An assessment of poverty determinants in US census tracts, 1970–2010*

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Abstract

This paper deals with the determinants of poverty in the United States at the census tract level. By proceeding in this way, potential aggregation errors that may occur when using larger areas as the unit of observation are avoided. Our empirical analysis exploits a geographically consistent dataset covering the period 1970–2010 and all metropolitan statistical areas. The estimations have been carried out using a system generalized method of moments framework for dynamic panels. Our results show that poverty is a persistent phenomenon, especially in tracts with higher levels. Those variables with a more robust relationship with poverty reflect labor market conditions. We also obtain evidence of a higher vulnerability of women to poverty. These findings have been framed within the debate about the optimal design of local development strategies. The main conclusion drawn is that place-based and person-centered policies can be considered as complementary rather than as substitutes.

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Keywords: Poverty, US census tracts, geographically consistent data, dynamic panel estimation, local development strategy.

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1 Motivation

Poverty is one of the main concerns of citizens, in general, and altruistic organizations, in particular. Although the percentage of the population living below the poverty line is higher in less developed countries, a non-negligible number of people and families are at risk of social exclusion in wealthy nations[1]. Even some rich people are worried about their neighbors having difficulties in making ends meet (Firebaugh and Schroeder 2009). To some extent, it can be stated that poverty affects all human beings and has direct consequences on their daily welfare. A first step towards mitigating the incidence of poverty is to try to disentangle its main driving factors.

The distribution of poverty in US cities and its location determinants have been studied by Glaeser, Kahn, and Rappaport (2008) and Brueckner and Rosenthal (2009). Furthermore, statistical and econometric methods have been applied to analyze the poverty data of metropolitan statistical areas (MSAs, Madden 1996), counties (Levernier, Partridge, and Rickman 2000; Partridge and Rickman 2007, 2008), and zip codes (Murphy and Wallace 2010). Nevertheless, the consideration of these units of analysis may mask important labor market features and does not permit us to capture developments at more disaggregated geographical levels. In particular, the use of units other than census tracts underestimates suburban poverty and blurs the heterogeneity within MSAs, counties, and zip codes (Allard 2004; Holliday and Dwyer 2009). As pointed out by Partridge and Rickman (2008, p. 284), *"Most explanations for intra-M[S]A poverty disparities are oriented towards individuals or relatively small neighborhoods with corresponding empirical analysis using micro-level data"*.

Previous arguments suggest that poverty is related to characteristics of the neighborhood that influence the day-to-day quality of life, such as housing, amenities, and the intensity of crime, drugs and violence. This motivated Jargowsky (2014), Kneebone (2014), and Allard (2017) to carry out exhaustive descriptive analyses of poverty at the census tract level. However, to the best of our knowledge, this topic has only been addressed with econometric techniques by Rosenthal (2008), who used relative income as a proxy to study the evolution of the socio-economic status of US census tracts. However, the analysis of the poverty rate seems to be more suitable for

[1] For instance, and according to data from the Bureau of the Census, around 15 per cent of the US population was living below the poverty line in 2010.

the optimal design of local development strategies and the debate about the implementation of place-based or person-centered policies.

This paper contributes to this literature by carrying out an empirical analysis of the variables that explain poverty rates in US census tracts. In doing so, potential aggregation errors that may occur when using larger areas because the units of observation are avoided. The analysis exploits a geographically consistent dataset covering 368 MSAs during 1970–2010. Our study begins by testing for the the unit root character of poverty rates. Given their stationarity and persistence, a dynamic panel data framework has been adopted. The application of a system generalized method of moments (GMM) estimator (Arellano and Bover 1995; Blundell and Bond 1998) has allowed us to control for the possible presence of unobserved heterogeneity, on the one hand, and of reverse causality between poverty and some of its potential determinants, on the other hand. The variables that have a positive and significant relationship with poverty are total population, its percentage with Hispanic origin, female-headed families, and renter-occupied housing. In contrast, educational attainment, the percentage of population under 18, and the employment and female labor force participation rates are negatively associated with poverty. Moreover, our results suggest that the influence of employment on poverty has a sectoral composition. We have not found a significant relationship between the age of the housing stock and poverty. These results are framed within the debate about the design of local development strategies, establishing under which circumstances place-based policies should prevail over person-centred ones, and vice versa. In brief, our findings lead us to conclude that these two perspectives are complementary rather than substitutes.

The rest of the paper is organized as follows. Section 2 contextualizes the present study by discussing issues related to the definition and measurement of poverty, providing theoretical underpinnings, and selectively reviewing the related literature. Section 3 describes the data sources and the variables included in the empirical framework. Section 4 justifies the geographical level of disaggregation adopted, presents a preliminary analysis of the stationary character of poverty rates at the census tract level, and establishes the estimation strategy. Section 5 shows the main results, which are later discussed within the debate about the design of optimal local development strategies in Section 6. Finally, Section 7 concludes.

2 Background

2.1 Conceptualization

The concept and measurement of poverty are elusive. Poverty can be established with respect to a fixed level of reference (i.e., in absolute terms) or to a threshold that varies with the mean or median of the standard of living (relative terms), see Bourguignon (2019). Following the contributions of Sen (1992, 2009), poverty should be understood as the lack of functioning and capabilities. As explained in Atkinson (2019), poverty can be defined from different points of view: consumption or income and basic needs, deprivation of capabilities, and minimum rights. This implies that poverty indicators based on a single monetary measure may not be appropriate. This idea is behind the theoretical approach to measure poverty from a multi-dimensional perspective proposed by Bourguignon and Chakravarty (2003) or the global Multidimensional Poverty Index developed by Alkire and Jahan (2018).

The poverty line in the United States has been established each year by the Bureau of the Census since 1965. This *"threshold is set at three times the cost of a minimum food diet in 1963, updated annually for inflation using the consumer price index. This measure takes account of family size, composition and age of householder"* (Atkinson 2019, page 370). However, Madden (1996) claims that the official definition of poverty in the United States has two main shortcomings: it only takes into account monetary income, and it does not control for geographical differences in prices and/or wages.

2.2 Theoretical underpinnings

A theoretical explanation for the emergence of poverty with psychological roots is based on the concept of 'aspirations failure' (Dalton, Ghosal, and Mani 2016). This is related to the fact that poverty reduces the aspirations of the affected people with respect to their optimal attainable level. According to this theoretical strand of the literature, poverty traps arise by external restrictions–such as imperfections in the credit or insurance markets, institutional or government failures, and the familiar context–or by individual behavior. Therefore, policies against poverty should be devoted to improving the goals and ambitions of the poor. Two examples are the 'supporting parents on kids education' (SPOKE) program in the United Kingdom and the anti-poverty program for poor women in Bangladesh, which consisted of cattle transfers and formation, see Bandiera et al. (2017).

