The Effects of Location-based Tax Policies on the Distribution of Household Income: Evidence from the Federal Empowerment Zone Program

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Current Version: September 2014

Abstract:
Location-based tax policies are redistributive in nature evident by their placement in distressed areas. However, the previous literature has focused on mean effects which can mask important effects that the program has on the distribution of households. Therefore, we extend the literature by studying changes in the entire household income distribution, in the context of the federal Empowerment Zone (EZ) program. We do not find evidence that the impoverished residents benefited from the program. Our findings are consistent with the areas becoming more attractive to high-income households. The improvements in the areas were concentrated in those portions of each zone that were relatively better-off prior to EZ designation. The results confirm the prior literature findings that the areas, on average, became more attractive but also suggest that the benefits of the program likely did not accrue to the lower-income residents of the EZ areas.

1. Introduction

Policymakers are increasingly relying on location-based tax policies to help their constituents spurring a proliferation of studies that attempt to determine their effectiveness. However, despite the potential redistributive nature of these policies researchers have predominately studied the policy effects at the mean instead of throughout the income distribution. To investigate the importance of studying distributional changes in the context of location-based tax policies we study the federal Empowerment Zone (EZ) program, which offers a set of tax incentives to firms if they locate their business in specified distressed areas and hire workers who reside in the area. Specifically, the EZ program offers wage and capital tax incentives as well as service block grants to the community in order to induce businesses to locate in specified distressed areas. The largest and most utilized incentive (Hanson 2011), the wage tax credit, provides employers tax credit worth 20 percent of the wages of employees who live in these distressed areas, up to $3,000. Overall, this program is the largest location-based redevelopment program evident by the Department of Housing and Urban Development (HUD) estimated annual cost of $11 billion.[1]

While the program was designed to stimulate economic activity in distressed areas, which could manifest in a variety of possible outcomes or metrics, at least part of the impetus for the program was to improve the lives of people living in the areas. In a 2002 joint letter to President George W. Bush, Senator Rick Santorum and Congressman J.C. Watts, Jr. stated that the goal of the EZ program is

> "…to create an environment that enables distressed urban and rural communities to have hope for the future through economic and social renewal. Our belief is that when private industry flourishes

[1] The HUD estimate does include costs pertaining to the less generous and smaller Renewal Community and Enterprise Community areas which are not included in this paper.

in these communities, it directly, and positively, impacts peoples' lives." [2]

Researchers interested in how the federal EZ program, or other economic development programs, impacts individuals' lives typically study socioeconomic indicators such as the poverty rate (e.g. Oakley and Tsao, 2006, and Hanson, 2009), income (e.g. Hanson, 2009, and Busso, Gregory, and Kline, 2013), or housing costs (e.g. Hanson, 2009, Krupka and Noonan, 2009, and Busso, Gregory and Kline, 2013). To evaluate whether or not the EZ program improves the lives of people residing in these impoverished areas, we propose to investigate changes in the income distribution that would suggest that households are being moved out of poverty.

Estimated effects on mean and median income or the overall poverty rate, as have been produced in the prior literature, may provide little information about this question. In fact, evidence about the success of the federal EZ program is mixed.[3] While some of the differences in estimates within the literature are due to methodological choices, a possible partial explanation is that the program has a complicated effect on the distributions of households across economic measures. These distributional effects could in turn affect mean impacts, potentially differently based on empirical methodology.

For illustration, suppose that the federal EZ program causes firms to hire some workers who are very low income and that doing so moves these households from severe to moderate poverty. This would have no effect on the estimated poverty rate, since all of the movement is below the poverty line, and could have little effect on the estimates of either median or mean household income, the latter because the distribution of incomes is highly skewed. Such

[2] See U.S. Department of Housing and Urban Development, ''Questions and Answers on Renewal Community and Empowerment Zone Tax Incentives,'' at http://www.hud.gov/offices/cpd/economicdevelopment/programs/rc/index.cfm

[3] For Example, Busso, Gregory and Kline (2013), Ham et al. (2012), HUD (2001), Krupka and Noonan, and Reynolds and Rohlin (forthcoming) find positive effects of the federal EZ program while Hanson (2009), Hanson and Rohlin (2011a, 2011b) and Oakley and Tsao (2006) find negative effects of the program.

estimates of the average effect could lead researchers and policymakers to conclude that the program has little overall effect on reducing poverty. However, investigation of the changes in the poverty distribution would suggest that the program was successful, but needed to be expanded further to move households out of poverty.

Alternatively, suppose instead that the EZ program causes an increase in the density of households at the top of the income distribution. This could result because the program attracted higher income individuals to reside in the area. This could produce a positive estimated effect of the program on mean income. While this would be an accurate estimate of the mean effect, the result could be misconstrued as generally increasing the incomes of residents of the EZ area while the target impoverished population has not benefited from the program. Of course, there are other possibilities for how the EZ program affects the distribution of economic outcomes but the larger point is that understanding the distributional impacts could be critical for policy analysis.

We investigate how the federal EZ program affects the density of individuals and households across the income distribution, as well as the distributions of other previously considered outcomes such as housing costs. Our approach is similar to previous studies in other contexts, such as Neumark, Schweitzer and Wascher (2005) who study how the distribution of family incomes is impacted by minimum wages and find no evidence of an increased density of households just above the poverty line. In our analysis, we use block group data from the 1980, 1990 and 2000 censes. While the prior literature has used this data, or the more aggregated tract-level data, on average incomes and wages, we utilize information on the counts of households and individuals within specified ranges of household income. These counts allow us to construct estimates of the density of individuals and households across the income distribution, as well as other distributions, in each year of our data. Thus, we can estimate how the densities of individuals and households changes at various points in these distributions, thereby providing a more complete picture of the effects of the program compared to average estimates.

For identification, we utilize the selection process of the program that chose distressed areas from a set of qualified applicants. Specifically, we compare changes in the distribution in areas that received EZ designation with areas that qualified and applied for the EZ program but were rejected. While this control group has been utilized frequently in the previous literature, there is evidence that the EZ program selected areas with worse observable characteristics (Ham et al. (2011), Busso, Gregory and Kline (2013), Reynolds and Rohlin (forthcoming)). Similar to Busso, Gregory and Kline (2013), we account for these differences by reweighting the control group to be more similar to the areas selected for the EZ program. For each outcome we consider, we use weights based on the propensity score to construct a set of control areas that have the same empirical distribution of households or individuals, in both 1980 and 1990, as those areas ultimately selected for the EZ program in 1994. We will demonstrate that our procedure produces a control group with nearly identical empirical distributions in both 1980 and 1990, and therefore changes in the pre-designation distributions, compared to the EZ areas.[4]

Overall, we find that EZ designation has a polarizing effect on the distribution of households relative to the poverty line. Estimates show an increase in the density of households making twice the poverty rate as well as an increase in the density of households whose income is less than half the poverty rate. This polarizing effect may provide a partial explanation for the mixed evidence in the previous literature on the effect of the EZ program on the poverty rate in EZ areas. We further find that the increase in households with income more than twice the

[4] It is well-known that the use of lagged variables in difference-in-difference strategies can lead to division bias (Borjas, 1980). We discuss this issue in Section 3 and argue that such bias is unlikely to drive our estimated changes in the distributions of household incomes and housing costs.

poverty rate is driven by an increase in households making more than $100,000. This increase at the upper part of the income distribution explains at least part of the positive mean income effects of the EZ program found in the previous literature.

These results provide little evidence that the existing impoverished residents experienced gains from the EZ program. First, there appears to be an increase in the severely impoverished in the EZ areas compared to the control group. Second, the increased density above $100,000 occurs at roughly four times the pre-designation average household income in EZ areas. While there could be wage and employment gains associated with the program, either through the $3,000 wage credit or other program components described later, it seems unlikely that such gains could move the existing impoverished households so high up into the income distribution. Instead, the change in the distribution is more likely to be explained by the EZ areas becoming more attractive to higher income households.

Further evidence that the EZ areas have become more attractive to high-income households is found by looking at changes in other distributions within the EZ area. For example, we find changes in the distributions of housing costs, with an increase in high rental rates and an increase in housing prices that extends into the upper part of the distribution. Additionally, we find increases in educational attainment, including increases in the proportion of the population with a college or graduate degree, that are unlikely to be caused by any wage or employment increases among the existing EZ residents due to the program. Furthermore, despite the increase in housing costs, we find evidence that households are spending less of their income on housing following the program, consistent with higher-income individuals moving into relatively low-cost areas. While these results do suggest that the areas became more attractive, which is one metric by which the program could evaluated, there is little evidence that the benefits are accruing to the impoverished population previously living in these areas.

Finally, we present evidence of a spatial variation in the effect of the EZ program on poverty reduction within EZ areas, and this variation provides a further explanation for the polarizing effects we find on the poverty rate. In particular, we find that poverty improved in the portion of each EZ that was less impoverished in 1990 prior to the program. In contrast, the portion of each EZ area that was initially more impoverished shows no improvement in poverty, and point estimates actually suggest that poverty worsened. Thus, any benefit of the EZ program appears to be concentrated in those portions of the areas that were initially better off.

The following section describes the federal Empowerment Zone program and Section 3 presents our data and empirical methodology. Section 4 begins with a presentation of mean and median estimates of the program effects, similar to the prior literature, before presenting our estimates of the distributional effects. We provide a discussion and interpretation of these results in Section 5 and the last section concludes.

2. The Federal EZ Program

Faced with economically depressed areas, federal and state officials have instituted a myriad of location-based economic development policies. This proliferation has spawned many different types of incentive programs, such as investment tax credits (Chirinko and Wilson, 2008), tax increment financing (Dye and Merriman, 2000), and location-based tax incentives to name a few. These types of programs typically focus on attracting or retaining businesses in these areas by offering financial assistance, often in the form of tax relief. The hope of these policies is that by luring business activity to these blighted areas they offer economic opportunities to the local residents and bring back economic prosperity.

