Journal of Policy Practice and Research
https://doi.org/10.1007/s42972-022-00054-5

ORIGINAL PAPER

Demographic, Economic, and Geographic Factors Associated with Uptake of the Earned Income Tax Credit

Paul Lanier[1] · Whitney Afonso[2] · Gerard Chung[1] · Katherine Bryant[1] · Danny Ellis[3] · Alexandria Coffey[1,4] · Anita Brown-Graham[2] · Sarah Verbiest[1]

Accepted: 20 March 2022

Abstract
The US federal Earned Income Tax Credit (EITC) is an economic support program for low- and moderate-income workers. About 80% of individuals eligible for the EITC participate in the program. However, improving awareness and full uptake of the EITC program has proven a challenge, and few studies have examined factors associated with EITC participation. The purpose of this study was to use county-level data to model the association of demographic, geographic, and economic factors with EITC participation rates in North Carolina from 2010 to 2017. We calculated three rates of EITC uptake: per capita, per persons in poverty, and per persons with low-income. Multilevel linear growth modeling was used to examine between-county variability in within-county trajectories of change in EITC uptake. County rurality and proximity to Internal Revenue Service Volunteer Income Tax Assistance sites were not associated with EITC participation. We found no evidence that residents of urban and rural counties had differences in EITC uptake but findings suggest that counties with larger proportions of African American, Hispanic, and Native American individuals had higher levels of uptake. Our findings have implications for policymakers and researchers seeking to understand EITC participation and set an empirical foundation for future research.

Keywords Earned Income Tax Credit · Participation · Race · Rural

✉ Paul Lanier
planier@email.unc.edu

[1] School of Social Work, Jordan Institute for Families, The University of North Carolina at Chapel Hill, 325 Pittsboro Street, Chapel Hill, NC 27599-3550, USA

[2] School of Government, The University of North Carolina at Chapel Hill, Chapel Hill, NC, USA

[3] College of Business, East Carolina University, Greenville, NC, USA

[4] Gillings School of Global Public Health, Department of Maternal and Child Health, The University of North Carolina at Chapel Hill, Chapel Hill, NC, USA

Published online: 06 April 2022

Introduction

The Earned Income Tax Credit (EITC) is a federal program designed to provide economic benefits to low- and moderate-income working families. The EITC is currently one of the largest and most effective anti-poverty programs in the USA (Internal Revenue Service [IRS], 2020). More than 25 million workers received the federal EITC for tax year 2019, totaling almost $63 billion dollars in benefits (National Conference of State Legislatures [NCSL], 2020). Despite the successes of the EITC, many individuals who are eligible for this important benefit do not apply for it and therefore do not receive the benefit. The IRS estimates that the national EITC uptake rate is 80% (Beecroft, 2012). A 20% participation gap requires policymakers and researchers to consider questions such as who is left out, what are the individual and systemic barriers to their participation, and how can EITC participation improve.

The Federal Earned Income Tax Credit

The federal EITC began in 1975 and while initially enacted on a temporary basis, the EITC is now considered the most effective anti-poverty program in the USA for working-aged people (Center on Budget and Policy Priorities [CBPP], 2019; Crandall-Hollick, 2018). In early phases, the federal EITC was considered a "work bonus plan" and the maximum credit was $400, which increased slightly over the next decade. In 1986, the program expanded, the maximum credit grew to $800, and the policy was reframed as a strategy to reduce unemployment and welfare participation. Due to the success and bipartisan support of the federal EITC, 30 states have implemented a state EITC program. The focus of this paper is on the federal EITC.

The modern EITC began in the 1990s, when the credit increased again and expanded to include a modest credit for childless workers (Crandall-Hollick, 2018). Recently, in response to the economic effects of the pandemic, the EITC benefit for childless workers expanded to $1,500 and the individual income limit was raised to $21,000 (Marr et al., 2021). Although the EITC has continued to evolve over time, the same basic function has remained: to reduce poverty through cash transfer and encouraging workforce participation.

Poverty Reduction Tool

As one of the primary federal and state policies to reduce poverty, the EITC has been demonstrably successful, raising an estimated 5.6 million people above the poverty line in 2018 via their EITC benefit (CBPP, 2019). Literature suggests the EITC decreases welfare program entries (Grogger, 2004), encourages entry into the labor force (Eissa & Hoynes, 2006; Neumark & Wascher, 2000; Nichols & Rothstein, 2015), and promotes education and economic mobility of the children of workers claiming the EITC (Bastian & Michelmore, 2018). The EITC tends to yield the greatest positive impacts for single parent households and people of color

(Baughman & Dickert-Conlin, 2003; Bayaz Ozturk, 2018; Cancian et al., 2010; Eissa & Hoynes, 2006; Komro et al., 2019; Nichols & Rothstein, 2015). Given these substantial results, it is not surprising the EITC has become a popular bipartisan poverty reduction policy.

Eligibility

While there are many nuances, eligibility is broadly based on earned income, age, presence of social security number, citizenship/residence status, and number, age, and residence of dependent custodial children (IRS, 2019). The EITC provides a credit as a fixed percentage of household earnings at an increasing rate until it reaches a maximum level, at which it plateaus and eventually decreases as increasing incomes begin to exceed eligible levels. The EITC benefit varies according to the number of children in the household and the household's overall earnings. For instance, in 2020, a worker with no children making \$15,820 would be eligible for an EITC benefit up to \$538; a worker with the same salary and one child would qualify for up to \$3,584; and if that same worker had three or more children, they would qualify for up to \$6,660 (IRS, 2021c).

