Overcoming Financial Constraints and Migrating Out of Rural and Distressed America

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Abstract

There is a strong and growing interest in helping families move to areas with higher economic opportunity. We exploit variation in the Earned Income Tax Credit (EITC) to examine how relaxing budget constraints affects migration, with a focus on women from rural and economically distressed areas. We find that relaxing budget constraints increases migration out of rural and distressed areas, to areas with higher labor force participation and lower unemployment rates. Many of these moves occur across counties or commuting zones, but we find no effect on moving across states. We also find decreases in living "doubled up" with another family, and reductions in commute length. We are the first to show that the EITC relaxes budget and credit constraints and helps women move to economic opportunity.

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Economic opportunity is not distributed evenly across the U.S. (Chetty et al., 2014; Gaubert et al., 2021) and economic convergence across regions appears to be slowing (Austin et al., 2018). Economically distressed areas are often rural and have experienced years of decreased employment (David et al., 2013) and deteriorating health (Case and Deaton, 2015; Snyder, 2016). Two unresolved questions are: whether policymakers should focus assistance on these places or the people in these places; and whether or not policy should nudge these households to migrate to areas with more economic opportunity (Ziliak, 2019). For millions of families, moving is not an option because of budget and credit constraints. This project is the first to exploit variation in the Earned Income Tax Credit (EITC) to examine whether relaxing financial constraints affects migration out of rural and economically distressed regions.

Sjaastad (1962) made one of the first contributions to the modern economics of migration, viewing migration as an investment, where workers take advantage of differential prices of human capital across locations. Indeed, with workers facing sufficiently low migration costs, one should obtain the spatial equilibrium—where identical workers are indifferent among cities (Haurin, 1980; Roback, 1982).

When migration costs are high, however, this spatial equilibrium may not hold and the migration response to economic shocks may be inefficiently slow and limited. For instance, Blanchard et al. (1992) estimates that this out-migration takes 5 to 7 years; Black et al. (2005) finds that migration out of Appalachia after the decline in coal prices took several years; and Autor et al. (2016), Amior and Manning (2018), and Hershbein and Stuart (2020) find low rates of migration in response to economic shocks. Why this slow, limited response?

One important reason for delayed, limited response is financial constraints. While wealthier, more skilled workers fund their migration from existing resources, not all workers are able to do so. Many families struggle to find the resources to put down a security deposit and the first month's rent, to transport possessions to a new location, and to move away from family and friends that may have been helping with childcare. These families often lack access to capital markets, especially because investments in migration generate no assets that may be used for collateral. Access to most capital markets are restricted to those with good credit scores, often with high incomes. Thus, investment in migration is much like investment in education: despite substantial returns, capital markets cannot fund these investments efficiently. But unlike education, there is little financial assistance available to finance migration.

There is strong evidence that financial constraints limit migration. It is well known that those with more human capital are more likely to move than those with less human capital (Wozniak, 2010). This fact is consistent with Sjaastad (1962): that migrants are attempting to arbitrage price differentials in human capital, and those with more human capital have greater incentives to engage in this arbitrage. But this fact is also consistent with the view that workers with more human capital are wealthier and better able to meet capital expenses. Earlier periods of mass migration also illustrate how financing constraints limit migration.[1]

Households with sufficiently low-income to qualify for the EITC (the maximum income in 2018 for a single parent and two children is $45,802[2]) face extreme financial pressures and limited availability to unsecured credit. Among households earning less than $40,000, only 64 percent report being fully banked, 37 percent report being rejected last year on a credit application, and only 61 percent report having at least one credit card (Chen et al., 2019).[3] For households earning over $100,000, these three statistics are 92, 15, and 92 percent.

To test how relaxing budget and credit constraints affects migration, we look at the EITC and examine whether the lump-sum nature of EITC payments allows families to migrate. Jones and Michelmore (2018) shows that the EITC increases household savings and access to credit; and Barrow and McGranahan (2000) and Goodman-Bacon and McGranahan (2008) find the EITC increases spending on more expensive items, such as vehicles and durable goods. Given the size of these payments (often over $5,000), it is plausible that the EITC may increase geographic mobility. In addition to providing lump-sum tax refunds, the EITC also increases employment and earnings, since families must work to receive the EITC.[4]

[1] To fund migration to the New World, many Europeans could not afford the relocation costs and resorted to selling themselves into indentured servitude (Smith, 2014; Galenson, 1984). In the Great Migration, African Americans relied heavily on "pioneers" who faced low migration costs (Carrington et al., 1996; Stuart and Taylor, 2019).

[2] Source: https://www.irs.gov/credits-deductions/individuals/earned-income-tax-credit/earned-income-and-earned-income-tax-credit-eitc-tables accessed 3/5/2022.

[3] Nor do these households have access to secured credit: only 40 percent of households with income under $40,000 own their housing, compared to 88 percent for those earning over $100,000 (Chen et al., 2019).

[4] The EITC distributes over $65 billion a year to almost 30 million families, lifting more than 6 million people out of poverty, and improves the short- and long-run economic well-being of families (Hoynes and

Whether the EITC increases migration out of rural and distressed areas is theoretically ambiguous. For example, the EITC may encourage people to stay in these areas by subsidizing low-paying jobs and decreasing the incentive to migrate; however, the EITC may enable out-migration for people that want to migrate but are budget constrained. The EITC may also have differential effects on different families: helping some families afford to stay in their home, while allowing others to move.

We examine how the EITC affects geographic mobility and whether a transfer program—not specifically tied to migration—enables people to overcome budget constraints and migrate to places with more economic opportunity. We focus on three questions: Does the EITC affect migration? Do these moves reflect economic opportunity? Does the EITC affect the composition of the population that remains in rural and distressed areas? Our results will inform policymakers about how households may respond to an expanded—or regionally targeted—EITC.

We estimate the EITC's impact on various migration-related outcomes using 2005 to 2017 American Community Survey (ACS) data, a sample of all adult women ages 19 to 55, and an identification strategy that exploits variation in state and federal EITC policy changes. Our main approach uses OLS and the maximum possible EITC benefits available to each household ($MaxEITC$, henceforth), which varies by year, state, and number and age of children.

We find that the EITC increases net migration out of rural and distressed areas, to areas with higher labor force participation and lower unemployment rates. Our estimates imply that the 2009 federal EITC expansion can explain 6 percent of the 2005–2017 decrease in the rural female population. The effect on migration is similar for Black and White women, and is larger for unmarried, working, younger, and lower-education women.[5] We find larger effects in states with a higher fraction of EITC-eligible rural women. We find null effects on non-working women and those with higher levels of education. These heterogeneous effects

Rothstein, 2016; Bastian and Michelmore, 2018).

[5] We find that low-income workers move to areas with greater economic opportunities. Using more detailed geographic data, Bergman et al. (2019) and Golosov et al. (2021) find little evidence that families move to better neighborhoods, suggesting that both information to and support for disadvantage families could improve moving decisions.

show that EITC-led migration is largest for groups that benefit the most from the EITC. Our results are robust to various sets of controls, using state and/or federal EITC variation, and using alternate data sets and time periods.

We find that the EITC fosters relatively local moves: occasionally across counties or commuting zones (CZs), but within states. For unmarried women from rural areas, about half of EITC-led moves are to a different CZ, two-thirds are to more-urban areas, and over a third are to a less distressed area (Bartik, 2020).

Moving can reflect economic opportunity (Kennan and Walker, 2011) or economic hardship marked by housing instability, living "doubled up" with another family, or eviction (Collinson et al., 2021). EITC-led migration appears to reflect economic opportunity since women move out of distressed areas to areas with better labor-market conditions, are less likely to live doubled up, and have shorter commutes to work. We find that a quarter of moves are at least partially motivated by a desire to live on one's own (Costa, 1999).

We conclude that the EITC helps women overcome budget constraints and move to economic opportunity. These moves out of rural and distressed areas may have positive effects on children (Chetty et al., 2016; Chyn, 2018). Without the EITC, the decades-long decrease in U.S. migration (Molloy et al., 2011, 2014; Kaplan and Schulhofer-Wohl, 2017) may have been even larger.

1. ACS Data and Migration Trends

To investigate how the EITC affects migration, we use the 2005–2017 ACS (Ruggles et al., 2021) and the sample of all women aged 19-55.[6] Table 1 shows sample descriptive statistics. We focus on women because previous EITC research has found that the EITC has a significantly larger effect on the incomes and behavior of women, especially unmarried mothers (Eissa and Hoynes, 2004; Bastian, 2020). While many men benefit from the EITC, they do not change their behavior in response to the program. We do not include men in our control group because married men are largely redundant with married women, and unmarried men make up a small fraction of EITC recipients.

[6] In Appendix B, we also use 1980–2000 Census data and 1993–2017 IRS migration data. ACS results are similar when we exclude younger women who may be moving to college.

While the ACS does not provide county for rural households, it does provide PUMA.[7] The ACS has large samples and detailed information about where people lived in years t and $t-1$, including metropolitan status. The ACS has five categories of metropolitan status that we define as rural, semi-rural, suburban, semi-urban, and urban.[8] Table 2 is a transition matrix showing women's metropolitan status in years t and $t-1$. For most of the analysis, we simplify and combine the first two categories into our definition of "rural" (about a quarter of the sample) and the latter three categories into "urban." With our relatively short sample period, reclassifying an area's metropolitan status is uncommon (Johnson and Lichter, 2020).

There is substantial heterogeneity among rural areas and many are not economically distressed (Goetz et al., 2018); we also examine whether families live in economically distressed areas. Bartik (2020) defines distressed as places with a prime-age employment rate at least 5 percentage points below the national average, comprising 14.7% of the U.S. population or 47.6 million people.[9]

2. EITC Policy Details and Identification Strategy

EITC benefits are determined by household earnings, number and age of children, state, and marital status. The EITC contains a phase-in region, where benefits increase with earnings; a plateau region, where benefits do not change with earnings; and a phase-out region, where benefits decrease with earnings. Households that earn beyond this phase-out region are not eligible for the EITC. The relationship between EITC benefits in 2018 and household earnings—by number of children and marital status—are shown in Figure 1. In 2018, federal EITC benefits for households with 3 or more children was worth 45% of household earnings (for low earners), peaking at a maximum of about $6,500 for families earning between about $14,000 and $24,000. Maximum benefits were about $5,700 and

[7] The ACS provides non-rural counties, but lumps all rural residents in a state into the same "county."

[8] The ACS variable "metro" has five values: not in metropolitan area; metropolitan status indeterminable (mixed); in metropolitan area, central/principal city status indeterminable (mixed); in metropolitan area, not in central/principal city; in metropolitan area, in central/principal city.

[9] We define distressed as laid out in Bartik (2020) appendix B, which describes how to crosswalk PUMAs (observed in ACS data) to local labor markets (the unit of geography for which "distressed" is defined). Many PUMAs lie partly in distressed areas; Figure B.1 shows the distribution of the fraction of one's PUMA that lies in a distressed local labor market.

$3,500 for households with exactly 2 children and 1 child.

Figure 2 shows how these maximum possible benefits—by number of children—have changed over time. The only federal EITC change during our sample period (2005–2017) occurred in 2009, when the maximum benefits for families with 3 or more children increased by almost $1,000 (and the phase-in rate increased from 40% to 45%).

In recent years, 29 states also had their own EITC. State EITC benefits generally "top-up" federal EITC benefits by a fixed percent (between 3 and 40 percent, and worth up to $220 to $2,800).[10] For example, a family receiving $3,500 in federal EITC benefits, and living in a state with a top-up rate of 20%, would receive $700 in state EITC benefits. Together, the federal and state EITC can be worth over $9,000 per year, with the average recipient receiving over $2,500 annually. Figure 3 shows how state EITC rates (as a fraction of federal benefits) have evolved over time. Figure 4 shows maximum possible federal plus state EITC benefits—by number of children—over time. These figures illustrate the considerable variation in maximum benefit levels by family size across states and over time.

Our main identification strategy exploits plausibly exogenous federal and state EITC policy changes between 2005 and 2017. We combine state and federal annual maximum EITC benefit amounts (based on state of residence, number and ages of children, and year) into the variable $MaxEITC$. Units of $MaxEITC$ are $2,500 CPI-U adjusted 2018 dollars (similar to $MaxEITC$'s standard deviation of $2,570). Importantly, $MaxEITC$ is independent of income and actually receiving the EITC. Our empirical strategy resembles previous EITC research (Hoynes et al., 2015; Bastian and Lochner, 2020; Agostinelli et al., 2020).

Figure 5 shows a histogram of $MaxEITC$ for the full sample of women. 45% of the sample have zero children and an average $MaxEITC$ of $550 (spanning $500 and $750). 22% of the sample have one child and an average $MaxEITC$ of $3,700 (spanning $3,300 and $5,000). 21% of the sample have two children and an average $MaxEITC$ of $6,100 (spanning $5,500 and $8,300). 12% of the sample have three or more children and an average $MaxEITC$ of $6,600 (spanning $5,500 and $9,300).

[10] We do not distinguish between refundable and non-refundable state credits. California's rate is 45%, but it only matches up to one-half of the maximum federal EITC benefits. We, therefore, assume one-half the stated match rate for California (i.e., 22.5%). Results are robust to alternate approaches.

Mothers with three or more kids provide the most identifying variation in $MaxEITC$. For these mothers, $MaxEITC$ increased by about \$900 after the 2009 federal expansion, and $MaxEITC$ increased by an average of \$1,200 after a state EITC expansion (compared to only \$300 for mothers with one child).

In using state and federal policy variation, we assume that changes in EITC generosity are uncorrelated with other policies or economic conditions that may also affect migration outcomes. In Appendix Table B.1, we regress state EITC generosity—maximum state EITC benefits, and state EITC rates—on other state policies, economic conditions, and demographics. Across four specifications, we find little evidence that state EITC expansions are endogenous with these other factors: only a handful of the dozens of estimates are marginally significant, and F-tests of joint significance yield p-values between 0.40 and 0.79.

In using state and federal policy variation, we also assume parallel migration trends by number of kids leading up to EITC changes. It would be problematic for our estimation strategy if migration rates for mothers with more children were steadily increasing, before and after EITC expansions. In Figure 6, we show unadjusted trends in migrating out of rural and distressed areas before and after state EITC expansions. These trends are in "event time" denoting the number of years before/after when a state created or expanded its EITC. These estimates come from a single regression without controls that estimates annual migration probabilities for women with 0, 1, 2, and 3+ kids. For this analysis, we omit states that do not change their EITC during the sample period, or do so in the first or last sample year. (While some states change more than once, we focus on the first time a state changes its policy.) Each trend is relative to the trend for women without kids.

Figure 6 panels A and B show that mothers were less likely to migrate out of rural and distressed areas than women without kids, and mothers with multiple kids were even less likely than mothers with one child. While these levels differ by number of kids, Figure 6 shows flat pre-trends for each type of mother leading up to a state EITC change. These trends also show a noticeable increase in migration after a state EITC change, with larger increases for mothers with multiple kids than for mothers with fewer kids. Since state EITCs were worth more to families with multiple kids, Figure 6 provides suggestive evidence that EITC expansions increase migration.

