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How the EITC Affects the Labor Supply of Single Women

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ABSTRACT

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By

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This thesis estimates a structural model of the EITC and the labor supply of single female heads of household using panel data. I do this by treating labor supply as a choice over a discrete set of income and labor bundles and estimating a flexible utility function defined over those goods, while modeling the distribution of wage offers. This allows me to overcome major technical limitations in the EITC and labor supply literature. I consider how effects on earnings and labor supply vary across the wage distribution and predict the effects of alternative EITC policies. I find that the EITC increased the employment of single mothers by about 7.5 percentage points, those single mothers induced into the workforce by the EITC worked an average of 1600 hours a year, and that the EITC caused single mothers already working to reduce their average labor supply by 15 hours a year. Finally, I find that increasing the rate at which better-off beneficiaries lose benefits for each additional dollar of income to fifty cents per dollar of income would result in a more efficient EITC in terms of welfare improvement per dollar spent.

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Michael Chennault Sikivie

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Acceptance

This dissertation was prepared under the direction of the candidate's dissertation committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements of the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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I. **Motivation**

The Earned Income Tax Credit (EITC) is the third largest social welfare program and the largest cash welfare program in the United States.[1] Two policy issues make it crucial to understand the effects of the EITC on labor supply. First, the EITC corrects the distortionary disincentive to work inherent in other social welfare programs. Food Stamp (SNAP), TANF, SSI, and other transfer program benefits all fall with increased earnings for beneficiaries. When these implicit taxes are combined with explicit taxes, effective marginal tax rates can be extremely high for low-income households. For example, Maag (2012) finds that households between 100 and 150 percent of the poverty line lose between 26.6 and 100 percent of their income for each additional dollar that they earn. However, if transfer programs that tax work are balanced by programs that subsidize work, the same poverty reduction goals might be achieved with less efficiency loss.

The other major reason for interest in the effect of the EITC on labor supply is the welfare of children. The EITC is designed to mainly benefit households with children. The labor supply incentives of the EITC can affect the welfare of children in EITC households in two primary ways. One way is through greater household earnings. If society values the welfare of children in poor households, one might prefer their parents to have higher income. Secondly, children might find it easier to find employment in adulthood if their parents work, due to their parents' knowledge of, and connections to, the labor market.

[1] https://www.heritage.org/budget-and-spending/report/Federal-spending-the-numbers-2013-government-spending-trends-graphics, April 2019.

There are three major contributions of this work relative to the existing literature. Perhaps the greatest original contribution is to be able to predict how any existing or hypothetical EITC policy, characterized by the way that benefits depend on earnings, will affect labor supply. I used this predictive ability to estimate an optimal EITC policy, defined alternately in terms of maximizing average beneficiary income or average utility from income, subject to a spending limit on the program. This insight is possible by using estimates of single head of household preferences over income and hours of work, estimated using heads' observed labor supply and after-tax income and the income they could have at alternative levels of labor supply. The existing literature has only estimated the effect of existing changes in the EITC law on labor supply.

A second contribution is the estimation of heterogeneous effects of the EITC by wage rate and existing labor supply. There is a small decrease in the labor supply of single mothers who are already working; single mothers induced into the labor force by the EITC work only slightly fewer hours than the average employed single woman; and there is an increase in the employment of single mothers that makes the net effect of the EITC on the average hours of single mothers positive. The effects of the EITC are broken down by wage rate, holding demographic characteristics constant, implying that the average net effect on labor supply and earnings before the EITC goes from positive to negative for single mothers with offered wage rates between \$15 and \$20 an hour.

The existing literature has mainly focused on the effect of the EITC on employment. The literature that has considered effects on hours has estimated effects only at two kink points in the EITC budget constraint,[2] or estimated the effect on hours conditional on working,[3] which conflates the selection effect caused by the hours choices of people induced into the labor force by the EITC and the change in the hours of people already working.

Finally, this thesis models the distribution of wage rates as a function of observable characteristics and unobserved labor supply preferences. The alternative in the literature has been to predict the income non-workers would have received had they worked as the mean wage of workers. This is likely to be biased because higher wage offers are more likely to be accepted and therefore observed. While one solution is to use a *point estimate* of the wage that the nonworker would receive in the labor market predicted from observables, one can do better by modeling the *distribution* of wage offers from observables. This provides a more accurate prediction of the probability of working because the probability of working is affected by the whole distribution over wage offers and not just one point estimate.

In Section 2, I give a brief description of the EITC. Section 3 provides a review of the existing literature on the topic as it relates to this work, and Section 4 details my theoretical model of the EITC and labor supply. Section 5 describes my empirical approach to the EITC and labor supply and is divided into subsections on the modeling of labor supply, the modeling of wages, and data sources. Section 6 provides summary statistics. Section 7 provides results and is divided into subsections on the goodness of fit of the wage model, the goodness of fit of the labor supply model, the estimated effect of the EITC on labor supply, the distributional effects of the EITC, and an optimal EITC program subject

[2]Eg, Saez (2010) or Jones (2013)
[3]Eissa and Liebman (1996)

to a spending limit. Optimal EITC is defined alternately in terms of maximizing the average household income of beneficiaries and maximizing the average income component of the additively separable utility function used to estimate labor supply preferences. Section 8 concludes.

