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

This paper applies the Marginal Value of Public Funds framework to calculate and compare the welfare impacts of the Earned Income Tax Credit (EITC) across the United States from 1993 to 2016 across three program expansions. Focusing on the effects on women aged 18-64 (a target demographic for this policy), the paper first replicates the methodology of Bastian & Jones but using publicly available data from the CPS and obtains similar results. Next, the paper extends the framework to group state-year combinations into quintiles and deciles of various underlying economic characteristics to see if and how these variables account for differences in policy effectiveness; characteristics such as poverty, income inequality, unemployment, and state welfare generosity. As a result, the paper concludes that measures of negative economic impact (such as poverty, high levels of inequality, and unemployment) reduce the net 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. Results are robust to several different classifications and extensions, and regression estimates suggest that the results are driven by both revenue and labor force participation effects.

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 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. In doing so, this paper is among the first to calculate the Marginal Value of Public Funds (MVPF) of the EITC by geography, examining how the welfare return on public spending varies across regions with different underlying economic conditions. This geographic dimension carries important implications for cost-benefit analysis of federal spending, as it demonstrates that a uniform national policy can yield substantially different returns depending on local economic characteristics, informing how policymakers might evaluate the allocative efficiency of decentralized public welfare provision across the country.

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 identification strategy used by

Bastian and Jones (2021). 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), it is worth noting that this is a limitation of the CPS data. Since the publicly available CPS data does not include EITC refund amounts, I use the NBER Taxsim simulator to calculate relevant federal income tax liabilities and impute EITC benefits. After replicating the results from Bastian and Jones (2021) using publicly available data, I then cluster the data in state-year combinations (and county-year combinations to capture more of the geographic variation as an extension) 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]. Additionally, to examine whether these patterns hold at a finer geographic level, I extend the analysis to sub-state units by clustering individuals into counties and dividing them by these same economic characteristics (see Table 16).

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

My sample consists of 1.3 million women between the ages 19 and 64. Similar to Bastian and Jones (2021), I first test whether MaxEITC impacts employment and income, as these represent the primary channel through which the EITC affects government revenue and thus the MVPF. 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. This employment effect is notably larger than some estimates in the literature, which may reflect differences in the use of publicly available survey data (CPS) rather than administrative records, as well as the broader sample and time period considered. 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 (2021), 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 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. It is worth noting, however, that the fiscal impact of a policy like the EITC may extend beyond the direct tax revenue and welfare channels captured here. As Bastian & Jones (2021, Appendix D) discuss, EITC-induced changes in income can also affect health outcomes, criminal behavior, and other domains, each of which carries its own implications for government spending. To the extent that these channels are not captured in the present analysis, the MVPF estimates presented here may be considered conservative. 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 the varying effects of the policy on earnings, tax revenue, and welfare income in each cluster—where a cluster refers to a group of state-year observations sorted into quintiles or deciles of an underlying economic characteristic such as poverty, inequality, or unemployment—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 (2021) 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. Specifically, I find that the MVPF of the EITC is highest in state-year observations with the lowest poverty rates, and declines as poverty increases—driven by a combination of lower earnings and tax revenue responses and higher EITC benefit claims in high-poverty areas. A similar pattern emerges when clustering by income inequality: states with more equal income distributions yield higher MVPFs, as employment and earnings responses are stronger and the resulting tax revenue gains offset more of the program's cost. In clusters of unemployment, the pattern is broadly consistent, with higher unemployment dampening the employment and earnings effects that drive the fiscal externality. The results for state welfare generosity, however, are more ambiguous and do not exhibit a clear monotonic relationship with the MVPF. While these underlying economic variables 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 (Greenstein and Shapiro, 1998). While Kleven (2019) maintains that EITC expansions since 1975 have had negligible effects on employment, evidence from all other research points to unequivocally positive impacts on not only employment (Bastian, 2020; Bastian, 2018), but also on earnings (Dahl et al, 2009), 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 (2021) 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 (2021) 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).

Beyond labor supply and earnings, a growing body of work documents the EITC's broader impacts on families. Bastian (2020) shows that the original 1975 EITC contributed to the rise of working mothers and may have shifted social attitudes toward greater approval of working women. Bastian & Michelmore (2018) find that childhood exposure to EITC expansions improves long-term education and employment outcomes, with an additional $1,000 in EITC exposure during adolescence increasing high school completion by 1.3 percent and college completion by 4.2 percent. Bastian & Lochner (2022) examine the time-use implications of increased maternal labor supply, finding that while EITC expansions reduce overall time spent with children, nearly none of the reduction comes from "investment" activities such as active learning and child development. Taken together, these studies suggest that the EITC's effects on families extend well beyond the immediate labor market, with meaningful consequences for intergenerational mobility and child well-being.

An important and emerging dimension of the EITC literature concerns geographic variation in the policy's effects. Bastian (2024) finds that the EITC has consistently larger positive effects on the labor supply of unmarried mothers in rural and economically distressed areas relative to urban areas, highlighting that the program may deliver more "bang per buck" precisely where economic conditions are most adverse. Relatedly, Bastian & Black (2024) show that EITC-induced income gains help women migrate out of rural and distressed areas toward places with higher employment and earnings, primarily by relaxing household financial constraints—with most moves occurring across counties or commuting zones rather than across state lines. These findings underscore the importance of examining EITC impacts at a sub-national level, as the policy's effects on both labor supply and geographic mobility vary meaningfully with local economic conditions—a central motivation for the geographic analysis undertaken in this paper.

