



Improving Population Health by Reducing Poverty:  
New York's Earned Income Tax Credit

Jeannette Wicks-Lim and Peter S. Arno

February 2015

**WORKINGPAPER SERIES**

Number 377

**POLITICAL ECONOMY  
RESEARCH INSTITUTE**

## **IMPROVING POPULATION HEALTH BY REDUCING POVERTY: NEW YORK'S EARNED INCOME TAX CREDIT**

Dr. Jeannette Wicks-Lim  
Assistant Research Professor  
Political Economy Research Institute  
University of Massachusetts, Amherst

Dr. Peter S. Arno  
Senior Fellow and Director of Health Policy Research  
Political Economy Research Institute  
University of Massachusetts, Amherst

### **JEL CODES: I140, I380**

**ABSTRACT:** The relationship between low socioeconomic status and higher levels of morbidity and mortality has been well-established in the literature. Researchers, however, rarely test the link between health improvements and social programs or economic policies designed to alleviate poverty. In this paper, we examine the health effects of the Earned Income Tax Credit (EITC), a broad-based income support program that operates at the federal, state, and local level. Specifically, we examine the health impact of expanding New York State and New York City's EITC benefits on low-income neighborhoods between 1997 and 2010. We estimate that the 15-percentage-point increase in the state and local EITC rates reduced the low birth weight rate in New York City's poor neighborhoods by 0.45 percentage points. This level of impact is substantial—from 1997 to 2010 low birth weight rates in these neighborhoods only fluctuated between 9.0 percent and 9.8 percent. Our estimates also suggest that EITC's impact on low-income neighborhoods is stronger than that experienced by the average EITC-recipient household. Aside from this study, we are aware of no other neighborhood-level analysis of EITC's impact on health. This evidence of health benefits associated with the EITC program should encourage policymakers to integrate the use of social and economic policies, such as the EITC, in their public health interventions.

**ACKNOWLEDGEMENTS:** We are grateful to Leonard Rodberg who provided us with health outcome data for New York City via the Infoshare Online database, Kenneth Knapp who constructed our original data set, and Andrew Maroko for creating the figure in our paper. We also want to thank Michael Ash, Deborah Viola, and Clyde Schechter for their substantive feedback and the research assistance provided by Mia Ellis and Najah Levers. Finally, we would like to thank Len McNally and the New York City Community Trust for supporting this work.

# IMPROVING POPULATION HEALTH BY REDUCING POVERTY: NEW YORK'S EARNED INCOME TAX CREDIT

Dr. Jeannette Wicks-Lim  
Assistant Research Professor  
Political Economy Research Institute  
University of Massachusetts, Amherst

Dr. Peter S. Arno  
Senior Fellow and Director of Health Policy Research  
Political Economy Research Institute  
University of Massachusetts, Amherst

## 1. INTRODUCTION

A well-established literature exists describing the relationship between low socioeconomic status and higher levels of morbidity and mortality (Adler and Rehkopf, 2008; Lantz et al., 1998; Pappas et al., 1993). Center for Disease Control Director Thomas Frieden highlights the significance of this relationship in his health impact pyramid—a visual depiction of how public health interventions vary in their impact (Frieden, 2010). Frieden puts public health interventions that affect socioeconomic factors at its foundation due to their ability to have “the greatest population impact.” Despite this, researchers have rarely tested the link between health improvements and social programs or economic policies designed to alleviate poverty or otherwise improve economic well-being for large segments of the population (Bhatia, 2014; Rigby, 2013. Connor et al. 1999; Bos et al. 1999; Auspos et al., 2000). Consequently, policy analysts cannot appropriately gauge this potentially valuable feature of anti-poverty programs.

Since the push to reform welfare, embodied in the Personal Responsibility and Work Opportunity Reconciliation Act (PWRORA) of 1996, states have increasingly experimented with features of their social assistance programs. We now have a solid set of time-series and panel data that we can use to analyze the health impacts of these various policy configurations. Such analyses will enable policy makers to make more optimal decisions about these types of re-distributional programs.

In this paper, we examine the health effects of one of the federal government's largest anti-poverty programs, the Earned Income Tax Credit (EITC). The EITC is a refundable tax credit to lower-income families and serves as a broad-based income support program. Among means-tested programs, federal spending on the EITC is second only to Supplemental Nutrition Assistance Program (SNAP, formerly known as food stamps), and only since the onset of the severe 2008-2009 recession.

In 2013, more than 28 million households across the country received over \$65 billion from the federal EITC,<sup>1</sup> lifting 9.4 million persons, including 5.4 million children, above

the poverty line (Center on Budget and Policy Priorities, 2014). States and a few municipalities have in increasing numbers added their own credit, typically as a top-off of the federal credit with the same eligibility requirements. As of 2014, 28 states and municipalities have local credits ranging between 3.5 and 50.0 percent of the federal benefit.

A growing body of research has begun to link these improved incomes resulting from EITC benefits and improved health outcomes. These health outcomes include children's overall health status and prenatal measures such as low birth weight (Hoynes et al., 2015; Evans and Garthwaite, 2014; Baughman, 2012; Larrimore, 2011; Strully et al., 2010; Arno et al., 2009). This study builds on this literature by examining how changes in New York State and New York City's EITC program affected health outcomes in the city's low income neighborhoods between 1997 and 2010. By 1997, New York State had adopted a 20 percent state-level EITC credit. This credit then increased incrementally to 30 percent by 2003. New York City then added a local EITC of five percent in 2004. Therefore, from 1997 to 2010, the combined state and local EITC benefits for low-income workers in New York City rose by more than 50 percent.<sup>2</sup>

This study also adds a new dimension to this research by examining the EITC's health impact at the neighborhood level. We expect to detect health effects from EITC benefits for poor communities that are distinctive from what we can observe at the individual or household level. This is because EITC dollars flow into high poverty areas in a concentrated way. As a result, the EITC can expect to have a magnified impact, not only on EITC recipient households but also EITC non-recipient households living in the same neighborhoods. A neighborhood-level analysis should more fully capture the EITC's impact on health than an individual-level analysis. Ours is the only study that we are aware of that measures neighborhood-level effects of the EITC on health outcomes.

We find that New York's EITC benefits lead to measurable health improvements among low-income children of New York City. For an EITC rate increase from 20 percent to 35 percent, low birth weight rates in the City's low-income neighborhoods fall by 0.45 percentage points. An improvement of this size is substantial when we consider that low birth weight rates have only fluctuated between 9.0 percent and 9.8 percent in these neighborhoods over the years of this study.

The size of this estimated health effect suggests that the EITC's health benefits are amplified in high-poverty neighborhoods. The magnitudes of our estimates, from our preferred specifications, are about 50 percent larger than the only comparable estimates available to-date of how EITC benefits impact low birth weight rates among EITC recipients (proxied by single mothers with a high school degree or less). In their 2012 paper, Hoynes, Miller and Simon estimate that a \$1,000 (in 2009\$) increase in EITC dollars received by these single mothers, i.e., a \$1,000 "treatment on treated," would reduce low birth weight rates by between 7 and 11 percent.<sup>3</sup> We estimate that an average \$1,000 treatment on the households in New York City's poor neighborhoods would result in a 13 to 15 percent reduction in low birth weight rates in those neighborhoods. The

midpoint between our estimates is roughly 50 percent larger than the midpoint between Hoynes et al.'s estimates.

The paper is organized as follows: Section 2 situates our study within the existing research. Section 3 provides details on our data and empirical approach. Section 4 presents our results, including robustness tests. Section 5 discusses the implications of our results. Section 6 concludes.

## **2. Related Literature**

### *2.1 Evidence of EITC's Impact on Health Outcomes*

A limited number of studies have directly examined the link between the EITC and health outcomes. These studies predominantly use a difference-in-difference strategy around policy parameter changes to identify its impact on the health outcomes of individuals most likely to receive EITC benefits (e.g. single mothers with a high school degree or less).

Two studies focus on the large federal increases that occurred during the mid-1990s, embodied in Omnibus Budget Reconciliation Act of 1993 (OBRA93). In particular, these analyses take advantage of the fact that families with two or more children received a much larger boost in EITC benefits than other family types (i.e. families with no children or families with only one child) and try to link changes in health to these differently-sized EITC benefit increases.

Evans and Garthwaite (2014) find a link between EITC benefits and improved self-reported mental and overall health and biomarkers of physical and mental stress among mothers with a high school degree or less. Their findings are consistent with past research that indicates that low socioeconomic status affect health through stress or other related physiological conditions (Seeman et al., 2008; Kubzansky et al., 1999).

Hoynes, Miller and Simon (2015) find that EITC benefits improve the birth weights of newborns to single mothers with a high school degree or less. They also consider the channels by which EITC benefits may improve low birth weight rates. They find some evidence that increased EITC benefits raise the rate of prenatal care and reduce maternal smoking, but has no impact on access to health insurance.

Two other studies examine the health impact of state-level supplemental EITC programs. Nearly all state-level EITC programs “top-off” federal EITC benefits. State programs typically use the same eligibility requirements as the federal program and set the state benefits equal to a percent of the federal benefit. Strully et al. (2010) examine state programs that operated between 1980 and 2002—up to 15 by 2002—and find that the presence of state EITC programs produces higher average birth weights among single mothers with a high school degree or less. They propose that this outcome results from the ability of small, short-term, income increases to boost expectant mothers’ nutritional intake, mitigating prenatal poverty.

Baughman and Duchovny (2010) analyze the health impacts of state programs on children's health between 1992 and 2006, when up to 20 states had adopted their own supplemental programs. They found a measurable impact on one of the four health outcomes they examined: parents' self-reported health status of older children (6-14 years old). They conclude these health improvements result from higher rates of maternal employment and the associated higher earnings.

## *2.2 Potential Neighborhood Effects: The Role of Concentrated Poverty*

A number of poverty studies have found that those living in areas of concentrated poverty experience more severe, negative effects from poverty than do poor households living in areas that have an average level of poverty.<sup>4</sup>

During 2006-2010, half of the country's poor lived in what the U.S. Census Bureau defines as "Areas of Poverty"—neighborhoods with a poverty rate of at least 20 percent. The other half lived in more mixed income neighborhoods: 31 percent in areas with a poverty rate of less than 14 percent and 19 percent in areas with a poverty rate between 14 and 20 percent (Bishaw, 2011).

The Brookings Institute's Concentrated Poverty research summarizes the unique features of living in poor neighborhoods:

Areas of concentrated poverty inflict greater negative consequences on the members of those communities above and beyond the challenges associated with individual poverty... They [areas of concentrated poverty] contribute to higher crime rates and negative health outcomes... the stress and marginalization of poverty contribute to the poor physical and mental health outcomes, such as higher incidences of asthma, depression, diabetes, and heart ailments among residents of high-poverty communities (Kneebone and Berube, 2008, p. 3).

This feature of neighborhood-level measures of poverty has two potential implications for how EITC benefits—or any income subsidy program aimed to mitigate poverty—impact health outcomes.

First, EITC benefits may improve the health of poor households residing in poor neighborhoods more than poor households residing in more mixed income neighborhoods. The positive relationship between income and health appears to be nonlinear—health improves significantly with movements up the income ladder from low to average levels, with increasingly diminishing returns to health from gains at high incomes (Robert and House, 2000). In other words, the social gradient between health and income is steepest for the lowest income levels. Poor households located in areas of concentrated poverty may be considered to occupy the very lowest rung of the income ladder, and therefore may experience a greater positive health impact from an income boost than poor households more generally. This spatial dimension of poverty however has not been distinguished in past studies of how the EITC impacts health.