During our sample period (2005–2017), $MaxEITC$ captures three sources of EITC policy variation. First, the 2009 federal expansion increased $MaxEITC$ for families with 3+ kids, equally in all states. Second, since state EITCs are generally a fixed fraction of the federal EITC (e.g., 10% or 30%), state EITCs are larger for families with more children (i.e., 0 vs 1 vs 2 vs 3+). Third, the 2009 federal expansion raised $MaxEITC$ more in states with larger state EITCs (via higher state EITC benefits). The first component varies by year × number of kids, while the other two vary by year × state × number of kids.[11]

We estimate the impact of $MaxEITC$ in year $t-1$ ($MaxEITC_{t-1}$) on where women migrate to and live in year t. $MaxEITC_{t-1}$ is determined by year, state in year $t-1$, and number of children age 18 or less in year $t-1$. We impute number of kids in year $t-1$ by taking the value from year t and subtracting the number of children under age 1 in year t. Ideally we would also add children that are age 19 in year t, but we only observe a selected sample of 19 year olds living with their parents. EITC eligibility also includes 19–23 year old dependents that are students, and disabled dependents of any age, but we ignore these dependents since we observe only a selected sample.

We use equation (1) to estimate the EITC's net effect on female migration:

$$Y_{i,s,t} = \beta_1 MaxEITC_{f(i,s-1,t-1)} + X'_{i,s,t}\beta_2 + \delta^1_{s-1} + \delta^2_t + \delta^3_{f(i)} + \epsilon_{i,s,t}. \tag{1}$$

We first estimate the impact of $MaxEITC$ on EITC benefits—imputed using TAXSIM (Feenberg and Coutts, 1993)—since this is the main channel enabling women to move. Then we look at whether $MaxEITC$ affects migration and living in a rural or distressed area, along with traits of where women live: the local (PUMA-level) labor force participation (LFP) and unemployment rates.[12]

$X_{i,s,t}$ contains controls for married, an age cubic, years of education FE, three race indicators (Black, White, other), age of youngest child, children under age 5, and interactions

[11] State EITCs that do not change over the sample period vary by state × number of kids.

[12] We create these PUMA-level measures using the main sample and averaging across all sample years. We link these measures with one's PUMA of residence in years $t-1$ and t. Since the ACS only identifies a subset of PUMAs for year $t-1$—whereas it identifies all PUMAs for year t—these variables are sometimes measured at a pooled-PUMA level. For example, the Alabama PUMA code of 290 in year $t-1$ corresponds to the combined PUMAs 200, 301, 302, and 500. (See: https://usa.ipums.org/usa-action/variables/migpuma1#codes_section.) For consistency, we use these pooled-PUMAs to assign these variables for both year t and $t-1$. Finally, for these two outcomes, we control for lagged $Y_{i,s,t-1}$.

of marital status (and race) with state FE, year FE, education FE, and age, as well as married $\times$ race FE. We also control for lagged metropolitan or distressed status ($Y_{i,s-1,t-1}$).[13] We also control for annual state economic policies and conditions: GDP, GDP growth rate, minimum wage, unemployment rate, and welfare benefits for families with 1, 2, or 3 children; and interactions of these factors with marital status and having 3+ children, to allow state factors to differentially impact different types of women, and to help disentangle the 2009 federal EITC expansion and the Great Recession.[14] δ^1_{s-1}, δ^2_t, and $\delta^3_{f(i)}$ are FE for state, year, and number of kids. $\epsilon_{i,s,t}$ is an idiosyncratic error term. We use ACS individual weights and report heteroskedasticity-robust standard errors, clustered at the state (in year $t-1$) level.

Since time-varying controls can bias two-way FE estimates (Borusyak et al., 2021), we exclude these annual state factors from the main specification (but we also show that these controls have little effect on the estimates).

We identify our key parameters from variation in state and federal EITC policy changes. While year $\times$ state $\times$ number of kids FE would absorb all $MaxEITC$ variation (and year $\times$ number of kids FE would absorb most of it), we show that results are robust to controlling for year $\times$ state FE, and state $\times$ number of kids FE. Any potential confounder would therefore have to vary by year $\times$ number of kids, or year $\times$ state $\times$ number of kids.

While equation (1) estimates an average effect, the EITC likely has different effects on different groups of women. We estimate heterogeneous effects in two ways: one, we estimate equation (1) for various subgroups of women; two, we estimate equation (2) to look at more outcomes and estimate effects by marital status and metropolitan status in year $t-1$.

$$\begin{aligned} Y_{i,s,t} = \alpha_1 MaxEITC_{f(i,s-1,t-1)} \cdot Unmarried_{i,t} \cdot Rural_{i,t-1} + \\ \alpha_2 MaxEITC_{f(i,s-1,t-1)} \cdot Unmarried_{i,t} \cdot Urban_{i,t-1} + \\ \alpha_3 MaxEITC_{f(i,s-1,t-1)} \cdot Married_{i,t} \cdot Rural_{i,t-1} + \\ \alpha_4 MaxEITC_{f(i,s-1,t-1)} \cdot Married_{i,t} \cdot Urban_{i,t-1} + \\ X'_{i,s,t}\alpha_5 + \gamma^1_{s-1} + \gamma^2_t + \gamma^3_{f(i)} + \epsilon_{i,s,t}. \end{aligned} \tag{2}$$

To distinguish women **previously** vs **currently** living in rural areas, we use the notation

[13] Using this control requires the assumption that $Y_{i,s-1,t-1} \perp \epsilon_{i,s,t}$. This control variable does not meaningfully change the estimates. An alternative approach is to define outcomes as moving from, for example, rural to urban, which we use in equation (2).

[14] While these are potentially valid concerns *ex ante*, they end up not affecting the results much.

$Rural_{t-1}$ and $Urban_{t-1}$ to refer to living in a rural and urban area in year $t-1$. Estimates of α_1, α_2, α_3, and α_4 represent the impact of an additional \$2,500 in $MaxEITC$ on various outcomes for four separate groups of women: $Unmarried \times Rural_{t-1}$, $Unmarried \times Urban_{t-1}$, $Married \times Rural_{t-1}$, and $Married \times Urban_{t-1}$.[15]

The outcomes we consider are EITC benefits, moving at all (i.e., living in a different house), and moving to a more-urban area. Then we decompose more-urban moves into within or across counties. Then we look at moves across CZs and moves to less-distressed areas (see footnote 9). Finally, we look at household traits—including living "doubled up" or in a multi-generational household—and commute length.[16] We use the same set of controls as equation (1), except we do not control for lagged metropolitan status (see footnote 13).

While we expect the EITC to have a smaller impact on married women, this group still benefits from the EITC (though some may choose to decrease their labor supply (Eissa and Hoynes, 2004)) and should not be considered a control group. $MaxEITC$ is a continuous treatment variable and the control group can be thought of as women without dependent children, and more-treated groups are mothers with more children and mothers living in years and states after EITC expansions (see Figures 1–4).

3. Results: The EITC and Migration

If the EITC increases migration by relaxing budget constraints, we should find effects roughly proportional to the EITC's impact on family resources.[17] Previous research shows that the EITC has the largest impact—via EITC benefits and increased earnings—on unmarried, younger, and lower-educated mothers (Hoynes and Rothstein, 2016; Bastian, 2020; Bastian and Jones, 2021). Notably, the EITC also has a larger impact on the employment of rural mothers (Fitzpatrick and Thompson, 2010; Bastian, 2021).

[15] Throughout the analysis, we use marital status in year t. Ideally, we would use status from year $t-1$, since migration may be related to changes in marital status. However, we observe whether one got married in the last year for 2008–2017, but we do not for 2005–2007, and we do not observe whether unmarried women were married a year ago. Using status in year t could bias our results, which we explore in Appendix Table B.2, where we impute status in year $t-1$.

[16] While there are various reasons one may choose a living arrangement with a longer commute, a shorter commute is generally preferable.

[17] To the degree that the EITC has any negative wage spillovers (Rothstein, 2010), the EITC may harm workers without children—our control group—and bias up our estimates.

3.1. Migrating Out of Rural and Economically Distressed Areas

In Table 3, we estimate equation (1) and $MaxEITC$'s effect on EITC benefits, moving to a new PUMA, the probability of living in a rural or distressed area, and traits of where women live: the change in local LFP and unemployment rates between where they live and where they lived a year ago. If women are moving to areas with more economic opportunity, then we should observe them living in areas with higher LFP and lower unemployment rates. Panel A uses the full sample of women; Panels B–F restrict the sample to younger, Black, White, married, and unmarried women; and Panel G looks at women living in their birth state (in year $t-1$). Panels B–G illustrate (1) which subgroups are most most likely to migrate out of rural and distressed areas, and (2) conditional on moving, which subgroups are most likely to move to areas with stronger economic conditions.

Columns 1–4 in panel A show that each \$2,500 in $MaxEITC$ increases EITC benefits by \$283, increases moving to a new PUMA by 1.42 percentage points, and decreases the probability of living in (i.e., increases the probability of moving out of) a rural or distressed area by 0.46 and 0.31 percentage points (or 2.2 and 1.0 percent). While \$283 is not enough to finance most moves, it appears to be enough for those on the margin of being resource constrained. Our estimates imply that the 2009 federal EITC expansion can explain 6 percent of the 2005–2017 decrease in the rural female population.[18]

Our results suggest that the average inter-PUMA move costs \$20,000 (=\$283/0.014). It is difficult to put this magnitude in context since most migration research focuses on inter-state migration, and finds that moving costs average hundreds of thousands of dollars (Davies et al., 2001; Kennan and Walker, 2011; Bayer and Juessen, 2012). However, these average estimates have substantial heterogeneity, and moving costs are low for some people. Some recent work (Heise and Porzio, 2019; Koşar et al., 2021) finds lower average moving costs—around \$25,000—close to what we find. Overall, the literature has not reached a consensus on moving-cost magnitudes (Jia et al., 2022), especially for shorter moves.

In Panel B, we look at women under age 45 and find larger effects on EITC benefits (\$368), moving to a new PUMA (1.58 percentage points), and migration out of rural and

[18] 22.1 and 19.3 percent of the sample lived in rural areas in 2005 and 2017 (a 2.8 point decline). The 2009 federal EITC expansion raised $MaxEITC$ by about \$900. $(0.46 \times (900/2500))/2.8 = 0.06$.

distressed areas (0.51 and 0.56 percentage points).

In Panels C and D, we find similar migration effects for Black and White women. Each \$2,500 in $MaxEITC$ increases migration to a new PUMA (1.25 and 1.32 percentage points for Black and White women), and migration out of rural and distressed areas by 0.44 and 0.28 percentage points for Black women, and 0.47 and 0.35 percentage points for White women. Increases in EITC benefits are larger for Black vs White women (\$329 vs \$218), suggesting larger migration effects per EITC dollar for White vs Black women.

In Panels E and F, we find much larger effects for unmarried vs married women. Each \$2,500 in $MaxEITC$ increases migration to a new PUMA (1.73 and -0.24 percentage points for unmarried and married women), and migration out of rural and distressed areas by 0.52 and 0.59 percentage points for unmarried women, and 0.24 and -0.04 percentage points (statistically insignificant) for married women. Increases in EITC benefits are also larger for unmarried vs married women (\$481 vs \$182). These results align with previous research showing that the EITC has smaller effects on married women.

Finally, in Panel G, we look at women living in their state of birth (in year $t-1$). People living in rural and distressed areas are usually born there and have strong local ties (Zabek, 2019), meaning that the EITC's out-migration effect may be weaker on these women. We find that the EITC has smaller effects on migration to a new PUMA, and out of rural and distressed areas (0.38, 0.48, and 0.19 percentage points). These effects would likely be even smaller if we could restrict to women still living in their county or city of birth.

Are effects larger for some groups because the treatment (i.e., EITC benefits) is larger or because the treatment per EITC dollar is larger? Comparing the percent change in living in a rural or distressed area with the percent change in EITC benefits suggests that the different effects by subgroup are largely driven by differences in EITC benefits.[19]

Columns 5–6 in Table 3 look at the change in each woman's local LFP and unemployment

[19] For unmarried women, each \$2,500 in $MaxEITC$ leads to a 2.8% and 1.8% decrease in living in rural and distressed areas (-0.52/18.6=0.028; -0.55/31.0=0.018) and \$481 in EITC benefits: rescaling, \$500 in EITC benefits leads to a 2.9% and 1.9% reduction in living in rural and distressed areas. The same calculation shows that \$500 in EITC benefits leads to a 3.6% and 2.4% reduction for young women; a 5.2% and 1.3% reduction for Black women; a 4.4% and 2.6% reduction for White women; a 2.9% and 0.5% reduction for married women; and a 5.1% and 1.6% reduction for women living in their birth state. While suggestive, most of these differences are not significantly different when confidence intervals are taken into account, whereas differences in EITC benefits are significantly different across groups.

rates, among women that move. Panel A shows that \$2,500 in $MaxEITC$ leads women to move to areas with higher LFP and lower unemployment rates (1.37 and -0.33 percentage points). Panels B–F show that this pattern holds for each subgroup (p-values<0.01 for most estimates). When these regressions are run on the full sample of women—unconditional on moving—the estimates remain significant and fall by about 80%.

Table 3 shows that EITC expansions help mothers—and their children—migrate out of rural and distressed areas, to places with better economic conditions. In section 4, we show that these five outcomes are robust to alternate specifications.

3.2. EITC's Impact on the Composition of the Population of Rural Women

We now examine the EITC's impact on the composition of women that remain in rural areas. Building on equation (1), we interact living in a rural area (in year t) with education, age, and age of children. We drop controls that are collinear with the outcome (details in Figure 7 notes). These regressions will show which types of women are more or less likely to live in rural areas after EITC expansions.

Figure 7 Panel A looks at women with less than 12, 12, 13, 14, 16, and 18 years of education. Each \$2,500 in $MaxEITC$ decreases the probability that mothers with 12 or less years of education live in a rural area by 0.4 percentage points, and has a null effect (less than 0.1 percentage points) on women with 13+ years. These results are consistent with previous evidence that the EITC has larger effects on mothers with lower education.

Panel B looks at women at each age between 19 and 55, and shows that EITC expansions decrease the probability that 24–45 year olds live in rural areas, and increase the probability that younger (less than 23) and older (46+) women live in rural areas.

Panels C and D look at the age of women's youngest and oldest children. The EITC has larger effects for mothers with an infant youngest child, and mothers with a teenage oldest child. We find null effects for mothers with an infant oldest child. These moves out of rural and distressed areas may have positive effects on children, especially younger children (Chetty et al., 2016; Chyn, 2018).

3.3. EITC's Impact on Moving Out of Rural Areas, by Number of Kids

Most of our identifying variation comes from comparing mothers with different numbers of children. This comparison by number of kids makes it difficult to isolate the impact on mothers with a specific number of kids. However, regressions that are restricted to mothers with 1, 2, or 3+ children shows consistent (although noisier) evidence that EITC expansions increase migration. Estimates of $MaxEITC$ on living in a rural area—when the sample is restricted to mothers with 1, 2, or 3+ kids—are -1.86 (1.39), -0.72 (0.67), and -0.72 (0.51). When women without kids are also included in each regression as a control group, the three estimates of $MaxEITC$ are -1.37 (1.02), -0.95 (0.63), and -0.49 (0.26). That the effect of $MaxEITC$ is smaller for mothers with more children may reflect the fact that moving is more costly—and migration rates are lower—for these families.

