Geographic Variation in the Marginal Value of Public Funds: Exploring the Interaction of Local Economic Conditions and Earned Income Tax Credit Expansions

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Abstract

Notes: This paper applies the Marginal Value of Public Funds framework to calculate and compare the welfare impacts of the EITC across the United States from 1993 to 2016. Focusing on the effects on women aged 18-64 (a target demographic of this policy), the paper first replicates the methodology of Bastian & Jones but using publicly available data from the CPS and finds similar results. Next, the paper extends the framework to group state-year combinations into quintiles and deciles of various underlying economic characteristics (such as poverty, income inequality, unemployment, and state welfare generosity) to see if and how these variables account for differences in policy effectiveness. As a result, the paper concludes that measures of negative economic impact (such as poverty, high levels of inequality, and unemployment) reduce the return on the additional dollar invested in EITC by increasing the burden on the local government's budget, while the results for the positive measure of welfare generosity have more noise; the results are driven by both revenue and labor force participation effects. The study by no means provides an exhaustive list of characteristics that might affect the end welfare figure; it instead aims to provide a starting point in understanding why differences might exist in policy effectiveness and how these can be identified and navigated to achieve better allocative efficiency in decentralised provision of public welfare programs.

Introduction

Policymakers and stakeholders often consider the budgetary cost of a given policy before making spending decisions however, the net cost of a policy (taking into account the causal effects on tax revenue, among other variables) is a measure that has been gaining traction in the field of economics. Fiscal externalities (Hendren, 2016) account for the behavioral responses that create a wedge between the budgetary and the net cost of a policy. It is not only important for both policymakers and their constituents to have a better understanding of the fiscal impact a policy expansion will have, but equally important to determine identify underlying factors which may result in higher or lower costs. This paper adds to the body of literature calculating a program's net cost using publicly available data in the CPS, while seeking to identify some of the various economic factors that may add or subtract from this net cost.

Targeting low and middle income families and helping 25 million of those eligible with approximately $63 billion in tax credits in 2019, the Earned Income Tax Credit (EITC) is one of the main social welfare policies in the U.S.. While the program's many benefits to families (and especially to lower-income mothers and their children) are well documented (discussed in the next section), there is less consensus on its net cost to the government's budget and as a result, to taxpayers. If, as previous research suggests, the program leads those eligible to participate in the labor force, this might impact the government's budget and the program's net cost via direct (additional spending on EITC benefits claimed) and indirect (e.g. less take-up in unemployment benefits, higher tax revenue, etc.) channels. Furthermore, the labor force participation effects might happen both at the intensive or the extensive margins. Given that the policy itself is inequality and poverty alleviating in nature (Hardy et al 2022; Schanzenbach, 2021), these effects might vary with underlying economic factors. For example, states with a less equal income distribution could be burdened by higher or lower net costs depending on the magnitude (and interplay) of labor force participation and earnings elasticities. Namely, those with higher poverty rates could experience higher EITC take-up after expansion of the policy thereby increasing the budgetary and net costs, but the resultant revenue effects from higher labor force participation might be enough to offset these additional costs thereby reducing the net cost overall.

Bearing these motivating factors in mind, I estimate the EITC's impact on earnings, employment, taxes paid, and welfare received following the identifcation strategy used by Bastian and Jones (2019). By using the maximum possible EITC benefits (MaxEITC) each household is eligible for - which varies by state, year, and number and age of children, and is independent of actual eligibility or income - the strategy "exploits variation in EITC eligibility, generated from three decades of plausibly exogeneous EITC policy changes." Initially, I use publicly available data from the Current Population Survey and its Annual Social and Economic Supplement (CPS & ASEC) from 1993 to 2016 to estimate the causal impacts of the policy on the aforementioned variables with a difference-in-differences approach. In an environment where misreporting of incomes in survey data by lower-income households is increasing (Blank and Schoeni, 2003; Meyer and Sullivan, 2003; Meyer et al., 2018) I also use the NBER Taxsim simulator to increase predictive accuracy. After replicating the results from Bastian and Jones (2019) using publicly available data, I then cluster the data in year-state combinations of various economic factors (such as but not limited to the income distribution) to see if and how the results change. In doing so, I use poverty rates, income inequality, unemployment, and state welfare generosity as clusters [1].

My sample consists of 1.3 million women between the ages 19 and 64. Similar to Bastian and Jones (2019), I first test whether MaxEITC impacts employment and income (since indirect effects on government revenue wouldn't exist otherwise). I find that for each $1,000 increase in MaxEITC, raises annual earnings by $1,924, and binary employment by four percentage points, yielding a participation elasticity of 0.47. Having found effects on earnings and employment, the results on the main outcome variables show that a $1,000 increase in MaxEITC results in a $253 increase in claimed EITC benefits, $141 increase in federal income taxes paid, and a $46 decrease in supplemental welfare income. While these results are higher in magnitude than those found by Bastian & Jones (2019), they are directionally the same. The directionality of the results also hold when the analysis is carried in clusters of underlying economic variables. That being said, it is interesting to note that the magnitude of the effects on employment, earnings, taxes paid, and supplemental welfare income claimed all dampen as poverty, inequality, or unemployment increases, while the reverse is true for EITC benefits claimed. This suggests that the policy comes at a higher net cost

[1] Note that while the reason for choosing each of these is outlined in detail in Section II, this is by no means meant to be an exhaustive list.

in areas where the underlying economic conditions are adverse.

In terms of social welfare analysis, in order to quantify the net cost of a policy to the government (and therefore to its taxpayers), Hendren (2016) posits that it is sufficient to calculate said policy's impact on government revenue (Chetty, 2009a). Hendren (2016) thus defines the marginal value of public funds (MVPF) as the ratio of a policy's marginal benefits to its marginal costs. In my initial analysis, I calculate the MVPF of the EITC as 3.88, which means each additional dollar of spending on this policy by the government generates more than threefold its cost in social value. Despite the magnitudal differences previously stated, this figure is in line with Bastian & Jones's finding which ranges between \$3.18-\$4.23. Furthermore, I find that that the varying effects of the policy on earnings, tax revenue, and welfare income in each cluster showcase themselves in a higher MVPF where the income distribution is more equal, there is less poverty and unemployment. These results seem to be driven by both employment and earnings effects. The results on welfare generosity are more ambiguous and noisy.

Hence, my initial results use publicly available data to add to the body of literature showing how policies can in fact pay for themselves given the right conditions, as Bastian & Jones do for the EITC among others, while my cluster analysis highlights some underlying economic factors which might help or hinder this self-financing from a social welfare standpoint. While the underlying economic variables I've used (poverty, income inequality, unemployment, and state welfare generosity) offer a good initial starting point, they are not meant to offer an exhaustive list as the policy transmission mechanism is no doubt affected by many other variables. Finally, while my results can act to provide the impetus to expand such self-funding policies, they should also act as a cautionary tale with regards to the miring effects an adverse economic environment can have on the state's budget.

Existing Literature

EITC

Since its enaction in 1975, the program has seen several expansions (see Figure 1) and is now recognized as one of the main programs in assisting low and moderate income working families in the United States (Shapiro, 1998). Evidence points to unequivocally positive impacts on earnings

(Dahl, 2019), employment (Bastian, 2018), various health outcomes (Hoynes et al, 2015), educational attainment (Chetty, 2011), as well as reduction in poverty rates (Jones & Ziliak, 2019) and criminal recidivism (Agan & Makowski, 2018). Furthermore, Hendren (2016) and Bastian & Jones (2019) provide estimates of the impact of the policy on the government's budget, with the latter highlighting that considering the policy's indirect effects is crucial in appreciating its true positive contributions. Finally, Nichols & Rothstein (2016) and Bastian & Jones (2019) provide a more comprehensive list of the relevant literature. Hence, the ever-increasing recognition of the EITC as one of the main social welfare programs to assist these families makes it an ideal candidate for the purpose of this study, as expenditure on these programs make up roughly a quarter of local governments' budgets (Urban Institute, 2020).