Second, in poor neighborhoods, the positive affect of EITC benefits on health outcomes could spillover to non-recipient households as the EITC income subsidies reduce the neighborhood's overall level of poverty. This is simply the corollary of the well-established finding, described above, that a high neighborhood-level poverty rate has a negative impact on individual households that is independent of the individual household's economic status.<sup>5</sup> Examining the neighborhood-level impact of EITC income subsidies on health outcomes may capture these spillover effects.

### *2.3 Potential Neighborhood Effects: EITC's Multiplier Effect*

Due to the geographic clustering of poor households, the EITC effectively provides large cash injections into circumscribed areas. As a result, EITC dollars could potentially boost consumer spending in a local community that supports a higher level of local economic activity.<sup>6</sup> This increased economic activity, in turn, can generate greater income for other households in the community, "multiplying" the economic impact of each EITC dollar. In this way, the economic boost from the EITC income subsidies can spillover to their neighbors. A few studies have attempted to measure the economic benefits of the EITC program that extend beyond recipient households to the local community more broadly.

Estimates of this multiplier effect range widely. According to the various studies, every \$1 increase in consumption directly supported by the EITC generates \$1.44, \$1.58, and \$1.07 worth of economic activity in Baltimore, Maryland; San Antonio, Texas, and Nashville, Tennessee, respectively (Jacob France Institute, 2004; Texas Perspective, 2003; Haskell, 2006). If EITC benefits raise household incomes in a local economy this way, then we can expect that the overall impact on health outcomes will be larger than what we observe among EITC-recipient households alone. Therefore, the overall impact of the EITC benefits may be larger than what researchers have observed thus far by looking only at the health outcomes of recipient households.

## **3. Background, data and methods**

### *3.1 The Earned Income Tax Credit*

EITC benefits are determined primarily by two factors: the number of dependent children in the family and the total level of earnings from all working members in the family. As of 2014, the number of dependent children places households on one of four benefit schedules: those with no children; those with one child and; those with two children, and those with three or more children.<sup>7</sup> Households with no children get a maximum credit of 7.65 percent of earnings whereas households with 3 or more children get the most generous EITC benefit equal to 45 percent of earnings. This benefit structure directs the majority of the subsidies to households with young children.

On each schedule, the EITC benefit initially rises at a fixed rate along with earnings (the "phase-in" range) before hitting a maximum where the benefit stays constant as earnings

increase (the “plateau” range). As earnings go beyond the plateau range, the benefit decreases at a fixed rate until the total benefit is zero (the “phase-out” range). Owing to the refundable nature of the credit, even if workers have no federal income tax liability, as is true of most families below the poverty threshold, they can still receive the full value of the credit; thus, it effectively serves as a wage subsidy.

In 2014, for a single parent with three or more qualifying children, the phase-in range extends up to \$13,650. Therefore, as a household’s earnings move from 0 to \$13,650, the EITC benefit rises from 0 to the maximum federal EITC credit of \$6,143 (45 percent of \$13,650). Once one’s earnings exceed \$13,650, the EITC credit remains at this maximum amount of \$6,143 until the beginning of the phase-out range. When a household’s earnings reach \$17,830, EITC credits begin to fall as earnings rise above this amount. The EITC is deducted at a rate of about 21 percent. That is, 21 percent of every dollar earned above \$17,830 is subtracted from the maximum EITC credit of \$6,143. When one’s earnings reach \$46,997, the amount is equal to zero. This structure of EITC credits—with the phase-in, plateau, and phase-out ranges—means that the benefits are largest for those earning roughly 25 percent below the federal poverty line.<sup>8,9</sup>

### *3.2 New York’s State and Local EITC Supplements*

Over the last two decades, state and local governments have enacted a series of EITC reforms. In 1990, only five states had state-specific EITC policies. By 2014, 24 states and Washington DC have enacted EITC programs. New York’s state EITC rate has ticked up to among the highest, starting at 20 percent in 1994 and reaching 30 percent where it remains in 2014. Two municipalities have also adopted supplementary EITC programs. These include: New York City, which adopted its local 5 percent local EITC program in 2004 and Montgomery County, Maryland, which enacted its program in 1999, with a county credit equal to the state’s refundable credit.<sup>10</sup>

Most state and local EITC programs usually provide credit equal to a simple percentage match of the federal benefit level. For example, a New York City three-child household eligible for the 2014 maximum of \$6,143 federal EITC described above would also be eligible for a \$1,843 New York State EITC (30 percent x \$6,143) and a \$307 New York City EITC (5 percent x \$6,143).

### *3.3 Empirical Strategy*

We use a basic difference-in-difference empirical strategy to identify the impact of the EITC on the health outcomes of neighborhoods. We use panel data with annual observations of about 90 low- and middle- income ZIP codes that proxy as New York City (NYC) neighborhoods. Our treatment group includes NYC neighborhoods that have a high concentration of low-income households (more on this below) over the period of our study, 1997-2010. Our control group includes NYC moderate-income neighborhoods over the same period. Each set of neighborhoods is fixed over time. The local and state EITC benefits constitute the “treatment” and credit rate changes over time provide variations in the treatment amount. Therefore the first “difference” is the change in health



outcome observed among poor neighborhoods over time, as EITC rates increase. The second “difference” is the change in these health outcomes observed among poor neighborhoods net of any change observed among moderate-income neighborhoods occurring at the same time.

In other words, we identify the health effect of EITC benefits as the difference in health outcome trends between the control and treatment group that correlates with changes in the local EITC rate. The local EITC rate equals the New York state plus city EITC rates.<sup>11</sup> Note that we use the terms neighborhoods and ZIP codes interchangeably here.<sup>12</sup>

As noted above, our study takes advantage of recent changes in New York City’s local EITC rates: increasing from 20 percent to 35 percent of the federal benefit over the period of our study (see Table 1).<sup>13</sup>

#### TABLE 1 BELONGS HERE

Our basic model parameterizes the EITC affect, rather than using a simple indicator (before/after) measure. By parameterizing the EITC effect, we can use information from the full range of EITC credit rates implemented in New York State and New York City between 1997 and 2010.<sup>14</sup> We also add controls to better account for variations in health outcomes over time and across neighborhoods unrelated to EITC benefits, particularly local economic trends and neighborhood demographic differences:

$$\text{Health outcome}_{zt} = a + B_1 (\text{state and local EITC rate})_{t-1} + B_2 (\text{low-income neighborhood})_z + B_3 (\text{state and local EITC rate})_{t-1} \times (\text{low-income neighborhood})_z + B_4 (\% \text{ HS Deg or Less})_z + B_5 (\% \text{ African American})_z + B_6 (\% \text{ Latino})_z + B_7 (\text{NYC unemployment rate})_t + B_8 (\text{NYC minimum wage rate})_t + B_9 (\text{County indicators})_z + B_{10} (\text{Year 2001})_t + \text{Other controls for local economic trends} + e_{zt}$$

where the subscripts refer to ZIP code (z) and year (t). The interaction term between the EITC rate and the EITC-treated neighborhood indicator is our variable of interest. The coefficient B<sub>3</sub> captures changes in the health of poor communities with increasing amounts of EITC benefits while controlling for unrelated trends in health outcomes, as measured by middle-income communities that are relatively unaffected by the EITC program. In other words, we identify the EITC impact by the annual, ZIP code-level variations in health outcomes. Note that we lag our EITC rate variable by one year. This is because most households receive their EITC in a lump sum when they receive their tax refund, the amount of which is determined by the EITC rate of the previous year.<sup>15</sup>

Racially and ethnically segregated neighborhoods tend to have worse health outcomes, even while looking at neighborhoods that share similar economic features. Therefore we include demographic measures (% High school degree or less, % African American, % Latino) to control for fixed differences in health outcomes across neighborhoods.

We also include county-level indicators that may capture any spatial heterogeneity specific to the New York City boroughs. The counties are (with the corresponding

borough in parens): New York County (Manhattan), Kings County (Brooklyn), Bronx County (The Bronx), Richmond County (Staten Island), and Queens County (Queens).

The monotonic increase of New York's local EITC rate poses a difficult challenge for this statistical analysis. Since many other economic trends taking place at the same time also rise (or fall) over time in a monotonic way (e.g. price levels, worker productivity, overall economic output), it can be difficult to differentiate between changes occurring as a result of EITC rate increases as opposed to other trends. Therefore, we implement several strategies for controlling for such spurious trends.

First, we exclude from our control group above-average income neighborhoods to construct a control group that is more economically similar to the treated group than all non-poor neighborhoods. By doing so, the control group will more likely difference out simultaneously occurring trends in health outcomes caused by economic factors affecting both groups but which are unrelated to EITC credit rate change.

Second, we include two specific local economic trends, the City's unemployment rate and effective minimum wage rate. Both factors directly impact households' earnings and overall income, particularly among low- to middle- income households.

Third, we include two different sets of control variables to account for, as much as possible, other local economic trends occurring within New York City, as well as within the five counties. These two sets include:

1. A linear time trend
2. County indicators interacted with a linear time trend

Note that we do not include year indicator controls because our model contains several regressors—local EITC rate, unemployment rate, and minimum wage—that only vary by year and therefore are perfectly collinear with such controls. We do include a single indicator variable for the year 2001 to absorb some of the exogenous shock caused by the Sept. 11, 2001 terrorist attacks.

**Health outcomes.** We chose two poverty-sensitive health outcome measures for children from the Agency for Health Care Policy, Research and Quality (AHRQ) Prevention Quality Indicators. These include low birth weight rate and pediatric asthma hospitalizations per 1,000.<sup>16</sup>

Low birth weight rate, as a health predictor, has two significant advantages. First, low birth weight rate serves as a more global measure of health because past research has linked it to a wide range of longer-term affects, including future education (e.g., math test scores and high school completion) and economic outcomes (e.g., future earnings) (Hyson and Currie, 1999; Currie and Moretti, 2007; Black et al., 2007). Additionally, low birth weight rates are less prone to measurement error, allowing for more precise estimates. Finally, birth weights respond, in the short-term, to maternal diets, which EITC benefits can improve quickly (McGranahan and Schanzenbach, 2013).

Pediatric asthma hospitalizations have been strongly linked to household-level income, as well as, ZIP code-level average income. A multitude of factors have been shown to increase asthma hospitalization rates including: poor environmental conditions (e.g., air pollution, exposure to allergens indoors), improper diagnosis of asthma, inadequate management of asthma symptoms with medications, inconsistent prophylactic and maintenance therapy, and irregular access to a physician (Agency for Healthcare Research and Quality, 2001). For pediatric asthma hospitalizations specifically, past research also finds that comorbidities and genetic factors are important, along with environmental triggers. Less clear is the role of parental compliance with treatment strategies.

Smeeding et al. (2000) found that families receiving EITC payments spend some of their refund to “make ends meet” (e.g., buy food and clothes, pay bills), and a larger share to invest in “economic and social mobility” (e.g., better housing, car repairs or purchases, education). The “lump-sum” form of payment that families usually receive their EITC refunds likely influences this spending pattern. Both of these types of EITC spending can help address the wide range of factors that contribute to pediatric asthma hospitalizations such as providing reliable transportation to doctor’s visits, paying for house repairs to deal with allergens or even, moving to better housing, as well as, insuring a sufficient supply of asthma-related medications.