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,

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

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. 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 above 1 signifies that the behavioral responses to the policy generate enough feedback revenue to reduce its net fiscal cost below the headline expenditure, while a measure of infinity

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[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.

signifies that the policy fully 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. It is also worth noting that Bastian & Jones (2021, Appendix D) calculate MVPFs for the EITC that account for additional channels beyond direct tax revenue and welfare transfers—such as the policy's effects on health expenditures, crime-related costs, and children's future earnings—yielding even higher estimates of the EITC's return on public investment.

That said, the MVPF framework is not without its critics. García and Heckman (2022) argue that the MVPF does not adopt a social optimality perspective, as it evaluates the optimality of expenditures assuming a predetermined aggregate budget without considering the social costs of raising that budget. They contend that more traditional criteria—such as the Net Social Benefits (NSB) criterion, which accounts for the deadweight loss of taxation and program scale—may be more appropriate for evaluating programs that expand or contract the total government budget. In response, Hendren and Sprung-Keyser (2022) defend the MVPF framework, arguing that its advantage lies precisely in allowing researchers to separate the question of *how* to spend from the question of *how much* to spend, and that the MVPF's ratio-based approach facilitates direct comparison across policies without requiring assumptions about the marginal cost of public funds. While this paper employs the MVPF as its primary welfare metric, this ongoing debate is worth noting as it highlights important methodological considerations in the interpretation of the results.

Finally, and most directly related to the geographic dimension of this paper, Darling (2024) constructs 66 "geographic" MVPFs tied to specific places and times from existing studies across several policy domains, including workforce development, housing, and college access programs. While that study does not find a statistically significant relationship between MVPFs and underlying geographic economic variables such as unemployment rates, the authors note that this null result may reflect insufficient statistical power rather than a true absence of geographic variation. The present paper differs from Darling (2024) in important respects: rather than comparing MVPFs across heterogeneous policy types and locations, this study holds the policy constant (the EITC) and systematically varies the underlying economic conditions under which the policy operates, providing a more controlled test of geographic variation in policy effectiveness.

Data & Methodology

Following from Bastian & Jones (2021) 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 Survey (CPS) (Flood et al., 2024).

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 (2021) paper highlights that similar results are obtained when the same variable is taken at the state or the state and federal levels combined. Indeed, Bastian (2020; 2024) has employed state-level EITC

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

variation in other work to productive effect. However, Bastian & Jones (2021) also find that when taken at the state level, EITC generosity is endogenous to other underlying economic conditions and state policies. This endogeneity concern is particularly salient for the present study, which explicitly clusters observations by state-level economic characteristics such as poverty, inequality, and unemployment. Using a state-level MaxEITC in this context would risk confounding the policy variation with the very economic conditions the paper seeks to interact it with, undermining identification. Though using the variable $MaxEITC$ at the federal level sacrifices some within-state variation, it ensures that the instrument is plausibly exogenous to the local economic conditions under study. 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. Labor supply outcomes 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 government budget variables will be operationalized through federal income taxes paid[6], total EITC earnings claimed, as well as other welfare income received. Since the publicly

[6] The tax variable used here is federal income tax liability as computed by the NBER TAXSIM simulator, which does not include EITC refunds; EITC benefits are tracked separately as a distinct outcome variable. This differs from Bastian & Jones (2021), who use payroll taxes as their tax revenue measure. The use of federal income taxes here reflects the variables available in the publicly accessible CPS data processed through TAXSIM.

available data in question does not include 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) [7] figures will be used to derive the welfare impact of the EITC in the following manner:

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

At this juncture, it is important to be transparent about which fiscal channels factor into the net cost calculation. The fiscal externality as computed here captures three components: (i) the change in federal income taxes paid (as imputed by the NBER TAXSIM simulator); (ii) the change in supplemental welfare income (reflecting means-tested cash transfers such as TANF and general assistance as reported in the CPS); and (iii) the change in EITC benefits claimed

[7] The fiscal externality figure will thus be calculated as the ratio of the policy's impact on the government's budget (considering 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).

(which represents the policy's direct cost). These three components - FE = [ΔTaxes − ΔWelfare] / ΔEITC - represent the fiscal channels that are directly observable in the publicly available CPS data[8].

Up until now, the paper has relied on the methodology used in Bastian & Jones (2021) 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

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[8] Channels not captured in this calculation include payroll taxes (FICA/Social Security/Medicare), state and local sales taxes, health expenditure savings from improved maternal and child health (Evans & Garthwaite, 2014; Hoynes et al., 2015), crime-related fiscal savings (Agan & Makowsky, 2018), and the long-run effects on children's future earnings and tax contributions (Bastian & Michelmore, 2018). Bastian & Jones (2021) capture payroll taxes because they use administrative IRS records; the remaining channels are discussed in their Appendix D. Since every omitted channel would likely increase the fiscal externality, the MVPF estimates presented here should be interpreted as conservative lower bounds on the true welfare return.

said for state welfare generosity: the labor impact of expanding the policy in the more generous states 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. While the primary analysis clusters at the state level, a sub-state extension using county-level variation is also presented in Table 16 to capture finer geographic heterogeneity in economic conditions that state-level aggregation may obscure.

