

# Effective Policy for Reducing Poverty and Inequality? The Earned Income Tax Credit and the Distribution of Income

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## **Abstract:**

In this paper, we examine the effect of the EITC on the poverty and income of single mothers with children. We provide the first comprehensive estimates of this central safety net policy on the full distribution of after-tax and transfer income. We use a quasi-experiment approach, using variation in generosity due to policy expansions across tax years and family sizes. We find that the income increasing effects of the EITC are concentrated between 75% and 150% of income-to-poverty with little effect at the lowest income levels (50% poverty and below) and at levels of 250% of poverty and higher. Specifically, a policy-induced \$1000 increase in the EITC leads to a 9.4 percentage point reduction in the share of families with after-tax and transfer income below 100% poverty. These results are robust to a rich set of controls and whether we compare single women with and without children or compare women with one child versus women with two or more children. They are also robust to whether we limit our analysis to the sharp increase in the 1993 expansion or use the full period of policy expansion, back to the 1986 Tax Reform Act. Importantly, event study estimates show no evidence of differential pre-trends, providing strong evidence in support of our research design. We use these results to show that by capturing the indirect effects of the credit on earnings, static calculations of the anti-poverty effects of the EITC (such as those released based on the Supplemental Poverty Measure, Short 2014) may be underestimated by as much as 50 percent.

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## 1. Introduction

Since the mid-1970s, earnings for less skilled workers have stagnated (Autor 2014). Hourly wages for men with less than a high school degree have fallen in real terms by more than 20 percent since 1973. Declines, though of a smaller degree, have occurred for men with a high school degree and for those with some college. Real wages for women with a high school degree or some college show small gains, though high school dropouts have seen no real increases. These factors combine to show losses or no change in real family income for the bottom 20 percent of the population (Mishel et al 2012). This is particularly salient given the high and persistent premium paid to college educated workers (Autor 2014) and the steady gains in income held by the top one percent of taxpayers (Piketty and Saez 2003).

Given this backdrop of stagnating wages and income for lower income Americans, there is a renewed interest in policies aimed at reducing inequality and increasing income and opportunity of the less advantaged population. At the same time, there is also concern about the related problem of secular declines in employment rates among prime aged men, and more recently, women (Economic Report of the President 2015). Commonly mentioned policies include raising minimum wages, increasing the Earned Income Tax Credit, and pre-market interventions aimed at increasing human capital and skills.

In this paper, we comprehensively evaluate the central “post-market” policy aimed at the twin concerns of stagnant earnings and low employment – the Earned Income Tax Credit (EITC). In particular, we use a quasi-experimental research design to comprehensively estimate the effect of the EITC on the distribution of after-tax and transfer income. We are the first paper to examine the degree to which the large expansions in the federal EITC increases income, and where in the income distribution these changes occur. Our approach captures three central

channels through which the EITC may affect after-tax income. We capture the direct effect of the tax payment (*credit* effect) as well as the indirect effect of increasing earnings (*earnings* effect) as well as any reduction in other public assistance (or other) income (*income adjustment* effect).<sup>1</sup>

The EITC provides a refundable tax credit to lower income working families. Tax expansions over the past two decades have made the EITC a central element of the U.S. safety net (Bitler, Hoynes and Kuka 2015). In 2013, the EITC reached 28.8 million tax filers at a total cost of \$68.1 billion, with an average credit amount of \$3,063 for families with children (Internal Revenue Service 2015). Almost 20 percent of all tax filers and 44 percent of filers with children receive the EITC. In contrast, only 1.75 million families received cash welfare benefits (TANF) in 2013, a 65 percent decline since 1994.

Given the prominence of the EITC in the U.S. safety net, it is not surprising that many studies have evaluated its effects. We have two decades of research on the effect of the EITC on labor supply (see reviews by Hotz and Scholz 2003, Eissa and Hoynes 2006, Nichols and Rothstein 2015). The evidence shows that the EITC leads to substantial increases in employment for single parent families with children and small reductions in employment for secondary earners in married couples (e.g., Eissa and Liebman 1996, Meyer and Rosenbaum 2000, 2001, Eissa and Hoynes 2004). There is less evidence on the intensive margin of labor supply, though some studies show that workers adjust to maximize the credit along the phase-in region (Chetty, Friedman and Saez 2013, Saez 2010, Chetty and Saez 2013). There is a recent, and growing, literature leveraging the presumed gains in family resources that are generated by the EITC and finds that the credit leads to increases in infant health (Baker 2008, Baughman 2012, Hoynes, Miller and Simon 2015, Strully et al 2010), maternal health (Evans and Garthwaite 2014),

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<sup>1</sup> In theory, the reduction in other income may exceed the increase in earnings, leading to a reduction in pre-tax income.

children's cognitive outcomes (Dahl and Lochner 2012, Chetty, Friedman, and Rockoff 2011) and educational attainment (Micheltmore 2013, Manoli and Turner 2014).

Despite its importance, we know much less about how the EITC affects poverty and, more generally, the distribution of income. Calculations based on the Supplemental Poverty Measure show that the EITC (together with the child tax credit) removed 4.7 million children from poverty in 2013 (Short 2014), making the EITC the largest anti-poverty program for children in the U.S.<sup>2</sup> However, this estimate is a static calculation, constructed by zeroing out observed EITC income and recalculating poverty; thus capturing only the direct credit effect (and not the indirect effects of earnings and other income). Incorporating the effect of the credit on earnings is expected to lead to *larger* poverty reductions. This static or simulation approach has also been used by Liebman (1998) and Meyer (2010).

A handful of studies estimate the effect of the EITC on earnings (e.g., Grogger 2003, Newmark and Wascher 2001, 2011) and income or poverty (Bollinger et al 2009, Grogger 2003, Gunderson and Ziliak 2004). We expand on these studies in four ways. First, we focus on the federal credit while many of the others focus on the much smaller state EITCs.<sup>3</sup> Second, we comprehensively examine the effects across the distribution of after tax and transfer income relative to poverty. Third, we exploit tax-policy-driven differences between women without children compared to those with children as well as differences across women with one versus two or more children. Finally, we present event study models to evaluate the validity of the quasi-experimental approach. The result is a full picture of the antipoverty effects of the program.

Our main results leverage the significant variation in the 1993 expansion of the credit

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<sup>2</sup> The next largest is SNAP, which removed 2.1 million children from poverty in 2013.

<sup>3</sup> In addition, the timing of state introduction and expansions of EITCs may not be exogenous. State legislation is typically passed in times of strong labor markets and healthy state revenues.

across family size (as first presented in Eissa and Liebman 1996), by employing a difference-in-difference and event time approach. We extend that analysis in a parameterized difference-in-difference approach that takes advantage of credit expansions over the longer period 1984-1998. Both approaches leverage variation across family size and tax year. Throughout our analysis, we focus on single women, who have the largest participation rates in the program. In fact, single filers with children account for almost 60 percent of EITC filers and about three-quarters of the cost of the credit.

We find that the 1993 expansion led to a 7.9 percentage point decrease in the share with after tax and transfer income below poverty (for families headed by these single women), implying a 9.4 percentage point effect per \$1000 in federal EITC. Additionally, by examining the effects of the EITC at different points of the income distribution we find that the income-increasing effects of the EITC are concentrated between 75% and 150% of the federal poverty threshold, with smaller effects at extreme poverty levels (where there is less connection to the labor market) and at higher income levels. Importantly, we find that the static calculations of the effects of the EITC, by ignoring the induced earnings effect, underestimate the anti-poverty effects of the credit by up to 50 percent.

As part of our analysis, we also apply our empirical framework and data to replicate and update the employment effects of the EITC. We find that the 1993 expansion of the credit led to a 6.1 percentage point increase in the employment of single mothers, which is large relative to the mean employment rate of 84 percent. These effects translate to a 7.3 percentage point increase per \$1000 of EITC, and an extensive margin elasticity of 0.36. These results are maintained through the early 2000 recession and Great Recession period.

Our results are robust to several alternative specifications including whether or not we

include a conservative set of controls, whether we use variation across single women with no children versus those with children or single women with one versus two or more children, and whether we use the sharp change in 1993 or the full set of EITC expansions back to 1984. Finally, our event time graphs provide compelling evidence that the research design – comparing outcomes across different family sizes – is valid.

Our paper also contributes to the broader literature on the effects of social policies on the distribution of income. Many studies have used variation in state minimum wages to examine the effects on inequality and the distribution of income (for example see Burkhauser and Sabia 2007, Card and Krueger 1995, Dube 2013, Gunderson and Ziliak 2004, and Neumark et al 2005 as well as reviews in Autor et al 2010, Dube 2013, and Neumark and Wascher 2008). Frandsen (2012) estimates the effects of unionization on the distribution of earnings. Havnes and Mogstad (2015) estimate the effect of universal child care on the distribution of income. It is worth pointing out that many of these studies use *relative* measures of inequality, such as the ratio of the median to the 10<sup>th</sup> percentile of income (or earnings). We take a slightly different approach, examining the effects of the EITC on *absolute* measures of inequality, such as the share of the population with income below the poverty threshold or 1.5 times the poverty threshold. We measure absolute inequality for two reasons. First, it provides a link to the static poverty calculations that provide the basis of an important comparison and illustration of the magnitude of the induced earnings effects. Second, our research design is based on comparisons across demographic groups (e.g. families with different numbers of children) and the relative inequality approach would effectively lead to making comparisons between family-size-specific income distributions. While making comparisons across state income distributions, as in the minimum wage literature, seems natural given local labor markets, comparisons across demographic groups is less natural.

In the following section we describe the EITC and its evolution. In section 3, we explore the predictions for the effect of the EITC on the distribution of after tax and transfer income. The dataset is presented in section 4 (also see data appendix), and we detail our estimation strategy in section 5. In section 6 we briefly present estimates of the effect of the EITC on employment, providing a replication and extension of the existing literature. In section 7 we present our main results on the effects of the EITC on the distribution of after tax and transfer income. We use the estimates to calculate the effects of the EITC on the aggregate number of individuals and children in poverty in section 8, and we conclude with section 9.

## **2. The Earned Income Tax Credit**

A taxpayer may claim the EITC on a federal income tax return. To be eligible for the EITC, a taxpayer must have earned income during the tax year.<sup>4</sup> Taxpayers must have less than a specified amount of adjusted gross income (AGI) and earned income. The value of the credit is determined by a benefit schedule that generally has three regions. In the phase-in region, the credit increases by a share of each additional dollar earned. Once the credit reaches its maximum (capped) value, the taxpayer is in the second “flat” region. In the final region, the credit is phased-out with each additional dollar of AGI until it is zero. There are separate schedules, with the same basic shape, by filing status and by the number of qualifying children claimed.<sup>5</sup> Figure 1 displays the schedule in 2013 (as a function of earned income) for single taxpayers with no, one, two, and three or more children. The phase-in or subsidy rate is substantial at 34 (40) percent for those with one (two) children. The phase-out rate is much lower at 15.98 (21.06)

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<sup>4</sup> Earned income is the sum of wages, tips, salary, union strike benefits, some disability payments, and net self-employment earnings (IRS 2013).