The so-called 'membership theory' (Durlauf 2006) establishes that the existence of inequality and poverty traps can be explained by the composition and behavior of the groups to which an individual belongs (neighborhood, race, school, work, etc.). This theory claims that the group and its characteristics influence the constraints, preferences, and restrictions of its members. More specifically, the group affects individuals both through its old (role model effect) and contemporaneous (peer effect) behavior. Together with the classical income redistribution, this line of reasoning also suggests that membership or associational reallocation can be an effective way to fight poverty.

2.3 Literature review

Levernier, Partridge, and Rickman (2000) analyze the factors that determine poverty in US counties, and conclude that economic and demographic variables, the employment growth rate, the industrial mix, and structural change play an important role. These authors also find evidence favourable to the 'spatial mismatch' hypothesis (Ihlanfeldt and Sjoquist 1998). In a related study, Partridge and Rickman (2007) establish that poverty in a given county is persistent if its corresponding rate is higher than 20 per cent in 1979, 1989, and 1999. These authors claim that this persistence may give rise to 'ethno-geographic poverty traps'. After discussing the convenience of implementing place-based or person-based policies, and using a set of control variables similar to that used in the present study, Partridge and Rickman (2007) explore whether or not employment creation exerts, ceteris paribus, a larger negative effect on the poverty rate in those counties where its displays a higher persistence. The main conclusion drawn is that, in effect, those counties with persistent poverty rates are more sensitive to employment variations. Furthermore, the conjunction of place-based policies with person-based policies is advocated in the most in need regions.

Using a sample of low-income families, Fisher (2007) studies why rural areas display higher poverty rates than urban ones. Partridge and Rickman (2008) analyze how employment growth influenced the evolution of the poverty rate from 1989 to 1999 in 824 counties, concluding that space played a key role. More in line with the main aim of the present paper, these authors proposed that poverty may follows a disequilibrium adjustment process. The latter consists of considering that poverty rates not only depend on current factors, but also on their own history. Glaeser, Kahn, and Rappaport (2008) study the tendency of poor people to live in the city center, rather than in the suburbs. The exposition is grounded on the classic monocentric model. However, given that US cities are polycentric and the income elasticity of the demand for land is smaller than one, the explanation is provided in terms of the role played by public transportation, which is more important in the dense center than in the suburbs.

Kneebone and Berube (2013) point out that, for the first time in history, the percentage of poor people in the suburbs of US cities is now larger than in the center. Rather than extending the place-oriented policy approach to the suburbs, these authors propose a new 'Metropolitan Opportunity Agenda' to cope with poverty. Although the rise in suburban poverty has not coincided with a decline at the urban level, Murphy and Allard (2015) detect a change in the geography of US poverty with the advent of the twenty-first century. One of the main implications of their findings is that policies suitable to handle urban poverty might not work in suburban areas. Furthermore, measures that get results in a suburb may not be successful in others. It should also be taken into account that the safety net currently established to deal with suburban poverty is much more evolved than several decades ago. Similar results and conclusions are obtained by Murphy and Wallace (2010) at the zip code level. After acknowledging that poverty is a multidimensional phenomenon, Lemanski (2016) state that its growth is linked to the urbanization process.

3 Data sources and variable description

The study of poverty in US census tracts requires the construction of a consistent dataset that is unaffected by changes in their delimitation. The main source of information at this geographical level is the Longitudinal Tract Database (LTDB; Logan, Xu, and Stults 2014), which provides data standardized to tract borders in 2010. We have constructed a panel covering all the 368 MSAs existing for that year, from 1970 to 2010 on a decennial basis[2]. This data has been complemented with information extracted from the National Historical Geographic Information System (NHGIS; Manson, Schroeder, Van Riper, and Ruggles 2017), standardized using the cross-walk file provided by the LTDB. Table 1 provides a description of the variables included in our empirical analysis and their specific sources.

[Insert Table 1 about here]

[2]The division of the US territory into census tracts began in 1970. Since then, the process advanced progressively until the whole country was covered. This fact, together with the creation of new tracts due to population and urban growth, determines the unbalanced character of our panel dataset.

The main variable of interest is the poverty rate, which is defined as the percentage of persons in a tract living in poverty. The average poverty rate in adjacent tracts has been included as a regressor to control for the possible presence of spatial dependence (Jargowsky 2014). This variable has been calculated as a spatial lag using a row-standardized contiguity spatial weights matrix. In other words, the arithmetic mean of the poverty rates in neighboring tracts, according to a contiguity criterion, has been considered as an explanatory variable in our empirical framework. The other variables described in Table 1, that measure potential determinants of poverty, are in line with those used by Levernier, Partridge, and Rickman (2000) and Partridge and Rickman (2007, 2008).

A first group of regressors reflects labor market conditions: the rates of employment, female labor force participation, and the percentages of persons employed in different occupations. The latter have been distinguished using the sectoral classification adopted by the Bureau of the Census: farming, fishing and forestry; production, transport and material moving; sales and office; and services. The educational level of the tracts has been proxied by the percentages of the population aged 25 or more with either a high school degree or a four-year college degree. Other socio-economic characteristics that have been taken into account are the total population, the age structure (percentages of persons under 18 and over 60), the relative size of racial groups, and the percentages of female-headed families and renter-occupied housing units. Finally, four variables have been included in the estimations to try to disentangle whether or not there is a relationship between the age of the housing stock and poverty, specifically: the percentage of housing units built less than 5 years ago, between 5 and 10 years ago, between 10 and 20 years ago, and between 20 and 30 years ago.

Table 2 reports descriptive statistics for the poverty rate and its potential determinants in 2010, both for the full sample and distinguishing the tracts by their location, the size of the MSA to which they belong, and their level of poverty. The Bureau of the Census considers a suburb to be a municipality characterized by having more than 2,500 inhabitants and not being a central city. To classify MSAs according to their size, the whole distribution in each period for which data is available has been used[3]. Small (large) MSAs are those whose sizes belong to the lower (upper)

[3]This explains that a non-negligible number of tracts appear in more than one category throughout the sample period that has been analyzed.

quartile. A similar distinction has been applied to the poverty rates of census tracts to rank them according to their level of poverty.