Hence, income inequality (as measured by the top 10%'s share of total income) data is taken from Frank (2009), 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. Importantly, all quintile (or decile) interactions are estimated within a single regression for each outcome variable and clustering variable. That is, for a given clustering variable with K quintiles, the estimating equation includes the full set of interactions simultaneously:

$$Y_{ist} = \alpha_0 + \sum_{k=1}^{K} \alpha_k \left(MaxEITC_{g(i),t} \times \mathbf{1}\left[Z_{s,t} \in Q_k\right] \right) + \alpha_{K+1} X_{ist} + \gamma_s^1 + \gamma_t^2 + \epsilon_{ist}$$

where $\mathbf{1}\left[Z_{s,t} \in Q_k\right]$ is an indicator for whether state s in year t falls in the k-th quintile of the clustering variable Z, and each α_k gives the effect of a $1,000 increase in MaxEITC for observations in quintile k. This approach allows the coefficients to vary across quintiles while using the full sample in a single estimation, rather than running separate regressions for each quintile.

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 period is determined by data availability in the publicly available CPS ASEC: several key variables used in this study—including detailed EITC-relevant income components, welfare receipt, and state-level identifiers necessary for the clustering analysis—are not consistently available in the CPS prior to 1994, while the most recent ASEC data available at the time of analysis corresponds to the 2016 survey year. 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. This relatively low figure reflects the inclusion of childless women, who face much smaller maximum credits. Conditional on having at least one qualifying child, EITC eligibility rises to 33.88 percent (SD = 47.33 pp) and the average total EITC benefit increases to $827.23 (SD = $1,482.49), composed of $785.07 (SD = $1,394.93) in federal EITC and $42.16 (SD = $179.49) in state EITC. Table 1 reports descriptive statistics for the full sample; conditional means for women with at least one child are noted where relevant. 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, after controlling for individual demographics (race, age, education, marital status), state-level economic conditions (GDP, employment, minimum wage, welfare generosity), and state, year, and number-of-children fixed effects along with their interactions, 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. Following Bastian & Jones (2021), elasticities are calculated as log-log elasticities with respect to net income. Specifically, the participation elasticity is computed as:

$$\varepsilon_p = \frac{\log(\bar{E} + \Delta E) - \log(\bar{E})}{\log(\bar{NI} + \Delta NI) - \log(\bar{NI})}$$

where $\bar{E}$ is the sample mean of binary employment, ΔE is the estimated change in employment from a $1,000 increase in MaxEITC, $\bar{NI}$ denotes mean net income (defined as earned income plus welfare income plus EITC benefits minus federal income taxes), and ΔNI is the corresponding estimated change in net income. The earnings elasticity is computed analogously, replacing employment with annual earnings in the numerator. 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. These magnitudes are notably larger than some estimates in the literature, which may partly reflect differences between the CPS-based sample used here and the administrative data employed in other studies, as well as the broader sample of women (ages 18-64) and longer time period considered. Although different in magnitude, these results are directionally in line with the findings of Bastian & Jones (2021). 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 [9]. This leads to an MVPF figure that is well above 1 at 3.88, meaning that each dollar of net government spending on the EITC generates $3.88 in benefits to recipients—or equivalently, that the behavioral responses to the policy (increased earnings, taxes paid, and reduced welfare receipt) substantially offset its direct costs, so that each dollar spent costs the government well less than a dollar on net. An MVPF above 1 indicates that the policy generates enough feedback revenue to reduce its net fiscal cost below the headline expenditure, while an MVPF of infinity would indicate that the policy fully pays for itself. 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.
Having reached similar conclusion to Bastian & Jones (2021) 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 the Introduction, 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

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

and the cost of living (and more specifically the geographic variation in housing costs) [10], 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 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

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

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 (2024) 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 federal income 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). Second, and perhaps more importantly, the estimate for taxes paid being negative and statistically insignificant which skews 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.

Max EITC in Various Clusters

This section examines whether the EITC's effectiveness (as measured by its MVPF) varies with underlying state-level economic conditions, and if so, how. The central finding is that the MVPF of the EITC is decreasing in poverty, income inequality, and unemployment: states with more adverse economic conditions see higher EITC take-up but weaker labor market and tax revenue responses, resulting in a higher net cost per dollar of EITC spending. The results for welfare generosity are more ambiguous. I first motivate why each clustering variable might affect EITC effectiveness and document that there is sufficient cross-state variation to warrant the analysis. I then present summary statistics by quintile to see if there are underlying differences in each cluster to begin with, followed by the regression results for each clustering variable in turn. I conclude the section with an explanation of the overall patterns and robustness checks using base-year poverty rates and county-level data.

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.

It is worth asking whether these four variables adequately capture the welfare dimensions relevant to the EITC. Seeing as how the EITC is a tax credit conditioned on earned income, it operates at the intersection of the labor market and the income distribution: it incentivizes work, supplements low earnings, and reduces poverty. The clustering variables chosen here relate directly to these channels. Poverty rates reflect the share of the population the EITC is designed to reach; income inequality captures the breadth of the earnings distribution from which EITC-eligible workers are drawn; unemployment proxies the labor market conditions that determine whether the policy's work incentives can translate into actual employment; and state welfare generosity measures the broader safety net environment in which the EITC operates, capturing potential substitution or complementarity with other transfer programs. Taken together, these four variables cover the demand side (who needs the policy), the supply side (whether the labor market can absorb new workers), and the policy environment (how the EITC interacts with other programs). While this set is by no means exhaustive—other dimensions such as the cost of living, the availability of childcare, or local industry composition could also matter—it provides a useful starting point for understanding geographic variation in EITC effectiveness.

