tracts.

Column (6) of Table 8 shows the drivers of component D, measuring convergence in tract poverty incidence. Our estimates reveal that the explanatory variables are less informative about the convergence component than the re-ranking one. The pooled regression model shows that the incidence and segregation of poverty respectively affect positively and negatively the convergence component. Demographic, housing, education, and labor market variables (except the share of vacant dwellings and the commuting time) do not affect the convergence component. Only the average income level and the income dispersion across tracts are positively correlated with the convergence component.

4.4 Decomposition results

The previous sections illustrate the contributions of different drives of poverty concentration on the trends in concentrated poverty and urban poverty indices. However, this analysis cannot distinguish whether such effects are mainly due to changes of the drivers across MSAs or to changes in the magnitude of association between the drivers and the concentration of poverty

	G(·) (nbh) (1)		G(·) (no-nbh) (2)		Δ G(·) (nbh) (3)		Δ G(·) (no-nbh) (4)		R (5)		D (6)	
A) % Black	-0.026	(0.10)	0.052	(0.09)	-0.024	(0.03)	0.041**	(0.01)	0.010	(0.03)	-0.018	(0.04)
A) % Hispanic	0.069	(0.08)	-0.067	(0.09)	-0.019	(0.03)	0.037**	(0.01)	-0.005	(0.02)	-0.015	(0.03)
A) % Asian	-0.033	(0.14)	0.008	(0.13)	-0.037	(0.04)	-0.018	(0.05)	0.005	(0.04)	-0.073	(0.07)
A) % White	-0.053	(0.11)	0.018	(0.11)	0.016	(0.04)	0.053**	(0.02)	-0.012	(0.03)	0.065	(0.05)
A) Population size (ln)	-0.042	(0.03)	0.062**	(0.03)	-0.022**	(0.01)	0.024**	(0.01)	0.014	(0.01)	-0.008	(0.02)
A) % 65 plus yrs old	0.100	(0.13)	-0.047	(0.12)	-0.000	(0.05)	0.156**	(0.07)	0.052	(0.05)	0.080	(0.08)
A) % 25-64 yrs old	0.250*	(0.13)	-0.216*	(0.12)	-0.023	(0.06)	0.058	(0.05)	-0.005	(0.05)	0.025	(0.07)
A) % Foreign	0.016	(0.13)	-0.084	(0.13)	-0.031	(0.03)	-0.025	(0.03)	-0.003	(0.03)	-0.016	(0.06)
A) Moved from outside of state	-0.128*	(0.07)	0.143**	(0.06)	-0.027	(0.03)	-0.043**	(0.02)	0.015	(0.02)	-0.058*	(0.03)
B) % New Houses (10 less yrs old)	-0.054	(0.07)	0.006	(0.06)	-0.023	(0.02)	-0.015	(0.03)	-0.023	(0.02)	-0.015	(0.05)
B) % Old houses (20 plus yrs old)	-0.072	(0.05)	0.047	(0.05)	-0.043**	(0.02)	-0.037**	(0.02)	-0.037**	(0.02)	-0.036	(0.03)
B) % Owner occupied	0.271	(0.20)	-0.190	(0.20)	0.001	(0.06)	0.111	(0.07)	0.128**	(0.07)	-0.056	(0.13)
B) % Vacant	-0.083	(0.06)	0.069	(0.06)	-0.002	(0.02)	-0.005	(0.02)	0.050**	(0.02)	-0.064**	(0.03)
B) % Rented	0.227	(0.17)	-0.176	(0.17)	0.024	(0.07)	0.228**	(0.07)	0.108	(0.08)	0.091	(0.12)
B) Avg. value house (ln)	0.004	(0.01)	0.003	(0.01)	0.001	(0.00)	-0.001	(0.00)	-0.001	(0.00)	-0.002	(0.01)
B) Median value house by CT (ln)	-0.012	(0.01)	0.022*	(0.01)	0.010*	(0.01)	-0.008	(0.01)	0.006	(0.00)	-0.006	(0.01)
B) p25% value house by CT (ln)	0.011	(0.01)	-0.018	(0.01)	-0.014**	(0.00)	0.001	(0.01)	-0.000	(0.00)	-0.010	(0.01)