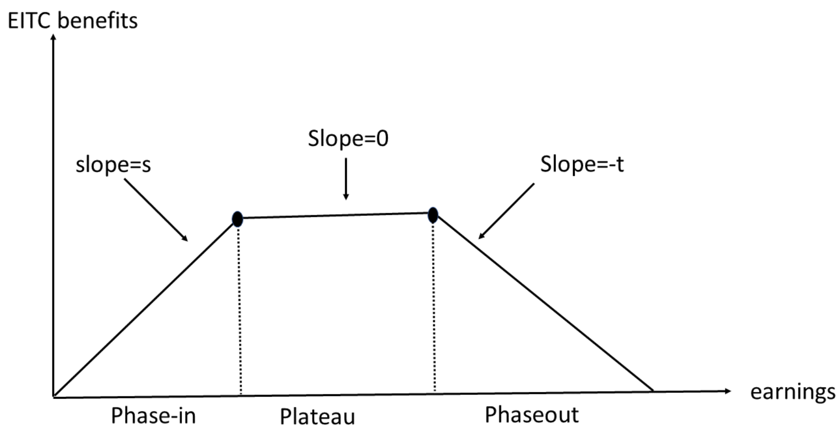
II. **A Description of the EITC and Identification**

The EITC works as follows. A tax filer whose annual earnings are below a certain upper limit is in what is known as the phase-in earnings range and receives a wage subsidy. That means for every dollar she receives in labor income, she receives some fraction of a dollar, s, in addition as a refundable tax credit. I refer to that fraction as the subsidy rate. Note that this payment raises the wage rate for each additional (marginal) hour of work, because it multiplies the wage rate by (1+s).

If her earnings are in the next highest range, the flat or plateau earnings range, she receives the maximum benefit, but no wage subsidy. Her income is higher than it would be without the EITC, but her wage rate for each additional (marginal) hour of work is unchanged from what it would be without the EITC, since additional hours of work do not affect the level of benefits.

Beyond the plateau earnings range is the phaseout earnings range, in which a household receives EITC benefits but is considered too well-off to receive the maximum benefit. For every dollar earned, some fraction of a dollar in EITC benefits, t, is lost. This lowers the marginal wage rate. The phaseout earnings range ends when benefits are reduced to zero. Tax filers with earnings beyond that point do not qualify for the EITC and their budget constraint is unaffected by the EITC. Figure 1 below depicts how EITC benefits relate to earnings, where "s" represents the subsidy rate and "t" the tax rate.

Figure 1: Labor Income and EITC Benefits

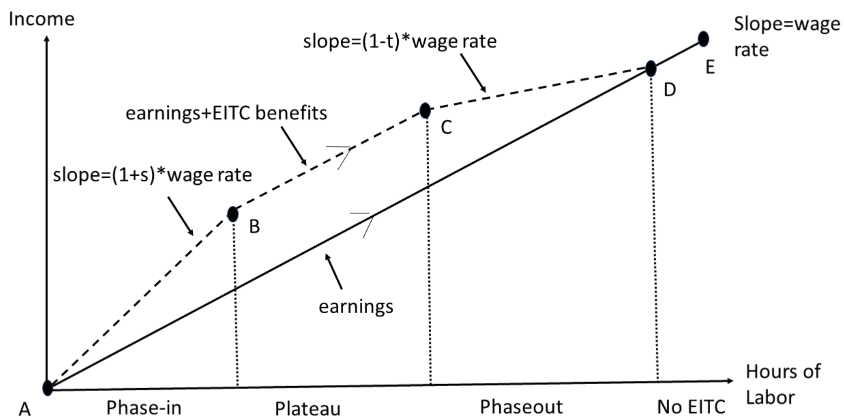


I model labor supply by treating it as a choice among a set of income and labor supply bundles. Figure 2 shows how the EITC changes the set of choices over income and labor supply. I again use the letter s to represent the subsidy rate and t for the tax rate. The EITC changes the budget set represented by the solid line segment A-D-E to A-B-C-D-E. Since the number of hours of labor is increasing to the right on the horizontal axis, leisure consumption is increasing to the left on the horizontal axis. Figure 2 highlights how the marginal wage rate is increased in the phase-in region, unchanged in the plateau region, and decreased in the phaseout region.

The EITC has always been primarily targeted to families with dependents, usually children.[4] A large change came in 1991 as part of the Tax Reform Act of 1986, when the system became more generous to households with two or more dependents relative to

[4]The dependent need not be a biological child of the tax payer, but must be related by blood, marriage, or law, such as a stepson, stepdaughter, or adopted child, and must have lived with the tax filer for more than half of the tax year. Unless declared "permanently and totally disabled" by a doctor, the dependent must also be younger than the tax filer and either under 18 years old or a full time student for at least 5 months of the tax year and under 24.

Figure 2: Labor Supply and Income with the EITC



households with only one dependent. In 2009 the system became more generous to households with 3 or more dependents relative to households with 2 dependents, as part of the American Recovery and Reinvestment Act (ARRA). This differential increase in generosity towards families of different sizes from the late 1980s to 2012 is one source of identification of the effect of the EITC on labor supply. I control for other factors affecting labor supply over time with repeated observations of the labor supply of childless female heads of household. Appendix table A1 in section (i) of the Appendix details how EITC benefits have been calculated for families of different sizes over the study period, 1988-2012.

The second source of identification is the wage rates, or the predicted distribution of wages in the case of non-workers. Workers with higher wage rates will have too much income to qualify for the EITC at many levels of labor supply, while some workers with low wage rates qualify even at a high level of labor supply. I take advantage of identifying variability in wage rates where the existing literature does not, because I observe wage rates directly in my data. I also have a richer set of variables that predict wages, allowing me to better predict the wages non-workers would receive if they worked. Furthermore, because I have repeated observations on individuals, I can model the correlation between wage rates and labor supply preferences across individuals. This allows me to control for the endogeneity of wages in the labor supply model. Since I model the choice of labor supply as a function of income net of payroll and Federal and state income taxes, variation in wage rates comes not only from the wage rate before taxes but also from variation in federal and state tax rates.

III. **Literature Review**

The existing literature on the EITC and labor supply can be divided into difference-in-difference (DID) approaches and binary budget constraint approaches. The DID approach is limited in the type of EITC effect it can estimate; it also relies on weak proxies for EITC eligibility. The binary budget constraint approaches incorporate a basic utility function and budget constraint but fail to model the wage offers adequately and do not include the multiple levels of labor supply that define the actual budget constraint.