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 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. Figure 2 displays a snapshot of poverty levels across U.S. states in 1994, chosen simply to illustrate the cross-sectional variation at a point in time. 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[11]. Seeing as there is ample variation in these variables 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. Importantly, the clustering is based on each state's contemporaneous value of the relevant variable in each year—not on a single base year. That is, a given state may fall into different quintiles or deciles in different years as its poverty rate, inequality, or unemployment changes over time. 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 16 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.

A brief note on the poverty measure is warranted. The poverty rates used for clustering in this study are based on the official poverty measure (OPM), which compares pre-tax cash income to thresholds that vary by family size but not by geography. An alternative is the Supplemental Poverty Measure (SPM), which uses a broader resource definition that includes near-cash government transfers—crucially, EITC refunds—as well as tax

[11] An animated map showing the evolution of poverty rates across states over the study period is available at https://drive.google.com/file/d/1KaPU1Wqf_1c8pGlZtBDVCzQQk5e1rsto/view?usp=drive_link. Animated maps for inequality and unemployment measures can be found in the supplementary materials.

liabilities, work expenses, and medical out-of-pocket costs, and adjusts thresholds for geographic variation in housing costs. Because the SPM captures the EITC as income, it more directly reflects the policy's poverty-reducing effects and may therefore be a more appropriate measure when evaluating how poverty interacts with EITC effectiveness. However, state-level SPM rates are not consistently available for the full panel used in this study, as the SPM was only officially adopted by the Census Bureau beginning in 2011. The OPM is therefore used for practical reasons, with the caveat that it does not account for the EITC's direct contribution to household resources and may thus overstate poverty in states where EITC take-up is high.

To provide context for the cluster analysis, it is useful to describe which states tend to populate the extreme quintiles. In poverty clusters, the lowest quintile (Q1) is most frequently composed of state-year observations from New Jersey, New Hampshire, Maryland, Connecticut, and Minnesota, while the highest poverty quintile (Q5) is dominated by Texas, California, New York, New Mexico, and the District of Columbia. For inequality, the most equal quintile (Q1) is populated by states such as Ohio, Iowa, Hawaii, Alaska, and Nebraska, whereas the most unequal quintile (Q5) includes California, New York, Florida, Connecticut, and Massachusetts. In unemployment clusters, the lowest quintile features North Dakota, Nebraska, Florida, South Dakota, and Virginia, while the highest unemployment quintile is led by California, New York, Texas, Florida, and Illinois. Note that because clustering is based on contemporaneous state-year values, a state like Florida can appear in different quintiles of different variables (e.g., low unemployment but high inequality), and can shift quintiles over time as conditions change.

Turning to the summary statistics within these clusters, women in the highest poverty quintile (Q5) are markedly less likely to be employed than those in the lowest quintile (Q1), with an employment gap of roughly 9.8 percentage points. They are also 6.3 percentage points less likely to be married, though differences in average years of education across quintiles are negligible. Perhaps most relevant for the EITC analysis, take-up rates differ substantially: 25.1 percent of women in the highest poverty quintile claim EITC benefits compared to only 19.2 percent in the lowest poverty quintile. The trends in employment and marriage also apply to higher rates of income inequality. These patterns suggest that the economic environment in high-poverty and high-inequality states may simultaneously increase the demand for EITC benefits while dampening the labor market responses that drive the policy's fiscal externality.

Poverty. The key finding is that EITC take-up increases with poverty while labor market responses weaken, resulting in lower MVPFs in higher-poverty states. When broken down to quintiles of poverty (using the official poverty rate, as discussed above), 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 federal income taxes aren't significantly affected by the change in policy. The fact that their claimed EITC benefits are the highest of any quintile 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, 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 [12]. 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. These patterns are corroborated when the analysis is repeated in deciles, where results are directionally identical albeit with more noise in the 9th and 10th deciles. 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 next clustered into quintiles of inequality. The summary statistics, found in the appendix, show the same patterns by quintile in the percentage of women aged 18-64 being employed, married, or having children (lowest in the highest inequality quintile, and highest in the lowest inequality quintile). There are, however, no apparent trends by quintile in EITC take up, education, or age.

Inequality. The pattern mirrors that of poverty: more unequal states exhibit weaker employment and earnings responses but higher EITC take-up, resulting in lower MVPFs. 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). Specifically, a $1,000 increase in Max EITC raises

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

binary employment by 4.4 percentage points in the most equal quintile (Q1) compared to 3.4 percentage points in the most unequal quintile (Q5). Annual earnings increase by $2,212 in Q1 versus $1,759 in Q5, while EITC benefits claimed rise from $231 in Q1 to $266 in Q5—again suggesting that more unequal states see greater EITC take-up but weaker labor market responses. Federal income taxes paid increase by $179 in Q1 compared to $153 in Q5, and welfare income decreases by $49 in Q1 versus $42 in Q5. The earnings elasticities become less elastic as inequality increases [13]. Results in deciles are directionally consistent, though there is considerable noise in the response of federal income taxes paid and welfare income claimed in the highest inequality deciles.