These policies tend to be redistributive in nature as the policies benefit some people directly or indirectly as well as potentially inducing individuals and businesses to relocate across geography. While the specific effects of such policies could vary from one program to the next, we focus our study on the Federal Empowerment Zone program which was created as a part of the 1993 Omnibus Budget Reconciliation Act (OBRA 1993, P.L. 103–66) to help improve the most distressed areas in the U.S. by offering a set of tax incentives to firms that operate inside specific zones. The Department of Housing and Urban Development chose from a pool of applicants that had met the requirements that 20 percent of the residents lived in poverty and have an unemployment rate of at least 6.3 percent.[5] The largest and most utilized tax incentive that the EZ program offers is a 20 percent employee wage tax credit up to $3,000 to businesses located within the zone for each worker that lives in the zone. The tax package also offers some capital investment incentives by giving firms additional capital expensing for a larger set of purchases. Lastly, each awardee was granted $100 million in social service block grants to subsidize things such as counseling, day care for children, employment services, legal services and substance abuse recovery for residents in the zone. For full details of the EZ incentives see Hanson (2009).

We chose to study the federal EZ program for a number of reasons. First, the EZ program is one of the largest location-based economic development programs in the United States with the estimated cost in 2009 being $1.7 billion.[6] Although we focus on the initial wave of recipients (Atlanta, Baltimore, Camden/ Philadelphia, Chicago, Detroit, and New York City),

[5] There is a rural component to the program which chose three rural areas (Kentucky Highlands, Mississippi Delta, and the Rio Grande Valley in Texas). These areas are not included in our analysis because they are substantially different to the urban areas and an entirely different department, the Department of Agriculture, chose the areas that received the funding. This is common in the literature that has studied the federal EZ program (e.g. Hanson (2009), Hanson and Rohlin (forthcoming), and Busso, Gregory and Kline (2013).

[6] This estimate does include the costs associated with the smaller Renewal Communities tax credit.

the program has since expanded to include an additional 38 cities giving further evidence of the size of the program. Second, because this is a national program we can study how a uniform set of incentives can impact different areas across the country, although there is some evidence that cities utilized the Social Service Block Grants in different ways (U.S. General Accounting Office, 2006). Additionally, the federal EZ program has been a blueprint of some of the over 40 state location-based economic development programs (Kenyon 2012).[7]

Third, the application process provides comparison areas that allow us to build counterfactuals by using the fact that the recipients were chosen from a group of qualified applicants. As is common in the EZ literature (e.g. Hanson (2009), Hanson and Rohlin (2011a, 2011b), and Busso, Gregory and Kline (2013)), we use areas that applied and qualified for the program but were not ultimately chosen as a basis for constructing counterfactuals for the areas that did receive the full benefits of the program. In particular, we utilize a propensity score matching approach, described below, to construct a counterfactual from these areas that were not selected that have similar pre-1994 trends in outcomes as the EZ areas that were actually selected, similar to Busso, Gregory and Kline (2013). Most of the areas that were not chosen did receive "Enterprise Community" (EC) designation which provided them some of the capital incentives and $3 million in Social Service Bock Grants but were not allowed to claim the generous wage tax credit. A final useful feature of the program is that the boundaries of both the recipients and the rejected applicants are clearly defined according to census tracts and recorded by HUD.

[7] There is a large literature that studies the effect of these state economic development programs. However, there does not appear to be a consensus on their efficiency. Papke (1994), O'Keefe (2004), Couch et al. (2005), Billings (2008), and Freedman (2012) find positive effects from state programs while others such as Boarnet and Bogart (1996), Bondonio and Engberg (2000), Faulk (2002), Greenbaum and Engberg (2004), Bondonio and Greenbaum (2007), Elvery (2009), Neumark and Kolko (2010) find small or no net effects. However, some opine that the lack of consensus among state programs is the result of researchers describing statistically insignificant results due to large standard errors but economically meaningful coefficients as null results.

3. Data and Empirical Methodology

Suppose that we are interested in estimating the economic effect of EZ designation as measured by some outcome θ. While the prior literature has generally focused on estimating the effect on some specific moment of θ, such as the average $\bar{\theta}$, we are interested in how EZ designation changes the distribution of θ across individuals and households within EZ areas. The main concern is that estimating average effects may miss important changes in the underlying distribution and those changes in the distribution can be informative for drawing policy conclusions. This may be particularly true in the case of location-based tax policies as the effects of programs could vary across agents within the area or could vary geographically within the area depending on the distribution of individuals and firms across space.

To investigate these issues we use block group data from the 1980, 1990 and 2000 Censes which is both publicly available and has been used frequently in the prior EZ literature.[8] In our data, there are 838 block groups in EZ areas and 3,649 in EC areas. However, while the prior literature has focused on outcomes such as the poverty rate, wage and salary income and the unemployment rate, we will use distributions of variables that are constructed in the block group data for some outcomes. For example, the data provides population counts within specified ranges of the ratio household income to the poverty line. While these numbers can be used to calculate the overall poverty rate, these counts can also be used to construct an estimate of the density of households across the distribution of income relative to needs within the block group.

[8] EZ and EC areas are designated by 1990 census geography so we convert 1980 and 2000 data to 1990 geographic equivalents using GIS maps to maintain consistent geography across the sample.

In our main analysis we focus on the density of individuals and household across four outcomes (θ): household income relative to the poverty line, household income, gross rent and house values. While the poverty rate, gross rent and house values have been previously considered in the literature, the prior studies have tended to focus more on wage and salary income as opposed to household income because that measure is tied more closely to the wage credit component of the EZ program. However, information on the distribution of wage income is not available in all years of the data so we use household income instead. This measure also is more closely related to the poverty measure. The ranges or buckets of each outcome in which individual or household counts are provided change over time in the data, consequently we combine some buckets in certain years to maintain consistent ranges over time.[9] However, to fully exploit the available distributional information we attempt to keep as many buckets as possible for each outcome.[10] Using our data, we are able to investigate changes in the density of individuals or households at 9 points in the distribution of household income relative to the poverty line, 13 points in the distribution of annual household income and 16 points in the distribution of monthly gross rent and house values.

Note that one concern with this approach is that ranges of income or rent are specified in consistent nominal buckets over time because there is no straightforward way to create consistent ranges in real terms. However, we are using a differencing approach where the EZ and control areas are both differenced over the same time span so changes in prices levels will be differenced

[9] Because we are estimating the changes in the distribution between 1990 and 2000 we focus on creating identical buckets between these two years of data. We only use information on the 1980 distribution to control for trends and therefore the buckets do not need to be identical and trying to force consistency across all three decades would greatly limit the number of buckets available to be used to measure the distribution.

[10] For household income we combine three income buckets into a single category for annual household income is $100K or higher. We also combine together three buckets of house values into a single category of $300K or higher. We do this because the impoverished nature of EZ and EC areas means that the density of households above these levels is very small in both 1990 and 2000. All results are robust to not making this adjustment and are available upon request.

out. Additionally, the poverty line is adjusted over time based on inflation so the ratio of household income to poverty line implicitly accounts for inflation. Finding similar results using the poverty measures as when we use household incomes suggests that our use of nominal buckets is not driving the results.

We are interested in estimating how EZ designation changes each of these distributions of individuals and households. To do so, however, requires the identification or construction of a relevant counterfactual distribution against which the observed changes in the EZ areas can be compared. Denoting the probability density function of outcome θ as $g(\theta)$, the change in the density of the distribution between 1990 and 2000 is defined as $\delta = g(\theta)_{2000} - g(\theta)_{1990}$. Letting δ_1 be the change in the distribution that would occur if an area receives EZ designation and δ_0 be the change that would occur without EZ designation, we are interested in identifying the treatment on the treated (TT) defined as

$$TT = (\delta_1 | EZ = 1) - (\delta_0 | EZ = 1)\ . \tag{1}$$

The primary identification problem is that while the first term is easily identifiable, it is simply the observed change in the probability density function for EZ areas, the second term is not. The second term is the counterfactual change in the probability density function that would occur in the areas that receive EZ designation if these areas did not receive EZ designation.

Similar to much of the previous literature studying the federal EZ program, we will use the EC areas as a basis for constructing the counterfactual distributions because these areas all applied and qualified for the program but were not selected. However as noted by previous researchers (e.g. Ham et al. (2012), Busso, Gregory and Kline (2013), and Reynolds and Rohlin (forthcoming)), while the EC areas all qualified for the EZ program, much of the EC areas were markedly better on a variety of observable characteristics than the EZ areas. Table 1 presents summary statistics for our main outcomes for the EZ and EC areas, as well as the differences in the outcomes between EZ and EC areas. In both 1980 and 1990, EZ areas had a higher poverty rate as well as lower annual household incomes, monthly gross rent and house values, all differences statistically significant from EC areas.

Similar to Busso, Gregory and Kline (2013), we construct our counterfactual by reweighting the EC areas to be more similar to the EZ areas in the years prior to EZ designation. We reweight using the propensity score $P(X)$, defined as the probability of being in the treatment group (EZ) conditional on some set observable characteristics X (Rosenbaum and Rubin, 1983). For each outcome we consider, we estimate the propensity score as a function of lagged 1980 and 1990 measures of the empirical distributions. Specifically, for each outcome θ we use a logit to estimate

$$EZ = f(g(\theta)_{1990}, g(\theta)_{1980}). \tag{2}$$

where $g(\theta)_{1990}$ and $g(\theta)_{1980}$ are the empirical probability density functions in the block group in 1990 and 1980, respectively. The propensity score $\hat{P}(g(\cdot))$ is the probability of a block group being in an EZ predicted by equation (2). Thus, when estimating the propensity score we are controlling for the pre-designation distribution of θ as well as any trends in the distribution prior to EZ designation.

The empirical probability density functions are represented by a set of variables measuring the fraction of total individuals or households within the available ranges of each distribution as described above. While block groups are constructed to be similar in population size, some variation in population does exist. Consequently, we estimate equation (2) and calculate propensity scores separately by quintiles of block groups based on population. In practice this has little impact on the estimates and similar procedures, for example including indicators for the size of the block group in equation (2), produce similar estimates.

Using the propensity score $\hat{P}(g(\cdot))$, we construct the counterfactual changes by reweighting the EC areas by weight $\omega = \frac{\hat{P}}{1-\hat{P}}$.[11] Implicitly, this procedure upweights those parts of the EC areas that are most similar in their 1980 and 1990 distributions of θ to EZ areas while downweighting those parts of the EC areas which are most unlike the EZ area. This particular use of the propensity score is often less biased and more efficient than other matching methods when there is sufficient overlap of the propensity scores in the treated and control sample (for a discussion see Busso, DiNardo, and McCrary (2013)). However, we later demonstrate that all of our substantive results are unchanged if we create counterfactuals using other algorithms based on the propensity score.

