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Urban Affairs Review 2007; 42; 851
DOI: 10.1177/1078087407300515

The online version of this article can be found at: http://uar.sagepub.com/cgi/content/abstract/42/6/851

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http://uar.sagepub.com/cgi/content/refs/42/6/851
Neighborhood Economic Development Effects of the Earned Income Tax Credit in Los Angeles

Poor Places and Policies for the Working Poor

James H. Spencer
University of Hawaii at Manoa

This paper explores the effect of the Earned Income Tax Credit (EITC) on poor neighborhoods of Los Angeles during the late 1990s. To date, few analyses have empirically examined the impact of people-based policies on the economies of poor neighborhoods. The paper first documents the magnitude of this individual wage subsidy in Los Angeles as an unrecognized investment in poor neighborhoods on par with place-based policies such as Enterprise Zones. The paper then uses IRS and Economic Census data by ZIP Code to test whether increased EITC income has an effect on the neighborhood retail job base. Findings suggest an independent correlation between EITC investments and retail job gain. The conclusion uses these results to suggest better policy coordination and recommend four productive areas for future research.

Keywords: EITC; economic development; concentrated poverty; economic base; antipoverty policy; working poor; retail employment

Recent studies have shown that the people-based Earned Income Tax Credit (EITC) program is a major form of investment in poor neighborhoods nationwide (Berube and Forman 2001a, 2001b), that this level of investment can outstrip place-based efforts to address spatially concentrated poverty (Spencer 2005), and that declines in family poverty are strongly associated with an increase in the employment of females—the

Author’s Note: The author would like to acknowledge the generous contributions of the Haynes Foundation for their financial support, Professor Paul Ong for his intellectual contributions, and three anonymous reviewers for taking the time to evaluate this paper. Any shortcomings are, of course, the author’s own.
primary beneficiaries of the EITC—who reside in those areas (McDonald 2004). These analyses provide policy makers with an expanded range of needed conceptual tools that go beyond a people-place dichotomy (Spencer 2004; Gyourko 1998; Lang and Hornberg 1998) and show promise for innovative solutions to the persistence of spatially concentrated poverty.

Although some recent research has examined positive policy interactions between people-based policies (e.g., Grogger 2004 for TANF1 and the EITC), fewer studies empirically examine the positive unintended benefits of people-based policy on places. This paper examines the implementation of the people-based EITC program in Los Angeles county and tests the program’s secondary effects on the demand for labor in poor places. Specifically, it describes the magnitude of the policy as an investment in poor neighborhoods and develops a model for estimating the job and business generation impact of its neighborhood income boost.

The program and its numerous benefits to poor people have been extensively described elsewhere, showing important effects in reducing poverty (e.g., Greenstein 2000; Quinn and Pawasarat 2001; Hotz and Scholz 2000), labor force attachment of poor people (e.g., Liebman 1998; Dickert, Houser, and Scholz 1995; Eissa and Liebman 1996), and increased investments in the future (e.g., Johnson 2000; Souleles 1999; Romich and Weisner 2000). A fourth area of research documents the EITC’s significance as neighborhood investment, suggesting that further study needs to be done on the EITC’s possible economic development effects (Spencer 2005; Berube and Forman 2001a, 2001b).

The EITC is a significant investment in poor neighborhoods because of the spatial concentration of the working poor. One question arising from this observation is whether this additional income contributes to the local economy. Given some estimates that up to 65% of recipients spend tax credits on consumption and 70% spend a portion of them on economic or social mobility investments (Smeeding, Phillips, and O’Connor 2000), one would expect a secondary impact on the economic base. Is this impact a local neighborhood one or a regional one?

Reports on the economic impact of the EITC at the metropolitan level suggest a significant positive impact that EITC investments have indirectly on the economic base at the municipal level through both job generation and tax revenue increases (Texas Perspectives 2004; Jacob France Institute 2004). Such metropolitan economic development impacts are an important benefit from the federal EITC program, but little is known about how these impacts may affect poor neighborhoods where a lack of employment opportunities can lead to spatial mismatch (e.g., Kain 1968; Holzer 1991; Ihlanfeldt and Sjoquist 1998) or socioeconomic isolation and segregation.
that leads, in turn, to long-term unemployment, intergenerational poverty, and the perpetuation of an economic “underclass” (e.g., Wilson 1996; Jencks 1991). For these two reasons, an exploration of the neighborhood-level effects of the EITC on the economic base can contribute to the emerging spatial analyses of EITC labor demand effects.

**Possible Economic Development Effects of the EITC**

The policy literature suggests that increased income density may provide benefits to neighborhoods through increased purchasing power in addition to the individual benefits to program participants (Berube and Forman 2001a, 2001b; Texas Perspectives 2004; Jacob France Institute 2004). My hypothesis is that such concentration of EITC dollar and employment benefits may stimulate local consumer markets and increase business and employment in poor neighborhoods.