<sup>5</sup> A qualifying child is younger than 19 (or younger than 24 and a full time student), lives with the taxpayer for more than half the year, has a valid social security number, and is not claimed as a dependent by another taxpayer (IRS 2013).

percent for those with one (two) children. The maximum allowable income for a taxpayer with one child (two or more children) was \$37,870 (\$43,038). The maximum benefit differs substantially across number of children, from \$487 for those without children to \$6,044 for those with three or more children. Finally, the credit is refundable: if the credit exceeds a taxpayer's tax liability, they receive the difference as refund.

EITC eligibility rules target working families who are relatively low in the income distribution. We can directly observe this in a sample of tax returns.<sup>6</sup> We define after-tax income as gross taxable income less taxes owed plus credits and apply federal poverty thresholds using family size within the tax unit. The results are displayed in figure 2. Panel (a) contains single taxpayers with children. The figure on the left tabulates the share of EITC claims by income-to-poverty bin while the figure on the right tabulates the total taxpayers in this bin who claim the EITC. The majority of single taxpayers with children who claim the EITC are between 50% and 200% of the federal poverty threshold (left graph).<sup>7</sup> Within each income-to-poverty bin, approximately 80% of filers claim the EITC up to 200% of the federal poverty threshold, declining after that (right graph). Among those filing a joint return and with children (panel b), EITC claimants have slightly more after tax income relative to those filing single, though they are still below 200% of the federal poverty threshold. Overall, the EITC eligibility rules accomplish a transfer to those who have relatively low income.

The EITC schedule has been expanded several times since its inception in 1975. Figure 3 illustrates the changes over time by plotting the maximum credit amount by tax year and number of qualified children (in real 2013 dollars). Figure 3 also identifies the four tax reforms

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<sup>6</sup> The Statistics of Income *Complete Report File* for 2011 is a 1 in 10,000 sample of tax returns from tax year 2011.

<sup>7</sup> Liebman (1998) finds a similar result using the 1993 CPS with EITC rules from 1996. He contrasts this with traditional welfare (AFDC and Food Stamps), which are targeted at families with lower multiples of the poverty threshold.



responsible for these changes.<sup>8</sup> The 1993 legislation produced the most dramatic changes to the policy, increasing the benefit for those with any children as well as for those with two or more children relative to those with one child. In contrast to tax year 1984, families claiming two or more children in tax year 1997 enjoyed an increase in the maximum credit of \$4,236 (2013 dollars). Eligible families with one child experienced a smaller increase of \$2,111. Finally, there were smaller increases for those without children (\$488, OBRA 93) and those with three or more children (\$670, ARRA 2009). We use differential expansions across family size over time as the basis of our quasi-experimental design.

In addition to the EITC, there were other changes to tax and transfer policy during this period. Those eligible for the federal EITC also saw changes to their federal exemptions, and to their tax bracket rates and thresholds. These families would also be eligible for an increasing number of state-level EITCs.<sup>9</sup> At the same time, traditional welfare benefits for families with children were curtailed (e.g., Moffitt 2003, Ziliak 2015). For example, states introduced changes to the Aid to Families with Dependent Children (AFDC) program through federally-approved waivers. These waivers allowed states to introduce various provisions aimed at reducing AFDC participation and enabling the transition from welfare to work.<sup>10</sup> In 1996, many of these benefit limits were introduced nationally with the Temporary Assistance for Needy Families (TANF) program, which also restricted the amount of federal funding available to states (Crouse 1999). In the empirical specification below, we control for these changes in other tax and transfer programs to isolate the effects of the EITC.

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<sup>8</sup> The four tax reforms are the Tax Reform Act of 1986 (TRA 86), the Omnibus Budget Reconciliation Acts of 1990 & 1993 (OBRA 90 & OBRA 93), and the American Recovery and Reinvestment Act of 2009 (ARRA 2009). In addition, the flat and phase-out regions were extended for married couples in the Economic Growth and Tax Relief Reconciliation Act of 2001.

<sup>9</sup> Currently, 28 states including DC have an earned income tax credit (IRS 2014).

<sup>10</sup> Changes to AFDC through waivers include work and training requirements, time limits on welfare receipt, family caps provisions, expanded income disregards, increased resource limits, Medicaid assistance for the transition to work, expanded eligibility for two-parent families, and improved child support enforcement (HHS 1997).

The evolution of these policies increased the relative importance of the EITC as an income support program. Figure 4 displays per capita expenditures for the EITC, the AFDC program, the TANF program and the Supplemental Nutrition Assistance Program (SNAP)<sup>11</sup> (Bitler and Hoynes 2010). Prior to 1986, per capita spending on the EITC was only a fraction of other welfare programs. After welfare reform, and even through the Great Recession, spending on the EITC was much larger than that on TANF cash grants.

### **3. The EITC, Employment and the Distribution of Income**

The expected effect of the EITC on after-tax and transfer (ATT) income operates through three primary channels (Liebman 1998, Grogger 2003, Bollinger, Gonzalez and Ziliak 2009, Meyer 2010, Hoynes, Miller and Simon 2015). Beginning with the definition, ATT income equals earnings plus other income plus government transfers less taxes. We simplify to broadly consider three components. First, direct EITC payments increase ATT income. Second, EITC-induced changes in earnings affect ATT income. Third, increases in earnings may lead to reductions in other income sources. In particular, the likelihood that the same family qualifies for traditional welfare payments such as cash welfare (AFDC/TANF) and SNAP is expected to decrease (as earnings increases). We call these the *credit* effect, the *earnings* effect, and the *income-adjustment* effect. At the core is basic labor supply theory and the incentives for employment and earned income more generally.

The EITC generates labor supply incentives on the intensive and extensive margins that likely differ depending on marital status. Among single parents, who represent the focus of our analysis, the EITC (overall or an expansion in the credit) increases the returns to entering employment for those outside of the labor force – leading to an increase in the extensive margin

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<sup>11</sup> SNAP was formerly called the Food Stamps Program.

of labor supply. The effects of the EITC on the intensive margin, for those already in the labor market, are less unambiguously work-promoting. In the phase-in region, the net-of-tax wage increases with the EITC; the effect on the intensive margin is ambiguous due to a positive substitution effect and a negative income effect. On the other hand, in the phase-out region, both substitution and income effects create a consistent incentive to reduce labor supply (in the flat region the pure income effect also is predicted to reduce labor supply).

Because the EITC is based on family income, the credit leads to a somewhat different set of incentives for married taxpayers. Overall, as with singles, we would expect higher rates of “family” employment for married couples, as a result of the credit being tied to work. Among secondary earners, though, the EITC is expected to reduce labor supply due to the increased after-tax income (and additional tax due to the phase-out rate) generated by the EITC schedule and the primary earner’s labor supply (Eissa and Hoynes 2004).

Among the single mother sample that we examine, we expect that the EITC will increase ATT income. For those induced by the EITC to enter the labor market, ATT income should increase due to the positive credit and earnings effects, but the increase could be offset by a potential decline in other income. For those single women already in the work force, the main channel for increasing ATT income is the credit effect. In principle, this positive credit effect could be offset by a negative earnings effect, to the extent to which workers respond to the phase-out rate. However, given the lack of evidence of a behavioral response in the phase-out region, we don’t expect the offset to be significant. Additionally, due to the shifting out of the labor supply curve induced by the EITC, market wages may decline as employers interact with increased labor supply on the extensive margin (Rothstein 2010).

As discussed above, and presented in Figures 1 and 2, the EITC schedule targets the

largest credit to incomes around the poverty threshold. For example, for a single woman with two children, the flat region of the credit (the maximum credit) corresponds to earnings between 0.7 and 0.9 times the poverty threshold and the phase-out region extends to 2.3 times the poverty threshold.<sup>12</sup> Accordingly, our prior is that the EITC is unlikely to have an effect on those with very low income (where families have less connection to the labor market) nor on those with income much beyond 200 percent of poverty.

Our approach, using a comprehensive measure of ATT income, allows us to capture the total effect of the EITC – the credit effect, the earnings effect, and the income adjustment effect. We do so by focusing on the largest group of recipients, single women with children. By exploiting large expansions in the credit, with a credible quasi-experimental design, we provide the first comprehensive analysis of the effect of the federal EITC on the distribution of income.

In the method described below, we leverage variation across family size and tax year to identify the effects of the EITC (figures 1 & 3). This approach relies on the assumption that women are not changing their fertility in response to this incentive. There is significant evidence to support this assumption. Baughman and Dickert-Conlin (2009) find a small negative impact of the EITC on higher order fertility within a large sample of birth certificate data. Dickert-Conlin and Chandra (1999) find that the income tax may be correlated with the *timing* of childbirth, but only within a short window of a few weeks. Taken together, the evidence suggests that the EITC does little to modify fertility behavior.

#### **4. Data**

The primary dataset is the Current Population Survey March Annual Social and

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<sup>12</sup> In 2014, for a single woman with two children, the flat region corresponds to earnings \$9,720-\$17,830 and the phase-out extends to \$38,511. The poverty threshold for this family is \$16,317.

Economic Supplement (CPS). The CPS contains representative income and demographic information, making it appropriate to estimate the effect of the EITC on the distribution of income. We begin with the 1985-2014 surveys, corresponding to income over calendar years 1984-2013. We limit to single women between the ages of 24 and 48, who are not ill, disabled or going to school. We further limit the sample to those who have some college education or less (see data appendix for more details). Where possible we augment the CPS data with information on the universe of tax returns (the Statistics of Income *Complete Report File*). The tax data is not sufficient to provide the main data for our analysis, given that we need to capture safety net income (not captured in the tax data) and we need to capture movements into and out of the labor force (taxable universe).

We explore the impact of the EITC on different points of the income distribution using multiples of the official poverty threshold (50% poverty, 100% poverty, 150% poverty, etc.). We use a comprehensive measure of after-tax and transfer (ATT) income defined as pre-tax cash income plus the cash value (as reported by the household or imputed by the Census Bureau) of non-cash programs (food stamps, school lunch, housing subsidies, and energy subsidies), minus payroll, federal and state income taxes (including the EITC, child and child care tax credits, and stimulus payments). We then use the poverty thresholds that are the basis of official poverty, resulting in an ATT income measure of absolute inequality. Our income measure differs from official poverty in our inclusion of in-kind transfers and taxes; it is similar to the Supplemental Poverty Measure and the earlier National Academy of Sciences recommendations (Citro and Michael 1995), but can be measured consistently back to the mid-1980s where we begin our analysis. We have developed this measure in earlier work (Bitler and Hoynes 2010, 2014).<sup>13</sup>

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<sup>13</sup> The main difference is that the SPM includes out of pocket medical costs and work expenses in its measure of after tax and transfer income. Additionally, the poverty threshold in the SPM in part reflects relative income

While the CPS does collect information regarding income and transfers, it does not collect income tax information. We calculate taxes using the NBER TAXSIM calculator (Feenberg and Coutts 1993). We first take the CPS households and construct tax units by linking each qualified child to his/her mother (if between 24 and 48 years of age), otherwise her youngest grandmother or great-grandmother between the ages of 24 and 48.<sup>14</sup> For example, suppose a household contains 3 individuals: a 25 year old mother, her infant child, and the child's 47 year old grandmother. We define the 25 year old mother as the primary tax filer, with one eligible child. If instead the mother was 17 years old, then the 47 year old grandmother is assigned as the primary tax filer, with two EITC eligible children. Using these tax units, we use TAXSIM to calculate income and payroll taxes (see data appendix for details). The resulting measure of after-tax and transfer income is consistent over the sample period.<sup>15</sup>

Appendix Table 1 presents summary statistics by the presence of children. Single women with children differ from those without children (Eissa and Liebman 1996, Meyer and Rosenbaum 2001). Women without children have more education, are more likely to be white, are less likely to be divorced, and are more likely to be employed. Average earned income is higher for women without children, but after-tax and transfer income is higher for those with children.<sup>16</sup> To better balance these two groups in our empirical specifications below, we include a rich set of demographic controls, as well as controls for policy changes and labor market conditions.