We also include a measure of prenatal care as a potential predictor for improved birth outcomes, including birth weight. Past studies have found suggestive evidence that prenatal care may be a mechanism by which EITC benefits may improve low birth weights (e.g., Hoynes et al., 2015). This could result directly from having more income that can be spent on health care. A number of studies have demonstrated that the EITC induces greater employment levels among poor working families. (Schmeiser, 2012; Wicks-Lim and Pollin, 2012; Dahl and Schwabish, 2009; Eissa and Liebman, 1996; Meyer and Rosenbaum, 2001; Hotz and Scholz, 2010; Hoynes, 2009; Eissa and Hoynes, 2006) Employment, in turn, may provide access to employer-provided health insurance, which can better enable women to use health care.

### *3.4. Data and variable definitions*

#### *3.4.1 Health outcomes*

Our data on low birth weight rates come from the New York State Department of Health Vital Statistics Program’s New York State County/ZIP Code Perinatal Data Profile.<sup>17</sup> Each year of data is based on a three-year period to create ZIP code based perinatal data. Low birth weight is defined as: percent of live births, newborns weighing between 100-2499 grams (2499 grams = 5.5 lbs.).

For our measure for prenatal care, we use the percent of live births with no or late (i.e., initiated in the 3<sup>rd</sup> trimester) prenatal care. These data also come from the same New York State Department of Health Vital Statistics Program’s New York State County/ZIP Code Perinatal Data Profile as the low birth weight data, and are also three-year averages.

Our prenatal care data clearly suffer from measurement errors. For example, 50 out of 88 ZIP codes had a value of zero for this measure in 2009. This compares to only 1 or 2 ZIP codes having a value of 0 percent no or late prenatal care for all other years.

Additionally, we observed dramatic spikes in the prenatal measure for only the years of 1999 and 2008 and for two ZIP codes (11224 and 11235).

To remedy these data quality issues we did the following. We simply drop ZIP codes 11224 and 11235 and data for 2009.<sup>18</sup> We replaced the values for 1999 and 2008 with an average of the data from the year immediately preceding and the year immediately following (for 2008, we used an average of 2007 and 2010).

Our pediatric asthma health outcome measure is the number of hospital discharges with a principal diagnosis code of asthma among children 5-14 years old per 1,000. Infoshare supplied these data and are sourced from the Statewide Planning and Research Cooperative System (SPARCS) of the New York State Department of Health.<sup>19</sup>

Finally, to reduce noise from these measures due to small sample sizes, we drop from our analysis of low birth weight and prenatal care observations from ZIP codes with very few live births (i.e., less than 30). This results in dropping less than 0.5 percent of our annual ZIP code observations. For our analysis of asthma hospitalization rates, we drop ZIP codes with very few youth (again, less than 30). This exclusion results in dropping 2.1 percent of our annual ZIP code observations.

### 3.4.2 Neighborhood definitions: Treatment and Control Groups

**Treatment Group.** We use three different ways to identify low-income neighborhoods—our treatment group—that are particularly impacted by EITC benefit changes. For each definition, the treatment group includes those neighborhoods that fall into the highest quartile of a specific measure (for the real median income measure, the treatment group includes ZIP codes that fall into the lowest quartile), averaged over the entire 1997-2010 time period:

- 1) EITC filers as % of All Tax Filers (Treatment group = at least 30%)
- 2) Real EITC benefit per capita (Treatment group = at least \$300 per capita, 2012\$)
- 3) Real Median income (Treatment group = Real median income falls below \$43,000 in 2012 dollars)

By using three different definitions for our treatment group, we can assess how sensitive our results are to any one particular definition.

Our EITC benefit data come from the Brookings Institute's Metropolitan Policy Program. Brookings receives ZIP code-level administrative data from the IRS on taxpayers, including detailed information about those who claimed the EITC, and offers the data at various levels of geography through an interactive on-line database (see: EITC Interactive at:

<http://www.brookings.edu/~media/Multimedia/Interactives/2014/eitc/UserGuideUpdateTY12.pdf>).

To convert the EITC benefit amount published by Brookings into a per capita measure, we use the average population size from two points in time. These data are from U.S. Census Bureau's 2000 Census and the 2006-2010 5-Year data set American Community Survey (ACS). The data from each year separately are highly correlated with each other and the average measure.

For our income measure, we also average data from the same sources and points in time. These data are likewise highly correlated with each other and the average measure. See discussion on demographic variables below for more details about how we used Census data with ZIP code-level data.

**Control Group.** Our control group consists of moderate-income ZIP codes that are less impacted by EITC benefit changes.<sup>20</sup> Moderate income ZIP codes are defined as those ZIP codes not in our treated group and with an average real median income below \$60,400. This income cutoff of \$60,400 is the “average average income”: \$60,500 is the 50th percentile value, across ZIP codes, of real median incomes averaged over 1997-2010.

### 3.4.3 Demographic variables

We add demographic data published by the U.S. Census Bureau. Note that the U.S. Census does not publish data by U.S. postal ZIP code. We constructed ZIP code level data for these demographic variables by aggregating the U.S. Census Bureau's census tract-level data to ZIP codes that existed during January-March 2010 using the Housing and Urban Development (HUD) USPS ZIP Code Crosswalk Files. These data are available from the 2000 Census and for the 2006-2010 5-Year American Community Survey data. The HUD files also provide ratios of the number of residential addresses in each tract assigned to a specific ZIP code. We use these ratios (RES\_RATIO) to weight the demographic characteristics of the residents in each tract that contributes to a ZIP code and use the weighted values to construct the demographic characteristic for each ZIP code.

ZIP codes, constructed to make mail delivery more efficient, can vary somewhat over time with population shifts, whereas Census tracts do not. Therefore some variations over time in demographics of ZIP codes constructed this way inevitably introduce error. At the same time, the high level of correlation between the demographic characteristics of the ZIP codes at the two points in time in this analysis suggests that this error is limited (See Table 2).

TABLE 2 BELONGS HERE

Ideally, we would be able to measure the demographic variables annually but these data are unavailable. However, as noted in Table 2, these measures are highly correlated over

time and therefore basically behave as “fixed” characteristics (i.e., fixed over time). Given the high levels of correlation we treated these variables as fixed over time and used the average value from 1999 and 2006-2010.

#### 3.4.4 Economic trend variables

The U.S. Department of Labor’s Bureau of Labor Statistics publishes the data for the economic trend variables including the New York City unemployment rate and the New York minimum wage rates.

### 4. Results

#### 4.1. Summary Statistics

We begin by providing summary statistics to describe our different neighborhood groupings and how they relate to each other and the EITC policy changes.

In Table 3 we present summary statistics of all the main variables in our analysis. Our three low-income neighborhood definitions largely group ZIP codes in similar ways. Compared to our middle income neighborhoods, our low income neighborhoods have noticeably higher proportions of African American (roughly 55 percent vs. 25 percent) and Latino residents (roughly 40 percent vs. 20 percent), and residents with less than a high school degree or less (roughly 65 percent versus 50 percent).

Even within our low-income communities there exist distinct racial and ethnic neighborhoods. Among these neighborhoods, about a quarter have about 20 percent or less African American and 20 percent or less Latino residents. This contrasts with another quarter of low-income neighborhoods that have at least 60 percent African American residents and at least 65 percent Latino residents. The differences across low-income neighborhoods in terms of the percent with a high school degree is much less dramatic: the 25<sup>th</sup> and 75<sup>th</sup> percentiles for this measure are much closer: 60 percent and 70 percent, respectively. The range in median incomes across low-income neighborhoods also falls within a relatively limited range—between \$30,000 and \$40,000.

The EITC receipt definition does a somewhat better job of narrowing our low-income neighborhoods—our treatment group—to those that receive larger injections of EITC dollars. For all three definitions, the control groups’ EITC participation rates are about 20 percent and the treatment groups’ EITC participation rates are about 40 percent. The actual dollar receipt of EITC benefits, however, differs between the treatment and control groups most when we use the “Per capita EITC benefit” definition.

Based on the “Per capita EITC benefit” definition, the difference in the actual dollar receipt of EITC benefits per capita between the treated and control neighborhoods exceed \$200. When we use the EITC participation rate or low median income definitions to group our neighborhoods, the difference between the treated and control groups is somewhat less at about \$150 to \$160.

The figures at the bottom of Table 3 indicate the variation of health outcomes by neighborhood grouping. Evidence of the income/health gradient is apparent. For each of the three measures, low-income neighborhoods have worse health outcomes compared to middle income neighborhoods. The lower income neighborhoods have higher rates of low birth weights, higher rates of no/late prenatal care, and higher prevalence of pediatric asthma-related hospitalizations.

TABLE 3 BELONGS HERE

Finally, Figure 1 maps which neighborhoods belong to our low-income and middle-income neighborhoods, as well as the neighborhoods we exclude from our analysis. We use the “Per Capita EITC benefit” definition for this map. As is clear from the figure, for the most part, our low-income neighborhoods cluster together. These low-income areas appear in four of the five New York City counties. The Bronx and Brooklyn counties have a larger share of low-income neighborhoods, whereas Staten Island County has none. Of the four counties that do have low-income neighborhoods, all also contain middle-income neighborhoods that serve as controls.

FIGURE 1 BELONGS HERE

We present in Table 4, summary statistics of EITC benefits at two points in time for our treatment and control groups separately. These figures illustrate how much the flow of EITC dollars has changed over the time period of our study. Specifically, we show how the average EITC per capita changed from 1997-99 to 2005-2007. Over this same time period, New York’s EITC increased from 20 percent to 35 percent. We chose these two points in time because they span the full range of changes in local EITC rates, coincide with business cycle peaks and precede the onset of the Great Recession.

During this period, our low-income neighborhoods, defined by EITC per capita, experience the largest overall income gain of \$126. These households’ gain *relative* to the households in the middle-income neighborhoods however is a smaller \$105. Given that the average household includes 3 members, this represents a net household income gain of about \$315 ( $\$105 \times 3$ ). Moreover, when we take into account that about 40 percent of tax filers in this neighborhood file for EITC credits, this income gain per recipient household, amounts to about \$788 ( $\$315/0.40=\$788$ ). This is a meaningful, but modest, relative income gain equal to a two percent increase in the average real income in these neighborhoods.

TABLE 4 BELONGS HERE

#### *4.2 Regressions Results*

We use two different regression methods to estimate our model for our two health outcomes with values bound between 0 and 1—proportion low birth weight and proportion no/late prenatal care. We use both a linear probability model (LPM) and a

generalized linear model (GLM) that uses the logit function to link the probability of the health outcome variable to a linear predictor function. This latter approach has the advantage of specifically limiting the predicted values between 0 and 1 to match the actual observed data.

Note that estimating a linear probability model (LPM) with a dependent variable that has a bounded range can produce biased coefficients (Kennedy, 1998, p. 249). This is particularly true when estimating marginal effects for values near either the 0 or 1 limit. At the same time, LPMs frequently produce estimates similar to those using methods technically more suited to this type of data, and has the advantage of ease of interpretation. Therefore, we use both the LPM and GLM to produce our regression results. The LPM results provide an immediately straightforward way to interpret our results. We can then compare the LPM results to the more oblique GLM results.

We take advantage of the fact that our data set is a panel (annual ZIP codes observations). With both the LPM and GLM, we estimate standard errors assuming heteroskedastic errors that are contemporaneously correlated across panels, and exhibit within-panel first-order autocorrelation. Note that our third health outcome measure—pediatric asthma-related hospitalizations per 1,000—is not bound between 0 and 1 and is not a proportion. Therefore, we do not estimate the regressions with this dependent variable using a generalized linear model.

Table 5 presents our LPM (or just linear regression model in the case of the asthma-related outcome) results. We show only the estimate and standard errors for the parameterized EITC “treatment” affect interacted with our low-income community indicator (Col. 1). Each entry in the table represents a different regression.