One potential concern is that the use of lagged outcomes as controls when estimating the propensity score could result in division bias (Borjas, 1980) because the 1990 measures are included in both the controls and in the outcome. We argue that measurement error in 1990 variables is unlikely to drive our estimated distributional changes because it would depend on systematic mis-measurement in specific parts of each distribution in that year across EZ and EC areas. While possible, we have no reason to suspect that such measurement error exists, particularly across the distributions of multiple outcomes. Additionally, measurement error in the distributions is likely a smaller problem than would occur with average levels. For example, our poverty estimates rely on the number of households that fall within various ranges of

[11] In practice, we normalize ω to sum to one.

household income. Measurement error in the income of each household may have little effect on the counts of households in each range of household income.[12]

Our main identifying assumption for the reweighting procedure is

$$(\delta_0 | P(X), EZ = 1) = (\delta_0 | P(X), EZ = 0)\ , \tag{3}$$

meaning that conditional on the propensity score, there is no difference in the change in the distribution of θ under non-treatment across EZ designation. This assumption simply states that, conditional upon the propensity score, the observed change in the distribution of θ in EC areas serves as the appropriate counterfactual to estimate equation (1). We will demonstrate that the reweighting procedure produces a control group with 1980 and 1990 empirical distributions that are nearly identical to the corresponding distributions in the EZ areas. Thus, our control experiences the same changes as the EZ areas throughout the distribution of each outcome prior to EZ designation. Thus, any bias in our distribution estimates must be due to our control areas systematically beginning to trend differently after 1990, despite having trended similarly throughout the distribution prior to 1990. While we acknowledge that this is possible, we feel that it is unlikely given our rich data on the pre-designation distributions for each outcome we consider.[13]

4. Results

4.1 Average Effects

[12] Our substantive results are unchanged when we use census tracts, for which measurement error in distributions is less likely because of the larger level of aggregation, which provides additional evidence that division bias is not driving our estimates.

[13] Equation (3) is less strong than the assumption required to use the observed changes in EC areas as counterfactuals, which has been done frequently in the literature. The corresponding identifying assumption to use the observed changes in EC areas as counterfactuals could be expressed as $(\delta_0 | EZ = 1) = (\delta_0 | EZ = 0)$, meaning that regardless of any differences in the observed characteristics of the areas, the distribution of θ would change the same over time regardless of EZ designation. This is only likely to hold if there is little difference between EZ and EC areas. Our procedure attempts to account for the fact that significant differences do exist between those areas that did and did not receive EZ designation.

To understand the importance of studying distributional changes we first use our matching procedure and block group data to estimate the average effects of our primary outcomes, similar to much of the prior literature. For each of our outcomes, we first estimated the propensity score on the 1990 and 1980 levels of the outcome and then used the reweighting procedure to construct the counterfactual change from the EC areas. Appendix Table A-1 demonstrates that the reweighting procedure produces counterfactual 1980 and 1990 levels for each of the four outcomes considered that are much closer to those of the EZ areas and any small differences are not statistically significant.[14]

Table 2 presents the estimated effects of EZ designation on the poverty rate and real mean and median annual household income, monthly gross rent and house values using our matching methodology. For each outcome, the observed change in EZ areas from 1990 to 2000 is presented in column 1, the estimated counterfactual change constructed from the EC areas using the reweighting procedure is presented in column 2, and column 3 presents the TT, the difference between the observed and counterfactual change as defined by equation (1). Asterisks denote statistical significance based on the empirical confidence intervals produced by bootstrapping the estimates using 1000 replications; 95% confidence intervals are presented in square brackets below point estimates.[15]

We begin by considering the poverty rate in EZ areas. The prior literature is somewhat mixed about whether EZ designation affects the poverty rate with some studies finding reduced poverty (see Oakley and Tsao (2006)) and other studies finding negligible effects (see Hanson

[14] The first two columns present the average levels of each outcome for the EZ and EC areas, columns 3 and 4 present the equivalent levels following the reweighting procedure for EZ and EC areas, respectively. The EZ areas are not reweighted but a few EZ block groups are dropped during the logit estimation of the propensity score, accounting for the slight difference in average pre-designation values for EZ areas seen in columns 1 and 3.
[15] Throughout the paper, we use a block-bootstrap procedure where we sample from within the EZ and the EC areas so that each sample has the same proportion of EZ and EC block groups that we observe in the block group data.

(2009)). The result in the first row suggests that the proportion of the population in EZ areas below the poverty line fell by 7.8 percentage points from 1990 to 2000. However, the estimated counterfactual suggests that the poverty rate would have fallen by 6.7 percentage points in the absence of the EZ program. Therefore, the effect of receiving the EZ program for the designated areas is a reduction in the poverty rate of 1.0 percentage point, an effect that is neither economically nor statistically significant.[16] Thus, we find little evidence that the EZ program reduced average poverty.

Somewhat in contrast, however, the results in the middle panel suggest that the federal EZ program on average increased annual household income by approximately $2,044. This is roughly an 11 percent increase relative to the baseline household income level in EZ areas in 1990. Additionally, we find that EZ designation increased gross rents in these areas by approximately $33 a month from 1990 to 2000 and increased house values by $27,130. These results are broadly consistent with the previous literature which has found little increase in gross rents (Busso, Gregory and Kline (2013)) but large increases in house values (e.g. Hanson (2009), Krupka and Noonan (2009), and Busso, Gregory and Kline (2013)).

The results in Table 2 suggest that there may be potentially interesting changes in the distributions of these measures. For example, while the poverty rate does not decline, household income appears to increase on average which would be consistent with an increase in household incomes among households above the poverty line. Additional evidence that analysis of mean effects are missing potentially important changes in the underlying distributions can be found in the bottom panel of Table 2 where instead of using the mean values of household income, gross rent and house values in each block group, which can be skewed by extreme values, we instead

[16] In contrast, the observed change in the poverty rate in EC areas is only -0.044. Using this as the counterfactual change for the EZ areas would produce a larger estimated effect of the EZ program on the poverty rate.

look at median values. The results in column 3 suggest that EZ designation had less effect on both median household income and median gross rent than was estimated using average values. For neither median household income nor median gross rent are the estimated effects large or statistically significant. Additionally, the estimated impact on median house values is smaller than the estimated mean effect, although the effect is still large. Overall, these results suggest that estimates of EZ designation on average household income and gross rents could be influenced by large increases at the top of the distributions, and thus analysis of the entire distribution would be valuable in determining who is benefiting from this policy.

4.2 Distributional Effects

4.2.1 Household Income Relative to the Poverty Level

We begin our exploration of the potential distributional effects of the federal EZ program by examining how EZ designation changes the density of households across the distribution of household income relative to the poverty line. We first estimate the propensity score using measures of the 1980 and 1990 densities of the population in specified ranges of the distribution of household income relative to the poverty line. We then use the estimated propensity score to construct the counterfactual changes in the density between 1990 and 2000 across the distribution.

We focus the discussion using a graphical presentation of the results because it more clearly illustrates the complex changes in the densities of the relevant distributions. However, for convenience we also provide tables of our main estimates in either the main text or in the appendix. For example, Figure 1 presents a graphical investigation of the balancing property of our reweighting procedure for the 1990 and 1980 densities of households across the distribution of household income relative to the poverty level. Consistent with the evidence in Table A-1 about the differences between EZ and EC areas in the overall poverty rate, both the 1990 and 1980 poverty distribution is more highly skewed in the EZ areas with a larger density of households at very lower poverty levels compared to the EC areas. However, the counterfactual distributions in each year, constructed by reweighting the EC areas, closely matches the distribution in EZ areas. Appendix Table A-2 presents the corresponding estimates of the balancing exercise for both the 1980 and 1990 distributions and demonstrates that there are no statistically significant differences between the density of households in either 1980 or 1990 following the reweighting procedure. Thus, the matching method produces a counterfactual distribution that closely follows the pre-EZ designation trends in the distribution of households relative to the poverty line.

The effect of EZ designation on the density of households relative to the poverty line is depicted in Figure 2. The first row of figures presents the observed distributions in 1990 and 2000 for EZ areas (2a) and the equivalent counterfactual distributions (2b). Both demonstrate a decrease in the density of households in extreme poverty and an increase in the density of households with incomes at least twice the poverty line. These changes in the densities along the distributions are displayed, with 95% confidence intervals, in the second row for EZ areas and the counterfactual, respectively. Figure 2c corresponds to $\delta_1|EZ = 1$ and Figure 2d corresponds to the estimated counterfactual $\delta_0|EZ = 1$ needed to calculate the treatment on the treated in equation (1).

These figures, and the corresponding point estimates in columns 1 and 2 of Table 3, suggest that the EZ areas experienced a 5.1 percent decrease in the density of individuals with household income less than half the poverty line and smaller declines in the densities of individuals with household income at least half, but still below, the poverty line. While there is an increase in the density of individuals slightly above the poverty line, potentially because of individuals moving out of poverty, most of the change in the distribution appears to be occurring at the top of the distribution with a 5.8 percent increase in the density of individuals with household income twice the poverty line.

While the counterfactual shows a similar pattern in terms of the location and direction of changes in the densities of the distribution (Figure 2d or column 2 of Table 3), the magnitudes are not identical. Designation of EZ status in EZ areas, the treatment on the treated (TT) or difference between the observed and counterfactual changes, appears to polarize the poverty distribution. Figure 2e shows that relative to the counterfactual, the density of households in EZ areas increases at both ends of the distribution while the density decreases in the middle of the distribution. The corresponding point estimates in column 3 of Table 3 suggest that the density of individuals in extreme poverty, with household incomes less than half of the poverty line, increases by 1.1 percent. However, there is also a 1.9 percent increase in the density of individuals with household income at least twice the poverty line.