Uptake of Earned Income Tax Credit

EITC uptake (i.e., participation) is the proportion of eligible individuals who file for and receive the EITC benefit. The IRS estimates that nationally about 20% of the workers eligible for the EITC do not apply to the program (Beecroft, 2012). However, it is difficult to know exactly who is eligible for the EITC, but not claiming, as eligible individuals may not file taxes (Plueger, 2009) in part due to not being required to submit taxes because their annual income is below a certain threshold. The IRS, states, scholars, and non-profits continue to explore potential policies and practices to increase EITC uptake and improve understanding about why 20% of eligible individuals do not claim the EITC. For example, because receiving the recent Economic Impact Payments (i.e., pandemic stimulus checks) and monthly Child Tax Credit payments is dependent on filing taxes, it is thought policies tying eligibility to tax filing may encourage non-filers to file (IRS, 2021d, e).

Outreach to Improve Uptake of Earned Income Tax Credit

Prior research has also sought to identify ways to increase EITC uptake. Recently, six randomized experiments in California used "nudges" (i.e., text messages and letters) to raise awareness about the EITC, but researchers found no effect on recipients' rates of filing taxes or EITC uptake (Linos et al., 2020). Another study found when tax preparers provided individuals with information about the EITC, they did not change their EITC enrollment behavior, but when tax preparers explained how they could maximize their EITC return, their behavior was modified (Chetty & Saez, 2013). Many states have policies to promote uptake (e.g., requiring employers to provide information to employees on the EITC), but the sizeable non-uptake rates across states emphasize the need for further enrollment strategies. Indeed, there is no evidence that notification policies have an impact on uptake (Cranor et al., 2019). In contrast, a recent IRS field experiment found that receiving a letter encouraging tax filing increased EITC uptake by 0.32 percentage points, a 7% increase relative to those who did not receive any communication (Goldin et al., 2021). While the effect is small, these findings support the concept that policies and programs aimed at improving tax filing can impact EITC uptake (Goldin et al., 2021). Identifying factors associated with EITC uptake could inform more targeted efforts, potentially resulting in larger increases in uptake. To date, there is little empirical evidence of factors associated with EITC uptake to inform future policy or practice interventions.

Factors Associated with Earned Incomes Tax Credit Uptake

Relatively little is known about factors associated with claiming the EITC among those who are eligible. According to the , para. 5), EITC-eligible non-participants are more likely to be “people who are living in rural areas, self-employed, receiving disability income or have children with disabilities, without a qualifying child, not proficient in English, [or] grandparents raising grandchildren.” However, it is not clear what research the IRS used to produce these conclusions. Administrative burdens, such as learning how to apply and audit costs, stress, and stigma, have been identified as barriers to EITC uptake among other government-sponsored programs, including the Supplemental Nutrition Assistance Program (SNAP; Herd & Moynihan, 2020; Pinard et al., 2017; Thomson et al., 2020). A recent review also identified lengthy applications, strict verification and recertification, race, and ethnicity, particularly Hispanic, as factors associated with decreased SNAP participation (Pinard et al., 2017).

One large rigorous study in Virginia found that about 70% of eligible households using public assistance claimed the EITC, leaving well over $100 million in unclaimed benefits (Beecroft, 2012). Individuals with lower and inconsistent incomes were least likely to file their taxes, and therefore could not receive the EITC benefit. However, about 80% of EITC-eligible households who did not file their taxes were not required to do so due to their lower income levels, and many of these individuals may not have been aware that filing would have made them eligible for EITC support. Participation rates were higher among households with children compared to those with no children, perhaps due to higher benefit levels for filers with children or the ways in which information about the EITC is disseminated. Interestingly, the study found that families with multiple children were actually less likely to claim the EITC than families with one child.

Demographic Factors

EITC uptake may differ by race or ethnicity; however, research in this area is thin and little available evidence suggests that uptake rates differ by race or ethnicity. For instance, Beecroft (2012) found that eligible non-claimants of the EITC did not differ by race or ethnicity. To date, no focused analysis has assessed how race and ethnicity may or may not play a role in EITC uptake, despite previous research showing the EITC meaningfully impacts birth outcomes for African American and Hispanic mothers (Komro et al., 2019). Given the EITC's impact as a poverty reduction and public health tool, more research is needed to understand any differences by race or ethnicity.

Geographic Factors

Although working poor families are equally distributed in urban and rural communities, one prior study suggested that families in urban areas are most likely to enroll in the EITC (Berube & Tiffany, 2004). This may be due to better access to information, transportation, and other resources related to the EITC. The digital divide between rural and urban areas may also affect EITC uptake. For example, small businesses in rural NC utilize technology- and e-commerce-based practices 21% less than those in NC's urban areas (Richmond et al., 2017). Without electronic filing accessibility or utilization, the EITC could be overlooked in tax preparation.

Additionally, personal views and socio-cultural norms regarding government support may differ between urban and rural communities to the extent that rural workers may be more skeptical about the EITC and avoid tax preparation altogether. A Pew Research Center opinion poll found that 49% of adults in rural areas believed that the "government is doing too many things better left to businesses and individuals," compared to 28% of urban residents (2018). Distrust of government—although now at a historic high nationally—is higher among rural residents than among urban residents (Pew Research Center, 2019). Reflecting on the failed "nudge" experiments, researchers have suggested that perceived messages about the EITC informing low-income individuals "they are eligible for large sums of cash" may "feel too good to be true" (Linos et al., 2020, p.15).