3.4. EITC's Impact on Moving Out of Rural Areas, by State

We now examine whether the EITC's migration effects are larger in states with more EITC-eligible women. To do so, we estimate a regression that resembles equation (1), except we interact $MaxEITC$ with dummies for each state.

Figure 8 Panel A shows that EITC expansions decreased the rural population in all states, with the largest effects in the Upper Plains, South, and Midwest. This map suggests that the EITC had larger migration effects in states with a higher fraction of EITC-eligible families, which we formally test in panel B. To do so, we first predict the probability that each woman has low earnings by regressing having positive earnings below \$30,000 (in 2018 \$) on demographic traits, and saving the predicted probability.[20] Then we calculate the state fraction of rural women that have low predicted earnings ($\widehat{LowIncome}$). Finally, we regress the EITC's state-level impact on migration out of rural areas (from Panel A) on $\widehat{LowIncome}$, weighted by each state's 2010 rural population. We bootstrap standard errors since the treatment variable is a generated regressor (Murphy and Topel, 2002).

We find that each 10 percentage point increase in $\widehat{LowIncome}$ leads to a 1 percentage point increase in migration out of rural areas. The magnitude appears plausible: the

[20]We use the same demographic traits as before: state in year $t-1$ FE, year FE, children FE, age cubic, married, age of youngest child, race FE, education FE, children under age 5.

interquartile values of $\widehat{LowIncome}$ are 35 and 42 percent, implying a migration-effect difference of 0.7 percentage points. These results speak to intent-to-treat effects, and confirm that the EITC had the biggest impact in states with a higher fraction of women earning in the EITC-eligiblity range.

3.5. *Effects by Marital Status and Metropolitan Status (in Year $t-1$)*

We now estimate equation (2) to look at additional migration outcomes and to estimate the EITC's effect by marital status and metropolitan status (in year $t-1$). Each regression estimates the impact of \$2,500 in $MaxEITC$ on various outcomes for four groups of women: $Unmarried \times Rural_{t-1}$, $Unmarried \times Urban_{t-1}$, $Married \times Rural_{t-1}$, and $Married \times Urban_{t-1}$.

We first look at how $MaxEITC$ affects EITC benefits. Table 4 column 1 shows that each \$2,500 increase in $MaxEITC$ leads to \$807 and \$693 in EITC benefits for $Unmarried \times Rural_{t-1}$ and $Unmarried \times Urban_{t-1}$ women, and only \$155 and \$99 for $Married \times Rural_{t-1}$ and $Married \times Urban_{t-1}$ women. Even though the EITC does not increase the LFP of married women (Eissa and Hoynes, 2004), $MaxEITC$ mechanically increases EITC benefits for already-working women. EITC benefits are larger in rural areas because (1) the EITC has a larger labor supply effect in rural areas (Fitzpatrick and Thompson, 2010; Bastian, 2021), and (2) more workers are EITC-eligible since wages are lower in rural areas.

We next test whether the EITC affects the probability that women move at all. In column 2, we find positive effects among $Unmarried \times Rural_{t-1}$ and $Unmarried \times Urban_{t-1}$ mothers: each \$2,500 in $MaxEITC$ increases the probability of moving by 5.0 and 2.7 percentage points (or 21 and 12 percent, from baseline subgroup means of 23.6 and 22.8 percent).[21] For $Married \times Rural_{t-1}$ and $Married \times Urban_{t-1}$ mothers, we find insignificant increases of 0.7 and 0.8 percentage points.

In column 3, we look at how many of these moves are to more-urban areas. For $Unmarried \times Rural_{t-1}$ and $Married \times Rural_{t-1}$, \$2,500 in $MaxEITC$ increases the probability of moving to a more-urban area by 3.6 and 2.2 percentage points.[22] For $Unmarried \times$

[21] For $Unmarried \times Rural_{t-1}$ women, our 95 percent confidence interval spans 2.2 and 7.8 percentage points.

[22] 3.6 of the 5.0 percentage point increase in moves (72%) are to more urban places; twice as high as the

$Urban_{t-1}$ and $Married \times Urban_{t-1}$, estimates are an insignificant 0.8 and 0.8 percentage points. (Recall, $Urban$ includes suburban, semi-urban, and urban: see footnote 8.) Subtracting estimates in column 3 from column 2 shows that the estimates—in percentage points—for moving to a less-urban or same-urban area are 1.4 (for $Unmarried \times Rural_{t-1}$), -1.5 (for $Married \times Rural_{t-1}$), 1.9 (for $Unmarried \times Urban_{t-1}$), and 0.0 (for $Married \times Urban_{t-1}$).

A few takeaways: first, the EITC enables all women from rural places to move to more-urban areas, with larger effects for unmarried mothers; and second, the EITC may allow $Unmarried \times Urban_{t-1}$ mothers to move to less urban places.[23]

In columns 4–5, we decompose more-urban moves into within- and across-county moves. (This is an imperfect measure of county: the ACS provides county for non-rural residents, and lumps all rural residents in a state into the same "county.") For $Unmarried \times Rural_{t-1}$ mothers, about two-thirds of more-urban moves are within county (2.4 of 3.6), and one-third are across counties (1.2 of 3.6). For $Married \times Rural_{t-1}$ mothers, about two-thirds of more-urban moves are also within county (1.6 of 2.2), and one-third are across counties (0.7 of 2.2). For both unmarried and married $Urban_{t-1}$ mothers, results are insignificant but suggest that all more-urban moves are within the same county.

In column 6, we find that the EITC increases migration across CZs. For $Unmarried \times Rural_{t-1}$ women, each \$2,500 in $MaxEITC$ leads to a 2.3 percentage point increase in migration to a different CZ (almost half of all EITC-led moves). For the other three types of women, we find positive but insignificant effects on moving CZs (between 0.8 and 1.1 percentage points).

Finally, in column 7 we find that the EITC helps women move to less-distressed areas. Similar to previous results, effects are largest for $Unmarried \times Rural_{t-1}$, and are smaller—but still marginally significant—for the other three groups of women. The estimates—in percentage points—are 2.0 (for $Unmarried \times Rural_{t-1}$), 1.2 (for $Married \times Rural_{t-1}$), 0.8 (for $Unmarried \times Urban_{t-1}$), and 0.9 (for $Married \times Urban_{t-1}$). These results do not just reflect churn in and out of distressed areas, since the four estimates for "moving to a more

unconditional 35% of all moves by rural unmarried women to more urban areas.

[23]While not statistically significant, we find evidence that the EITC increases Black women's migration out of urban areas to semi-urban areas, consistent with Frey (2018).

distressed area" (not shown) are insignificant: 0.4 (0.5), -0.1 (0.4), -0.1 (0.4), and -0.2 (0.4).

Overall, we find that the EITC fosters local moves out of rural and distressed areas: occasionally across counties or CZs, but largely within states.[24]

How large are these effects? Relative to the baseline means for $Unmarried \times Rural_{t-1}$ women, a \$2,500 increase in $MaxEITC$ is associated with a 21%, 44%, 28% and 48% increase in moving, moving to a more urban area, moving CZ, and moving to a less distressed area.[25] While $MaxEITC$ units are \$2,500, this is over twice as large as the 2009 federal EITC expansion for mothers with 3+ kids, and is akin to the largest state EITC expansions. Thus the 2009 federal EITC expansion is predicted to increase moving, moving to a more urban area, moving CZ, and moving to a less distressed area by 7%, 16%, 10%, and 17%.

3.6. Living Doubled-Up, Household Traits, and Commute Time

We now examine household traits and commute time to better understand whether these moves reflect financial independence and economic opportunity. By increasing family resources, we expect the EITC to decrease living "doubled up" with another family (as found by Pilkauskas and Michelmore (2018)), and to allow families to move somewhere where their commutes are shorter. In addition to migrating to places with better opportunity, many moves are motivated by a desire for more independence (Costa, 1999).

Table 5 column 1 shows that each \$2,500 in $MaxEITC$ decreases the probability that $Unmarried \times Rural_{t-1}$ and $Unmarried \times Urban_{t-1}$ mothers are "doubled up" by 1.3 and 1.2 percentage points. For $Unmarried \times Rural_{t-1}$ mothers, the EITC also decreases the probability of living in a multi-generational (defined as 3+) household (-0.10), and decreases the number of household families, mothers, and siblings by 0.09, 0.08, and 0.09, respectively. For $Unmarried \times Urban_{t-1}$ mothers, these effects are also negative, though a bit smaller. For married mothers, the effect on each outcome is negative and insignificant, except for small positive effects on "doubled up." Overall, the EITC appears to help unmarried mothers move into their own households. About a quarter of EITC-led moves by $Unmarried \times Rural_{t-1}$ women (1.3 out of 5.0 percentage points) seem to be motivated by independent living.

[24] For $Unmarried \times Rural_{t-1}$, $Married \times Rural_{t-1}$, $Unmarried \times Urban_{t-1}$, and $Married \times Urban_{t-1}$ women, the estimates on moving across states are 0.20, -0.06, 0.10, and 0.02 percentage points.

[25] Mean values of these variables for $Unmarried \times Rural_{t-1}$ women are: 23.5%, 8.2%, 8.2%, and 4.2%.

In Table 5 column 6, we restrict the sample to working women and find that each $2,500 in $MaxEITC$ decreases the commute length for $Unmarried \times Rural_{t-1}$ women (1.8 minutes) and $Married \times Rural_{t-1}$ women (1.7 minutes). The EITC leads to smaller decreases for married and unmarried $Urban_{t-1}$ women. In Figure B.2, we look at the distribution of commute time for $Unmarried \times Rural_{t-1}$ women and find reductions in all commutes up to 55 minutes, with the largest decreases occuring for commutes over 10–15 minutes.

In addition to migrating to places with better opportunity, moves described in Table 5 reflect a desire to consume a different bundle of housing services and local amenities.

4. Robustness: Alternate Specifications and Data

Alternate Controls: In Tables 6 and 7, we show that our key outcomes are similar across various sets of controls. Column 1 controls for state FE (in year $t-1$), year FE, number of kids (in year $t-1$) FE, and geographic area (in year $t-1$). Column 2 adds demographic controls. Column 3 adds annual state economic conditions and policies, and contains the main set of controls. Columns 4 and 5 include—either—state $\times$ year FE and state $\times$ number of kids FE, and column 6 includes each of these. Finally, column 7 uses the main set of controls and adds the annual out-migration rate for the control group of women without kids (the omitted group in Figure 6) to net out any general trends in migration.

Table 6 uses equation (1) and shows that—across controls—the estimate of $MaxEITC$ on EITC benefits ranges from $194 to $444; living in a rural area ranges from -0.24 and -0.48; living in a distressed area ranges from -0.05 to -0.31; the change in the local LFP rate ranges from 0.15 to 0.28; and the change in the local unemployment rate ranges from -0.01 to -0.06 (the units of these last four outcomes are percentage points).

While the magnitudes in Table 6 vary across controls, results in Table 7 are more stable when effects are allowed to vary by marital status and metropolitan status.

Table 7 estimates equation (2), and the controls in columns 1–6 correspond to the controls in Table 6 columns 2–7. There are numerous estimates in this table (4 panels with 6 columns, each with 4 estimates), and we will focus the discussion here on the effects on $Unmarried \times Rural_{t-1}$. For this group of women, the effect of $MaxEITC$ on (1) EITC benefits ranges from \$781 to \$943; (2) on living doubled up ranges from -1.1 to -1.5; on moving to a less distressed area ranges from 1.5 to 2.0; and moving to a more urban area ranges from 3.1 to 3.6. Estimates across controls for the other three types of women are also similar to the main results shown in Tables 4 and 5.

Migration Effects by Employment Status: While we have shown that migration effects are largest among groups most likely to benefit from the EITC, we explicitly test whether migration effects are concentrated among working mothers by interacting labor force participation with several key outcomes. Table 8 shows that our main results are indeed concentrated among working mothers, while we find much smaller—and largely null—effects among non-working mothers.

Imputing Marriage in Year $t-1$: Appendix Table B.2 shows results are robust to using marital status in year t or imputing it for year $t-1$.

Age of Women: Women without kids are not eligible for the EITC before age 25. Alternate approaches include (1) removing women without kids under age 25 from the sample, and (2) restricting the sample to women over age 25. Since younger women have larger migration responses (see Table 3), these samples should lead to slightly smaller estimates, which is what we find. For example, the average effect of $MaxEITC$ on moving out of a rural and distressed area becomes -0.33 (0.19) and -0.27 (0.09) with the first sample, and -0.32 (0.19) and -0.25 (0.09) with the second sample, compared to 0.46 (0.24) and -0.31 (0.11) with the full sample (see Table 3).

Variation in Treatment Timing: Recent research shows that variation in treatment timing can lead to contamination by picking up effects from other periods (Sun and Abraham, 2020; Callaway and Sant'Anna, 2020; Goodman-Bacon, 2021). Variation in $MaxEITC$ comes from one federal policy change and several state policy changes.

Appendix Table B.3 shows that results are similar when we only use variation from the 2009 federal EITC expansion, which also helps remove concerns that women are moving to more generous state EITCs.[26]

[26] Kennan and Walker (2010) finds little evidence of cross-state moves to benefit from more generous welfare benefits. While not the focus of this paper, we find no evidence that women move to states with higher EITC rates: among women that move states, the new state EITC rate is on averge a bit smaller.

Another approach is to restrict the sample to the subset of states that do not change their EITC policy over the sample period. This approach relies only on the 2009 federal EITC policy change (although this change will be larger in states with larger state EITCs). Table 9 uses equation (1) and the outcomes from Table 3: panel A uses all state-years; panel B uses state-years before state EITC changes;[27] and panel C uses states that never change their EITC during our sample years (about half the sample). Relative to results in panel A, results in panels B and C are: insignificantly larger for EITC benefits, LFP rate, and unemployment rate; significantly larger for living in a distressed area; and insignificantly smaller for living in a rural area. Overall, results for these five outcomes are similar across samples. If anything, results are largest in Panel C, suggesting that there may be a confounder correlated with state EITC expansions biasing the estimates down.

All Five Types of Metropolitan Status: In Appendix Table B.4 Panels A–G, we look at $MaxEITC$'s effect on living in each of the five types of metropolitan areas (i.e., rural, semi-rural, suburban, semi-urban, and urban) identified in the ACS (see footnote 8). These results are largely redundant with Table 3, and not all results are statistically significant. One interesting result is that most moves out of rural areas are to suburban and semi-urban areas, rather than to the largest urban areas (where costs of living may be prohibitively high). Panel C column 5 shows suggestive—but statistically insignificant—evidence that the EITC increases Black women's migration out of urban areas to semi-urban areas, consistent with Frey (2018).