The DID approach is well-illustrated by Eissa and Liebman (1996) and Hotz et al. (2001). The explanatory variable of interest is assignment to an EITC treatment or control group, with the treatment group being a group of less educated adults with children and the control group having more education or no children. For example, Eissa and Liebman (1996) obtained their main result that the EITC raised the labor force participation (LFP) of single women by 2.8 percentage in a probit regression with single female heads of household with children as the treatment group and single female heads of household without children as the control group, with controls for education and other demographic variables. Hotz et all (2001) exploit the increased generosity of the EITC towards families with two children relative to one child and found that a $1000 increase in the maximum EITC benefit raised the employment of welfare recipients in California by 6.6 percentage points.

Interpreting DID estimates as the causal effect of the EITC on labor supply is difficult, however, because the EITC can have general equilibrium effects on the labor supply of the control group. For instance, employers will capture some of the EITC benefits by offering a lower wage, lowering the labor supply of the control group.

The DID approach also ignores heterogeneous effects on labor supply from the workers' wage rates and different EITC parameters. One would expect the EITC to have heterogenous effects on workers of different wage rates because lower-earning workers receive a wage subsidy on the margin, while higher-earning workers are more likely to be taxed on the margin. These heterogeneous effects are important given the redistributive goals of the EITC. Effects of alternative EITC policies on labor supply are important because EITC benefits are determined by several policy parameters that can affect labor supply, such as the subsidy rate and tax rate, but the DID literature can only evaluate the total effect of existing changes in the EITC law.

Finally, the DID approach cannot estimate effects on labor supply on the intensive margin well. That is because only average hours conditional on working is observed, which is a summation of two effects. One effect is how the entrance of new workers into the labor force due to the EITC affects average hours conditional on working. It is reasonable to suspect that these new workers reduce average hours conditional on working, since they most likely have a higher taste for leisure than those workers who would work even without the EITC. The other effect is how the EITC impacts the hours of workers who would still be working were the EITC not implemented; this is the actual effect on the intensive margin. In the DID literature the intensive margin is either ignored or, in the case of Eissa and Liebman (1996), estimated with the change in hours conditional on working observed in the treatment group, relative to the same change observed in the control group.

The binary budget constraint approach, as exemplified by Dickert et al (1995) and Meyer and Rosenbaum (2001), estimates the probability of employment as a probit function of income net of taxes and transfer program benefits if one works, and the same net income if one does not work. It is closer to the approach adopted here, in the sense that it incorporates the EITC through a budget constraint, which in turns affects labor supply through a utility function. The weaknesses of this strand of literature at present are that it considers only two possible levels of labor supply in the budget constraint, zero and some fixed, positive number of hours, and does not estimate differential effects on labor supply by the wage rate. Nor does it model the unobserved wage offers well. Eissa and Hoynes (2004) employ both a binary budget constraint and DID approach to the question of the effect of the EITC on the employment of married women.

Dickert et al (1995) model the probability of work as a function of the difference in net income, including the EITC and other transfer program benefits, at 0 hours and 1000 hours of work. Meyer and Rosenbaum (2001) take the probability of employment as a probit function of the same difference in income between 0 hours and the mean hours of work observed among those who work. Two drawbacks of including only two possible choices over hours of work are that it limits their study to labor supply on the extensive margin, and that the non-zero alternative hours choice is arbitrary. The most likely alternative level of labor supply to working zero hours, for someone on the margin between working or not, is probably lower than the average hours of those who do work, given that working reveals a lower taste for leisure. The relevant margin may or may not be near 1000 hours, though, and likely varies over individuals. If their budget constraints had included several alternative hours of work choices, the data could determine which hours choices are the most relevant alternatives to not working, and this could vary over individuals and observables.

The income at a given level of labor supply also depends on the wage rate, which is unobserved for non-workers. Meyer and Rosenbaum (2001) assume that these unobserved wage offers are equal to the mean of observed wage rates, which is surely an overestimate since the unobserved wage offers were rejected. Dickert et al (1995) do better in this regard by predicting unobserved wage offers from observables. However, they could do even better by modeling the whole distribution of wage offers as a function of covariates. To the extent that the probability of working is not linear in the wage offer, the probability of working depends on the entire distribution of the unobserved wage offer and not just its median or expected value. Therefore, the labor supply literature can do better by modeling the entire distribution of unobserved wage offers as a function of covariates.

One can also estimate a pure substitution effect by exploiting the discontinuous drop in marginal wage rates near where the phase-in earnings range ends and the plateau earnings range begins, and where the plateau earnings range ends and phaseout earnings range begins. Saez (2010) and Jones (2013) appear to be the only researchers who do this with regard to the EITC. Jones presents a consistent estimate of the marginal effect of the subsidy and tax rates on labor supply at those two kink points. Chetty and Saez (2010) observed income reported to the IRS rather than earnings, and they concluded that the bunching in reported incomes at the kink points that they observed was the result of tax evasion because it was only observed in the self-employed. Their approach, however, ignores the labor supply of new entrants to the labor market induced by the EITC and the effect on the labor supply of workers away from those two kink points.

IV. **Theory**

My approach is to treat the EITC as a change in the budget constraint over leisure and consumption, defined as net of tax income. Income and leisure are both goods, but acquiring more income requires you to increase labor supply by sacrificing leisure. I define the budget constraint as the sum of income from earnings, EITC benefits and nonlabor income minus taxes at each possible level of labor supply, and use observed labor supply choices to estimate a utility function defined over income and leisure. I then use those estimated preferences and the budget constraint to simulate the effect of various EITC policies on labor supply.

