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Who Does the Earned Income Tax Credit Benefit? A Monopsony View

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Suggested Citation: Davis, O. and Farmand, A. (2021) "Who Does the Earned Income Tax Credit Benefit? A Monopsony View." Schwartz Center for Economic Policy Analysis and Department of Economics, The New School for Social Research, Working Paper Series 2021-2.

WORKING
PAPER #2
2021
MAR

Who Does the Earned Income Tax Credit Benefit? A Monopsony View

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March, 2021

Abstract: The Earned Income Tax Credit (EITC) targets refundable tax credits to low-income workers, incentivizing labor supply and raising the incomes of tens of millions of Americans. One possible consequence of subsidizing low-wage work, however, is to reduce wage growth. A monopsony model of the EITC is developed in order to analyze its impacts on labor market outcomes, which are identified by exploiting variation in state EITC supplements. A first set of results focused on the food service industry find that the EITC increases employment and reduces turnover among young women. Further results suggest that the EITC reduces wages for workers without college degrees. These findings prompt a reconsideration of the redistributive effects of the EITC, particularly for groups like older low-wage workers who face slower wage growth as a result of the policy but do not receive the same level of benefits on average.

The Earned Income Tax Credit (EITC) is the largest need-tested cash-transfer program for low-income families in the United States. By providing working parents with refundable tax credits that vary based on family size and income, the program incentivizes work while providing significant cash supplements to the working poor. Yet the program has potential drawbacks for workers who are ineligible for or unaware of the EITC. By enlarging labor supply in the low-wage labor market, the EITC has the potential to drive wages down. In practice, the policy might fall short of its redistributive goals, making work pay for some while paying less for others. In this latter category are workers who do not have any dependents under the age of 19, particularly older workers in low-wage industries.

This study explores the redistributive effects of the EITC from the perspective of monopsony theory. This approach has been employed extensively in the analysis of labor market institutions such as the minimum wage and unions but is virtually absent from research on the EITC. From the monopsony perspective, the wage-setting power of employers depends on how sensitive workers are to a small change in the wage level (the elasticity of the labor supply). If employers can cut wages without losing all their workers, they have some monopsony power. By providing a supplement to low wages, the EITC makes workers less sensitive to changes in wages and promotes stability among workers who claim the credit. If the EITC promotes hiring and reduces turnover for a given wage—as we show follows from simple assumptions about the labor supply—employers will find they don't have to pay as much to maintain a stable level of employment. In other words, if employers reduce wages 1%, fewer workers leave with an EITC in place than otherwise. Under plausible assumptions, the result is lower wage.

We identify the effects of the tax credits on employment, turnover, and wages by exploiting the variation in state-level supplements to the federal EITC. We employ a two-part empirical strategy. First, we use the Quarterly Workforce Indicators (QWI) database in a to examine the association between state EITC policy changes and employment and turnover in the food service industry, utilizing a study design that exploits diverging trends between neighboring counties across state borders for identification. Our results are consistent with both the typical findings regarding the extensive margin in the literature as well as the EITC-turnover pathway suggested by the monopsony framework.

Next, we use Current Population Survey (CPS) data to explore the association between state EITC policy and wages. Using a fixed effects model that helps account for confounding variables by measuring changes within groups across time, we find that state EITC generosity is associated with lower wages among those without a college education. This result holds both for the target population (predominantly younger workers with children) and for populations who are less likely to receive the tax credits, namely, older workers.

Background: EITC and related research

The federal EITC is a refundable income tax credit offered to low-income workers and working parents through the federal income tax code. Lawmakers introduced the EITC in 1975 as part of an effort to reform welfare programs, and it has undergone several large expansions since (Crandall-Hollick, Falk and Boyle 2020). The amount of the credit depends on family structure and is calculated on a sliding scale which starts small at low levels of income, increases to a certain point where it plateaus, then phases out as the worker's income continues to rise, giving the schedule a trapezoid shape. In 2020, a single adult with two children received a maximum tax credit of $5,920, with the benefit fully phased out at an income of $47,440. The maximum credit for a childless adult between the ages of 25 and 65 was $538, phasing out fully at $15,820. After the passage of the American Rescue Plan in March 2021, benefits for childless adults were roughly tripled and eligibility was expanded to workers older than 65 and workers 19-25 who aren't full-time students.

In addition to the federal EITC program, some states have introduced their own add-on refundable tax credits. In 2020, 28 states and the District of Columbia offered their own supplemental EITCs; 23 of which are refundable. Most states with an EITC add-on define a percentage of the federal credit for determining the level of the state EITC. Taxpayers entitled to a federal credit multiply the amount of the federal credit by the applicable state percentage to determine the benefit amount.

A large literature documents positive impacts of the credit on workers and their families. Hoynes and Patel (2015) found that a $1,000 increase in the EITC led to a 7.3 percentage point increase in employment and a 9.4 percentage point reduction in the share of families with after tax and transfer income in poverty. Dahl and Lochner (2012) estimated the impact of changes in family income resulting from EITC expansions on child cognitive achievement, concluding that a $1,000 increase in income from EITC benefits raised combined math and reading test scores by 6% of a standard deviation. Other benefits associated with family EITC receipt include positive effects on infant health (Hoynes and Patel 2015) and college enrollment (Manoli and Turner 2018).

One of the most extensively studied aspects of the EITC is its effect on labor market participation. Eissa and Liebman (1996) found that the federal EITC expansion of 1986 increased employment of single women with children by 2.8 percentage points. Similarly, Meyer and Rosenbaum (2001) found that the 1993 expansion raised employment rates of single mothers by 3.1 percentage points, suggesting an extensive margin elasticity of 0.7. In a recent working paper, however, Kleven (2019) disputed previous findings of large extensive margin effects, arguing that economic growth and the simultaneous scaling back of welfare programs in the 1990s confounds the estimates. Schanzenbach and Strain (2020), adopting Kleven's long-time-frame approach but disputing his methodology, reconfirmed the broader literature on the extensive margin effects of the EITC.

The EITC also entails potential negative side effects, such as a reduction of work on the intensive margin. Standard labor supply theory implies that the EITC will decrease hours worked among those already working because most recipients are on the plateau or phase-out portions of the schedule. For these recipients, the EITC can discourage work through the income effect of the credit. But Eissa and Liebman (1996) and Meyer and Rosenbaum (2001) showed hours-worked patterns for EITC-eligible individuals do not appear to fit this prediction and that most responses happen on the extensive margin. Chetty, Friedman and Saez (2013) documented that some earnings responses can come from intensive margin increases in labor supply by individuals in the phase-in region and as a result, behavioral responses to the EITC reinforce its direct impacts in raising the incomes of low-income families with children. There is also some evidence for reduced hours by workers on the plateau or phase out regions of the credit. Eissa and Hoynes (2014) argued that since the EITC is based on family income, it can lead to traditional welfare-type disincentives for most eligible secondary earners and is thus likely to reduce overall family labor supply among married couples.

Another potential negative labor market impact of the EITC is that it reduces wages, harming non-eligible workers in particular. Workers without qualifying children miss out on anti-poverty and employment effects of the EITC. The EITC available to workers without children and non-custodial parents is small and phases out at very low incomes. The seminal research on the unintended consequences of the policy on wages can be found in Rothstein (2010) and Leigh (2010). Leigh used variation across states' generosity of EITC add-ons and found a very strong negative effect of the credit on wages. He found that a 10% increase in the generosity of the EITC is associated with a 5% fall in the wages of high school dropouts and a 2% fall in the wages of those with only a high school diploma, while having no effect on the wages of college graduates. Rothstein (2010) used variation from the 1993 federal credit expansion along the wage distribution and found that low-skill women's wages actually increased slightly even as their labor force participation increased, though these wage increases were smaller than they would have been with a stable EITC. Taking into account a heterogenous labor supply and different tax rates across demographic groups, Rothstein estimated that the EITC achieved only 28 cents of redistribution toward low-income individuals for every dollar of EITC.

This literature predominantly focuses on behaviors and labor market outcomes of prime-aged workers (between 25-54). Most workers who do not belong to this age group do not receive EITC benefits. According to estimates from the Annual Social Economic Survey of the Current Population Survey, only 12% of workers outside of this age range received EITC benefits in 2019 compared to 33.5% of prime-aged workers.

Monopsony and the EITC

The literature on the labor market effects of the EITC typically proceeds from the assumption of perfect competition, in which the monopsony power of employers plays no role. In this literature, the EITC shifts the labor supply curve outward but does not affect its shape. Wage effects depend on the magnitude of the labor supply response, as well as the relative elasticities of labor supply and demand (which remain fixed) and substitution elasticities between different types of labor.

We explore the EITC from a different perspective, considering how the policy changes the shape of the labor supply curve facing the firm. In monopsony theory, the elasticity of the labor supply curve facing the firm plays an essential role (Manning 2021). If firms can lower wages without losing all their workers—or have to increase wages to expand employment—then the model of perfect competition with infinite labor supply elasticity does not hold. The more inelastic is the labor supply curve to the firm, the more power employers have to set wages. In the analysis presented below, we examine how the EITC can reduce the firms' labor supply elasticity.

For a straightforward illustration of the potential monopsony effects of the EITC, we expand on the model presented in Card and Krueger (2015: 523-525; Manning 2003: 32). In order to employ a stable number of workers L, a firm chooses a wage that brings quits and hires into equilibrium:

$$\mathrm{H}(w) = \mathrm{q}(w)\mathrm{L} \qquad (1)$$

Given this equilibrium condition, and assuming constant-elasticity hire and quit functions, the elasticity of labor supply with respect to the wage can be expressed as

$$\eta_0 = \overline{\varepsilon_H} - \overline{\varepsilon_q} \qquad (2)$$

where $\overline{\varepsilon_H}$ is the wage elasticity of the hire function and $\overline{\varepsilon_q} \leq 0$ is the wage elasticity of the quit function. Perfect competition, in which employers are wage-takers, amounts to the assumption that the absolute value of at least one of these elasticities is infinite. The closer each of these elasticities is to 0, the lower is the overall labor supply elasticity, and the greater is employers' wage-setting power.