B) S.d. value house by CT (ln)	-0.001	(0.01)	-0.004	(0.01)	-0.003	(0.00)	-0.002	(0.00)	-0.000	(0.00)	-0.005	(0.00)
B) Avg. rent (ln)	0.012	(0.03)	-0.024	(0.03)	0.026**	(0.01)	-0.020**	(0.01)	-0.013	(0.01)	0.013	(0.03)
B) Median rent by CT (ln)	0.081	(0.07)	-0.076	(0.06)	-0.017	(0.02)	0.025*	(0.01)	0.015	(0.02)	0.004	(0.03)
B) p25% rent by CT (ln)	-0.082	(0.07)	0.074	(0.06)	0.011	(0.02)	0.003	(0.01)	-0.002	(0.01)	0.016	(0.02)
B) S.d. rent by CT (ln)	0.011	(0.01)	-0.010	(0.01)	0.003	(0.00)	0.001	(0.00)	0.004	(0.00)	-0.003	(0.00)
C) College Town	-0.005	(0.01)	0.002	(0.01)	0.002	(0.00)	0.001	(0.00)	-0.000	(0.00)	0.003	(0.00)
C) Student Town	0.007	(0.02)	-0.014	(0.02)	-0.002	(0.00)	-0.006**	(0.00)	-0.003	(0.00)	-0.006	(0.00)
C) % less than high school	-0.001	(0.00)	0.001	(0.00)	-0.000	(0.00)	-0.000	(0.00)	0.000	(0.00)	-0.000	(0.00)
C) % with high school	-0.075	(0.13)	0.045	(0.12)	0.110**	(0.04)	-0.024	(0.06)	0.017	(0.04)	0.087	(0.06)
C) % with college	-0.001	(0.00)	0.000	(0.00)	0.000*	(0.00)	-0.000	(0.00)	0.000	(0.00)	0.000	(0.00)
C) % enrollment (any)	0.126*	(0.07)	-0.090	(0.06)	0.098**	(0.03)	0.097**	(0.03)	0.114**	(0.03)	0.063	(0.05)
D) % Managerial position	-0.082	(0.12)	0.117	(0.11)	0.023	(0.02)	0.033	(0.03)	-0.005	(0.04)	0.054	(0.05)
D) % Timework	0.005**	(0.00)	-0.004**	(0.00)	0.001**	(0.00)	0.001**	(0.00)	0.000	(0.00)	0.001**	(0.00)
E) Avg hh income (ln)	-0.027	(0.03)	0.040	(0.03)	0.003	(0.01)	0.028**	(0.01)	0.006	(0.01)	0.034**	(0.02)
E) Median hh income by CT (ln)	-0.159**	(0.05)	0.093**	(0.05)	0.026	(0.02)	0.011	(0.02)	0.032*	(0.02)	-0.018	(0.03)
E) p25% hh income by CT (ln)	0.030	(0.03)	0.015	(0.02)	-0.019**	(0.01)	-0.021**	(0.01)	-0.001	(0.01)	-0.028	(0.02)
E) S.d. hh income by CT (ln)	0.052**	(0.01)	-0.026**	(0.01)	0.008*	(0.00)	-0.003	(0.00)	-0.014**	(0.00)	0.021**	(0.01)
E) % of poor	-0.250*	(0.13)	-0.118	(0.12)	0.158**	(0.06)	0.025	(0.04)	-0.115**	(0.04)	0.275**	(0.08)
E) Dissimilarity poor	0.574**	(0.05)	0.440**	(0.05)	-0.236**	(0.02)	-0.159**	(0.02)	-0.113**	(0.01)	-0.263**	(0.03)
E) Dissimilarity whiteblack	0.124	(0.07)	-0.148**	(0.07)	-0.027	(0.02)	0.012	(0.02)	0.003	(0.03)	-0.027	(0.03)
E) Dissimilarity black	-0.120	(0.08)	0.147*	(0.08)	0.008	(0.02)	-0.005	(0.01)	0.015	(0.03)	-0.003	(0.03)
E) Dissimilarity hispanic	-0.026	(0.03)	0.034	(0.03)	0.011	(0.01)	0.009	(0.01)	-0.002	(0.01)	0.015	(0.02)
E) Dissimilarity asian	0.017	(0.03)	-0.009	(0.02)	0.013	(0.01)	0.004	(0.01)	0.002	(0.01)	0.013	(0.01)
E) Dissimilarity white	-0.109	(0.13)	0.038	(0.12)	0.098*	(0.05)	0.022	(0.03)	-0.001	(0.04)	0.141**	(0.06)
Great Recession	0.024	(0.13)	-0.072	(0.13)	0.000	(.)	0.000	(.)	0.000	(.)	0.000	(.)
F) % gentrified CT (BSM def.)					-0.026	(0.02)	-0.035**	(0.01)	-0.025	(0.02)	-0.034	(0.03)
State fe	y		y		y		y		y		y	
Regional fe	y		y		y		y		y		y	
Year fe	y		y		y		y		y		y	
N. of obs.	2342		2342		1936		1936		1936		1936	
MSA	395		395		394		394		394		394	
N. of years interval	6		6		5		5		5		5	
R-squared	0.624		0.725		0.329		0.277		0.511		0.361	
Root MSE	0.055		0.053		0.022		0.020		0.019		0.034	