[Insert Table 2 about here]

4 Preliminary analysis and empirical strategy

4.1 Descriptive analysis

As a first approximation to the geographical distribution of poverty across the United States, Tables 3 and 4 report the 30 MSAs with the lowest and highest rates, respectively, in 1970 and 2010. There has been an increase in the poverty rates of richer MSAs, while the lowest rate in 1970 was 5.97 per cent (Janesville, WI) it rose to 8.31 per cent in 2010 (Norwich-New London, CT). In contrast, the highest poverty rate decreased from 49.04 per cent in 1970 (McAllen-Edinburg-Mission, TX) to 36.42 per cent in 2010 (Brownsville-Harlingen, TX). Despite these changes, it is worth noting that there exists some degree of persistence in poverty rates at the MSA level, especially in those displaying higher values. In particular, half of them are among the poorest both in 1970 and 2010. In fact, those in the top three rows of Table 4 are the same. Figures 1 and 2 plot the location of MSAs with the lowest and the highest poverty rates, respectively, showing that they present a geographical pattern: while MSAs with the highest poverty rates are located in the south, those with the lowest values are in the northeast.

[Insert Tables 3 and 4 about here]

[Insert Figures 1 and 2 about here]

The information presented so far provides a view of urban poverty across the United States. To motivate the geographical level of disaggregation adopted in the present paper, Table 5 shows descriptive statistics of poverty rates in MSAs and census tracts. Although poverty has increased, on average, in both cases, the rise has been more important in tracts. This fact, together with the greater dispersion that they display, suggests that poverty is more concentrated at higher levels of geographical disaggregation. Therefore, more attention should be paid to this phenomenon. This argument is corroborated by Figure 3, which plots kernel density estimations of poverty rates in census tracts and shows that the probability mass in the upper tail of the distribution has increased from 1970 to 2010.

[Insert Table 5 about here]

[Insert Figure 3 about here]

Table 6 reports the evolution of the average poverty rates and their standard deviations throughout the sample period covered by our dataset. This is done for the whole sample as well as different subsamples. These figures corroborate the general increase of poverty in US census tracts. There are important differences between average poverty rates of tracts located in the suburbs and in the center. More specifically, poverty tends to be higher in the latter, especially at the end of the sample period. This finding suggests that it may be of interest to analyze the determinants of poverty in these two types of tracts separately. In addition, tracts located in large MSAs display, on average, lower poverty rates. The distributional classification shows that urban poverty is clustered at the tract level. Therefore, this differentiation may be helpful for a better understanding of the self-perpetuating effects of poverty.

[Insert Table 6 about here]

4.2 Dynamic properties

Poverty rates can be conceptualized either as an equilibrium process, in which they quickly react to exogenous shocks, or as a disequilibrium adjustment process, according to which poverty rates are related to both their own evolution and other socio-economic variables (Partridge and Rickman 2008, page 288). This adjustment mechanism implies that there may be self-perpetuating effects in the tails of the distribution of poverty rates and that the transition towards equilibrium can be slow. Consequently, this empirical standpoint assumes that poverty rates are related to both recent factors and their own past development. Similar to Partridge and Rickman (2007), we consider that poverty in the US census tracts can be potentially determined by labor market conditions, educational attainment levels, socio-economic characteristics and the age structure of the housing stock. Nonetheless, poverty may also generate its own detrimental effects through persistence and poverty traps. This temporal perspective makes it interesting to test for the possible presence of a unit root in poverty rates[4], which sheds some light on the permanent or transitory character of the effects derived from shocks to their evolution.

[4]In theory, the poverty rate cannot contain a unit root because it is a bounded variable. The nonstationarity displayed by this rate in finite samples may be a consequence of its prolonged adjustment towards the long-run mean.

It is difficult to obtain reliable inferences about the order of integration of a variable from a short time series with decennial frequency. This problem can be mitigated through the implementation of panel unit root tests that exploit both the cross-sectional and the temporal dimensions of the data. In doing so, we consider that all tracts that belong to a MSA also conform to a panel. Nonetheless, and although panel unit root tests are a powerful alternative to univariate methods, they may be biased (size-distorted) in the presence of cross-sectional dependence (Banerjee, Marcellino, and Osbat 2004). To check whether or not this is the case for poverty rates at the tract level in each MSA, the weak cross-sectional dependence test (CD) developed by Pesaran (2015) has been applied.

[Insert Figure 4 about here]

The graphs at the top of Figure 4 show the histogram and cumulative density function (CDF) of the CD test statistics calculated for the MSAs included in our sample. In each graph, the red-vertical line represents the 95 per cent critical value. The values obtained for the CD test imply that the null hypothesis of the absence of cross-sectional dependence across poverty rates at the tract level can be rejected in most MSAs. Having provided this evidence, the next step is to obtain a measure of the degree of dependence using the characterization proposed by Bailey, Kapetanios, and Pesaran (2016). The distribution of point estimates for their α exponent is reflected in the two central graphs, which show that the estimated exponents for poverty rates are concentrated between 0.9 and 1. This reflects that poverty rates have a strong dependence within MSAs and suggests that a factor structure should be used to control for this dependence.

Pesaran (2007) developed a panel unit root test robust to cross-sectional dependence. In line with the previous results, this data feature is controlled by this method assuming the presence of a single common factor that, following the spirit of the common correlated effects estimator (CCE; Pesaran 2006), is proxied by the cross-sectional mean of the individual time series. An explanation for the good performance of the CCE estimator is provided by Pesaran and Tosetti (2011), who show that it eliminates the effects of all forms of correlations, irrespective of whether or not they are due to spatial and/or unobserved common factors. Similarly, Breinlich, Ottaviano, and Temple (2014) consider the common factor structure to be a reasonable alternative to the spatial econometric approach where cross-sectional correlation is determined by location and the distance between units.

The unit root test proposed by Pesaran (2007) for heterogeneous panels (CIPS) is implemented by obtaining individual statistics for each tract in the panel and then calculating their average. Individual unit root test statistics are obtained from standard augmented Dickey-Fuller auxiliary regressions that include cross-sectional averages of lagged levels and first differences of the individual series. A summary of resulting CIPS test statistics for poverty rates is shown in the lower panel of Figure 4. The unit root null hypothesis is rejected in around 90 per cent of the MSAs included in our sample. This implies that shocks to poverty rates have a transitory effect, and so they can be considered to be stationary processes evolving around a long-run mean.

4.3 Empirical framework

As pointed out earlier, fitting a disequilibrium adjustment process to poverty entails assuming that it is influenced by its own history. This, together with our previous results that poverty rates at the tract level generally behave as stationary processes, suggests that it is appropriate to include a temporal lag of poverty to empirically analyze its drivers. The long-run equilibrium relationship between poverty and its determinants will be given by:

$$y_{it} = \alpha_i + \mu_t + \delta_{s(i)} + \rho_1 y_{it-1} + \rho_2 y_{a(i)t} + \beta X_{it} + \varepsilon_{it} \tag{1}$$

where y_{it} denotes the poverty rate of census tract i in year t. Its potential determinants are included in the matrix X_{it}. Unobserved heterogeneity at the census tract level will be captured by the individual fixed effects α_i. As suggested by Roodman (2009b), to prevent contemporaneous correlation, our empirical model also considers time dummies μ_t. The influence of governance and policy issues has been controlled for using state fixed effects $\delta_{s(i)}$. The average poverty rate in the adjacent tracts is denoted as $y_{a(i)t}$, and ε_{it} is the error term.