To incorporate the impact of refundable tax credits on the labor supply schedule of eligible workers, we express hiring and quits as functions of after-tax earnings $\mathrm{w} + \mathrm{c}$, where c is the dollar amount of the maximum refundable tax credit. For ease of presentation, we assume earned income w is within the "plateau" region of the EITC schedule, so that the size of the refund does not change with a marginal change in w (as detailed in footnote 1 below, the results hold when the phase-in and phase-out regions are explicitly modeled). We define the following hire and quit functions, whose form follows from the isoelasticity assumption in (1):

$$\mathrm{H}(w,c) = \alpha_H (w+c)^{\overline{\varepsilon_H}}, \overline{\varepsilon_H} \geq 0 \tag{3}$$

$$\mathrm{q}(w,c) = \alpha_q (w+c)^{\overline{\varepsilon_q}}, \overline{\varepsilon_q} \leq 0 \tag{4}$$

The elasticities of the hire and quit functions with respect to *pre-tax* wages are

$$\varepsilon_H(w,c) = \overline{\varepsilon_H} \frac{w}{w+c} \tag{5}$$

$$\varepsilon_q(w,c) = \overline{\varepsilon_q} \frac{w}{w+c} \tag{6}$$

The new expression for the overall supply elasticity is

$$\begin{aligned} \eta(w,c) &= \varepsilon_H(w,c) - \varepsilon_q(w,c) \\ &= \left(\overline{\varepsilon_H} - \overline{\varepsilon_q}\right) \frac{w}{w+c} \qquad (7) \\ &= \eta_0 \frac{w}{w+c} \end{aligned}$$

With no tax credit ($c = 0$), equation (7) above reduces to equation (2). The effect of a positive tax credit *c* is to reduce the absolute value of both the hiring elasticity and the quits elasticity, reducing the overall labor supply elasticity of claiming workers. Using the 2020 federal EITC formula, this model predicts a 24% reduction in the supply elasticity among single parents with two children and earned income just below the upper plateau threshold of $19,330.[1] The simple reason for the reduction of the supply elasticity is that for a dollar change in wages, post-tax earnings change by less than a dollar.

[1] Calculating the changes in elasticities for the phase-in and phase-out regions yield results that are virtually the same in overall impact. A calculation of the average supply elasticity $\bar{\eta}$ over the entire range of the EITC schedule for a single parent with two children (2020 policy) finds $\bar{\eta} = 0.749\eta_0$, nearly identical to the simpler estimate given above.

To explore wage effects explicitly, we first present the limiting case in which every worker can and does claim the tax credit, every worker's household earnings fall in the "plateau" region of the EITC, and demand for labor is fixed (see Rothstein [2010] for a similar approach). The labor supply function facing the firm is:

$$\begin{aligned} \mathrm{L}(w,c) &= \frac{H(w,c)}{q(w,c)} \\ &= \frac{\alpha_H}{\alpha_q}(w+c)^{\overline{\varepsilon_H}-\overline{\varepsilon_q}} \end{aligned} \tag{8}$$

Inverting the above equation to express the wage required to employ a constant L workers:

$$\mathrm{w}(L,c) = \left(\frac{\alpha_q}{\alpha_H}L\right)^{\frac{1}{\overline{\varepsilon_H}-\overline{\varepsilon_q}}} - \mathrm{c}$$

In the limit, every dollar paid in EITC refunds is captured by employers, who find they can pay less to maintain the same workforce.[2] This extreme case only applies under two unrealistic limiting conditions: (1) all employees claim the EITC, and (2) firms' labor demand elasticity is 0. Softening either of these assumptions reduces the negative effect on wages. The greater is the share of non-claiming workers in the relevant labor market, the smaller will be the decrease in the supply elasticity. Moreover, when firms have some elasticity in their labor demand, they respond to the increased labor supply not solely by cutting wages but by accepting fewer vacancies at any given time, expanding employment.

Below we present the labor supply function when we account for non-claiming workers. Under three assumptions—that the share of claiming workers is a constant ϕ, that claiming and non-claiming workers have the same hire and quit function parameters, and that workers are all in the "plateau" region of earned income—the aggregate labor supply function is:

[2] An analogous result follows from Rothstein's (2010: 181) formula for tax incidence in a labor market with homogenous workers.

$$L_S(w,c) = \frac{H_{all}(w,c)}{q_{all}(w,c)} = \frac{H_{claim}(w,c)+H_{non-claim}(w)}{q_{claim}(w,c)+q_{non-claim}(w)}$$

$$= \frac{\phi\alpha_H(w+c)^{\overline{\varepsilon_H}}+(1-\phi)\alpha_H w^{\overline{\varepsilon_H}}}{\phi\alpha_q(w+c)^{\overline{\varepsilon_q}}+(1-\phi)\alpha_q w^{\overline{\varepsilon_q}}} \qquad (9)$$

We also assume a simple isoelastic labor demand function $L_D(w) = \beta w^{\rho}, \rho \leq 0.$ Tractability prevents a closed-form expression for wages as a function of the tax credit given the labor supply and demand functions represented above. Using first-order linear approximations of the hire and quit functions, however, it can be shown that for any $w > c$, $\partial w/\partial c < 0$.

Figure 1 plots labor market equilibrium, showing an increase in the tax credit from *c=0* to *c=0.25*, with all other parameters held constant. The pre-tax equilibrium starting wage and employment are set to 1.0 for ease of comparison.[3]

[Figure 1]

While Figure 1 looks very much like a classic outward shift in the labor supply curve, the interpretation here is different. The change in the shape of the labor supply curve from pre-EITC to post-EITC results from a reduced supply elasticity for one set of workers (EITC claimants) alongside an unchanged supply elasticity for another set of workers (non-claiming workers). The mechanisms by which the labor supply elasticities change is the hire and quit functions, which are tied directly to firms' recruitment and compensation strategies.

The EITC can affect hires and quits in several distinct ways. As is well-documented, the EITC affects the hiring function by increasing the return to work. The quit function concerns separations that arise for three separate reasons: workers accepting outside job offers, workers entering non-employment voluntarily, and workers entering non-employment involuntarily as a result of adverse shocks such as injury, illness, childcare responsibilities, or transportation

[3] The parameter values are: H=q=1, H=2,q=-1,β=1,ρ=-1,andϕ=0.5

difficulties. Leaving aside job-to-job transitions,[4] the EITC plausibly reduces the incidence of both voluntary and involuntary separations to non-employment (Wilson 2020). Tax credits diminish the rate of voluntary quits due to a higher opportunity cost of quitting and involuntary separations by reducing the incidence of adverse shocks.

It is this latter pathway—diminished incidence of job-ending shocks—that we wish to highlight. Research has connected EITC receipt to outcomes that may help employees to find and retain jobs, namely improved financial stability and access to transportation. In a survey of parents in Chicago who expected to receive the EITC, Smeeding, Phillips and O'Connor (2000) found that 19% of respondents planned to buy or maintain vehicles with their tax refunds. In addition, 40% planned to use the refunds for utilities payments and 36% intended to use them to pay rent. Subsequent research has found that between one-quarter and one-third of EITC recipients use their tax refunds on transportation-related expenses (Romich and Weisner 2000; Mendenhall et al 2012; Goodman-Bacon and McGranahan 2008). Because car ownership encourages labor supply, particularly among vulnerable communities (Baum 2009; Raphael and Stoll 2001; Anderssen et al 2018), these expenditures likely boost the labor market attachment of EITC recipients.

The business community has also highlighted the beneficial effect of EITC on turnover. The company National Enrollment Service helps businesses sign their employees up for government benefits including the EITC. The firm's website lists several advantages of the EITC, including "lowering employee turnover," and "incentive to work which stabilizes employee retention while growing a business's bottom line."[5] In a similar vein, a 2007 report

[4] The effect of the EITC on job-to-job transitions may operate in the opposite direction as the effect on other quits (Mancino and Mullins 2020).
[5] URL: https://nesbenefits.com/tax-credit-programs. Accessed February 21, 2021.

from the Institute for a Competitive Workforce (ICW), an affiliate of the U.S. Chamber of Commerce, advised that community leaders raise awareness of the EITC specifically as a way to reduce employee turnover:

> [E]mployee turnover is expensive for businesses and can be especially crippling to small employers. Because the tax credits help workers take care of day-to-day needs, these credits can help them keep their jobs and promote a more stable workforce. In other words, the credit helps workers to keep working and care for themselves at no cost to the business itself. Workers use their credits to: Pay for transportation to the job; Keep a car in working order; Pay for job training or education; Cover child-care costs. All of these factors contribute to an employee's stability and productivity on the job, which directly influences the company's sustainability and profit margin. (ICW 2007: 7).

This analysis highlights the role of employers in mediating the impacts of the EITC on labor market outcomes. Employers can decrease turnover by raising awareness of the EITC and by subsidizing tax preparation services. EITC take-up is estimated to be only 78% among eligible workers (IRS 2021). Encouraging these workers to claim is equivalent to raising the value of the parameter ϕ in equation 9, which reduces the equilibrium wage. Note that none of these employer responses involve the putative pathways that Nichols and Rothstein (2015: 24) identify as having created "some confusion in the literature," including discrimination against EITC recipients or employers otherwise identifying which workers receive tax refunds. The extensive margin effect of the EITC may also counteract some of the turnover effect by bringing workers into employment who have less prior labor market experience and potentially higher instability.

While reducing turnover is undoubtedly beneficial to EITC recipients and employers, under the monopsony model this outcome also enhances the labor market power of employers, to the possible detriment of non-eligible workers. Absent the EITC, employers have to pay more to maintain their target headcount; excess vacancies force firms to raise wages in order to attract more hires and reduce the incidence of voluntary and involuntary separations.[6] Over time, this monopsony effect may lead to lower wage growth among low-income workers in states with more generous EITC policies.

Our empirical applications of the theory presented above use state-level variation in EITC supplements as an identification strategy. All states share the same values of federal EITC benefits but vary in whether and how much they supplement this baseline with state-level tax credits. There is evidence, however, that it is not only the maximum tax refund that varies between states, but also the share of eligible workers who claim. Neumark and Williams (2020) found that the introduction of state-level EITC supplements increased the share of federal EITC-eligible workers who claim. In our model, this participation effect increases the value of ϕ, further enhancing the wage-setting power of employers.

State EITCs, Employment and Turnover

Our empirical strategy consists of two parts: an analysis of the employment and turnover effects of state-level EITCs, and a separate analysis of wages using Current Population Survey data. This section concerns the first part.

[6] Again, from the ICW (2007: 7): "Through EITC, employers can potentially raise their employees' wages by $1 to $2 per hour at no cost. . . . By introducing employees to these benefits, businesses help their employees—and help themselves."

Data

To estimate the impact of state-level EITC supplements on employment and turnover, we use Quarterly Workforce Indicators (QWI) data. The QWI is a public-release aggregate of the U.S. Census Longitudinal Employer-Household Dynamics (LEHD) database, a matched employee-employer database assembled from state unemployment insurance records. The QWI aggregates provide quarterly data on employment flows by industry at the county level for select age and gender groups. (See Abowd et al [2009] for a complete description.)