Table 8: Drivers of levels and changes in G: different components.

Note: Dependent variables are measured in terms of realizations of urban poverty as measured by G index, both in pooled levels and in pooled period-to-period variations (1980-1990, 1990-2000, 2000-2008, 2008-2012, 2012-2014). Pooled OLS regression controlling for years fixed effects and Great Recession (2008-2012) fixed effects. All models controls for state and regional FE (Regions: Northeast, Midwest, South, West). Standard errors, clustered at state level, are in parenthesis. Significance levels: * = 10% and ** = 5%.

over the time interval considered. To answer this question, we use the Oaxaca-Blinder (hereafter, O-B) threefold decomposition technique (Blinder 1973, Oaxaca 1973).

The O-B decomposition breaks down the difference between the means of an outcome variable Y calculated for two different groups, say A and B, into three components. To obtain such components, consider the linear model $Y = \mathbf{X}'\boldsymbol{\beta} + \epsilon$ where $\mathbf{X}$ is a set of predictors observed for each group. The O-B decomposition divides the difference in the expected value of Y between the two groups into the sum of three terms (Jann 2008), so that $E\left[Y_A\right] - E\left[Y_B\right] = \Delta_E + \Delta_C + \Delta_I$. Component $\Delta_E = \left\{E\left[\mathbf{X}_A\right] - E\left[\mathbf{X}_B\right]\right\}' \boldsymbol{\beta}_B$ measures the contribution of group differences in the means of predictors (the so-called endowments), corresponding to the *endowments effect.* Component $\Delta_C = E\left[\mathbf{X}_B\right]' \left(\boldsymbol{\beta}_A - \boldsymbol{\beta}_B\right)$ measures the contribution of differences in the coefficients; i.e., the *coefficients effect.* Component $\Delta_I = \left\{E\left[\mathbf{X}_A\right] - E\left[\mathbf{X}_B\right]\right\}' \left(\boldsymbol{\beta}_A - \boldsymbol{\beta}_B\right)$ is the *interaction effect* of differences in endowments and coefficients between the two groups. As in the study by Iceland and Hernandez (2017), the two groups compared are the selected 395 MSAs with their endowments in the starting year of the considered period (1980) and the same MSAs with their endowments in the ending year (2014). We use the available measures of urban poverty as outcomes. The O-B decomposition is obtained from the perspective of MSAs in 2014, which then play the role of group B in the above-described formulation of the O-B decomposition. The results of the decomposition are shown in Table 9, where also the contribution of each group of explanatory variables (e.g., demographics) to each of the three components (endowments, coefficients and interaction) is shown.