As we demonstrated in Table 2, these changes at both the top and the bottom of the poverty distribution are not observed when estimating the effect of EZ designation on the overall poverty rate. Additionally, this polarized effect could provide a partial explanation for the missed evidence of the effect of the EZ program on poverty rates, depending on estimation strategy and at what point in the distribution poverty is measured at. Finally, this polarization pattern is robust to using other implementations of our reweighting procedure or using other matching algorithms based on the propensity score although, as discussed, other algorithms are less precisely estimated (see Appendix Table A-3).

4.2.2 Household Income

The possibility that the EZ program has effects at the very top of the income distribution can be investigated with the same methodology using data on the distribution of household income. Importantly, the household income data has more buckets, particularly at incomes higher than twice the poverty line (approximately $35,000 in 2000), allowing for a more detailed exploration of where in the income distribution changes are occurring. Figures 3a through 3c demonstrate that EZ areas see a large decrease in the density of households with less than $10,000 in annual income and a comparative increase in the density of households with income above $50,000. As discussed previously, to maintain consistent buckets in which to calculate densities, these income ranges are specified in nominal terms so much of this increase in income is due simply to inflation, which is reflected in a similar pattern being seen in the counterfactual distributions in Figures 3b and 3d. However, since both areas are changing over the same period of time, the difference between the observed changes in EZ areas and the counterfactual accounts for national price trends.

The results depicted in Figure 3e, also presented in Appendix Table A-4, depict a similar polarization of the distribution as seen in the poverty distribution. EZ areas experience a 1.4 percent increase in the density of households with annual income below $10,000 compared to the counterfactual, consistent with the increase in extreme poverty previously seen in Figure 2. Additionally there is a small positive, but not always statistically significant, increase in the density of households with income above $50,000. However, there is a larger statistically significant increase of 0.8 percent in the density of households with incomes above $100,000. These results suggest that the increase in households incomes is occurring well beyond twice the poverty line, which seems unlikely to be caused by either increased wages or employment associated with the $3,000 wage credit. Instead, Figure 3 provides further evidence that prior estimates of increased incomes and wages may be skewed by increases at the top of the income distribution, consistent with the large mean but not median effects on household income that we demonstrated in Table 2.

4.2.3 Gross Rent and House Values

In addition to the poverty rate and income, the previous literature on the EZ program has frequently investigated house values and gross rents because these measures can be interpreted as a proxying for local amenities and the overall attractiveness of the areas. Similarly, we can use our methodology to investigate how the EZ program affected the distributions of rental rates and house values in EZ areas. For simplicity, we only present the difference between the observed change and the counterfactual change (TT) for each outcome in Figure 2 but full estimates are provided for monthly gross rent in Appendix Table A-5 and for house values in Appendix Table A-6.

Compared to the household income estimates, there is less evidence of a polarizing effect of EZ designation on housing costs. There appears to be an increase in the density of households paying monthly gross rents above $600 and a decrease in the density of households paying gross rents between $350 and $550. This does suggest an increase in rental rates, but an increase that occurs in the top half of the distribution consistent with an increase in the rental rates of mid-range rental units only. This movement in the middle of the distribution may explain why prior estimates have generally found only modest, or no, positive effects on average rental rates.

In contrast, there are appears to be a large increase in house values starting at $100,000 and extending above $300,000. This increase at levels several times the average or median 1990 house value in EZ areas partly explains why the prior literature has consistently found increases in mean house values. Overall, this evidence suggests that the attractiveness of the EZ areas to households increased due to the program, as reflected in higher costs of living, but the fact that the effect is larger for owner-occupied housing and the effects on house values extends so far up the distribution makes one question what is driving these changes.

5. Discussion

Our results suggest complex effects of EZ designation on the distribution of individuals and households that may be missed when analyzing mean or median outcomes. We find a polarizing effect of EZ designation on the distribution of individuals relative to the poverty line and the corresponding overall distribution of household income. How should we interpret this polarized effect? Remember Senator Rick Santorum and Congressman J.C. Watts, Jr stated to President Bush that they hoped the program would “directly, and positively, impacts peoples’ lives.” Our results do not make a strong case for the EZ program lifting households out of poverty. First, while the overall density of the very poor did decrease in EZ areas, there was less of a decrease compared to the counterfactual areas. This may indicate that the program either did not raise the incomes of the very poor or that the program attracted some low income households to the area, relative to the counterfactual. Second, even if the EZ program did increase wages for the poor, the increased density of high-income households we observe is likely not due to a movement up the income distribution of those individuals living in the EZ areas prior to 1994. It seems implausible to believe that a $3,000 wage credit and the Social Service Block Grants could move households from below the poverty line to more than twice the poverty line, or cause households to earn more than $100,000 in 2000 when the average pre-designation income in EZ areas was approximately $25,000 (in real $2000).

Instead, it may be that EZ designation makes the areas more attractive to higher income households who move into the area causing gentrification of the zone, which would support the evidence of increased house values at the upper portion of the distribution.[17] Additionally, the fact that EZ areas appear to see an increase in the proportion of individuals in severe poverty also raises concerns about whether the program is aiding original residents of the areas. The increased density at the bottom of the distribution either suggests that some individuals have become poorer following EZ designation, or the program has attracted poor households to the area. Regardless, any potential positive benefits of the program do not appear to accrue equally to all individuals within EZ areas and the results demonstrate the importance of analyzing distributional changes along with estimates at the mean.

5.1 Educational Attainment and Housing Expenditures

To further investigate whether household migration explains some of the changes in the distributions above, and by extension some of the prior mean effects estimated in the literature, we examine both changes in educational attainment and gross rent relative to household income. Table 4 presents the estimated impact of EZ designation on these two distributions of the population. Consistent with their impoverished nature, EZ areas had very low rates of educational attainment in 1990 prior to EZ designation with approximately 55% of individuals aged 25 or older having not completed high school and another 25 percent only completing high school. However, the top panel demonstrates that EZ-designation is associated with an increase in educational attainment with a 3.3 percent decrease in the density of individuals aged 25 or higher with less than a high school diploma. Furthermore, this reduction in the density is due to

[17] There is some prior evidence about in-migration of residents to EZ areas. Busso, Gregory and Kline (2013) find a 0.02 percent change in households, a 0.06 percent change in population in EZ areas and a small decrease in the 5-year housing turnover rate, although none of the estimates are statistically significant. Similar to evidence we will present, they do find that the proportion of the population with a college degree increases by 0.02.

an increase in the density of individuals with at least some college experience or higher, including a 0.8 percent increase in the proportion of individuals with a bachelor's degree and a 1.0 percent increase in the proportion of individuals with a graduate degree. This is almost certainly due to an in-migration of highly educated individuals as it is unlikely that a $3,000 wage credit and any corresponding employment increase among the EZ population would have caused large increases in educational attainment within 6 years, particularly at the level of bachelor or graduate degree holders.

The results in the previous section suggested that both household incomes and housing costs increased. However, the lower panel suggests that the increase in household incomes in the EZ areas is outpacing the increase in housing costs, at least for renters, as the proportion of households paying comparatively little of their annual income in the form of rent increases while the proportion of households committing a larger portion of their annual income to rent decreases. Given the increase in rental rates at the middle to the top of the distribution observed in Figure 4, these results would be consistent with higher income individuals moving to a relatively low cost area.

5.2 Spatial Distribution

One interpretation of our results is that they could be due to the movement of individuals and households into the EZ areas but they could also be due to spatial variation in the concentration of effects within EZ areas. To further explore these possibilities, we investigate whether the changes in poverty varies within each city based on the initial level of poverty in 1990. Importantly, while EZ areas are defined according to census tracts and the area overall had to meet the minimum criteria to qualify for the EZ program, each individual census tract within the EZ area did not have to meet the criteria. Thus, there is variation within each EZ area in terms of the poverty level.[18] The question is whether there is a different effect of EZ designation in the portion of each EZ area that is initially worse (ie. has higher initial poverty) or better (ie. has lower initial poverty) in 1990 prior to EZ designation.

To investigate this question, we take each of the six EZ areas and divide the area into a "low initial poverty" or a "high initial poverty" area. We construct these areas based on whether the 1990 poverty rate in the census tract is lower or higher than the median poverty within each EZ area.[19] We then separately estimate the distributional effects of EZ designation within the worse parts of the EZs and the better parts of the EZs using our reweighting procedure. Specifically, we first drop the "better" portions of EZ areas and then estimate the propensity score among the "worse" portion of each EZ area and the entire EC areas. We then reweight the EC areas to have a similar 1980 and 1990 poverty distributions to the "worse" EZ areas and then use the reweighted distribution as the relevant counterfactual for such areas. Similarly, to construct the counterfactual for the "better" portions of the EZ areas, we first drop the "worse" portions and then estimate the propensity score and conduct the reweighting procedure.[20]

Figure 5 presents the estimated effects of EZ designation on the density of households relative to the poverty line, first for the part of each EZ that has lower initial poverty in Figure 5a ("better") and then for the part of each EZ area that has higher initial poverty ("worse"). The results in Figures 5a and 5b provide a partial explanation for why we observed an overall polarizing effect of EZ designation on the poverty distribution in Figure 2. In Figure 5a, the

[18] For example, the average tract-level poverty rate varies from 0.418 to 0.560 across EZ areas while the inter-quartile range within each area varies from 0.113 to 0.248 across EZ areas.
[19] We define these areas based on census tracts, which are larger areas than block groups, to avoid having neighboring block groups within the same census tract being placed in opposite categories since it is likely that these areas would be viewed fairly similarly by residents or potential movers.
[20] Note that we are defining the "worse" and "better" portions of the EZ areas separately within each EZ. This means that we are separating each EZ into a "worse" or "better" portion. While this means that the definition of "worse" varies across cities, we do this to try to capture how different parts of each EZ may be viewed by residents within each of the respective cities as migration into EZ areas is more likely to come from the surrounding city than inter-city.

parts of EZ areas that were better in 1990 (ie. had lower initial poverty) see a decrease in the density of individuals below the poverty line and increase in the density of individuals above the poverty rate, particularly for the density of individuals with household incomes greater than twice the poverty line. Thus, the "better" parts of EZ areas within each city appear to improve in terms of the poverty distribution. In contrast, in Figure 5b, the parts of EZ areas with higher 1990 poverty show no improvement in poverty and instead show a large increase in the density of individuals in extreme poverty. However, the result is not quite statistically significant at the 95% level because the precision of our estimates in both portions of the EZ decreases because we are effectively cutting our treated sample in half. Figure 5b suggests that the "worse" areas certainly did not experience decreased poverty levels and may have actually have experienced a worsening poverty distribution.