Another feature of geography that may impact EITC uptake is the ability to access a tax preparation site. Because tax filing is a complicated process, the majority of filers use a professional for tax preparation. The federal Volunteer Income Tax Assistance (VITA) program was started in 1969 as a free tax preparation service for low-income individuals (below $57,000 a year), the elderly, and limited English-speaking taxpayers. VITA provides community-based services in over 4,000 sites (Prosperity Now, 2018; Weinstein & Patten, 2016). In 2018, VITA sites processed over 1.3 million total returns and generated over $646 million in EITC refunds (Prosperity Now, 2018). While many taxpayers have turned to online tax preparation services in recent years, clearly many use in-person VITA sites for tax preparation and EITC benefits. However, it is not clear whether geographic distance to a VITA site is a barrier to quality tax preparation services and therefore a barrier to receiving EITC benefits.

Study Aims

This study seeks to fill a large gap in the literature regarding the demographic, geographic, and economic factors associated with EITC uptake. Although the presumption has been that a lack of knowledge about the EITC is the primary driver of under-enrollment, evidence suggests that knowledge about the EITC is insufficient for closing the gap between its availability and enrollment (Chetty & Saez, 2013; Cranor et al., 2019). This study aims to understand and estimate the association of several county-level demographic, geographic, and economic factors on county-level EITC participation in NC over an 8-year period, with particular focus on two underexplored factors: county urbanicity (i.e., urban vs. rural) and county racial or ethnic composition.

Methods

This quantitative study was part of a larger mixed methods study of EITC uptake. As a sequential mixed methods design, we sought to use quantitative analysis of available secondary data to better understand EITC uptake, test prevailing theories regarding predictors of uptake, and use results in subsequent qualitative focus groups in specific communities. The purpose of the modeling approach was both descriptive and explanatory. The quantitative study was reviewed and determined to be not human subjects research by the institutional review board at the University of North Carolina at Chapel Hill.

Data and Sample

We created a dataset of annual county-level data collected from federal and state government data sources, including the United States Census Bureau (CB), Internal Revenue Service (IRS), U.S. Bureau of Economic Analysis (BEA), and the North Carolina (NC) Office of State Budget and Management (OSBM). All data were collected from the websites of the respective organizations (Table 1). Data represented aggregate county-level information for all 100 counties in NC from 2010 to 2017.

Measures

Dependent Variables

Individual-level data for tax filers is not publicly available. Therefore, because we cannot directly measure individual EITC uptake; indeed, even the IRS does not have information about non-filers, we created three county-level aggregate measures to serve as its proxy. In the absence of a clear population-level indicator for EITC participation, we developed three outcome variables to operationalize EITC uptake differently, which also serves as a sensitivity test for predictor variables. Data for the annual number of EITC returns in each county from tax years 2010–2017 was publicly accessible from the IRS (IRS, 2021a). Using this data, we created the following three outcomes.

The first outcome is the *per capita EITC uptake*, or the annual number of EITC returns per 1,000 people at the county-level population from 2010 to 2017. We divided the annual number of EITC returns for each county by the county's total population

Table 1 Key variables and descriptions for EITC analysis

Key construct	Variable	Year	Data source	Univariate *M* (*SD*)/average % all counties in 2010
Dependent variables				
Per capita EITC uptake	# returns per 1000 people in each county	2010–2017	IRS	103.4 (21.3)
Per poverty EITC uptake	# returns per 1000 people in poverty in each county	2010–2017	IRS	566.7 (92.6)
Per low-income EITC uptake	# returns for people earning between $25,000 and $50,000 per 1000 people in the county population	2010–2017	IRS	26.5 (5.7)
Demographic				
% Race and ethnicity	% African American/Black; % Asian; % American Indian/Alaskan Native; % Hispanic	2010–2017	US Census	African American (21%); American Indian/Alaska Native (1.9%); Asian (1.1%); Hispanic (6.5%)
Geographic				
Urban/rural status	Urban or rural status of county	2013	USDA	Urban (84%); rural (16%)
VITA sites	4-level categorical variable indicating: (a) no VITA sites within 50 miles, at least one VITA site, (b) within 25–50 miles, (c) within 10 to 25 miles, and (d) within 10 miles	2020	IRS's VITA locator	(a) No VITA sites within 50 miles (12%); at least one VITA site, (b) within 25–50 miles (46%), (c) within 10 to 25 miles (29%), and (d) within 10 miles (13%)
Economic				
Unemployment	% Unemployment	2010–2017	NC OSBM	10.7% (2.0)
Income per capita	Income per capita ($ thousands)	2010–2017	BEA	$31.3 (5.1)
Income inequality	Gini coefficient	2010–2017	Census Bureau	0.45 (.03)
Earnings of working poor	Median earnings for food stamp recipients ($ thousands)	2012	NC Food & Nutrition Services	$12.4 (3.8)

Table 1 (continued)

Key construct	Variable	Year	Data source	Univariate *M* (*SD*)/average % all counties in 2010
Industry establishments and payroll	% Total establishment and payroll (thousands of dollars) by industry type: (a) Forestry, Fishing and Hunting, and Agricultural Support Services; (b) Construction; (c) Manufacturing; (d) Health Care and Social Assistance; and (e) Accommodation and Food Services	2017	US Census Bureau	Forestry (1.2%); Construction (11.4%); Manufacturing (4.5%); Health Care (10.7); Accommodation (9.3%)

Univariate statistic is the arithmetic mean for all counties for all years data is available

BEA US Bureau of Economic Analysis, *IRS* US Internal Revenue Services, *OSBM* NC Office of State Budget and Management, *VITA* Volunteer Income Tax Assistance, *USDA* United States Department of Agriculture from 2010 to 2017. The data for each county's population was available from NC's OSBM website (OSBM, 2020a). However, using per capita EITC uptake as a proxy for actual individual uptake is problematic because any individual filer making more than approximately $16,000 and any family making more than approximately $50,000 (depending on the number of children) would not be eligible for the EITC.