To simplify the labor supply estimation problem, I assume that each household chooses labor supply from a discrete set of H possible choices of hours of work, $\{L_1, ..L_H\}$. This allows me to address the issue of corner solutions and nonconvexities in the budget set. Many nonconvexities in the budget set are caused by the maximum income to qualify for some transfer program, such as at point D in Figure 2. The marginal wage rate is increased when this income is exceeded because the agent no longer faces the loss of benefits from additional income. This model approximates the continuous case as additional labor supply choices are added, and I show in Section 7 that finer labor supply choices do not change results substantially.

This thesis also limits itself to the labor supply of single female heads of household to avoid the complication of how each spouse's income can affect the other's labor supply and how their labor supplies might be simultaneously determined. For single women, utility is simply an increasing function of two goods: after-tax disposable income, denoted c for consumption, and leisure, denoted l. Let E denote one's time endowment and L be the amount of labor time supplied to the market. Leisure, l, is then equal to l=E-L. Letting i index individuals and t index years, her optimization problem is then

$$\max_{L_{it} \in \{L_1, L_2, .. L_H\}} u(c_{it}(L_{it}), l_{it} | n_{it}, x_{it}) \tag{1}$$

where u is the utility function, n_{it} is the number of dependents in the household, and x_{it} is a vector of other demographic characteristics that could affect labor supply preferences, such as age and a time trend. Note that disposable income depends on the chosen number of hours of work and the parameters of the EITC and tax system. A function $\hat{u}$ of income and leisure predicts the expected utility of each labor supply choice to the econometrician. Deviations from the expected utility maximizing choice are attributed to a preference shock, ϵ_{ith}. Those shocks are observed by the economic agent but not the researcher. Hence, the individual's utility at labor supply choice L_{it} is given by:

$$u_{it}(c_{it}(L_{it}), l_{it} | n_{it}, x_{it}) = \hat{u}(c_{it}(L_{it}), l_{it} | n_{it}, x_{it}) + \epsilon_{ith} \tag{2}$$

Identifying the effect of the EITC on labor supply depends on variation in the budget set that is independent of variation in preferences over labor supply. Three identifying assumptions each allow me to use a source of variation in the budget constraint that is not correlated with the utility function. One is that after conditioning on the number of dependents in the household, labor supply changes caused by EITC expansions are not perfectly simultaneous with labor supply changes caused by changes in labor supply preferences. I allow preference parameters to depend on the number of dependents in the household and a time trend. The interaction of time and the number of dependents in the household provides variation in the EITC budget constraint faced by people who earn the same wage rate.

A second assumption is that unemployment rates are correlated with a worker's wage offers but are not correlated with her labor supply preferences. By unemployment rates I refer to both the national unemployment rate and the unemployment rate in the state where the head of household lives, although in an alternative specification I use only national level unemployment rates. Therefore, I implicitly assume that there is no involuntary unemployment. Unemployment rates are a proxy for low labor demand and wage offers, but a head of household who is willing to accept any job offer will always remain employed. I also assume that the national labor force participation rates of men aged 25-54, women aged 25-54, and state level labor force participation rates are also correlated with wage offers but not labor force participation, although in an alternative specification I do not use state level labor force participation. That assumption allows me to use predicted wage variation to identify labor supply preferences. It also allows me to estimate preferences over income and leisure even though wage offers are missing for women who do not work.

The third assumption is that holding person-specific heterogeneity fixed, shocks to an individual's wage rate over time are not correlated with shocks to her preferences. That allows me to use idiosyncratic shocks to wage offers to identify labor supply preferences. I emphasize that I do allow correlation between wage offers and a time-constant, unobserved component of preferences. How I do that is discussed towards the end of Section 5.

Another important assumption is that I know what a household's budget constraint would look like in a world without the EITC. This is not necessarily just the observed budget constraint minus EITC benefits, because the EITC can have general equilibrium effects on low-skilled wages due to its effect on low-skilled labor supply. To satisfy this assumption, it is sufficient that preferences (u) and the wage offers predicted by the model are not correlated with changes in EITC parameters over time. That will be true to the extent that the wage variables used are not correlated over time with the size of the EITC program and its labor supply effects. While this assumption is not related to identifying variation in the budget constraint that is not correlated with variation in labor supply preferences, it is necessary in order to estimate the missing counterfactual of labor supply without the EITC, which is needed to consistently estimate the effect of the EITC on labor supply.

V. **Empirical Approach**

I break each observed value of annual hours of labor supply, L_{it}, into one of H bins, and round that value to the midpoint of the bin that it falls into. If we assume that the ϵ_{ith} in equation (2) are Gumbel distributed, the probability that any given labor supply choice offers the highest utility, given the set of H possible labor supply choices, is

$$pr(L_{it}) = \frac{exp\Big(\hat{u}(c_{it}(L_{it}), l_{it}|x_{it}, n_{it})\Big)}{\sum_{h=1}^{H} exp\Big(\hat{u}(c_{it}(L_h), l_{it}|x_{it}, n_{it})\Big)} \quad (3)$$

This expression gives the probability of each possible labor supply choice for a given utility function, $\hat{u}$, and budget constraint, $c_{it}(L_{it})$, which allows me to estimate the parameters in $\hat{u}$ by maximum likelihood. While equation (3) assumes that labor supply choices follow independence of irrelevant alternatives, in the wage offers subsection of this section I describe how I relax that assumption by introducing unobserved heterogeneity. In the subsection that follows I describe the functional form of this utility function. In the subsection after that I describe how I model wage offers, which is necessary to model the budget constraints of non-workers because their wage rates conditional on working are unobserved.

i. Labor Supply

Omitting the i and t subscripts for simplicity, the functional form of $\hat{u}$ is as follows.