There may be reverse causation between the poverty rate and the variables that refer to the housing stock (rented units and age). There are also endogeneity concerns regarding total population, which is used to calculate the dependent variable, and average poverty in adjacent tracts, as is common wisdom in the spatial econometrics literature (Elhorst 2014). Furthermore, the lagged dependent variable is predetermined but not strictly exogenous. For these reasons, given the structure of our dataset, and due to the presence of the temporal lag of the poverty rate in expression (1), its estimation has been carried out by adopting a dynamic panel data framework.

Dynamic panel data estimators are mainly designed for information sets that cover a large number of units during a few time periods. An ordinary least squares (OLS) estimation of (1) will be biased because the individual fixed effects are correlated with the temporal lag of the dependent variable. To circumvent this problem, the difference GMM estimator (Arellano and Bond 1991; Holtz-Eakin, Newey, and Rosen 1988) transform the data to remove the fixed effects. Moreover, and to cope with endogeneity, temporal lags of the affected regressors are used as instruments. However, it may be the case that past levels contain little information about future changes. This has led us to apply a system GMM estimation (Arellano and Bover 1995; Blundell and Bond 1998), which consists of further instrumenting endogenous variables in levels with their first differences. All available lags for the predetermined and endogenous regressors have been used as instruments in our empirical analysis. This implies that, although our dataset covers the period 1970–2010, the first observation for the poverty rate corresponds to the year 1980.

5 Estimation results

Table 7 reports the system GMM estimation results of equation (1). The statistical significance of the positive coefficients for the temporal lag of poverty in the full sample and most subsamples reflects its persistence. This is especially the case of the suburbs and tracts with high levels of poverty. The presence of negative externalities reflected by the average poverty rate in adjacent tracts is corroborated in small and medium MSAs, and also in tracts with intermediate levels of poverty. The estimated coefficients for the variables that proxy labor market conditions are quite homogeneous across subsamples. There is a robust inverse relationship between employment and poverty rates. Furthermore, the estimated parameter for the female labor force participation rate is negative.

Although there is no *a priori* sign for the percentages of employment in different occupations, we obtain evidence that the share of sales and office occupations tends to be inversely related to poverty. With the exception of large MSAs, the poverty rate is higher when the share of farming, fishing and forestry occupations is higher. This result may be driven by the fact that these jobs tend to be seasonal and receive low wages. Jobs in the service sector also seem to be mainly occupied by people belonging to poor groups. In fact, Lauer, Coleman, and Haywood (2016) define the 'average poor' as women with children, black or Hispanic, with a low level of education, and a part-time job in the service sector. Tracts with more educated residents are expected to suffer lower poverty rates because workers with higher skills will receive higher wages. This intuition is corroborated by the estimated coefficients for the variables reflecting educational attainment, which is robustly associated with lower poverty rates in the full sample, and when tracts are distinguished by their location or by MSA size.

[Insert Table 7 about here]

Regarding the socio-economic variables included as potential poverty determinants, total population is positive and is significantly associated with poverty. Tracts with higher shares of the population under 18 tend to display lower poverty rates. Among the variables that measure the relative size of racial groups, only the share of population with Hispanic origin has a positive and statistically significant relationship with poverty. In line with previous findings in the literature, and reflecting the vulnerability of women to poverty, the share of families with children headed by women has a robust and positive relationship with poverty across all subsamples; see, among others, Levernier, Partridge, and Rickman (2000) and Jargowsky (2014).

Tunstall et al. (2013) concluded that owners are less poor than renters. Similarly, our results suggest that there is a direct relationship between poverty and renter-occupied housing units in US census tracts. Following Glaeser, Kahn, and Rappaport (2008), we hypothesize that the age of the housing stock is one of the mechanisms that determines poverty at this geographical level of disaggregation. In particular, it should be expected that tracts with a more recent housing stock will display lower poverty rates, and vice versa. Our estimation results do not confirm this intuition because the sign and statistical significance of the coefficients for the variables that measure the age of the housing stock display an important variability across subsamples.

As pointed out earlier, the differentiation of tracts taking into account the distribution of poverty rates may provide some further insights on the possible presence of self-perpetuating effects. The last three columns in Table 7 suggest that differences across subsamples defined over poverty levels are more important than when tracts are classified according to their location or MSA size. In addition, there are conflicting results about the determinants of poverty along its distribution. While the temporal lag of the dependent variable is not significant in tracts with low and intermediate poverty levels, its estimated coefficient becomes positive and statistically different to zero in the upper tail of the distribution. This finding can be interpreted as evidence that the persistence of poverty increases with its magnitude.

The negative association of employment and female labor force participation rates with poverty becomes more important when the level of poverty is higher. There is no link between the sectoral composition of employment and poverty in the lower quartile. While the estimated coefficient for the percentage of persons employed in sales and office occupations is positive in tracts with high levels of poverty, it turns negative for the tracts in the center of the distribution. Estimation results for educational variables also change across quartiles. The percentage of population with a high school degree is only positively related to poverty at the bottom of the distribution. This may indicate that this educational level is not enough to reduce poverty, and that it could even be harmful in those areas with better economic prospects. A higher share of population with a college degree is associated with a lower (higher) poverty rate in the first (fourth) quartile. This may be a reflection that people leave poor tracts once this educational level is achieved, which worsens the situation of these deprived areas.

Total population size is not related to poverty in the upper tail of the distribution. The higher the percentage of population under 18 (over 60) the lower the poverty rate in the intermediate (fourth) quartiles. None of the variables that proxy the racial composition are statistically significant in tracts with low levels of poverty. The percentages of persons of black race or with Hispanic origin are more related to poverty in those tracts with higher levels. The magnitude of the positive estimated coefficient for the percentage of female-headed families with children increases as we move towards the upper tail of the distribution. Finally, while the percentage of rented housing units is not associated with poverty only in tracts with high levels, the influence of the age of the housing stock on poverty is mostly not statistically significant when tracts are classified according to their poverty rates.

The dynamic panel data estimation framework that has been applied seems to be adequate for the study of poverty determinants in US census tracts because the validity of the lags of predetermined and endogenous regressors as instruments is confirmed by the serial correlation test for the differenced residuals proposed by Arellano and Bond (1991). The exceptions are the regressions for tracts located in the suburbs and with high levels of poverty. Nonetheless, it is worth noting that, in these two cases, the over-identifying restrictions test statistic developed by Hansen (1982) does not reject the null hypothesis that the instruments are not correlated with the error term and, hence, are correctly excluded from the estimated equation.