Although QWI records begin in 1991, states enter into the sample at different times, with the final state to enter being Massachusetts in 2010. Larger states were overrepresented in the early years, but by 2000, 42 states had entered the sample. This makes the year 2000 a natural beginning point for estimation, though we present results for both the entire sample and for the shorter one.[7] To comply with federal privacy protection guidelines, some cells of the QWI are fuzzed; others are missing due to lack of data, which occurs especially when cells are specified narrowly (e.g., county-level hires of women 22-24 in NAICS industry 722 in Q4 2012). We drop missing data but keep the fuzzed data.

The main QWI measures of interest are employment and turnover. For employment, hires and separations, QWI provides "stable" subtotals of each variable. Stable employment reflects the employment level of those who have already recorded at least one full quarter of employment with the same firm. Stable hires and separations reflect transitions into or out of at least a full quarter of employment. The QWI provides a stable turnover measure, defined as $Turnover_t = \frac{hires_t + separations_{t+1}}{\{2 \cdot employment_t)}$ where the component variables are all stable (non-short-term) versions. A

[7] Of the 25 states with refundable EITCs at any point in the sample, 9 implemented their supplements before 2000. Four of these 25 states enter the QWI sample only *after* instituting EITC policies. Two states introduced and then discontinued refundable EITC programs: North Carolina (2008-2013) and Oklahoma (2002-2015).

similarly constructed variable for total turnover (stable plus non-stable) can be constructed directly from the underlying data. Yet this measure suffers from an upward bias due to the way the hire and separation data are recorded. Since overall separations over a quarter can exceed beginning-of-quarter employment, it is possible for this rate variable to exceed 1. By design, the stable turnover variable does not suffer this defect. With this drawback in mind, we will report results for employment and turnover both for their total measures and their stable subtotals. Since QWI earnings measures do not specify hours of work it is inappropriate to use this data to estimate EITC effects on wages.

For our main results we focus on the Food Service subsector, NAICS 722. Due to the limited availability of QWI data at the county level, most three-digit industries lack sufficient observations analysis of the EITC by sex and age group. The Food Service subsector is both a large sample and a low-wage industry, making it ideal for testing the effects of the EITC. In 2019, 11.9 million workers were employed in food service jobs, making it the second-largest of the NAICS subsectors. It is also the second-lowest-paying subsector, with median annual earnings of $23,890 in 2019.[8] Although in the later wage regressions using Current Population Survey, we present results by educational category, data and methodological concerns preclude us from doing so for the QWI data.[9] Taking a sample of all workers is unlikely to facilitate identification since only about 15% of the working population receives the EITC.

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[8] Earnings and employment data by industry come from the Occupational Employment Statistics produced by the Bureau of Labor Statistics.

[9] Two main concerns arise here. First, as detailed below, our empirical model controls for county population and total private-sector employment as a proxy for labor market trends. But when using a group as large as workers by educational attainment, the private-sector employment variable will exhibit endogeneity with the dependent variable. The second concern is that QWI imputes education attainment at the state rather than county level, so that county-level heterogeneity in education within a state will not be captured in the aggregates.

The data set of state EITC policy changes is constructed using the NBER State EITC provisions 1977-2018 table, double-checked against the list maintained by the nonprofit Tax Credits for Workers and Families.[10] Minimum wage data are drawn from the U.S. Department of Labor's timeline of state minimum wage changes.[11]

Method

One of the major challenges in estimating the effect of state-level policy changes on labor market outcomes is to account for policy endogeneity. Changes to labor market policy may be endogenous to unobserved variables, biasing the ultimate estimates. To overcome the problem of unobserved spatial heterogeneity, we employ the county-border discontinuity methodology of Dube et al (2016). We observe outcomes at the county level, using the sample of counties lying on state borders. Each county is matched with its neighbor(s) across the state border, and fixed effects are estimated on these county pairs. By effectively using border counties as controls, this methodology requires less stringent assumptions regarding unobserved spatial heterogeneity. As Dube et al (2016) show, contiguous county-border pairs exhibit consistently smaller differences in observable covariates than counties noncontiguous pairs. In other words, counties that share a state border are reliably more similar along observables than they are with counties that do not border them. We also follow Dube et al (2016) in restricting the county-pair sample to pairs whose centroids lie within 75 kilometers, further reducing the risk of unobserved spatial heterogeneity.

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[10] As of March 2021, the NBER table is available at https://users.nber.org/~taxsim/state-eitc.html and the TCWF table at http://www.taxcreditsforworkersandfamilies.org/state-tax-credits/.
[11] As of March 2021, available at https://www.dol.gov/agencies/whd/state/minimum-wage/history.

To estimate the effect of state EITC variation, we use a two-way fixed effects regression with county fixed effects and county-pair-specific time effects. The full form of the model is:

$$Y_{ipt} = \alpha + \sum_{l=0}^{L} \beta_l EITC_{i,t-l} + \Gamma X_{it} + \mu_i + \nu_{pt} + \varepsilon_{ipt}$$

The covariate vector X_{it} includes county population (from U.S. census population estimates), county private-sector employment, and state minimum wage. All variables are logged, including dependent variables and EITC. The EITC measure is the state supplement as a percentage of the federal EITC plus 100%, logged. The state EITC variable is treated as 0 if the EITC is non-refundable. The minimum wage is included since state minimum wage increases may be endogenous to EITC policy. Errors are clustered at the state border segment and state levels. Estimates are obtained using the user-written reghdfe package in STATA (Correia 2017). For any given county pair, the sample is constructed to begin when both counties in the pair have all non-missing data from that date forward, since missing data may be nonrandom.

Due to informational frictions, the full impact of changes to state EITC policy may take several years to manifest (Neumark and Williams 2020; Schanzenbach and Strain 2021), which necessitates including multiple years' lags in the regression. Due to the multicollinearity of EITC levels, however, individual estimates of the coefficient on the state EITC variable may be biased when multiple lags are introduced. For this reason, we estimate a linear combination of the sum of the EITC lag coefficients in order to produce an estimate of the cumulative effect (Meer and West 2016). Regressions are estimated separately for 1-, 3-, and 5-year cumulative effects.

Results

Results of our main regressions are presented in Table 1 below. These regressions are limited to the sample of women in the Food Service subsector (NAICS 722), both for all ages and for ages 25-34. The regressions are estimated on each of the four dependent variables listed in the leftmost column: employment, stable employment, turnover and stable turnover. Three different lag structures are estimated. The reported coefficients are the cumulative effects of the EITC variable (sum of coefficients), using the linear combination methodology described above. For example, the 3-year cumulative effect includes $EITC_t$, $EITC_{t-1}$, $EITC_{t-2}$ and $EITC_{t-3}$. The sample period is 2000-2019.

[TABLE 1]

For the women all-ages sample, none of the estimated coefficients is significant at any conventional level. When focusing on the high-recipiency group of women aged 25-34, however, we find significant associations between the state EITCs and employment, stable employment, and stable turnover. For the elasticities of employment with respect to EITC, estimates are positive and statistically significant for cumulative lags of 3 and 5 years, though not for the 1-year cumulative lag. These results are consistent with the broader literature on the extensive margin effects of the EITC. Counties in states that institute state EITCs or increase their supplements see increased employment among young women in restaurants than their neighboring counties across state borders.

For overall turnover, the null hypothesis cannot be ruled out for any lags. For stable turnover, the estimated cumulative elasticity with respect to EITC is -0.24 at a 3-year lag (significant at the 10% level) and -0.31 at a 5-year lag (significant at the 5% level). These results are consistent with state EITCs reducing turnover among those already working in somewhat stable jobs (Wilson 2020). The aforementioned data issues with the total turnover variable may also hinder identification, however. In robustness checks, we restrict attention to stable turnover.

To visualize these results, in Figure 2 we present the coefficient estimates and 95% confidence intervals for the cumulative effects of EITC on employment for women in the restaurant industry by age group. We group these estimates by each of the age groups available in the QWI dataset except for 65 and older, which lacks sufficient observations. The resulting hump-shaped pattern is consistent with state EITC policy having its strongest effects on women in their 20s and early 30s. The estimated point estimates consistently grow with time, reaching a maximum at the cumulative 5-year lag. This is consistent with informational barriers preventing immediate adjustment to tax policy changes.

[Figure 2]

In Figure 3 we present the same set of estimates for stable turnover. The age pattern observed for employment occurs here as well. Yet only for women 25-34 at the 5-year lag is the cumulative effect estimate significant at the 5% level. Note that due to the way stable turnover is constructed in QWI, the observation counts are much lower for the age group-specific samples than for the all-ages samples, particularly for narrower age groups.[12]

[Figure 3]

The results presented in the previous section were obtained on a sample beginning in 2000, while the QWI data reach back to 1991. In order to ensure that our choice of starting date does not affect our conclusions, we run the same regressions for the entire available sample. Although the post-1990 sample is biased toward larger states, the longer sample allows us to include 4 additional state EITC implementations. Though the exact number varies by the dependent variable used, this longer sample adds about 10,000 additional observations, making the sample roughly 8% larger. The results are largely similar, with the one notable difference that with the longer sample, coefficients on stable turnover for the all-ages group are statistically significant for 3- and 5-year lags, which was not the case for the shorter 2000-2019 sample.

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[12] The stable turnover variable is built from separations and hires measures which generally contain far fewer observations than does employment. For smaller counties, these cells may contain suppressed data.

[TABLE 2]

Next, we examine the results for the models with the sample restricted to men. The EITC was designed with a particular focus on the labor force outcomes of single mothers, and much of the literature focuses on this group. Since fewer young men claim eligible dependents, we would expect the results to be weaker for men. As we found for women, the all-ages male sample produces no statistically significant coefficient estimates on the dependent variables of interest, although the signs of the coefficients match our theory. When we limit the sample only to men 25-34, we find positive coefficients on stable employment statistically significant at the 10% for 1- and 3-year cumulative effects. These results are consistent with the hypothesis that, while some men do claim the EITC, their eligibility rate is lower than for women and thus the effects on labor market outcomes are less pronounced (results available on request).

We also run our main specification over both genders and both time periods for NAICS sector 72, Accommodation and Food Service. In addition to the Food Service subsector used in our results above, the broader sector 72 includes traveler accommodation and hotels subsectors, which also employ a large share of low-wage workers. In 2019, Food Service employment made up 85% of total NAICS 72 employment. Tables A1 and A2 in Appendix A report the four sets of results for the larger sector. In general, these results produce more statistically significant coefficient estimates, both for men and women, especially for the 1991-2019 samples. One interesting result is the relatively large and statistically significant set of coefficient estimates for men, 1991-2019, in the broader sector-level regression. These results suggest that the employment effects of state EITCs are not limited to young women, but also extend to men. But are they plausible as direct effects of state EITC policy? If they are not, then we have to consider alternate explanations: there are indirect effects of state EITCs on male workers (for instance, young men benefitting from EITC recipiency elsewhere in their households). Alternatively, we may be picking up on unobserved employment heterogeneity despite the research design or sample bias arising from longer the sample period.