Because our per capita EITC uptake measure does not account for the specific eligibility criteria for the EITC, we included two additional outcome variables to measure EITC uptake specifically among individuals who would likely be eligible for the EITC. The second outcome is the *per poverty EITC uptake*, or the annual number of EITC returns per 1,000 people in poverty at the county-level. To create this outcome, we divided the annual number of EITC returns for each county by the number of persons in poverty in that county and multiplied by 1,000. We obtained data for the number of persons in poverty in each county from the U.S. CB's Small Area Income and Poverty Estimates program (CB, 2020a). A limitation of this measure as a proxy for uptake is that many individuals in poverty do not earn income and would not be eligible for the EITC. Outcomes one and two use the same numerator (i.e., annual number of EITC returns) but different denominators (i.e., per 1,000 county inhabitants and per 1,000 county inhabitants in poverty, respectively).

The third outcome uses a different numerator and denominator to measure EITC uptake. This measure is *per low-income EITC uptake*, or the annual number of EITC returns among those with an annual adjusted gross income between $25,000 and $50,000. IRS data is broken down into several income categories, including those who make between $25,000 and $50,000 annually, which comprises a high proportion of individuals likely eligible for the EITC. We created this third outcome by dividing the annual number of EITC returns for those who earned between $25,000 and $50,000 in adjusted gross income by the total number of filers who earned between $25,000 and $50,000. This measure is limited by the fact that we cannot differentiate between individual filers and filers with children, which largely determines the EITC eligibility threshold.

Independent Variables

Predictor and control variables were selected based on extant literature and theory on tax preparation as well as feedback from the study's advisory group. Depending on the availability of data, predictors were either time-invariant (i.e., taken from one point in time) or time-varying (i.e., data varied for each year).

Demographic Predictors Our main demographic predictor of interest was *county race and ethnicity*. One of the broader purposes of the project was to understand whether county-level EITC uptake varied by the racial and ethnic composition of that county. Data on the percentage of racial and ethnic groups using US Census groupings (i.e., Black/African American, American Indian/Alaska Native, Asian, Native Hawaiian/Other Pacific Islander, and Hispanic) in each county by year was obtained from the CB (CB, 2020b).

Geographic Predictors Two variables examined predictors of EITC uptake related to county geography. First, we included a time-invariant measure of *urban or rural status* of the county. To identify each county's status, we used the 2013 Rural–Urban Continuum Codes (RUCC; Economic Research Service, 2019), a classification scheme that distinguishes metropolitan counties by the population size of their metro area and nonmetropolitan counties by their degree of urbanization and adjacency to a metro area (Economic Research Service, 2019). We modeled all nine RUCC levels and categorized each county as either urban or rural.

Second, we calculated each county's *proximity to VITA sites* by tracking the distribution of VITA sites in each county relative to the county seat using the locator tool services provided by the IRS (IRS, 2021b). Using the ZIP code of the county seat of, we identified the number of VITA sites within 10 miles, 25 miles, and 50 miles (these are fixed choices provided by the VITA locator tool). We then created a four-level categorical variable indicating at least one VITA site (a) within 10 miles (referent group), (b) within 10 to 25 miles, (c) within 25–50 miles, and (d) no VITA sites within 50 miles.

Economic Predictors We used five measures to characterize the economic features of each county. First, the county *unemployment rate* was calculated as the percentage of the county's population that was unemployed, using annual data from the NC OSBM (2020b). Because this data was reported as a monthly statistic, we computed an average yearly unemployment percentage by averaging across the 12 months for each year from 2010 to 2017. Second, we examined the average income in the county using data on the *income per capita* (calculated in thousands of dollars) for each county, provided by the BEA (BEA, n.d.). Third, we were interested in understanding the median wages for low-income workers in each county. Existing historical data tracked Food and Nutrition Services recipients' wages by county. As a proxy measure for the income of the working poor population in each county, we used each county's 2012 *median earnings for food stamp recipients* (calculated in thousands of dollars), who were required to register for work. Fourth, *income inequality* in counties was measured with the Gini index using annual data from the CB (2016). The Gini coefficient ranges from 0, indicating perfect equality (where everyone receives an equal share), to 1, perfect inequality (where only one recipient or group of recipients receives all the income).

Our fifth economic indicator used information on the industries and businesses in each county in 2017, and was obtained from the Economic Annual Surveys published by the CB (CB, 2019). It is possible that information networks and access to information regarding tax filing differ among economic sectors which constitute a given county. The data included the number of *industry type and annual payrolls* (in thousands of dollars) based on the North American Industry Classification System. We focused on five industry types: (a) Forestry, Fishing and Hunting, and Agricultural Support Services; (b) Construction; (c) Manufacturing; (d) Health Care and Social Assistance; and (e) Accommodation and Food Services. The percentage of establishments in each industry type across all industries was computed using the raw numbers of establishments in each industry type and for all industry types.

Data Analysis

We used multilevel linear growth modeling to develop three models predicting the three EITC uptake outcomes. The models were developed to examine between-county variability in within-county trajectories of change. Because data was collected from counties at multiple points in time, growth models can utilize time-variant information to estimate between-county and within-county differences over time (Curran et al., 2010). Multilevel linear growth modeling allowed us to estimate both within-county and between-county variations in specified outcomes (Singer & Willett, 2003).

We first estimated an unconditional growth model in which the observed repeated outcome was expressed as a linear function of time (i.e., in years, from 2010 to 2017). This model captured the within-county outcome trajectory (Singer & Willett, 2003). A key element of the unconditional growth model is that it allows the intercept and the slope to vary randomly across counties in order to capture variabilities in trajectories across counties. That is, each county can have a different initial status in terms of the dependent variable, and that variable can change more quickly or slowly over time. The model estimated fixed effects representing the average initial level of outcome and average rate of change in outcome across all counties; it also estimated random effects representing the county-specific deviations from both of those means. The variance of random effects summarizes the variation in individual intercept and slope around these means, allowing us to estimate the within-county and inter-county differences in outcome trajectories (Curran et al., 2010).