6 Discussion

Our empirical analysis highlights relationships that have policy implications. Consequently, the estimation results presented in the previous section are interpreted within the ongoing debate about the optimal design of local development strategies. On the one hand, place-based policies consist of giving subsidies or tax breaks to disadvantaged tracts with the aim of improving the economic conditions of their residents. On the other hand, person-centred policies are targeted at individuals in poverty levels, intending to directly enhance their quality of life and opportunities. We try to provide further insights into the arguments in favor of and against these two types of policies[5], given that the present study deals with the persistence in time and, especially, the determinants of poverty in US census tracts.

A structural and persistent character of poverty at the tract level would strongly support the implementation of place-based policies. Despite this, the stationary nature of poverty rates implies that these measures will only exert transitory effects. Nevertheless, and taking into account our estimation results, place-based policies should not be completely discarded. The statistical significance and positive sign of the coefficients for past values of poverty rates endorse the application of these measures, especially in poorer tracts. One argument against place-based policies is that arbitrage through the free mobility of persons will make geographic income differences disappear. Therefore, we should pay attention to the link between employment and poverty rates. The evidence that we obtained of an inverse relationship between these variables supports the implementation of place-based policies intended to promote employment. This seems to be especially the case of tracts with higher levels of poverty, given the magnitude of the estimated coefficient in the upper tail of the distribution. Our results also show that the female labor force participation rate is inversely associated with poverty, regardless of tract location and MSA size. This finding, together with the estimation results for the percentage of families that are headed by a woman and for the share of population of Hispanic origin, support person-centred policies that are focused on vulnerable groups.

Estimation results for the percentages of persons employed in different economic sectors could be used as a guide to establish the types of jobs that should be created to fight poverty more effectively. The figures reported in Table 7 show that poverty increases with the share of employment

[5] The interested reader may consult the review in Partridge and Rickman (2007).

in the primary and service sectors. In contrast, and with the exception of tracts with higher levels of poverty, the estimated coefficient for the share of sales and office occupations is negative. Consequently, place-based policies intended to promote employment should be used with caution, while taking into account the idiosyncrasies of each area. Similar conclusions can be drawn for educational policies because the relationship between the educational level and poverty changes along with the distribution of poverty.

Fiscal policies aimed at increasing home-ownership may also alleviate poverty. On the one hand, they can be implemented by means of person-centred policies through tax benefits for home purchasing. On the other hand, fiscal policies can adopt a place-based character as subsidized dwellings in deprived areas. Given that there is no relationship between the age of the housing stock and the poverty rate at the census tract level, the empirical analysis that we have carried out does not permit us to take a stance on the suitability of policies directed at the replacement or maintenance of old dwellings.

7 Concluding remarks

A necessary but insufficient condition to alleviate poverty is to know its main drivers. The related literature on this topic has generally considered counties as the unit of reference, which may be masking important behaviors because poverty affects particular persons living in definite areas who influence and are affected by the economic status of their neighbors. Therefore, a deeper knowledge of the factors behind poverty requires the adoption of a higher level of geographical disaggregation. Following this argument, this paper tries to shed some light on the determinants of poverty rates in US census tracts analyzing geographically-consistent data covering 368 MSAs during 1970–2010 on a decennial basis.

Our results suggest that poverty rates are stationary processes displaying persistence and, with the exception of tracts in large MSAs, some degree of spatial dependence. Employment and female labor force participation rates are inversely and significantly related to poverty. Furthermore, a higher level of educational attainment is generally related to lower poverty rates. We have also provided evidence of the sectoral, demographic, and ethnic origins of poverty. Higher percentages of home renters and female-headed families exert a robust and positive influence on poverty rates at the tract level. However, there is no clear relationship between the age of the housing stock and poverty. Given that these results have policy implications, our findings have been framed within the debate about the optimal design of local development strategies. There are arguments to be made both for and against place-based and people-centred policies. Nonetheless, it can be stated that the most effective method to cope with poverty is to treat them as complementary rather than as substitutes.

There are some avenues of future research that are worth recommending. The first, which depends on data quality and availability, would be to carry out a similar analysis to that in the present paper in other–less developed–countries. A second extension could be to further explore the geographical dimension of the relationship between poverty and its determinants. In this regard, some issues that deserve more investigation are the multi-dimensional link between employment, poverty, and space (Partridge and Rickman 2008), the prevalence of the 'spatial mismatch' hypothesis (Ihlanfeldt and Sjoquist 1998), and the efficiency of safety net programs (Kneebone and Berube 2013; Murphy and Allard 2015; Murphy and Wallace 2010). This last topic is of interest because, for the first time in the history of the United States, a profound change in the geography of poverty has taken place: there are more poor people living in suburban areas than in the city centers. Astoundingly, this fact has not been accompanied by a reduction of poverty rates in the latter. Following Allard (2017, page 38), who points out that a tipping point was reached with the advent of the twenty-first century, a longer time dimension than that used in the present paper would be needed to assess the causes, effects, and policy implications of this shift in the geographical distribution of the US poor.

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Figure captions

Figure 1: Metropolitan statistical areas with the lowest poverty rates. Note: Anchorage, AK; Fairbanks, AK and Honolulu, HI have been omitted.

Figure 2: Metropolitan statistical areas with the highest poverty rates.

Figure 3: Poverty rates in US census tracts, 1970 and 2010: Kernel density estimation.

Figure 4: Cross-sectional dependence and unit root testing. Histograms and cumulative density functions of test statistics (Pesaran 2007, 2015) and the estimated measure of dependence (Bailey, Kapetanios, and Pesaran 2016). Red vertical lines represent, respectively, 95% critical values and the interval for the case of strong dependence.

Table 1: Poverty and its potential determinants: Description of variables and data sources.

Variable	Description	Source
povrate	Persons below the poverty level, as percentage of total population	LTDB
wpovrate	Average poverty rate in adjacent tracts	LTDB, NHGIS
empl	Employed persons, as percentage of population 16 years and over	LTDB
femlab	Women in labor force (except in armed forces), as percentage of population 16 years and over	LTDB
farming	Persons employed in farming, fishing and forestry occupations, per cent	NHGIS
transport	Persons employed in production, transport and material moving occupations, per cent	NHGIS
sales	Persons employed in sales and office occupations, per cent	NHGIS
services	Persons employed in service occupations, per cent	NHGIS
highsch	Persons with high school degree, as percentage of population 25 years and over	NHGIS
college	Persons with at least a four-year college degree, as percentage of population 25 years and over	LTDB
popul	Total population	LTDB
under18	Persons aged 17 years and under, per cent	LTDB
over60	Persons aged 60 years and over, per cent	LTDB
black	Persons of black race (not Hispanic origin), per cent	LTDB
hispanic	Persons of Hispanic origin, per cent	LTDB
asian	Persons of Asian race (and Pacific Islander), per cent	LTDB
femhead	Female-headed families with children, as percentage of total number of families	LTDB
rent	Renter-occupied housing units, per cent	LTDB
housing5	Housing units built less than 5 years ago, per cent	NHGIS
housing10	Housing units built from 6 to 10 years ago, per cent	NHGIS
housing20	Housing units built from 11 to 20 years ago, per cent	NHGIS
housing30	Housing units built from 21 to 30 years ago, per cent	NHGIS

Note: The poverty level is established by the US Census Bureau taking into account the cost of a minimum food diet. This figure is multiplied by three to incorporate other family expenses. To give an example, the threshold for a four members family in 2010 was 22,050 dollars. The data have been extracted from the Longitudinal Tract Database (LTDB; Logan, Xu, and Stults 2014) and the National Historical Geographic Information System (NHGIS; Manson, Schroeder, Van Riper, and Ruggles 2017).