As with most people-based antipoverty programs, neighborhood-level improvements are not explicit program objectives. Since the EITC provides an individual asset that the recipient can take wherever he or she moves, program participation may facilitate a family’s move out of a high-poverty neighborhood. While economically beneficial to the individual family, this kind of move is likely to be detrimental to the neighborhood from which they move (Jargowsky 1997; Wilson 1996).

In addition, the marginal income boost may enable a consumer behavior creaming effect that undermines the neighborhood economy even if the families are not spatially mobile. Local retail and consumer goods are often more expensive in poor neighborhoods because of the spatial and other constraints that poor people often face, and modest income boosts through the EITC may serve to help participants overcome what Taylor and Ong (1995) call “transportation mismatch” in their consumer behavior. Thus rather than having neighborhood economic development effects, EITC-enhanced local consumer purchasing power may depress the local economy rather than stimulate it.

What little scholarly evidence exists (Spencer 2005) has shown that a comparison of EITC investments in neighborhoods can put place-based antipoverty policies such as Enterprise Zones (EZs) in perspective, suggesting that the EITC may have significant neighborhood economic development impacts in Los Angeles’s EZs rivaling the EZ economic impacts themselves. The following analysis is the first attempt to develop a model for testing the hypothesis that EITC income improves the neighborhood job base.
Data Sources and Method

Following Dowall (1996) and Rosenthal and Strange (2003), this study brings together a number of ZIP Code–level spatially referenced data sources to analyze the neighborhood economic development effects of the EITC.

Income Data

I use Internal Revenue Service (IRS) data by ZIP Code for the years 1997 and 1998 for the primary independent variables, EITC participation and dollar amount. These data—available from 1997 on—are available from the IRS by ZIP Code and include information on the EITC participation and aggregate dollar amount.

The data contain an extensive range of about twenty variables. Most relevant here, each ZIP Code record contains information on the number of tax returns filed, the number of returns filed that claimed an EITC, the number of returns claiming salaries and wages, and the total dollar amount of EITC credits claimed per ZIP Code for each of the two years. In addition, each ZIP Code contains five separate records showing the above variables for a set of income ranges. These categories were “all returns,” “returns claiming under $10,000,” “$10,000 to $25,000,” “$25,000 to $50,000,” and “$50,000 or more.” Thus I am able to compute a variety of indicators such as neighborhood EITC use rates, neighborhood EITC take-up rates among the lowest income category, and total EITC investment by neighborhood.

Employment and Business Data

The basic dependent variable for the analysis is retail employment. These data are available from the U.S. Census Bureau at the ZIP Code level in two forms. The Economic Censuses for 1987, 1992, and 1997 describe employment levels and number of businesses for each of those years, broken down by sector. They are collected for a single week for each of the relevant years and, for the 1987 and 1992 data, record the number of businesses and number of jobs by ZIP Code for the categories of Retail Trade and Service Industries. For 1987 and 1992, the data differ slightly for Manufacturing, which records data by ZIP Code for the number of businesses by firm size only. The 1997 data from the Economic Census are classified in this way for all sectors. Thus I estimate the number of retail sector employees by ZIP Code by taking the midpoint of each firm-size category
and multiplying that figure by the number of firms in that size category for that ZIP Code. Summing the results of these calculations for each ZIP Code provides an estimate of the number of retail sector employees for each ZIP Code. In addition to the 1997 retail employment levels, I use the 1987 retail employment levels as a control variable, as well as the 1987 and 1997 service and manufacturing employment levels for cross-sectoral comparative purposes.

Home Values Data

As related economic indicators I use ZIP Code–level data on housing from the Association of California Realtors that record the quarterly average price of all home sales by ZIP Code, the average price of single-family homes, and the number of transactions for each of these two categories. From these data, I developed an average annual single family home sales price assigning equal weight to each quarter.

*Multivariate regression model.* Ordinary least squares regression models have been used to test the impact of spatial public policies on spatial units of analysis such as ZIP Codes (Dowall 1996), Census tracts (Engberg and Bondonio 2003; Greenbaum and Engberg 2000), and addresses (Spencer and Ong 2004). Such studies generally use binary variables as proxies for area-based programs. While useful for policies with simple “either-or” targets, dummy variables are insufficient for nonspatial programs, where there is wide variation in the degree to which neighborhoods participate in the policy through residents’ participation rates. This study tests the impact of a nonspatial public policy on spatial units of analysis. It tests the secondary impact of the EITC people-based cash transfer on the neighborhood availability of jobs, treating the density of policy participation as an independent neighborhood characteristic estimated as a metric variable rather than a binary one.

The author is not aware of any previous studies that have tested the cumulative neighborhood economic impact of such people-based antipoverty policies, and this study may have widespread implications for researching the secondary and unintended neighborhood impacts of a wide range of social policies on the economic base. One would expect that, all other factors being equal, those poor neighborhoods where EITC program participation is higher would show greater changes in the neighborhood economic base than those similarly poor areas where EITC participation is lower. In particular, local retail jobs are more likely to be driven by local consumption patterns related to the EITC than manufacturing or service jobs, which
often have intermediate consumers or produce goods and services exported from the region and are therefore more insulated from local resident consumer behavior. Moreover, although the working poor are concentrated in the service sector, their consumption lies mainly in retail rather than services.