Unemployment. The same directional pattern holds: higher unemployment dampens the employment and earnings effects of EITC expansions while increasing take-up, again lowering the MVPF. The same analysis is then carried with the data clustered in quintiles of another state level negative outcome variable, unemployment. The summary statistics in Table 11 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 D1 shows that the results are directionally identical to the previous cases of poverty and inequality, where the responses for employment, earnings, taxes paid, and welfare claimed are lowest in the highest quintile of unemployment, and highest in the lowest unemployment quintile, and the reverse pattern holds for EITC benefits claimed as before. The participation and

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

earnings elasticities are also highest and lowest in the fifth quintile respectively, as was the case in the previous clusters. Results in deciles corroborate these findings, though with more noise in the coefficients. Hence, we see similar patterns in the way these variables respond to increases in Max EITC across quintiles of nominally regressive measures in poverty, income inequality, and unemployment. To reiterate, all clustering in the main analysis is based on each state's contemporaneous value of the relevant variable in a given year, meaning that a state's quintile or decile assignment can change over time as conditions evolve. It is worth noting that a concern with this approach is that contemporaneous poverty rates may themselves be affected by prior EITC expansions, potentially introducing endogeneity into the clustering variable. Hence, as a robustness check, the analysis is also conducted using poverty rates fixed at pre-expansion base years (1994 and 2001), as discussed below.

Welfare generosity. Unlike the three regressive measures above, welfare generosity does not show a clear linear relationship with the MVPF; instead, the results suggest a parabolic pattern where policy effectiveness is dampened at both extremes. The sample is next clustered by state welfare generosity, a measure that proxies a state's allocation to social welfare programs other than the EITC. The summary statistics show that state-year combinations where 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. First, the employment response to a change in Max EITC is highest in the least generous states and lowest in the most generous states. 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, 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 quintiles (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. Namely, whereas the change in earnings and federal income 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. These patterns largely persist in deciles, though with considerably more noise, particularly in the response of annual earnings and taxes paid in the middle deciles.

Explanation of Results

Hence, examining the results across quintiles, 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. Decile-level results are directionally consistent and are reported in the accompanying tables and figures.

Robustness Checks

As the most apparent trend in MVPF variation happens at different poverty clusters (with higher poverty rates being associated with lower policy MVPF), it might prove beneficial to isolate poverty at various base years as another robustness check. A concern with the contemporaneous approach is that poverty rates in later years may themselves have been affected by prior EITC expansions, potentially biasing the quintile assignments. Fixing poverty at a pre-expansion base year avoids this issue by assigning states to quintiles based on their initial conditions. Hence, Tables 14 and 15 (Panels A2 and A3, respectively) show how those variables used in estimating policy MVPFs change when states are clustered in quintiles of their poverty rates in 1994 and 2001 respectively[14]. The main finding—that MVPF decreases with poverty—holds under both base years. In Panel A2 (1994 base), the implied MVPF is infinite in the two lowest poverty quintiles and falls to 1.03 in the highest poverty quintile, driven by EITC benefits rising from $238 in Q1 to $274 in Q5 while federal income taxes fall from $370 to a statistically insignificant −$55. In Panel A3 (2001 base), the pattern is similar: MVPF is again infinite in Q1 and Q2, and falls to 1.46 in Q5, with

[14] 1994 is chosen as it is the first year after the 1993 EITC expansion for which data is available, and 2001 is chosen as there was another EITC expansion that year.

federal income taxes declining from $408 in Q1 to $49 in Q5. It is interesting to note that the Q5 MVPF is somewhat higher under the 2001 base year (1.46 versus 1.03 under 1994), suggesting that the specific base year affects the magnitude of the results but not the overall trend. Albeit slightly more noisy in the third quintile, both panels corroborate the main result that implied EITC MVPF is decreasing in rates of poverty.

Finally, the scope of the analysis is expanded to the county level, where Table 16 shows the responses of the EITC policy variables to MaxEITC. The results are based on poverty rates in 1996 (the first year of county-level data availability) for 203 counties across 47 states. It is worth noting that the counties identifiable in the CPS are predominantly metropolitan counties, as the Census Bureau only discloses county-level identifiers for sufficiently large geographic areas; rural counties are therefore largely absent from this subsample. The results are even more stark at the county level: while the MVPF is (much) greater than 1 for counties in the three lowest poverty quintiles (implying that each dollar of EITC spending generates substantial net benefits and costs the government well less than a dollar on net), policy-effectiveness decreases significantly in those counties where poverty rates are highest. More specifically, in those top 40 percent of counties where poverty rates were highest in 1996, the MVPF falls below 1, meaning that each dollar spent by the Federal government on expanding the policy generated only 47 and 44 cents in benefits respectively.

Concluding Remarks

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.

It is also worthwhile to consider how these results relate to the business cycle. The clustering variables used in this study - poverty, unemployment, and to a lesser extent income inequality - are all cyclically sensitive: states experiencing a recession will therefore mechanically appear in higher quintiles of poverty and unemployment, where the MVPF is lowest. This raises the question of whether the geographic patterns documented here reflect persistent structural differences across states or capture transitory cyclical conditions. The base-year robustness checks (Tables 14 and 15) partially address this concern, as fixing poverty at its 1994 or 2001 levels assigns states to quintiles based on pre-cyclical conditions and yields the same monotonic pattern - therefore suggesting that the results are driven at least in part by structural rather than purely cyclical factors. That being said, the contemporaneous results likely capture some cyclical dampening of labor market responses: during downturns, the EITC's work incentives may be less effective simply because there are fewer jobs to enter, weakening the employment and earnings responses that drive the fiscal externality. This carries a somewhat paradoxical policy implication: the EITC may be least self-financing precisely during the periods when it is most needed as a safety net, and policymakers should bear this countercyclical dimension in mind when evaluating the program’s cost-effectiveness across economic conditions.