MVPF

The idea of Marginal Value of Public Funds (MVPF) attempts to quantify the societal benefit derived from an additional unit of public expenditure on a given policy, or (conversely) the societal cost of financing public programs through taxation (the deadweight loss). In the doing so, the measure provides a unified comparison across government programs and spending policies. Put simply, the MVPF gauges the cost-effectiveness of a given policy, by comparing the benefits to the recipients of that policy to its net cost to the government [2]. The measure's main advantage over simple cost-benefit ratios lie in the denominator, where by subtracting the benefits that accrue to the government as a result of the policy (e.g. increases in tax income, reduction in other welfare spending, etc.) from the costs associated with the policy, the measure can identify policies that pay for themselves [3]. Hence, the measure is strongly tied to the concept of allocative efficiency. Namely, by measuring the long-run policy efficacy from the government's standpoint and identifying policies that recoup a substantial amount of the upfront costs, utilizing the MVPF ensures that funds are allocated to policies where the marginal benefits exceed the marginal costs, where efficiency is achieved [4]. Hence, assessing the MVPF of different policies helps policymakers identify the most effective and efficient allocation of scarce public resources.

[2] $MVPF = \frac{BenefitsToRecipients}{NetGovernmentCost}$

[3] Note that the MVPF is defined as ∞ when net cost < 0.

[4] Also note that this focus on the marginal impacts derives from the fact that the measure uses the envelope theorem and applies to smaller policy changes rather than large ones.

In his seminal paper on the subject, Hendren (2016) argues that the MVPF can be estimated by examining how individuals and businesses respond to changes in taxes and public expenditures. By analyzing these responses, policymakers can gauge the effectiveness and efficiency of public spending. Furthermore, when the behavioral responses to these policy changes don't affect individual utility, the measure becomes a sufficient statistic to calculate the impact of the policy in question in terms of social welfare (Chetty, 2009). In essence, the MVPF is a measure of the ratio of the costs and benefits of a given policy, where benefits are captured by beneficiaries' willingness to pay for said policy and the costs entail initial program spending as well as fiscal externalities. A measure of 1 or above signifies the policy pays for itself. The next section goes into further detail on how the measure is calculated.

Albeit relatively novel in its application, use of the MVPF is gaining more traction in economic research. Hendren and Sprung-Keyser (2020) uses the framework to assess the social welfare impact of a variety of historical U.S. policies (among which the EITC). Since then, the measure was applied in federal level research on the Early Childhood Development Program (Rude, 2022), various child allowance programs (Garfinkel et al, 2022), programs concerning employment such as the Subsidized Employment Program (Barham et al, 2023) and reforms to raise retirement age (Ferrari et al, 2023), and various form of taxation and tariffs (Adachi, 2022; Kotchen, 2022; Jaccard, 2022). Additionally, Hyman et al (2022) apply the framework at the state level for the California Competes Tax Credit program, and Agrawal et al (2023) extend the application by denoting the difference between state and federal level MVPF of a given policy as the Marginal Corrective Transfer (MCT). While these latter studies are closer in line with what this research is seeking to achieve, clustering states with certain characteristics provides the added benefit of starting to understand why a non-zero MCT might exist.

Data & Methodology

Following from Bastian & Jones (2019) where the authors estimate the effects of EITC expansions on the government's net budget[5], this paper sets out estimate the welfare impact of this policy by using publicly available in Integrated Public Use Microdata Series (IPUMS) Current Population

[5] As discussed in Hendren (2016), this is then used as a sufficient statistic to assess the welfare impacts of a policy change.

Survey (CPS).

To be more specific, this paper's main goal is to estimate the following generalized difference-in-differences equation:

$$Y_{ist} = \alpha_0 + \alpha_1 MaxEITC_{g(i),t} + \alpha_2 X_{ist} + \gamma_s^1 + \gamma_t^2 + \epsilon_{ist}$$

where Y_{ist} is the relevant outcome variable, X_{ist} is a vector of control variables and their interactions, the gammas are state and time fixed effects, and epsilon gives the idiosyncratic error term clustered at the state level. The main variable of interest in the right hand side ($MaxEITC$) is defined as the maximum possible federal EITC benefit a family can receive at a given time for a given number of children, the evolution of which (for the time period considered) is plotted in figure 1.

Since labor supply responses mostly happen at the extensive margin, the MaxEITC variable captures most of the added work incentives an EITC expansion provides. While this paper defines the variable at the federal level, the Bastian & Jones (2019) paper highlights that similar results are obtained when the same variable is taken at the state or the state and federal levels combined. However, they also find that when taken at the state level, EITC is endogenous to other underlying economic conditions and state policies. Though using the variable $MaxEITC$ can attenuate this problem, endogeneity of variables of interest with underlying state conditions and policies might present a more significant issue with regards to the current study at hand. Hence, for the purposes of this study, the federal MaxEITC will be the appropriate measure to use.

Throughout the study, several outcome variables will be used on the left hand side relating to labor supply outcomes and variables that have a direct impact on the government's budget. The former will be operationalized by 1) the number of weeks worked in the previous year (as well as the number of hours worked in an average week, and a binary employment variable measuring whether the person worked any hours in the previous week for robustness), and 2) a labor income variable in earned wages; while the latter will be operationalized through federal income taxes paid, total EITC earnings claimed, as well as other welfare income received. Since the publicly available data in question is missing EITC refunds and not all who qualify actually take the program up, the NBER Taxsim simulator will be used to calculate the relevant federal income taxes. Finally, to control for potential factors that might influence the results, various state level demographic and economic variables are included in the regression. Demographic factors such as race, age, education, and marital status, and economic factors such as state level GDP, employment, minimum wage, and a measure of welfare generosity are used as controls. Fixed effects for number of children, state, and year (as well as their interactions with one another) are also included as controls in each regression (unless stated otherwise).

Hence, having estimated the labor supply responses to policy changes and their respective effects on the relevant level of the government's budget, these "Fiscal Externality" (FE) [6] figures will be used to derive the welfare impact of the EITC in the following manner:

$$MVPF = \frac{1}{1 + FE}$$

Up until now, the paper will have relied on the methodology used in Bastian & Jones (2019) using publicly available data. It is at this juncture that this paper makes its second contribution to literature, by diving into a state-level analysis of policy MVPF for the EITC, seeing if and how it varies with underlying state-level economic factors. The main factors used in this study are poverty, income inequality, unemployment, and welfare generosity. These factors - though by no means exhaustive - could each of them affect the impact of the EITC on the outcome variables. For example, expanding the policy in states with a less equal income distribution could result in either higher or lower net costs depending on the magnitude of labor force participation and earnings elasticities. More specifically, states with higher poverty (or inequality, or unemployment) rates could experience higher EITC take-up after expansion of the policy thereby increasing the budgetary and net costs to the government, but the resultant revenue effects from higher labor force participation might be enough to offset these additional costs thereby reducing the net cost to the state; the overall effect on the MVPF would therefore be ambiguous ex-ante. The converse could be said for state welfare generosity: the labor impact of expanding the policy in the more generous states

[6] The fiscal externality figure will thus be calculated as the ratio of the policy's impact on the government's budget (taking into account the change in federal income taxes paid as well as the change in welfare income claimed) to the cost of the policy itself (additional EITC claims made).

could be relatively low, meaning effects on EITC take-up could be less pronounced, but as would increases in tax revenue and decreases in supplemental welfare spending - the resultant effect on the MVPF remaining ambiguous.

Hence, income inequality (as measured by the top 10%'s share of total income) data is taken from the World Inequality Database (WID), and the remaining variables are published by the Kentucky Center for Poverty Research. Put simply, the final analysis is run with the sample divided into different clusters (quintiles and deciles) of these variables that potentially impact policy effectiveness, and MVPFs are calculated accordingly. Each cluster of the chosen factor Z is thus interacted with MaxEITC to yield the modified estimating equation :

$$Y_{ist} = \alpha_0 + \alpha_1 MaxEITC_{g(i),t} Z_{c,t} + \alpha_2 X_{ist} + \gamma_s^1 + \gamma_t^2 + \epsilon_{ist}$$

Part 2: EITC at the Federal Level - Descriptive Statistics and Results

Table 1 displays the descriptive statistics for the sample of some 1.3 million women aged between 18-64 between the years 1994 and 2016, with dollar denominated variables reported at 2016 dollars. The sample consists of women with an average of approximately 40 years of age, having one child, working 67 percent of the time in a year, and making approximately 20.6 thousand USD. Just over 22 percent of these women claim EITC benefits with an average approximately $472 each. Tables 2 to 4 present the regression results to show the effects of a $1,000 increase in Max EITC on the desired outcome variables.