These results suggest that the EZ program has effects not just across the distribution of poverty but furthermore across the spatial distribution of EZ areas. The results suggest that the EZ program appeared to have a more positive effect on the distribution of poverty among those portions of the EZ areas that were less impoverished initially, essentially more marginal for the EZ areas.

6. Conclusion

The focus of this paper is to add to the discussion about the importance of analyzing distributional effects along with mean changes by investigating whether location-based tax incentives have uniform effects across the entire income distribution as well as across all geography. We find a disparate effect across different parts of the income distribution. Specifically, we find compared to similar areas that also applied to the EZ program there is an increase in the number of households that make less than half the poverty rate as well as an increase households with more than twice the poverty rate. Additionally, we find that not all areas experience the growth of higher-income households with those EZ areas that were relatively well-off receiving the majority of the growth.

Our results may be unique to the federal program; however, given that other types of economic development programs have similar potential for redistribution, studying the distributional effect of these programs should be an area of future research. Our results highlight one of the benefits of studying distributional effects which is that distributional analysis can provide a more complete picture as to what is causing these mean changes. All of our results suggest that the EZ areas became more attractive to households, as seen for example with the increases in housing costs, but the evidence also suggests that at least some of the previous literature's findings of positive effects on poverty or incomes may be due to in-migration of higher-income households to the area. If the goal of the program is simply to make these economically distressed areas better or more attractive, then the program appears to have been successful. If instead, the program was supposed to aid the impoverished existing residents of the EZ areas then our results suggest that the program may have had little impact. Either way, the results of this paper suggest that interesting things happen throughout the entire distribution and that researchers should consider measuring program effects beyond the mean.

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Table 1: Selected Summary Statistics for EZ and EC Areas

	EZ		EC		Difference
	Mean	St. Dev.	Mean	St. Dev.	
1990					
Poverty rate	0.466	0.171	0.407	0.168	0.059***
Household income ($1,000)	18.346	7.332	19.765	7.509	-1.419***
Gross rent ($1,000)	0.346	0.101	0.378	0.124	-0.033***
House value ($1,000)	45.530	44.468	64.051	45.619	-18.521***
1980					
Poverty rate	0.304	0.139	0.234	0.128	0.070***
Household income ($1,000)	10.820	3.497	11.898	3.709	-1.078***
Gross rent ($1,000)	0.185	0.049	0.197	0.051	-0.011***
House value ($1,000)	21.312	12.870	30.932	17.008	-9.620***
N	838		3649		

Notes:
1) Asterisks denote whether the difference in means between the EZ and EC areas are statistically significant at the 10% (*), 5% (**) and 1% (***) levels.

Table 2: Effects of EZ Designation on the Poverty Rate and Mean and Median Annual Household Income, Monthly Gross Rent and House Values

Outcome	Change in EZ (1)	Counterfactual Change (2)	Difference (ATT) (3)
Poverty rate	-0.078***	-0.067***	-0.010
	[-0.091,-0.063]	[-0.077,-0.058]	[-0.022,0.003]
Average			
Annual Household Income ($1,000)	13.599***	11.555***	2.044***
	[12.686,14.577]	[11.063,12.115]	[1.021,3.092]
Monthly Gross Rent ($1,000)	0.139***	0.128***	0.010*
	[0.130,0.148]	[0.126,0.135]	[-0.001,0.022]
House Value ($1,000)	50.042***	22.912***	27.13***
	[42.253,59.040]	[21.366,24.444]	[19.545,36.152]
Median			
Annual Household Income ($1,000)	8.121***	7.870***	0.251
	[7.406,8.792]	[7.447,8.337]	[-0.570,1.077]
Monthly Gross Rent ($1,000)	0.132***	0.132***	0.000
	[0.121,0.142]	[0.125,0.139]	[-0.012,0.014]
House Value ($1,000)	42.962***	21.880***	21.082***
	[35.843,50.899]	[19.926,23.933]	[13.428,29.456]

Notes:
1) Column (1) presents the observed change in EZ areas from 1990-2000, column (2) presents the counterfactual change constructed by propensity score reweighing of the EC areas. Column (3) presents the difference between the observed and counterfactual change, the average treatment on the treated (ATT). Each row represents a separate estimation procedure.
2) 95% confidence intervals are presented in square brackets below the point estimates. The confidence intervals are based on the empirical distributions following a bootstrap procedure with 1000 replications. Asterisks denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels.

Table 3: Effect of EZ Designation on the Density of Population Across the Distribution of Household Income Relative to the Poverty Level

Ratio of Household Income to Poverty Level	Change in EZ (1)	Counterfactual Change (2)	Difference (TT) (3)
0-0.49	-0.051***	-0.062***	0.011**
	[-0.063,-0.040]	[-0.075,-0.052]	[0.001,0.024]
0.50-0.74	-0.018***	-0.012***	-0.006**
	[-0.025,-0.012]	[-0.018,-0.005]	[-0.012,-0.001]
0.75-0.99	-0.008***	-0.000	-0.008***
	[-0.014,-0.002]	[-0.005,0.005]	[-0.013,-0.003]
1.00-1.24	0.003	0.011***	-0.008***
	[-0.002,0.008]	[0.007,0.015]	[-0.012,-0.003]
1.25-1.49	0.011***	0.015***	-0.004*
	[0.007,0.016]	[0.011,0.019]	[-0.008,0.001]
1.50-1.74	0.005*	0.007***	-0.002
	[-0.000,0.009]	[0.004,0.011]	[-0.007,0.002]
1.75-1.84	0.001	0.002	-0.001
	[-0.002,0.004]	[-0.000,0.004]	[-0.003,0.001]
1.85-1.99	-0.000	0.000	-0.001
	[-0.004,0.003]	[-0.002,0.003]	[-0.004,0.002]
2.00+	0.058***	0.039***	0.019***
	[0.045,0.070]	[0.030,0.049]	[0.007,0.030]

Notes:
1) Column (1) presents the observed change in EZ areas from 1990-2000, column (2) presents the counterfactual change constructed by propensity score reweighing of the EC areas. Column (3) presents the difference between the observed and counterfactual change, the treatment on the treated (TT).
2) 95% confidence intervals are presented in square brackets below the point estimates. The confidence intervals are based on the empirical distributions following a bootstrap procedure with 1000 replications. Asterisks denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels.

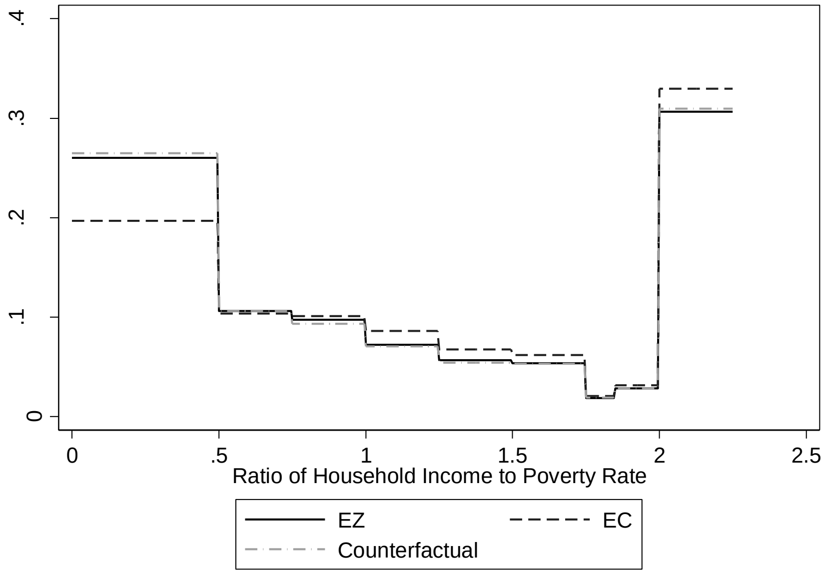
Table 4: Effect of EZ Designation on the Density of Population Across Levels of Educational Attainment and by Gross Rent as a Percent of Household Income

	Change in EZ (1)	Counterfactual Change (2)	Difference (TT) (3)
Highest Level of Educational Attainment			
Less than High School	-0.097***	-0.064***	-0.033**
	[-0.108,-0.087]	[-0.073,-0.055]	[-0.045,-0.020]
High School Degree	0.011***	0.011***	0.000
	[0.003,0.018]	[0.004,0.17]	[-0.007,0.008]
Some College	0.048***	0.032***	0.016***
	[-0.041,0.055]	[0.026,0.038]	[0.009,0.023]
Bachelor’s Degree	0.023***	0.015***	0.008**
	[0.018,0.027]	[0.010,0.021]	[0.001,0.014]
Graduate Degree	0.016***	0.007***	0.010***
	[0.012,0.020]	[0.004,0.009]	[0.005,0.014]
Gross Rent as a Percentage of Household Income			
0-0.20	0.063***	0.032***	0.031***
	[0.051,0.072]	[0.023,0.043]	[0.016,0.042]
0.20-0.25	0.006	0.007*	-0.001
	[-0.002,0.013]	[-0.001,0.014]	[-0.009,0.007]
0.25-.30	-0.002	-0.000	-0.002
	[-0.009,0.006]	[-0.008,0.008]	[-0.011,0.006]
0.30-0.35	-0.003	-0.000	-0.003
	[-0.009,0.003]	[-0.006,0.006]	[-0.010,0.002]
0.35+	-0.063***	-0.039***	-0.025***
	[-0.075,-0.050]	[-0.051,-0.025]	[-0.039,-0.009]