Although the effects of state minimum wages are not the focus of this paper, our results are consistent with Dube et al (2016). In the vast majority of cases, we do not observe a negative coefficient on the minimum wage when regressed on total employment. This holds across all combinations of industry specification, gender, time period and age group, with the sole exception of men aged 14-18 in the Accommodation and Food Service sector (NAICS 72). Notably, the estimated coefficient on the next older group, ages 19-21, is positive and statistically significant at the 1% level, suggesting substitution between the youngest age groups.

Robustness

The first robustness check we provide is to test the effect of EITC leads on stable employment and stable turnover. This is effectively a check for pre-trends in the data. An association between future state EITC policy changes and our dependent variables would cast doubt on the results for lagged EITCs. Due to the structure of the data, however, regressing the outcome variables on leads of state EITC policy is not a perfectly clean test for pre-trends. This is because state EITC increases exhibit autocorrelation in our sample, as states sometimes engage in staggered changes to their EITC supplements. For states in our sample that have ever enacted refundable state EITC supplements, 42% of policy changes were preceded by a policy change in the previous three years. In a simple logit regression—controlling for changes in minimum wage policy and lagged changes in unemployment (1 to 5 years)—a state EITC policy change in any of the previous three years is associated with a 250% increase in the likelihood of a change in EITC policy in the reference year.

With these caveats in mind, we present the results for leads of up to five years for the 2000-2019 sample in Figure 4. These figures present the cumulative effects on employment and stable turnover of specified leads and lags of the log EITC variable. For leads, regressions do not include the reference period EITC, only EITC values for subsequent period(s). Results for women, both for the all-ages sample (green dots) and for the 25-34 group (blue squares), are provided. For turnover, cumulative effects are not statistically significant prior to the reference period, nor are pre-trends evident. Still, the signs of the point estimates are consistent between the lead and lag estimates. This may be a result of the autocorrelation of state EITC policy indicated above.

[Figure 4]

Similar results hold when we expand the sample back to 1991 for women Food Service (Figure A1) or when we expand the sample from Food Service to Accommodation and Food Service (from 2 digit to 3-digit NAICS) for the 2000-2019 period (Figure A2). For the results for Accommodation and Food Service, 1991-2019 (Figure 5), however, coefficients on the leads for employment are statistically significant at the 5% level and positive for all three lag groups. Two possibilities outside of sample-related bias may explain these results. One is that there are spatially heterogeneous employment pre-trends that the county-pair fixed effects are unable to purge. Another possibility is the issue of EITC policy autocorrelation explained above.

[Figure 5]

As a further robustness check for the turnover results, we add overall private-sector, county-level stable turnover as a covariate.[13] Since turnover in Food Service makes up a significant part of overall private-sector turnover, this is a particularly stringent test (Dube et al

[13] A similar check does not apply for employment, since total private-sector employment is already included as a covariate.

2016: 690-691). Table 4 presents the original estimates for women, NAICS 722, for both the time periods; beneath each row of original results are the results with overall turnover variable included.

[Table 3]

Including overall private-sector turnover reduces the magnitude and precision of the coefficient estimates on stable turnover in Food Service. Yet for all but one of the samples (all ages, 3-year cumulative lag, 1991-2019), the estimates retain their previous level of statistical significance.

In a final pair of robustness tests we change how the time effects are applied and relax the geographical constraint on counties in the sample. For the time effects, we use common time effects in the robustness check rather than the county-pair specific effects. This amounts to a more restrictive assumption regarding the spatial heterogeneity present in the sample. Next we lift the sample constraint that county-pairs centroids (geographical county centers) be no greater than 75 kilometers apart. Tables 5 and 6 present the baseline results as well as results from these two robustness checks for employment and stable turnover, respectively. The samples are restricted to women in Food Service.

[Table 4]

[Table 5]

For employment, original results are robust to both specifications. In fact, the coefficient estimates are generally greater in magnitude for the common time fixed effects specification. For stable turnover, the new specifications reduce both the magnitude and the precision of the estimates, though for five-year cumulative effects, the estimates remain statistically significant at the 10% level for the 1991-2019 sample (ages 25-34) and significant at the 5% level for the 2000-2019 sample (ages 25-34).

State EITCs and wages

Data

To estimate the impact of state-level EITC supplements on wages we utilize data from the Current Population Survey (CPS), a nationally representative monthly survey of approximately 60,000 households. We use two types of CPS data, the Annual Social Economic Supplement (ASEC) and the basic monthly data. During each monthly interview household members are asked about their employment status, earnings, hours of work, whether they worked last week and other indicators. In the March interviews, individuals are asked to provide detailed retrospective information including hours, earnings, and weeks unemployed during the previous year. We use responses from participants in the ASEC supplement to construct log hourly wages, determine EITC eligibility, industry of work and their level of education. We use basic monthly data to track workers' flows between industries by income quintile. All data are extracted from Integrated Public Use Microdata Series (IPUMS)- CPS (Flood et al. 2021).

Incidence and Method

As discussed in section III, labor supply decisions will have follow-on effects on other labor market outcomes, including market wages. In particular, a negative effective tax rate (like the EITC) that encourages increased labor force participation will lead to reduction in turnover that reduces the elasticity of labor supply and a decline in pre-tax wages. This implies that a portion of the money spent on the EITC will be captured by employers. Because the effectiveness of EITC depends on its economic incidence, understanding the effect of the EITC on wages helps us to assess if the program is achieving its redistributive goals.

To determine the impact of changes in EITC generosity on wages we utilize the variations in state based EITC programs to estimate a state fixed effect model. If workers suffer wage loss from the net increase in labor supply from eligible individuals, we expect to see a more pronounced dampening effect on wage growth in states that have a more generous state based EITC supplements. In effect, this analysis estimates the change in labor market conditions, specifically hourly wages when a state has a more generous EITC supplement[14]. Generous states are defined as states that offer a refundable add-on credit greater than 20% of the federal credit.

Although data restrictions prevent us from conducting an analysis based on educational groups when we are measuring turnover effects of the EITC, in this section we are going to group workers into educational groups. Although most workers in the specified low wage industries discussed in the previous section have low education, we use education as the main source of identification. Grouping people by education instead of their industry provides us with a bigger sample size and allows us to capture low wage workers that might work in an industry that has a small share of workers claiming EITC benefits. Different regressions are run for each education-age pair, to account for heterogeneous effects of each group.

To estimate the effect of state EITC variation on labor market outcomes, we use a two-way fixed effects regression with time and state fixed effects. The full form of the model is

$$\ln(W)_{ij} = \beta_0 + \beta_1 \mathrm{GEN}R_{ij} + \beta_2 \mathrm{YEA}R_{ij} + \beta_3 \mathrm{YEARGEN}R_{ij} + \beta_4 X_{ij} + \varepsilon_{ij}$$

[14] In this context we need to consider whether changes in state EITCs can be treated as exogenous. To address this issue, Leigh (2010) performs a series of tests to identify factors that might confound the results due to the endogeneity of the EITC policy. His results indicate that state GDP is significantly related to state EITC generosity. On average, a 1% increase in state GDP is associated with a 0.1 percentage point increase in the state EITC supplement (Leigh 2010). Moreover, our own analysis from the previous section shows a strong correlation between state-based EITC benefits and state minimum wage provisions.

where $\ln(w)_{ij}$ represents the natural logarithm of real hourly wages in education or industry group i and age group j. *GENR* is an independent binary variable indicating whether the respondent resided in a state with generous EITC benefits. Year represents normalized year. *YEARGENR* is the interaction term that represents the wage growth overtime for generous versus non-generous states. The vector of controls X_{ij} includes binding minimum wages, log of state GDP, and the mean number of weeks people were unemployed last year in each U.S. state.

Results

Table 7 reports the results of the fixed effect model for each age and education group from 1991 to 2019. Younger workers in non-generous states without a college degree have seen an increase of 5.3% in their real hourly wages from 1991 to 2019 while non college educated older workers in non-generous states have experienced a 9.2% increase in their real hourly wages. But during the same time period real hourly wages for older workers without a college degree who resided in generous states decreased by 3.1% in the past 28 years while for younger non-college educated workers in the generous states wage growth has been stagnant.

[Table 6]

One reason the impact on low educated older workers' wages could be more severe is because they are less substitutable. If workers are substitutable for other employees, then wage fall for workers would be lower since other employees would then share in the wage reduction (Leigh 2010). When a fraction of workers is targeted by a policy that alters incentives to work, spillovers on their co-workers may arise depending on whether the employer finds close substitutes or complements among incumbent employees (Paradisi 2019). Using linked basic monthly data from the Current Population Survey we calculate the share of job switches among workers based on income, sex and age groups as a measure of their relative substitutability. Table 8 and Table 9 describe the general structure of labor flows in terms of average share of job switchers and the degree to which job switchers cross industry lines on a monthly basis. Results show that workers frequently cross industry boundaries, even at the aggregate level of the industry classification system. But a smaller share of older low-wage workers (both female and male) change employers from month to month compared to young workers. For instance, on average 1.4% of full-time female workers in the second income quintile change employers monthly, compared to 2.5% of young full-time workers. (Results for men are available upon request).

Older low-paid workers are also less likely to cross industry boundaries both at detailed and major industry levels. These results indicate that the stagnation in wage growth due to the existence of EITC benefits is exacerbated for older workers since they are less substitutable and their labor market is less fluid.

[Table 7]

[Table 8]

Conclusions and Policy Recommendations

We explored the redistributive effects of the EITC from the perspective of monopsony theory by considering how the variation in state based EITC policy changes the shape of the labor supply curve facing the firm. We examined how these changes reduce the firms' labor supply elasticity through lower turnover rates which in turn enhances the wage-setting power of employers and allows them to capture a portion of the benefit. Increased employee retention translates to increased labor supply without needing to increase workers' compensation. Through our analysis we reached three findings. First, we found support for the employment effects of the EITC previously found in similar literature. Second, we documented reduced turnover rates for accommodation and food service workers in states with EITC supplements, which translates to reduced labor supply elasticity. Lastly, we turned our attention to wages and found that increasing the generosity of EITC stunts wage growth for workers without college degrees.

Despite these results for wages, it is important to note that EITC has reached many of its redistributive goals. For many eligible workers the EITC has raised living standards by supplementing low wages and encouraging higher labor force participation. But predominantly working under assumptions of perfect competition has barred researchers from further exploring the increasing impacts of wage subsidy policies on monopsony power of employers.