$$\hat{u}(c,l) = A\Big(\alpha\, sign(\delta_1)(\kappa_1 + c)^{\delta_1} + sign(\delta_2)(\kappa_2 + l)^{\delta_2} + f(x)l - M\Big)^{\gamma} \tag{4}$$

where A, α, κ_1, κ_2, δ_1, δ_2, and γ, along with the parameters that define f as a function of the variables in x, are parameters to be estimated.

f is a linear function of a set of observables that can affect the marginal valuation of leisure. In other words, if f is a positive function of some variable in x, the variable makes you value each hour of leisure more relative to income. The amount you would have to be paid to be willing to work an additional hour is higher and you work less. The opposite is true of a variable that is negatively related to f. I refer to those variables contained in x that can affect the valuation of leisure as preference variables throughout the thesis. Important preference variables include a time trend, which allows me to control for factors other than the EITC or tax code affecting labor supply over time, and indicators for one, two, or three or more children, which control for effects of children on labor supply that do not act through the EITC or tax code. The complete set of preference variables and the coefficient estimates associated with them is listed with all other parameter estimates in subsection (vii) of the appendix.

Parameters κ_1 and κ_2 insure that utility is defined even if c and/or l equal 0 and δ_1 and δ_2 are negative. To insure this, κ_1 and κ_2 must be positive, which I constrain them to be.

δ_1 and δ_2 affect the substitutability between consumption and leisure and whether labor supply is increasing or decreasing in the wage rate. α affects how much one values income relative to leisure. Other parameters equal, a higher value of α predicts a higher labor supply.

The parameter M is not estimated. It is the lowest value of utility over all observations and labor supply choices of $\hat{u}$, if the parameters A and γ were removed or equal to 1. It adds stability to the function and insures that utility is always a real number. Variables c_i and l_i are normalized so that the median levels of annual income and leisure hours reported in the data are equal to 1.

The parameters A and γ are monotonic transformations of utility. They do not change the rank order of possible income and consumption bundles in terms of their expected utility. Since the predicted likelihood of each bundle is increasing in its expected utility, that means they do not change the rank order of consumption bundles in terms of how likely they are. They do affect the size of the difference in expected utility between any two bundles, however, so they do affect *how much* more likely a more likely labor supply choice is relative to a less likely labor supply choice.

I also allow for two fixed cost parameters associated with working a positive number of hours. One is defined in terms of leisure time and represents time lost to commuting or finding, and remaining trained for, a job. The other parameter is defined in terms of utility. Fixed costs of work in utility are also a function of the highest degree level of the head of household and the number of children in the household. I show in subsection (ii) of the Appendix that $\hat{u}$ has the following flexible properties:

(1) The fraction of time devoted to work can be 0, 1, or any value in between.

(2) Leisure and income can be perfect complements as $\delta_1, \delta_2 \to -\infty$, perfect substitutes if $\delta_1 = \delta_2 = 1$, or anything in between.

(3) *Non-homotheticity.* Define the head of household's resources as the head's maximum possible income, which is her wage rate times her time endowment plus all nonlabor income, or $E * w_{it} + g_{it}$, where E is the time endowment, w_{it} is her wage rate, and g_{it} is all of her nonlabor income. Define the budget share of leisure as the fraction of this maximum potential income that is lost by consuming leisure rather than working for income. This budget share of income can vary by the size of the head's resources, and not just at a corner solution where all time or no time is devoted to leisure. In the case of a Cobb-Douglas utility function, this budget share would be constant outside of those corner solutions.

(4) The budget share defined above need not be a monotonic function of resources

The labor supply bins are defined as follows. The first bin represents 0 hours of work in the year of observation. All remaining bins represent positive hours of work, are mutually exclusive, ordered from fewest to most annual hours of work,[5] and defined to represent an equal fraction of non-zero observations of work hours. Observations of annual work hours in the data are then rounded to the midpoint of the bin that they fall into, and those midpoints represent the labor supply choices, or $\{L_1, L_2, ..L_H\}$. For example, one of the hours bins is 1840-1920 hours in the year, and anyone observed to work some number of

[5] The maximum labor supply that respondent's could report in the PSID was 5840 hours a year

hours between 1840 and 1920 is said to have chosen the choice of 1880 hours out of the H possible choices.

I did not assume complete take up of the EITC by eligible households, or that all households are aware of how the program affects their budget constraint. Since a great deal of the existing literature, such as Eissa and Liebman (1996), found an effect of the EITC on the extensive margin but not on the intensive margin, I allowed for separate probabilities of incorporating the EITC in the decision to work and of incorporating the EITC in the hours choice, conditional on working. Parameter p_1 represents the probability of incorporating the EITC in the budget constraint in the decision of whether to work. Conditional on incorporating the EITC in the decision of whether to work, parameter p_2 represents the probability of incorporating the EITC in the budget constraint in the hours of work decision. Therefore, the household ignores the EITC with probability $1-p_1$, considers the EITC on the extensive but not intensive margin with probability $p_1(1-p_2)$, and considers the EITC on both margins with probability $p_1 p_2$. More formally, this means

$$pr(L_{it}=0) = (1-p_1)pr(L_{it}=0|\text{no EITC}) + p_1 pr(L_{it}=0|EITC) \tag{5}$$

and for labor hours choices greater than 0 hours

$$\begin{aligned} pr(L_{it}|L_{it}>0) = (1-p_1)&\frac{pr(L_{it}|\text{no EITC})}{1-pr(L_{it}=0|\text{no EITC})} \\ &+ p_1(1-p_2)\frac{pr(L_{it}|\text{no EITC})}{1-pr(L_{it}=0|EITC)} \\ &+ p_1 p_2 \frac{pr(L_{it}|EITC)}{1-pr(L_{it}=0|EITC)} \end{aligned} \tag{6}$$

where $pr(L_{it}|\text{no EITC})$ is the predicted probability of labor supply choice L_{it} with the Federal EITC excluded from the budget constraint and $pr(L_{it}|EITC)$ is the probability of labor supply choice L_{it} with the Federal EITC included in the budget constraint. Given those respective budget constraints, $pr(L_{it}|\text{no EITC})$ and $pr(L_{it}|EITC)$ are calculated using utility function parameter values according to equations (3) and (4).