There are several alternative explanations for changes to the economic base for each ZIP Code. Factors such as investment trends, non-EITC income, safety, or other public policies likely influence employment levels. Thus the multivariate regression model for EITC includes controls for income, neighborhood quality, and alternative policy incentives. Regional growth is controlled for by inclusion of all ZIP Codes in Los Angeles County in the model, and I use EITC and income data for both tax years 1997 and 1998 to test the robustness of the model.

The basic model can be expressed by

\[ Jit_2 = Jit_1 + Pit_2 + Dit_1B + Hit_2 + lit_2 \]  

(1)

and

\[ Jit_2 = Jit_1 + Ait_2 + Dit_1B + Hit_2 + lit_2, \]  

(2)

where

- \( Jit_1 \) = the density of jobs in any given ZIP Code \( i \) in 1987 \( (t_1) \)
- \( Jit_2 \) = the density of jobs in any given ZIP Code \( i \) in 1997 (1998) \( (t_2) \)
- \( Pit_2 \) = the geographic density of tax returns claiming an EITC in ZIP Code \( i \) in 1997 (1998) \( (t_2) \)
- \( Ait_2 \) = the geographic density of EITC dollars taken for ZIP Code \( i \) in 1997 (1998) \( (t_2) \)
- \( Hit_2 \) = the average sales price of a single-family home in ZIP Code \( i \) in 1998 \( (t_2) \)
- \( lit_2 \) = the 1997 (1998) \( (t_2) \) average adjusted gross income (AGI) for ZIP Code \( i \)
- \( Dit_1B \) = a dummy variable denoting ZIP Code \( i \)'s participation in the EZ program from \( t_1 \) to \( t_2 \)

I run the model with two different definitions of the income variables (AGI and EITC) to account for different kinds of consumer markets. Elevated consumer purchasing can result from either high average incomes
or from the spatial concentration of consumers. Large income boosts to a relatively small number of consumers could result in the same job changes as a relatively small income boost to a large number of neighborhood residents. Each scenario would represent a secondary, consumer market effect of the EITC—albeit for different types of retail goods—and each should be considered. Using the generic average adjusted gross income per tax return as the income control variable accounts for variation in individual purchasing capacity, but not for variation in the number of income earners per ZIP Code. Alternatively, using income density as the income control variable accounts for variation in the number of income earners per ZIP Code, but not for variation in their individual purchasing capacity. Using these two definitions generates a range of possible program impacts.

Similarly, for the EITC program effect variable I use two alternative definitions: the number of EITC returns per ZIP Code to measure the number of program participants, and the total EITC credit amount (per ZIP Code) to measure degree of program benefit. Both of these figures are standardized by geographic area of each ZIP Code rather than by the total number of tax returns filed by ZIP Code. This decision assumes that changes in the local economic base that may be because of the EITC are most likely to occur where there is sufficient density of program participants or density of credit dollars to affect business and job levels. In concrete terms, a $200 income boost per resident in a dispersed population is much less likely to be reflected in the local economy than it is in a dense population.

This decision has mathematical implications for the model. There is likely to be much greater variation in the EITC density measures than in the per-tax-return measures. Table 1 confirms that estimates by geographic area are much more likely to detect variations in the effect of the EITC than estimates by number of total returns. The four spatial EITC program effect estimates show coefficients of variation that are much greater than those for the four estimates of program effect standardized by total tax returns. This aspect of the data indicates that a decision to standardize the EITC variables by square mile—consistent with the idea that the economic base is supported by spatial density rather than relative proportions in the taxpaying population—is more likely to accurately isolate neighborhood-level EITC program effects.

Given this difference, and the fact that the hypotheses tested here are models of spatial concentration, not of population ratios, the decision to standardize program effect variables by square mile is appropriate. Using these two variables for each year, then, I am able to estimate a range of policy impacts that numbers of EITC participants and aggregate values of EITC credits have on local consumer markets.
Table 1

<table>
<thead>
<tr>
<th></th>
<th>M</th>
<th>SD</th>
<th>Coefficient of Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density measures</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of EITC returns per square mile, 1997</td>
<td>7,169</td>
<td>96,607</td>
<td>1,347.6</td>
</tr>
<tr>
<td>EITC dollar amount per square mile, 1997 (000s)</td>
<td>1,250,344</td>
<td>1,316,234</td>
<td>105.3</td>
</tr>
<tr>
<td>Number of EITC returns per square mile, 1998</td>
<td>7,023</td>
<td>94,444</td>
<td>1,344.8</td>
</tr>
<tr>
<td>EITC dollar amount per square mile, 1998 (000s)</td>
<td>1,302,615</td>
<td>1,368,453</td>
<td>105.1</td>
</tr>
<tr>
<td>Per capita (consumer) Measures</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of EITC returns per total returns, 1997</td>
<td>.2372</td>
<td>.14201</td>
<td>59.9</td>
</tr>
<tr>
<td>EITC dollar amount per total returns, 1997</td>
<td>382.1</td>
<td>276.35</td>
<td>72.32</td>
</tr>
<tr>
<td>Number of EITC returns per total returns, 1998</td>
<td>.2283</td>
<td>.13755</td>
<td>60.2</td>
</tr>
<tr>
<td>EITC dollar amount per total returns, 1998</td>
<td>385.5</td>
<td>278.42</td>
<td>72.2</td>
</tr>
</tbody>
</table>