The endowments effect is the contribution of the differences in the explanatory variables between 1980 and 2014. It expresses the expected difference in predicted 2014 mean outcome (the urban poverty level) if the distribution of endowments across MSAs were that of 1980. The second component, the coefficients effect, measures the contribution of differences in period-to-period regression coefficients. This component indicates that the explanatory variables also differ in the influence they have across periods. The third component, the interaction effect, takes into account that the differences in terms of endowments and coefficients co-occur between 1980 and 2014. Ultimately, this decomposition method allows us to single out the extent

to which the MSAs characteristics explain the differences between 1980 and 2014 (the endowment component), while holding as fixed the coefficients component and their interaction with endowments.

We consider the same drivers as in the previous tables, but we group them by categories of interest to simplify the reading of the decomposition results. Unlike the model structure in the previous regressions, we do not include fixed effects for regions and years to avoid zero-variance cases. However, we do include fixed effects for states.[13]

In column (1) of Table 9, concentrated poverty at a 20% poverty line is estimated at $CP = 0.317$ in 1980 and $CP = 0.503$ in 2014. These estimates result in a significant difference of -0.186, which is additively split into the contributions of the three components described above. While the contributions of the endowments and interaction terms are positive, the difference due to the coefficients is negative and large, thus driving the sign of the overall difference observed between the two periods. The contribution of endowments, equal to 0.321, suggests that the overall difference could have been even more considerable if the MSAs had been similarly endowed between the two periods.

Each component is further broken down by the contribution of each group of explanatory variables in the following rows of Table 9. The detailed decomposition makes it possible to study the contribution of each group of variables to the decomposition. First, it can be observed that the difference due to endowments originates mainly from the housing-related variables. However, this difference is not significant. Moreover, each group's sign, magnitude, and significance vary considerably in terms of coefficient and interaction components. The fixed effects (not shown) almost cancel out this effect with an opposite sign. Overall, the coefficients effect is negative, implying that the influence of the explanatory variables on concentrated poverty changed between 1980 and 2014, contributing to increase CP.

The effects estimated in the remaining columns have a similar interpretation. As in column (1), the indicators are systematically higher in 2014 than in 1980, resulting in significant negative differences. Endowments account for most of the difference in $CP(., 0.4)$, $CP^*(., 0.2)$,

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[13]We do not report the fixed effects, which explains why the reported overall difference due to coefficients is not entirely explained by the variables shown in Table 9.

Table 9: Oaxaca-Blinder decomposition.