For each health outcome, there are nine estimates. We use each of the three different definitions for our low-income neighborhoods discussed above and three different sets of controls. In the first column, the only control we include for local economic trends is the unemployment rate and the real value of the minimum wage. In the second column, we add a linear time trend to control for other local economic trends. The controls added to column 3 allow the linear time trend to vary by county. Each panel of Table 5 display results for one of our three health outcome measures.

Panel A shows our results for the health outcome measure “percent low birth weight rate.” These estimates measure how much the low birth weight rate changes for low-income neighborhoods given a change in the local EITC rate. These estimates are net of any changes in the low birth weight rate occurring in middle-income neighborhoods at the same time.

The nine estimates for low birth weight rate are all negative, indicating that increases in EITC benefits are associated with reductions in low birth weight rates. The estimates range between about -0.02 and -0.03, indicating that a 10 percentage point increase in the local EITC rate typically results in a -0.2 to -0.3 percentage point decline in the low birth weight rate among low-income neighborhoods.



The estimates based on the per capita EITC definition and our median income definition for our low-income neighborhoods are sufficiently precise to draw some conclusions about the relationship between EITC benefits and low birth weight rates. This is true regardless of which controls we include.

Panel B shows our results for the outcome measure “percent no or late prenatal care.” Similar to the results for the percent low birth weight rates, the nine estimates are all negative. Only one estimate out of nine is precise enough to rule out an estimate of zero. This result, however, is not robust to adding the time trend controls.

Panel C shows our results for the outcome measure pediatric asthma-related hospitalizations per 1,000. As with the other health outcome measures, these estimates are consistently negative. About half of these estimates, however, are not precise enough to achieve statistical significance by conventional standards. At the same time, the statistically significant results appear with all three sets of controls when we define our low-income neighborhoods by their “average median income” and not by actual EITC receipt. This pattern may be due to the fact that the “average median income” definition is likely to be more susceptible to producing spurious results. Out of the three neighborhood definitions, the “average median income” definition is the only one that does not rely on a measure of actual EITC receipt. Moreover, adding controls for county-specific time trends substantially reduces the magnitude of the estimated impact of the local EITC rate on pediatric asthma-related hospitalizations in low-income neighborhoods.

TABLE 5 BELONGS HERE

Table 6 presents analogous GLM results for the percentage low birth weight and percent late/no prenatal care dependent variables. In order to facilitate the interpretation of the GLM results, we present alongside the GLM coefficient and standard errors, the difference between the average marginal effect of the EITC rate for our low-income neighborhoods and our middle-income neighborhoods.<sup>21</sup> This measure provides a comparable metric to the LPM coefficient on the local EITC rate interacted with the low-income neighborhood indicator.

The results remain largely the same for both health outcomes. For low birth weight rates, nearly all of the estimates are precise enough to rule out an estimate of zero effect at conventional levels. The magnitudes of the estimated average marginal effect of the EITC for low-income neighborhoods on low birth weight rates are somewhat larger compared to the LPM results, ranging between about 0.03 and 0.04. As before, none of the estimates for the no/late prenatal care measure are precise enough to rule out an estimate of zero effect at conventional levels.

Overall, taking into account all our results from Tables 5 and 6, we conclude that our regression estimates for our prenatal care and asthma outcomes are not robust to modest variations in model specification. Only our estimates for low birth weight rates are stable

across the specifications we have presented thus far. In the next section we will focus further robustness tests on our estimated negative relationship between the EITC and low birth weight rates.

TABLE 6 BELONGS HERE

### *4.3 Robustness tests*

#### 4.2.1 Alternative controls for geographic heterogeneity

In this section, we examine whether the relationship we observed between the EITC and low birth weight rates is robust to including a more fine-grained level of geographic controls to account for geographic heterogeneity. We can use ZIP code level, rather than County level indicators in our model.

We do not interact our ZIP code indicators with a time-trend variable. ZIP code level indicators interacted with a time trend would absorb much of the variation in health outcomes by neighborhood that could be correlated with the EITC rate, including between low- and middle- income neighborhoods. This is because the correlation coefficient between the local EITC rate and a year trend variable is nearly perfect at 0.94 and we are using annual ZIP code observations. Therefore, at most, we would want to control for spatially heterogeneous trends at the County level.

Recall that for our empirical strategy, the differences in health trends between the two types of neighborhoods—neighborhoods that benefit substantially from the EITC program expansions and neighborhoods that benefit only modestly—are crucial for identifying the EITC affect. When we include county indicator variables interacted with a year trend variable, we can still identify the EITC affect on health by examining within-County differences in trends between the two types of neighborhoods.

In Table 7, we provide both LPM and GLM estimates, this time including ZIP code indicators with year indicators. We can see that including controls at the zip code level do not meaningfully change the results.

TABLE 7 BELONGS HERE

#### 4.2.2: Testing Whether Regional Trends in Low Birth Weight Rate Explain Low Birth Weight Rates in New York’s Poor Neighborhoods

In this section we probe further the question of whether the negative relationship we observe between the low birth weight rates within NYC’s low-income neighborhoods and the local EITC rate is spurious.

It is possible, for example, that there is a secular decline in low birth weight rates among low-income households in the region specifically—and not among nearby middle-income neighborhoods—that is unrelated to the EITC.

Unfortunately, we are unable to identify any way to divide low-income neighborhoods within NYC further to form a new set of treatment and control groups that we could analyze. This is because EITC benefits are high for any subset of NYC's low-income neighborhoods. Therefore, we cannot directly control for trends that are specific to low-income neighborhoods—and different from middle-income neighborhoods—within NYC.

Two obvious alternative tests exist. First, we could examine trends in low birth weight rates prior to our study period so that, in effect, low-income neighborhoods act as their own control group. For low-income neighborhoods to serve as their own control group during this pre-study period, however, they must not be exposed to any “treatment” (i.e., increase in EITC benefits). Federal EITC expansions during the years immediately preceding our study period preclude this test.

The second approach is to look just outside of New York for a group that is similarly low-income, but unexposed to New York's City and State EITC expansions. After identifying such a group, we can include a measure of the low birth weight rate for such a group as an additional control in our basic model. This alternative group should be similar to our low-income NYC neighborhoods along the dimensions of income level, average low birth weight rate, and geographic location, but would actually not experience any increase in EITC benefits (i.e., would be “untreated”).<sup>22</sup>

If the trends in low birth weight rates of the alternative group explain well the trends in NYC, this would suggest that the decline in low birth weight rates among NYC's low-income neighborhoods from 1997 to 2010 resulted from some factor other than New York's EITC programs. We consider the two states that flank the NYC area—New Jersey and Connecticut—to find an alternative low-income group for an additional control.

We rule out New Jersey because it expanded its EITC program during the study period. Beginning in 2000, New Jersey adopted a 10 percent state EITC that subsequently increased in steps each year through 2004 to 20 percent.

To measure low birth weight rate trends for communities in Connecticut similar to our low-income NYC neighborhoods, we use Black and Latino households statewide. Ideally, we would have ZIP code level data and we could construct trends based on low-income communities in Connecticut defined in a similar way as our NYC neighborhoods. However, we do not have access to ZIP code level data for Connecticut, and no metropolitan areas in Connecticut resemble our NYC neighborhoods in terms of their average low birth weight rates or income levels. Based on data over two decades—from 1990 to 2010—we find that on both dimensions, Black and Latino Connecticut families most closely approximate these characteristics of our low-income NYC neighborhoods.

The average low birth weight rate between 1990 and 2010 for Connecticut's Black and Latino families is 10.5% versus 9.7% for our NYC low-income neighborhoods.<sup>23</sup> With regard to income, in 2009, the median incomes for African American and Latino Connecticut households are \$41,800 and \$39,500, respectively.<sup>24</sup> These medians fall

between the roughly \$33,000 median for our NYC low-income neighborhoods and \$47,000 for our middle-income NYC neighborhoods (these are the average medians in comparable 2009 dollars).

Correlation coefficients indicate that the low birth weight rates among these lower income households in Connecticut and NYC move broadly together (see Table 8). This is in contrast to the negative correlation between the low birth weight rates of NYC's low-income and middle-income neighborhoods.

#### TABLE 8 BELONGS HERE

We add the trend in low birth weight rates among Black and Latino Connecticut households to our model as a control in two different ways. First, we include the trend variable by itself to examine whether there appears to be any relationship between the Connecticut low birth weight rates among Black and Latino households and among low- and middle- income neighborhoods in NYC. Specifically we add to our model the term:

*B<sub>11</sub> (low birth weight rate among Black and Latino Connecticut households)<sub>t</sub>*

We then add a second control that allows the relationship between the low birth weight rates to vary between low- and middle-income NYC neighborhoods. Specifically we add to our model the following term:

*B<sub>12</sub> (EITC-treated neighborhood)<sub>z</sub> x (low birth weight rate among Black and Latino Connecticut households)<sub>t</sub>*

In other words, this interaction term enables our regression to separately estimate: (1) a relationship between the trend in low birth weight rates of Black and Latino Connecticut households and our low-income NYC neighborhoods and (2) a relationship between the trend in low birth weight rates in the Black and Latino Connecticut households and our middle-income NYC neighborhoods. With this additional control, the model can account for regional trends in low birth weight rates among low-income households specifically. Our other controls will continue to account for trends in low birth weight rates within the City itself.

In Tables 9 (LPM estimates) and 10 (GLM estimates), we present our results with these new controls. In each table, we include in column 1, our County-specific time trend controls and in column 2, our ZIP code-level indicators with an overall time trend control.

#### TABLES 9 AND 10 BELONG HERE

The coefficients on the Connecticut measure cannot be distinguished from zero. These results suggest there is no measurable regional trend in low birth weight rates that may explain the trends in NYC. Additionally, there appears to be no distinguishable difference in the relationship between the Connecticut low birth weight rates and low-income and

middle-income NYC neighborhoods separately. In other words, regional trends in low birth weight rates, as measured by Black and Latino Connecticut households, do not appear to explain the trends in low birth weight rates among NYC's low-income households.

At the same time, our coefficients of interest—the EITC rate interacted with our low-income neighborhood indicator variable—are consistently negative. And, in most cases, these estimates are sufficiently precise to achieve statistical significance at conventional levels. The magnitudes of these coefficients suggest a marginal effect of the EITC in the range of a 0.20-0.50 percentage-point improvement in low birth weight rates for a 10-percentage-point increase in the EITC rate.

The results of these robustness tests increase our confidence in our main results: i.e., that the rise in the local (New York) EITC rate has lowered the low birth weight rate in NYC's low-income neighborhoods.

Our preferred specifications use: (1) GLM because it is a more appropriate estimation method for the low birth weight rate outcome; (2) EITC Benefit Per Capita to define our low-income neighborhoods because it divides our neighborhoods to produce the clearest contrast in EITC benefits between our treatment and control group (see Table 4); and (3) includes county-specific time trends because these seem to most thoroughly control for potential spurious trends. Based on these criteria, our results suggest that increasing the local EITC rate by 10 percentage points reduces low birth weight rates between 0.26 and 0.30 percentage points.

## **5. Discussion**

### *5.1 Evaluating the magnitude of our estimated EITC effect*

The results above provide empirical evidence that increased EITC benefits improves at least one measure of health for low-income NYC neighborhoods—low birth weight rates.

We estimate that, while controlling for trends in low birth weight rates among NYC middle-income neighborhoods as well as Black and Latino Connecticut households, a 10-percentage point increase in the local EITC rate (New York State and City's combined) reduces low birth weight rates in the range of 0.3 percentage points. Over the time period of our study, the New York State and New York City EITC rates combined increased from 20 percent to 35 percent by 2004. Our estimates indicate that these rate increases would lead to a 0.45 percentage-point reduction in low birth weight rates.