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amounts while we use the official poverty thresholds absolute measures. We make these changes to facilitate consistent measurement back to 1980.

<sup>14</sup> IPUMS provides information on the relationship of between children and adults in the household (see data appendix for more details).

<sup>15</sup> Meyer, Mok and Sullivan (2008) note that observed income values in the CPS have deteriorated over time relative to administrative aggregates.

<sup>16</sup> See section 6 for statistics by tax year.

## 5. Methods

The differences-in-differences (DD) estimator is used extensively in the EITC literature to overcome endogeneity arising from the relationship between the EITC, labor supply and unobserved correlates (Eissa and Liebman 1996, Meyer and Rosenbaum 2000, Hotz and Scholz 2003, Eissa and Hoynes 2006). The DD estimator compares a treatment group to a control group, before and after a legislative change in the EITC. The control group captures common changes across the timing of the legislation. We use the following DD specification to examine the largest of the expansions, OBRA 93 (figure 3), in a transparent way,

$$y_{it} = \alpha + \beta(\text{post}_t \times \text{treat}_c) + \eta_{st} + \gamma_c + \Phi X_{it} + \varepsilon_{it}, \quad (1)$$

where  $i$  is an individual taxpayer,  $t$  is a tax year,  $\eta_{st}$  is a set of state by year fixed effects, and  $\gamma_c$  are dummies indicating the number of children (0, 1, 2, 3+). Demographic controls,  $X_{it}$ , include age, education, race, ethnicity, and divorced status of the mother. To focus on OBRA 93, we only use tax years 1991 through 1998, including two years before and after the legislation has fully phased in (figure 2). The DD estimate is  $\beta$ , where  $\text{post}$  is equal to one for any year after 1993. The structure of the OBRA 93 expansion creates two natural comparisons: First, we assign those with children to the treatment group and those without children to the control group. Second, to leverage the larger expansion in OBRA 93 for those with two or more children (figure 3), we also estimate models in which women with two or more children are the treatment group and those with exactly one child are the control group (excluding those without children). The dependent variables ( $y$ ) include a series of indicators equal to one if ATT income is above given multiples of the poverty threshold. To facilitate a link to the prior literature, we also estimate effects on employment.

We can modify equation (1) to test the validity of our design by interacting the treatment

group indicator with year specific indicators instead of a single post-event indicator. In subsequent discussion we call the following equation the event time model,

$$y_{it} = \alpha + \sum_{j=t^0}^T \beta_j [I(t = j) \times \text{treat}_c] + \eta_{st} + \gamma_c + \Phi X_{it} + \varepsilon_{it}, \quad (2)$$

where  $t^0$  is the first year in the sample,  $T$  is the final tax year in the sample, and  $I(t = j)$  is an indicator equal to one if the current year is equal to  $j$ . A coefficient of interest,  $\beta_j$ , is the difference between the treatment and control groups, in period  $j$  (relative to the omitted year<sup>17</sup>), given the same set of controls used in equation (1). In the figures below we define treatment and control groups in three ways. First, we compare those without children to those with children. Second, we compare those without children to those with exactly one child separately from those with two children. Finally, we exclude those without children and include only those with two or more children in the treatment group. When we plot the estimates of  $\beta_j$  we are specifically looking for trends away from zero in the periods before the treatment took effect. These pre-period differences may indicate unobserved differences in the treatment and control groups that we are not adequately controlling for.

The DD estimator naturally works well when there is a single treatment event. However, as described above, there were several EITC expansions over time and across groups. To fully utilize the variation in EITC policy, we replace  $(\text{post} \times \text{treat})$  in (1) with a “simulated” EITC that varies by tax year and number of children.<sup>18</sup> The simulated EITC is a single variable that summarizes changes in the EITC schedule over time and within group (figures 1 & 3). We

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<sup>17</sup> We normalize to drop the coefficient for the year prior to the policy expansion, 1993 for OBRA 93.

<sup>18</sup> This method of summarizing complex policy parameters has been used for other programs including Medicaid (Brown et al 2014, Cutler and Gruber 1996, Currie and Gruber 1996a, Currie and Gruber 1996b, Gruber and Yelowitz 1999) and income taxes (Gruber and Saez 2002, Eissa and Hoynes 2004, Dahl and Lochner 2012, Milligan and Stabile 2011).



calculate the simulated federal EITC in the following way<sup>19</sup>: We begin with our sample of single women in tax year 1982, before the first major expansion in 1986 and free of behavior modifications due to the EITC expansions. We then replicate the sample for each tax year in which we would like a simulated EITC. Next, we use the CPI-U to convert the income values in the sample from 1982 dollars into current dollars. Then, we use TAXSIM to calculate the amount of EITC each of these replicated taxpayers would receive if they had existed in the current year. Finally, for each tax year and group (0, 1, and 2 or more children) we take the (sample weighted) average of the EITC value. In this calculation, except for inflation, the sample remains a collection of taxpayers from 1982, but the tax code changes with each replicated year. The result is an average benefit that summarizes changes in policy (and varies by tax year and family size) without including changes in benefits due to family labor supply decisions. Equation (1), modified for the simulated EITC, is

$$y_{it} = \alpha + \beta \overline{\text{SIMEITC}}_{ct} + \eta_{st} + \gamma_c + \Phi X_{it} + \varepsilon_{it}, \quad (3)$$

where  $\overline{\text{SIMEITC}}_{ct}$  is the simulated EITC, and captures the average generosity of the credit for family size  $c$  in tax year  $t$ . Equation (3) also allows us to extend the sample backwards to tax year 1984, taking advantage of variation caused by several expansions and smaller changes in the EITC schedule across earnings, over time and across group. As with the OBRA 93 DD model, this approach (a “parametrized difference in difference”) relies on identification at the tax year by family size level.

Across the models, we test the robustness of our findings by introducing a rich set of

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<sup>19</sup> To be clear, in this paper we calculate income taxes in two ways. The first uses observed individual taxpayer information to approximate actual tax liability. The second we call “simulated”. Our goal with simulated income taxes and transfers is to summarize policy changes across time and groups without including individual taxpayer behavior.

controls that vary by year and family size (we call this our “conservative controls”).<sup>20</sup> First, we control for generosity of cash welfare policies by using a simulated measure of AFDC and TANF benefits calculated using the same procedure described for the federal EITC, but employing a state-specific welfare calculator (Hoynes and Luttmer 2011). This simulated measure captures changes in benefit parameters across state, year and family size (e.g. and equals 0 for those with no children). We also include an indicator equal to one if a particular state had any type of welfare waiver in a particular year and allow the coefficient to differ depending on the number of children.<sup>21</sup> To account for other changes in the tax code, we include simulated income taxes before credits (which like the simulated EITC varies by tax year and family size). Finally, local labor market conditions may play an important role; our conservative controls include state-level unemployment rates interacted with number of children. This amounts to adding variables  $Z_{cst}$  and  $Z_{st} \times treat_c$  to the models in (1), (2) and (3).

The reduced form estimates from equations (1) and (3) are not directly comparable; one is a simple DD and the other parametrizes the changes in the credit over time. To make comparisons across specifications easier, we rescale our reduced-form estimates. We estimate a first stage using equations (1) and (3) but change the outcome ( $y_{it}$ ) to the federal EITC, calculated using observed individual taxpayer information (including income). Dividing the reduced form equations (1) and (3) by this first stage (indirect least squares) reinterprets the effect in terms of policy-driven increases in federal EITC dollars. We can then divide the indirect least squares estimate by the dependent mean to get a percent impact. We also calculate an

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<sup>20</sup> See data appendix for more details regarding the construction of these controls.

<sup>21</sup> We construct these control variables to capture variation at the state-year-family size level to address the potential for unobserved differences across family sizes over time (our identifying variation). When estimating the model comparing single women with children to women without children, we include the main effect for the control and the control interacted with a dummy for having one or more children (the treatment). When estimating the model comparing single women with two or more children to women with one child, we include the main effect for the control and the control interacted with a dummy for having two or more children (the treatment).

“extensive margin elasticity” to compare estimates across specifications and with estimates in the literature (Chetty, Guren, Manoli and Weber 2013).<sup>22</sup>

## 6. Initial Findings: Effects on Employment

We begin by presenting results for employment to present a link to the existing research and to extend that work to the post-Great Recession period. For brevity, we focus on the estimates of the event time model (2), estimated using the base model without conservative controls. Figure 5a plots the coefficients and 95 percent confidence intervals for the model where the treatment group is those with children and the omitted year is 1993 (the year prior to the policy expansion). The graph also displays (the dashed line) the change in the real average maximum credit for those with children relative to those without children (right axis) to give some guidance as to how the EITC is changing over time and across group. Figure 5b plots a similar graph, where the effect is estimated separately for those who have one child and for those who have two or more children (for each the control is women without children). These figures combine to show that the differential labor supply increases after 1993 closely follow the pattern of EITC expansions—women with children increase their employment relative to women without children with larger effects for women with two or more children (who experienced a larger expansion). Further, and importantly, there is little evidence of pre-event trends, validating our research design. To get a sense of the magnitudes, Figures 5a and 5b also record the estimate and standard error of  $\beta$  from the DD model (1). Figure 5a shows that the OBRA93 EITC expansion led to an increase in the employment of single women with children of 6.1 percentage points, an implied extensive margin elasticity of 0.36. Figure 5b shows the effect of the EITC on employment was larger for mothers with two or more children (8.9 percentage point increase)

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<sup>22</sup> See data appendix for more details regarding the calculation of the extensive margin elasticity.

than for mothers with one child (2.5 percentage point increase), as expected given the larger expansion for larger families. These are large increases in employment, and are also evident in the unconditional trends (Appendix Figure 2).

To facilitate comparisons across groups, following the description in Section 5 above, we normalize the DD estimates by the magnitude of the EITC “treatment” (the indirect least squares estimates). These results imply that a \$1,000 policy-induced increase in federal EITC income increases employment by 7.3 percentage points for single women with children. These estimates, and those for other treatment groups, are presented in Appendix Table 2.