If the EITC encourages low wages, a policy that could remedy this shortcoming is to pair EITC benefits with a higher federal minimum wage and other constraints on low wages (Bluestone and Ghilarducci 1996; Kochan 2006: 190). Unions boost workers' bargaining power and wages and likely reduce the share of workers receiving the EITC (Sojourner and Pacas 2019). Our results also suggest that eligibility for EITC be expanded to include workers over 65, below 25 and childless workers. The 2021 American Rescue Plan extends eligibility to these groups (excluding full-time students) but is set to expire after one year. Some states (California, Maine, Maryland) have already independently expanded their eligibility criteria to include childless workers. The uneven impacts of the EITC disappear entirely when it is transformed into a negative income tax or universal basic income, as Rothstein (2010) and Kasy (2018) argue. Rather than enhancing the wage-setting power of employers, these policies boost workers' bargaining power.

References

Abowd, John M., Bryce E. Stephens, Lars Vilhuber, Fredrik Andersson, Kevin L. McKinney, Marc Roemer, and Simon Woodcock. 2009. The LEHD Infrastructure Files and The Creation of The Quarterly Workforce Indicators. Pp. 149–230 in *Producer Dynamics: New Evidence from Micro Data*. University of Chicago Press.

Allegretto, Sylvia, Arindrajit Dube, Michael Reich, and Ben Zipperer. 2017. Credible Research Designs for Minimum Wage Studies. *ILR Review* 70(3):559–92.

Andersson, Fredrik, John Haltiwanger, Mark Kutzbach, Henry O. Pollakowski, & Daniel Weinberg. 2018. Job displacement and the duration of joblessness: The role of spatial mismatch. *Review of Economics and Statistics*, 100(2), 203–218.

Baum, Charles L. 2009. The Effects of Vehicle Ownership on Employment. *Journal of Urban Economics* 66(3):151–63.

Bluestone, Barry and Teresa Ghilarducci. 1996. Making Work Pay, Wage Insurance for the Working Poor. Economics Public Policy Brief Archive. No. 28. Levy Economics Institute.

Card, David and Alan Krueger. 2015. *Myth and Measurement: The New Economics of the Minimum Wage-Twentieth-Anniversary Edition*. Princeton University Press.

Chetty, Raj, John N. Friedman, and Emmanuel Saez. 2013. Using Differences in Knowledge Across Neighborhoods to Uncover the Impacts of the EITC on Earnings. *American Economic Review* 103(7):2683–2721.

Correia, Sergio. (2017). Linear models with high-dimensional fixed effects: An efficient and feasible estimator. Working Paper available at: (20/02/19) http://scorreia.com/research /hdfe.pdf

Crandall-Hollick, Margot L., Gene Falk, and Boyle Conor. 2021. The Earned Income Tax Credit (EITC): How It Works and Who Receives It. U.S. Congressional Research Service. Accessed at https://fas.org/sgp/crs/misc/R43805.pdf

Dahl, Gordon B. and Lance Lochner. 2012. The Impact of Family Income on Child Achievement: Evidence from the Earned Income Tax Credit. *American Economic Review* 102(5):1927–56.

Dube, Arindrajit, T. William Lester, and Michael Reich. 2016. Minimum Wage Shocks, Employment Flows, and Labor Market Frictions. *Journal of Labor Economics* 34(3):663–704.

Eissa, Nada and Jeffrey Liebman. 1996. Labor Supply Response to the Earned Income Tax Credit. *The Quarterly Journal of Economics* 111(2):605–37.

Eissa, Nada and Hilary Williamson Hoynes. 2004. Taxes and the Labor Market Participation of Married Couples: The Earned Income Tax Credit. *Journal of Public Economics* 88(9–10):1931–58.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. 2021. “Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [Dataset]. Minneapolis, MN.”

Goodman-Bacon, Andrew and Leslie McGranahan. 2008. How Do EITC Recipients Spend Their Refunds? *Economic Perspectives* 32(2).

Hoynes, Hilary and Ankur Patel. 2015. Effective Policy for Reducing Inequality? The Earned Income Tax Credit and the Distribution of Income. NBER Working Paper No. 21340 Cambridge, MA: National Bureau of Economic Research

Internal Revenue Services. 2021. “About EITC.” Retrieved https://www.eitc.irs.gov/eitc-central/about-eitc/about-eitc.

Kasy, Maximilian. 2018. Why a Universal Basic Income Is Better Than Subsidies of Low-Wage Work. Accessed at https://www.semanticscholar.org/paper/Why-a-Universal-Basic-Income-Is-Better-Than-of-Work-Kasy/334f52ad4dbaf7e9d780bba7152bb084e77a988c#citing-papers

Kleven, Henrik. 2019. The EITC and the Extensive Margin: A Reappraisal. NBER Working Paper No. 26405 Cambridge, MA: National Bureau of Economic Research

Kochan, Thomas A. 2006. Restoring the American dream: A working families' agenda for America. MIT Press.

Leigh, Andrew. 2010. Who Benefits from the Earned Income Tax Credit? Incidence among Recipients, Coworkers and Firms. *The B.E. Journal of Economic Analysis & Policy* 10(1).

Manning, Alan. 2003. *Monopsony in Motion: Imperfect Competition in Labor Markets*. Princeton University Press.

Manning, Alan. 2021. Monopsony in labor markets: a review. *ILR Review*, 74(1), 3-26

Manoli, Day and Nicholas Turner. 2018. Cash-on-Hand and College Enrollment: Evidence from Population Tax Data and the Earned Income Tax Credit. *American Economic Journal: Economic Policy* 10(2):242–71.

Meer, Jonathan and Jeremy West. 2016. Effects of the Minimum Wage on Employment Dynamics. *Journal of Human Resources* 51(2):500–522.

Mendenhall, Ruby, Kathryn Edin, Susan Crowley, Jennifer Sykes, Laura Tach, Katrin Kriz, and Jeffrey R. Kling. 2012. The Role of Earned Income Tax Credit in the Budgets of Low-Income Households. *Social Service Review* 86(3):367–400.

Meyer, Bruce D. and Dan T. Rosenbaum. 2001. Welfare, the Earned Income Tax Credit, and the Labor Supply of Single Mothers. *The Quarterly Journal of Economics* 116(3):1063–1114.

Mancino, Antonella and Joseph Mullins. 2020. Frictional Adjustment to Income Tax Incentives: An Application to the Earned Income Tax Credit.

Neumark, David and Katherine E. Williams. 2020. Do State Earned Income Tax Credits Increase Participation in the Federal EITC? *Public Finance Review* 48(5):579–626.

Nichols, Austin and Jesse Rothstein. 2015. The Earned Income Tax Credit (EITC). NBER Working Paper No. 21211 Cambridge, MA: National Bureau of Economic Research

Paradisi, Matteo. 2019. Essays on Firms and Public Policies. Doctoral dissertation, Harvard University, Graduate School of Arts & Sciences.

Raphael, Steven and Michael Stoll. 2001. Can Boosting Minority Car-Ownership Rates Narrow Inter-Racial Employment Gaps. *Brookings–Wharton Papers on Urban Affairs* 99–137.

Romich, Jennifer L. and Thomas Weisner. 2000. How Families View and Use the EITC: Advance Payment Versus Lump Sum Delivery. *National Tax Journal* 53(4):1245–66.

Rothstein, Jesse. 2010. Is the EITC as Good as an NIT? Conditional Cash Transfers and Tax Incidence. *American Economic Journal: Economic Policy* 2(1):177–208.

Schanzenbach, Diane Whitmore and Michael R. Strain. 2020. Employment Effects of the Earned Income Tax Credit: Taking the Long View. *Tax Policy and the Economy, Volume 35*. University of Chicago Press.

Smeeding, Timothy M., Katherine Ross Phillips, & Michael O'Connor. 2000. The EITC: Expectation, knowledge, use, and economic and social mobility. *National tax journal*, 1187-1209.

Sojourner, Aaron, & José Pacas. 2019. The Relationship Between Union Membership and Net Fiscal Impact. Industrial Relations: *A Journal of Economy and Society*, 58, 86-107.

U.S. Chamber of Commerce Foundation. 2007. Community Building Through the Earned Income Tax Credit (EITC). *U.S. Chamber of Commerce Foundation*. Accessed at https://www.uschamberfoundation.org/sites/default/files/publication/edu/ICW_EITCToolkitrdc.pdf

Wilson, Riley. 2020. The EITC and Employment Transitions: Labor Force Attachment and Annual Exit. *National Tax Journal* 73(1):11–46.

Tables and Figures

Table 1: EITC Elasticities for Food Service by Cumulative Lag Length, Women, 2000-2019

	All ages			Ages 25-34		
	1y	3y	5y	1y	3y	5y
Employment	0.083	0.145	0.159	0.268	0.402**	0.459**
	(0.159)	(0.184)	(0.201)	(0.174)	(0.180)	(0.185)
	133,746	133,746	133,746	115,776	115,776	115,776
Stable employment	0.085	0.150	0.169	0.281	0.423**	0.488**
	(0.159)	(0.187)	(0.206)	(0.182)	(0.187)	(0.19)
	133,538	133,538	133,538	111,034	111,034	111,034
Turnover	0.089	0.057	-0.002	0.105	0.039	-0.042
	(0.203)	(0.232)	(0.241)	(0.245)	(0.232)	(0.219)
	116,002	116,002	116,002	74,702	74,702	74,702
Stable turnover	-0.069	-0.119	-0.155	-0.175	-0.241*	-0.313**
	(0.119)	(0.134)	(0.134)	(0.134)	(0.139)	(0.127)
	97,000	97,000	97,000	43,896	43,896	43,896

Significance levels: * 10% ** 5% *** 1%

Note: This table reports the linear combination of coefficients associated with the regression of log EITC and specified lags on variable listed in first column. Regression controls include county population, county-level private employment and log minimum wage, as well as county fixed effects and pair-specific time effects. Samples are restricted to women employed in NAICS 722 in the age ranges indicated in the first row. Standard errors and observations reported below coefficient estimates.

Table 2: EITC Elasticities for Food Service by Cumulative Lag Length, Women, 1991-2019

	All ages			Ages 25-34		
	1y	3y	5y	1y	3y	5y
Employment	0.185	0.218	0.212	0.318*	0.393**	0.409**
	(0.165)	(0.179)	(0.183)	(0.159)	(0.157)	(0.157)
	143,452	143,198	142,672	124,450	124,210	123,712
Stable employment	0.199	0.239	0.233	0.336**	0.418**	0.435**
	(0.177)	(0.193)	(0.198)	(0.163)	(0.162)	(0.162)
	143,244	142,990	142,464	119,384	119,158	118,676
Turnover	-0.044	-0.089	-0.108	-0.088	-0.139	-0.163
	(0.183)	(0.191)	(0.196)	(0.209)	(0.198)	(0.202)
	124,670	124,430	123,932	80,160	80,032	79,744
Stable turnover	-0.182*	-0.220**	-0.230**	-0.236*	-0.277**	-0.313**
	(0.106)	(0.106)	(0.109)	(0.125)	(0.125)	(0.133)
	103,572	103,428	103,098	46,922	46,826	46,622

Significance levels: * 10% ** 5% *** 1%

Note: This table reports the linear combination of coefficients associated with the regression of log EITC and specified lags on variable listed in first column. Regression controls include county population, county-level private employment and log minimum wage, as well as county fixed effects and pair-specific time effects. Samples are restricted to women employed in NAICS 722 in the age ranges indicated in the first row. Standard errors and observations reported below coefficient estimates.