Is this estimated impact large or small? One way to gauge the magnitude of our estimates is to consider that the average low birth weight rate across NYC's poor neighborhoods only varied between 9.8 percent and 9.0 percent over this study's entire 14-year period, from 1997 to 2010 – i.e., a range of 0.8 percentage points. Therefore, the magnitude of our estimates suggests that recent policy changes in the EITC program may have played a

sizable role in any improvements in the low birth weight rates among NYC's poor neighborhoods.

As discussed above, of primary interest to us is whether the impact of EITC benefits on neighborhood-wide health outcomes are larger than those observed at the individual household level. We attempt, in this study, to capture more fully the potential health impact of EITC benefits by measuring its affect at the neighborhood level. By doing so, our estimates should capture health affects that result from any positive neighborhood-wide economic impacts from EITC benefits, not just those that occur within EITC-recipient families.

Our neighborhood-level observations allow us to generate estimates of the EITC health effect at the neighborhood level, but not the individual/family level. Fortunately, Hoynes et al.'s 2012 study present estimates of how the EITC affects low birth weight rates at the individual/family level appropriate for comparison with our own estimates.<sup>25</sup> Specifically, they present figures on the percent reduction in low birth weight rates which they link to a \$1000 EITC (2009\$) "treatment on treated" (ToT) that occurred as a result of the federal EITC expansions of the mid-1990s.

In the Hoynes et al. study, single mothers with a high school degree or less constitute their treated (or "high-impact") group since a large share of that demographic group qualifies for EITC benefits. Hoynes et al. (2012, p. 13) estimate that 42 percent of single women 18-45 years old with a child under age 3 and a high school education or less receive EITC benefits. Our treated group – low-income neighborhoods, variously defined – has a near-equal level of EITC eligibility (39-40 percent) as indicated by the share of EITC tax filers (see Table 3).<sup>26</sup> In other words, our poor neighborhoods, with respect to EITC "exposure", resemble the demographic group of single mothers with young children and a high school degree or less. This similar degree of EITC exposure between the two different treated groups allows us to directly compare our estimates of a \$1,000 (2009\$) ToT to that of Hoynes et al. (2012). Thus, we can gauge whether differences exist between the individual/household level and neighborhood-level health effects associated with EITC benefits. We present the comparison figures in Table 11.

Our regression estimates suggest that a 15-percentage-point EITC rate increase reduces the low birth weight rates in NYC's impoverished neighborhoods by between 0.39 percent and 0.45 percent. We know from our figures presented above in Table 4 that households experienced a net gain, on average, of \$315 (in 2012\$) in EITC benefits from 1997-99 to 2005-07 when the local EITC rate increased by 15-percentage points. If we scale this figure to show the impact of a \$1,000 (2009\$) EITC treatment, the ToT per \$1,000 would be between 1.2 and 1.4 percentage points, representing a 13 to 15 percent reduction in the average low birth weight rate in those neighborhoods (see Table 11).

In the last row, we present Hoynes et al.'s (2012) comparable estimates of the impact of the ToT per \$1000 at the individual levels. Their estimates for this figure range between 6.7 percent and 10.8 percent. Our point estimates of the EITC health impact measured at the neighborhood level, therefore, appear substantially larger than when measured at the

individual level. A comparison between the midpoints of these two ranges suggests a neighborhood-level affect roughly 50 percent larger.<sup>27</sup>

#### TABLE 11 BELONGS HERE

Our estimates of EITC's magnified affect on low birth weight rates among low income neighborhoods suggests that it may be a useful policy tool for reducing health disparities by race and income.

#### *5.2 Why no measurable impact on pediatric asthma-related hospitalizations and rates of no/late prenatal care?*

In contrast to our estimate of EITC's impact on low birth weight rates, our results for pediatric asthma-related hospitalizations and the no/late prenatal care rates indicate no consistent relationship with EITC benefits.

It may be that of our three health-related outcomes, low birth weight rate is the most likely to respond in the short term to the meaningful, but still modest, relative income gains that our low-income neighborhoods experience. Note that due to our difference-in-difference type analysis, we are examining the impact of the *net* gain in income due to a rise in EITC rates – i.e., how much more of an EITC increase households in low-income neighborhoods receive relative to households in middle-income neighborhoods. As we indicated in Table 4, for EITC-recipient households, these increases typically represent an income gain of about two percent. Even assuming that the impact of the EITC on recipient household spills over to their neighbors, the fact remains that the impact on the direct beneficiaries is modest.

Improving one's diet can be done quickly, with relatively few barriers to doing so, and in any range of increments—small or large. And, birth weights respond quickly to changes in maternal diets. Therefore, given the size of the relative income gains we are examining, birth weights may be the most likely outcome to respond.

Reducing pediatric asthma hospitalizations and increasing prenatal care, on the other hand, may demand a combination of changes that require a larger infusion of income, and greater levels of effort not adequately supported by the EITC benefit increases we are examining. For example, our estimated net annual household income gains of about \$790 may only allow for limited improvements in housing conditions. Moreover, a two-percent income gain may not be adequate to improve one's ability to find appropriate health services and/or coordinate medical care appointments that improve asthma management.

The same could also be said for access to prenatal care. In other words, the EITC gains we examine may facilitate the kind of spending that Smeeding et al. (2000) referred to as “making ends meet” (e.g., buy food and clothes, pay bills), rather than investing in “economic and social mobility” (e.g., better housing). At the same time, our results are inconsistent with past findings of a positive impact of EITC on prenatal care (Hoynes et al., 2015).

Our study, unfortunately, does not provide any way to examine the specific channels by which EITC benefits do or do not influence these various health-related outcomes. We can only speculate as to reasons behind our uneven results. The data quality issues for our measure of prenatal care outcomes, however, likely contribute to our inconsistent and imprecise estimates for that measure.

We want to add one final note about the unevenness of our results. The fact that health outcomes did not improve across the board allows us to rule out one type of spurious relationship that we cannot control for within our model: neighborhood gentrification over this period that should lead to across-the-board improvements in health outcomes.<sup>28</sup> That is, if, over the time period of our study, higher income households replace lower income households within the same neighborhood, we would expect that this would cause all three health outcomes to measurably improve, not just one.

## **6. Conclusion**

Our analysis suggests that the New York State and City EITC expansions between 1997 and 2010 improved health outcomes in the City's low-income neighborhoods. Specifically, our estimates suggest that the 15-percentage-point increase in New York's EITC rate (state and city combined) reduced the low birth weight rate in poor neighborhoods by 0.45 percentage points. This level of impact is substantial. During this time period, low birth weight rates fluctuated between a relatively narrow range—between 9.0 percent and 9.8 percent.

Our estimates also suggest that EITC's impact on low-income neighborhoods is greater than the health improvements experienced by the average EITC-recipient household across all neighborhoods. Ours is the only study that we are aware of that does a neighborhood-level analysis of EITC's impact on health. The magnitudes of our estimates of how the EITC affects low birth weight rates are substantially larger than comparable estimates in previous research by Hoynes et al. (2012). Our results therefore suggest that the EITC is even more effective at improving health when targeted at high poverty areas in particular. Due to the large overlap between economically-segregated and racially-segregated neighborhoods (see Table 3), the EITC may prove to be a useful tool for reducing both racial and socioeconomic disparities in health outcomes.

Beyond evaluating the impact of this specific policy, the findings of this study provide useful insight into the relationship between income and health more generally. Examining the relationship between EITC policy changes and health outcomes is especially useful for enhancing our understanding of how income impacts health. Social policy changes can provide a source of income variation that is relatively exogenous to individual or household characteristics. This allows the researcher to avoid the endogeneity problem that frequently arises in studying the income/health gradient, i.e., the problem of distinguishing between changes in health that lead to changes in income and changes in income which cause changes in health. This study provides evidence that some of the



well-established correlation between improved health and earnings can be explained by how income gains result in improved health, rather than the reverse.

The positive health benefits associated with the EITC should encourage policymakers to integrate the use of social and economic policies, such as the EITC, in their public health interventions and at the same time lend additional support to the viability and utility of such programs.

## References

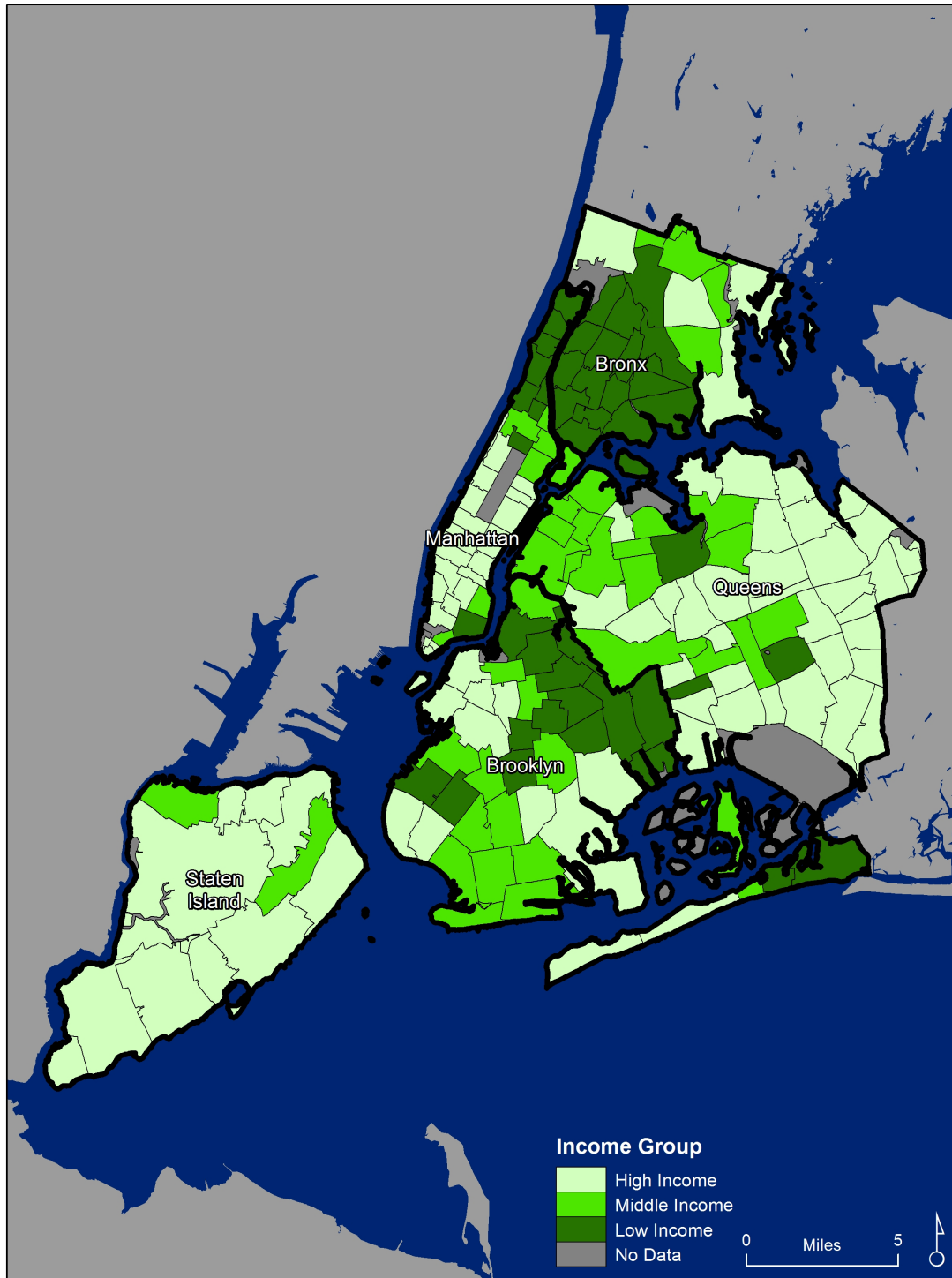
- Adler, N. E., Rehkopf, D.H. 2008. US disparities in health: descriptions, causes, and mechanisms. *Annu Rev Public Health*. 29, 235–52.
- Agency for Healthcare Research and Quality. (2001, rev. 2002). AHRQ quality indicators—guide to prevention quality indicators: hospital admission for ambulatory care sensitive conditions (AHRQ Pub. No. 02-R0203). Rockville, MD: Agency for Healthcare Research and Quality.
- Arno, P.S., Sohler, N., Viola, D., Schechter, C. 2009. Bringing health and social policy together: the case of the earned income tax credit. *Journal of Public Health Policy*. 30, 198-207.
- Auspos, P., Miller, C., Hunter, J.A. 2000. Final report on the implementation and impacts of the Minnesota family investment program in Ramsey County. New York: MDRC.
- Baugham, R.A. 2012. The effects of state EITC expansion on children’s health. Carsey Institute, Issue Brief No. 48, Spring.
- Bhatia, R. 2014. Health impacts of raising California's minimum wage. Human Impact Partners, Oakland, CA. May. Available at: <http://bit.ly/1pFhOeW>
- Bishaw, A. 2011. Areas with concentrated poverty: 2006-2010. American Community Survey Briefs, December.
- Black, S. E., Devereux, P. J., Salvanes, K.G. 2007. From the cradle to the labor market? The effect of birth weight on adult outcomes. *The Quarterly Journal of Economics*, 122(1), 409-439.
- Bos, J., Huston, A., Granger, R., Duncan, G., Brock, T., McLoyd, V. 1999. New hope for people with low incomes: Two-year results of a program to reduce poverty and reform welfare. New York: MDRC.
- Center on Budget and Policy Priorities. 2014. Policy basics: Earned Income Tax Credit, January 30. Available at: <http://www.cbpp.org/files/policybasics-eitc.pdf>.
- Connor, J., Rodgers, A., Priest, P. 1999. Randomized studies of income supplementation: A lost opportunity to assess health outcomes. *J Epidemiol Community Health*, 53, 725-30.
- Currie, J., Moretti, E. 2007. Biology as destiny? Short- and long-run determinants of intergenerational transmission of birth weight. *Journal of Labor Economics*. 25, 231-264.