I am also aware of the literature on legally ineligible tax filers successfully claiming the EITC. IRS tax return studies estimate that 23.8% to 25.6% of EITC benefits paid in 1997 and 27% to 31.7% of EITC benefits paid in 1999 were overclaims, meaning that they went to ineligible households or were dollars paid in excess of what households were eligible for.[6,7] According to Liebman (2000), ineligible claimants are demographically quite similar to eligible recipients, however. Only 11-13% of all tax year 1990 EITC recipients who responded to the March 1991 Current Population Survey (CPS) did not have a child in their household one year before they received the credit, and overclaims are more common among male household heads than female household heads.

ii. Wage Offers

Calculating the utility of alternative labor supply choices requires a budget constraint, which requires an hourly wage rate. Since hourly wage rates are missing for non-workers, I estimate a probability distribution over offered wage rates for all observations. To avoid restrictive assumptions on the shape of that wage offer distribution, I divide observed wages into K disjoint bins with probabilities assigned to each and round observed wages to the midpoint of the bin that they fall into.[8]This allows the wage offer distribution to take any shape that permits a discrete approximation. This distribution will be a function of observables x_i in a manner described below. The likelihood of an observation on head of household i in year t, given that i works in year t and the model parameters, π, is then

$$\ell_{it}(\pi, w_{it}, x_{it}, L_{it}) = pr(w_{it}|x_{it}, \pi) pr(L_{it}|w_{it}, x_{it}, \pi) \tag{7}$$

[6]Scott, Christine A., and Margot L. Crandall-Hollick. "The Earned Income Tax Credit (EITC): An Overview." Congressional Information Service, Library of Congress, 2007.

[7]Internal Revenue Service (IRS). "Compliance Estimates for Earned Income Tax Credit Claimed on 1999 Returns." (2002).

[8]Wages in the highest bin were rounded to the mean wage in that bin rather than its midpoint, due to the right skewness of wages in that bin.

If i is a non-worker in year t, the likelihood of that observation is then the probability of working 0 hours. This is given by

$$\sum_{w_{it}=w_1}^{w_K} pr(w_{it}|x_{it},\pi)pr(L_{it}=0|w_{it},x_{it},\pi) \tag{8}$$

Stated in words, if household head i works in year t, the likelihood of the observation on her from that year is the product of the probabilities of her observed wage rate and her observed labor supply choice being optimal, conditional on that wage rate. If she did not work in year t, the likelihood of that observation on her is the product of the probabilities of a wage rate and of 0 hours being her optimal labor supply, conditional on that wage rate, integrated over the distribution of the unobserved wage rate. The wage bins provide a discrete approximation to that integral.[9]

The probability associated with each wage bin is determined by ordering the bins in ascending order and using a discrete hazard model over wage bins. The hazard in each bin is a logit function of a constant term, the bin number, covariates specific to the household in year t, and interactions of the covariates with the bin number. Appendix (iii) briefly describes what a discrete hazard model is within the context of wages and gives the cutoffs I used for each wage bin, and Gilleskie and Mroz (2004) provide details on this approach.

Identification of the effect of covariates on wages comes from their effect on observed wages, as well as their effect on the probability of working, since higher wage offers are more likely to be accepted. Wage covariates include age, age-squared, highest degree level,

[9] About a quarter of 1% of observations reported an hourly wage rate conditional on working but zero hours of work. I defined their likelihood by the first line of equation (7), as I did for the workers

the unemployment rate, the unemployment rate squared, a 3rd order polynomial in the year of observation, interactions of age and unemployment with each other and highest degree level, and an interaction of highest degree level with the year of observation. I report results both with the unemployment rate defined at the national level and the state level.

Besides heterogeneity in labor supply preferences based on observables, I allow for unobserved heterogeneity by using a mixture model. It is a mixture model because I allow for multiple sets of parameter values, each with a probability associated with it. Let π be the vector of all model parameter values, including the utility function parameters, the effects of covariates on the utility parameter α, and the effects of covariates on the wage distribution. I allow for unobserved heterogeneity by allowing for multiple sets of the parameters, π. In particular, I allow for J sets of parameter values, $\pi_1, ...\pi_J$, which I also refer to as discrete factors or heterogeneity types.

To exploit the panel structure of the data, I use a form of mixture model known as a categorical mixture model. That means the heterogeneity types are assumed to vary across people, but not to vary over time for the same people. All observations on the same individual head of household must belong to only one of the possible types, although types can differ across individuals and I do not observe to which type any particular individual belongs. So given $j = \{1, 2, ..J\}$ types, each household i being observed in some set of years τ_i, the log likelihood of the model across all observations on all n individuals is

$$\sum_{i=1}^{n} ln\Big[\sum_{j=1}^{J}\Big(pr(\pi_j)\prod_{t\in\tau_i}\ell_{it}(\pi_j, w_{it}, x_{it}, L_{it})\Big)\Big] \tag{9}$$

$$\text{subject to, } \sum_{j=1}^{J} pr(\pi_j) = 1$$

with ℓ_{it} defined by equation (7) for every worker observation and by (8) for every non-worker observation. The estimation strategy is to maximize the likelihood given by equation (9) over the values of wage parameters, utility parameters, and type probabilities.