Next, we estimated a conditional growth model in which the change in outcome over time was conditioned on a group of time-invariant and time-varying predictors and controls. Time-varying predictors and controls were added to the model, and the coefficients of these variables in the model represented the average change in outcome with each unit change in the predictor/control across time. All models were estimated in Stata version 16 using restricted maximum likelihood estimation (Singer & Willett, 2003). In each model, the variance/covariance matrix of the residuals was specified as unstructured. Information criteria (i.e., Akaike information criterion [AIC]; Bayesian information criterion [BIC]) were used to evaluate the relative goodness-of-fit across the models (Singer & Willett, 2003). Lower values for these statistics indicate better model fit (Schwarz, 1978). We report results from the final model that provided the best fit to the data.

Results

Multilevel Modeling

We first estimated an unconditional linear growth model for all three outcomes to examine the mean change in the outcome from 2010 to 2017. We then fitted a quadratic curve, and the results—including the model fit indices (i.e., decrease in AIC and BIC)—indicated that a quadratic model fitted the data better for all three outcomes. Thus, we used a quadratic model of change for the remaining analyses.

Demographic Predictors

Table 2 presents the results of final multilevel models for all three dependent variables. In all three models, a county's proportion of Black/African American residents was associated with greater EITC uptake. Findings for other racial and ethnic groups differed across models. For *per capita EITC uptake*, the rate of returns was also associated with a higher percentage of American Indian/Alaska Native residents in the county ($b=51.40$; $p<0.05$). For *per low-income EITC uptake*, uptake was associated with higher percentage of American Indian/Alaska Native ($b=21.71$; $p<0.05$) and Hispanic residents in the county ($b=35.30$; $p<0.001$).

Geographic Predictors

County rural or urban status was not associated with EITC uptake in any models. Relatedly, proximity to VITA sites was not associated with EITC uptake. These two variables were correlated at the bivariate level ($r=0.21$; $p<0.05$), indicating that neither proxy measures of rurality nor access to in-person tax preparation services were associated with EITC uptake.

Economic Predictors

Unemployment rate was negatively associated with all three EITC uptake measures ($p<0.01$). This finding is unsurprising because employment is required for EITC eligibility. Other significant findings for economic predictors were not consistent for all three models. Per capita income was associated with *per capita EITC uptake* ($b=-0.15$; $p<0.05$) and *per poverty EITC uptake* ($b=5.26$; $p<0.001$). Income inequality, measured using the county Gini index, was negatively associated with *per poverty EITC uptake* ($b=-1169.70$; $p<0.001$) and *per low-income EITC uptake* ($b=-15.67$; $p<0.001$). Industry proportion and annual payroll were not consistently related with EITC uptake.

Discussion

After analyzing data from 2010 to 2017 for all 100 counties in NC, we found evidence that residents of rural counties are just as likely to claim the EITC as their urban counterparts. We also found that counties with larger African American, Hispanic, and Native American populations had more EITC claims on average, after accounting for factors like poverty, unemployment, and access to VITA sites. These findings highlight the need for researchers and policymakers to further explore why specific communities have greater than expected EITC uptake to inform efforts to improve uptake in other communities. The qualitative component of this study will entail working in communities around NC and exploring how networks such as communities of faith and non-profits may contribute to these higher levels of EITC uptake among Black, Hispanic, and Native American populations.

Table 2 Results of three multilevel models for county EITC uptake

Variable	Per capita EITC uptake			Per poverty EITC uptake			Per low-income EITC uptake		
	b	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*
Intercept	91.31	20.16	***	894.80	143.31	***	27.96	8.08	***
Year	0.99	0.16	***	−16.97	3.08	***	0.71	0.07	***
Year * Year	−0.33	0.01	***	2.38	0.34	***	−0.06	0.01	***
Demographic									
% Black/African American	90.31	8.61	***	256.52	50.26	***	23.15	3.42	***
% American Indian/Alaskan Native	51.40	24.02	*	−94.89	147.70		21.71	9.98	*
% Asian	−121.33	74.61		−458.80	679.77		−49.95	33.14	
% Hispanic	8.30	24.97		−236.82	177.21		35.30	10.71	***
Geographic									
Rural (ref: Urban)	1.76	3.82		−13.39	21.44		0.99	1.51	
VITA Sites (ref: > 0 sites within 10 miles)									
> 0 sites within 10–25 miles	2.24	3.46		−30.39	19.69		−0.26	1.37	
> 0 sites within 25–50 miles	4.71	3.25		−27.26	18.28		−0.16	1.28	
0 sites within 50 miles	1.39	4.91		−1.84	27.48		−0.70	1.94	
Economic									
Income per capita	−0.15	0.08	*	5.26	1.19	***	0.03	0.04	
% unemployed	−0.63	0.09	***	−4.36	1.83	**	−0.13	0.04	***
Income inequality (Annual Gini)	−13.65	7.88		−1169.70	150.55	***	−15.67	3.76	***
Working poor average income	0.27	0.31		0.27	1.71		0.11	0.11	
% Industry total									
% Accommodations and Food Services	114.63	70.90		477.92	394.04		−14.10	27.84	
% Forestry, Fishing, and Agricultural	−146.09	107.85		−1853.64	611.44	**	−45.01	43.11	
% Construction	−117.62	52.70	*	−9.18	297.69		−22.08	20.88	
% Health care and Social Assistance	−33.89	71.56		−367.74	406.10		−12.15	28.41	
% Manufacturing	222.44	78.45	**	1200.40	453.03	**	58.22	31.11	
Industry payroll (in $ millions)									
Accommodations and Food Services	−0.01	0.04		0.68	0.24	**	0.02	0.02	
Forestry, Fishing, and Agricultural	0.11	0.57		5.81	3.20		−0.10	0.22	
Construction	−0.00	0.02		−0.09	0.09		−0.00	0.01	
Health Care and Social Assistance	−0.00	0.01		−0.17	0.05	**	−0.00	0.00	
Manufacturing	0.01	0.01		0.05	0.03		−0.00	0.00	
Variance components									