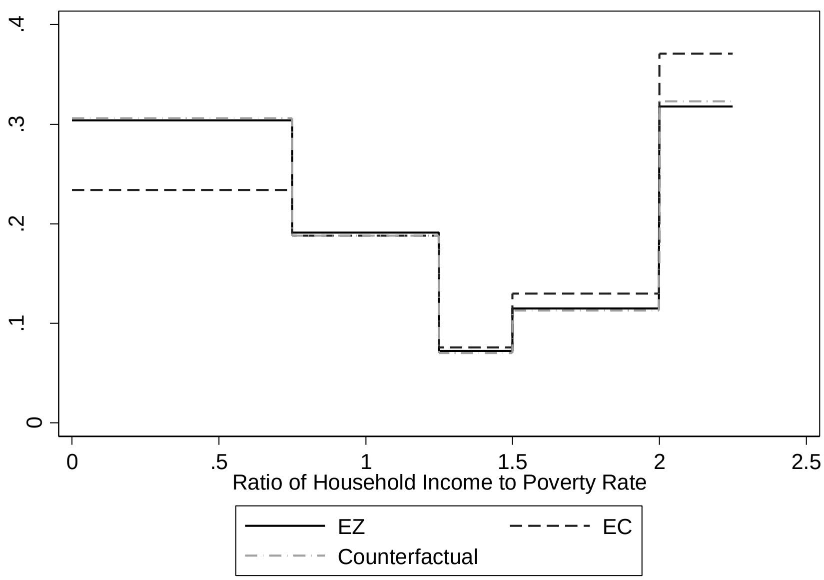
Notes:
1) Column (1) presents the observed change in EZ areas from 1990-2000, column (2) presents the counterfactual change constructed by propensity score reweighing of the EC areas. Column (3) presents the difference between the observed and counterfactual change, the treatment on the treated (TT).
2) 95% confidence intervals are presented in square brackets below the point estimates. The confidence intervals are based on the empirical distributions following a bootstrap procedure with 1000 replications. Asterisks denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels.
3) Educational attainment is measured for the population aged 25 or older. Gross rent as a percentage of household income is measured for renters.

Figure 1: Densities of Population Across the Distribution of Household Income Relative to the Poverty Level in 1990 and 1980 in EZ and EC Areas

a) 1990



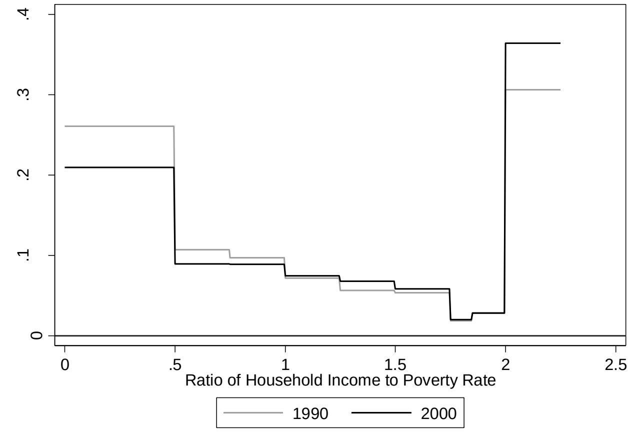
b) 1980



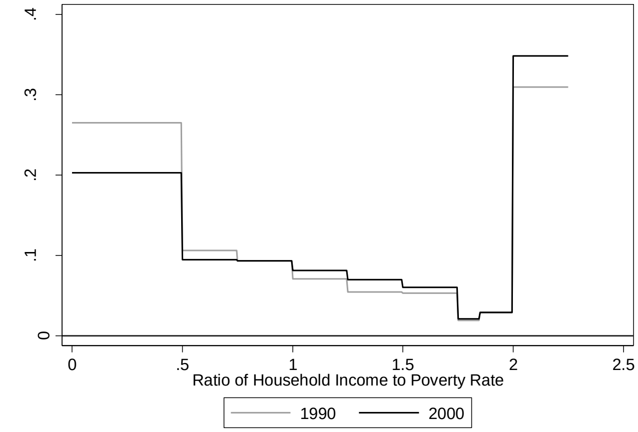
Notes:
1) The counterfactual distribution is produced by propensity score reweighting of the EC distribution.

Figure 2: Effect of EZ Designation on the Density of Population Across the Distribution of Household Income Relative to the Poverty Level

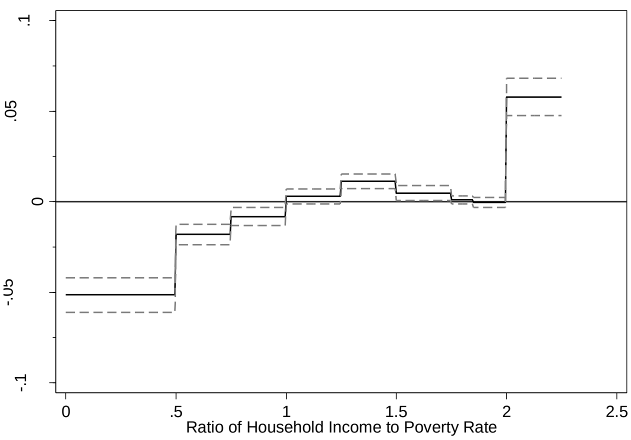
a) Distribution in EZ Areas



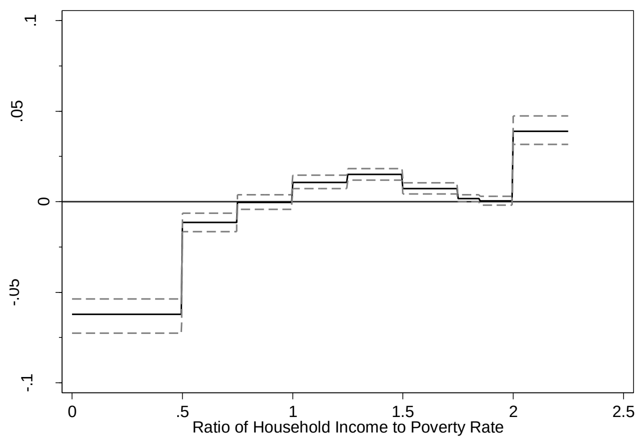
b) Counterfactual Distribution



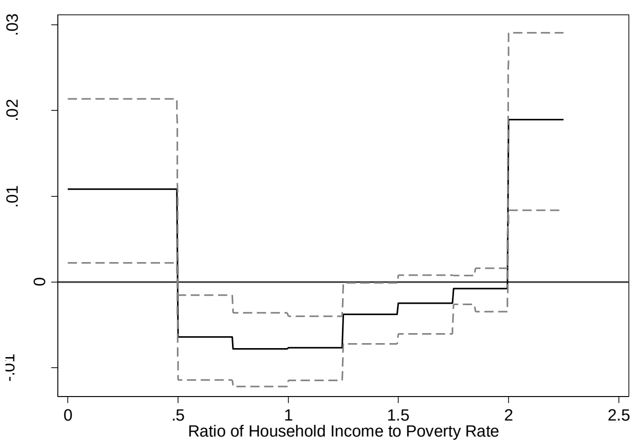
c) Change in Distribution in EZ Areas



d) Change in Counterfactual Distribution



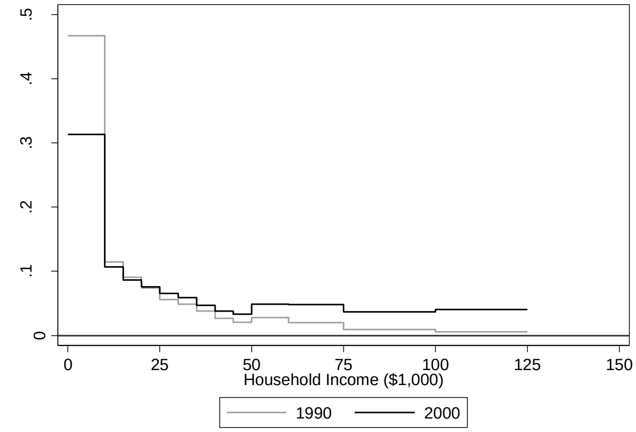
e) Difference (TT)



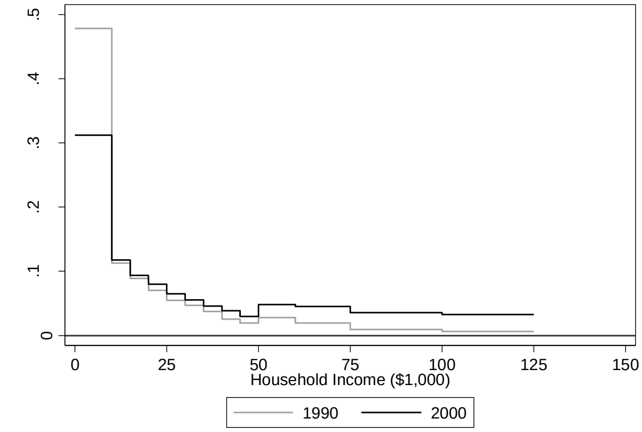
Notes:
1) Counterfactual distributions are calculated from EC areas using propensity score reweighting.
2) Dashed lines in figures c) – e) represent 95% confident intervals calculated from a bootstrapping procedure with 1000 replications. Corresponding point estimates and confidence intervals are presented in columns 1 through 3 of Table 3, respectively.