The estimation of multiple heterogeneity types is useful empirically because it controls for correlation between time-constant preferences and wage rates, which can bias the estimation of those preferences. For example, having a "type-A personality" with a low taste for leisure over the long-run might cause one to be offered higher wage rates, as opposed to the causality only running from one's offered wage rate to one's labor supply choice. It also allows for time-constant individual specific shocks to the utilities of different labor supply choices to be correlated, relaxing the assumption of independence of irrelevant alternatives over labor supply choices. Finally, as outlined in Mroz (1999), it reduces bias caused by the correlation of explanatory variables and unobservables. As additional points of support are added, the joint distribution of parameter values can asymptotically approach any distribution that permits a discrete approximation.

iii. Data

The main data source is the Panel Study of Income Dynamics (PSID), which is a longitudinal survey data set at the household year-level. It provided all household level data, such as on age, highest degree level, race, hours of labor supply in the previous year, wage rates, and the levels of various sources of income. Data on national and state level unemployment, national and state level labor force participation, and the average monthly value of the CPI in each year were downloaded from the Bureau of Labor Statistics. The budget constraint for each observation was calculated from earnings minus taxes owed for each possible labor supply bin. Taxes owed at each labor supply bin are calculated using the internet tax calculation program TAXSIM as documented by Feenberg and Couts (1993), and input data from the PSID. That process is described in more detail after the paragraph that follows this one.

The study period is from 1987 to 2012. That time period ranges from a few years before the largest EITC expansion, which was in the early 90s, to three years after the most recent EITC expansion, which was part of the American Recovery and Reinvestment Act (ARRA). The data were restricted to single female heads of household between the ages of 18 and 60 inclusive who did not describe themselves as "permanently and completely disabled" in the survey.

For each interview year, the PSID data identified one person in each household as the head of household, reported the hourly wage rate of the head of household, and reported the age and relationship to the head of the other household members. The age and relationship to head variables allowed me to identify household members who count as dependents for determining EITC benefits. The survey also recorded respondents' income from labor, dividends, interest, rent, trust funds and royalties, alimony, and child support in the year prior to the interview. Interviews were conducted annually through the year 1997, and biannually from 1999 onwards. This means that from 1987 through 1996, wage rates were reported directly, while from 1998 on I observed only hours and earnings.

When hourly wage rates reported directly by respondents were available, they were used. However, for about 50% of respondents who reported positive work hours, the only available wage measure was a division wage, defined as reported earnings divided by reported hours. Such a wage measure will be negatively correlated with reporting errors in hours, a problem known as "division bias". Borjas (1980) presents some evidence on how large a problem division bias can be in empirical work on labor supply.

For those observations, I reduced division bias by imputing wages as follows: I first regressed the log of all available wages, which were directly reported wages when available and division wages when reported wages were unavailable, on an individual fixed effect, age, age-squared, year dummies, and a dummy for division wages. My new wage measure then took the value of the directly reported wage when available and the predicted wage when only division wages were available. This eliminates most division bias. This wage measure, together with the CPI, was used to calculate the real wage rate in 2014 dollars for each observation that had wage data. Each real wage rate is then rounded to the midpoint of the wage bin that it falls into.

For every household with an observed wage rate, I calculated household earnings at each of the H possible discrete hours of work choices as the product of the number of hours worked and the wage rate. For every household with an unobserved wage rate, I calculated earnings as the product of wage rates and hours for every possible combination of the H hours of work choices and the K hourly wage rates associated with each wage bin. TAXSIM then used the household's earnings, tax year, state of residence, marital status, age, labor income,[10] number of dependents and their ages, dividends, interest income, rental income, trust and royalty income, and private transfer income[11] as reported in the PSID, to calculate payroll taxes, Federal income taxes, state income taxes, and EITC benefits. These tax calculations performed by the TAXSIM program took full account of state and Federal personal exemptions and allowed for deductions, the alternative minimum tax, the child tax credit, state property tax credits, the Federal EITC, and all state EITCs. Since the Federal income tax and state income tax includes any respective Federal and state earned income tax credits, which are refundable, output for Federal and state income taxes could be negative.

These tax liabilities figured by TAXSIM were then subtracted from the sum of household labor income, dividends, other property income, and transfer income to estimate net income for each combination of household i, year t, labor supply $L_{it} \in \{L_1, L_2, ..L_H\}$ and wage rate $w_{it} \in \{w_1, w_2, ..w_K\}$. Define y as nonlabor income and the sum of investment income and the transfer income measure, and Tax as the sum of Federal income taxes,

[10]Earnings were converted to nominal earnings when used as a TAXSIM input because tax brackets are defined in nominal terms

[11]I defined private transfer income as child support plus alimony received, minus any alimony paid, since other forms of transfer income could vary with earnings

state income taxes, and payroll (FICA) taxes as calculated by TAXSIM, net of EITC benefits. The income at any given level of labor supply in the budget constraint $c_{it}(L_{it})$, was calculated as

$$(c_{it}|i,t,L_{it},w_{it},..) = L_{it}w_{it} + y_{it} - (Tax|L_{it}w_{it},\text{nonlabor income,state..}) \tag{10}$$

The budget constraint of each worker was then defined as her net real income at every possible hours choice, given her wage rate, w_{it}. Non-workers were assigned K different budget constraints for each of the K possible real wage rates, w_{it}, that could be received conditional on working.

I considered how other social welfare programs might affect the budget constraint. In 2013, the seven largest social welfare programs and categories of spending in the United States were Medicaid ($266 billion), Food Stamps ($82.6 billion), EITC ($55.1 billion), Supplemental Security Income ($50 billion), housing assistance ($49.7 billion), childhood nutrition ($20.9 billion), and Temporary Assistance for Needy Families (TANF) ($20.8 billion).[12] I ignored Medicaid, housing assistance, and childhood nutrition programs because they are in-kind benefits, making it hard to measure the dollar value of benefits received per household and hard to model without additional goods in utility and interactions between them. I ignored SSI because it is for the disabled who cannot work and because I dropped the permanently disabled from my sample, so its effect on labor supply is most likely negligible. I neglected TANF because it is small compared to the

[12] https://www.heritage.org/budget-and-spending/report/Federal-spending-the-numbers-2013-government-spending-trends-graphics

EITC, has had time limits since 1996, and has widely varying eligibility rules and generosity from state to state.