These estimates on employment are consistent with the range of estimates in the literature. For example, Meyer and Rosenbaum (2001) find that the EITC raised labor force participation increased by 7.2 percentage points for single women with children relative to those without children between 1984 and 1996. Chetty, Guren, Manoli and Weber (2013) estimate extensive margin elasticity of 0.43 for Meyer and Rosenbaum (2001) and 0.30 for Eissa and Liebman (1996), the most cited studies on employment. Our extensive margin elasticities, also reported in Appendix Table 2, fit well in that range.

Before preceding to our main results for the effects on the distribution of income, we consider one more comparison. Referring back to Figure 3, the EITC schedule for women with children had virtually identical schedules prior to the OBRA 93 expansion. This produces a natural check on the validity of our design: When we compare taxpayers with two or more children to those with exactly one child (excluding those without children), we should find no trending differences between treatment and control groups prior to tax year 1994. Appendix Figure 3a contains estimates from the event time model, using tax years 1984 through 1998, comparing those with two or more children to those with one child. This facilitates a pre-trend

check for almost 10 years. There is some noise in the estimates for periods prior to tax year 1994, but the difference in the share employed between the two groups clearly diverges beginning after tax year 1993, and increases through the years of the EITC expansion. Appendix Figure 3b shows that these differences remain to the present, through the Great Recession period.

## **7. Main Results: Effect on the Distribution of ATT Income**

We begin with examining the basic trends over time for our sample of single women, separately for those with zero, one and two or more children. Figure 6 plots the share of single women whose family ATT income is above 100% of the federal poverty threshold, for 1984 to 2012. In the mid-1980s, the share above poverty were much lower for single women with children compared to those without children (with the largest differences for those with 2 or more children). Beginning in the early 1990s, there is a trend break for those with children and by the early 2000s differences in the share with ATT income above poverty narrowed significantly across the groups. Those with two or more children exhibit a change that is larger than those with only one child, mirroring the differential EITC benefit expansions of the 1990s.

We now turn to the difference-in-difference model using the variation induced by OBRA 93, following equation (1), where the outcome variable ( $y_{it}$ ) is a dummy equal to one if a woman's ATT income is above a given multiple of the federal poverty threshold. We begin by examining estimates for income above 100 percent of poverty; below we extend this to consider effects more comprehensively on the distribution of income (from 25 percent of poverty to 500 percent of poverty). The estimates are presented in table 1. The first two columns define the treatment group as single women with one or more children (compared to the control with no children). The second two columns limit the sample to single mothers and compare women with

two or more children (the treatment group) to women with one child (the control group). For each model we present results with and without the conservative control set. Relative to single women without children, single women with children experienced an increase in the share with ATT income above the poverty threshold of 7.9 percentage points with OBRA 93 (column 1). Adding the conservative controls (column 2) leads to similar effects. We rescale these reduced form estimates in the same way as those above; column 1 shows that a \$1000 policy-induced increase in the EITC leads to a 9.4 percentage point increase in the propensity to have ATT income above poverty. If we utilize just the expansion across 1 versus 2 or more children (column 3 and 4), we find that a \$1000 policy-induced increase in the EITC leads to a 4.7 to 5.4 percentage point increase in the propensity to have ATT income above poverty, although the estimate with the conservative control is no longer statistically significant.

These estimates capture the full behavioral effect of the EITC including the direct effect of the credit as well as the indirect effect through changes to earnings and other income. Note that the elasticities for ATT poverty are larger than those of employment, reflecting the density of single taxpayers with children whose income puts them around 100% of the federal poverty threshold (figure 2).<sup>23</sup>

Tables 2 and 3 contain estimates of equation (3), in which we replace the traditional DD interaction with a simulated measure of the EITC. First, for comparison to the OBRA 93 DD estimates, table 2 presents the parameterized difference-in-difference estimates for the same period (1991-1998). Here we find percent impacts (per \$1000 in EITC) that are very similar to those from the DD specification (but are more precise). For example, when comparing single

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<sup>23</sup> Appendix table 3 contains the DD estimates for other levels of education. These estimates, normalized by the first stage, are generally similar to those for our preferred sample of single women with some college education or less. Appendix table 5 contains DD estimates in which the control group remains the same, but the treatment group only contains families with at least one child below the age of 6. The estimates from this comparison are moderately higher than those including families with older children.

women with children to those with no children, the DD estimate (table 1, column 1) shows that a policy-induced \$1000 increase in the EITC leads to a 9.4 percent increase in the share with ATT income above poverty for an extensive margin elasticity of 0.64. The parametrized difference-in-difference (table 2, column 1) shows an 8.1 percent increase in the share with ATT income above poverty for a elasticity of 0.55.<sup>24</sup>

We can extend the parametrized DD analysis and the simulated EITC, utilizing the full period of policy expansions covering 1984-1998 (TRA86, OBRA90 and OBRA93). Table 3 contains the results where the dependent variable equals one if ATT income is above 100% of the federal poverty threshold. The results show that a \$1000 increase in policy-induced EITC income leads to a 13 percent (for children versus no children) to 13.9 percent (for 2 children versus 1 child) increase in the propensity to have ATT income above poverty. This implies elasticities of 0.57 to 0.68. (The results are little changed by adding the conservative controls.) Looking back at table 1, these estimates are very similar to the difference-in-difference estimates for OBRA 93.

Overall the results in Tables 1-3 show that our estimates of the effects of the EITC on the share with ATT income above 100% poverty are remarkably stable across groups, over time, whether we use the base or conservative control set and whether we use a DD or parameterized DD model.

We now turn to the estimates from equation (2), the event time model (estimated using the base model without conservative controls) where the dependent variable is equal to one if ATT income exceeds 100% of the poverty threshold. Figure 7a plots the coefficients and 95 percent confidence intervals for the model where the treatment group is those with children and

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<sup>24</sup> The simulated EITC is constructed using the 1983 CPS. This may be “too far” from OBRA 93 to accurately reflect the changes the act induced in the income tax code or from welfare reform. Appendix table 4 contains estimates that use the 1993 CPS to construct the simulated EITC, and finds similar results.

the omitted year is 1993 (the year prior to the policy expansion). The graph also displays the change in the real average maximum credit for those with children relative to those without children (dashed line, right axis) to give some guidance as to how the EITC is changing over time and across group. Figure 7b plots a similar graph, where the effect is estimated separately for those who have one child and for those who have two or more children (for each the control is women without children). These event time figures show a sharp increase in the propensity to have ATT income above poverty beginning in 1994, with larger increases for women with two or more children (who experienced a larger expansion). The increases follow closely the expansions in the EITC. Additionally, and importantly, the share above poverty prior to OBRA 93 looks to be quite flat between the treatment and control, confirming the validity of the quasi-experimental design.<sup>25</sup>

As with our analysis of employment, if we limit the sample to women with children and compare those with two or more children to those with one child, we can analyze the effects of OBRA 93 with a much longer (10 year) pre-period. Recall that as shown on Figure 3, the generosity of the EITC was virtually identical for all women with children, regardless of family size, for all years prior to 1993. The estimates of that event study, again applied to the propensity to have ATT income above 100 percent poverty, is plotted in Figure 8. Using this 1984-1998 time frame, the estimates provide striking evidence that the share with ATT income above poverty increases sharply with the expansion of the EITC. Additionally, it is reassuring that there is no evidence of any differential trending in the treatment versus control group over this long pre-trend period.

The differential in the propensity to have ATT income above 100% of the federal poverty

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<sup>25</sup> When comparing women with children to women without children (Figures 6a-6b), we include only two years of pre data given that there was another expansion due to OBRA 90.



threshold has endured over time. Appendix figures 4-6 estimate the event model for all available tax years (1984-2013) using three different designs (0 vs 1+ children, 0 vs 1 vs 2+ children, and 1 vs 2+ children). The results show that the propensity to have ATT income above poverty follows closely the changes in the EITC over time. Additionally there has not been deterioration in the effects with the weak labor market of the 2000s.

We extend these results to examine effects comprehensively across the distribution of income. To do so, we estimate a series of difference-in-difference models for OBRA 93 where the dependent variable is an indicator equal to one if after-tax and transfer-income is above a multiple of the poverty threshold. In particular, we estimate models as presented in Table 1 (for the share above 100 percent of the poverty threshold); we vary the threshold in 25 percentile bins from ATT income above 25 percent of poverty to ATT income above 500 percent of poverty. Figure 9 contains estimates in which we compare families with children to those without children. In the figure, each estimate (and 95 percent confidence interval) comes from a separate regression; we graph them together to illustrate the effects of the credit on the distribution of income. For example, consider the point for ATT income above 100 percent poverty plotted in Figure 9. The estimate, 0.079, is the same as that presented previously in Table 1—the interpretation is that OBRA 93 increased the propensity for single women with children to have ATT income above the poverty threshold by 7.9 percentage points.<sup>26</sup> We overlay on the figure the change in the difference-in-difference in the EITC credit at each of these income-to-poverty bins. Figure 10 presents estimates for those with two or more children compared to those with only one child.

These figures suggest several important findings. First, the EITC has little effect on the

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<sup>26</sup> In each case we are plotting the coefficient on post x treat (as in equation 1); the estimates are not scaled as we want to illustrate the reduced form “program evaluation” of the credit, rather than the effect per dollar of treatment.

very lowest income groups: the EITC has an estimated zero effect on the share above poverty for those with income below 50% of the poverty threshold. This may reflect that those in extreme poverty and the very lowest income groups have little attachment to the labor market. Second, the effects of the EITC are large and statistically significant between 75% and 150% of the poverty line. The largest effects occur around 100% of the federal poverty threshold. The estimated effects decay and fall to zero by 250% poverty. These patterns of results are very consistent with expectations, based on the shape and location of the EITC schedule (relative to poverty thresholds), as illustrated by the overlay of the EITC policy changes on the figure. This concordance between our estimated impacts (capturing the direct and indirect effects of the credit) provides strong evidence that we are indeed capturing the causal effects of the EITC on the distribution of income. Further, and substantively, these are large effects and illustrate the potential for this important safety net policy to affect lower tail income inequality.

We extend these results by using the parametric difference-in-difference model to estimate a series of coefficients where we vary the threshold in 25 percentile bins (from ATT income above 25 percent of poverty to ATT income above 500 percent of poverty). This allows for us to use data and expansions back to 1984. Figure 11 presents estimates for single women with 0 versus 1+ children (filled circles) and single women with 1 versus 2+children (open circles). As above, we combine the models and plot together the estimates (and 95 percent confidence intervals) across bins of income to poverty. These results confirm our earlier findings based on the OBRA93 expansion. We find no effect at the lowest levels of income (25% and 50% poverty), large effects centered on 100% of poverty, and decaying effects going to zero by 250% of poverty. The parametrized difference-in-difference model is more precisely estimated and the results remain significant through 225% poverty. Appendix Figure 7 shows that the

estimates are very similar with and without the conservative controls.

## **8. The Direct and Indirect Effects of the EITC on the Distribution of Income**

We began, in the introduction, by pointing out that the prior evidence on the effects of the EITC on poverty took a static approach, capturing the direct effects of the credit but omitting the dynamic or indirect effects operating through the incentivized increases in earnings. We demonstrated the importance of the extensive margin effect (with our estimates for employment) and went on to estimate the effect of the EITC on ATT income (relative to poverty) thereby capturing the direct and indirect effects. Here, we can apply these estimates to simulate the aggregate number of individuals and children who are raised above poverty from the EITC.