As tables 2 through 4 show, a $1,000 increase in Max EITC yields increases in employment in all three measures of around 5.5-6.5 percent of their individual means. Using binary employment (whether a person is working or not in a given week) as proxy, the labor force participation elasticity is at 0.47. Increases in Max EITC also lead to increases in annual earnings ($1,924), taxes paid ($140), EITC benefits claimed ($256), as well as decreases in other state welfare income claimed ($47) for a given woman between the ages 18-64 in the time period considered. Although different in magnitude, these results are directionally in line with the findings of Bastian & Jones (2019). The earnings elasticity is roughly 0.76 using annual earnings, and the fiscal elasticity (calculated as the ratio of the inflow of funds into the state's budget resulting from the policy to the additional costs associated with expanding the policy) equals 0.74 [7]. This leads to an MVPF figure that is well above 1 at 3.88, meaning the policy more than pays for itself when its indirect effects are taken into consideration. This final figure is also in line with the afore-mentioned study, where the authors calculate an MVPF in the range of 3.18 to 4.23, meaning each extra dollar of EITC spending leads to over three dollars being returned in social value.

Having reached similar conclusion to Bastian & Jones (2019) in terms of policy MVPF using publicly available data, I now extend the analysis to see what factors might affect the effectiveness of this policy and how. Remaining at the federal level for now, I look at the degree of urbanization first.

Max EITC and Urbanization

As outlined in the last paragraph of Section I, there might be various economic reasons as to why MVPF of a given policy might vary from state to state. At this juncture, it is equally important to ask why we might expect to see changes in policy effectiveness based on demographic variables, such as (but decisively not limited to) whether a person lives in an urban, suburban, or rural area. Due to well documented links between wages and the cost of living (and more specifically the geographic variation in housing costs) [8], the EITC is expected to have different impacts on labor supply in different areas. This implies that depending on where they live, low-skilled workers may face different EITC outcomes. On the one hand, a Brookings Institute report (Berube, 2004) highlights that large cities and rural areas house roughly the same number of low-income families, and that these are almost equally likely to be eligible for the EITC, suggesting there shouldn't be big differences. On the other hand, Efird (2021) notes that those of the eligible who live in rural areas are much less likely to claim these benefits than their urban counterparts, suggesting there could be differences after all. It is thus conceivable to have a more effective policy in urban and suburban areas than in rural ones. Hence, to see if and how the level of urbanization might affect EITC policy effectiveness, I divide the sample and carry out the analyses in these smaller strata, before proceeding to economic clusters. The summary statistics in Table 5 show that at a first glance, there aren't any meaningful differences in the demographic characteristics of the average

[7] where $FE = [(140.84) - (-46.72)]/(253.36) = 0.74$

[8] See Fitzpatrick and Thompson (2010) for a detailed outline of the literature.

woman living in rural, urban, or suburban locations. The main differences lie in employment and education (taken as a factor variable), where these are slightly higher for women in urban and suburban settings than those in rural settings, while EITC take up is highest among rural women.

The regression results in Table 6 show that the effects of the policy on employment (in all three measures) is similar but lowest among women who live in an urban setting, as is the change in claimed welfare income as a response to a change in Max EITC. This finding is in line with research from Fitzpatrick and Thompson (2010) who find that the 1993 expansion of the EITC increases labor force participation for single mothers in the areas with the lowest cost of living, but not in areas of high costs of living, as well as with Bastian (2023) who finds that the EITC has small but positive impacts on labor force participation of unmarried women living in rural areas, but negative effects for those living in suburban and urban areas. Conversely, the change in annual earnings as a response to a change in Max EITC is lowest in rural areas (by a stark amount). The same can be said of the change in taxes paid, with the added layer of the estimate losing its statistical significance. In fact, while a $1,000 increase in Max EITC increases payroll taxes in urban and suburban areas, there is a decrease in taxes paid of a large magnitude ($530) in rural areas. Finally, the results show that changes in Max EITC affect the suburban areas the least in terms of extra EITC benefits claimed.

Using these results and the same calculations as before, the implied MVPF is only 0.18 in rural areas. This result is likely driven by two aspects. The first is that the earnings effect of a MaxEITC expansion is the least in rural areas (some $42 per $1,000 expansion). Secondly, and perhaps more importantly, the estimate for taxes paid being negative and statistically insignificant which eschews the results. However, taking these results at face value, it can be said that at least in suburban and urban areas, the policy more than offsets its costs (with an infinite MVPF). This stark difference (albeit with caveats) suggests that different economic characteristics might make states more or less able to have effective transmission of the intended policy for welfare purposes. I start exploring what some of these factors might be in the next section.

Part 3 - Max EITC in various clusters

Extending the study's findings from the federal to the state level, looking at policy MVPFs for each state over time could be an undertaking in and of its own. However, a deeper question to ask would be whether states that share certain characteristics could be grouped together to see if and how these characteristics affect the policy's effectiveness. Various measures of the income distribution (poverty and inequality), the unemployment rate, and state welfare generosity are chosen as the main dividing characteristics for this study.

At this juncture, it is again important to ask why we might expect to see changes in policy effectiveness (at least with regards to the EITC) based on clusters of these variables (poverty, inequality, unemployment, and welfare generosity). First and foremost, the EITC being a poverty alleviating (Schanzenbach, 2021) and inequality reducing (Hardy et al, 2022) policy would suggest a relationship between the policy transmission and these variables. Seeing as how the EITC targets those at the bottom of the income distribution, it could be that areas with high poverty or income inequality will benefit the most and policy MVPF will be highest. Conversely, since EITC expansions in areas with a more regressive income distribution are also likely to burden the state's budget more (by virtue of having a higher share of the population benefit from the tax credit), the cost to the state might outweigh the benefits relative to other, more equitable states in terms of income. A similar argument could be made for the unemployment rate. Seeing as how the EITC's labor supply effect heavily impact the extensive margin and reduce unemployment (Francis, 2006), while the affected population might benefit the most in areas with high unemployment, so will the burden on the state's budget be higher, thereby pulling the MVPF figure in opposite directions. Finally, welfare generosity (a measure that proxies the a state's allocation on social welfare programs other than the EITC) could also be a factor that affects the effect of increasing Max EITC. For example, a state ranking high on this measure could be there as a response to immediate necessity (to cater to the many in need already there) or as a preemptive measure (to avoid people falling into abject poverty by providing a wider safety net). As Nell (2006) notes, while welfare generosity is associated with a reduction in post-transfer poverty rates, it is also associated with higher pre-transfer inequality rates. Hence, it could be worthwhile to see if generosity in other social welfare programs have a discernible affect on the MVPF of this policy.

Another important question to ask before carrying out this analysis is whether these variables differ across states and over time. Fig 2 displays a snapshot of poverty levels across U.S. states in 1994, and Fig x (this needs to be an html) shows the animated evolution of this variable over the time period considered in this study. As the snapshot displays, there are ample differences in poverty rates to begin with. Namely, poverty rates in 1994 range from a low of 7.6% in Utah, Vermont, and New Hampshire, to 25.7% in Louisiana - this last figure being the highest poverty rate in the entire sample. The lowest inequality across state and time was also in New Hampshire, in the year 2000, and the highest was in Florida, 2010[9]. Seeing as there is ample variation in these variables rates across state and time, it is worthwhile to ask how this impacts social welfare policy.

Hence, to consider if the MVPF is a deeper variable that is affected by these underlying economic variables, I divide the sample in state/year clusters of poverty, inequality (as measured by the Top 10% share of total income) and unemployment. I cluster in quintiles and deciles for all of these measures, and add an extra inequality variable in the Gini index for robustness. Table 7 through Table 20 display these results, as well as the summary statistics reported in quintiles to explore if there are other underlying differences in each cluster to begin with.