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Limitations of the Data and Model

Geographic Units

The basic geographic units for the analysis are ZIP Codes, which unlike smaller levels of geography allow for detailed sectoral analysis of the economic base over time. Using this level of analysis, however, presents two problems. First, ZIP Codes are based on the amount of mail flowing into each geographic unit and if this volume changes, then the number of ZIP Codes will change over time. This process involves the Postal Service either “splitting” one existing ZIP Code receiving an increased level of mail into separate ZIP Codes, each with a unique area assigned to a unique ZIP Code number, or alternatively locating a post office with a separate ZIP Code number in an existing ZIP Code spatial area. In other words, it will create a separate ZIP Code number without its own unique spatial area. Since many of the data sources do not distinguish between ZIP Code data points with unique spatial area codes and ZIP Code data points that are part of other ZIP Code spatial areas, I had to aggregate those without a unique spatial area into the data for the ZIP Code assigned to the area within which the new post office was located in 1999. The assumption underlying this
decision is that, on average, the data for the new post office ZIP Codes are for addresses within the enclosing ZIP Code areas. Second, ZIP Codes are midsized definitions of neighborhoods that may or may not detect block-by-block neighborhood variance that might be detected by Census tract-level analyses. However, retail purchasing should not be limited to small definitions of neighborhoods, and a larger definition would better account for daily purchasing radii, especially in Los Angeles, where neighborhoods generally characterize relatively extensive areas.

**Changes in Industrial Classification Codes**

The 1997 Economic Census replaced the Standard Industrial Classification code (SIC) system (used in 1987 and 1992) with the North American Industrial Classification System (NAICS). For this reason, the 1997 data differ slightly from those for 1987 and 1992. Nonetheless, I have reconstructed the NAICS data to estimate what the 1997 figures for the manufacturing, retail trade, and services sectors would have been if categorized by the SIC. Thus some of the variation between 1987 (or 1992) and 1997 may be because of classification estimation errors. The aggregation of all three sectors, however, should be highly reliable since most of the relevant sector reclassifications were changes across those three sectors that were limited to the larger three-category grouping. For example, “research and development for physical/life sciences” was reclassified from SIC 37 (Manufacturing) to NAICS 54 (Services: professional, scientific and technical). Although several categories such as “agriculture” and “minerals” manufacturing were taken out of manufacturing and put into new categories, these categories are likely of little relative importance to the economic base of urbanized Los Angeles.

**Collinearity**

As with any multivariate model, collinearity can be an issue. In this case, distinguishing job growth because of EITC effects on firms that make jobs cheaper for them to maintain from job growth because of increased consumer spending is difficult to overcome given the data. However, few workers work where they live in Los Angeles (Taylor and Ong 1995), and one would expect EITC-related job growth resulting from its benefits for the affordability of labor to be equally spread throughout the metropolitan area rather than clustered in poor neighborhoods. In either case, though, the policy would be shown to create jobs.
Moreover, ethnicity may be collinear with EITC participation because EITC use depends on residency status and English language proficiency. In particular, neighborhoods with high concentrations of Asian and Pacific Islanders or Latinos, other factors being equal, likely have lower EITC participation rates. Partial correlations of the percentages of Latino (Asian and Pacific Islanders) and EITC participation rates, however, were not significant at the .05 level, when controlling for AGI. Moreover, the inclusion of these two ethnicity variables in the model did not alter the results of the EITC variable.

Results

Descriptive Statistics

Because poverty is spatially concentrated in Los Angeles, it is not surprising that the use and distribution of Earned Income Tax Credit benefits are similarly concentrated; concentration of benefits is endogenous to concentration of the working poor. Figure 1 portrays a major cluster of participation immediately south of downtown Los Angeles, with smaller, less concentrated clusters in parts of the San Fernando Valley and Long Beach. The basic pattern of a ring of low EITC participation surrounding these areas is consistent with the existence of spatially concentrated poverty in these areas. The five ZIP Codes that comprise the core of South Central Los Angeles—a neighborhood of high poverty and high unemployment—have between 40% and 60% of IRS tax returns claiming an EITC credit, while less than 10% claimed it in the neighborhood of West Los Angeles, for example. In general, this spatial distribution confirms that the working poor taking the credit reside disproportionately in the poverty cluster.

Using Census data, I delineate areas of high poverty and compare EITC use and benefits in poor neighborhoods with the Los Angeles region. Table 2 shows that neighborhoods of Los Angeles with greater than 20% poverty rates use the EITC at about twice the levels as do the nonpoor areas and receive almost three times the amount of financial benefit per square mile and one and a half times the amount per capita.