This analysis starts with the CPS including single women with children ages 24-48 with some college education or less, for calendar year 2012.<sup>27</sup> For these simulations, we consider the entire family including the mother and each of her children and use the CPS weights to generate aggregate counts. First, as a reference, we calculate the total number of children (figure 12) and individuals (figure 13) that the EITC lifts out of poverty using the Supplemental Poverty Measure or SPM (labeled “Static SPM” in the figures). Second, we use our ATT income measure along with the official poverty thresholds to provide a similar static calculation (labeled “Static ATT poverty” in the figures). Both of these are calculated by zeroing out the EITC credit, recalculating the poverty measure and, using the CPS weights, aggregating up the number of children (or total individuals) who are raised above poverty *assuming no other change in behavior* (hence the calculation is static). Figure 12 shows that, based on the Static SPM, the EITC lifts 1 million children out of poverty. Our static ATT poverty shows a similar result,

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<sup>27</sup> The 2012 data comes from the 2013 CPS survey year. Our last year of data corresponds to the 2014 CPS (with 2013 calendar year data) but, at the time of this writing, the SPM variables have yet to be added to the IPUMS-CPS. See data appendix for more details on the calculations in this section.

through a bit larger at 1.2 million.<sup>28</sup> You will notice that our calculation, that the EITC raises 1 million children above poverty, is below the 4.7 million estimated from the SPM (reported above, see Short 2013). This is because our calculations derive from our sample (single mothers 24-48 with some college or less, along with their children) and despite their relatively high poverty rate, our sample accounts for only about 17.5% of individuals who are poor (based on official poverty).<sup>29</sup> The static calculations, though, are only used here as a reference to compare to the calculations that incorporate the indirect or behavioral effects.

Also plotted in Figures 12 and 13 are aggregate counts of “ATT poverty with behavior,” simulated based on our estimates from Section 7. Using estimates from our parameterized difference-in-difference model (estimated including data from 1984-2013), we simulate the number of persons (and children) lifted above the poverty threshold by predicting the model at the observed simulated EITC (for 2012) and comparing to the prediction with the simulated EITC zeroed out (for details see the data appendix).

The results, presented in Figures 12 and 13, are dramatic. The number of children that the 2012 EITC raised above poverty increases from 1.2 million to 2.3 million when we use our estimates to predict the effects of the EITC. Similarly, the total number of individuals lifted above poverty by the 2012 EITC rises from 1.8 million to 3.4 million. Ignoring the indirect effects of the EITC, and the incentivized increase in earnings, underestimates the number of persons raised out of poverty by about 50 percent.

We extend this analysis by making similar calculations at other points in the income-to-

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<sup>28</sup> Our ATT poverty measure differs from the SPM in two central ways. First, the SPM includes a more comprehensive resource measure deducting out of pocket medical expenses and work expenses and including the cash value of medical expenses. Second, the SPM is based on a new poverty threshold that builds in geographic variation and expenses on housing, utilities and food. We developed and use the ATT income and poverty (instead of the SPM) because we can measure it consistently back to 1980. This cannot be done easily with the SPM.

<sup>29</sup> Additionally, the number reported in Short (2013, 2014) includes the effects of the EITC and the Child Tax Credit.

poverty distribution: 50%, 150%, 200%, 250% and 300% of the federal poverty threshold. The results show significant underestimates of the effects of the EITC on the propensity to raise incomes above 150% and 200% of poverty. Overall, these results suggest that the already sizable contribution to increasing income and reducing poverty attributed to the EITC is significantly understated when all of the programs incentives are taken into account.

## **9. Conclusion**

In this paper we comprehensively examine the effects of the EITC on employment and the distribution of income. We use a quasi-experimental research design that leverages the variation in the generosity of the EITC across family sizes and over time. Our analysis of employment largely updates the literature, and presents event study graphs to test and validate the well-used research design. More importantly, we provide the first comprehensive estimates of the federal EITC on the distribution of family income relative to poverty. Our approach quantifies the effects on pre-tax income as well as the direct effect of the credit. We explore the effects of the EITC on the distribution of income, capturing where the program leads to increases income and how after-tax and transfer-income poverty is affected.

Our results show that a \$1000 policy-induced increase in the EITC lead to a 7.3 percentage point increase in employment and a 9.4 percentage point reduction in the share of families with after-tax and transfer income below 100% poverty. These results are robust to a rich set of controls including income from other safety net programs (such as AFDC/TANF and SNAP that decrease with the EITC expansion), controls for welfare reform, and labor market conditions; all allowed to vary by family size (our identifying variation). They are also robust to using tax-policy driven reforms across single women with and without children, as well as single

women with one versus two or more children and whether we use the sharp changes in the 1993 EITC expansion or policy changes back to the 1986 Tax Reform Act.

Furthermore, we also provide estimates on how the EITC effects the income distribution more broadly. We find little effect on incomes below 50% poverty. The effects of the EITC are large and statistically significant between 75% and 150% of poverty (peaking at 100% poverty), and decay down to zero at 250% of poverty. The pattern of effects across the income distribution reflects where the credit is providing the largest transfers. Importantly, by capturing the indirect effects of the credit on earnings, our results show that static calculations of the anti-poverty effects of the EITC (such as those released based on the Supplemental Poverty Measure) may be underestimated by as much as 50 percent.

Future work could extend this analysis to other groups. The increase in after tax incomes from the EITC may be the largest for this group – single women with children – given their well-documented large extensive margin labor supply response to this policy. Married couples, though representing less than a quarter of EITC expenditures, may exhibit smaller increases in income.

Given that the goal of the EITC is to increase family income while encouraging work, these estimates provide important evidence on the efficacy of this central element of the U.S safety net not only to encourage work, but to potentially reduce inequality, raise family income, and move families out of poverty.

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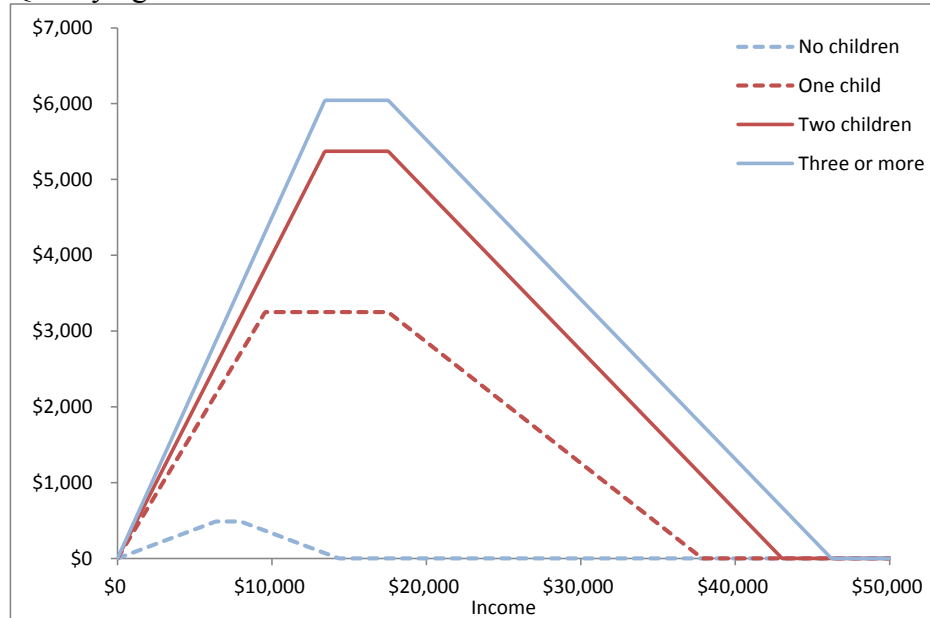
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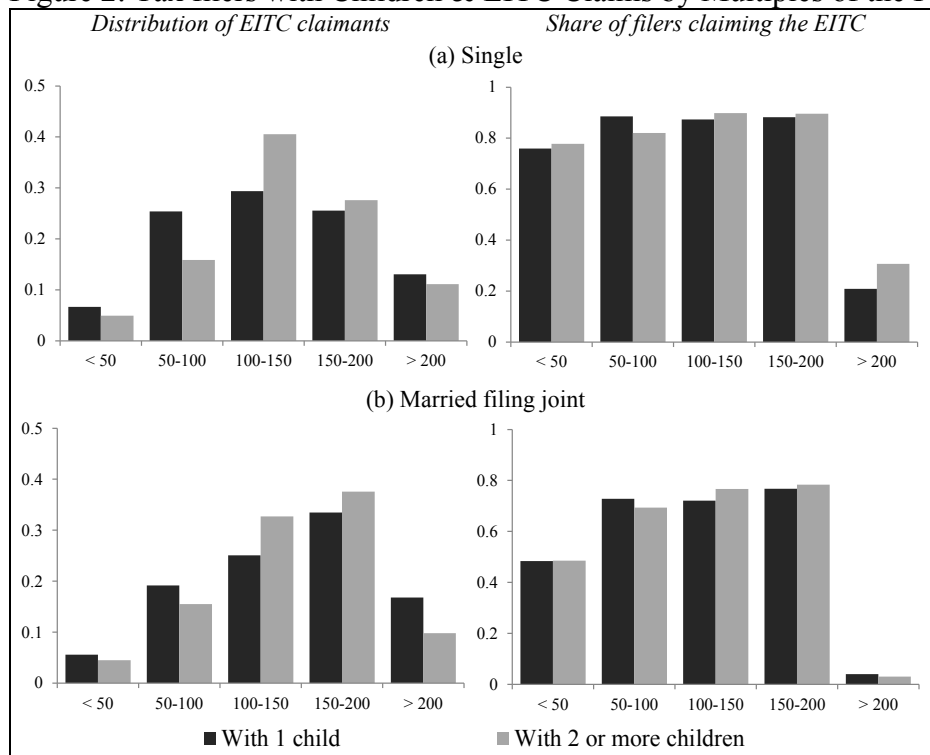
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Figure 1: Federal EITC Schedule for Taxpayers Filing Single in Tax Year 2013 by Number of Qualifying Children



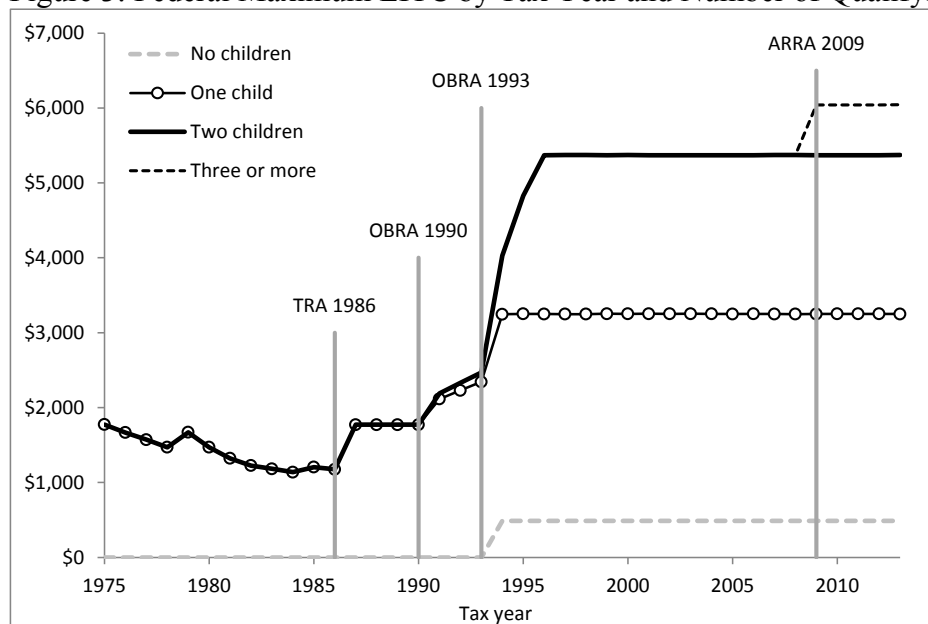
Notes: Tax Policy Center (2014), 2013\$.