Already at a first glance, we see that areas with the higher poverty rates (cluster 5) are also associated with women who have the lowest education and employment levels, as well as the youngest (albeit by a small margin), the least likely to be married or to have children. These women are also the most likely to take up EITC benefits. The trends in employment and marriage also apply to higher rates of income inequality.

When broken down to quintiles of poverty, the women in states with highest poverty levels show the least response in any employment measure to a $1,000 increase in Max EITC. As such, their annual earnings increase by the least amount, their claimed welfare benefits decrease by the least amount, and they are the only ones whose payroll taxes aren't significantly affected by the change in policy. The fact that their claimed EITC benefits are the highest of any cluster suggests that the change in employment happens at the extensive margin. Conversely, the change in all other variables is highest in states and years where poverty is in the lowest quintile (except for EITC benefits claimed,

[9]Animated maps showing across state and year variation in inequality and unemployment measures can be found in the Appendix.

which is lowest), potentially hinting that the changes are happening in the intensive margin, and calling to mind previous findings of the EITC's poverty diminishing effects. Table 9 displays the earnings and labor participation elasticities of each quintile of poverty [10]. While the participation elasticity (using binary employment) seems to exhibit a u-shape (being higher at each tail end quintile), response of earnings seem to get more inelastic as the poverty rate increases. Similar tables for when the data is clustered using income inequality, unemployment, and state welfare generosity can be found in the appendix (to be included).

When broken into deciles, the results obtained in quintiles mostly persist, with the results of the 9th decile supplanting the 10th in terms of directionality (potentially due to noise and outliers). Namely, the employment response to the change in policy is highest in the least poor decile and the lowest in the 9th decile, as are taxes paid and the change in welfare income claimed. Similarly to the results obtained when clustering in quintiles, states and years with the lowest poverty rates in deciles experiences the least increases in EITC benefits as a response to a $1,000 change in Max EITC, while states with the highest poverty rates display the highest increases in EITC benefits claimed. Finally, while there is some noise in the change in annual earnings, the shift is again at its lowest in states where poverty is most rampant. Hence the results indicate that whereas EITC takeup is increasing in poverty rates, the labor and earnings responses to the policy are decreasing in this same variable.

Looking at the whole income distribution in a state through the top 10% share of total income (as opposed to only the lower tail end through poverty rates), the sample is clustered into quintiles and deciles of inequality next. The summary statistics can be found in the appendix, and show the same patterns in the percentage of women aged 18-64 being employed, married, or having children (lowest in the highest inequality cluster, and highest in the lowest inequality cluster). There are, however, no apparent trends in EITC take up, education, or age.

In quintiles of inequality, we see the same results that hold in quintiles of poverty, with the most unequal states having the lowest responses in all variables except for EITC benefits claimed (where the change is highest). Panel x in the appendix displays the same results when the Gini Index is

[10]Note that the fifth quintile isn't reported as the coefficients taxes paid were insignificant and therefore skewed the results.

used as a measure of inequality instead of the top 10% share of income, suggesting the findings are robust to the measure of income inequality employed. When taken in deciles, the same patterns persist in the employment and earnings variables (lowest employment response to a change in Max EITC in the highest inequality clusters), as well as in the EITC benefits (highest EITC claims come from highest inequality states, and vice versa). That being said, there is considerable noise in the response of federal income taxes paid to the change in policy (where the last two deciles yield statistically insignificant coefficients, as was the case in clusters of poverty) and welfare income claimed (which doesn't display any apparent pattern). Furthermore, the earnings elasticities in each quintile are around the same level as they were in the previous case, becoming less elastic as inequality increases [11].

The same analysis is then carried with the data clustered in quintiles and deciles of another state level negative outcome variable, unemployment. The summary statistics in Table 15 show that women in states and years with the highest unemployment rates are least likely to be married or employed, and the most likely to take up EITC benefits, as was the case in quintiles of inequality and poverty. Furthermore, Panel D shows that the results are directionally identical in quintiles to the previous cases of poverty and inequality, where the responses for employment, earnings, taxes paid, and welfare claimed are lowest in the highest clusters of unemployment, and highest in the lowest unemployment cluster, and the reverse pattern holds for EITC benefits claimed as before. When the analysis is broken down to deciles of unemployment, while there is a lot more noise in the coefficients, the employment responses remain highest in the lower unemployment deciles, as do responses for taxes paid and welfare income claimed in absolute terms. Similarly, the change in annual earnings is lowest in the 9th decile of unemployment, and the EITC benefits claimed are highest in states/years with the most unemployment. The participation and earnings elasticities are also highest and lowest in the fifth quintile respectively, as was the case with in the previous clusters. Hence, we see similar patterns in the way these variables respond to increases in Max EITC in various clusters of nominally regressive measures in poverty, income inequality, and unemployment.

[11] The participation elasticies are also around the same level, but they spike in the last quintile to 0.52, which wasn't available in the previous case.

So far, the clusters have looked at the effects of (regressive) outcome variables in poverty, income inequality, and unemployment. The study now looks in the other direction to see if and how policy responses change when taken in clusters of a nominally progressive policy variable: one that proxies for a state's generosity in its welfare programs. In line with the previous findings (but in the reverse direction), the summary statistics show that state/year combinations where state welfare generosity was lowest also had women that were least likely to be employed, or have children, and the most likely to take up EITC benefits; they were also the least educated.

When we look at the regression results in quintiles, we see a different picture however. Firstly, the employment response to a change in Max EITC is highest in the least generous states and lowest in the most generous states, a pattern that persists when the analysis is carried in deciles. The relatively high marginal effects of increasing EITC benefits in those states where welfare policy is least generous could be explained by the higher incentives to enter the workforce than in those states that are more generous in their non-employment related welfare policies. Conversely, both in quintiles and deciles, the response of claimed welfare income is highest (in absolute terms) in those least generous states and lowest in the most generous ones. More intuitively, a $1,000 increase in Max EITC decreases other welfare income claimed in all clusters (as before) but this decrease is lowest in the most generous states. It is also interesting to note that the coefficients of other variables no longer exhibit a linear trend, but instead take on a parabolic one when taken in quintiles. Namely, whereas the change in earnings and payroll taxes are lowest in states where welfare generosity is either very high or very low, claimed EITC benefits are highest in those same states. This last would again point that the impact of the increase in EITC happens at the extensive margin. When taken in deciles however, there is considerably more noise. The response of EITC benefits are highest in the most generous states, the response of taxes paid are lowest in the least generous states (perhaps because the shift in EITC policy does little to offset other, regressive tax laws), and the response of annual earnings is lowest in the most generous states, albeit with considerable noise in the middle.

Explanation of Results

Hence, examining the results in both quintiles and deciles, we can say that policy MVPF (as it pertains to the EITC) is decreasing in the rate of poverty, income inequality, and unemployment (albeit with some noise for the latter two). These more negative, regressive measures increase the burden of a poverty alleviating policy on the government's budget when they are higher as they result in 1) higher EITC benefits claimed; 2) lower increases in taxes paid; 3) smaller decreases in supplemental welfare spending; thereby acting together to decrease MVPF. The results for welfare generosity (a more progressive measure) are more ambiguous, though they seem to suggest that being in either the lower or higher end of the generosity variable could dampen policy effectiveness, with a potential sweet spot in the middle quintiles and deciles.

The 3D plot in Figure 3 displays these results in a different manner, taking a snapshot of how claimed EITC benefits interact with each decile of the relevant cluster and the resultant MVPF. The relationship is noisy with regards to deciles of welfare generosity, though policy MVPF seems to decrease after $240 in EITC benefits claimed per $1,000 increase in Max EITC, which coincides with the least generous deciles of the strata. With regards to this factor, it seems like a state can be hurt by either being too generous or too stingy, with a maximal point in the middle deciles where MVPF is highest. There is again some noise when it comes to unemployment however, it is not hard to deduce that MVPF is lowest where unemployment rates and claimed EITC benefits are highest. In general, it seems to be the case that policy MVPF is high where unemployment is low. Finally, with regards to poverty, there is a much clearer trend where the response in claimed EITC benefits are highest in the poorest regions, which result in the lowest policy MVPFs. Hence, it can be said that policy MVPF is decreasing in poverty rates.