Similarly, a closely related concern is the interplay between labor supply and labor demand over the business cycle. Namely, the EITC operates primarily as a labor supply incentive - by raising the effective wage for low-income workers in the phase-in region, it encourages labor force participation - yet its effectiveness in doing so depends critically on whether labor demand is sufficient to absorb those willing to work. In this regard, Bitler, Hoynes, and Kuka (2017) demonstrate that the EITC's cyclical response is theoretically ambiguous: a downturn that reduces earnings among higher-income workers may draw them into the EITC-eligible range (thereby increasing recipiency), while a downturn that eliminates earnings altogether for low-income workers removes their eligibility entirely. The net direction of this effect, hence, differs by household type. More specifically, Bitler, Hoynes, and Kuka (2017) find that the EITC is countercyclical for married couples - where two potential earners reduce the likelihood that family earnings fall to zero - but essentially neutral for single parents with children, who face a higher risk of exiting the labor market when jobs disappear. In line with this, and using linked CPS-IRS data spanning the Great Recession, Jones (2014) finds that EITC eligibility increased for married earners (consistent with a marriage-insurance effect whereby spousal earnings cushion the household from eligibility loss) while remaining flat for unmarried earners, with low-skill single mothers facing a particularly elevated risk of losing eligibility due to no annual earnings. These findings bear directly on the MVPF patterns documented here: in high-unemployment state-year observations, where labor demand is weakest, the demand-side constraint limits the EITC's ability to stimulate employment and earnings, attenuating the very responses that underpin a high fiscal externality and, hence, a high MVPF. Put simply, the program's capacity to pay for itself depends not only on workers' willingness to supply labor, but on the availability of jobs to enter - a distinction that the unemployment clustering variable in this paper at least partially captures.

Undoubtedly, a similar study 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: Evolution of Maximum EITC Benefits (2016 Dollars)

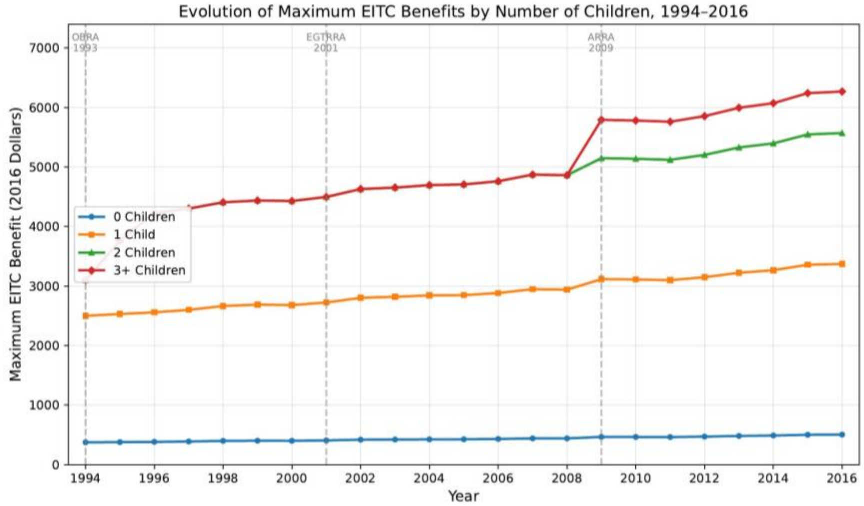

Table 1: Summary Statistics

Statistic	Mean	Std. 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
Federal Income Taxes	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. *p<0.1; **p<0.05; ***p<0.01*

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

	Annual Earnings	*EITC Benefits*	*Federal Income Taxes*	*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. *p<0.1; **p<0.05; ***p<0.01*

Table 4: Participation and Earnings Elasticity with Max EITC; Implied MVPF

Variable	**Implied Participation, Earnings, Fiscal Elasticities; MVPF**
Employment (binary)	0.47
Earnings	0.76
Fiscal Elasticity	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 Eligible	25.25	22.06	21.16
	(0.43)	(0.41)	(0.41)
Education (1–3)	1.91	1.95	1.98
	(0.47)	(0.44)	(0.45)

Note: Education: 1 = High school or less; 2 = Some college; 3 = Bachelor's or 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)
Federal Income Taxes	-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 estimate represents a separate regression where the location variable is interacted with MaxEITC. *p<0.1; **p<0.05; ***p<0.01*

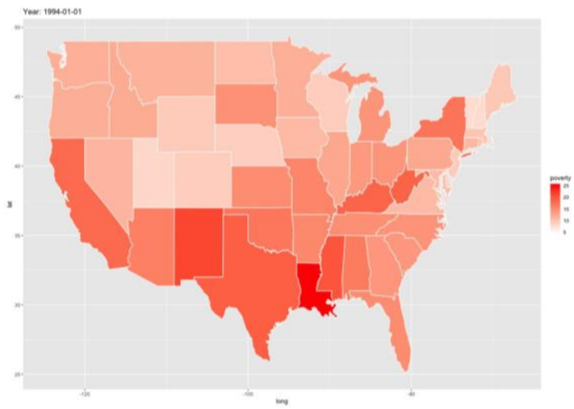

Figure 2: Snapshot of Poverty Rates Across U.S. States, 1994

Table 7: Summary Statistics – Quintiles of Poverty

	(1) Low	**(2)**	**(3)**	**(4)**	**(5) High**
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 Eligible	18.33	20.58	21.83	23.35	25.58
	(0.37)	(0.40)	(0.41)	(0.42)	(0.44)
Education (1–3)	2.00	1.99	1.95	1.95	1.93
	(0.43)	(0.43)	(0.46)	(0.48)	(0.49)