Table 2: Poverty and its potential determinants: Descriptive statistics, year 2010.

	Full sample		Tract location				MSA size						Poverty level					
			Center		Suburbs		Small		Medium		Large		Low		Intermediate		High	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
povrate	0.16	0.13	0.21	0.15	0.12	0.10	0.17	0.14	0.15	0.13	0.15	0.13	0.03	0.02	0.12	0.04	0.34	0.11
wpovrate	0.15	0.10	0.20	0.11	0.12	0.07	0.17	0.10	0.15	0.10	0.14	0.10	0.08	0.05	0.14	0.07	0.27	0.10
empl	0.91	0.07	0.90	0.08	0.92	0.05	0.91	0.07	0.91	0.07	0.91	0.06	0.95	0.04	0.92	0.05	0.85	0.08
femlab	0.60	0.11	0.60	0.11	0.60	0.10	0.58	0.10	0.61	0.11	0.60	0.11	0.62	0.10	0.61	0.10	0.55	0.11
farming	0.01	0.10	0.00	0.15	0.01	0.02	0.01	0.20	0.00	0.02	0.00	0.01	0.00	0.01	0.00	0.02	0.01	0.20
transport	0.11	0.08	0.11	0.09	0.11	0.08	0.13	0.10	0.10	0.08	0.10	0.07	0.07	0.05	0.11	0.06	0.14	0.12
sales	0.24	0.10	0.23	0.13	0.24	0.06	0.23	0.14	0.24	0.07	0.24	0.09	0.24	0.07	0.24	0.06	0.22	0.15
services	0.16	0.12	0.18	0.12	0.15	0.12	0.17	0.12	0.16	0.13	0.16	0.11	0.11	0.06	0.16	0.06	0.22	0.20
highsch	0.27	0.24	0.26	0.34	0.28	0.11	0.31	0.15	0.27	0.11	0.25	0.40	0.21	0.11	0.28	0.11	0.31	0.43
college	0.30	0.19	0.30	0.21	0.30	0.18	0.25	0.16	0.30	0.19	0.33	0.21	0.45	0.18	0.29	0.17	0.17	0.15
popul	4.33	2.04	3.96	1.92	4.61	2.08	4.30	2.00	4.30	2.05	4.40	2.07	4.58	2.12	4.49	2.02	3.77	1.91
under18	0.23	0.07	0.23	0.08	0.24	0.06	0.23	0.07	0.23	0.07	0.23	0.08	0.23	0.06	0.22	0.06	0.25	0.09
over60	0.19	0.09	0.17	0.09	0.20	0.10	0.20	0.09	0.18	0.09	0.18	0.09	0.21	0.10	0.20	0.09	0.15	0.07
black	0.15	0.23	0.21	0.28	0.09	0.17	0.11	0.19	0.15	0.23	0.17	0.26	0.05	0.11	0.11	0.18	0.30	0.31
hispanic	0.17	0.22	0.21	0.24	0.14	0.20	0.11	0.18	0.15	0.20	0.26	0.26	0.08	0.10	0.16	0.19	0.28	0.30
asian	0.05	0.09	0.07	0.11	0.04	0.08	0.02	0.04	0.05	0.10	0.08	0.12	0.07	0.10	0.05	0.09	0.04	0.08
femhead	0.15	0.12	0.19	0.14	0.11	0.09	0.14	0.11	0.15	0.12	0.15	0.12	0.07	0.05	0.13	0.08	0.26	0.14
rent	0.33	0.21	0.43	0.21	0.25	0.17	0.30	0.18	0.31	0.20	0.37	0.24	0.17	0.14	0.31	0.18	0.50	0.19
housing5	0.04	0.07	0.03	0.06	0.04	0.07	0.04	0.06	0.04	0.07	0.03	0.07	0.05	0.08	0.04	0.06	0.03	0.07
housing10	0.08	0.10	0.06	0.10	0.09	0.11	0.08	0.09	0.09	0.12	0.06	0.10	0.11	0.13	0.08	0.10	0.05	0.07
housing20	0.13	0.13	0.09	0.12	0.15	0.13	0.14	0.11	0.13	0.14	0.09	0.13	0.17	0.17	0.13	0.12	0.08	0.09
housing30	0.13	0.13	0.11	0.14	0.15	0.12	0.13	0.10	0.14	0.14	0.12	0.14	0.15	0.17	0.14	0.12	0.10	0.11

Note: The distinction between tracts located in the center or suburbs has been carried out using the classification of the US Census Bureau. Metropolitan statistical areas (MSAs) have been classified by taking into account their size distribution in each period. Small (large) MSAs are those in the first (fourth) quartile. A similar approach has been used to distinguish tracts by their poverty level.

Table 3: Metropolitan statistical areas with the lowest poverty rates (%).