	CP(.,0.2) (1)	CP(.,0.4) (2)	CP*(.,0.2) (3)	CP*(.,0.4) (4)	UP(.,0.2) (5)	UP*(.,0.4) (6)	G(.) (7)
Prediction 1980	0.317** (0.01)	0.062** (0.01)	0.100** (0.00)	0.010** (0.00)	0.092** (0.00)	0.009** (0.00)	0.326** (0.00)
Prediction 2014	0.503** (0.01)	0.136** (0.01)	0.180** (0.00)	0.026** (0.00)	0.163** (0.00)	0.025** (0.00)	0.351** (0.00)
Difference	-0.186** (0.01)	-0.074** (0.01)	-0.080** (0.01)	-0.016** (0.00)	-0.070** (0.01)	-0.015** (0.00)	-0.025** (0.01)
Endowments	0.321 (0.31)	-0.877** (0.31)	-0.225** (0.09)	-0.174** (0.08)	-0.192** (0.09)	-0.160** (0.07)	-0.047 (0.07)
Demographics	-0.103 (0.06)	0.071 (0.06)	0.023 (0.02)	0.018 (0.02)	0.023 (0.02)	0.019 (0.02)	-0.014 (0.01)
Housing	0.308 (0.32)	-0.514 (0.32)	-0.144 (0.09)	-0.108 (0.08)	-0.125 (0.09)	-0.098 (0.08)	-0.031 (0.07)
Education	0.043 (0.11)	-0.096 (0.11)	-0.006 (0.03)	-0.030 (0.03)	-0.016 (0.03)	-0.031 (0.03)	0.024 (0.02)
Employment	0.020 (0.03)	0.011 (0.03)	-0.007 (0.01)	-0.009 (0.01)	-0.004 (0.01)	-0.009 (0.01)	-0.006 (0.01)
Distribution	0.053 (0.07)	-0.350** (0.07)	-0.093** (0.02)	-0.045** (0.02)	-0.069** (0.02)	-0.041** (0.02)	-0.020 (0.02)
Coefficients	-1.627** (0.48)	0.239 (0.42)	0.002 (0.16)	0.196** (0.08)	0.061 (0.15)	0.193** (0.08)	-0.045 (0.13)
Demographics	-0.400 (1.38)	1.273 (1.33)	0.610 (0.43)	0.363 (0.31)	0.516 (0.41)	0.333 (0.30)	-0.658** (0.32)
Housing	-2.064 (1.71)	-1.326 (1.63)	-0.671 (0.54)	-0.381 (0.38)	-0.408 (0.51)	-0.320 (0.36)	-0.265 (0.41)
Education	-0.313 (0.53)	0.296 (0.50)	0.050 (0.17)	0.205* (0.12)	0.008 (0.16)	0.181 (0.11)	0.045 (0.13)
Employment	0.289* (0.16)	-0.059 (0.14)	-0.092* (0.05)	-0.090** (0.03)	-0.102** (0.05)	-0.087** (0.03)	-0.005 (0.04)
Distribution	4.768** (1.66)	-2.696* (1.57)	0.264 (0.53)	-0.300 (0.36)	0.000 (0.50)	-0.294 (0.34)	0.137 (0.40)
Interaction	1.120** (0.57)	0.564 (0.53)	0.144 (0.19)	-0.038 (0.11)	0.060 (0.17)	-0.048 (0.11)	0.066 (0.14)
Demographics	0.098 (0.08)	-0.040 (0.08)	-0.040* (0.02)	-0.018 (0.02)	-0.041* (0.02)	-0.019 (0.02)	0.003 (0.02)
Housing	1.405** (0.60)	0.396 (0.56)	0.245 (0.20)	-0.058 (0.12)	0.150 (0.18)	-0.068 (0.11)	0.135 (0.15)
Education	0.107 (0.17)	-0.107 (0.16)	-0.104* (0.05)	-0.024 (0.04)	-0.086* (0.05)	-0.020 (0.03)	-0.059 (0.04)
Employment	-0.091* (0.05)	0.056 (0.05)	0.037** (0.02)	0.027** (0.01)	0.032** (0.01)	0.025** (0.01)	0.009 (0.01)
Distribution	-0.398** (0.09)	0.261** (0.08)	0.006 (0.03)	0.035* (0.02)	0.004 (0.03)	0.033* (0.02)	-0.021 (0.02)
N. of obs.	790	790	790	790	790	790	790
MSA	395	395	395	395	395	395	395

Note: Oaxaca-Blinder decomposition of the levels in 1980 and 2014 in concentrated poverty and urban poverty. OLS regression controlling for state fixed effects. Standard errors, clustered at state level, are in parenthesis. Significance levels: $^{*} = 10\%$, $^{**} = 5\%$, and $^{***} = 1\%$.

$UP(.,0.2)$, and $G(.)$. Conversely, the coefficients are the main contributors of the changes in $CP(.,0.2)$, $CP^*(.,0.4)$, and $UP(.,0.4)$. In all cases except $G(.)$, the elements explaining most of the difference are significant. The contributions of the different components are not uniform across the various models considered. Endowments' contribution is negative in all columns except for $CP(.,0.2)$. This result indicates that endowments in 2014 are distributed differently from 1980 and amplify the two periods' overall difference. Conversely, the coefficients seem to have a positive counterbalancing effect but are sparsely significant.

If we further decompose each component, it appears that only a few groups of variables are significant. When looking at the endowments, several variables contribute negatively except demographics, owing to the fact that the group of demographics includes several variables that do not necessarily act in the same direction, creating a sizeable intra-group variability. Moreover, the distribution variables are the sole endowments that are consistently significant and negative across most of the concentrated and urban poverty measures except $CP(.,0.2)$, playing a major role in endowments' contribution.

Conversely, several variables are sparsely significant among the sub-components of the coefficients. The impact of housing on the coefficients is negative but not significant. Employment contributes positively to the difference due to the coefficients for $CP(.,0.2)$ but negatively to the difference due to the other indices' coefficients while being significant in both cases. A large part of the variation due to the coefficients is indeed attributed to fixed effects. This finding indicates a sizeable unexplained gap due to differences at the state level between 1980 and 2014.