- Hyson, R., Currie, J. 1999. Is the impact of health shocks cushioned by socioeconomic status? The case of low birthweight. *American Economic Review*. 89(2), 245-250.
- Eissa, N. and Hoynes, H. Behavioral responses to taxes: Lessons from the EITC and labor supply." *Tax Policy and the Economy*. 2006; 20:74-110.
- Evans, W. N., Garthwaite, C.L. 2014. Giving mom a break: The impact of higher EITC payments on maternal health. *American Economic Journal: Economic Policy*. 6(2): 258–290.
- Frieden, T. 2010. A framework for public action: The health impact pyramid. *American Journal of Public Health*. 100(4), 590-595.
- Haskell, J. N. 2006. EITC boosts local economies. *Partners in Community and Economic Development*, Federal Reserve Bank of Atlanta. 16 (3) (Available from: [https://www.frbatlanta.org/commdev/publications/partners/partners-vol\\_16\\_no\\_3-eitc\\_boosts\\_local\\_economies.aspx](https://www.frbatlanta.org/commdev/publications/partners/partners-vol_16_no_3-eitc_boosts_local_economies.aspx); Accessed February 4, 2015).
- Hotz, J. V., Scholz, J.K. 2010. Examining the effect of the Earned Income Tax Credit on the labor market participation of families on welfare. Unpublished manuscript. Available from: [http://public.econ.duke.edu/~vjh3/working\\_papers/EITC2.pdf](http://public.econ.duke.edu/~vjh3/working_papers/EITC2.pdf).
- Hoynes, H. W. 2009. The Earned Income Tax Credit, welfare reform, and the employment of low-skilled single mothers. In M. Toussaint-Comeau and B. Meyer, eds. *Strategies for improving economic mobility of workers: Bridging theory and practice*. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.
- Hoynes H. W., Miller, D. L. , Simon, D. 2012. Income, the Earned Income Tax Credit, and infant health. NBER Working Paper No. 18206, July. Available from: <http://www.nber.org/papers/w18206>.
- , 2015. Income, the Earned Income Tax Credit, and infant health. *American Economic Journal: Economic Policy*. 7(1), 172-211.
- Jacob France Institute. 2004. *The importance of the Earned Income Tax Credit and its economic effects in Baltimore City*. Baltimore, MD: The Jacob France Institute, University of Maryland.
- Kennedy, P. 1998. *A Guide to Econometrics*, 4<sup>th</sup> ed. Cambridge, MA: The MIT Press.
- Kneebone, E. Berube, A. 2008. *Reversal of Fortune: A New Look at Concentrated Poverty in the 2000s*. Metropolitan Policy Program at Brookings, August. Available at: <http://bit.ly/1qCYBy5>

- Kubzansky, L., Kawachi, I., Sparrow, D. 1999. Socioeconomic status and risk factor clustering in the normative aging study: Any help from the concept of allostatic load? *Annals of Behavioral Medicine*. 21(4), 330–338.
- Larrimore, J. 2011. Does a higher income have positive health effects? Using the Earned Income Tax Credit to explore the income-health gradient. *Milbank Quarterly*, 89(4), 694-727.
- Lantz, P.M., House, J.S., Lepkowski, L.M., Williams, D.R., Mero, R.P., Chen, J. 1998. Socioeconomic factors, health behaviors, and mortality. *JAMA*. 279, 1703-8.
- McGranahan, L., Schanzenbach, D.W. 2013. The Earned Income Tax Credit and food consumption patterns. November 20, Federal Reserve Board Working Paper, WP 2013.14. Available at: [https://www.chicagofed.org/digital\\_assets/publications/working\\_papers/2013/wp2013\\_14.pdf](https://www.chicagofed.org/digital_assets/publications/working_papers/2013/wp2013_14.pdf).
- Meyer, B. and Rosenbaum, D.T. 2001. Welfare, the Earned Income Tax Credit and the employment of single mothers. *Quarterly Journal of Economics*. 116(3), 1063-114.
- Pappas, G., Queen, S., Hadden, W., Fisher, G. 1993. The increasing disparity in mortality between socioeconomic groups in the United States, 1960 and 1986. *N Engl J Med*. 329,103-109.
- Rigby, E. 2013. Economic policy: An important (but overlooked) piece of “Health in all policies.” Discussion Paper, Institute of Medicine, Washington, DC. September 18. Available at: <http://bit.ly/TnAUvm>
- Robert, S. A., House, J. S. 2000. Socioeconomic inequalities in health: Integrating individual, community and societal-level theory and research. In G. Albrecht, R. Fitzpatrick and S. Scrimshaw (eds.), *Handbook of Social Studies in Health and Medicine*. Thousand Oaks, CA: Sage Publications.
- Schmeiser, M.D. 2012. Expanding New York State's Earned Income Tax Credit program: The effect on work, income and poverty. *Applied Economics*. 44(16), 2035-2050.
- Seeman, T., Merkin, S. S., Crimmins, E., Koretz, B., Charette, S., Karlamangla, A. 2008. Education, income and ethnic differences in cumulative biological risk profiles in a national sample of US adults: NHANES III (1988–1994). *Social Science and Medicine*. 66(1), 72-87.
- Smeeding, T., Ross Phillips, K. and O’Connor, M. 2000. The EITC: Expectation, knowledge, use, and economic and social mobility. *National Tax Journal*. 53(4), 1187-1210.

- Spencer, J. H. 2007. Neighborhood economic development effects of the earned income tax credit in Los Angeles: Poor places and policies for the working poor. *Urban Affairs Review*. 42(6) July, 851-873.
- Stringer, S. 2014. *The growing gap: New York City's housing affordability Challenge*. New York: Bureau of Fiscal and Budget Studies, City of New York.
- Strully, K.W., Rehkopf, D. H., Xuan, Z. 2010. Effects of prenatal poverty on infant health: state earned income tax credits and birth weight. *American Sociological Review*. 75(4), 534-562.
- Texas Perspectives, Inc. 2003. Increased participation in the EITC in San Antonio. Cited in: Berube, A. *Using the Earned Income Tax Credit to Stimulate Local Economies*. 2006. The Living Cities Policy Series. New York: Living Cities.
- Williams, R. 2012. Using the margins command to estimate and interpret adjusted predictions and marginal effects. *The Stata Journal*. 12(2), 308-331.

**Figure 1. New York City Neighborhoods by Level of EITC Receipt Per Capita**



Notes: Neighborhoods are defined by Per Capita EITC at the ZIP code level. High income ZIP codes receive below-average EITC benefits per capita, middle income ZIP codes receive average EITC benefits per capita; and low income ZIP codes receive above-average EITC benefits per capita. See text for details.

**Table 1: Recent Changes in the New York EITC Programs, 1997-2014**

Year	State EITC Rate	Local EITC Rate	Total
1997	20.0%	None	20.0%
2001	25.0%	None	25.0%
2002	27.5%	None	27.5%
2003	30.0%	None	30.0%
2004	30.0%	5%	35.0%

\*NY state credit enacted in 1994.

**Table 2: Correlations Coefficients of Demographic Variables, Measured at Two Points in Time by ZIP code**

Demographic Variable	Correlation Coefficients between 1999 and 2006-10
% High school degree or less	0.94
% African American	0.98
% Latino	0.97

Source: U.S. Census Bureau



**Table 3. Means of Main Variables**

Means	Definition 1: Proportion of EITC filers		Definition 2: Per Capita EITC benefit		Definition 3: Median income	
	Middle- income (Control)	Low- income (Treated)	Middle- income (Control)	Low- income (Treated)	Middle- income (Control)	Low- income (Treated)
Variable						
% African American	25.2%	45.7%	26.1%	45.5%	27.0%	44.4%
% Latino	21.5%	40.3%	22.3%	40.0%	20.9%	41.2%
% HS Degree or Less	52.8%	64.5%	52.8%	64.9%	53.4%	64.3%
Median Income	\$51,228	\$34,870	\$49,839	\$35,676	\$52,075	\$33,710
% EITC filers	22.5%	40.0%	23.8%	39.3%	23.5%	39.5%
EITC \$ per capita	\$244	\$408	\$220	\$436	\$252	\$404
% Low Birth Weight	8.3%	9.3%	8.3%	9.3%	8.2%	9.4%
% No/Late Prenatal Care	7.5%	8.3%	7.7%	8.2%	7.6%	8.3%
Pediatric Asthma Hospitalizations Per 1,000	4.45	8.52	4.77	8.48	4.51	8.64

Notes: Sample sizes are about 600 for each separate group (e.g., the Definition 1 low-income group has an N of about 600 and, the Definition 1 middle-income group has an N of about 600).