Therefore, the results in this paper not only suggest that the EITC is by and large a self-financing policy, but its effects are even more pronounced in areas where there is a more equal income distribution. While this might be a cause for concern for those states where poverty rates, income inequality, and unemployment are high, the MVPF is above the self-financing rate in almost all cases. This means that allocative efficiency could be achieved (and even enhanced) by increasing spending on this policy for the most part, with further alleviation in poverty and inequality leading to an even higher MVPF. Undoubtedly, a similar studies could be carried out to see if another policy (say increasing unemployment benefits, or switching to universal basic income) would yield higher MVPF in a given cluster to make investment decisions in an ex-ante constrained government. However, considering the many studies linking the EITC to improved health benefits for both mothers (Evans and Garthwaite, 2014) and their children (Hoynes et al, 2015; Averett and Wang, 2015) the benefits accrued to the government are likely to be higher in the long run, especially in light of the Goodman-Bacon (2016) study which estimates a discounted annual return of two to seven percent of the original cost in Medicaid spending in terms of lower cash transfers from the government.

Tables and Figures

Figure 1:

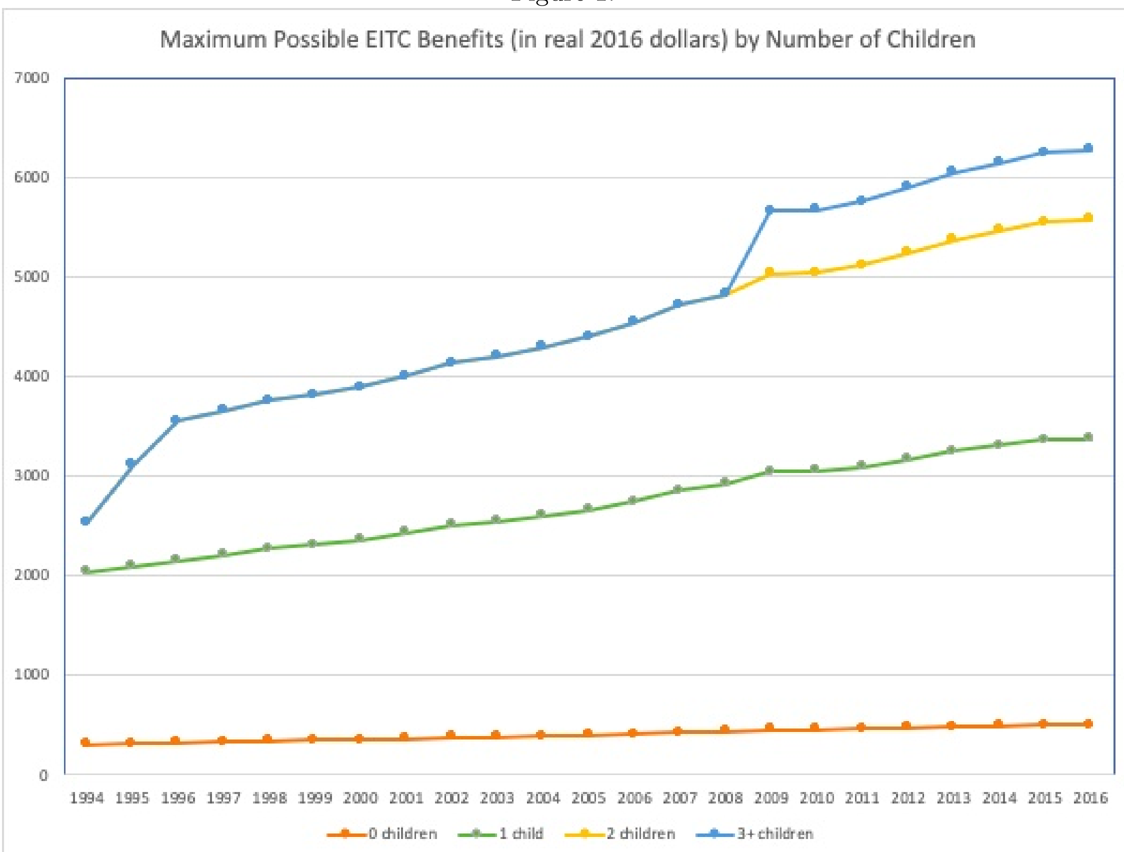


Table 1: Summary Statistics

Statistic	Mean	St. Dev.
Number of Children	1.08	1.21
Number of Children (under 5)	0.23	0.54
Age	39.92	12.61
Employed	0.67	0.47
Usual Hours Worked (weekly)	23.29	20.14
Total Weeks Worked	33.78	22.87
Individual Income	20,647.53	31,712.73
Taxes Paid	5,157.99	16,218.81
State Minimum Wage	6.27	1.36
State Unemployment Rate	5.89	1.96
State Welfare Generosity	1,321.23	497.00
Gross State Product	475,370.00	549,272.20
Welfare Income	80.47	687.40
Federal Top Marginal Tax Rate	36.10	2.78
State Top Marginal Tax Rate	5.45	3.51
Total Top Marginal Tax Rate	41.55	3.31
EITC Takeup (Percentage)	22.28	0.42
Federal EITC Benefits	447.81	1,112.86
State EITC Benefits	24.07	136.12
Total EITC Benefits	471.88	1,181.53
Maximum EITC	2,354.34	1,925.74
Observations:	1,330,809	

Table 2: EITC's Effect on Labor Supply - Employment

	Employment (binary)	*Usual Hours (weekly)*	*Annual Weeks Worked*
Max EITC	0.04***	1.55***	1.93***
	(0.01)	(0.19)	(0.22)
Full Controls	Yes	Yes	Yes
Observations	1,330,809	1,330,809	1,330,809
R-squared	0.06	0.06	0.07
Mean Dep. Var.	0.67	23.29	33.78

Note: Max EITC in 1,000 real 2016 Dollars.

Table 3: EITC's Effect on Earnings, Benefits, and Taxes (Federal)

	Annual Earnings	*EITC Benefits*	*Taxes Paid*	*Welfare Income*
Max EITC	1,924.10***	253.36***	140.84***	-46.72***
	(339.37)	(10.89)	(17.37)	(7.12)
Full Controls	Yes	Yes	Yes	Yes
Observations	1,330,809	1,330,809	1,330,809	1,330,809
R-squared	0.10	0.23	0.09	0.06
Mean Dep. Var.	20,647.53	471.88	5,157.99	80.47

Note: Max EITC in 1,000 real 2016 Dollars.

Table 4: Participation and Earnings Elasticity with Max EITC (Federal), full controls; Implied MVPF

Variable	Implied Participation, Earnings, Fiscal Elasticities; MVPF
Employment (binary)	0.47
Earnings	0.76
FE	0.74
MVPF	3.88

Table 5: Summary Statistics - Rural, Urban, Suburban

	Rural	Urban	Suburban
Age	39.80	39.89	39.93
	(12.68)	(12.56)	(12.62)
Number of Children	1.06	1.06	1.07
	(1.18)	(1.21)	(1.22)
Percent Married	57.54	59.44	56.98
	(0.49)	(0.49)	(0.50)
Percent Employed	64.17	68.29	69.05
	(0.48)	(0.46)	(0.46)
Percent EITC Takeup	25.25	22.06	21.16
	(0.43)	(0.41)	(0.41)
Education (factor)	1.91	1.95	1.98
	(0.47)	(0.44)	(0.45)

Note: Education: 1 (HSD); 2 (College) ; 3 (More)

Table 6: Max EITC Estimates - Rural, Urban, Suburban

	Rural	Urban	Suburban
Max EITC and Urbanization			
Employment (binary)	0.013***	0.008***	0.013***
	(0.003)	(0.001)	(0.003)
Usual Hours (weekly)	0.54***	0.47***	0.57***
	(0.02)	(0.02)	(0.02)
Annual Weeks Worked	0.68***	0.47***	0.69***
	(0.03)	(0.03)	(0.03)
Annual Earnings	42.20***	899.64***	1,166.7***
	(31.60)	(27.70)	(24.36)
EITC Benefits	118.43***	113.84***	65.73***
	(10.31)	(9.00)	(7.89)
Taxes Paid	-530.24	201.11***	537.42***
	(16.14)	(14.15)	(12.44)
Welfare Income	-18.98***	-3.81***	-19.64***
	(6.56)	(5.80)	(5.13)

Note: Max EITC in $1,000 real 2016 Dollars.