Table 3: Robustness—EITC Coefficients on Stable Turnover for Women in Food Service, With and Without Total County Turnover Control

	All ages			Ages 25-34		
	1y	3y	5y	1y	3y	5y
1991-2019						
Baseline	-0.182*	-0.220**	-0.230**	-0.236*	-0.277**	-0.313**
	(0.106)	(0.106)	(0.109)	(0.125)	(0.125)	(0.133)
	103,572	103,428	103,098	46,922	46,826	46,622
Turnover control	-0.145*	-0.169*	-0.175**	-0.184**	-0.209**	-0.234**
	(0.085)	(0.085)	(0.084)	(0.089)	(0.091)	(0.098)
	103,572	103,428	103,098	46,922	46,826	46,622
2000-2019						
Baseline	-0.069	-0.119	-0.155	-0.175	-0.241*	-0.313**
	(0.119)	(0.134)	(0.134)	(0.134)	(0.139)	(0.127)
	97,000	97,000	97,000	43,896	43,896	43,896
Turnover control	-0.064	-0.097	-0.124	-0.166	-0.211*	-0.268**
	(0.107)	(0.120)	(0.121)	(0.109)	(0.114)	(0.105)
	97,000	97,000	97,000	43,896	43,896	43,896

Significance levels: * 10% ** 5% *** 1%

Note: This table reports the linear combination of coefficients associated with the regression of log EITC and specified lags on variable listed in first column. Regression controls include county population, county-level private employment and log minimum wage, as well as county fixed effects and pair-specific time effects. For the "robust" models, covariates also include total private-sector stable turnover. Samples are restricted to women employed in NAICS 722 in the age ranges indicated in the first row. Standard errors and observations reported below coefficient estimates.

Table 4: Robustness—EITC Coefficients on Employment for Women in Food Service, Alternate Specifications

	All ages			Ages 25-34		
	1y	3y	5y	1y	3y	5y
1991-2019						
Baseline	0.185	0.218	0.212	0.318*	0.393**	0.409**
	(0.165)	(0.179)	(0.183)	(0.159)	(0.157)	(0.157)
	143,452	143,198	142,672	124,450	124,210	123,712
Common-time FE	0.001	-0.014	-0.045	0.374**	0.450**	0.482**
	(0.286)	(0.318)	(0.337)	(0.170)	(0.182)	(0.193)
	144,909	144,639	144,080	125,626	125,371	124841
No distance cutoff	0.105	0.181	0.217	0.267**	0.375***	0.438***
	(0.128)	(0.151)	(0.166)	(0.127)	(0.134)	(0.139)
	172,796	172,220	171,128	150,430	149,924	148,924
2000-2019						
Baseline	0.083	0.145	0.159	0.268	0.402**	0.459**
	(0.159)	(0.184)	(0.201)	(0.174)	(0.180)	(0.185)
	133,746	133,746	133,746	115,776	115,776	115,776
Common-time FE	-0.118	-0.124	-0.151	0.346*	0.469**	0.544**
	(0.323)	(0.374)	(0.390)	(0.188)	(0.205)	(0.212)
	134,791	134,791	134,791	116,600	116,600	116600
No distance cutoff	0.050	0.152	0.214	0.212*	0.362**	0.478***
	(0.109)	(0.142)	(0.172)	(0.123)	(0.144)	(0.156)
	159,484	159,484	159,484	138,656	138,656	138,656

Significance levels: * 10% ** 5% *** 1%

Note. This table reports the linear combination of coefficients associated with the regression of log EITC and specified lags on variable listed in first column. Regression controls include county population, county-level private employment and log minimum wage, as well as county fixed effects and pair-specific time effects. For the common-time fixed-effects models, pair-specific time effects are replaced with general time fixed effects. The other specification lifts the restriction that county centroids be a maximum 75 km apart. Samples are restricted to women employed in NAICS 722 in the age ranges indicated in the first row. Standard errors and observations reported below coefficient estimates.

Table 5: Robustness—EITC Coefficients on Stable Turnover for Women in Food Service, Alternate Specifications}

	All ages			Ages 25-34		
	1y	3y	5y	1y	3y	5y
1991-2019						
Baseline	-0.182*	-0.220**	-0.230**	-0.236*	-0.277**	-0.313**
	(0.106)	(0.106)	(0.109)	(0.125)	(0.125)	-0.133
	103,572	103,428	103,098	46,922	46,826	46622
Common-time FE	-0.099	-0.130	-0.157	-0.146	-0.177*	-0.223*
	(0.087)	(0.088)	(0.094)	(0.094)	(0.102)	-0.112
	105,533	105,369	104,979	47,784	47,676	47450
No distance cutoff	-0.076	-0.150	-0.183*	-0.091	-0.179	-0.256*
	(0.105)	(0.102)	(0.102)	(0.118)	(0.123)	-0.134
	122,772	122,480	121,808	53,532	53,364	53048
2000-2019						
Baseline	-0.069	-0.119	-0.155	-0.175	-0.241*	-0.313**
	(0.119)	(0.134)	(0.134)	(0.134)	(0.139)	-0.127
	97,000	97,000	97,000	43,896	43,896	43896
Common-time FE	-0.069	-0.110	-0.154	-0.142	-0.183*	-0.253**
	(0.103)	(0.112)	(0.117)	(0.094)	(0.107)	-0.118
	98,396	98,396	98,396	44,528	44,528	44528
No distance cutoff	0.023	-0.054	-0.109	-0.023	-0.125	-0.250**
	(0.095)	(0.115)	(0.118)	(0.102)	(0.117)	-0.113
	114,122	114,122	114,122	49,806	49,806	49,806

Significance levels: * 10% ** 5% *** 1%

Note. This table reports the linear combination of coefficients associated with the regression of log EITC and specified lags on variable listed in first column. Regression controls include county population, county-level private employment and log minimum wage, as well as county fixed effects and pair-specific time effects. For the common-time fixed-effects models, pair-specific time effects are replaced with general time fixed effects. The other specification lifts the restriction that county centroids be a maximum 75 km apart. Samples are restricted to women employed in NAICS 722 in the age ranges indicated in the first row. Standard errors and observations reported below coefficient estimates.

Table 6: Impact of the Generosity of EITC on Log Hourly Wages by Education and Age

1991-2019	Ages 15-54		Ages 55+	
	No College	College	No College	College
Generosity	-0.0218***	-0.0106	0.00273	-0.000878
	(0.00666)	(0.0147)	(0.0188)	(0.037)
Year	0.00190***	0.00140**	0.00331***	0.000681
	(0.000215)	(0.000638)	(0.000643)	(0.00169)
Generosity*Year	-0.00183**	-0.00242*	-0.00442**	-0.000684
	(0.000729)	(0.0014)	(0.00192)	(0.00322)
Unemployment	0.000315	0.0133***	0.00286	0.00971**
	(0.000741)	(0.0017)	(0.0021)	(0.00413)
Log GDP	0.144***	0.207***	0.189***	0.116*
	(0.0058)	(0.0216)	(0.0182)	(0.0595)
Log Minimum Wage	0.0202	0.0623	-0.111**	0.029
	(0.0162)	(0.0393)	(0.0484)	(0.0952)
Constant	-1.729***	-2.774***	-2.391***	-0.0841
	(0.155)	(0.576)	(0.484)	(1.581)
Observations	597,692	116,697	88,545	30,374

Significance levels: * 10% ** 5% *** 1%

Note. This table reports coefficients associated with the regression of log hourly wages on variable listed in first column. Robust standard errors in parentheses

Table 7: Cross Industry Labor Flows, 2008-2018

Labor Market Segment: Young Full-Time Female Workers					
2008-2018	Wages				
Workers	1st Quantile	2nd Quantile	3rd Quantile	4th Quantile	5th Quantile
Job Switchers	3.5%	2.5%	1.7%	1.3%	1.4%
No Industry Switch	43.7%	55.2%	58.2%	63.2%	66.1%
Major Industry Switch	56.3%	44.8%	41.8%	36.8%	33.9%
Detailed Industry Switch	71.6%	67.5%	59.4%	58.1%	48.6%

Table 8: Cross Industry Labor Flows, 2008-2018

Labor Market Segment: Old Full-Time Female Workers					
2008-2018	Wages				
Workers	1st Quantile	2nd Quantile	3rd Quantile	4th Quantile	5th Quantile
Job Switchers	2.5%	1.4%	1.4%	1.1%	1.2%
No Industry Switch	69.5%	54.1%	75.1%	65.9%	68.2%
Major Industry Switch	30.5%	45.9%	24.9%	34.1%	31.8%
Detailed Industry Switch	52.2%	59.4%	41.5%	49.3%	52.5%