Figure 2: Tax filers with Children & EITC Claims by Multiples of the Federal Poverty Threshold



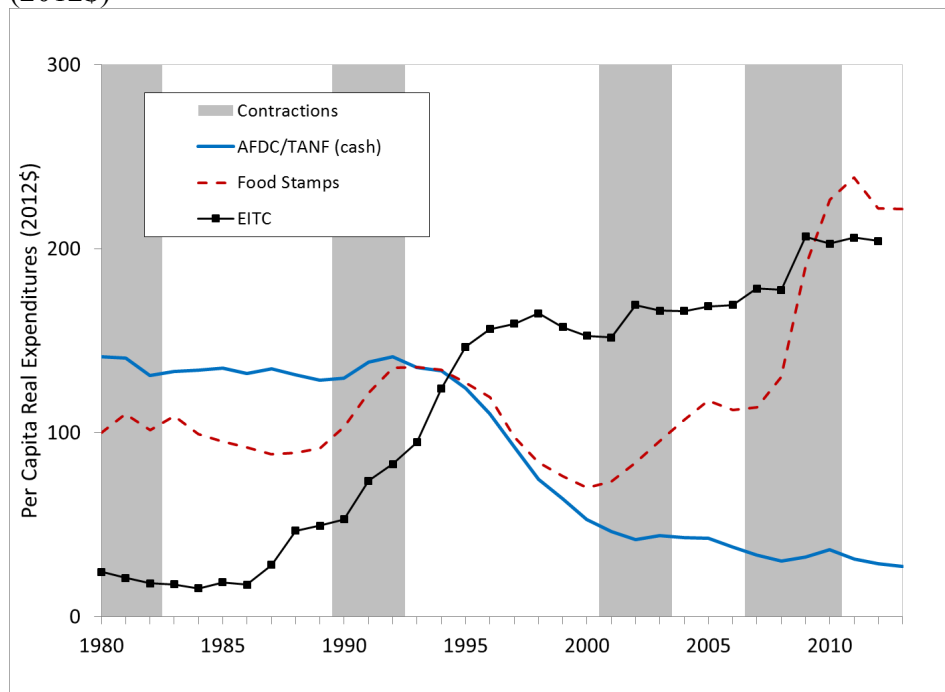
Notes: Statistics of Income Individual Complete Report File (tax year 2001) and Federal Poverty Thresholds (FPT). After tax income is computed as total income less taxes plus payments. Payroll taxes are imputed using total wages.

Figure 3: Federal Maximum EITC by Tax Year and Number of Qualifying Children



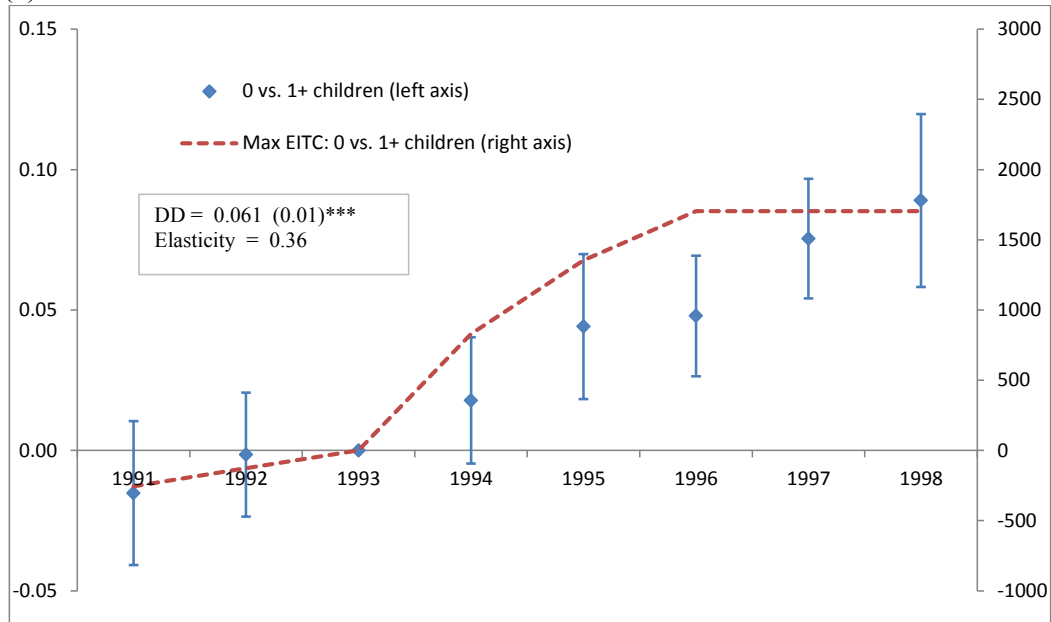
Notes: Tax Policy Center (2014), 2013\$.

Figure 4: Per Capita Expenditures on Cash and Near Cash Transfer Programs for Families (2012\$)

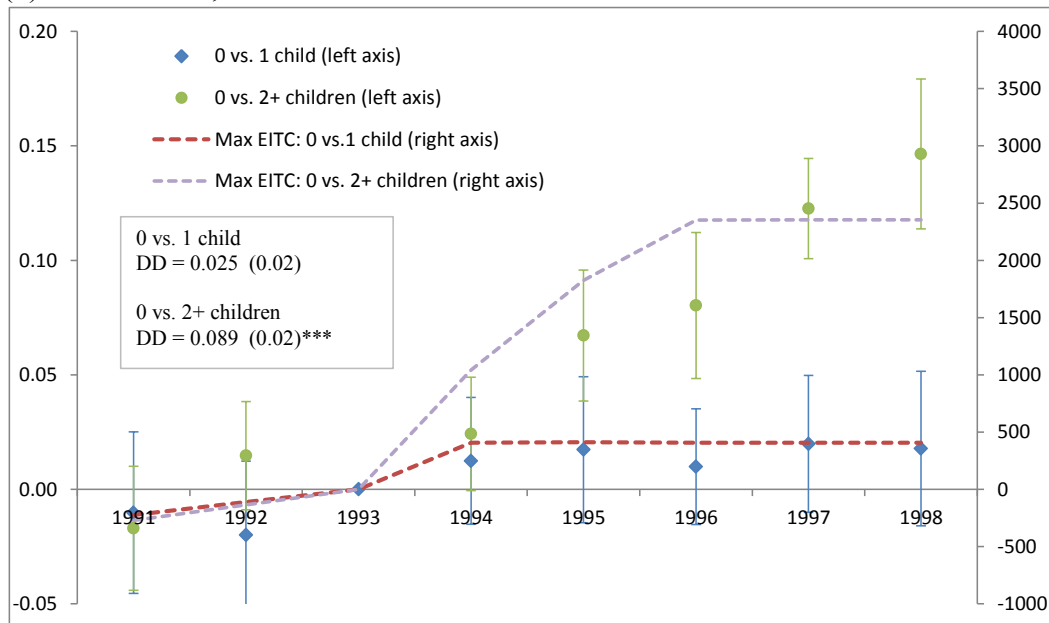


Notes: Bitler and Hoynes (2010), updated to include data through 2013 (or 2012 for the EITC).

Figure 5: Event Time Model Estimates of OBRA 93 on Employment  
(a) 0 vs. 1+ Children

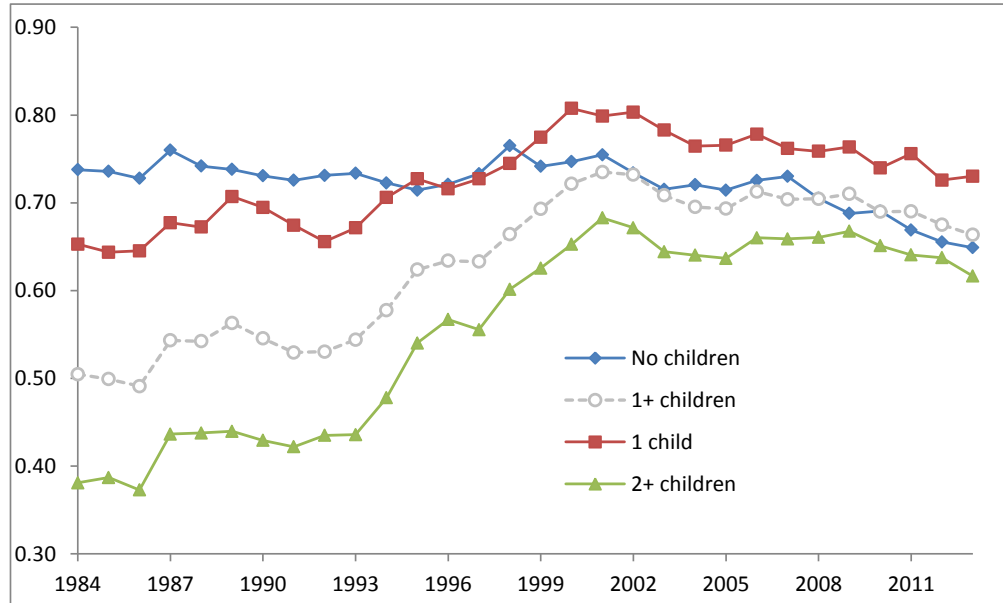


(b) 0 vs. 1 Child, 0 vs. 2+ Children



Notes: The sample includes single women, ages 24 through 48 with some college education or less from the 1992 through 1999 Current Population Survey (March). See equation (2) in text and data appendix for details. 95% confidence intervals clustered on state.