Each column represents a separate regression where the location variable is interacted with MaxEITC.

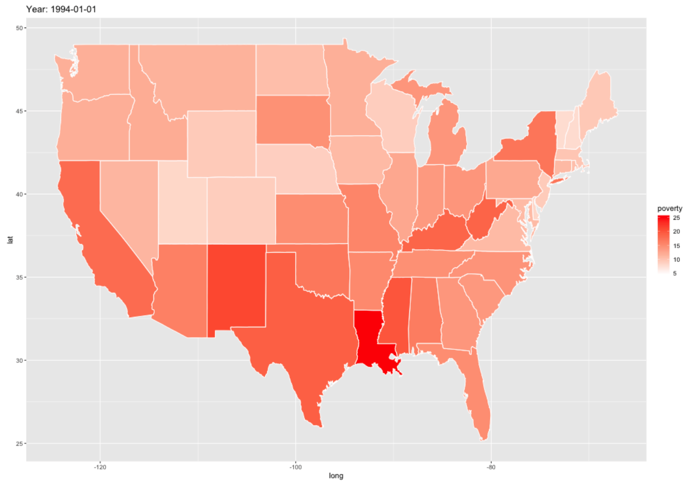


Figure 2: Animated GIF Snapshot

Table 7: Summary Statistics - Quintiles of Poverty

	(1)	(2)	(3)	(4)	(5)
Age	39.98	39.96	39.82	40.01	39.87
	(12.27)	(12.56)	(12.59)	(12.68)	(12.86)
Number of Children	1.10	1.09	1.07	1.07	1.04
	(1.21)	(1.22)	(1.21)	(1.21)	(1.21)
Percent Married	61.15	59.44	58.10	56.11	53.52
	(0.49)	(0.49)	(0.49)	(0.49)	(0.50)
Percent Employed	72.57	71.32	67.78	65.13	62.44
	(0.45)	(0.45)	(0.47)	(0.48)	(0.48)
Percent EITC Takeup	18.33	20.58	21.83	23.35	25.58
	(0.37)	(0.40)	(0.41)	(0.42)	(0.44)
Education (factor)	2.00	1.99	1.95	1.95	1.93
	(0.43)	(0.43)	(0.46)	(0.48)	(0.49)

Note: Education: 1 (HSD); 2 (College) ; 3 (More)

Table 8: Max EITC Estimates - Quintiles

	(1)	(2)	(3)	(4)	(5)
		Panel A1: Poverty Rate			
Employment (binary)	0.039***	0.036***	0.036***	0.035***	0.033***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Usual Hours (weekly)	1.64***	1.55***	1.59***	1.55***	1.51***
	(0.31)	(0.30)	(0.30)	(0.28)	(0.29)
Annual Weeks Worked	2.12***	1.99***	1.98***	1.91***	1.84***
	(0.31)	(0.29)	(0.31)	(0.32)	(0.31)
Annual Earnings	2,099.3***	2,150.7***	2,046.2***	1,834.5***	1,730.7***
	(462.00)	(407.89)	(391.71)	(377.42)	(389.84)
EITC Benefits	225.04***	235.05***	243.50***	263.13***	269.91***
	(14.82)	(13.13)	(12.56)	(12.10)	(12.47)
Taxes Paid	395.46***	279.21***	162.64***	107.06***	1.36
	(23.65)	(20.88)	(20.05)	(19.32)	(19.95)
Welfare Income	-52.14***	-48.92***	-49.32***	-45.84***	-42.82***
	(9.71)	(8.56)	(81.65)	(7.87)	(8.21)

Note: Max EITC in 1,000 real 2016 Dollars.

Table 9: Max EITC Estimates - Quintiles

	(1)	(2)	(3)	(4)	(5)
Implied Participation and Earnings Elasticities in quintiles of poverty					
Employment (binary)	0.48	0.43	0.43	0.46	.
Earnings	0.81	0.83	0.79	0.76	.

Note: Max EITC in 1,000 real 2016 Dollars.

Figure 3:

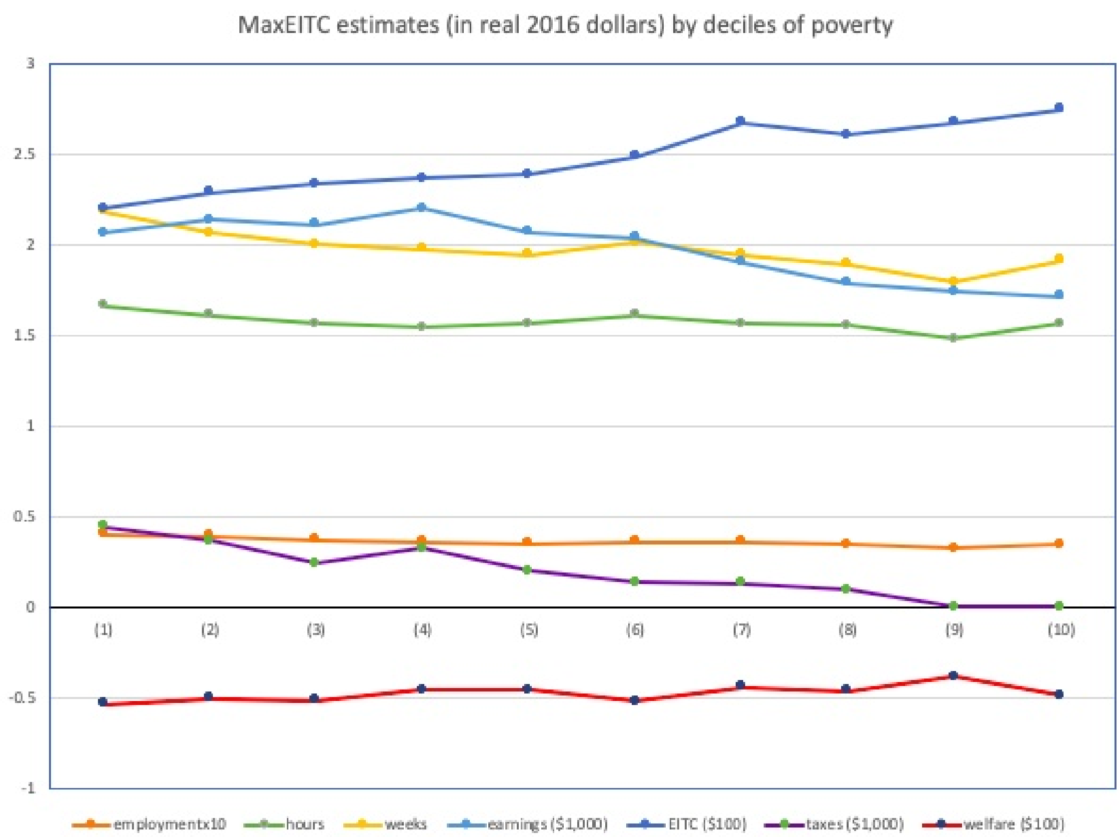


Table 10: Max EITC Estimates - Quintiles

	(1)	(2)	(3)	(4)	(5)
Panel B1: Inequality (Top 10% Share)					
Employment (binary)	0.044***	0.039***	0.037***	0.034***	0.034***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Usual Hours (weekly)	1.94***	1.72***	1.63***	1.52***	1.50***
	(0.33)	(0.31)	(0.33)	(0.23)	(0.20)
Annual Weeks Worked	2.35***	2.12***	2.05***	1.89***	1.86***
	(0.37)	(0.28)	(0.32)	(0.31)	(0.29)
Annual Earnings	2,211.9***	2,193.2***	2,036.7***	1,961.0***	1,759.2***
	(511.78)	(430.33)	(400.71)	(371.28)	(376.80)
EITC Benefits	230.50***	235.73***	240.64***	251.93***	266.01***
	(16.39)	(13.81)	(12.90)	(11.87)	(12.07)
Taxes Paid	178.71***	193.69***	136.78***	115.21***	153.04***
	(26.20)	(22.03)	(20.51)	(19.00)	(19.29)
Welfare Income	-49.12***	-51.80***	-48.08***	-49.87***	-41.68***
	(10.70)	(9.05)	(8.39)	(7.78)	(7.92)

Note: Max EITC in 1,000 real 2016 Dollars.