**Table 4. Average Change in EITC benefits from 1997-99 to 2005-07**

	EITC benefit per capita (2012\$)		
	20% EITC (1997-99)	35% EITC (2005-07)	Difference
Definition 1: Proportion of EITC filers			
Middle-income (Control)	\$202	\$252	\$50
Low-income (Treated)	\$329	\$429	\$100
Difference-in-Difference			<i>\$50</i>
Definition 2: Per Capita EITC benefit			
Middle-income (Control)	\$201	\$222	\$21
Low-income (Treated)	\$336	\$462	\$126
Difference-in-Difference			<i>\$105</i>
Definition 3: Median income			
Middle-income (Control)	\$207	\$262	\$55
Low-income (Treated)	\$328	\$424	\$96
Difference-in-Difference			<i>\$41</i>

**Table 5: Linear Regression Model Main Results**

Dependent variable:	EITC rate, lagged x Treatment indicator					
	1		2		3	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
<b>(A) PCTLBW</b>						
Treatment Group:						
<i>High % of EITC Tax Filers</i>	-0.024	(0.015)	-0.024	(0.015)	-0.027#	(0.016)
<i>High Per Capita EITC Benefit</i>	-0.021##	(0.008)	-0.021##	(0.008)	-0.022###	(0.008)
<i>Low Median Income</i>	-0.019#	(0.011)	-0.019#	(0.011)	-0.023#	(0.012)
<b>(B) PRENATAL*</b>						
Treatment Group:						
<i>High % of EITC Tax Filers</i>	-0.023	(0.022)	-0.023	(0.022)	-0.016	(0.019)
<i>High Per Capita EITC Benefit</i>	-0.009	(0.019)	-0.009	(0.020)	-0.012	(0.015)
<i>Low Median Income</i>	-0.033#	(0.020)	-0.033	(0.020)	-0.008	(0.020)
<b>(C) ASTHMA</b>						
Treatment Group:						
<i>High % of EITC Tax Filers</i>	-6.03##	(2.69)	-6.16##	(2.83)	-1.51	(2.79)
<i>High Per Capita EITC Benefit</i>	-3.13	(2.84)	-3.28	(2.97)	-0.81	(2.67)
<i>Low Median Income</i>	-10.16###	(2.16)	-10.19###	(2.28)	-4.40#	(2.67)
<i>Controls:</i>						
County Indicators	X					
County Indicators + Time Trend	X					
County Indicators x Time Trend	X					
Notes: Control Group: Moderate Income ZIPs; used panel corrected standard errors. Sample size approx. 1,100. *Prenatal regressions exclude 2009 data; sample sizes are approx. 1,050. # p-value<0.10; ## p-value<0.05; ### p-value<0.01.						

**Table 6: Generalized Linear Model Main Results**

Dependent variable:	EITC rate, lagged x Treatment indicator					
	1		2		3	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
<b>(A) PCTLBW</b>						
Treatment Group:						
<i>High % of EITC Tax Filers</i>	-0.397##	(0.132)	-0.395##	(0.160)	-0.414##	(0.176)
Avg. Marginal Effect (Treatment – Control)	-0.034		-0.037		-0.039	
<i>High Per Capita EITC Benefit</i>	-0.331##	(0.162)	-0.330##	(0.161)	-0.330#	(0.173)
Avg. Marginal Effect (Treatment – Control)	-0.028		-0.030		-0.030	
<i>Low Median Income</i>	-0.280#	(0.164)	-0.279#	(0.163)	-0.279	(0.226)
Avg. Marginal Effect (Treatment – Control)	-0.023		-0.024		-0.024	
<b>(B) PRENATAL**</b>						
Treatment Group:						
<i>High % of EITC Tax Filers</i>	-0.517	(0.477)	-0.524	(0.482)	0.039	(0.463)
Avg. Marginal Effect (Treatment – Control)	-0.034		-0.032		0.064	
<i>High Per Capita EITC Benefit</i>	-0.316	(0.470)	-0.314	(0.475)	0.086	(0.447)
Avg. Marginal Effect (Treatment – Control)	-0.013		-0.003		0.074	
<i>Low Median Income</i>	-0.699	(0.454)	-0.710	(0.458)	0.347	(0.518)
Avg. Marginal Effect (Treatment – Control)	-0.053		-0.057		0.017	
<i>Controls:</i>						
County Indicators	X					
County Indicators + Time Trend			X			
County Indicators x Time Trend					X	
<i>Notes: Corrected for within panel first order autocorrelation and hetereskedasticity. *Prenatal regressions exclude 2009 and 2010 data. Sample size approx.: 1,000. # p-value&lt;0.10; ## p-value&lt;0.05; ### p-value&lt;0.01.</i>						

**Table 7. Robustness Test I: Using ZIP code level indicators**

<b>Estimation Method:</b>	<b>LPM</b>		<b>GLM</b>		
<b>Dep. Var.: PCTLBW</b>	EITC rate, lagged x Treatment indicator		EITC rate, lagged x Treatment indicator		
Treatment Group:	Coeff.	SE	Coeff.	SE	Avg. Marg. Effect (Treatment – Control)
<i>High % of EITC Tax Filers</i>	-0.022##	(0.010)	-0.386##	(0.159)	-0.072
<i>High Per Capita EITC Benefit</i>	-0.017###	(0.006)	-0.302#	(0.160)	-0.064
<i>Low Median Income</i>	-0.018##	(0.008)	-0.316##	(0.161)	-0.065
<i>Controls:</i>					
ZIP Indicators + Year Indicators					

Note: # *p-value*<0.10; ## *p-value*<0.05; ### *p-value*<0.01.

**Table 8. Correlation Coefficients Between the Proportion Low Birth Weight Rate of New York and Connecticut Communities, 1990-2010**

Proportion Low Birth Weight Rate Among:	Low-Income NYC neighborhoods	Middle-Income NYC neighborhoods	Black and Latino Connecticut households
Low-Income NYC neighborhoods	1.00		
Middle-Income NYC neighborhoods	-0.24	1.00	
Black and Latino Connecticut households	0.63	-0.50	1.00

**Table 9. Robustness Test II:  
Controlling for Trends in Low Birth Weight Rates Among Black and Latino  
Connecticut Households, Linear Regression Results**

<b>Dep. Var.: PCTLBW</b>				
<b>Estimation Method: LPM</b>				
Treatment Group:	Coeff.	SE	Coeff.	SE
<i>High % of EITC Tax Filers</i>				
CT % low birth weight rate	0.116	(0.113)	0.123	(0.118)
EITC rate, lagged x Treatment indicator	-0.027#	(0.015)	-0.022###	(0.010)
CT % low birth weight rate x Treatment indicator	0.164	(0.269)	0.145	(0.247)
EITC rate, lagged x Treatment indicator	-0.025	(0.016)	-0.019#	(0.011)
<i>High Per Capita EITC Benefit</i>				
CT % low birth weight rate	0.116	(0.117)	0.123	(0.118)
EITC rate, lagged x Treatment indicator	-0.022###	(0.008)	-0.017###	(0.006)
CT % low birth weight rate x Treatment indicator	-0.024	(0.153)	-0.036	(0.144)
EITC rate, lagged x Treatment indicator	-0.022###	(0.008)	-0.018###	(0.007)
<i>Low Median Income</i>				
CT % low birth weight rate	0.116	(0.117)	0.123	(0.107)
EITC rate, lagged x Treatment indicator	-0.023	(0.012)	-0.018##	(0.012)
CT % low birth weight rate x Treatment indicator	0.109	(0.198)	0.023	(0.189)
EITC rate, lagged x Treatment indicator	-0.022#	(0.012)	-0.018##	(0.009)
<i>Controls:</i>				
County Indicators x Year Trend	X			
ZIP Indicators + Year Trend			X	

Note: #p-value<0.10, ## p-value<0.05; ###p-value<0.01.

**Table 10. Robustness Test II:  
Controlling for Trends in Low Birth Weight Rates Among Black and Latino  
Connecticut Households, Generalized Linear Model Results**

<b>Dep. Var.: PCTLBW</b>				
<b>Estimation Method: GLM</b>				
Treatment Group:	Coeff.	SE	Coeff.	SE
<i>High % of EITC Tax Filers</i>				
CT % low birth weight rate	1.453	(1.408)	1.544	(1.407)
<b>EITC rate, lagged x Treatment indicator</b>	<b>-0.352###</b>	<b>(0.115)</b>	<b>-0.297##</b>	<b>(0.107)</b>
Avg. Marginal Effect (Treatment – Control)	-0.032		-0.054	
CT % low birth weight rate x Treatment indicator	1.862	(2.441)	1.475	(2.487)
<b>EITC rate, lagged x Treatment indicator</b>	<b>-0.326###</b>	<b>(0.115)</b>	<b>-0.267##</b>	<b>(0.111)</b>
Avg. Marginal Effect (Treatment – Control)	-0.030		-0.052	
<i>High Per Capita EITC Benefit</i>				
CT % low birth weight rate	1.454	(1.409)	1.544	(1.406)
<b>EITC rate, lagged x Treatment indicator</b>	<b>-0.287##</b>	<b>(0.113)</b>	<b>-0.234</b>	<b>(0.107)</b>
Avg. Marginal Effect (Treatment – Control)	-0.026		-0.048	
CT % low birth weight rate x Treatment indicator	-0.520	(2.461)	-0.820	(2.477)
<b>EITC rate, lagged x Treatment indicator</b>	<b>-0.294###</b>	<b>(0.112)</b>	<b>-0.251</b>	<b>(0.110)</b>
Avg. Marginal Effect (Treatment – Control)	-0.026		-0.050	
<i>Low Median Income</i>				
CT % low birth weight rate	1.456	1.410	1.545	(1.406)
<b>EITC rate, lagged x Treatment indicator</b>	<b>-0.310##</b>	<b>(0.150)</b>	<b>-0.253##</b>	<b>(0.108)</b>
Avg. Marginal Effect (Treatment – Control)	-0.025		-0.050	
CT % low birth weight rate x Treatment indicator	1.225	(2.401)	-0.182	(2.426)
<b>EITC rate, lagged x Treatment indicator</b>	<b>-0.295##</b>	<b>(0.149)</b>	<b>-0.256##</b>	<b>(0.193)</b>
Avg. Marginal Effect (Treatment – Control)	-0.023		-0.050	
<i>Controls:</i>				
County Indicators x Year Trend	X			
ZIP Indicators + Year Trend			X	

Note: # p-value<0.10; ## p-value<0.05; ### p-value<0.01.



**Table 11. Evaluating the Estimated Impact of New York Local EITC Rate Increases on Low Birth Weight Rates in Low-Income Neighborhoods**

	GLM with County Indicators x Time Trend Controls	GLM with County Indicators x Time Trend Controls and CT controls
1. Treatment Effect*	0.45%	0.39%
2. EITC Increase per household** (2012\$)	\$315	
3. Treatment on Treated (ToT) per \$1000 (2009\$)***	1.43%	1.24%
4. Mean of dependent variable****:	9.50%	9.50%
5. ToT per \$1000 (2009\$), % impact (row 3/row 4)	15.04%	13.03%
6. Hoynes et al. (2012, p. 43) estimate of ToT per \$1000 (2009\$), % impact	-6.7% to -10.8%	

Notes: \*Treatment effect is evaluated for the 15-percentage-point EITC state and local credit rise that occurred over the study period, coefficients used are from our preferred specifications presented in Tables 6 and 10 (multiplied by 0.15). \*\*See Table 4 for net change in average EITC benefit. \*\*\*To ease comparisons, we adopted the same real value benefit increase used in Hoynes et al. (2012). \$1,000 in 2009\$ is equivalent to \$1,070 in 2012\$. \*\*\*\*Average % Low Birth Weight Rate in Poor Neighborhoods (1997-99)

## Endnotes

<sup>1</sup> These 2013 numbers refer to EITC receipts based on tax year 2012. Data are from the Internal Revenue Service’s SOI Tax Stats, Historical Table 1. Available at: <http://www.irs.gov/uac/SOI-Tax-Stats-Historical-Table-1>; accessed January 30, 2014.