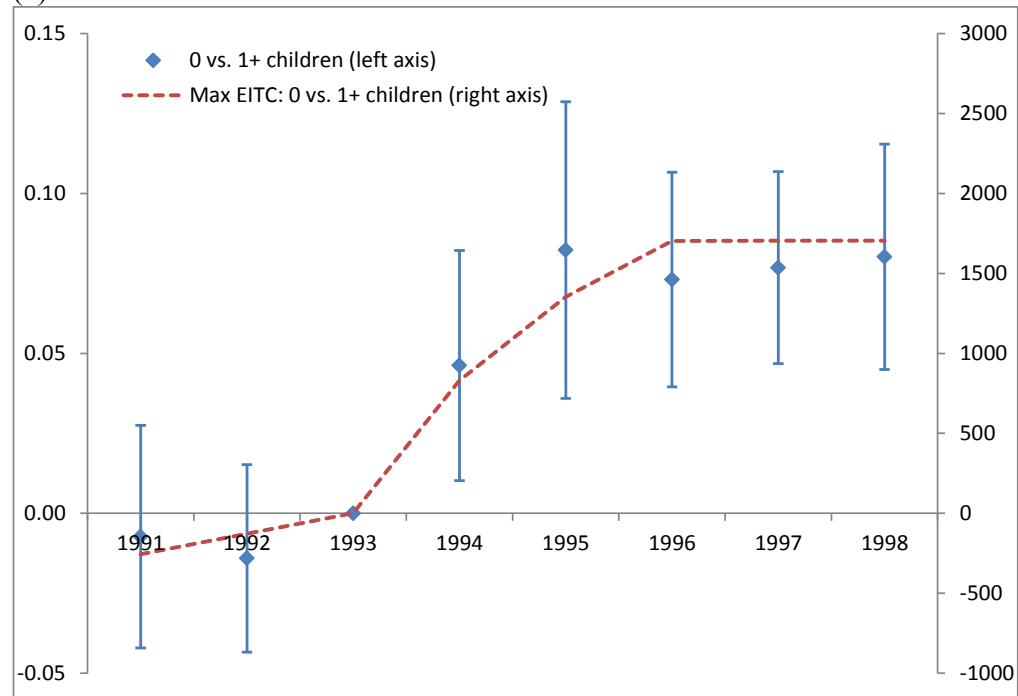
Figure 6: Share with ATT Income Above 100% of Federal Poverty Threshold by Presence and Number of Children



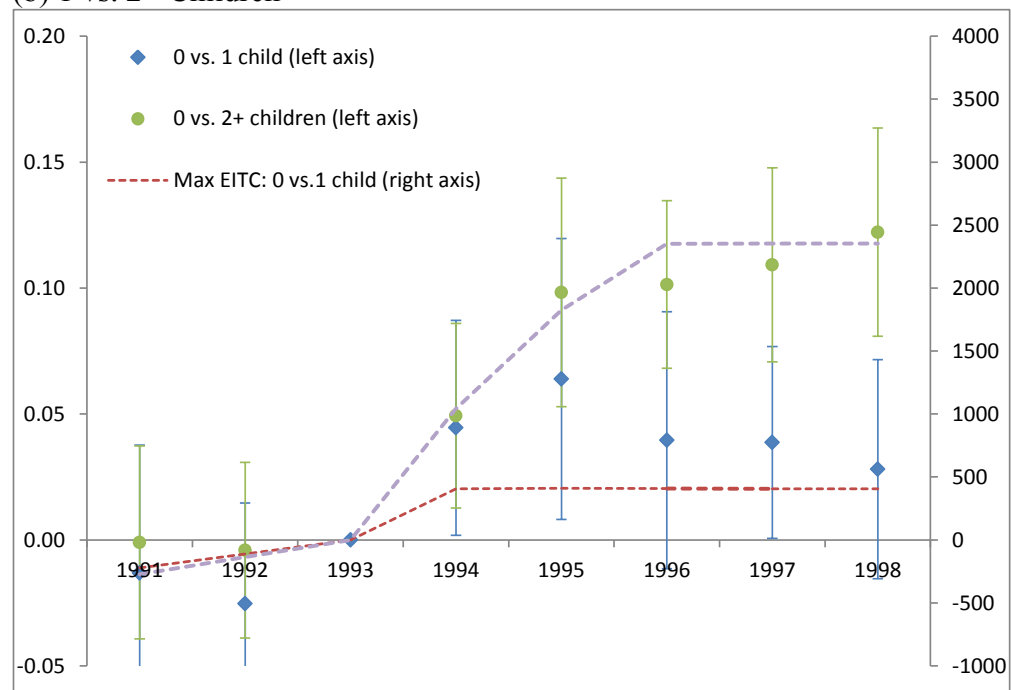
Notes: 1985-2014 CPS, single women, 24-48 years old, with some college education or less. Figure plots share of taxpayers with after-tax and transfer income above 100% of the federal poverty threshold.

Figure 7: Event Time Model Estimates of OBRA 93 on ATT Income Above 100% of the Poverty Threshold

(a) 0 vs. 1+ Children

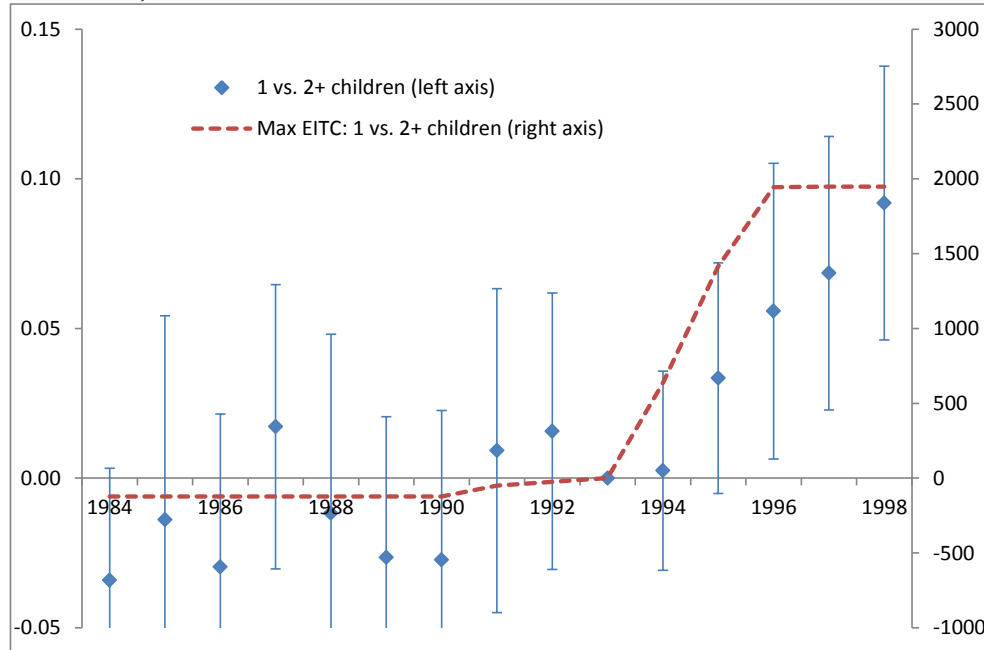


(b) 1 vs. 2+ Children



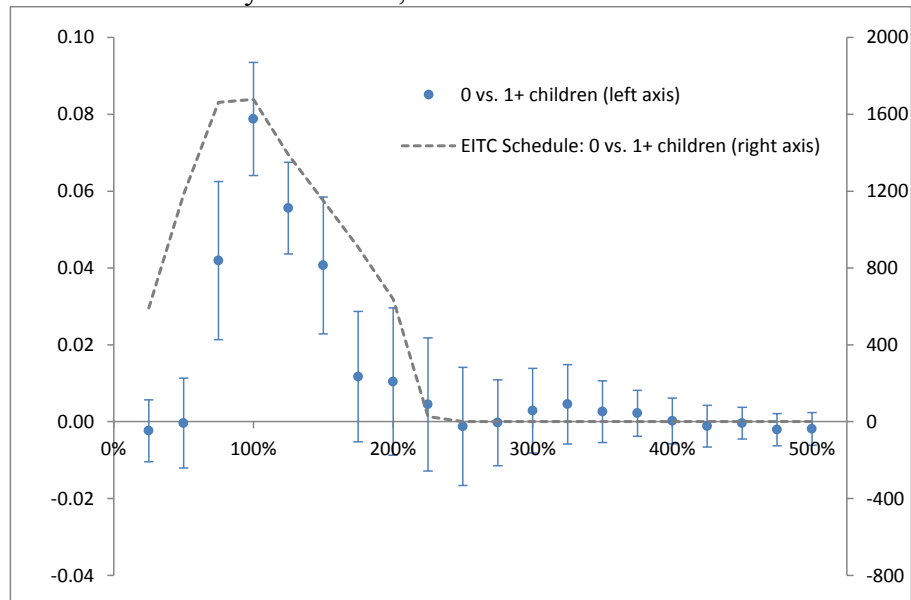
Notes: The sample includes single women, ages 24 through 48 with some college education or less from the 1992 through 1999 Current Population Survey (March). See equation (2) in text and data appendix for details. 95% confidence intervals clustered on state.

Figure 8: Event Model Estimates of OBRA 93 on ATT Income Above 100% of the Poverty Threshold, 1 vs 2+ Children



Notes: The sample includes single women with children, ages 24 through 48 with some college education or less from the 1985 through 1999 Current Population Survey (March). See equation (2) in text and data appendix for details. 95% confidence intervals clustered on state.

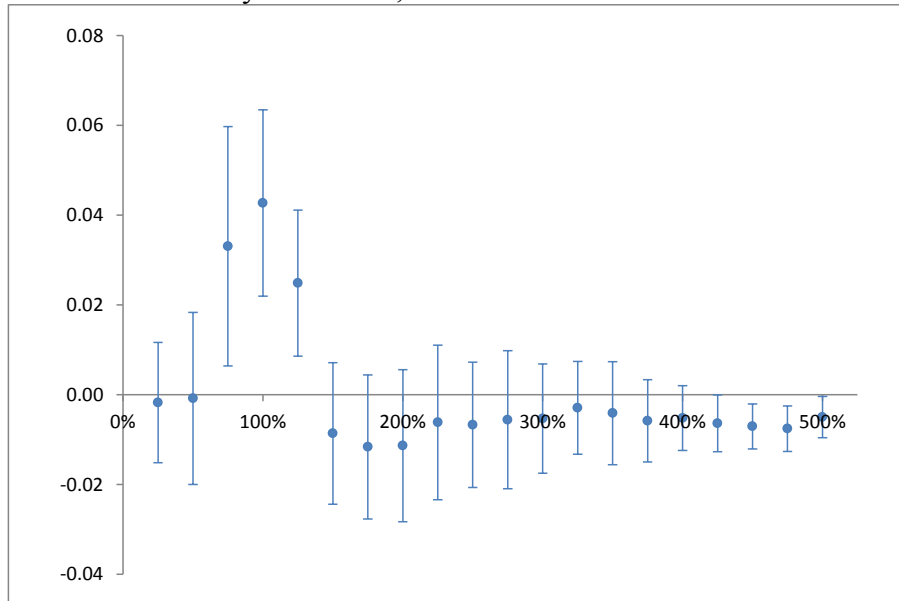
Figure 9: Difference-in-difference Estimates of OBRA 93 on ATT Income Above Multiples of the Federal Poverty Threshold, 0 vs 1+ Children



Notes: The sample includes single women, ages 24 through 48 with some college education or less from the 1992 through 1999 Current Population Survey (March). Each dot and whisker represents a single regression estimate and confidence interval. See equation (1) in text and data appendix for details. 95% confidence intervals clustered on state. The dashed line is the weighted change in EITC benefits for families with children versus those without children across the OBRA 93 expansion.