Alternate Data Sources and Sample Years: In Appendix B, we use alternate data sources: 1980–2000 Census data (following Heckman and Robb (1985) and Black et al. (2015)) and 1993–2017 IRS county-level migration data. Across a variety of specifications, we find corroborating evidence that $MaxEITC$ increases migration out of rural areas. See Appendix B for complete details and further discussion.

[27] For example, if a state EITC change occurs in 2013, then women from this state for 2005–2012 would be included in the sample.

5. Discussion

Policymakers have been looking for ways to help people living in economically distressed areas. One approach is to focus assistance on areas left behind by rising spatial inequality (Bartik, 1991; Shambaugh and Nunn, 2018). Another approach is to help people migrate to places with more opportunity (Bergman et al., 2019; Ziliak, 2019). We focus on the latter, and show that the EITC—a transfer program not specifically tied to migration—enables people to migrate to economic opportunity. Migration is a risky endeavor that requires learning about—and adapting to—a new location and finding a new job (Bryan et al., 2014; Yagan, 2014).[28] Combining our results with those in Bergman et al. (2019) suggests that providing information to EITC recipients about the economic conditions of various places could further improve migration decisions.

We find that the EITC relaxes credit constraints and allows mothers to move out of rural and economically distressed areas. This interpretation is consistent with previous evidence showing that the EITC increases household savings and access to credit (Jones and Michelmore, 2018).

Results are robust to various specifications and are larger for groups of women that receive more EITC benefits. These results do not just reflect churn in and out of distressed areas, since estimates on "moving to a more distressed area" are small and insignificant. Consistent with the EITC being the causal mechanism, we find strong migration effects among working mothers, and null effects among non-working mothers not eligible for the EITC.

In addition to migrating to places with better economic opportunity, many moves appear to be motivated by a desire for more independence (Costa, 1999). About a quarter of EITC-led moves reflect mothers no longer living "doubled up" with another family. Related, Bailey et al. (2020) shows that the 1960s introduction of Food Stamps increased the likelihood that individuals move away from their birth county and reside in a single-family home. Our results suggest that the EITC—and perhaps other transfer programs, like the Child Tax Credit (Bastian, 2022)—helps women become financially independent and migrate to places with shorter commutes and better amenities. Responses are concentrated among mothers—

[28] There is also a literature on financial constraints and international migration (e.g., Angelucci, 2015).

and in states—most likely to benefit from the EITC.

If the EITC affects migration by relaxing budget constraints, we should see more moves occuring just after peak tax-return season of February and March (LaLumia, 2013). Unfortunately, we have no way of investigating this timing in the ACS data, but it is something that future research may be able to examine.[29]

While most economic models show that smaller, frequent payments would increase utility and consumption smoothing, many credit-constrained households appreciate the EITC's "forced savings" (Halpern-Meekin et al., 2015). In fact, until 2010, households could opt in to the "Advanced EITC" to receive some EITC benefits in each paycheck (Holt, 2015). Only about 1 percent of eligible households opted in, however, even when given information about the option (Jones, 2010) To us, the low take-up rate of "Advanced EITC" strongly suggests that poor families find themselves constrained in financial markets, which may impact their ability to purchase consumer durables and perhaps to change residential locations.

We leave it to future research to further characterize these moves, the amenities of these locations, and the longer-run effects on these mothers and their children. It is possible that these moves to places with more economic opportunity have positive effects on children (Chetty et al., 2016; Chyn, 2018). Future work should also examine how these moves affect earnings, labor supply, and family structure over time.

The EITC is one part of the tax code that may move people towards more productive—and higher quality of life—locations, unlike many other federal taxes (Albouy, 2009). Without the EITC, the decades-long decrease in U.S. migration (Molloy et al., 2011, 2014; Kaplan and Schulhofer-Wohl, 2017; Dao et al., 2017) may have been even larger.

[29] Most moves occur during the summer when children are not in school. See https://www.movinglabor.com/blog/when-is-peak-moving-season.

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Table 1: Summary Statistics

Sample:	All Women		All Mothers		Unmarried Mothers	
	Mean (1)	S.D. (2)	Mean (3)	S.D. (4)	Mean (5)	S.D. (6)
Age	37.4	10.6	39.0	8.8	37.3	9.6
Married	0.49	0.50	0.65	0.48	0.00	0.00
Years of Education	13.5	2.7	13.3	2.8	12.6	2.5
Black	0.14	0.34	0.14	0.34	0.26	0.44
White	0.72	0.45	0.71	0.45	0.59	0.49
Children	1.04	1.21	1.92	1.00	1.78	0.99
#Kids Under Age 5	0.23	0.54	0.42	0.67	0.40	0.64
Employed	0.76	0.43	0.73	0.44	0.79	0.41
Individual Earnings (1,000s)	27.87	38.22	27.65	39.12	24.20	31.33
Total Household Income (1,000s)	84.20	86.91	90.22	91.21	45.76	47.88
Max Possible EITC in Year t-1 (1,000s)	3.08	2.56	5.22	1.45	4.97	1.45
EITC Benefit Eligibility (100s)	5.61	14.25	10.17	18.14	17.62	20.58
Living Doubled-Up	0.04	0.20	0.00	0.07	0.01	0.10
Rural Area (Year t-1)	0.11	0.32	0.12	0.32	0.12	0.32
Semi-Rural Area (Year t-1)	0.10	0.30	0.10	0.30	0.10	0.30
Surburban Area (Year t-1)	0.27	0.44	0.28	0.45	0.23	0.42
More Urban Area (Year t-1)	0.40	0.49	0.39	0.49	0.41	0.49
Urban Area (Year t-1)	0.12	0.33	0.11	0.32	0.15	0.36
Moved Houses	0.17	0.38	0.14	0.35	0.21	0.41
Moved Counties	0.05	0.22	0.03	0.18	0.04	0.20
Moved CZs	0.05	0.21	0.03	0.18	0.04	0.20
More Urban, Different CZ	0.02	0.13	0.01	0.10	0.01	0.12
Moved to Same Urban/Rural Area	0.10	0.30	0.09	0.28	0.13	0.34
Moved to More Urban Area	0.04	0.19	0.03	0.16	0.04	0.20
Moved to More Rural Area	0.04	0.19	0.03	0.17	0.04	0.20
Moved Out of State	0.03	0.16	0.02	0.14	0.02	0.14
State GDP Growth Rate	3.66	2.91	3.67	2.94	3.63	2.92
State GDP (100s of Billions)	8.35	7.44	8.35	7.42	8.32	7.33
State Minimum Wage	8.16	1.03	8.14	1.03	8.13	1.02
Max TANF with 1 Kid (100s)	4.05	1.65	4.03	1.65	3.96	1.65
Max TANF with 2 Kids (100s)	5.02	2.08	5.00	2.08	4.91	2.09
Max TANF with 3 Kids (100s)	5.93	2.46	5.90	2.46	5.80	2.48
State Unemployment Rate	6.50	2.20	6.50	2.21	6.57	2.20
Observations	9,268,908		5,096,894		1,536,191	

Notes: 2005–2017 ACS data. Sample includes all women 19–55 years old. EITC data from NBER and IRS. EITC benefits calculated using TAXSIM. Unemployment rates from BLS. GDP from BEA regional data. Minimum wage from the Tax Policy Center's Tax Facts. Welfare benefits from the Urban Institute's Welfare Rules Database.

Table 2: Migration Transition Matrix: Five Categories of Metropolitan Status

Metro Status	Metropolitan Status in Year t					
in Year $t-1$]	Rural	Semi-Rural	Suburban	Semi-Urban	Urban	**Total**
Rural	1,252,939	9,032	9,669	18,710	4,709	1,295,059
	96.75%)	(0.70%)	(0.75%)	(1.44%)	(0.36%)	(100.00%)
Semi-Rural	12,064	951,692	25,640	41,349	14,674	1,045,419
	(1.15%)	(91.03%)	(2.45%)	(3.96 %)	(1.40 %)	(100.00%)
Suburban	5,296	5,960	2,372,942	21,124	10,493	2,415,815
	(0.22%)	(0.25%)	(98.23%)	(0.87%)	(0.43%)	(100.00%)
Semi-Urban	29,434	29,904	199,067	3,082,650	133,169	3,474,224
	(0.85%)	(0.86%)	(5.73%)	(88.73%)	(3.83%)	(100.00%)
Urban	1,175	1,563	12,933	9,073	1,013,647	1,038,391
	(0.11%)	(0.15%)	(1.25%)	(0.87%)	(97.62%)	(100.00%)
Total	1,300,908	998,151	2,620,251	3,172,906	1,176,692	9,268,908
	(14.04%)	(10.77%)	(28.27%)	(34.23%)	(12.70%)	(100.00%)

Notes: 2005-2017 ACS data. Sample includes all women 19–55 years old.

Table 3: EITC's Effect on Living in a Rural or Economically Distressed Area

Outcome in Year t:	EITC Benefits (1)	Moved PUMA (2)	Living in a Rural Area (3)	Living in a Distressed Area (4)	Δ in PUMA LFP Rate (5)	Δ in PUMA Unemp. Rate (6)
Panel A: All Women (N=9,268,908 with 1,421,364 Movers)						
$MaxEITC_{t-1}$	283	1.42	-0.46	-0.31	1.37	-0.33
	(49)	(0.88)	(0.24)	(0.11)	(0.38)	(0.13)
Mean Dep Var	561.1	13.9	20.6	30.2	0.03	-0.03
Panel B: Women Under Age 45 (N=6,012,897 with 1,172,279 Movers)						
$MaxEITC_{t-1}$	368	1.58	-0.51	-0.56	1.41	-0.33
	(52)	(1.06)	(0.29)	(0.21)	(0.39)	(0.13)
Mean Dep Var	655.2	17.0	20.0	30.5	0.04	-0.03
Panel C: All Black Women (N=1,011,390 with 173,605 Movers)						
$MaxEITC_{t-1}$	329	1.25	-0.44	-0.28	0.94	-0.41
	(86)	(0.87)	(0.19)	(0.08)	(0.27)	(0.11)
Mean Dep Var	838.3	16.2	12.8	31.4	0.10	-0.06
Panel D: All White Women (N=7,012,025 with 1,048,532 Movers)						
$MaxEITC_{t-1}$	218	1.32	-0.47	-0.35	1.64	-0.37
	(44)	(0.85)	(0.29)	(0.12)	(0.42)	(0.13)
Mean Dep Var	477.5	13.2	24.2	28.7	0.01	-0.02
Panel E: All Unmarried Women (N=4,214,120 with 903,393 Movers)						
$MaxEITC_{t-1}$	481	1.73	-0.52	-0.59	1.27	-0.29
	(83)	(0.88)	(0.27)	(0.22)	(0.37)	(0.13)
Mean Dep Var	671.5	12.6	18.6	31.0	0.04	-0.02
Panel F: All Married Women (N=5,054,788 with 517,971 Movers)						
$MaxEITC_{t-1}$	182	-0.24	-0.24	0.04	1.54	-0.36
	(45)	(0.33)	(0.16)	(0.09)	(0.42)	(0.13)
Mean Dep Var	447.5	9.3	22.7	29.5	-0.00	-0.04
Panel G: Women Living in State of Birth, in Year $t-1$ (N=5,011,852 with 723,151 Movers)						
$MaxEITC_{t-1}$	189	0.38	-0.48	-0.19	0.89	-0.22
	(51)	(0.98)	(0.22)	(0.11)	(0.27)	(0.11)
Mean Dep Var	520.9	18.4	24.7	31.1	0.03	-0.02

Notes: 2005–2017 ACS data. $MaxEITC_{t-1}$ and EITC benefits are in 2018 dollars. Columns 1–3 use full sample; columns 4–5 restricted to movers. Table 4 defines $MaxEITC$ and describes standard errors and weights used.

Table 4: EITC's Effects on Migration

Outcome	EITC Benefits	Moved	Moved More Urban	Moved More Urban Within County	Moved More Urban Different County	Moved CZ	Moved to Less-Distressed Area
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MaxEITC × Unmarried	807.4	5.0	3.6	2.4	1.2	2.3	2.0
× Rural$_{t-1}$	(44.5)	(1.4)	(1.0)	(0.8)	(0.4)	(1.0)	(0.5)
MaxEITC × Unmarried	693.4	2.7	0.8	1.0	-0.2	0.8	0.8
× Urban$_{t-1}$	(51.4)	(1.0)	(0.6)	(0.4)	(0.4)	(0.9)	(0.4)
MaxEITC × Married	155.0	0.7	2.2	1.6	0.7	1.1	1.2
× Rural$_{t-1}$	(40.2)	(1.2)	(0.8)	(0.6)	(0.4)	(1.0)	(0.4)
MaxEITC × Married	98.6	0.8	0.8	0.9	-0.1	0.8	0.8
× Urban$_{t-1}$	(37.8)	(1.1)	(0.6)	(0.4)	(0.4)	(0.9)	(0.4)
R-squared	0.275	0.065	0.030	0.027	0.013	0.026	0.013
Mean Dep Var	561.1	17.38	3.618	2.210	1.408	4.762	2.181
F-Test P-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: 2005–2017 ACS data. N = 9,268,908. Sample includes all women 19–55 years old. $MaxEITC$ defined as maximum possible federal plus state EITC benefits that a family could receive. $MaxEITC$ units are $2,500 in 2018 dollars. $MaxEITC$ is a function of year, state, and number and age of children. Rural$_{t-1}$ and Urban$_{t-1}$ based on where women lived in year $t-1$. The F-test is that all four estimates are identical. Mean dependent variables for columns 1–7 for $Unmarried \times Rural_{t-1}$ women are: 794, 23.5, 8.2, 4.6, 3.6, 8.2, and 4.2. Standard errors robust to heteroskedasticity and clustered at the state (in year $t-1$) level. State-by-metropolitan status (in year $t-1$) clustering yields similar results. ACS weights used.

Table 5: Characterizing Quality of Moves: Living "Doubled-Up" and Commuting Length

	Houshold Traits					
Outcome	Doubled Up	Multi-Gen HH	#Families in HH	#Mothers in HH	#Siblings in HH	Commute Time
	(1)	(2)	(3)	(4)	(5)	(6)
MaxEITC × Unmarried × Rural	-1.28	-0.10	-0.09	-0.08	-0.09	-1.75
	(0.12)	(0.02)	(0.01)	(0.02)	(0.02)	(0.50)
MaxEITC × Unmarried × Urban	-1.19	-0.09	-0.08	-0.07	-0.07	-0.62
	(0.13)	(0.02)	(0.01)	(0.01)	(0.02)	(0.36)
MaxEITC × Married × Rural	-0.43	-0.00	-0.00	-0.01	-0.02	-1.67
	(0.14)	(0.02)	(0.01)	(0.01)	(0.02)	(0.44)
MaxEITC × Married × Urban	-0.44	0.00	-0.00	-0.01	-0.03	-1.16
	(0.14)	(0.02)	(0.01)	(0.01)	(0.02)	(0.36)
R-squared	0.083	0.531	0.078	0.560	0.178	0.032
Mean Dep Var	4.3	1.781	1.125	0.758	0.126	21.10
F-Test P-Value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Table 4 defines data, sample, $MaxEITC$, and describes standard errors, weights used, and F-test. Column 6 restricts to working women (N=7,055,948). Doubled up measured in percentage points. Commute time in minutes.