Note: Education: 1 = High school or less; 2 = Some college; 3 = Bachelor's or more

Table 8: Max EITC Estimates – Quintiles of Poverty

	(1) Low	(2)	(3)	(4)	(5) High
			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)
Federal Income Taxes	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. *p<0.1; **p<0.05; ***p<0.01*

Table 9: Implied Elasticities – Quintiles of Poverty

	(1) Low	(2)	(3)	(4)	(5) High
			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. *p<0.1; **p<0.05; ***p<0.01*

Figure 3: EITC Estimates by Poverty Rate Deciles

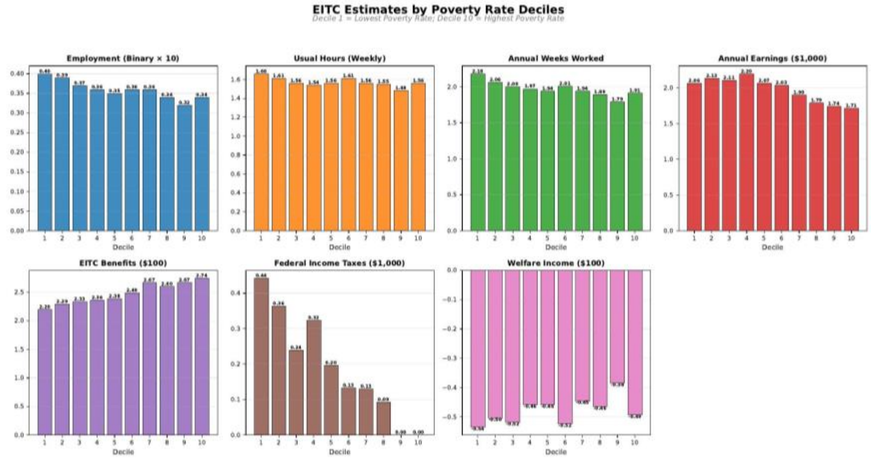

Table 10: Max EITC Estimates – Quintiles of Inequality

	(1) Low	(2)	(3)	(4)	(5) High
		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)
Federal Income Taxes	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. *p<0.1; **p<0.05; ***p<0.01*

Figure 4: EITC Estimates by Inequality (Top 10% Share) Deciles

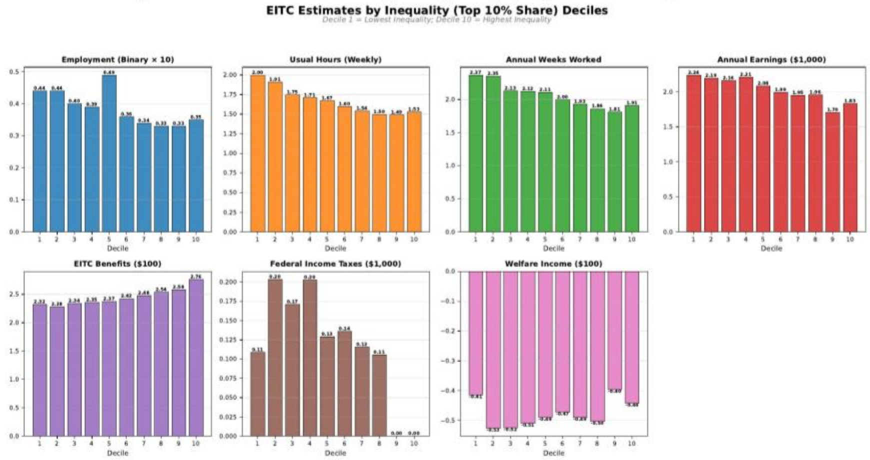

Table 11: Summary Statistics – Quintiles of Unemployment Rate

	(1) Low	(2)	(3)	(4)	(5) High
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 Eligible	20.95	21.56	22.38	22.84	24.12
	(0.41)	(0.41)	(0.42)	(0.42)	(0.43)
Education (1–3)	1.98	1.96	1.94	1.94	1.96
	(0.41)	(0.45)	(0.47)	(0.47)	(0.48)

Note: Education: 1 = High school or less; 2 = Some college; 3 = Bachelor's or more

Table 12: Max EITC Estimates – Quintiles of Unemployment

	(1) Low	(2)	(3)	(4)	(5) High
			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)
Federal Income Taxes	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. *p<0.1; **p<0.05; ***p<0.01*