Figure 4:

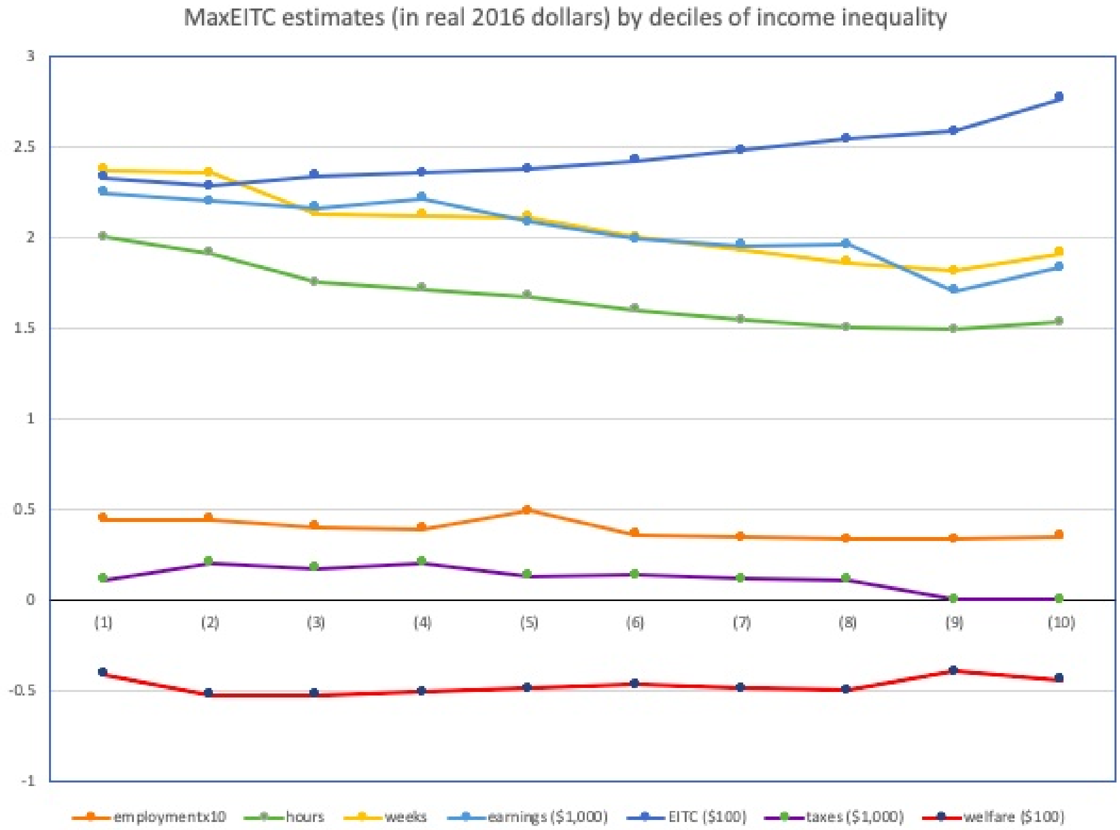

MaxEITC estimates (in real 2016 dollars) by deciles of income inequality
3
2.5
2
1.5
1
0.5
0
-0.5
-1
(1)
(2)
(3)
(4)
(5)
(6)
(7)
(8)
(9)
(10)
employmentx10
hours
weeks
earnings ($1,000)
EITC ($100)
taxes ($1,000)
welfare ($100)

Table 11: Summary Statistics - Quintiles of Unemployment Rate

	(1)	(2)	(3)	(4)	(5)
Age	39.81	39.91	39.69	39.76	40.32
	(12.51)	(12.53)	(12.52)	(12.61)	(12.85)
Number of Children	1.09	1.07	1.08	1.07	1.07
	(1.24)	(1.20)	(1.21)	(1.21)	(1.21)
Percent Married	61.85	58.49	58.08	56.04	54.73
	(0.49)	(0.49)	(0.49)	(0.50)	(0.50)
Percent Employed	74.15	68.80	67.14	64.98	63.25
	(0.44)	(0.46)	(0.47)	(0.48)	(0.48)
Percent EITC Takeup	20.95	21.56	22.38	22.84	24.12
	(0.41)	(0.41)	(0.42)	(0.42)	(0.43)
Education (factor)	1.98	1.96	1.94	1.94	1.96
	(0.41)	(0.45)	(0.47)	(0.47)	(0.48)

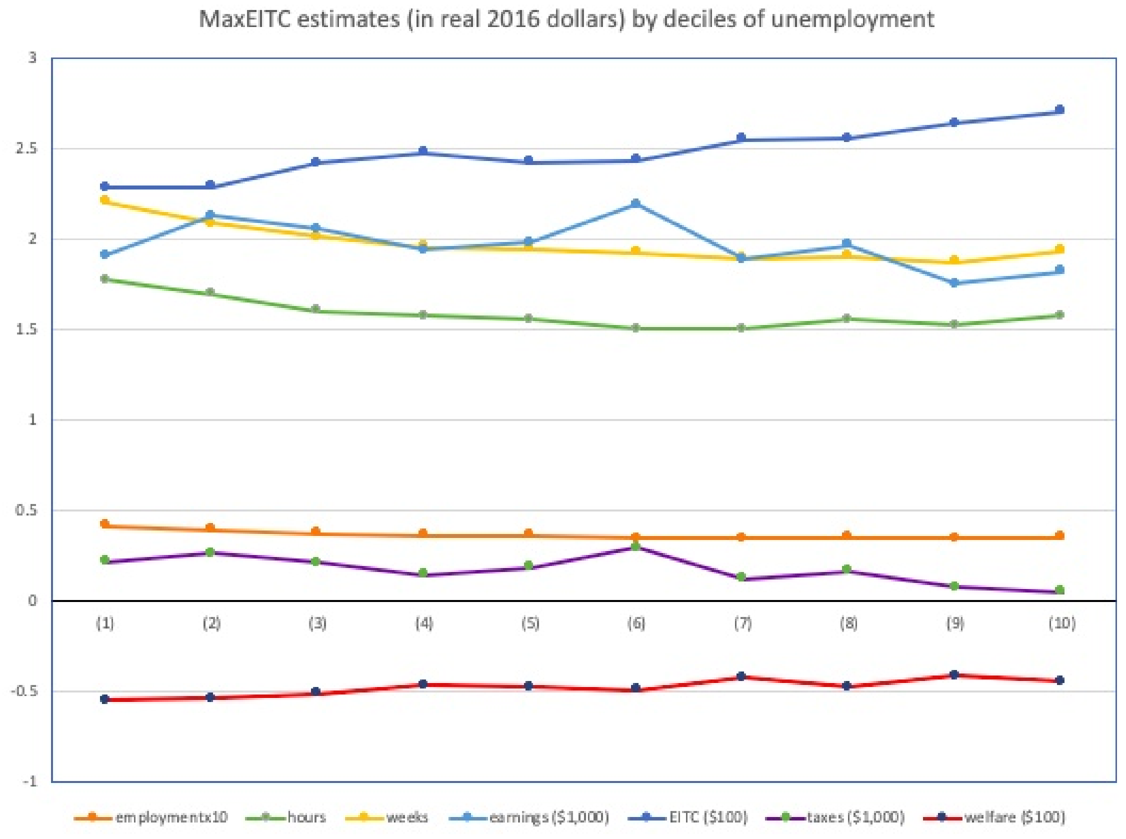
Note: Education: 1 (HSD); 2 (College) ; 3 (More)

Table 12: Max EITC Estimates - Quintiles

	(1)	(2)	(3)	(4)	(5)
	Panel D1: Unemployment				
Employment (binary)	0.040***	0.036***	0.035***	0.034***	0.034***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Usual Hours (weekly)	1.73***	1.59***	1.53***	1.52***	1.54***
	(0.35)	(0.32)	(0.32)	(0.32)	(0.31)
Annual Weeks Worked	2.13***	1.99***	1.93***	1.89***	1.90***
	(0.32)	(0.33)	(0.31)	(0.31)	(0.30)
Annual Earnings	2,042.6***	2,018.3***	2,071.3***	1,928.1***	1,777.0***
	(459.50)	(403.01)	(398.21)	(379.72)	(385.44)
EITC Benefits	229.02***	244.57***	242.93***	254.82***	266.44***
	(14.78)	(12.89)	(12.82)	(12.22)	(12.41)
Taxes Paid	239.38***	181.79***	225.77***	141.38***	59.01***
	(23.52)	(20.63)	(20.39)	(19.44)	(19.72)
Welfare Income	-55.13***	-50.08***	-48.95***	-45.49***	-43.23***
	(9.56)	(8.45)	(8.41)	(8.01)	(8.09)

Note: Max EITC in 1,000 real 2016 Dollars.