Table 6: The EITC and Living in a Rural or Distressed Area, Alternate Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Outcome = EITC Benefits							
MaxEITC	194	257	283	300	389	444	283
	(52)	(55)	(49)	(57)	(71)	(91)	(49)
R-squared	0.151	0.238	0.238	0.238	0.240	0.240	0.238
Panel B: Outcome = Living in a Rural Area							
MaxEITC	-0.32	-0.48	-0.46	-0.40	-0.39	-0.24	-0.48
	(0.19)	(0.23)	(0.24)	(0.22)	(0.24)	(0.10)	(0.28)
R-squared	0.875	0.876	0.876	0.881	0.876	0.881	0.876
Panel C: Outcome = Living in a Distressed Area							
MaxEITC	-0.27	-0.28	-0.31	-0.19	-0.09	-0.05	-0.30
	(0.12)	(0.12)	(0.11)	(0.08)	(0.12)	(0.04)	(0.11)
R-squared	0.936	0.936	0.936	0.952	0.936	0.952	0.936
Panel D: Outcome = Change in Average LFP							
MaxEITC	0.28	0.28	0.20	0.23	0.15	0.16	0.20
	(0.11)	(0.11)	(0.07)	(0.07)	(0.05)	(0.06)	(0.07)
R-squared	0.934	0.934	0.935	0.942	0.936	0.942	0.935
Panel E: Outcome = Change in Average Unemployment Rate							
MaxEITC	-0.06	-0.06	-0.05	-0.05	-0.02	-0.01	-0.05
	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
R-squared	0.920	0.920	0.921	0.925	0.922	0.926	0.921
Controls							
Year FE, State FE, #Kids FE, Lagged Metro Status FE	X	X	X	X	X	X	X
Demographics		X	X	X	X	X	X
State × Year Factors			X		X		X
State FE × Year FE				X		X	
State FE × #Kids FE					X	X	
Annual State Out-Rural Migration by Women w/ no Kids							X

Notes: Regressions are identical to Table 3 panel A, but with different sets of controls. State × Year Factors are redundant with State × Year FE. *MaxEITC* defined in Table 4.

Table 7: Migration Outcomes Robust to Additional Controls

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Outcome = EITC Benefits						
MaxEITC × Unmarried	781	807	829	886	943	807
× Rural	(53)	(45)	(48)	(66)	(80)	(45)
MaxEITC × Unmarried	667	693	714	774	830	693
× Urban	(63)	(51)	(53)	(80)	(94)	(51)
MaxEITC × Married	128	155	176	238	295	155
× Rural	(46)	(40)	(46)	(56)	(71)	(40)
MaxEITC × Married	72	99	120	181	237	99
× Urban	(42)	(38)	(45)	(48)	(65)	(38)
Panel B: Outcome = Living "Doubled Up" with Another Family						
MaxEITC × Unmarried	-1.1	-1.3	-1.4	-1.3	-1.5	-1.3
× Rural	(0.1)	(0.1)	(0.2)	(0.1)	(0.1)	(0.1)
MaxEITC × Unmarried	-1.0	-1.2	-1.3	-1.2	-1.4	-1.2
× Urban	(0.1)	(0.1)	(0.2)	(0.1)	(0.1)	(0.1)
MaxEITC × Married	-0.3	-0.4	-0.5	-0.5	-0.6	-0.4
× Rural	(0.2)	(0.1)	(0.2)	(0.1)	(0.1)	(0.1)
MaxEITC × Married	-0.3	-0.4	-0.5	-0.4	-0.6	-0.4
× Urban	(0.2)	(0.1)	(0.2)	(0.1)	(0.1)	(0.1)
Panel C: Outcome = Less Distressed						
MaxEITC × Unmarried	1.9	2.0	1.9	1.6	1.5	2.0
× Rural	(0.5)	(0.5)	(0.4)	(0.3)	(0.3)	(0.5)
MaxEITC × Unmarried	0.7	0.8	0.7	0.3	0.3	0.8
× Urban	(0.4)	(0.4)	(0.3)	(0.2)	(0.2)	(0.4)
MaxEITC × Married	1.1	1.2	1.1	0.8	0.7	1.2
× Rural	(0.5)	(0.4)	(0.4)	(0.3)	(0.2)	(0.4)
MaxEITC × Married	0.7	0.8	0.8	0.4	0.3	0.8
× Urban	(0.4)	(0.4)	(0.3)	(0.2)	(0.2)	(0.4)
Panel D: Outcome = More Urban						
MaxEITC × Unmarried	3.1	3.6	3.4	3.6	3.3	3.6
× Rural	(1.1)	(1.0)	(1.1)	(0.7)	(0.7)	(1.0)
MaxEITC × Unmarried	0.2	0.8	0.7	0.6	0.5	0.8
× Urban	(0.7)	(0.6)	(0.7)	(0.3)	(0.3)	(0.6)
MaxEITC × Married	1.6	2.2	2.0	2.2	2.0	2.2
× Rural	(0.9)	(0.8)	(0.9)	(0.5)	(0.4)	(0.8)
MaxEITC × Married	0.2	0.8	0.7	0.7	0.5	0.8
× Urban	(0.7)	(0.6)	(0.7)	(0.3)	(0.3)	(0.7)
Controls in columns 1–6 are identical to those in Table 6 columns 2–7						

Notes: Table 4 defines data, sample, $MaxEITC$, and describes standard errors, and weights used. Other outcomes are consistent across controls too, for example the estimate on $MaxEITC \times Unmarried$ for moving CZs ranges from 0.021 to 0.024.

Table 8: EITC's Effects Are Concentrated Among Working Mothers

Outcome	EITC Benefits	Moved	Moved More Urban	Moved CZ	Moved to Less-Distressed Area	Doubled Up
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Outcome Interacted with (LFP=1)						
MaxEITC × Unmarried	859.7	4.60	3.01	2.02	1.66	-1.04
× Rural	(37.3)	(1.28)	(0.83)	(0.95)	(0.39)	(0.10)
MaxEITC × Unmarried	748.8	2.96	0.78	0.81	0.75	-0.97
× Urban	(48.4)	(0.97)	(0.55)	(0.85)	(0.33)	(0.10)
MaxEITC × Married	33.9	0.63	1.62	0.83	0.91	-0.41
× Rural	(27.1)	(1.14)	(0.64)	(0.91)	(0.38)	(0.12)
MaxEITC × Married	6.7	0.84	0.78	0.72	0.74	-0.41
× Urban	(25.1)	(1.13)	(0.58)	(0.88)	(0.34)	(0.12)
R-squared	0.292	0.059	0.027	0.024	0.012	0.064
Mean Dep Var	422.7	13.25	2.760	3.479	1.591	0.033
Panel B: Outcome Interacted with (LFP=0)						
MaxEITC × Unmarried	-52.3	0.41	0.63	0.30	0.32	-0.24
× Rural	(32.1)	(0.17)	(0.14)	(0.13)	(0.09)	(0.04)
MaxEITC × Unmarried	-55.3	-0.25	-0.01	-0.03	0.01	-0.22
× Urban	(31.5)	(0.10)	(0.08)	(0.05)	(0.04)	(0.04)
MaxEITC × Married	121.1	0.10	0.59	0.27	0.24	-0.02
× Rural	(33.8)	(0.18)	(0.14)	(0.13)	(0.09)	(0.04)
MaxEITC × Married	91.9	-0.02	-0.00	0.10	0.08	-0.02
× Urban	(32.9)	(0.10)	(0.08)	(0.04)	(0.05)	(0.04)
R-squared	0.094	0.019	0.007	0.006	0.003	0.021
Mean Dep Var	138.3	4.128	0.859	1.284	0.590	0.011

Notes: 2005-2017 ACS data. Sample includes all women 19–55 years old. Observations for each column is 9,268,908. *MaxEITC* defined in Table 4. LFP defined based on status "last week" whereas EITC benefits imputed from earnings "last year." Standard errors robust to heteroskedasticity and clustered at the state level. ACS weights used.

Table 9: EITC's Effect on Migration: Restricting to States that Do Not Change EITC

Outcome:	EITC Benefits (2018 $) (1)	Living in a Rural Area (2)	Living in a Distressed Area (3)	Δ in PUMA LFP Rate (4)	Δ in PUMA Unemp. Rate (5)
Panel A: All State-Years (N=9,268,908)					
MaxEITC	283	-0.46	-0.31	0.20	-0.05
	(49)	(0.24)	(0.11)	(0.07)	(0.02)
Mean Dep Var	561.1	20.6	30.2	71.0	6.9
Panel B: Sample = State-Years Before State EITC Changes (N=7,554,773)					
MaxEITC	355	-0.32	-0.62	0.25	-0.08
	(60)	(0.28)	(0.14)	(0.08)	(0.02)
Mean Dep Var	555.0	20.2	32.9	70.5	7.0
Panel C: Sample = States that Never Change Their EITC (N=4,631,490)					
MaxEITC	369	-0.26	-0.73	0.33	-0.09
	(96)	(0.35)	(0.15)	(0.13)	(0.04)
Mean Dep Var	582.4	24.0	36.8	70.1	6.8

Notes: 2005–2017 ACS data. Table 4 defines $MaxEITC$ and describes standard errors and weights used. Outcomes in columns 2–5 measured in percentage points. Panel A results replicate Table 3 panel A. In panel B, the sample is restricted to women living in states and years before any state EITC policy changes: this includes states that do not change their EITC policy at all during the sample period; if a state changes their EITC during the sample period, only the years before that change are kept. In panel C, the sample is restricted to women living in states that never change their EITC policy (so that the 2009 federal EITC expansion is the only policy change).

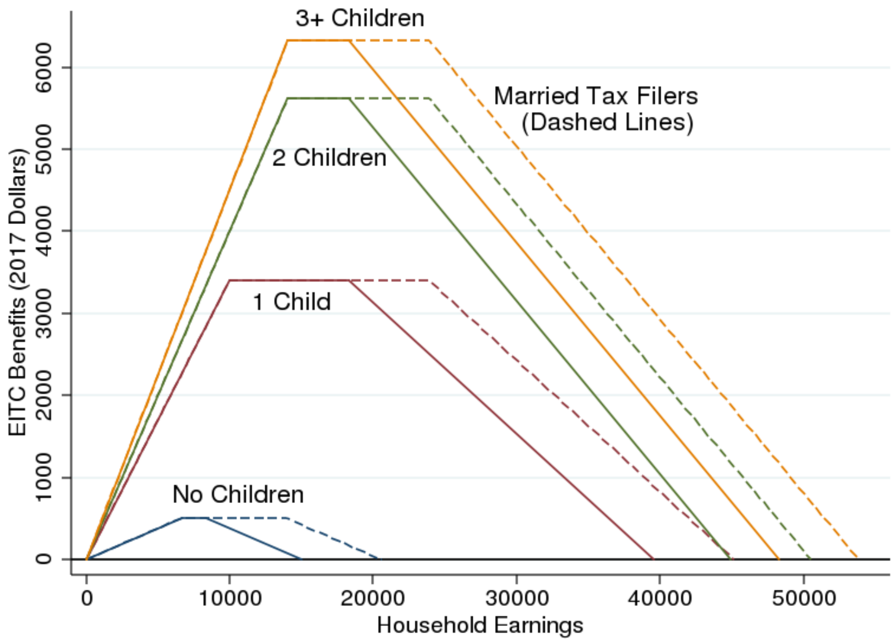


Fig. 1. Federal EITC Structure, 2017

Source: Bastian and Jones (2021).

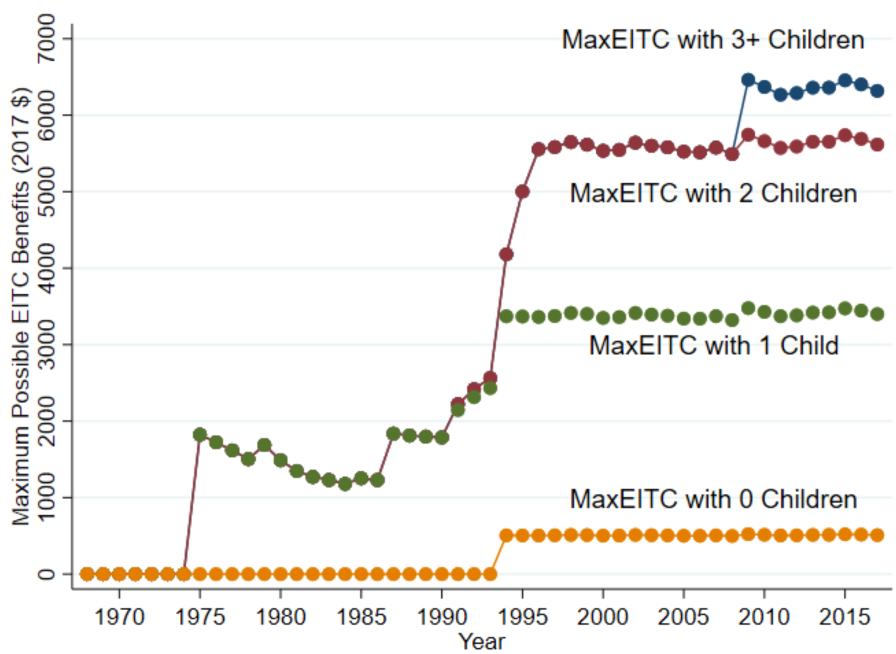


Fig. 2. Maximum Possible Federal EITC Over Time

Source: Bastian and Jones (2021). We use 2005-2017 ACS data and are only able to exploit EITC variation during these years.