Figure 1: Hypothetical Impact of EITC

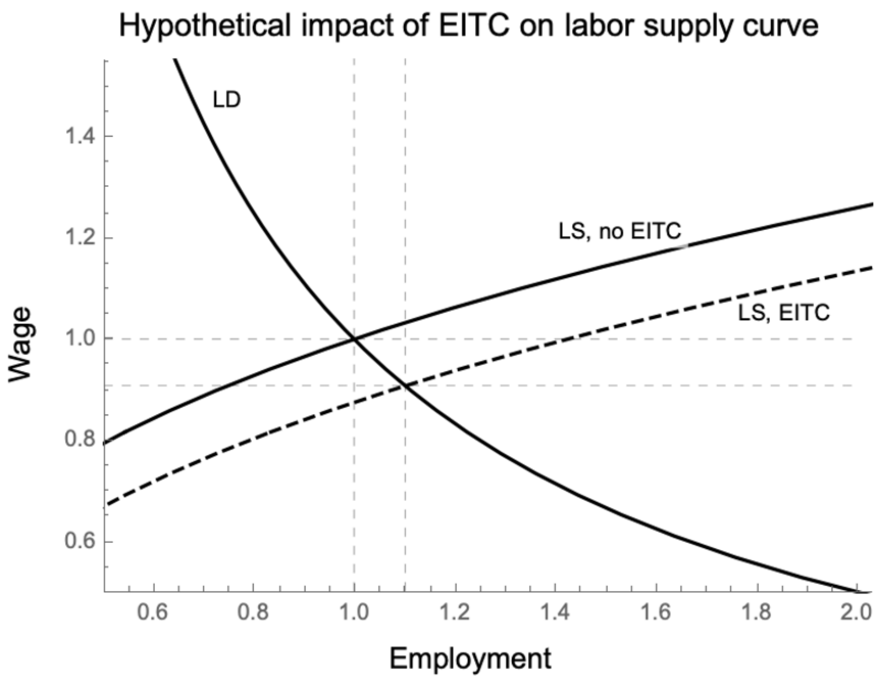


Figure 2

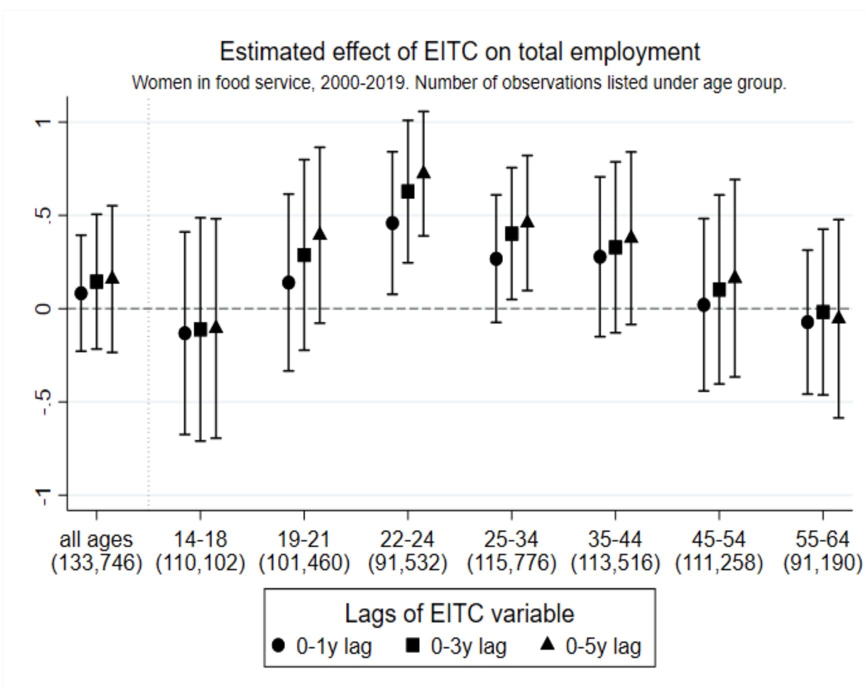


Figure 3

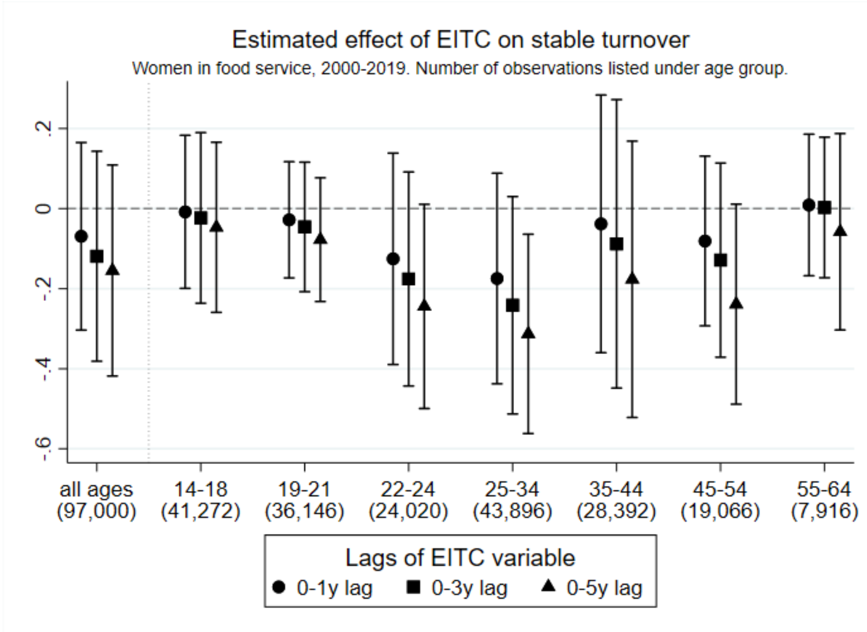


Figure 4

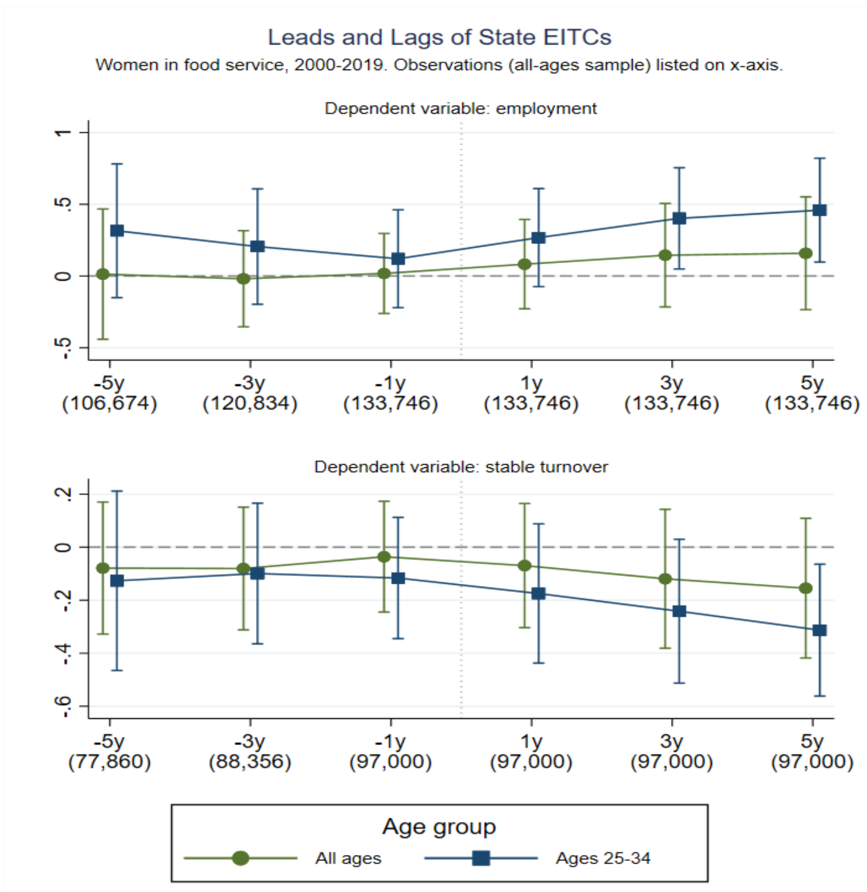
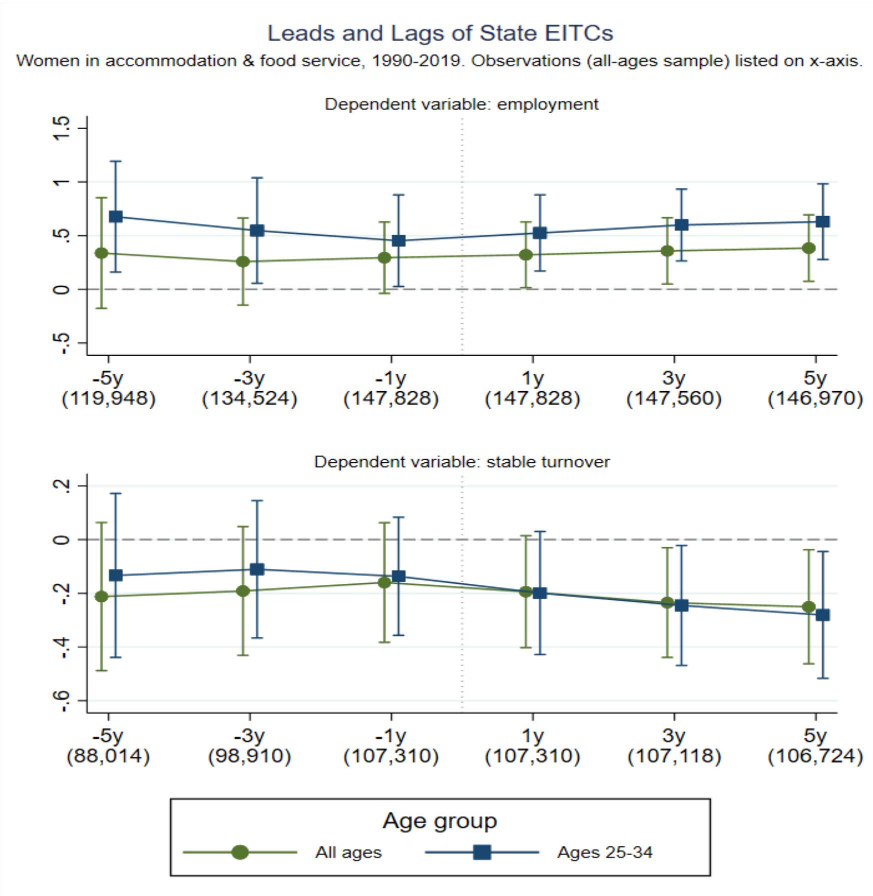


Figure 5



Leads and Lags of State EITCs
Women in accommodation & food service, 1990-2019. Observations (all-ages sample) listed on x-axis.
Dependent variable: employment
1.5
1
.5
0
-.5
-5y (119,948)
-3y (134,524)
-1y (147,828)
1y (147,828)
3y (147,560)
5y (146,970)
Dependent variable: stable turnover
.2
0
-.2
-.4
-.6
-5y (88,014)
-3y (98,910)
-1y (107,310)
1y (107,310)
3y (107,118)
5y (106,724)
Age group
All ages
Ages 25-34

Appendix

Table A1: EITC Elasticities for Women in Accommodation & Food Service

	All ages			Ages 25-34		
	1y	3y	5y	1y	3y	5y
1991-2019						
Employment	0.321**	0.358**	0.384**	0.525***	0.599***	0.630***
	(0.156)	(0.158)	(0.158)	(0.181)	(0.171)	(0.18)
	147,828	147,560	146,970	128,400	128,160	127,662
Stable employment	0.353**	0.400**	0.429**	0.555***	0.645***	0.679***
	(0.172)	(0.174)	(0.175)	(0.197)	(0.186)	(0.193)
	147,616	147,348	146,758	123,600	123,374	122,892
Turnover	-0.120	-0.163	-0.190	-0.126	-0.202	-0.247
	(0.175)	(0.181)	(0.187)	(0.211)	(0.195)	(0.195)
	130,578	130,338	129,840	86,426	86,270	85946
Stable turnover	-0.194*	-0.235**	-0.250**	-0.199*	-0.245**	-0.281**
	(0.106)	(0.104)	(0.108)	(0.117)	(0.114)	(0.12)
	107,310	107,118	106,724	51,588	51,492	51,278
2000-2019						
Employment	0.339*	0.427**	0.455**	0.543**	0.690***	0.749***
	(0.176)	(0.178)	(0.185)	(0.250)	(0.249)	(0.249)
	137,760	137,760	137,760	119,622	119,622	119622
Stable employment	0.364*	0.464**	0.502**	0.557**	0.720**	0.787***
	(0.196)	(0.201)	(0.205)	(0.277)	(0.275)	(0.268)
	137,548	137,548	137,548	115,026	115,026	115026
Turnover	0.000	-0.031	-0.096	0.027	-0.069	-0.169
	(0.200)	(0.219)	(0.223)	(0.259)	(0.241)	(0.211)
	121,676	121,676	121,676	80,292	80,292	80292
Stable turnover	-0.095	-0.144	-0.177	-0.134	-0.199	-0.258**
	(0.124)	(0.135)	(0.134)	(0.124)	(0.128)	(0.122)
	100,236	100,236	100,236	48,234	48,234	48,234

Significance levels: * 10% ** 5% *** 1%

Note: This table reports the linear combination of coefficients associated with the regression of log EITC and specified lags on variable listed in first column. Regression controls include county population, county-level private employment and log minimum wage, as well as county fixed effects and pair-specific time effects. Samples are restricted to women employed in NAICS 72 in the age ranges indicated in the first row. Standard errors and observations reported below coefficient estimates.