Table 2 (continued)

Variable	Per capita EITC uptake			Per poverty EITC uptake			Per low-income EITC uptake		
	b	*SE*	*p*	*b*	*SE*	*p*	*b*	*SE*	*p*
Level 1									
Within-county residual	2.27	0.14		1645.45	103.83		0.55	0.04	
Level 2									
Intercept	123.75	23.83		1937.61	478.93		12.13	2.17	
Slope	0.43	0.08		31.33	11.40		0.05	0.01	

$^{*}p<.05$; $^{**}p<.01$; $^{***}p<.001$

Implications for Policy

This study assessed potential differences between EITC uptake in urban and rural communities and among different racial and ethnic populations. Despite the evidence that both rural residents and people of color face systemic barriers that prevent their equitable access to government programs (Liu & He, 2019; Phillips, 2020), we find no evidence of systemic differences for EITC participation. In fact, we found no evidence that residents of urban and rural counties have differences in EITC uptake, and we found that counties with larger proportions of African American, Hispanic, and Native American residents had higher levels of EITC uptake. These findings indicate that policymakers and researchers should explore other possible causes of higher EITC uptake beyond rurality or race and ethnicity. Previous research has shown that knowledge of the EITC alone does not increase its rates of uptake (Chetty & Saez, 2013; Cranor et al., 2019), but that EITC benefit-maximizing behavior is noticeably different in high-knowledge areas (Chetty et al., 2013). Better understanding these high-knowledge areas—and any potential correlations to residents' race and ethnicity—will help inform future policy and outreach. Furthermore, as policymakers work to close disparities between urban and rural communities and minority populations, our results suggest that the EITC does not exacerbate those differences. In fact, they may be an effective tool in closing them.

Limitations

This study represents a first step toward disentangling the numerous factors that impact a complex behavior. However, several aspects of our study design limit the ability of our findings to describe EITC uptake. First, we used aggregated county-level data, and it is not sound reasoning to explain individual behaviors using group averages (i.e., the ecological fallacy). Future research must incorporate data from individuals and households. Furthermore, counties are often very heterogeneous, and smaller geographic units would better approximate actual individual behaviors. However, access to individual-level data or data at the ZIP code level, for example, was not available.

Second, prior research and theory suggest that human behavior is highly influenced by nuanced factors related to constructs like prior behavior, personal values, social norms, influential relationships, and political affiliation. Because we only focused on constructs related to economic, demographic, and geographic factors, future research should explicitly test and refine behavioral theories of EITC uptake. Third, the data used for this study does not actually measure individual uptake of EITC, an issue of measurement validity, but rather uses several imperfect proxy measures. Although rates use a denominator that limits the population to lower incomes, it does not precisely reflect the phase in and out ranges of EITC distribution. Last, this study is limited to NC and is not generalizable to other states or populations.

Conclusion

The EITC continues to be an important policy that returns wealth to communities and earned funds to the working poor. This policy remains an important mechanism for improving health and economic well-being as it continues to lift millions of Americans out of poverty (CBPP, 2019). However, with an estimated 20% of eligible workers not claiming the EITC, this study sought to understand whether those people were more likely to live in rural counties or in counties with larger populations of color. Although we were not able to look at data from individual taxpayers, our evidence suggests that there is not an urban–rural divide in EITC uptake and that counties with a higher percentage of residents of color are in fact more likely to have higher levels of EITC uptake, even after controlling for access to VITA sites, poverty, unemployment, and other socioeconomic factors.

This study establishes a foundational analysis for researchers who want to better understand EITC uptake. We believe that two streams of data should emerge and continue. First, qualitative work must be done to better understand patterns in knowledge and uptake of the EITC. Beginning by examining differences between White, African American, Hispanic, and Native American social networks (and differences within those networks) may be generative. This is not a question that the available data can answer without an in-depth qualitative analysis. The IRS does not collect data on the race or ethnicity of individual taxpayers, so researchers are not able to link that data to cultural, educational, or social networks. Second, we believe that more research needs to look for other factors that may impact EITC uptake to further inform future qualitative work. Exploring additional high-level relationships like those explored in this study will be critical to help steer future research.

Acknowledgements We want to acknowledge our state steering committee for their ongoing input and feedback throughout this study.

Funding This study was funded by a grant from the Robert Wood Johnson Foundation.

Declarations

Ethics Approval This study was reviewed and approved by the institutional review board (IRB) at the University of North Carolina at Chapel Hill (#20–0807).

Conflict of Interest The authors declare no competing interests.

References

Bastian, J., & Michelmore, K. (2018). The long-term impact of the Earned Income Tax Credit on children's education and employment outcomes. *Journal of Labor Economics, 36*(4), 1127–1163. https://doi.org/10.1086/697477

Baughman, R., & Dickert-Conlin, S. (2003). Did expanding the EITC promote motherhood?. *American Economic Review, 93*(2), 247–251. https://doi.org/10.1257/000282803321947137

Bayaz Ozturk, G. (2018). Anti-poverty effects of in-kind transfers among divorced or separated women in the United States: Anti-poverty effects of transfers. *Poverty & Public Policy, 10*(1), 57–80. https://doi.org/10.1002/pop4.203

BEA. (n.d.). Regional data. GDP and personal income. U.S. Department of Commerce, Bureau of Economic Analysis. https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1. Accessed 1 Oct 2020.