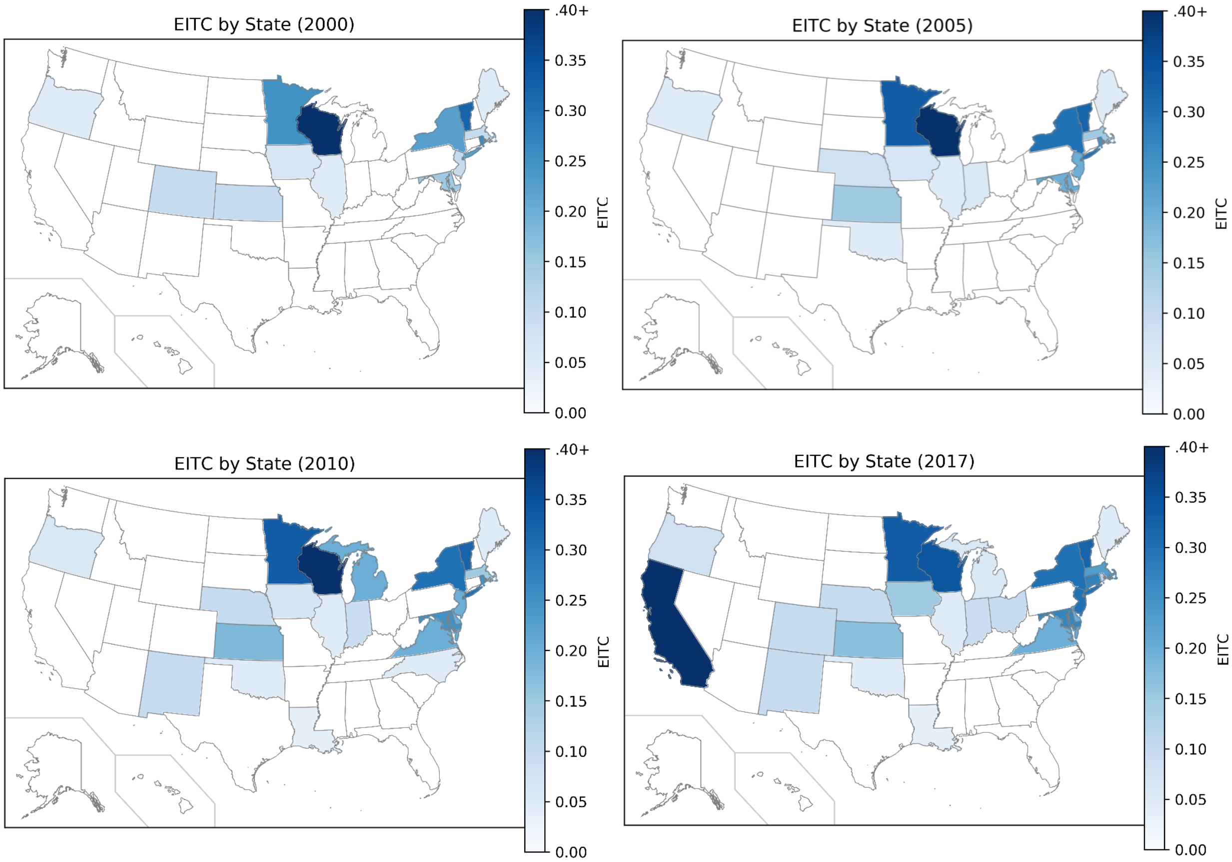


Fig. 3. State EITC Rates (as a Fraction of Federal Benefits) Over Time

Source: Bastian and Lochner (2020). State EITC benefits generally are a fixed fraction of federal EITC benefits. For example, a family that receives $3,500 in federal EITC benefits, and lives in a state with a top-up rate of 20%, would receive $700 in state EITC benefits.

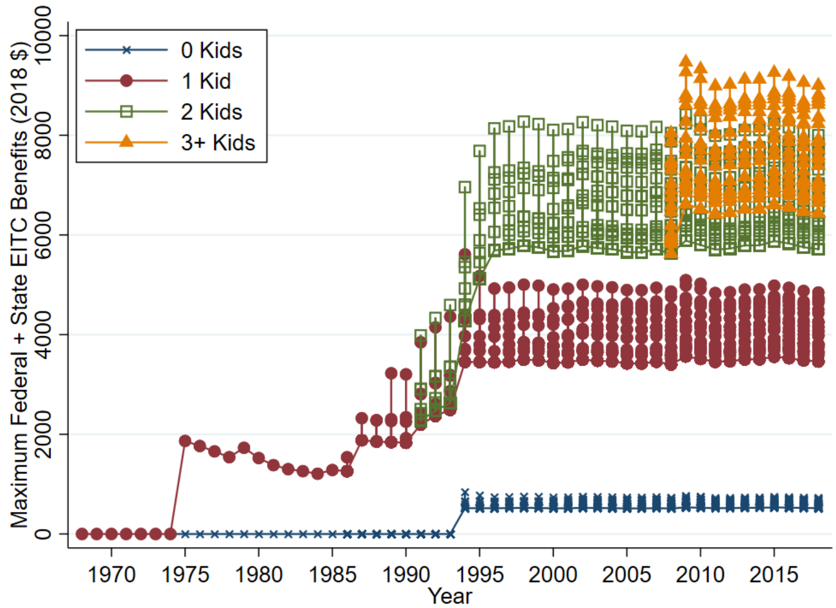


Fig. 4. Maximum Possible Federal + State EITC Over Time

Source: Bastian and Lochner (2020). We use 2005-2017 ACS data and are only able to exploit EITC variation during these years.

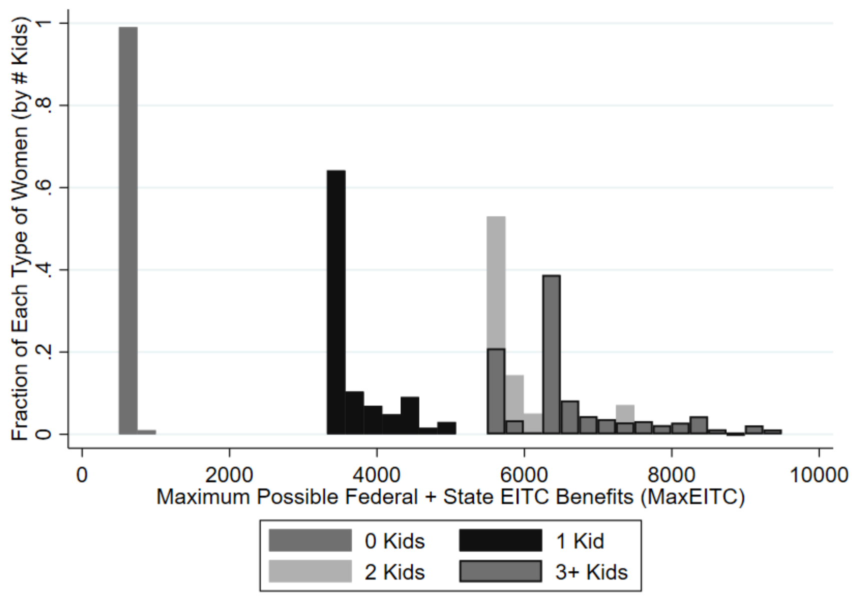


Fig. 5. Histogram of Maximum Possible Federal + State EITC Benefits ($333 Bins)

Notes: Authors' calculation from 2005-2017 ACS data and the sample of all women 19–55 years old.

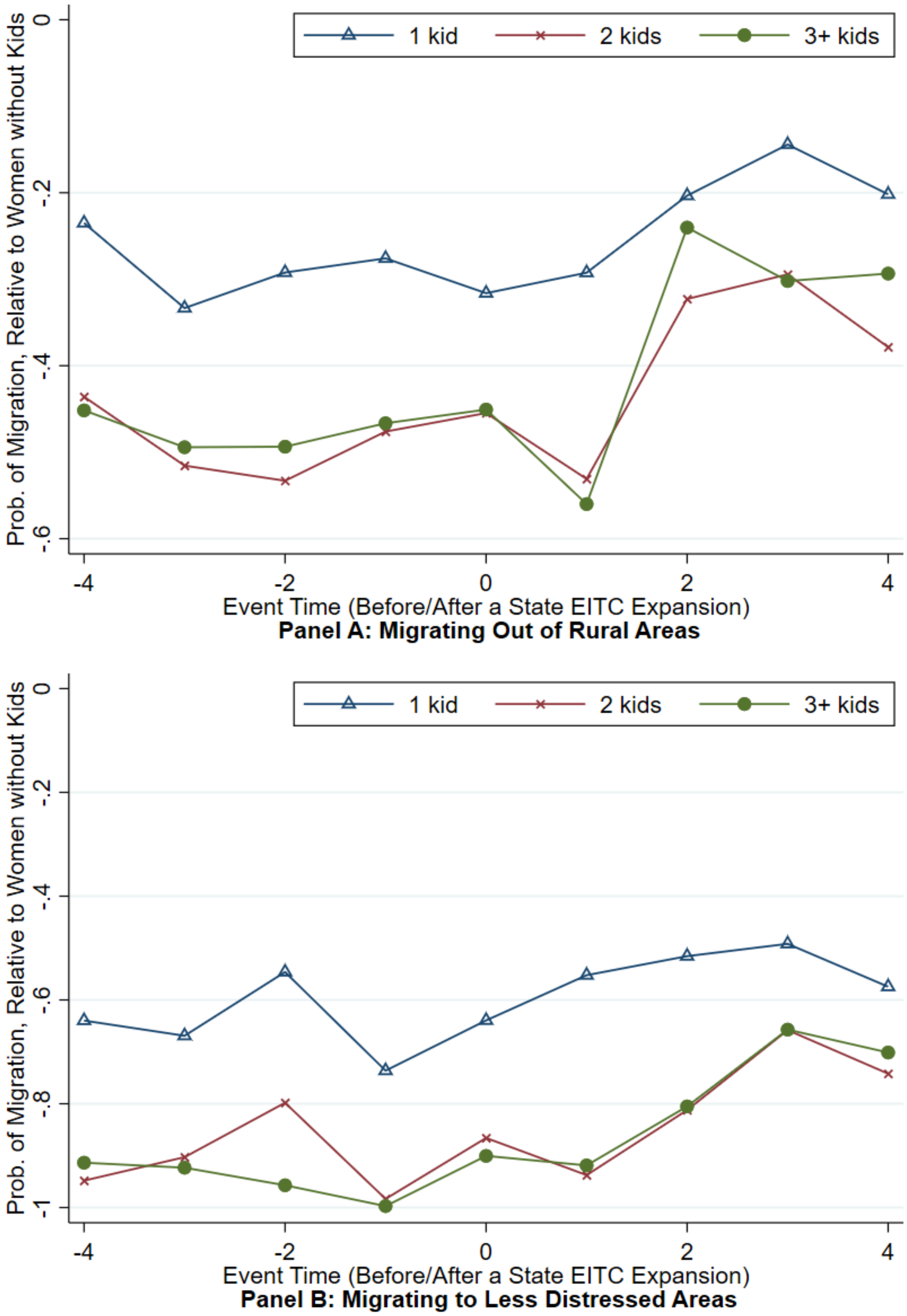


Fig. 6. Migrating Out of Distressed Areas: Unadjusted Trends by Number of Kids

2005-2017 ACS data. Event time refers to years before/after when a state creates or expands their state EITC. We drop states that never change their EITC policy during the sample period, or does so in the first or last year of data. These estimates come from a single regression without controls that compares the probability of moving to a less distressed area for mothers with 1, 2, and 3+ kids. Each estimate can be interpreted as relative to women without children in each year.

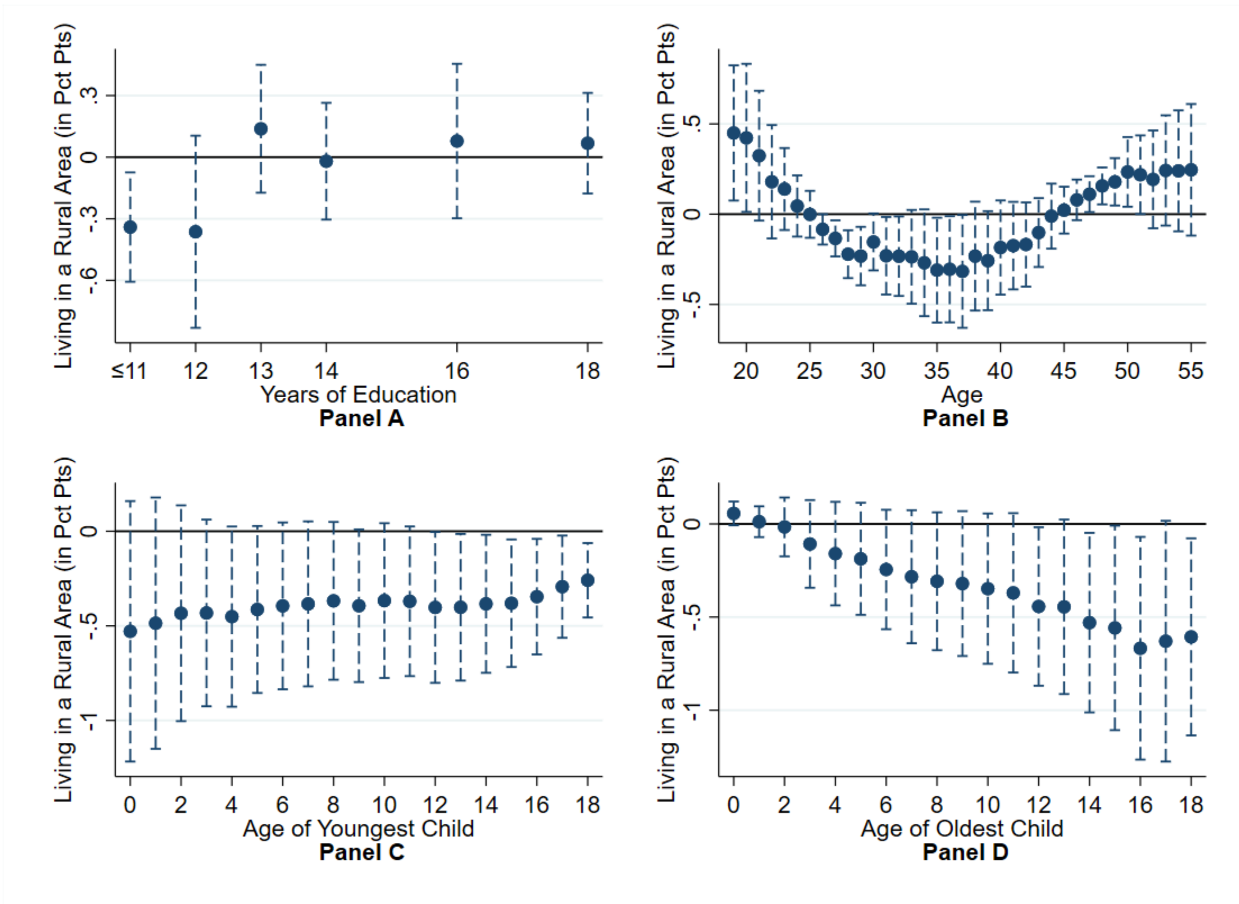
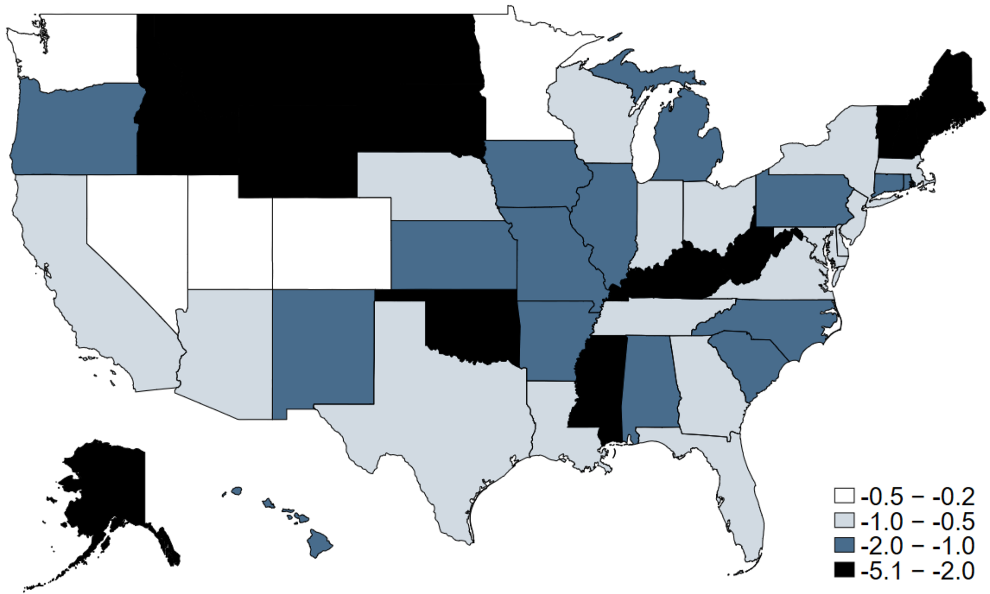


Fig. 7. EITC's Impact on the Composition of Women Living in Rural Areas

Source: Table 4 defines data, sample, $MaxEITC$, and describes standard errors, and weights used. Each estimate comes from a separate regression. These estimates build on equation (1), except we interact $Y_{i,s,t}$ with an indicator for each category of education, mother's age, or child's age. Regressions in each panel exclude controls that are collinear with the outcome of interest (e.g., education, age, age of children). A weighted average of the estimates in each panel will (approximately) equal the estimates in Table 3 panel A column 2.