Table A2: EITC Elasticities for Men in Accommodation & Food Service

	All ages			Ages 25-34		
	1y	3y	5y	1y	3y	5y
1991-2019						
Employment	0.388***	0.428***	0.446***	0.474***	0.490***	0.480***
	(0.116)	(0.117)	(0.126)	(0.163)	(0.166)	-0.174
	140,506	140,252	139,738	99,862	99,720	99394
Stable employment	0.373**	0.433***	0.459***	0.498***	0.506***	0.491***
	(0.148)	(0.145)	(0.153)	(0.166)	(0.169)	-0.179
	134,890	134,636	134,122	92,322	92,180	91868
Turnover	-0.101	-0.160	-0.202	-0.092	-0.129	-0.185
	(0.232)	(0.230)	(0.238)	(0.255)	(0.249)	-0.236
	112,340	112,142	111,724	67,750	67,622	67336
Stable turnover	-0.181	-0.226*	-0.256*	-0.079	-0.114	-0.148
	(0.125)	(0.126)	(0.132)	(0.141)	(0.145)	-0.148
	84,368	84,260	84,010	35,520	35,460	35,324
2000-2019						
Employment	0.348*	0.430**	0.471***	0.293	0.337	0.356
	(0.174)	(0.171)	(0.173)	(0.193)	(0.216)	-0.231
	130,940	130,940	130,940	93,066	93,066	93066
Stable employment	0.309	0.408*	0.466**	0.319	0.356	0.372
	(0.223)	(0.217)	(0.212)	(0.204)	(0.231)	-0.247
	125,732	125,732	125,732	86,068	86,068	86068
Turnover	0.032	-0.024	-0.095	0.229	0.202	0.106
	(0.283)	(0.297)	(0.297)	(0.295)	(0.292)	-0.261
	104,648	104,648	104,648	63,056	63,056	63056
Stable turnover	-0.081	-0.149	-0.195	0.083	0.050	0.012
	(0.127)	(0.144)	(0.146)	(0.097)	(0.110)	-0.112
	79,092	79,092	79,092	33,092	33,092	33,092

Significance levels: * 10% ** 5% *** 1%

Note: This table reports the linear combination of coefficients associated with the regression of log EITC and specified lags on variable listed in first column. Regression controls include county population, county-level private employment and log minimum wage, as well as county fixed effects and pair-specific time effects. Samples are restricted to women employed in NAICS 72 in the age ranges indicated in the first row. Standard errors and observations reported below coefficient estimates.

Figure 1A

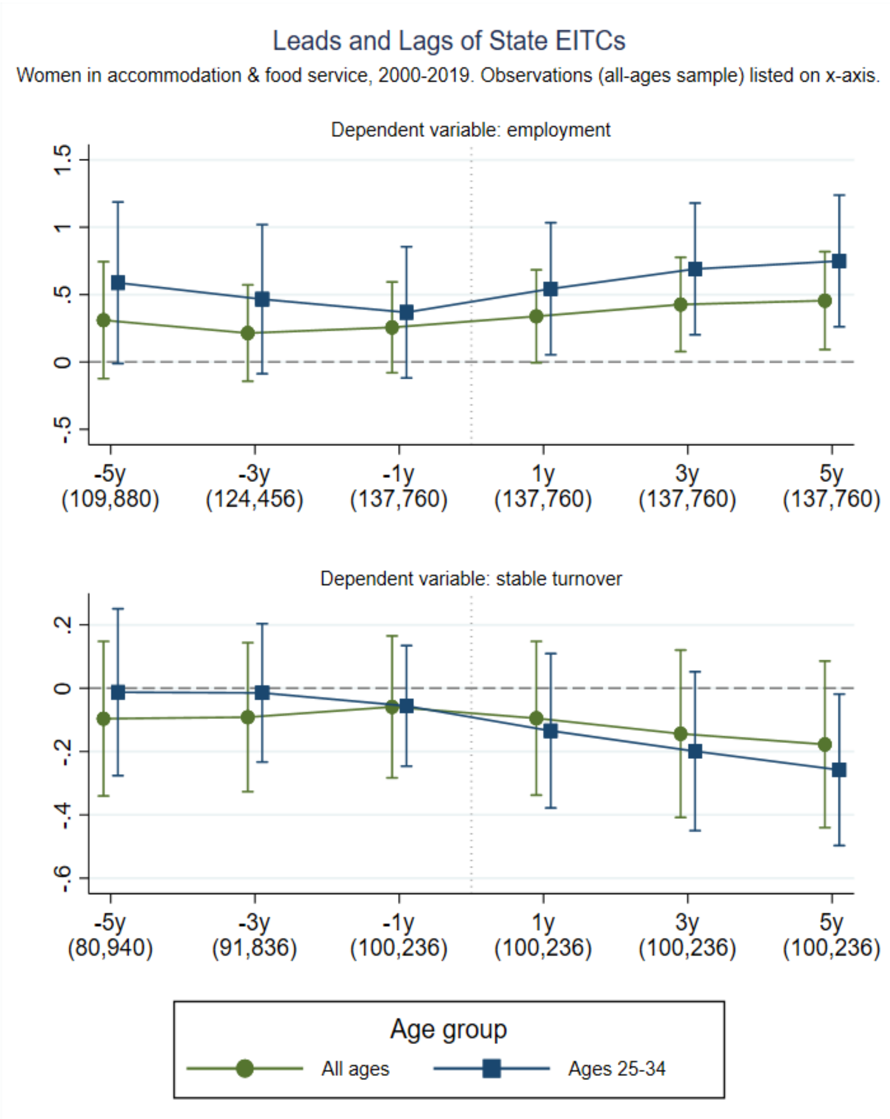
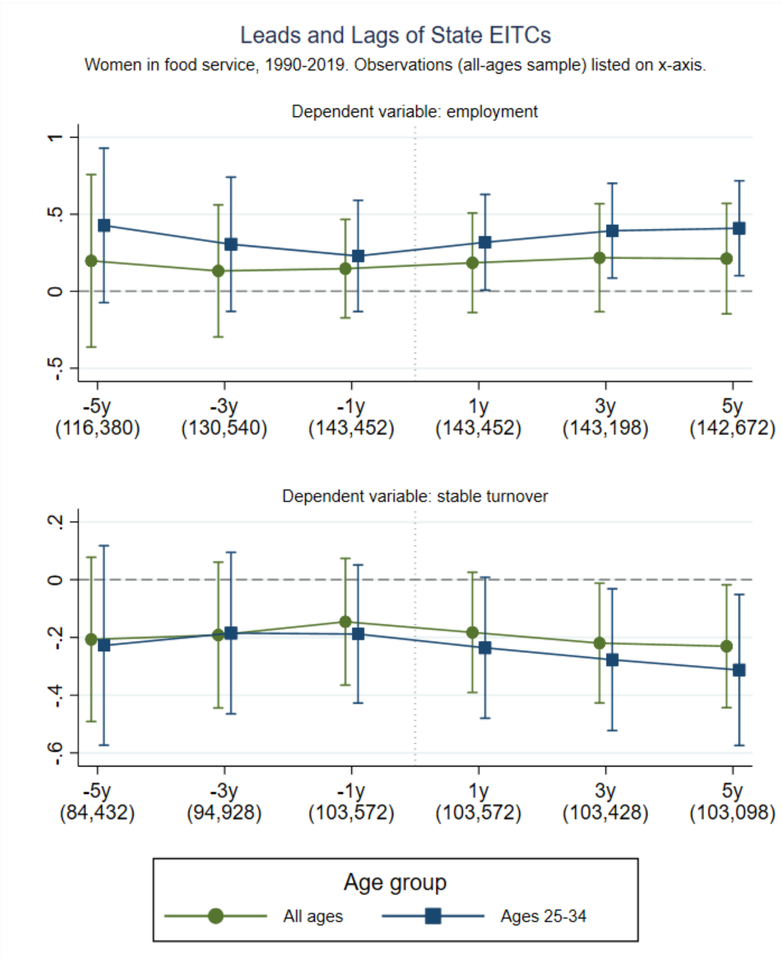

Leads and Lags of State EITCs
Women in accommodation & food service, 2000-2019. Observations (all-ages sample) listed on x-axis.
Dependent variable: employment
-.5
0
.5
1
1.5
-5y (109,880)
-3y (124,456)
-1y (137,760)
1y (137,760)
3y (137,760)
5y (137,760)
Dependent variable: stable turnover
-.6
-.4
-.2
0
.2
-5y (80,940)
-3y (91,836)
-1y (100,236)
1y (100,236)
3y (100,236)
5y (100,236)
Age group
All ages
Ages 25-34

Figure A2



Leads and Lags of State EITCs
Women in food service, 1990-2019. Observations (all-ages sample) listed on x-axis.
Dependent variable: employment
-.5
0
.5
1
-5y (116,380)
-3y (130,540)
-1y (143,452)
1y (143,452)
3y (143,198)
5y (142,672)
Dependent variable: stable turnover
-.6
-.4
-.2
0
.2
-5y (84,432)
-3y (94,928)
-1y (103,572)
1y (103,572)
3y (103,428)
5y (103,098)
Age group
All ages
Ages 25-34