About $2 million per square mile for each year is attributable to the EITC in poor areas, but only about $850,000 per square mile for the region as a whole.

In general, this descriptive analysis of the EITC as a form of neighborhood investment in Los Angeles shows that the program channels significant financial benefits into neighborhoods of concentrated poverty, both in aggregate and per capita measures. Since the poor neighborhoods increased
their EITC-related spending incomes by about $200 per person, and roughly half of the tax filers in these neighborhoods received an EITC benefit, it is reasonable to expect some significant boosts toward increased consumer spending from those residents, and possibly increases in the spending in the neighborhoods where they live. Alternatively, if consumer effects on the neighborhood job base are related to dollar density rather than per capita spending power, then an increase of between $800,000 and $2 million of extra EITC income per square mile is likely to have effects on the local economic base—again assuming a large portion of this income is spent locally. Whether this effect is positive or negative is an empirical question and depends on where residents spend this income boost. The following models of policy impact estimate the independent effect of the EITC on baseline job levels. As with any study of tax incentives, tax fraud and knowledge of eligibility for the program are difficult methodological challenges to overcome. Although important, these challenges are beyond
Table 2
Concentrated Poverty Areas and the EITC
(Earned Income Tax Credit), 1997, 1998

<table>
<thead>
<tr>
<th></th>
<th>1998</th>
<th>1997b</th>
</tr>
</thead>
<tbody>
<tr>
<td>% EITC use (weighted by number of returns)</td>
<td>17.44</td>
<td>17.97</td>
</tr>
<tr>
<td>Total financial benefit (000s)</td>
<td>$1,228,356</td>
<td>$1,201,063</td>
</tr>
<tr>
<td>Total number of EITC claims</td>
<td>748,768</td>
<td>752,983</td>
</tr>
<tr>
<td>Average benefit per claim (000s)</td>
<td>$1.64</td>
<td>$1.60</td>
</tr>
<tr>
<td>EITC amount per square miled (000s)</td>
<td>$860</td>
<td>$842</td>
</tr>
<tr>
<td>EITC amount per 2000 populatione</td>
<td>$142</td>
<td>$139</td>
</tr>
<tr>
<td>Poor Areas of Los Angeles</td>
<td>40.89</td>
<td>40.96</td>
</tr>
<tr>
<td>Poor Areas of Los Angelesc</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Los Angeles</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. The figures presented in this table as background data have also been presented in a previous article for the Journal of Planning Education and Research (Spencer 2005)
b. 1998 dollars.
c. Poor Areas defined by a 1990 Census poverty rate of greater than 20%. The EZ areas are a subset of the Poor Areas.
d. The area for the Poor Areas of Los Angeles in 1989 is 218 square miles. The area for Non-Poor 1989 areas is 1,144 square miles.
e. When estimated for ZIP Codes by assigning Census 2000 block group population values to the ZIP Code in which each block group’s centroid is located, the following population estimates are produced: Poor Areas = 2.3 million; All Urbanized Los Angeles County = 8.6 million.

the scope of the paper, which focuses on actual policy disbursements rather than potential or wrongly allocated ones.

Regression Results

Using the two definitions of the EITC program effect for each year of available data in the regression maximizes the robustness of the model’s findings, as does testing the model for both of the years 1997 and 1998. The first definition, density of EITC tax returns, measures the number of consumer families per square mile receiving an income boost. The second, density of total EITC amount, measures the dollar amount of EITC credit per square mile. Using these two measures for each year of data helps to overcome any inconsistencies in the original raw data and strengthens any conclusions suggested by the basic consumer model. For convenience’s sake, I break the findings down into Models 1-4.
Table 3

Regression Coefficients, ZIP Code Retail Employment Density, Tax Return–Standardized Income Variable

<table>
<thead>
<tr>
<th></th>
<th>Program Effect Estimated by Density of Participation (EITC = Pit2)</th>
<th>Program Effect Estimated by Density of Dollar Amount (EITC = Ait2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted R-square</td>
<td>.793</td>
<td>.798</td>
</tr>
<tr>
<td>Constant</td>
<td>86.913***</td>
<td>90.567***</td>
</tr>
<tr>
<td>1987 level of employment</td>
<td>0.365***</td>
<td>0.367***</td>
</tr>
<tr>
<td></td>
<td>(0.870)</td>
<td>(0.874)</td>
</tr>
<tr>
<td>Single-family home values 1998</td>
<td>0.000*</td>
<td>0.000**</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.100)</td>
</tr>
<tr>
<td>Non-EITC income per tax return, 1997 (1998)</td>
<td>−1.532*</td>
<td>−1.659***</td>
</tr>
<tr>
<td></td>
<td>(−0.102)</td>
<td>(−0.129)</td>
</tr>
<tr>
<td>Enterprise zone</td>
<td>29.313</td>
<td>25.70</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>EITC variable</td>
<td>−0.000005</td>
<td>−0.000006</td>
</tr>
<tr>
<td></td>
<td>(−0.001)</td>
<td>(−0.001)</td>
</tr>
</tbody>
</table>


* p < .05. ** p < .01. *** p < .001.