Panel A: EITC's State-Level Impact on Migration Out of Rural Areas



Panel B: EITC's Impact on Moving Out of Rural Areas is Larger in States with a Higher Fraction of Rural Women Predicted to Have Low Earnings (Weighted by State's Rural Population in 2010)

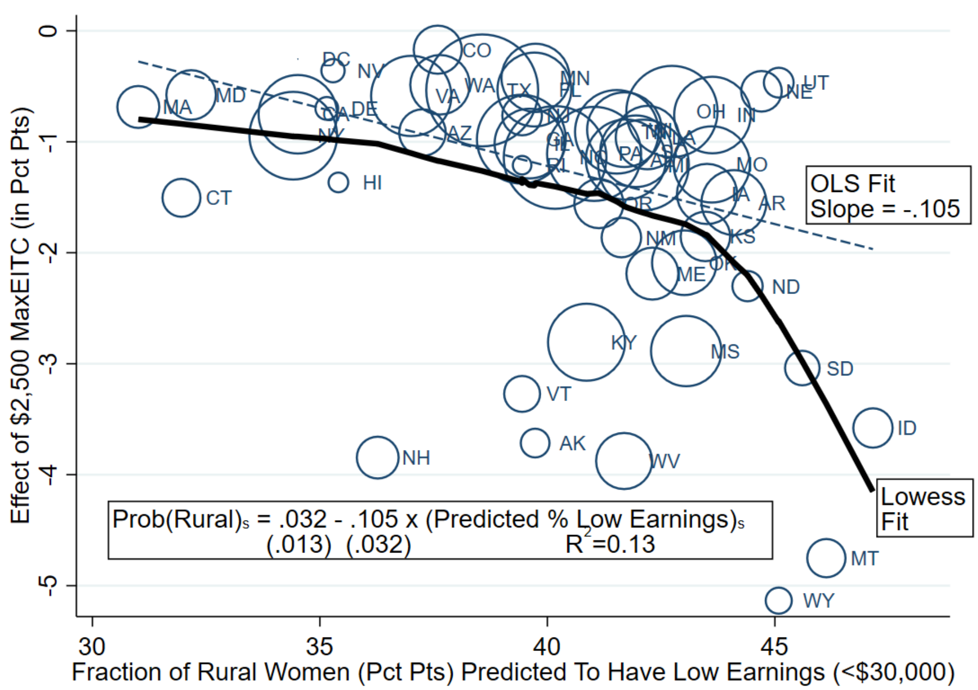


Fig. 8. **Migration Out of Rural Areas: Effects by State, Fraction Low-Earners**
Source: 2005–2017 ACS. Panel A reflects a regression similar to equation (1), but interacts $MaxEITC$ with state indicators. The scatterplot in Panel B uses the generated regressor from Panel A and the fraction of rural women predicted to have positive earnings below $30,000. We obtain similar results from using alternate earnings cutoffs, sets of controls, or probit or logit.

For Online Publication

"The Earned Income Tax Credit and Migrating Out of Rural America"

Jacob E. Bastian and Dan A. Black[1]

List of Appendices

Appendix A: Theoretical Model of Migration Under Financial Constraints

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Appendix A: Theoretical Model of Migration Under Financial Constraints

Consider a single woman with children who is deciding between living in two locations: her current location, denoted zero, and an alternative location, denoted one. Suppose that moving requires her to pay a fixed m, and that location one is more attractive in terms of employment and consumption alternatives.

If she stays in her location, her value function, $V_{0,t}$ is

$$V_{0,t} = v(\alpha_0, p_{0,t}, c_{0,t}) + \delta\ V_{0,t+1} \tag{3}$$

where $v(\alpha_0, p_{0,t}, c_{0,t})$ is her indirect utility function, α_0 are amenities in the location, prices are $p_{0,t}$, consumption expenditures, $c_{0,t}$, her discount factor δ, and her value function at time $t+1$, $V_{0,t+1}$. Her budget depends on her initial assets, $A_{0,t-1}$, her terminal assets, $A_{0,t}$, earnings net of taxes $w_{0,t}$, and her next transfer payments , $\tau_{0,t}$. She earns a rate of return r on her assets so the evolution of her budget equation if she does not move is given by

$$A_{0,t} = A_{0,t-1}(1+r) + w_{0,t} + \tau_{0,t} - c_{0,t}. \tag{4}$$

Her consumption decision is to choose $c_{0,t}$, but keep her assets non-negative ($A_{0,t-1} \geq 0$). Let $V_{0,t}^*$ denote the value of her value function given her optimal consumption decision.

If she moves, her consumption decision is in location one and her value function is

$$V_{1,t} = v(\alpha_1, p_{1,t}, c_{1,t}) + \delta\ V_{1,t+1} \tag{5}$$

and her budget equation is

$$A_{1,t} = A_{0,t-1}(1+r) - m + w_{1,t} + \tau_{1,t} - c_{1,t}. \tag{6}$$

Let $V_{1,t}^*$ denote the value of her value function given her optimal consumption decision provided she moves. She chooses to move if $V_{1,t}^* > V_{0,t}^*$.

In the absence of the constraint that $A_{1,t} \geq 0$, more moves would be optimal because she could amortize the relocation investment. With $A_{1,t} \geq 0$, consumption decisions may have to be restricted to keep $A_{1,t}$ non-negative. But as $v(\alpha_1, p_{1,t}, c_{1,t})$ is concave in $c_{1,t}$, restricting consumption for poor families is extremely costly in terms of utility relative to the corresponding utility loss of wealthier households. In fact, moving is infeasible if

$$m > A_{0,t-1}(1+r) + w_{1,t} + \tau_{1,t}. \tag{7}$$

As poor families often have few financial assets, this condition may hold for many households. If we now consider a large increase in $\tau_{1,t}$ that occurs annually—such as the EITC— this payment may relax the capital market constraint and allow the household to move.

Appendix B: Additional Tables and Figures

Table B.1: Testing the Exogeneity of State EITCs

	Max State EITC Benefits				State EITC Rates			
	(1)		(2)		(3)		(4)	
State GDP Growth Rate	6.2	(6.9)	5.3	(8.3)	8.2	(10.7)	6.4	(13.0)
Lag State GDP Growth Rate	-0.03	(2.9)	-0.7	(3.0)	-1.3	(4.7)	-2.5	(4.8)
State Unemp Rate	0.7	(20.0)	-0.4	(21.0)	0.8	(31.5)	1.6	(33.3)
Lag State Unemp Rate	-7.1	(21.9)	-9.2	(23.2)	-5.0	(34.6)	-9.6	(36.9)
Log State GDP	-4.3	(6.3)	-3.8	(7.3)	-8.2	(9.9)	-7.1	(11.7)
Lag Log State GDP	2.8	(5.5)	1.5	(6.4)	7.2	(8.4)	5.3	(9.9)
State Min Wage	-11.6	(17.6)	-8.6	(17.8)	-9.6	(27.4)	-5.2	(27.8)
Lag State Min Wage	14.4	(20.4)	12.7	(20.9)	38.3	(32.0)	35.1	(32.7)
Max TANF with 1 Child	-0.4	(0.3)	-0.5	(0.3)	-0.7	(0.6)	-0.8	(0.6)
Lag Max TANF with 1 Child	-1.1	(0.5)	-1.0	(0.5)	-1.6	(0.8)	-1.6	(0.8)
Max TANF with 2 Children	4.7	(2.7)	5.4	(2.7)	7.6	(4.6)	8.5	(4.5)
Lag Max TANF with 2 Children	11.3	(4.7)	11.3	(4.6)	17.3	(7.8)	17.5	(7.6)
Max TANF with 3 Children	-1.1	(0.8)	-1.4	(0.8)	-1.7	(1.2)	-2.0	(1.1)
Lag Max TANF with 3 Children	-1.7	(0.9)	-1.8	(0.8)	-2.8	(1.3)	-2.9	(1.3)
Avg Family Size			-3.8	(3.7)			-5.0	(5.8)
Avg Number of Kids			7.2	(8.6)			9.2	(13.9)
Avg Number of Kids Under 5			-13.3	(12.8)			-15.1	(20.6)
Fraction Female			-24.0	(20.9)			-37.5	(32.1)
Avg Age			-46.6	(41.8)			-39.5	(66.7)
Fraction Married			12.8	(10.5)			17.2	(16.7)
Fraction White			-12.6	(15.5)			-22.9	(25.2)
Fraction Black			8.2	(43.1)			17.5	(67.9)
Avg Years Education			-3.6	(2.6)			-4.8	(4.2)
Fraction Born Out of State			-14.0	(13.1)			-19.0	(21.3)
Fraction Non-Citizen			26.0	(23.9)			23.4	(38.9)
R-squared	0.957		0.958		0.960		0.960	
Observations	620		620		620		620	
Mean Dep Var	444.1		444.1		737.5		737.5	
Testing Joint Significance P-Value	0.664		0.412		0.791		0.611	

Notes: Observations at the state-by-year level and cover 2005–2017. Dollars all in 2017 dollars. Each regression controls for state FE, year FE, and state time trends. All dollars are in real CPI-adjusted 2018 dollars. EITC data from NBER and IRS. Unemployment rates from BLS. GDP from BEA regional data. Minimum wage from the Tax Policy Center's Tax Facts. Welfare benefits from the Urban Institute's Welfare Rules Database. Maximum state EITC benefits are for families with 3 or more children. State EITC rates in percentage points. Annual state average demographic traits calculated by authors from ACS data using the subsample of all adults at least 18 years old. Robust standard errors in parentheses. This table shows that out of two dozen state economic and policy conditions, only one factor (Max TANF with 2 Children) is significant at the 10% level and F-tests for joint significance of all state-level measures yield p-values greater than 0.40 across four specifications, suggesting that state-level EITC expansions during our sample period are not correlated with contemporaneous (or recent) state factors.

Table B.2: Alternate Approaches to Imputing Marital Status

Outcome	EITC Benefits	Moved	Moved More Urban	Moved CZ	Moved to Less-Distressed Area	Doubled Up	Multi-Gen HH	#Fam. in HH
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Using Marital Status in Year t, Sample Years 2008–2017 (N=7,087,617)								
MaxEITC × Unmarried × Rural	673.62	4.87	3.78	2.41	1.92	-1.32	-0.10	-0.09
	(49.85)	(1.42)	(0.95)	(1.07)	(0.44)	(0.15)	(0.02)	(0.01)
MaxEITC × Unmarried × Urban	571.67	2.54	0.79	0.81	0.73	-1.22	-0.09	-0.08
	(55.15)	(1.06)	(0.61)	(0.92)	(0.35)	(0.16)	(0.02)	(0.01)
MaxEITC × Married × Rural	50.22	0.73	2.29	1.20	1.11	-0.44	-0.00	-0.00
	(44.21)	(1.24)	(0.76)	(1.01)	(0.41)	(0.17)	(0.02)	(0.01)
MaxEITC × Married × Urban	-2.35	0.76	0.81	0.85	0.76	-0.44	0.00	-0.00
	(44.33)	(1.18)	(0.64)	(0.93)	(0.36)	(0.16)	(0.02)	(0.01)
R-squared	0.275	0.061	0.030	0.025	0.012	0.084	0.519	0.079
Panel B: Using Marital Status in Year t, Dropping Women Married in the Last Year, Sample Years 2008–2017 (N=6,902,225)								
MaxEITC × Unmarried × Rural	677.20	4.02	3.57	2.10	1.77	-1.28	-0.09	-0.08
	(50.51)	(1.43)	(0.94)	(1.04)	(0.43)	(0.16)	(0.02)	(0.01)
MaxEITC × Unmarried × Urban	574.68	1.70	0.59	0.50	0.58	-1.18	-0.09	-0.08
	(56.12)	(1.06)	(0.60)	(0.89)	(0.34)	(0.16)	(0.02)	(0.01)
MaxEITC × Married × Rural	46.82	0.91	2.23	1.23	1.10	-0.46	-0.00	-0.00
	(44.56)	(1.24)	(0.74)	(0.98)	(0.40)	(0.17)	(0.02)	(0.01)
MaxEITC × Married × Urban	-2.90	0.99	0.83	0.90	0.79	-0.46	-0.00	-0.00
	(44.60)	(1.18)	(0.62)	(0.90)	(0.35)	(0.17)	(0.02)	(0.01)
R-squared	0.276	0.061	0.030	0.024	0.012	0.084	0.514	0.079
Panel C: Using Marital Status in Year $t-1$, Sample Years 2008–2017 (N=7,087,617)								
MaxEITC × Unmarried × Rural	653.07	4.06	3.66	2.16	1.81	-1.25	-0.09	-0.08
	(50.81)	(1.45)	(0.96)	(1.08)	(0.44)	(0.15)	(0.02)	(0.01)
MaxEITC × Unmarried × Urban	556.75	1.75	0.62	0.54	0.60	-1.16	-0.09	-0.07
	(56.56)	(1.09)	(0.62)	(0.93)	(0.35)	(0.16)	(0.02)	(0.01)
MaxEITC × Married × Rural	47.74	1.06	2.30	1.30	1.14	-0.46	-0.00	-0.00
	(45.20)	(1.26)	(0.76)	(1.02)	(0.42)	(0.17)	(0.02)	(0.01)
MaxEITC × Married × Urban	-2.63	1.17	0.90	1.00	0.83	-0.47	-0.00	-0.00
	(45.16)	(1.20)	(0.64)	(0.94)	(0.36)	(0.16)	(0.02)	(0.01)
R-squared	0.273	0.064	0.030	0.025	0.013	0.080	0.514	0.075

Notes: See notes in Tables 4 and 5. Regressions in Panel A are identical to those in Tables 4 and 5, except instead of using sample years 2005–2017, we use 2008–2017 (since these years have information on "married within the past year"). Regressions in each panel are identical except for the treatment of marital status.