Figure 5:



MaxEITC estimates (in real 2016 dollars) by deciles of unemployment
3
2.5
2
1.5
1
0.5
0
-0.5
-1
(1)
(2)
(3)
(4)
(5)
(6)
(7)
(8)
(9)
(10)
employmentx10
hours
weeks
earnings ($1,000)
EITC ($100)
taxes ($1,000)
welfare ($100)

Table 13: Max EITC Estimates - Quintiles

	(1)	(2)	(3)	(4)	(5)
Panel E1: Welfare Generosity					
Employment (binary)	0.036***	0.036***	0.036***	0.033***	0.034***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Usual Hours (weekly)	1.65***	1.61***	1.57***	1.41***	1.48***
	(0.31)	(0.31)	(0.29)	(0.26)	(0.28)
Annual Weeks Worked	2.00***	1.98***	1.96***	1.80***	1.88***
	(0.31)	(0.31)	(0.30)	(0.27)	(0.29)
Annual Earnings	1,879.1***	1,980.7***	2,085.5***	1,926.8***	1,824.9***
	(404.32)	(433.56)	(424.45)	(433.21)	(413.18)
EITC Benefits	263.53***	239.93***	241.85***	245.59***	262.73***
	(13.00)	(13.91)	(13.56)	(13.89)	(13.33)
Taxes Paid	-6.96	118.52***	283.90***	159.62***	210.09***
	(20.70)	(22.19)	(21.73)	(22.18)	(21.15)
Welfare Income	-64.63***	-55.72***	-47.12***	-31.82***	-29.22***
	(8.36)	(9.07)	(8.91)	(9.07)	(8.67)

Note: Max EITC in 1,000 real 2016 Dollars.

Figure 6:

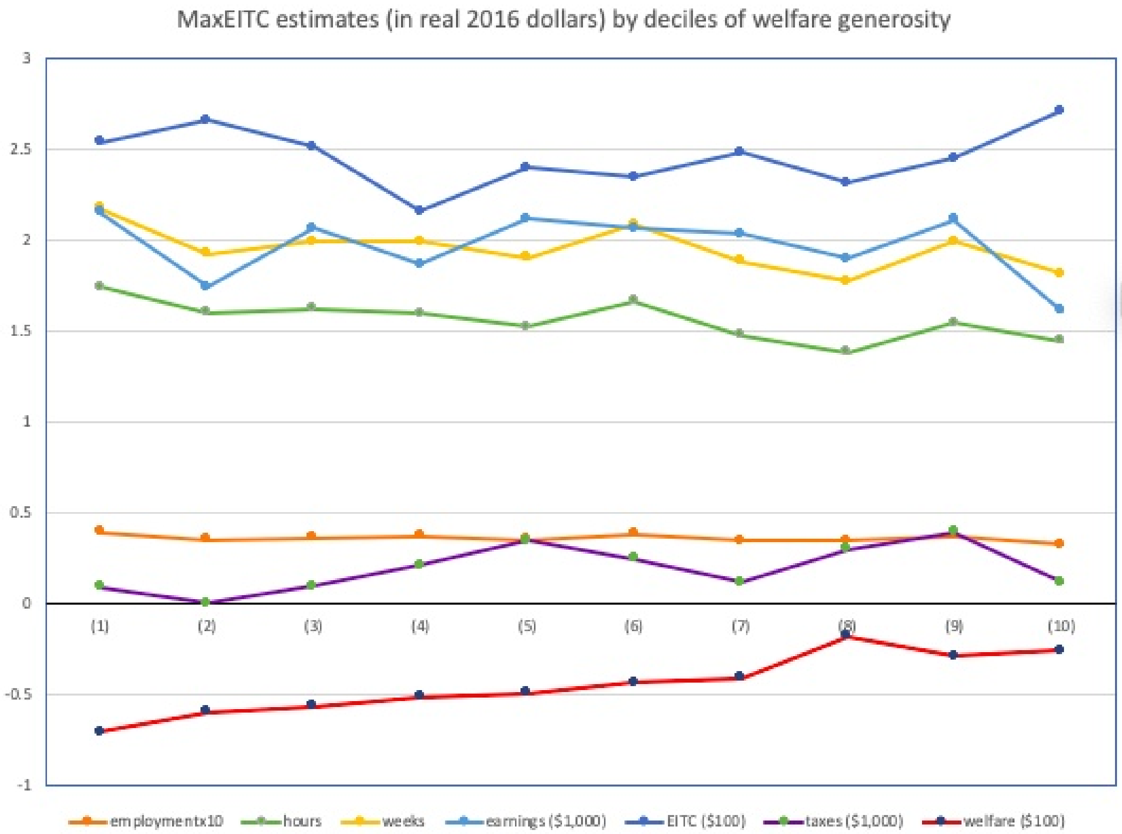
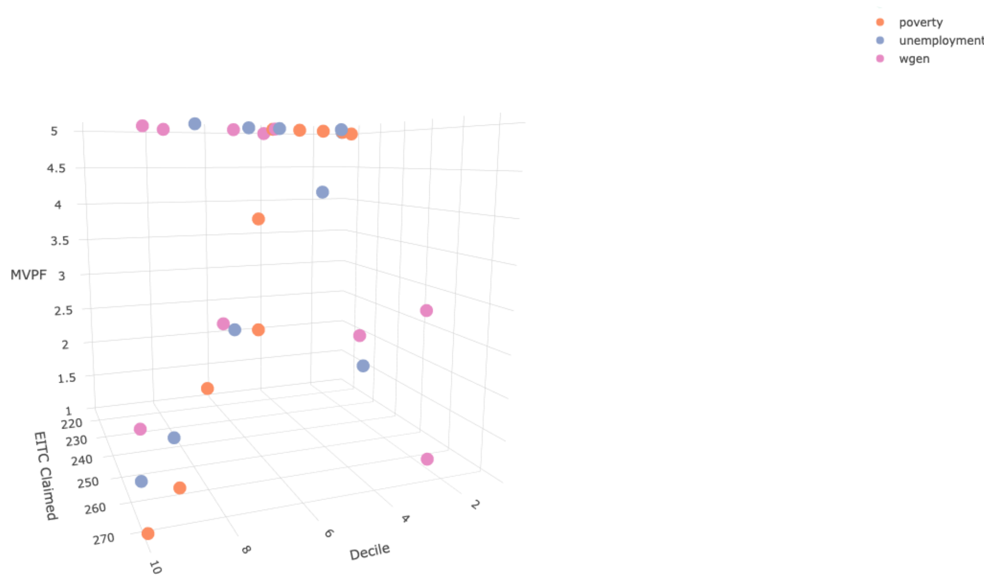

MaxEITC estimates (in real 2016 dollars) by deciles of welfare generosity
3
2.5
2
1.5
1
0.5
0
-0.5
-1
(1)
(2)
(3)
(4)
(5)
(6)
(7)
(8)
(9)
(10)
employmentx10
hours
weeks
earnings ($1,000)
EITC ($100)
taxes ($1,000)
welfare ($100)

Figure 7: MVPFs in Quintiles



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