Overall, Table 9 shows that the effects of the relevant groups of covariates on urban poverty changes are relatively similar across the urban poverty indices belonging to the family of urban poverty measures. The only exception is the first column, which uses $CP(.,0.2)$ as a dependent variable. We explain these discrepancies in results between $CP(.,0.2)$, often considered the golden rule in the study of urban poverty, and the other indices by the fact that CP disregards the information about the incidence and distribution of poverty across low-poverty neighborhoods.

Conversely, $CP(.,0.4)$ does not show different patterns than UP and CP^*, unlike $CP(.,0.2)$. This pattern is caused by the tolerance level increase from 20% to 40%, therefore addressing

a particular subset of census tracts where poverty is highly concentrated. While the group of people included in $CP(., 0.2)$ is relatively large, $CP(., 0.4)$ involves a tiny group of people in extreme poverty. This small group is likely to have specific characteristics that differ significantly from the rest of the population, resulting in endowments substantially determining incidence patterns. On the opposite, $CP(., 0.2)$ is likely to include a larger group of people with less specific characteristics, sharing several similarities with non-poor people. Therefore, it is relevant to examine what the rest of the population experiences to understand urban poverty.

Finally, it is also interesting to compare the results obtained for $CP(., 0.4)$ in column (2) with the results obtained by Iceland and Hernandez (2017). The whole difference is negative over the period, with a strong negative effect of endowments, a positive contribution of coefficients, and a positive interaction term. Our estimated effects for CP largely coincide with those estimated by Iceland and Hernandez (2017), thus validating their analysis.

5 Conclusions

The contribution of this article is twofold. First, we compare the effects of the main drivers of urban poverty concentration on alternative indices of urban poverty concentration. More specifically, the comparison deals with the widely-used concentrated poverty index, CP, and some indices belonging to the family of urban poverty measures which Andreoli et al. (2021) have axiomatically derived to overcome some drawbacks of CP. We run pooled-regressions to examine the impacts of several variables on the levels of concentrated poverty and urban poverty over the 1980-2014 period. Regression results show that demographic variables and those related to income distribution and housing affect the level of urban poverty concentration; however, their impact changes based on the index we use and the fixed threshold of poverty incidence. Overall, we find that CP, calculated for a 20% poverty incidence threshold, tends to behave differently from other indices, including CP when the poverty incidence threshold is equal to 40%. The share of poor residents and the degree of segregation of poor people are strongly positively correlated with every measure of urban poverty concentration, suggesting that the impact of such variables is consistent irrespective of the index considered.

Second, we examine the regression results on the pooled period-to-period changes in the measures of concentrated poverty and urban poverty, finding that demographics, education, and housing are the main drivers of changes in concentrated and urban poverty. However, these explanatory variables are less informative for the changes than for the levels of concentrated poverty and urban poverty. To further explore the analysis of changes in concentrated and urban poverty, the Oaxaca-Blinder threefold decomposition is used. Such a decomposition confirms that the choices concerning the index for measuring poverty concentration and the poverty incidence threshold have a role in explaining variations in urban poverty concentration. Indeed, while CP and all the indices belonging to family of urban poverty measures, for both a 20% and a 40% poverty incidence threshold, indicate an increase in poverty concentration from 1980 to 2014, the effects of the endowments, coefficients and interaction components differ based on the index and poverty incidence threshold considered. When setting a poverty incidence threshold equal to 20%, the contribution of endowments is statistically significant for CP^* and UP but not for CP. This difference may be explained by the fact that CP completely neglects what happens to non-poor people, whereas CP^* and UP also consider some information on the composition of poverty in the whole population. When the poverty incidence threshold increases to 40%, CP behaves similarly to the family of urban poverty measures, thus underlying the role of the fixed tolerance level to poverty in measuring poverty concentration. This apparently unexpected result may depend on the different sub-population involved in the calculation of CP at 40%. This index involves a relatively small group of people subject to extreme poverty (i.e. 40%), which is likely to have specific characteristics that differ significantly from those of the remaining population, resulting in endowments which substantially affect urban poverty trends.

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