Note: EITC = Earned Income Tax Credit.

a. All EITC variables standardized by geographic area.
Table 3 presents the case where AGI as a control variable is standardized
by tax return (not by square mile). Thus it does not account for spatial
concentrations of non-EITC dollar resources. In other words, the same
average income per tax return for West Los Angeles (a densely populated
neighborhood) might be assigned the same value as, for example, Malibu
(a more sparsely populated area). If changes in the retail employment
base were a function of higher average nonprogram incomes more than
they were a function of income spatial density, then this model would
accurately estimate program effect. The high values of the non-EITC
income variable, however, suggest that standardizing background income
by number of returns does not reflect reality. In this case, on average,
every additional dollar added to the average 1997 AGI would decrease
retail employment by about 1.5 per square mile. Thus a $1,000 increase
in average adjusted gross income would mean a decrease of about 1,500
jobs per square mile!

Alternatively, using the spatial density of AGI as the control suggests
that the geographic standard is more likely the basis for background retail
employment levels. Table 4 describes this case where the density of total
neighborhood income is central in determining the retail employment base
rather than the per-return measure.

Examining the significant AGI coefficients for the four models—all sig-
nificant at .000—strongly suggests that background income density has no
positive or negative impact on the retail job base no matter whether the
EITC program effect was measured by participation ($P_{it}$) or by dollar den-
sity ($A_{it}$). This finding is consistent with the hypothesis that retail pur-
chasing among the general population is not a local, neighborhood activity.

Results for the EITC variable in Models I and II, where program effect
is measured by the number of returns per square mile, show consistently
significant positive impacts. The EITC coefficients of (0.007) and (0.009)
for 1997 and 1998 respectively show that for every additional 1,000 EITC
returns per square mile the retail employment base increased by about
seven and nine jobs per square mile, respectively. Results for Models III
and IV, where the program effect is measured by EITC dollar amount per
square mile, show significant, though less consistent, positive results. The
EITC coefficient of ($3.0 \times 10^{-6}$) means that for every $1,000 increase
in EITC dollar value claimed per square mile, there is an associated retail job
increase of three per square mile. The data for 1998 show a similar positive
relationship, though the coefficient is not significant.

The regression models for the EITC program effect on retail employment
show, for all possible definitions of the EITC variable, that the secondary
Table 4
Regression Coefficients, ZIP Code Retail Employment Density, Geographically Standardized Income Variable

<table>
<thead>
<tr>
<th></th>
<th>Program Effect Estimated by Density of Participation (EITC = (P_{it2}))</th>
<th>Program Effect Estimated by Density of Dollar Amount (EITC = (A_{it2}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted R-square</td>
<td>.794</td>
<td>.798</td>
</tr>
<tr>
<td>Constant</td>
<td>73.012***</td>
<td>75.703***</td>
</tr>
<tr>
<td>1987 level of employment</td>
<td>0.378***</td>
<td>0.382***</td>
</tr>
<tr>
<td></td>
<td>(0.899)</td>
<td>(0.910)</td>
</tr>
<tr>
<td>Single-family home values 1998</td>
<td>0.000099</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>Non-EITC income per square mile, 1997 (1998)</td>
<td>0.0000**</td>
<td>0.000***</td>
</tr>
<tr>
<td></td>
<td>(−1.970)</td>
<td>(−2.537)</td>
</tr>
<tr>
<td>Enterprise zone</td>
<td>30.431</td>
<td>26.284</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>EITC variable</td>
<td>0.007**</td>
<td>0.009***</td>
</tr>
<tr>
<td></td>
<td>(1.972)</td>
<td>(2.560)</td>
</tr>
</tbody>
</table>


*\(p < .05\), **\(p < .01\), ***\(p < .001\).

Note: EITC = Earned Income Tax Credit.
a. All EITC variables standardized by geographic area.
Table 5  
EITC (Earned Income Tax Credit) Regression Coefficients by Sector  
(adjusted R-squared values in parentheses)a

<table>
<thead>
<tr>
<th>Program Effect Estimated by Density of Participation (EITC = ( P_{it} ))</th>
<th>Program Effect Estimated by Density of Dollar Amount (EITC = ( A_{it} ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density of all employment</td>
<td>Density of all employment</td>
</tr>
<tr>
<td>−0.142***</td>
<td>−0.180***</td>
</tr>
<tr>
<td>(0.928)</td>
<td>(0.938)</td>
</tr>
<tr>
<td>Density of retail employment</td>
<td>Density of retail employment</td>
</tr>
<tr>
<td>0.007**</td>
<td>0.009***</td>
</tr>
<tr>
<td>(0.794)</td>
<td>(0.798)</td>
</tr>
<tr>
<td>Density of services employment</td>
<td>Density of services employment</td>
</tr>
<tr>
<td>−0.034***</td>
<td>−0.045***</td>
</tr>
<tr>
<td>(0.982)</td>
<td>(0.982)</td>
</tr>
<tr>
<td>Density of manufacturing employment</td>
<td>Density of manufacturing employment</td>
</tr>
<tr>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>(0.659)</td>
<td>(0.659)</td>
</tr>
</tbody>
</table>


*p < .05, **p < .01, ***p < .001.

a. All EITC variables standardized by geographic area.
impact of the program on the employment base is significant. Is this the case for other sectors?