<sup>2</sup> Over the years of this study, the federal EITC program also expanded to provide larger benefits for tax filer filing married jointly, and for households with 3 or more children. This, in turn, affected the EITC credit amount that flowed to households through the New York State and City credits since the local credits equal a percentage of the federal credit. See footnote 11, which provides further details on these expansions.

<sup>3</sup> These figures come from an earlier 2012 NBER version of Hoynes et al.’s 2015 published article. Specifically, see Table 4, p. 43, of the 2012 paper (<http://www.nber.org/papers/w18206>; accessed January 15, 2015). In their 2012 paper, Hoynes et al. use the EITC credit received by single mothers with a high school or less to gauge the impact of the EITC expansion on health.

These figures are different from those presented in their 2015 published version of their 2012 paper. In their 2015 published paper, they assess the health impact of changes in less-educated single mothers’ *after-tax income* that result from an EITC expansion. Their measure of after-tax income incorporates changes in earnings as well as other income subsidies such as TANF or SSI, not just changes in EITC benefits. By using the after-tax income measure, they assess the impact of income changes specifically—as induced by EITC changes—on health, rather than the impact of changes in EITC benefits alone on health.

Our focus centers on how changes in the EITC policy specifically impacts health outcomes. We therefore use Hoynes et al.’s original 2012 approach to assess their results.

<sup>4</sup> For an overview of this research see the 2008 report, *The Enduring Challenge of Concentrated Poverty in America: Case Studies from Communities Across America*, published jointly by the Federal Reserve and the Brookings Institute Metropolitan Areas Program. This report summarizes the existing body of research on the specific consequences of living in high poverty areas, as well as, profiles of 16 such communities.

<sup>5</sup> In 2003, Leventhal and Brooks-Gunn documented a dramatic example of how reducing neighborhood-level poverty can improve the health of individual households in the absence of economic gains within individual households. They compared economic and health outcomes of households that participated in the “Move to Opportunity” social experiment conducted by the federal Housing and Urban Development agency. With the use of housing vouchers about 400 families, chosen at random, relocated from very poor to more mixed income neighborhoods. Households that relocated experienced a significant reduction in mental stress compared to those that did not, without any statistically significant improvement in their own economic well-being. Possible causes of reduced stress include a decrease in social disorder (e.g., crime, public drinking or drug use, conflicts) and access to a higher level of social resources such as improved quality of health services, schools, housing, and youth programs.

<sup>6</sup> See for example, Spencer (2007). This study measures the job impact of EITC benefits for low-income neighborhoods in Los Angeles. Spencer estimates that every additional \$1,000 in EITC benefits supports three additional retail jobs.

<sup>7</sup> In 2009, the American Recovery and Reinvestment Act temporarily added a fourth schedule for families with three or more children. Originally set to expire in 2012, it has been extended to 2017.

<sup>8</sup> A family of 4—including 3 children—had a poverty income threshold of \$24,100 in 2014. The beginning of the phase out range for this type of family, \$17,830, is 26 percent below this poverty line.

<sup>9</sup> These parameters differ based on whether or not the tax-filing unit files married jointly. Those filing married jointly follow a more generous benefit schedule: the phase out range starts and ends at a higher income level. See the Tax Policy Center’s “Tax Facts, Historical EITC parameters” at

<http://www.taxpolicycenter.org/taxfacts/displayafact.cfm?Docid=36> .

<sup>10</sup> For budgetary reasons, Montgomery County’s EITC refund was reduced to 72.5 percent of the state EITC in 2011, 68.9 percent in 2012, and 75.5 percent in 2013. See Tax Credits for Working Families at:

<http://www.taxcreditsforworkingfamilies.org/state/maryland/>

<sup>11</sup> At two different points during the time period of our study the federal EITC program expanded. Specifically, after the passage of EGRRTA of 2001, the federal EITC benefit schedule allowed for larger benefits and greater coverage rates for households with the tax filing status of married jointly. These expansions took place over 2002 to 2008. Then in 2009, with the passage of ARRA, the federal EITC program increased benefits again for tax filers filing as jointly married, and also added a fourth, more generous, benefit schedule for households with 3 or more children. To account for all these changes over this period, we adjust the local credit rate to reflect both the increase in the federal benefits as well as the increase in local benefits that would result since local EITC benefits are a proportion of federal benefits.

These adjustments result in the following local EITC rates shown in the table below, by year. Our adjustments are based on the Joint Tax Committee’s estimates of the overall tax revenue loss associated with each expansion. We use their estimates to calculate the average percentage increase in EITC benefit spending levels (i.e., revenue loss due to expansion/overall spending on EITC benefits). We then add the appropriate percentage point increase to the local rate to reflect the larger federal benefits, as well as the larger local EITC benefit resulting from the more generous federal EITC:

Year	Local Rate (no adjustment)	Local Rate (adjusted)
1997	20.0%	20.0%
1998	20.0%	20.0%
1999	20.0%	20.0%
2000	22.5%	22.5%
2001	25.0%	25.0%
2002	27.5%	31.1%
2003	30.0%	33.7%
2004	35.0%	38.8%
2005	35.0%	40.3%
2006	35.0%	40.3%
2007	35.0%	40.3%
2008	35.0%	40.3%
2009	35.0%	45.8%
2010	35.0%	45.8%

<sup>12</sup> The U.S. Postal Service determines the geographic units of ZIP codes by the number of residents in an area. The extremely high density of New York City insures that each ZIP code represents a very limited geographic area. Therefore, our ZIP-code level analysis of New York City allows us to effectively measure how EITC benefits and health outcomes interact at a geographic unit that can reasonably be described as a neighborhood. This is a particular advantage of studying New York City since more data are collected at the ZIP code level than other small geographic units. ZIP codes in New York City have a median area of 1.8 mi.<sup>2</sup> and a mean area of 4.3 mi.<sup>2</sup> Nationally, ZIP codes represent much larger geographic areas of 35.9 mi.<sup>2</sup> and 88.6 mi.<sup>2</sup>, respectively. Source:

[http://proximityone.com/cen2010\\_zcta\\_dp.htm](http://proximityone.com/cen2010_zcta_dp.htm)

<sup>13</sup> Rate changes, as opposed to changes in EITC benefits themselves, also better isolate how income changes unrelated to economic trends affect health. This is an important distinction: directly measuring how changes in EITC benefits impact health will likely produce a spurious correlation. This is because economic trends influence benefit levels and health outcomes at the same time. For example, a household's worsening overall economic situation can lead to both an increase in the EITC benefits it receives and to poor health outcomes in that household. This could occur if one earner in a dual earner household becomes unemployed and the household's decline in income leads to health problems related to stress. At the same time, this household could become newly eligible to receive EITC benefits. Such a pattern of outcomes would cause changes in EITC benefit receipt and health outcomes to have a negative, spurious correlation. We examine the change in EITC credit rates to identify the true relationship between EITC benefits and health since variations in EITC credit rates cause changes in EITC benefits unrelated to economic trends.

<sup>14</sup> This is in contrast to the study by Strully et al. (2010) that examines the impact of the *presence* of a state EITC, not the impact of varying benefit rates.

<sup>15</sup> Nearly all EITC recipients receive their benefit as a lump sum rather than "in advance." The tax filer receives the "lump sum" EITC payment during the year *after* they earn the income used to determine their benefit amount. "In advance," EITC payments, in contrast, occur throughout the same year that the tax filer earns the income used to determine his/her benefit amount (Smeeding et al., 2000).

<sup>16</sup> See the Agency for Healthcare Research and Quality's, "Pediatric Quality Indicators: Overview," available at: [http://qualityindicators.ahrq.gov/Modules/pdi\\_resources.aspx](http://qualityindicators.ahrq.gov/Modules/pdi_resources.aspx) (accessed Jan. 20, 2015).

<sup>17</sup> See <http://www.health.ny.gov/statistics/chac/perinatal/about.htm>.

<sup>18</sup> Note that for our generalized linear model (GLM) estimates below, dropping data for 2009 requires that we also drop data for 2010 since GLM does not allow for gaps between time periods.

<sup>19</sup> SPARCS is a cooperative effort between the healthcare industry and government, established in 1979, to collect healthcare claims data from both public and private payers. SPARCS collects patient level detail on patient characteristics, diagnoses and treatments, services, and charges for each hospital inpatient stay and outpatient (ambulatory surgery, emergency department, and outpatient services) visit, among other data.

<sup>20</sup> We excluded high-income ZIP codes (real median-income > \$60,400 in 2012 dollars) for two reasons: (1) As noted earlier, we believe this restriction makes the control group more appropriate because the affects of other economic trends will more likely overlap across low-income and moderate-income neighborhoods (as opposed to high-income neighborhoods); (2) this exclusion eliminates a spike of zero values in two of our health outcome variables—prenatal care and asthma measures. These spikes are clearly due to the inclusion of high-income neighborhoods. Excluding high income neighborhoods allows the our health outcome measures to have a more normal distribution and therefore better suited for GLM and OLS regression methods.

<sup>21</sup> Note that the average marginal effect (AME) for each group of neighborhoods captures the marginal change in the low birth weight rates associated with a change in the local EITC rate. The “average” in this term refers to a specific type of measure. The AME is an average of the marginal effect of a change in the local EITC rate on the health outcome while holding only the type of neighborhood (i.e., low income or middle income) indicator variable fixed and using the values for all other independent variables as observed. For a thorough discussion of this see Williams (2012).

<sup>22</sup> These neighborhoods would experience some EITC income gains due to Federal expansions, but these expansions are, relatively speaking, small.

<sup>23</sup> Connecticut’s Department of Public Health, Office of Vital Records, “Vital Statistics,” see: <http://www.ct.gov/dph/cwp/view.asp?a=3132&q=394598&dphNav=|46941|>, accessed January 26, 2015.

<sup>24</sup> These figures are from the 2009 American Community Survey of the U.S. Census Bureau cited in “Racial disparities in median household income remain enormous in most states,” by Mike Alberti as part of the “Remapping the Debate” website: <http://www.remappingdebate.org/map-data-tool/racial-disparities-median-household-income-remain-enormous-most-states?page=0,2>, accessed January 30, 2015.

<sup>25</sup> Again, as we noted in endnote 3, Hoynes et al. have since revised their 2012 paper. In their published version, they evaluate the impact of EITC benefits on health by using a measure of the EITC’s overall impact on a family’s after-tax income as their “treatment” dose rather than a measure of EITC benefits alone. Consequently, their 2015 published estimates of the impact of ToT per \$1,000 are much smaller.

<sup>26</sup> We use EITC filing status to proxy for EITC eligibility in our sample.

<sup>27</sup> Interestingly, our neighborhood-wide estimates substantially overlaps with Hoynes et al.’s (2012) estimated impact for Black single mothers of young children. For this demographic subgroup, they estimate an 8.1 percent to 15.8 percent reduction in their low birth weight rate (based on their ToT per \$1,000 in 2009\$ measure). The similarity of these estimates may reflect the fact that the percentage of Black people living in poverty areas has been at least double that of the average person between 2000 and 2010 (Bishaw, 2011). These figures are 25.7 percent vs. 50.4 percent for 2000 and 18.1 percent versus 46.3 percent in 2010. In other words, the greater impact of EITC benefits on Black single mothers observed by Hoynes et al. could be explained, in part, by the fact that roughly half of Black people live in *poverty areas*—areas with a poverty rate of 20 percent or more.

<sup>28</sup> For some evidence of recent gentrification, see Stringer (2014). We are grateful to Michael Carr for raising the question of how to account for New York City's gentrification in our model.