Beecroft, E. (2012). *EITC take-up by recipients of public assistance in Virginia, and results of a low-cost experiment to increase EITC claims*. Virginia Department of Social Services. Retrieved April 3rd 2020 from https://www.dss.virginia.gov/files/about/reports/financial_assistance/eitc/2012/The_Effectiveness_of_EITC_Outreach_2012-05-29.pdf

Berube, A., & Tiffany, T. (2004). *The "state" of low-wage workers: How the EITC benefits urban and rural communities in the 50 states*. Brookings Institution Reports. Retrieved April 3rd 2020 from https://www.brookings.edu/wp-content/uploads/2016/06/20040203_berube.pdf

Cancian, M., Meyer, D. R., & Reed, D. (2010). Promising antipoverty strategies for families. *Poverty & Public Policy, 2*(3), 151–169. https://doi.org/10.2202/1944-2858.1085

CBPP. (2019). *Policy basics: The Earned Income Tax Credit.* Retrieved April 3rd 2020 from https://www.cbpp.org/research/federal-tax/policy-basics-the-earned-income-tax-credit

Chetty, R., & Saez, E. (2013). Teaching the tax code: Earnings responses to an experiment with EITC recipients. *American Economic Journal: Applied Economics, 5*(1), 1–31. https://doi.org/10.1257/app.5.1.1

Chetty, R., Friedman, J. N., & Saez, E. (2013). Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings. *American Economic Review, 103*(7), 2683–2721. https://doi.org/10.1257/aer.103.7.2683

Crandall-Hollick, M. L. (2018). *The earned income tax credit (EITC): A brief legislative history*. Retrieved April 3rd 2020 from Congressional Research Service. https://crsreports.congress.gov/product/pdf/R/R44825

Cranor, T., Kotb, S., & Goldin, J. (2019). Evidence from EITC notification laws. *National Tax Journal*, *72*(2), 397–434. https://doi.org/10.17310/ntj.2019.2.04

Curran, P. J., Obeidat, K., & Losardo, D. (2010). Twelve frequently asked questions about growth curve modeling. *Journal of Cognition and Development, 11*(2), 121–136. https://doi.org/10.1080/15248371003699969

Economic Research Service. (2019). *Rural-urban continuum codes*. United States Department of Agriculture, Economic Research Service. Retrieved April 3rd 2020 from https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/

Eissa, N., & Hoynes, H. W. (2006). Behavioral responses to taxes: Lessons from the EITC and labor supply. *Tax Policy and the Economy, 20*, 73–110. https://doi.org/10.3386/w11729

Goldin, J., Homonoff, T., Javaid, R., & Schafer, B. (2021). *Tax Filing and Take-Up: Experimental Evidence on Tax Preparation Outreach and EITC Participation*. Retrieved April 3rd 2020 from http://www.nber.org/papers/w28398

Grogger, J. (2004). Welfare transitions in the 1990s: The economy, welfare policy, and the EITC. *Journal of Policy Analysis and Management, 23*(4), 671–695. https://doi.org/10.1002/pam.20042

Herd, P., & Moynihan, D. (2020). Administrative Burdens in Health Policy. *Journal of Health and Human Services Administration*, 3–16. https://doi.org/10.37808/jhhsa.43.1.2

IRS. (2020). *VITA locator tool*. U.S. Department of the Treasury, IRS. Retrieved April 3rd 2020 from https://irs.treasury.gov/freetaxprep

IRS. (2021a). *Earned Income Tax Credit & other refundable credits*. U.S. Department of the Treasury, IRS. Retrieved August 3rd 2021 from https://www.eitc.irs.gov/eitc-central/about-eitc/about-eitc

IRS. (2021b). *SOI tax stats—County data*. U.S. Department of the Treasury, IRS. Retrieved August 3rd 2021 from https://www.irs.gov/statistics/soi-tax-stats-county-data

IRS. (2021c). *Earned income and Earned Income Tax Credit (EITC) Tables*. U.S. Department of the Treasury, IRS. Retrieved August 3rd 2021 from https://www.irs.gov/credits-deductions/individuals/earned-income-tax-credit/earned-income-and-earned-income-tax-credit-eitc-tables

IRS. (2021d). *File a 2020 Tax Return if You're Missing Stimulus Payments—YouTube video text script*. Retrieved August 3rd 2021 from https://www.irs.gov/newsroom/file-a-2020-tax-return-if-youre-missing-stimulus-payments-youtube-video-text-script

IRS. (2021e). *Filing Season Statistics for Week Ending June 11, 2021e*. Retrieved August 3rd 2021 from https://www.irs.gov/newsroom/filing-season-statistics-for-week-ending-june-11-2021e

IRS. (2019). *Do I qualify for EITC?* Internal Revenue Service, Publication 5334. Retrieved April 3rd 2020 from https://www.irs.gov/pub/irs-pdf/p5334.pdf

Komro, K. A., Markowitz, S., Livingston, M. D., & Wagenaar, A. C. (2019). Effects of state-level Earned Income Tax Credit laws on birth outcomes by race and ethnicity. *Health Equity, 3*(1), 61–67. https://doi.org/10.1089/heq.2018.0061