Figure 3: Effect of EZ Designation on the Density of Households Across the Distribution of Household Income

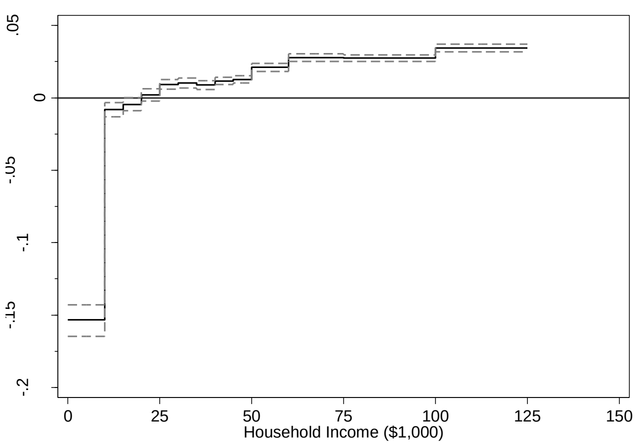
a) Distribution in EZ Areas



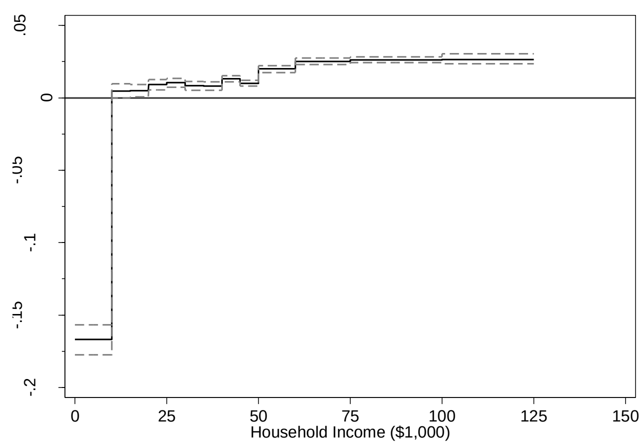
b) Counterfactual Distribution



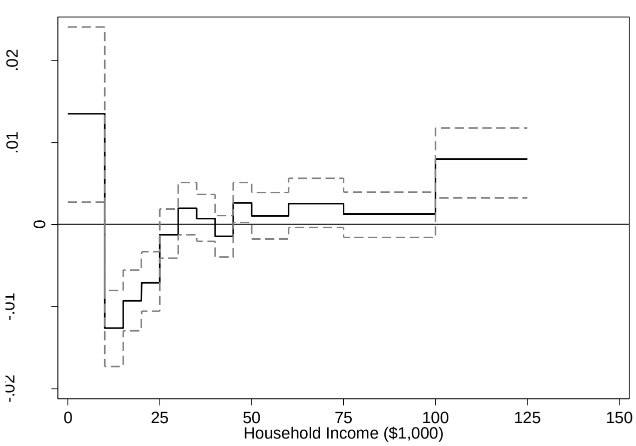
c) Change in the Distribution in EZ Areas



d) Change in the Counterfactual Distribution



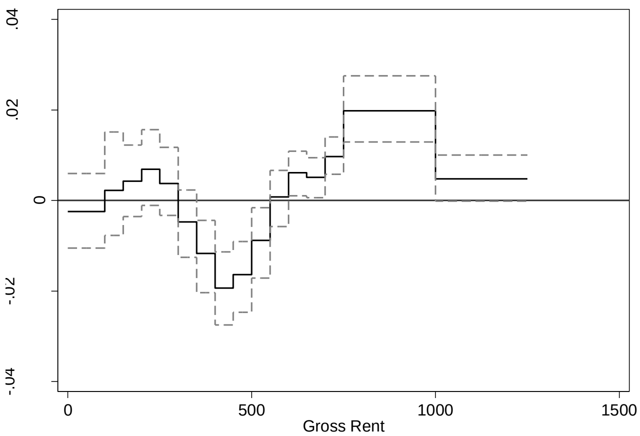
e) Difference (TT)



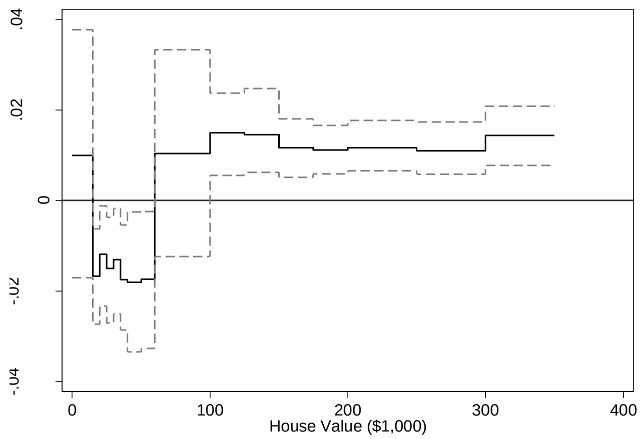
Notes:
1) Counterfactual distributions are calculated from EC areas using propensity score reweighting.
2) Dashed lines in figures c) – e) represent 95% confident intervals calculated from a bootstrapping procedure with 1000 replications. Corresponding point estimates and confidence intervals are presented in columns 1 through 3 of Appendix Table A-4, respectively.

Figure 4: Effect of EZ Designation on the Density of Households Across the Distribution of Monthly Gross Rent and House Values

a) Difference in Gross Rent (TT)



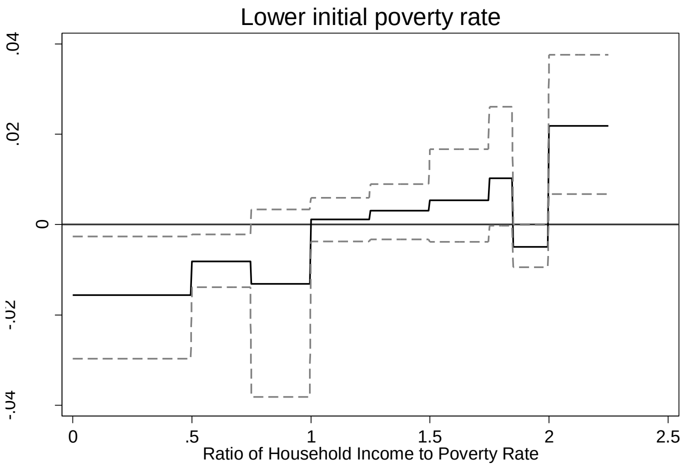
b) Difference in House Value (TT)



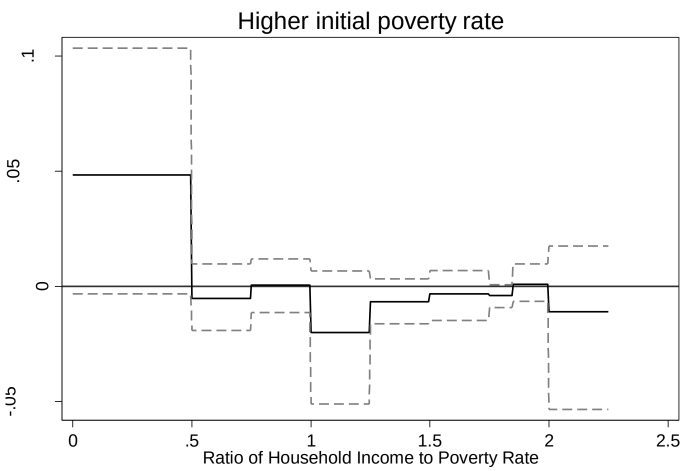
Notes:
1) Counterfactual distributions are calculated from EC areas using propensity score reweighting.
2) Dashed lines in figures a) – b) represent 95% confident intervals calculated from a bootstrapping procedure with 1000 replications. Corresponding point estimates and confidence intervals are presented in column 3 of Appendix Table A-5 and Appendix Table A-6, respectively.

Figure 5: Change in the Density of Households Across the Distribution of Household Income Relative to the Poverty Level by Initial Poverty Rate in 1990

a)



b)



Notes:
1) Dashed lines represent 95% confident intervals calculated from a bootstrapping procedure with 1000 replications.

Table A- 1: Balancing Tests for Estimating the Effects of EZ Designation on the Poverty Rate and Mean and Median Annual Household Income, Monthly Gross Rent and House Values

Outcome		EZ unmatched (1)	EC unmatched (2)	EZ matched (3)	EC matched (4)
Poverty rate	1980	0.304	0.234***	0.303	0.303
	1990	0.466	0.407***	0.465	0.463
<u>Average</u>					
Annual Household Income ($1,000)	1980	10.820	11.898***	10.573	10.690
	1990	18.346	19.765***	17.948	18.145
Monthly Gross Rent ($1,000)	1980	0.185	0.197***	0.182	0.186
	1990	0.346	0.378***	0.340	0.348
House Value ($1,000)	1980	21.312	30.932***	20.902	20.890
	1990	45.530	64.051***	41.252	39.775
<u>Median</u>					
Annual Household Income ($1,000)	1980	8.133	9.467***	7.864	7.990
	1990	13.318	15.154***	12.886	13.142
Monthly Gross Rent ($1,000)	1980	0.178	0.187***	0.175	0.177
	1990	0.324	0.361***	0.318	0.327
House Value ($1,000)	1980	21.312	30.932***	21.460	21.564
	1990	28.059	55.490***	36.300	35.825

Notes:
1) Column (1) presents the observed outcome in EZ areas in 1980 and 1990 and column (2) presents the corresponding observed outcome in EC areas. Columns (3) and (4) presents the outcomes in 1980 and 1990 following the propensity score matching procedure.
2) Asterisks denote whether the difference in means between the EZ and EC areas in the unmatched or matched samples is statistically significant at the 10% (*), 5% (**) and 1% (***) levels.

Table A-2: Balancing Tests for Estimating the Effects of EZ Designation on the Density of Households Across the Distribution of Household Income Relative to the Poverty Level

Variable	EZ unmatched (1)	EC unmatched (2)	EZ matched (3)	EC matched (4)
Income to poverty rate 0-0.74, 1980	0.304	0.234***	0.303	0.306
Income to poverty rate 0.75-0.124, 1980	0.191	0.188	0.194	0.188
Income to poverty rate 1.25-1.49, 1980	0.072	0.076*	0.072	0.070
Income to poverty rate 1.50-1.99, 1980	0.115	0.130***	0.114	0.113
Income to poverty rate 2.00+, 1980	0.318	0.371***	0.317	0.323
Income to poverty rate 0-0.49, 1990	0.266	0.200***	0.261	0.265
Income to poverty rate 0.5-0.74, 1990	0.106	0.106	0.107	0.106
Income to poverty rate 0.75-0.99, 1990	0.094	0.101***	0.097	0.093
Income to poverty rate 1.00-1.24, 1990	0.071	0.086***	0.072	0.071
Income to poverty rate 1.25-1.49, 1990	0.058	0.069***	0.056	0.054
Income to poverty rate 1.50-1.74, 1990	0.054	0.063***	0.054	0.053
Income to poverty rate 1.75-1.84, 1990	0.019	0.021	0.019	0.019
Income to poverty rate 1.85-1.99, 1990	0.029	0.032*	0.028	0.029
Income to poverty rate 2.00+, 1990	0.303	0.321***	0.306	0.310

Notes:
1) Column (1) presents the observed distribution in EZ areas in 1980 and 1990 and column (2) presents the corresponding observed distribution in EC areas. Columns (3) and (4) presents the distributions in 1980 and 1990 following the propensity score matching procedure.
2) Asterisks denote whether the differences in density in each portion of the distribution between the EZ and EC areas in the unmatched or matched samples is statistically significant at the 10% (*), 5% (**) and 1% (***) levels.