Table 5 provides a sectoral breakdown of the relationship between the economic base and the EITC, using the same model but substituting manufacturing and service sector employment, as well as total employment, for retail employment. The coefficients and adjusted $R^2$ values presented reflect the models in which non-EITC income variables were standardized by geographic area.

Results show that the EITC program had no demonstrable effect on manufacturing employment, but it was associated with a decrease in services employment. Further studies might explore whether these effects are the result of the EITC or of other collinear factors. The most relevant finding for the consumer behavior hypothesis, however, is the positive finding for retail employment.

**Discussion:**

**The Scale of Employment Growth in Retail**

The findings from this study describe a significant benefit for Los Angeles’s working poor population in the form of a direct transfer of wealth that creates incentives for work. In 1997 and 1998, about 750,000 workers took the credit in Los Angeles, receiving a total of over $1.2 billion dollars in each year. Using a Census 2000 population estimate, this credit provided about $140 for every resident of urbanized Los Angeles. Being targeted at the poor, the program provided, on average, about $1,600 for each tax return claim made. For every claim coming from a resident of a poor neighborhood, the amount of the claim rose to about $1,700. Thus it seems not only that EITC claims are a significant boost to annual family incomes, but that those living in poor neighborhoods tend to take higher claims than others.

This disproportionate effect on poor neighborhoods in terms of participants and amounts is significant. First, the program channeled about $495 million into Los Angeles’s poor neighborhoods in 1998 and about the same amount for 1997. Importantly, this injection of EITC dollars was about $2 million per square mile in the poor areas of the county, but only about $850,000 per square mile averaged throughout the urbanized parts of the county. It is clear, therefore, that even though it is primarily a people-based program, the EITC does channel a significant financial resource to poor neighborhoods.
The scale of investment resulting from the EITC is impressive. For example, the California EZ program invested about $5.70 million in Los Angeles in 1998. The EITC invested $148 million into those very same areas during the same year (Spencer 2005). Moreover, this investment was directly transferred to the working poor, the explicit targets of antipoverty policy, rather than to the businesses that create the jobs they may take.

Table 2 showed that the basic program costs of the EITC in 1998 throughout Los Angeles were $1.2 billion, $494 million of which was channeled to poor neighborhoods. The figures for 1997 were similar, at $1.2 billion and $483 million, respectively. These figures represent the direct and intended cost of the program associated with the benefits discussed above. An analysis of job changes in response to the EITC suggests that there are some secondary and unintended neighborhood effects. Using the coefficients for the EITC variables from 1997, it is possible to estimate the impact of the EITC program on the local retail job base for all poor neighborhoods in Los Angeles. If the impact is primarily through the dollar amount of EITC credit transferred to neighborhoods, then I can use the EITC amount per square mile coefficient, $3.0 \times 10^{-6}$, to calculate a retail job gain of 1,450 throughout the poor neighborhoods of Los Angeles.\(^3\)

On the other hand, if the impact is primarily through the number of EITC claimants, then I can use the coefficient for EITC claim density in 1997, 0.007, to estimate the retail job gain. In this case, the gain would be 2,029 throughout the poor areas of Los Angeles.\(^4\) Averaging the two alternative values generated for EITC program effect on the neighborhood job market produces an estimated gain of 1,736 throughout the poor areas of Los Angeles. This figure, however, must be placed in the context of a large Los Angeles County economy that hosted about 300,000\(^5\) retail jobs in 1997 (U.S. Bureau of the Census 2001). Nevertheless, this modest but significant positive finding suggests a reevaluation of claims that the effects of people-based policy on urban governments are minimal (Gyourko 1998).

The scale of economic development effects cannot compare to the magnitude of positive program impacts through the direct transfer of income and the employment benefits. Moreover, while the statistical analyses indicate a relationship, they, of course, do not confirm causality. Nevertheless, the findings do suggest that some of the speculations about the positive neighborhood impact of spatially concentrated EITC benefits are correct, and that findings on the positive effect of the EITC on the municipal-level economic base (Texas Perspectives 2004; Jacob France Institute 2004) are indeed reaching those neighborhoods most in need of economic development. Specifically, the argument that increased incomes for residents of poor neighborhoods will
increase consumer activity in the retail sector, thereby stimulating an increase in local retail jobs, can be made convincingly for Los Angeles.