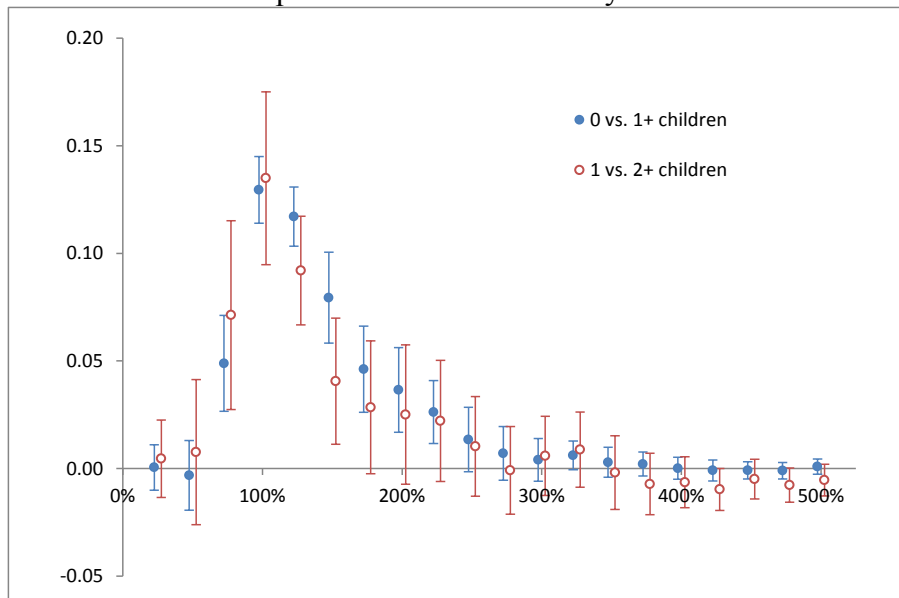


Figure 10: Difference-in-difference Estimates of OBRA 93 on ATT Income Above Multiples of the Federal Poverty Threshold, 1 vs 2+ Children



Notes: The sample includes single women with children, ages 24 through 48 with some college education or less from the 1992 through 1999 Current Population Survey (March). Each dot and whisker represents a single regression estimate and confidence interval. See equation (1) in text and data appendix for details. 95% confidence intervals clustered on state.

Figure 11: Parameterized DD Estimates of TRA86, OBRA90 and OBRA93 on ATT Income Above Multiples of the Federal Poverty Threshold



Notes: The sample includes single women, ages 24 through 48 with some college education or less from the 1985 through 1999 Current Population Survey (March). Each dot and whisker represents a single regression estimate and confidence interval. Simulated EITC constructed from 1983 CPS and TAXSIM. See equation (3) in text and data appendix for details. 95% confidence intervals clustered on state.

Figure 12: The Effect of the EITC on the Aggregate Number of Children Above Multiples of the Federal Poverty Threshold, 2012

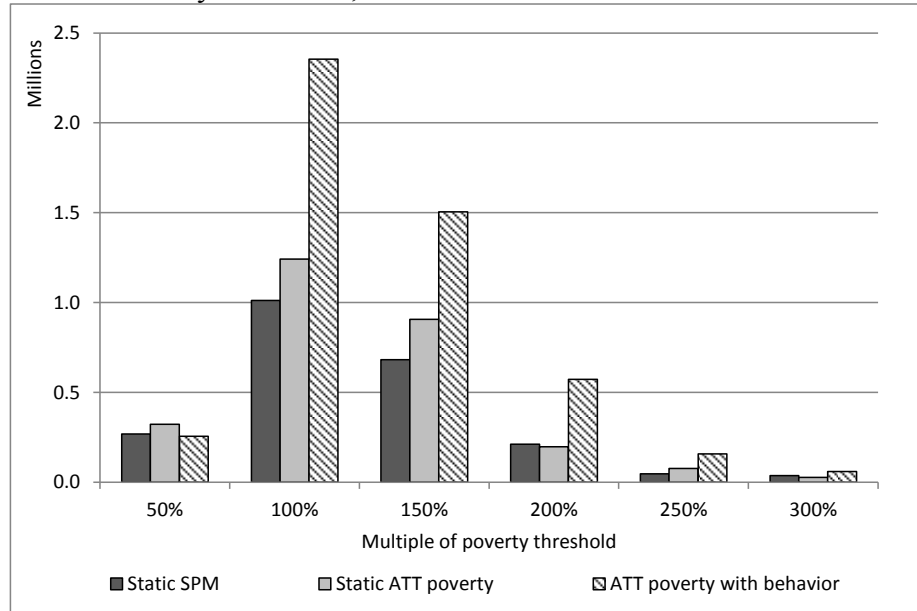
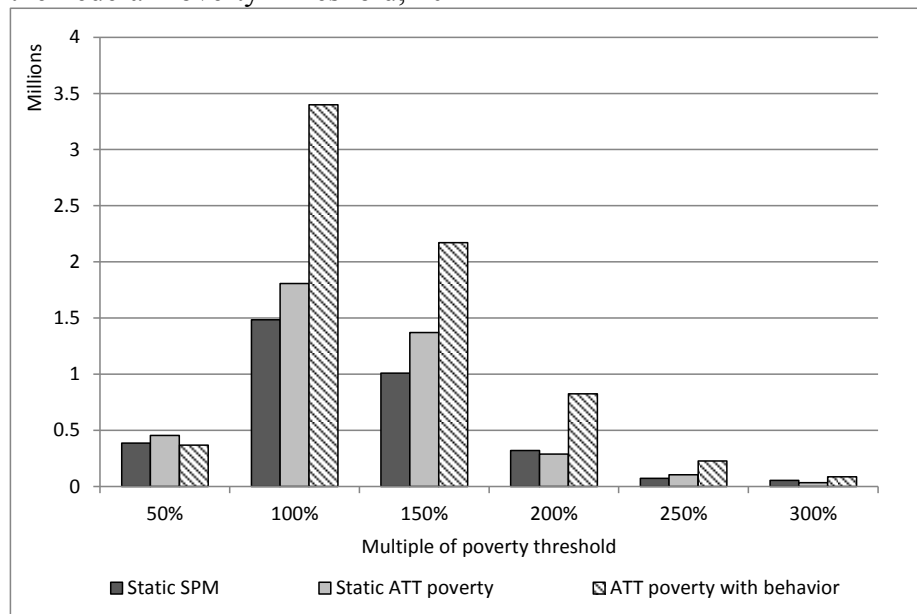


Figure 13: The Effect of the EITC on the Aggregate Number of Individuals Above Multiples of the Federal Poverty Threshold, 2012



Notes: Counts include all individuals (figure 12) or children (Figure 13) within families with a single female parent whose age is between 24 and 48 with some college education or less from the 2013 Current Population Survey (March, corresponds to the 2012 calendar year). Each column represents the difference between including and removing the EITC from an aggregate poverty calculation. “Static SPM” uses Census provided supplemental poverty measure variables within the CPS to exclude the EITC. “Static ATT poverty” excludes the EITC alone from after-tax and income when calculating poverty status. “ATT poverty with behavior” uses fitted values from a regression estimating the comprehensive effects of the EITC on poverty status (see data appendix for details).

Table 1: Difference-in-Difference Estimates of OBRA93 on ATT Income Above 100% of the Federal Poverty Threshold

Model:	0 vs. 1+ Children		1 vs. 2+ Children	
(Year > 1993) * (1+ children)	0.079*** (0.01)	0.081*** (0.02)		
(Year > 1993) * (2+ children)			0.043*** (0.01)	0.020 (0.01)
Per \$1000 of federal EITC	0.094	0.129	0.054	0.047
% impact	14.1%	19.2%	9.1%	7.8%
Extensive margin elasticity	0.64	0.84	0.48	0.41
Observations	50,508	50,508	25,101	25,101
Mean of the dependent variable	0.670	0.670	0.601	0.601
Controls				
Demographics	X	X	X	X
# of children indicators	X	X	X	X
State * year indicators	X	X	X	X
Simulated tax & transfer benefits		X		X
Any AFDC waiver * 1+ children		X		
Any AFDC waiver * 2+ children				X
Unemp rate * 1+ children		X		
Unemp rate * 2+ children				X

Notes: The sample includes single women, ages 24 through 48 with some college education or less from the 1992 through 1999 Current Population Survey (March). See text and data appendix for details. Standard errors clustered on state. Significance levels: \*10%, \*\*5%, \*\*\*1%.

Table 2: Parameterized DD Estimates of OBRA93 on ATT Income Above 100% of the Federal Poverty Threshold

Model:	0 vs. 1+ Children		1 vs. 2+ Children	
Simulated EITC (\$1,000)	0.141*** (0.01)	0.135*** (0.02)	0.109*** (0.02)	0.086** (0.04)
Per \$1000 of federal EITC	0.081	0.091	0.061	0.068
% impact	12.2%	13.5%	10.2%	11.3%
Extensive margin elasticity	0.55	0.61	0.53	0.59
Observations	50,508	50,508	25,101	25,101
Mean of the dependent variable	0.670	0.670	0.601	0.601
Controls				
Demographics	X	X	X	X
# of children indicators	X	X	X	X
State * year indicators	X	X	X	X
Simulated tax & transfer benefits		X		X
Any AFDC waiver * 1+ children		X		
Any AFDC waiver * 2+ children				X
Unemp rate * 1+ children		X		
Unemp rate * 2+ children				X

Notes: The sample includes single women, ages 24 through 48 with some college education or less from the 1992 through 1999 Current Population Survey (March). Simulated EITC constructed from 1983 CPS and TAXSIM. See text and data appendix for details. Standard errors clustered on state. Significance levels: \*10%, \*\*5%, \*\*\*1%.

Table 3: Parameterized DD Estimates of TRA86, OBRA90 and OBRA93 on ATT Income Above 100% of the Federal Poverty Threshold

Model:	0 vs. 1+ Children		1 vs. 2+ Children	
Simulated EITC (\$1,000)	0.129***	0.133***	0.135***	0.117***
	(0.01)	(0.01)	(0.02)	(0.03)
Per \$1000 of federal EITC	0.084	0.091	0.079	0.079
% impact	12.8%	13.8%	13.9%	13.8%
Extensive margin elasticity	0.57	0.61	0.68	0.67
Observations	96,204	96,204	47,215	47,215
Mean of the dependent variable	0.658	0.658	0.571	0.571
Controls				
Demographics	X	X	X	X
# of children indicators	X	X	X	X
State * year indicators	X	X	X	X
Simulated tax & transfer benefits		X		X
Any AFDC waiver * 1+ children		X		
Any AFDC waiver * 2+ children				X
Unemp rate * 1+ children		X		
Unemp rate * 2+ children				X

Notes: The sample includes single women, ages 24 through 48 with some college education or less from the 1985 through 1999 Current Population Survey (March). See text and data appendix for details. Standard errors clustered on state. Significance levels: \*10%, \*\*5%, \*\*\*1%.