Table B.3: Isolating the Impact from the 2009 Federal EITC Expansion

Outcome	EITC Benefits	Moved	Moved More Urban	Moved CZ	Moved to Less-Distressed Area	Doubled Up	Multi-Gen HH	#Fam. in HH
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MaxEITC × Unmarried	664.02	1.86	1.22	0.55	0.49	-0.64	-0.05	-0.05
× Rural	(18.06)	(0.32)	(0.29)	(0.18)	(0.11)	(0.04)	(0.00)	(0.00)
MaxEITC × Unmarried	624.01	0.92	-0.01	-0.10	-0.03	-0.61	-0.05	-0.04
× Urban	(15.34)	(0.18)	(0.14)	(0.13)	(0.04)	(0.04)	(0.00)	(0.00)
MaxEITC × Married	388.59	-0.01	0.62	0.03	0.13	-0.27	-0.01	-0.01
× Rural	(17.79)	(0.22)	(0.17)	(0.15)	(0.08)	(0.04)	(0.00)	(0.00)
MaxEITC × Married	362.95	-0.00	-0.02	-0.09	-0.01	-0.27	-0.00	-0.01
× Urban	(19.39)	(0.16)	(0.12)	(0.12)	(0.04)	(0.03)	(0.00)	(0.00)
R-squared	0.275	0.065	0.030	0.027	0.013	0.026	0.013	

Notes: See notes in Tables 4 and 5. Regressions in this table are identical to those in Tables 4 and 5, except here *MaxEITC* is based only on the federal EITC and does not include state EITCs.

Table B.4: EITC's Effect on Where Women Live, Detailed Metropolitan Status (Units in Percentage Points)

Outcome:	Living in Rural Area (1)	Living in Semi-Rural Area (2)	Living in Suburban Area (3)	Living in Semi-Urban Area (4)	Living in Urban Area (5)
Panel A: All Women					
MaxEITC	-0.13	-0.33	0.20	0.08	0.18
	(0.07)	(0.26)	(0.24)	(0.56)	(0.40)
Mean Dep Var	11.3	9.3	29.1	36.0	14.2
Panel B: Younger Women (Under Age 45)					
MaxEITC	-0.20	-0.33	0.17	0.28	0.08
	(0.09)	(0.29)	(0.28)	(0.68)	(0.52)
Mean Dep Var	10.9	9.1	28.3	36.6	15.1
Panel C: All Black Women					
MaxEITC	-0.20	-0.24	-0.05	0.53	-0.04
	(0.09)	(0.19)	(0.25)	(0.59)	(0.54)
Mean Dep Var	7.1	5.7	25.5	34.4	27.3
Panel D: All White Women					
MaxEITC	-0.11	-0.36	0.23	0.18	0.07
	(0.09)	(0.30)	(0.28)	(0.62)	(0.43)
Mean Dep Var	13.2	11.0	29.6	36.0	10.2
Panel E: All Unmarried Women					
MaxEITC	-0.27	-0.25	-0.32	0.68	0.16
	(0.10)	(0.28)	(0.32)	(0.73)	(0.67)
Mean Dep Var	10.2	8.5	26.8	36.6	18.0
Panel F: All Married Women					
MaxEITC	0.01	-0.25	0.19	-0.11	0.16
	(0.06)	(0.19)	(0.22)	(0.35)	(0.19)
Mean Dep Var	12.5	10.2	31.5	35.4	10.4
Panel G: All Women Living in State of Birth (in Year $t-1$)					
MaxEITC	-0.18	-0.30	0.22	0.24	0.01
	(0.07)	(0.22)	(0.23)	(0.48)	(0.38)
Mean Dep Var	13.9	10.8	28.5	34.0	12.7

Notes: 2005 to 2017 ACS data. Panel A includes all 9,268,908 women 19–55 years old in the ACS. Sample sizes in Panels B–G: 6,012,897; 7,012,025; 1,011,390; 4,214,120; 5,054,788; and 5,011,852. Table 4 defines $MaxEITC$ and describes standard errors and weights used.

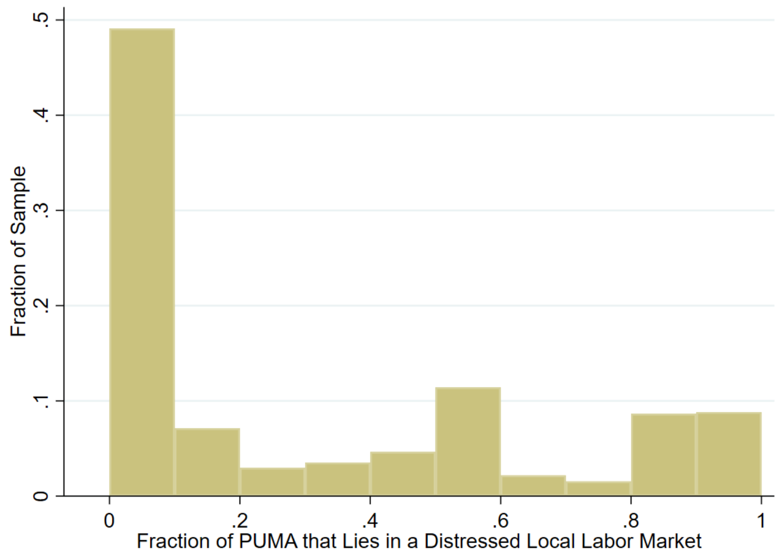

Fig. B.1. Histogram Showing Fraction of One's PUMA Lying in a Distressed Area

Notes: 2005–2017 ACS data. N=9,268,908. Distressed defined by Bartik (2020). Many PUMAs lie partly in distressed areas. Bartik (2020) appendix B describes how to crosswalk PUMAs (observed in ACS data) to local labor markets (the unit of geography for which "distressed" is defined).

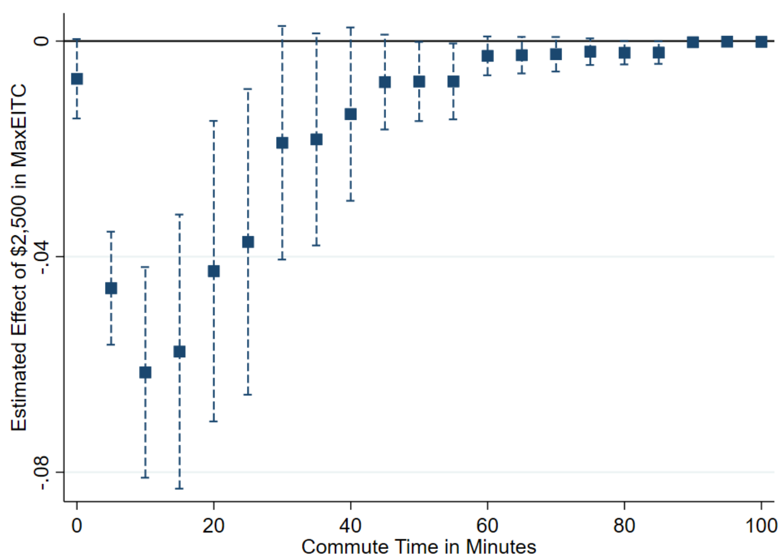

Fig. B.2. EITC Reduces Commuting Time for $Unmarried \times Rural_{t-1}$ Mothers

Source: 2005–2017 ACS data. Sample includes all working women 19–55 years old (N=7,055,948). Each estimate comes from a separate regression. Outcomes are binary for having a commute strictly larger than m minutes, where m = 0, 5, 10, 15, ..., 100.

Appendix C: The EITC and Migration: Evidence from Other Data Sources

1. 1980–2000 Census Data

In Table C.1, we use 1980, 1990, and 2000 Census data and the sample of all women 19–55 years old that did not live abroad 5 years earlier. The estimating equation is identical to equation (2) except $MaxEITC$ is based on factors from 5 years ago since Census data gives information about where one lives in years t and $t-5$. The federal and state EITC policy variation between 1980 and 2000 used to construct $MaxEITC$ is illustrated in Figure 1, Figure 2, Figure 3, and Figure 4.

In the baseline specification, we control for year FE, state (in year $t-5$) FE, number of kids FE, Black FE and White FE, high school graduate FE and college graduate FE, married, age cubic, number of children under 6. Demographic interactions include married interacted with FE for race, education, state, and year, as well as high school graduate FE and college graduate FE interacted with race FE, year FE, state FE, and an age cubic. We also control for state FE $\times$ year FE, and state FE $\times$ year FE $\times$ Unmarried. We show results for the full set of controls, and four subsets of these controls.

Results in Table C.1 Panel A resemble those in Table 3 and show that the EITC increases net migration out of rural areas (conditional on living in one in year $t-5$). Each $2,500 increase in $MaxEITC$ decreases the probability of living in a rural area by 0.7 to 1.0 percentage points, across five sets of controls. These results are larger than those in Table 3 and there are two likely reasons: one, the outcome is measured over a five year period (instead of just one) accounting for the fact that the EITC's effects likely grow over time; two, we look at a different time period when geographic mobility was higher.

Results in Panels B–E resemble those in Table 4 and—unlike Table C.1 Panel A—do not control for lagged metropolitan status. For unmarried mothers, we find that the EITC increases moving, moving from rural to urban areas, and moving across states, and decreases moving from urban to rural areas. For married mothers, we find decreases in moving, moving from rural to urban areas, moving from urban to rural areas, and moving across states.

These results show corroborating evidence that the EITC increases migration out of rural areas, with effects concentrated among unmarried mothers.

2. 1993–2017 IRS County-Level Migration Data

In Table C.2, we use 1993–2017 IRS county-level migration data. These are aggregate data on the number of households and people moving in and out of each county in each year. We define $MaxEITC$ as the state-year combination of the maximum EITC benefits available for families with 3+ children. (We cannot exploit differences in $MaxEITC$ by family size using aggregate data, so the variation used here is cruder than with micro-data.) For this analysis, $MaxEITC$ varies by year $\times$ state, whereas for the main analysis using individual data it varies by year $\times$ state $\times$ number of children.

We proxy for rural using county-level cost of living (COL), based on quality-adjusted rent for a 3-room home (results are similar if we use other home sizes). We divide counties into COL quintiles or quartiles (source: `https://www.huduser.gov/portal/datasets/fmr.html#history`) and weighted using 1990 county population (source: `https://library.duke.edu/data/sources/popest`). Lower COL counties are highly correlated with rural.

In Table C.2, we estimate $Y_{c,t} = \sum_q \beta_1 MaxEITC_{f(s-1,t-1)} + X'_{s,t}\beta_2 + \delta^1_c + \delta^2_t + \epsilon_{c,t}$. The outcome $Y_{c,t}$ is number of households in each county-year pair (variable named "returns" in the IRS data). $MaxEITC$ is interacted with county COL quantiles q to test whether EITC expansions affect the population inflows/outflows for different COL areas. County FE and year FE denoted by δ^1_c and δ^2_t. State-by-year controls (GDP growth rate, GDP, minimum wage, unemployment rate, any welfare waiver, and maximum welfare for a family of 2, 3, and 4) denoted by $X_{s,t}$.

Across sets of controls and using COL quintiles or quartiles, Table C.2 shows $MaxEITC$ decreases the population in the lowest COL counties. The largest population increase occurs in the highest COL quantile with the second highest increase occurring in the second highest COL quantile. We find insignificant effects on the second lowest COL quantile.

Overall, these results show corroborating evidence that the EITC increases migration out of rural (and low cost of living) areas.

Table C.1: EITC and Migration: Evidence from 1980, 1990, and 2000 Census Data

	(1)	(2)	(3)	(4)	(5)
Panel A: Outcome = Living in a Rural Area (Mean = 0.271)					
MaxEITC	-0.008	-0.010	-0.007	-0.009	-0.009
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Panel B: Outcome = Moved (Mean = 0.500)					
MaxEITC × Unmarried	0.119	0.119	0.115	0.115	0.115
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
MaxEITC × Married	-0.028	-0.028	-0.033	-0.033	-0.033
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Panel C: Outcome = Moved from Rural to Urban (Mean = 0.039)					
MaxEITC × Unmarried	0.004	0.006	0.004	0.005	0.005
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
MaxEITC × Married	-0.005	-0.003	-0.006	-0.004	-0.004
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Panel D: Outcome = Moved from Urban to Rural (Mean = 0.176)					
MaxEITC × Unmarried	-0.029	-0.031	-0.029	-0.030	-0.030
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
MaxEITC × Married	-0.005	-0.007	-0.002	-0.003	-0.003
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Panel E: Outcome = Moved Across States (Mean = 0.104)					
MaxEITC × Unmarried	0.008	0.008	0.007	0.007	0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MaxEITC × Married	-0.010	-0.010	-0.008	-0.008	-0.009
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls					
Year FE, State FE	X	X	X	X	X
Demographics	X	X	X	X	X
State FE × Year FE		X		X	X
Demographic Interactions			X	X	X
State FE × Year FE × Unmarried					X

Notes: 1980, 1990, 2000 Census data. Sample includes all women 19–55 years old (N=8,217,808). We exclude women who lived abroad 5 years earlier. Per IPUMS: In 1980, responses to questions about migration were coded for only half the persons included in the IPUMS. These cases provide accurate proportional distributions but not correct absolute numbers for the general population. For correct absolute numbers, users should multiply PERWT by 2. (Source: https://usa.ipums.org/usa-action/variables/MIGRATE5#comparability_section.) All effects by marital status are statistically different at the 99 percent level. The estimating equation resembles equation (2) except $MaxEITC$ is based on factors from 5 years ago to match the reference year for the outcome variables. Panel A also controls for living in a rural area in year $t-1$. Standard errors robust to heteroskedasticity and clustered at the state (in year $t-5$) level.

Table C.2: The EITC and Aggregate County-Level Migration: IRS Data

Dividing All Counties into:	Cost of Living Quartiles			Cost of Living Quintiles		
	(1)	(2)	(3)	(4)	(5)	(6)
MaxEITC	-145.3	-128.8	-128.8	-143.1	-130.0	-130.0
× Lowest COL	(41.9)	(44.1)	(88.7)	(40.4)	(42.8)	(85.1)
MaxEITC	28.0	-9.4	-9.4	3.9	-25.0	-25.0
× COL=2	(39.3)	(42.8)	(86.2)	(38.4)	(41.4)	(82.5)
MaxEITC	290.7	182.0	182.0	190.4	93.5	93.5
× COL=3	(44.6)	(47.0)	(96.1)	(39.6)	(43.9)	(86.5)
MaxEITC	477.1	284.7	284.7	297.7	171.0	171.0
× COL=4	(107.3)	(102.7)	(147.3)	(50.5)	(53.1)	(115.0)
MaxEITC				470.2	294.6	294.6
× Highest COL				(120.8)	(114.5)	(154.3)
R-squared	0.940	0.941	0.941	0.940	0.941	0.941
Observations	67,955	67,955	67,955	67,955	67,955	67,955
F-Test P-Value (Eq. Estimates)	0.000	0.000	0.000	0.000	0.000	0.000
Controls						
Year and County FE	X	X	X	X	X	X
State-Year Factors		X	X		X	X
SEs Clustered at County Level			X			X

Notes: 1993-2017 IRS data. Data are county-year observations. Negative estimates on lower-cost-of-living counties can be interpreted as *MaxEITC* leading to lower population in these counties. Lower cost of living counties are highly correlated with rural counties. Standard errors robust to heteroskedasticity and in columns 3 and 6 are clustered at the county level.