More important than the precise number of jobs gained or lost, estimating the impact of the EITC on the neighborhood retail economy has significant policy implications, not only for the EITC itself, but also for neighborhood development programs. Estimating the overall impact of the EITC on the job base of neighborhoods falling under the state Enterprise Zone program suggests that 972 retail jobs were gained in Los Angeles’s zones when calculated by EITC dollar amount, or 1,302 jobs when calculated by number of EITC participants. Averaging these two impacts suggests that roughly 1,137 retail jobs were gained in those areas where state policy was attempting to stimulate the economy through the EZs. While these are distinct programs, this empirical evidence suggests that antipoverty efforts have the potential to reinforce one another and offers a fruitful line of future research. More immediate, given that place-based programs such as Enterprise Zones are particularly susceptible to abuse in California (Halper 2006), policy makers might reassess multi-policy frameworks for developing jobs in poor neighborhoods.

As discussed in Spencer (2004), one of the challenges for policy makers is to find innovative ways to promote both people- and place-based policies that serve the poor. Current knowledge, however, is insufficient for pointing to innovative ways to integrate the two. This study poses an empirical question that may help decision makers maximize the aggregate welfare gains of antipoverty policy. For example, based on the results presented here, policy makers might consider how best to further retain the significant amounts of EITC dollars in the Enterprise Zones to help support local job development and local entrepreneurs. Similarly, they might streamline or enhance EITC credits for workers employed in Enterprise Zones. Such possibilities depend on good empirical evidence, and the present analysis provides one way to start meeting this need.

Concluding Thoughts: Individual Entitlements and the Politics of Poor Places

This paper examines the spatial significance of the EITC as an investment in poor neighborhoods as described in the literature (McDonald 2004; Spencer 2005; Berube and Forman 2001a, 2001b). Moreover, it provides some preliminary empirical evidence for policy makers on how to think about the relationship between place-based and people-based policy (Spencer 2004, 2005).
The literature on EITC program effectiveness generally shows strongly positive results in reducing poverty, attaching low-wage workers to the labor market, and generating the means to invest in the future. Since the original intent of the program was to reduce poverty and create incentives for work, the majority of evaluations have focused on these individual benefits to the working poor and how the structure of the program has improved job-seeking behavior.

Recently, however, some studies have placed the program’s findings in the broader context of how to deal with persistent spatially concentrated poverty. These original studies showing spatial concentration of benefits, combined with the additional analysis developed here, show that the amount of benefit is substantial enough to consider whether the policy has a broader impact felt at the neighborhood level. Moreover, it provides the basis for a more comprehensive study of the significance of spatial concentration. Speculation from previous reports (such as McDonald 2004; Spencer 2005; Berube and Forman 2001a, 2001b) suggests an important benefit to local neighborhood economies because of increased purchasing power where the EITC is spatially concentrated. This is one definition of welfare gains attributable to the EITC. To the best of my knowledge there have been no studies to provide evidence as to whether this speculation is correct, and the contribution of this paper is to help empirically answer this question.

Importantly, the findings also highlight an important political aspect of antipoverty policy. As the EITC channels huge financial resources to working and consuming residents of poor neighborhoods and cities, there is evidence that some of this benefit accrues locally, where many political decisions are made. In this way, the study questions Gyourko’s (1998) contention that cities do not benefit from people-based policies. Greater attention to these local neighborhood benefits might shift local political support from mayors, city council members, and other political elites toward people-based antipoverty programs and leave such officials with alternatives to place-based ones shown to have questionable impact (Peters and Fisher 2002).

Further study might take four policy-relevant directions. First, it might further refine statistical analyses to better control for neighborhood socioeconomic conditions and differential consumer behavior patterns. In addition, qualitative research on whether EITC participants would rather use their income on local retail and services if they were priced competitively, or if the appropriate goods and services were locally available, might suggest to policy makers that the EITC might both provide a significant income boost to the working poor and stimulate more significant local economic
growth. Second, it might examine the particular, nonspatial conditions under which EITC policy and its de facto concentration in space can have positive effects on the local neighborhood economic base (e.g., the business cycle). Third, scholars might extend the preliminary findings of the regional-level impact of the EITC. For example, if consumer purchasing happens at the regional rather than the neighborhood level, then a study of county-level EITC impacts on the economic base would suggest more comprehensively how labor policy may be an important form of economic stimulus. Finally, a spatial analysis of legislative support for the EITC would clarify whether greater spatial retention of EITC funds might increase city government support for the policy.

Notes

1. Temporary Assistance to Needy Families.
2. Rather than using Census 2000 figures to define poor Los Angeles neighborhoods, I use 1990 data. This choice enables a more accurate regression analysis that examines economic changes from the mid-1980s through the mid-1990s.
3. These figures were calculated in the following way: Poor Areas job gain = (Poor Area EITC dollar density) * (EITC dollar density coefficient) * (Number of Square miles in Poor Areas). Thus the Poor Areas job loss = (2,218,000)*0.000003*(218) = 1,450 retail jobs gained.
4. These figures were calculated in the following way: Poor Areas job gain = (Poor Area EITC claim density) * (EITC claim density coefficient) * (Number of Square miles in Poor Areas). Thus the Poor Areas job gain = (289,895/218)*(0.007)*(218) = 2,029 retail jobs gained.
5. This figure includes all the urbanized ZIP Codes of the county.

References


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