Figure 5: EITC Estimates by Unemployment Rate Deciles

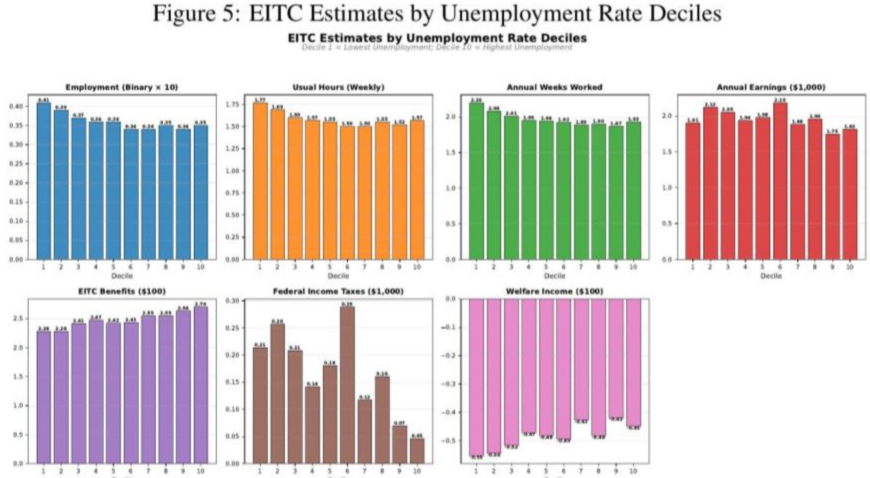

Table 13: Max EITC Estimates – Quintiles of Welfare Generosity

	(1) Low	(2)	(3)	(4)	(5) High
			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)
Federal Income Taxes	-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. *p<0.1; **p<0.05; ***p<0.01*

Figure 6: EITC Estimates by Welfare Generosity Deciles

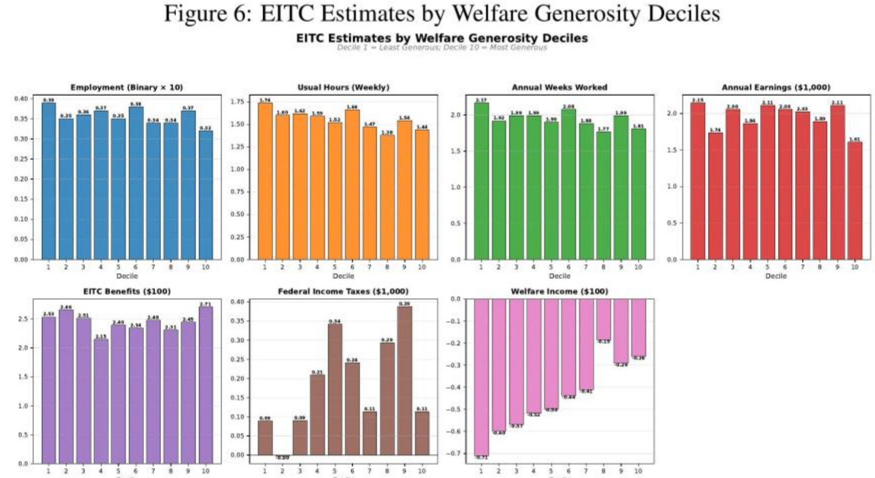

Table 14: Robustness Check: MVPF Estimates – Quintiles of Poverty

	(1) Low	(2)	(3)	(4)	(5) High
	Panel A2: Poverty Rate, Base Year 1994				
EITC Benefits	238.49***	239.60***	250.12***	263.90***	274.40***
	(19.72)	(15.08)	(12.86)	(13.12)	(15.12)
Federal Income Taxes	370.29***	270.46***	69.30***	103.30***	-55.48
	(22.31)	(22.18)	(20.03)	(18.74)	(19.12)
Welfare Income	-42.92***	-47.38***	-54.80***	-29.32***	-65.29***
	(8.67)	(7.46)	(8.15)	(7.77)	(9.32)
Implied MVPF	∞	∞	1.98	2.01	1.03

*Note: Max EITC in 1,000 real 2016 Dollars. *p<0.1; **p<0.05; ***p<0.01*

Table 15: Robustness Check: MVPF Estimates – Quintiles of Poverty

	(1) Low	(2)	(3)	(4)	(5) High
	Panel A3: Poverty Rate, Base Year 2001				
EITC Benefits	233.01***	223.21***	235.18***	263.35***	253.87***
	(20.21)	(16.34)	(13.82)	(14.14)	(18.24)
Federal Income Taxes	408.20***	394.83***	114.14***	117.39***	48.73**
	(58.42)	(47.18)	(39.09)	(32.86)	(19.22)
Welfare Income	-21.88***	-18.81***	-5.51*	-20.32***	-31.28**
	(7.86)	(6.44)	(8.15)	(7.13)	(7.33)
Implied MVPF	∞	∞	2.03	2.09	1.46

*Note: Max EITC in 1,000 real 2016 Dollars. *p<0.1; **p<0.05; ***p<0.01*

Table 16: Robustness Check: MVPF Estimates – Quintiles of Poverty at County Level

	(1) Low	(2)	(3)	(4)	(5) High
		Panel A4: Poverty Rate, Base Year 1996			
EITC Benefits	226.54***	238.20***	249.10***	280.50***	306.50***
	(21.21)	(24.42)	(27.80)	(28.14)	(30.02)
Federal Income Taxes	448.07***	298.64***	178.81***	-358.80*	-417.01*
	(59.14)	(52.12)	(49.00)	(72.86)	(79.22)
Welfare Income	-60.19***	-53.13***	-53.43***	-43.59***	-30.66***
	(9.96)	(8.54)	(8.55)	(7.19)	(7.02)
Implied MVPF	∞	∞	14.77	0.47	0.44

*Note: 203 counties across 47 states considered. *p<0.1; **p<0.05; ***p<0.01*

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