1970		2010	
Janesville, WI	5.97	Norwich-New London, CT	8.31
Holland-Grand Haven, MI	6.08	Bismarck, ND	8.42
Appleton, WI	6.13	Appleton, WI	8.43
Fort Wayne, IN	6.20	Washington-Arlington-Alexandria, DC-VA-MD-WV	8.48
Hartford-West Hartford-East Hartford, CT	6.24	Fairbanks, AK	8.59
Bridgeport-Stamford-Norwalk, CT	6.24	Rochester, MN	8.80
Elkhart-Goshen, IN	6.26	Anchorage, AK	9.09
Sandusky, OH	6.33	Sheboygan, WI	9.10
Anchorage, AK	6.34	Sioux Falls, SD	9.29
Minneapolis-St. Paul-Bloomington, MN-WI	6.37	Barnstable Town, MA	9.31
Racine, WI	6.47	Manchester-Nashua, NH	9.39
Poughkeepsie-Newburgh-Middletown, NY	6.58	Bridgeport-Stamford-Norwalk, CT	9.58
Monroe, MI	6.74	Ocean City, NJ	9.89
Dayton, OH	6.76	San Jose-Sunnyvale-Santa Clara, CA	9.96
Lebanon, PA	6.76	Cheyenne, WY	10.05
Oshkosh-Neenah, WI	6.99	Honolulu, HI	10.05
Las Vegas-Paradise, NV	7.02	Oxnard-Thousand Oaks-Ventura, CA	10.21
Detroit-Warren-Livonia, MI	7.03	Casper, WY	10.27
Pittsfield, MA	7.04	Fond du Lac, WI	10.29
Canton-Massillon, OH	7.12	Lebanon, PA	10.31
Indianapolis-Carmel, IN	7.14	Poughkeepsie-Newburgh-Middletown, NY	10.54
Allentown-Bethlehem-Easton, PA-NJ	7.18	Holland-Grand Haven, MI	10.61
Rochester, NY	7.28	Dubuque, IA	10.72
Flint, MI	7.22	Midland, TX	10.88
Cedar Rapids, IA	7.35	Cedar Rapids, IA	10.88
Youngstown-Warren-Boardman, OH-PA	7.37	Ogden-Clearfield, UT	11.07
Peoria, IL	7.44	Bremerton-Silverdale, WA	11.08
Worcester, MA	7.44	Portland-South Portland-Biddeford, ME	11.18
Reading, PA	7.49	Lancaster, PA	11.22
Lansing-East Lansing, MI	7.51	Seattle-Tacoma-Bellevue, WA	11.23

Table 4: Metropolitan statistical areas with the highest poverty rates (%).

1970		2010	
McAllen-Edinburg-Mission, TX	49.04	Brownsville-Harlingen, TX	36.42
Brownsville-Harlingen, TX	41.42	McAllen-Edinburg-Mission, TX	35.14
Laredo, TX	36.69	Laredo, TX	33.59
Merced, CA	34.79	Athens-Clarke County, GA	29.39
Maysville, KY	32.04	Albany, GA	27.46
Greenville, NC	30.50	Muncie, IN	27.43
Sumter, SC	29.92	Las Cruces, NM	27.33
Pine Bluff, AR	27.58	College Station-Bryan, TX	27.13
Goldsboro, NC	26.35	Monroe, LA	26.51
Auburn-Opelika, AL	26.27	Pine Bluff, AR	26.49
Farmington, NM	26.25	El Paso, TX	26.28
Montgomery, AL	26.00	Visalia-Porterville, CA	25.94
Las Cruces, NM	24.90	Hattiesburg, MS	25.41
El Paso, TX	24.69	Macon, GA	25.39
Charleston-North Charleston-Summerville, SC	24.26	Tallahassee, FL	25.27
Monroe, LA	23.60	Merced, CA	25.26
Fort Smith, AR-OK	23.55	Gainesville, FL	25.18
Ocala, FL	23.53	Fresno, CA	24.99
Jackson, TN	23.41	Corvallis, OR	24.78
College Station-Bryan, TX	23.08	Auburn-Opelika, AL	24.76
Tuscaloosa, AL	22.83	Valdosta, GA	24.73
Lafayette, LA	22.62	Greenville, NC	24.54
Shreveport-Bossier City, LA	22.43	Tuscaloosa, AL	23.95
Memphis, TN-MS-AR	22.06	Bloomington, IN	23.56
Danville, VA	21.95	Florence, SC	23.41
Florence-Muscle Shoals, AL	21.60	Goldsboro, NC	23.33
Jackson, MS	21.40	Columbia, MO	23.31
Gainesville, FL	21.38	El Centro, CA	23.31
Port St. Lucie, FL	21.10	Mobile, AL	23.15
Gadsden, AL	20.94	Gadsden, AL	23.14

Table 5: Poverty rates at different geographical levels (%): Descriptive statistics, 1970–2010.

	Census tracts				Metropolitan statistical areas			
Year	Mean	SD	Min	Max	Mean	SD	Min	Max
1970	10.80	9.40	0	86.48	13.08	6.21	5.97	49.04
1980	11.22	10.24	0	100	12.07	8.39	1.53	34.79
1990	12.36	12.02	0	100	13.98	10.21	5.75	42.17
2000	12.43	11.45	0	100	13.32	9.77	4.43	35.45
2010	15.60	13.18	0	100	16.99	4.43	8.31	36.42

Table 6: Evolution of poverty rates (%), 1970–2010.

			Tract location				MSA size						Poverty level					
	Full sample		Center		Suburbs		Small		Medium		Large		Low		Intermediate		High	
Year	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1970	10.80	9.40	12.60	10.65	9.23	7.83	13.55	11.14	10.30	8.66	9.06	8.26	3.07	1.03	8.26	2.49	23.63	10.14
1980	11.22	10.24	14.66	12.59	8.43	6.63	12.53	9.76	10.37	9.57	11.62	11.67	2.99	1.05	8.27	2.54	25.33	11.02
1990	12.36	12.02	16.91	14.65	8.91	8.00	14.36	12.14	11.70	11.70	11.64	12.31	2.64	1.03	8.78	3.20	29.22	12.33
2000	12.43	11.45	17.28	13.56	8.76	7.73	13.43	11.25	11.56	11.06	13.04	12.17	2.75	1.07	9.23	3.44	28.96	10.99
2010	15.60	13.18	20.97	15.20	11.55	9.59	17.37	13.53	15.27	13.12	14.55	12.79	3.43	1.55	12.29	4.34	34.41	11.45

Table 7: Poverty determinants in US census tracts, 1980–2010: System GMM estimations.