Table A-3: Effect of EZ Designation on the Density of Population Across the Distribution of Household Income Relative to the Poverty Level by Matching Method

Ratio of Household Income to Poverty Level	Re-weighting (base model) (1)	Re-weighting (alternate model) (2)	Nearest Neighbor (3)
0-0.49	0.011**	0.013*	0.012
	[0.001,0.024]	[-0.002,0.029]	[-0.015,0.029]
0.50-0.74	-0.006**	-0.005	-0.005
	[-0.012,-0.001]	[-0.011,0.002]	[-0.014,0.010]
0.75-0.99	-0.008***	-0.004	-0.001
	[-0.013,-0.003]	[-0.010,0.003]	[-0.010,0.013]
1.00-1.24	-0.008***	-0.006**	-0.009**
	[-0.012,-0.003]	[-0.011,-0.000]	[-0.020,-0.001]
1.25-1.49	-0.004*	-0.005*	-0.008
	[-0.008,0.001]	[-0.010,0.000]	[-0.017,0.002]
1.50-1.74	-0.002	-0.002	-0.001
	[-0.007,0.002]	[-0.007,0.003]	[-0.009,0.009]
1.75-1.84	-0.001	-0.002	-0.003
	[-0.003,0.001]	[-0.004,0.001]	[-0.006,0.003]
1.85-1.99	-0.001	-0.001	0.002
	[-0.004,0.002]	[-0.004,0.003]	[-0.006,0.007]
2.00+	0.019***	0.010	0.013
	[0.007,0.030]	[-0.002,0.024]	[-0.008,0.034]

Notes:
1) Column (1) presents the estimates of the base model which uses propensity score reweighting separately by quintiles of 1990 block group population.
2) Column (2) presents the estimates of an alternate propensity score reweighting procedure including controls for 1990 block group population quintiles when estimating the propensity score.
3) Column (3) presents the estimates using nearest neighbor matching with up to 10 matches within a caliper of 0.01.

Table A-4: The Effect of EZ Designation on the Density of Households Across the Distribution of Annual Household Income

Household Income ($1,000)	Change in EZ (1)	Counterfactual Change (2)	Difference (TT) (3)
0-9.0	-0.153***	-0.167***	0.013**
	[-0.167,-0.141]	[-0.179,-0.156]	[0.001,0.027]
10.0-14.9	-0.008**	0.005	-0.013***
	[-0.014,-0.002]	[-0.001,0.011]	[-0.018,-0.007]
15.0-19.9	-0.004	0.005*	-0.009***
	[-0.010,0.001]	[-0.000,0.010]	[-0.014,-0.005]
20.0-24.9	0.002	0.009***	-0.007***
	[-0.003,0.007]	[0.005,0.013]	[-0.011,-0.003]
25.0-29.9	0.009***	0.011***	-0.001
	[0.005,0.013]	[0.007,0.014]	[-0.005,0.002]
30.0-34.9	0.010***	0.008***	0.002
	[0.006,0.014]	[0.005,0.012]	[-0.002,0.006]
35.0-39.9	0.009***	0.008***	0.001
	[0.005,0.012]	[0.005,0.011]	[-0.003,0.004]
40.0-44.9	0.012***	0.013***	-0.001
	[0.009,0.015]	[0.011,0.016]	[-0.004,0.002]
45.0-49.9	0.013***	0.010***	0.003*
	[0.010,0.016]	[0.008,0.012]	[-0.000,0.005]
50.0-59.9	0.021***	0.020***	0.001
	[0.018,0.024]	[0.017,0.023]	[-0.002,0.004]
60.0-74.9	0.028***	0.025***	0.003
	[0.025,0.031]	[0.023,0.028]	[-0.001,0.006]
75.0-99.9	0.027***	0.026***	0.001
	[0.025,0.030]	[0.024,0.029]	[-0.002,0.004]
100.0+	0.034***	0.026***	0.008**
	[0.031,0.038]	[0.023,0.031]	[0.002,0.013]

Notes:
1) Column (1) presents the observed change in EZ areas from 1990-2000, column (2) presents the counterfactual change constructed by propensity score reweighing of the EC areas. Column (3) presents the difference between the observed and counterfactual change, the treatment on the treated (TT).
2) 95% confidence intervals are presented in square brackets below the point estimates. The confidence intervals are based on the empirical distributions following a bootstrap procedure with 1000 replications. Asterisks denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels.

Table A-5: The Effect of EZ Designation on the Density of Households Across the Distribution of Monthly Gross Rent

Monthly Gross Rent ($1,000)	Change in EZ (1)	Counterfactual Change (2)	Difference (TT) (3)
0.000-0.099	-0.027***	-0.024***	-0.002
	[-0.038,-0.017]	[-0.036,-0.015]	[-0.012,0.008]
0.100-0.149	-0.047***	-0.049***	0.002
	[-0.058,-0.036]	[-0.065,-0.037]	[-0.009,0.018]
0.150-0.199	-0.008**	-0.012***	0.004
	[-0.017,-0.000]	[-0.019,-0.005]	[-0.005,0.014]
0.200-0.249	-0.039***	-0.046***	0.007
	[-0.050,-0.029]	[-0.057,-0.036]	[-0.003,0.017]
0.250-0.299	-0.048***	-0.052***	0.004
	[-0.058,-0.038]	[-0.062,-0.042]	[-0.005,0.013]
0.300-0.349	-0.046***	-0.041***	-0.005
	[-0.056,-0.037]	[-0.050,-0.031]	[-0.015,0.004]
0.350-0.399	-0.039***	-0.027***	-0.012**
	[-0.048,-0.030]	[-0.036,-0.017]	[-0.022,-0.003]
0.400-0.449	-0.010**	0.009**	-0.019***
	[-0.019,-0.001]	[0.000,0.018]	[-0.029,-0.010]
0.450-0.499	0.009*	0.025***	-0.016***
	[-0.000,0.017]	[0.017,0.034]	[-0.026,-0.008]
0.500-0.549	0.031***	0.040***	-0.009**
	[0.023,0.040]	[0.033,0.049]	[-0.019,-0.000]
0.550-0.599	0.037***	0.036***	0.001
	[0.031,0.044]	[0.031,0.043]	[-0.007,0.008]
0.600-0.649	0.034***	0.027***	0.006**
	[0.028,0.039]	[0.023,0.033]	[0.000,0.012]
0.650-0.699	0.029***	0.024***	0.005*
	[0.025,0.034]	[0.020,0.028]	[-0.001,0.010]
0.700-0.749	0.030***	0.020***	0.010***
	[0.025,0.034]	[0.017,0.023]	[0.005,0.015]
0.750-0.999	0.067***	0.047***	0.020***
	[0.060,0.074]	[0.041,0.053]	[0.011,0.029]
1.000+	0.027***	0.022***	0.005
	[0.022,0.032]	[0.018,0.027]	[-0.001,0.011]

Notes:
1) Column (1) presents the observed change in EZ areas from 1990-2000, column (2) presents the counterfactual change constructed by propensity score reweighing of the EC areas. Column (3) presents the difference between the observed and counterfactual change, the treatment on the treated (TT).
2) 95% confidence intervals are presented in square brackets below the point estimates. The confidence intervals are based on the empirical distributions following a bootstrap procedure with 1000 replications. Asterisks denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels.

Table A-6: The Effect of EZ Designation on the Density of Households Across the Distribution of House Value

House Value ($1,000)	Change in EZ (1)	Counterfactual Change (2)	Difference (TT) (3)
0.000-14.999	-0.188***	-0.198***	0.010
	[-0.219,-0.161]	[-0.235,-0.170]	[-0.024,0.045]
15.000-19.999	-0.072***	-0.056***	-0.017***
	[-0.088,-0.057]	[-0.071,-0.041]	[-0.029,-0.004]
20.000-24.999	-0.039***	-0.027***	-0.012*
	[-0.053,-0.023]	[-0.039,-0.015]	[-0.025,0.001]
25.00-29.999	-0.020***	-0.005	-0.015**
	[-0.035,-0.006]	[-0.017,0.009]	[-0.029,-0.001]
30.000-34.999	-0.009	0.004	-0.013*
	[-0.024,0.007]	[-0.009,0.018]	[-0.027,0.001]
35.000-39.999	-0.006	0.012*	-0.017***
	[-0.019,0.008]	[-0.001,0.025]	[-0.031,-0.004]
40.000-49.999	0.017	0.035***	-0.018*
	[-0.004,0.038]	[0.019,0.051]	[-0.036,0.001]
50.000-59.999	0.040***	0.057***	-0.017*
	[0.024,0.055]	[0.043,0.072]	[-0.036,0.001]
60.000-99.999	0.130***	0.120***	0.010
	[0.104,0.155]	[0.099,0.139]	[-0.016,0.039]
100.000-124.999	0.036***	0.021***	0.015***
	[0.025,0.046]	[0.015,0.027]	[0.004,0.026]
125.000-149.999	0.030***	0.016***	0.015***
	[0.021,0.042]	[0.011,0.021]	[0.005,0.027]
150.000-174.999	0.019***	0.007***	0.012***
	[0.011,0.026]	[0.004,0.011]	[0.004,0.019]
175.000-199.999	0.017***	0.006***	0.011***
	[0.011,0.024]	[0.004,0.008]	[0.005,0.018]
200.000-249.999	0.016***	0.004***	0.012***
	[0.010,0.023]	[0.003,0.006]	[0.006,0.019]
250.000-299.999	0.013***	0.002*	0.011***
	[0.007,0.020]	[-0.000,0.003]	[0.005,0.019]
300.000+	0.017***	0.003***	0.014***
	[0.010,0.025]	[0.001,0.005]	[0.007,0.022]

Notes:
1) Column (1) presents the observed change in EZ areas from 1990-2000, column (2) presents the counterfactual change constructed by propensity score reweighing of the EC areas. Column (3) presents the difference between the observed and counterfactual change, the treatment on the treated (TT).
2) 95% confidence intervals are presented in square brackets below the point estimates. The confidence intervals are based on the empirical distributions following a bootstrap procedure with 1000 replications. Asterisks denote statistical significance at the 10% (*), 5% (**) and 1% (***) levels.