Linos, E., Prohofsky, A., Ramesh, A., Rothstein, J., & Unrath, M. (2020). *Can nudges increase take-up of the EITC?: Evidence from multiple field experiments* (Working Paper No. 2020–1). California Policy Lab. Retrieved April 3rd 2021 from https://www.capolicylab.org/wp-content/uploads/2020/11/Increasing-Take-Up-of-the-Earned-Income-Tax-Credit.pdf

Liu, H., & He, Q. (2019). The effect of basic public service on urban-rural income inequality: A sys-GMM approach. *Economic Research-Ekonomska Istraživanja, 32*(1), 3205–3223. https://doi.org/10.1080/1331677X.2019.1661005

Marr, C., Cox, K., Hingtgen, S., Windham, K., & Sherman, A. (2021). *American Rescue Plan Act includes critical expansions of Child Tax Credit and EITC*. Center on Budget and Policy Priorities. Retrieved August 3rd 2021 from https://www.cbpp.org/sites/default/files/3-12-21tax.pdf

NC OSBM. (2020a). *Population, voting age, density, migration* [Data Set]. Retrieved August 3rd 2021 from https://linc.osbm.nc.gov/explore/dataset/pop_migration/information

NC OSBM. (2020b). *Monthly labor force (LINC). Monthly labor force, employed, unemployed, and unemployment rate for North Carolina and counties* [Data Set]. Retrieved August 3rd 2021 from https://linc.osbm.nc.gov/explore/dataset/monthly-labor-force-linc/information/

NCSL. (2020). *Earned Income Tax Credit overview*. Retrieved August 3rd 2021 from https://www.ncsl.org/research/labor-and-employment/earned-income-tax-credits-for-working-families.aspx#:~:text=Quick%20Facts,first%20state%20EITC%20in%201986

Neumark, D., & Wascher, W. (2000). *Using the EITC to help poor families: New evidence and a comparison with the minimum wage* (Working Paper 7599). National Bureau of Economic Research. Retrieved August 3rd 2021 from https://www.nber.org/papers/w7599

Nichols, A., & Rothstein, J. (2015). *The Earned Income Tax Credit (EITC)* (Working Paper 21211). National Bureau of Economic Research. Retrieved August 3rd 2021 from https://www.nber.org/papers/w21211

Pew Research Center. (2018, May 22). *What unites and divides urban, suburban, and rural communities*. Retrieved August 3rd 2021 from https://www.pewsocialtrends.org/2018/05/22/urban-suburban-and-rural-residents-views-on-key-social-and-political-issues/

Pew Research Center. (2019, July 22). *Trust and distrust in America*. Retrieved August 3rd 2021 from https://www.pewresearch.org/politics/wp-content/uploads/sites/4/2019/07/PEW-RESEARCH-CENTER_TRUST-DISTRUST-IN-AMERICA-REPORT_2019-07-22-1.pdf

Phillips, R. (2020). *Barriers to social services fuel racial inequity*. Government Technology. Retrieved August 3rd 2021 from https://www.govtech.com/opinion/Barriers-to-Social-Services-Fuel-Racial-Inequity-Contributed.html

Pinard, C. A., Bertmann, F. M. W., Byker Shanks, C., Schober, D. J., Smith, T. M., Carpenter, L. C., & Yaroch, A. L. (2017). What factors influence SNAP participation? Literature reflecting enrollment in food assistance programs from a social and behavioral science perspective. *Journal of Hunger & Environmental Nutrition, 12*(2), 151–168. https://doi.org/10.1080/19320248.2016.1146194

Plueger, D. (2009). *Earned Income Tax Credit participation rate for Tax Year 2005*. IRS. Retrieved August 3rd 2021 from https://www.irs.gov/pub/irs-soi/09resconeitcpart.pdf

Prosperity Now. (2018). *Leveraging Tax Time for Working Families with VITA* (Federal Policy Brief). Retrieved August 3rd 2021 from https://prosperitynow.org/sites/default/files/resources/Leveraging_Tax_Time_for_Working_Families_VITA.pdf

Richmond, W., Radar, S., & Lanier, C. (2017). The "digital divide" for rural small businesses. *Journal of Research Marketing and Entrepreneurship, 19*(2), 94–104. https://doi.org/10.1108/JRME-02-2017-0006

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6*(2), 461–464. https://doi.org/10.1214/aos/1176344136

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. Oxford University Press.

Thomson, D., Gennetian, L. A., Chen, Y., Barnett, H., Carter, M., & Deambrosi, S. (2020). *State Policy and Practice Related to Earned Income Tax Credits May Affect Receipt among Hispanic Families with Children*. 21.

United States Census Bureau. (2016). *Gini index*. U.S. Department of Commerce, United States Census Bureau. Retrieved August 3rd 2021 from https://www.census.gov/topics/income-poverty/income-inequality/about/metrics/gini-index.html

United States Census Bureau. (2019). *All sectors: County business patterns by legal form of organization and employment size class for U.S., states, and selected geographies: 2017*. U.S. Department of Commerce, United States Census Bureau. Retrieved April 3rd 2020 from https://data.census.gov/cedsci/table?hidePreview=true&tid=CBP2017.CB1700CBP&vintage=2018&layer=VT_2018_040_00_PP_D1&cid=EMP

United States Census Bureau. (2020a). *County population by characteristics: 2010-2019*. U.S. Department of Commerce, United States Census Bureau. Retrieved April 3rd 2020 from https://www.census.gov/data/tables/time-series/demo/popest/2010s-counties-detail.html

United States Census Bureau. (2020b). *Small area income and poverty estimates (SAIPE)*. U.S. Department of Commerce, United States Census Bureau. Retrieved April 3rd 2020 https://www.census.gov/data-tools/demo/saipe/

Weinstein, P., Jr., & Patten, B. (2016). *The Price of Paying Taxes II:* (p. 14). Progressive Policy Institute.