		Tract location		MSA size			Poverty level		
	Full sample	Center	Suburbs	Small	Medium	Large	Low	Intermediate	High
lagpovrate	0.3041***	0.1974***	0.4375***	0.3698***	0.3031***	0.1754***	0.3418	0.1074	0.4065***
	(0.0370)	(0.0510)	(0.0652)	(0.0425)	(0.0471)	(0.0486)	(0.2105)	(0.1145)	(0.0663)
wpovrate	0.0183	-0.0017	-0.0200	0.1196***	0.0658**	0.0407	0.0070	0.0780***	0.0410
	(0.0343)	(0.0354)	(0.0337)	(0.0342)	(0.0319)	(0.0389)	(0.0148)	(0.0167)	(0.0402)
empl	-0.3741***	-0.4061***	-0.3235***	-0.3759***	-0.3440***	-0.3579***	-0.0350***	-0.1504***	-0.3626***
	(0.0159)	(0.0196)	(0.0236)	(0.0255)	(0.0189)	(0.0474)	(0.0058)	(0.0102)	(0.0418)
femlab	-0.2371***	-0.3187***	-0.1604***	-0.2016***	-0.2173***	-0.2451***	-0.0103***	-0.0875***	-0.3468***
	(0.0087)	(0.0222)	(0.0137)	(0.0123)	(0.0110)	(0.0092)	(0.0027)	(0.0059)	(0.0196)
farming	0.1330***	0.1979***	0.1213***	0.1476***	0.1710***	-0.0729	0.0241	0.0575	0.1700***
	(0.0369)	(0.0678)	(0.0351)	(0.0333)	(0.0277)	(0.0889)	(0.0207)	(0.0381)	(0.0612)
transport	0.0030	0.0246	0.0206	-0.0097	-0.0041	0.0137	0.0089	0.0332*	-0.0371
	(0.0191)	(0.0273)	(0.0194)	(0.0202)	(0.0153)	(0.0380)	(0.0113)	(0.0181)	(0.0288)
sales	-0.0644***	-0.0882***	-0.0339*	-0.0514***	-0.0768***	-0.0453***	-0.0038	-0.0343***	0.0538***
	(0.0172)	(0.0221)	(0.0184)	(0.0146)	(0.0195)	(0.0132)	(0.0040)	(0.0106)	(0.0176)
services	0.1878***	0.2335***	0.1151***	0.1920***	0.1769***	0.1640***	0.0101	0.0624***	0.1563***
	(0.0204)	(0.0228)	(0.0219)	(0.0206)	(0.0156)	(0.0567)	(0.0055)	(0.0104)	(0.0246)
highsch	-0.0820***	-0.1379***	-0.0279***	-0.0938***	-0.0571***	-0.1179***	0.0057**	0.0014	-0.1029
	(0.0122)	(0.0238)	(0.0088)	(0.0142)	(0.0172)	(0.0134)	(0.0027)	(0.0125)	(0.0246)
college	-0.0659***	-0.1012***	-0.0322*	-0.0680***	-0.0527***	-0.0924***	-0.0038*	-0.0192	0.0714***
	(0.0128)	(0.0263)	(0.0166)	(0.0219)	(0.0160)	(0.0159)	(0.0022)	(0.0191)	(0.0237)
popul	0.0085***	0.0085***	0.0071***	0.0037***	0.0079***	0.0043*	0.0009**	0.0019**	-0.0033
	(0.0026)	(0.0032)	(0.0024)	(0.0012)	(0.0023)	(0.0023)	(0.0004)	(0.0009)	(0.0017)
under18	-0.2139***	-0.2632***	-0.1083**	-0.1927***	-0.1403***	-0.1783*	-0.0130	-0.0493**	0.0784
	(0.0306)	(0.0497)	(0.0437)	(0.0311)	(0.0389)	(0.0957)	(0.0086)	(0.0244)	(0.0410)
over60	-0.0646	-0.0229	-0.0677**	-0.0788***	-0.0431	-0.0066	0.0067	-0.0306	-0.2741***
	(0.0436)	(0.0610)	(0.0303)	(0.0276)	(0.0360)	(0.0468)	(0.0093)	(0.0203)	(0.0286)
black	0.0117	0.0201	0.0028	0.0078	0.0046	0.0086	-0.0034	0.0027	-0.0592**
	(0.0105)	(0.0181)	(0.0118)	(0.0138)	(0.0099)	(0.0112)	(0.0026)	(0.0060)	(0.0235)
hispanic	0.0512***	0.0553***	0.0471***	0.0347***	0.0514***	0.0520***	-0.0013	0.0212***	-0.0406***
	(0.0096)	(0.0119)	(0.0150)	(0.0117)	(0.0132)	(0.0189)	(0.0063)	(0.0059)	(0.0156)
asian	0.0147	0.0330	-0.0181	0.0269	0.0299	0.0352***	-0.0001	0.0009	0.0248**
	(0.0115)	(0.0207)	(0.0127)	(0.0289)	(0.0188)	(0.0125)	(0.0023)	(0.0059)	(0.0119)
femhead	0.3534***	0.3708***	0.2935***	0.3054***	0.3398***	0.3606***	0.0657***	0.1468***	0.2054***
	(0.0196)	(0.0282)	(0.0341)	(0.0269)	(0.0317)	(0.0488)	(0.0127)	(0.0276)	(0.0158)
rent	0.0734***	0.1154***	0.0402***	0.1026***	0.0941***	0.0690***	0.0120**	0.0565***	0.0586
	(0.0229)	(0.0275)	(0.0119)	(0.0230)	(0.0212)	(0.0191)	(0.0056)	(0.0117)	(0.0454)
housing5	0.0794	0.2211**	-0.0323	0.1930***	0.1769***	0.1384	-0.0009	-0.0474	0.0404
	(0.0988)	(0.1109)	(0.0701)	(0.0431)	(0.0601)	(0.1591)	(0.0131)	(0.0571)	(0.1615)
housing10	0.1308*	0.4095*	-0.0475	0.0957	0.0162	0.7501***	0.0028	0.0376	-0.3511***
	(0.0731)	(0.2198)	(0.0820)	(0.1574)	(0.0833)	(0.1181)	(0.0259)	(0.0952)	(0.1657)
housing20	0.1809	0.0027	0.2566***	0.0627	0.0682	-0.2125	-0.0033	0.1196	-0.0429
	(0.1184)	(0.1361)	(0.0940)	(0.1134)	(0.0812)	(0.1555)	(0.0193)	(0.1063)	(0.3426)
housing30	-0.1803**	-0.1240	-0.1779***	-0.0752	-0.0857	0.0003	-0.0032	-0.0946	0.2334
	(0.0748)	(0.1057)	(0.0551)	(0.0612)	(0.0605)	(0.1175)	(0.0094)	(0.0510)	(0.1942)
Observations	215,044	95,173	119,871	50,499	100,296	53,926	35,339	76,715	40,518
Tracts	59,214	25,473	33,741	15,922	31,497	17,998	16,314	34,220	15,405
AR(1) test	-19.94	-2.05	-5.27	-7.26	-7.04	-1.93	-3.42	-4.27	-12.48
p-value	0.00	0.04	0.00	0.00	0.00	0.05	0.00	0.00	0.00
AR(2) test	-0.50	-0.30	3.76	0.68	0.88	0.39	1.59	0.20	2.68
p-value	0.61	0.76	0.00	0.50	0.38	0.70	0.11	0.84	0.01
Hansen test	5.91	3.62	4.40	20.77	0.00	0.00	2.87	2.99	5.66
p-value	0.32	0.61	0.49	0.00	1.00	1.00	0.72	0.70	0.34

Note: The dependent variable is the poverty rate. Estimations include state fixed effects. All available lags for the predetermined and endogenous regressors –lagpovrate, wpovrate, popul, rent, and housing–have been used as instruments. Following Roodman (2009a), they have been collapsed to reduce their count. Robust standard errors, clustered at the MSA level, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.