In most specifications, I do attempt to control for the effects of Food Stamp (SNAP) benefits on labor supply. My estimate of the SNAP benefits that the household is eligible for at each level of labor supply/earnings, if any, is added to the budget constraint used to estimate the model and simulate labor supply effects of the EITC. In one specification, I do not add estimated SNAP benefits to the budget constraint and estimate the same labor supply effects of the EITC as a robustness check. Appendix (iv) describes how SNAP eligibility and benefits are determined and how I estimated those benefits for the observations in the dataset.

In the final specification, the preference variables were indicators for one, two, and three or more dependents in the household, the number of children under six in the household, age, a time trend, and indicators for four levels of education. All of those preference variables could cause a constant increase or decrease in the utility of each hour of leisure through f(.) in equation (4). In addition, the 4 education indicators and 3 indicators for the number of dependents could affect the fixed utility cost of employment.

The set of wage variables included the year of observation, age, and four education indicators. Wage variables that were not used as preference variables included quadratic and cubic time trends; age-squared; the unemployment rate; [13] the unemployment rate squared; an indicator for household heads whose wage rates were not reported but

[13] in most specifications this was the national unemployment rate, since I suspect that state level unemployment is highly endogeneous do to the ease of moving from state to state, though I reported one specification that used state level unemployment

calculated by reported earnings divided by reported hours, and replaced with a predicted wage; interactions of age with the unemployment rate, the indicator for predicted wages, and each education level indicator; interactions of unemployment with each education level and of the time trend with each education level.

The PSID utilizes cluster sampling, which means that standard error estimates that assume independence of observations will understate standard errors due to the correlation of observations within sample clusters. I adjust the maximum likelihood standard errors accordingly, by calculating the variance-covariance matrix as

$$H^{-1}\sum_{c}[\frac{dL_c}{d\hat{\pi}}\frac{dL_c}{d\hat{\pi}}']H^{-1}, \tag{11}$$

where H is the hessian of the likelihood function and $\frac{dL_c}{d\hat{\pi}}$ is the score vector for the set of observations in cluster c. That is, $\frac{dL_c}{d\hat{\pi}}$ is the vector of derivatives of the likelihood function, summed over all heads of household in cluster c. This sums the contribution to variance from each independent cluster, unlike the case of independent observations where each observation is a cluster and the term in brackets converges to the negative of the Hessian matrix, causing equation (11) to converge to the information matrix. I use the variable sampling error cluster provided by the PSID to identify the clusters.[14]

[14]To preserve anonymity, these are actually half-samples, or two groups of clusters in each stratum that each contain half of the clusters in their respective stratum, but since the clusters are independent, the variance of a group of clusters is equal to the sum of the variances of each cluster in the group. Since the sample is stratified, $\frac{dL_c}{d\hat{\theta}}$ is actually the deviation of $\frac{dL_c}{d\hat{\theta}}$ from the average of the two half samples in the stratum that it belongs to.

The PSID is not a nationally representative sample of the US population for two reasons. One reason is oversampling of poorer households. Another reason is that the survey attempts to follow respondents and their descendants for life, so that the demographics of respondents tend to be more weighted towards the demographics of the country in the year of the first PSID survey in 1968 than the national population is. The survey has partly corrected this by adding a sample of recent immigrants and of Latinos in the mid nineteen-nineties. I correct for this by weighing each observation in simulations of the effect of the EITC on labor supply using the longitudinal weights provided by the PSID.

VI. **Summary Statistics**

Table 1 presents summary statistics for those households used in the maximum likelihood estimation. There were 25,329 household-year observations on 5434 individuals, each consisting of a single female headed household in the PSID in a given year, used in that estimation. From top to bottom, *Hours* consists of the female head of household respondent's reported annual hours of paid labor, *earn* is their reported earnings from that labor in 2014 dollars, *nonlabor* is nonlabor income, excluding government transfer income, or y in equation (10). *Dependents* is the total number of dependents that can be claimed for EITC purposes, including children in the household and adults under 24 who attend college while living with the respondent; *children* is the number of children in the household; *preschchn*, for preschool children, is the number of children under the age of six; *age* is the age of the female head of household respondent.

The last four variables are education level indicators and are not mutually exclusive. Each indicates a degree level and can only be equal to one if all lower degree variables are equal to one. Hence, coefficients on these wage variables test the *additive* effect of each additional degree level on wage rates, rather than their effect relative to a baseline of no degrees or high school diploma. *HS* is an indicator for the respondent having at least a High School degree; *twyr* is an indicator for the respondent having at least 2 years of college education, which could mean a completed two-year degree or two years in a bachelor's degree program; *bachelor* is an indicator for having at least 4 years of college education; and *grad* is an indicator for some post graduate education. All monetary figures are in 2014 dollars.

One concern in the labor literature is that since respondents do not precisely record how many hours in a year they worked, they will tend to report round numbers such as two thousand hours. The data are reported in integers, but no one positive value of hours represents more than 3% of observations. The five most common values, 2000, 2080, 2040, 1960, and 1920, represent 9.2% of observations. The next five most common values, not all multiples of 40, represented another 2.5% of observations. I conclude that rounding in reported hours of work is not a serious problem

Based on observed labor and investment income, the number of dependents, and the EITC policy parameters in place in the year of observation, about 32% of single, female-headed households in the dataset qualify for the EITC and the average benefit was about $620, or $1933 among those who qualify for positive benefits. Among single women with dependents, 58.9% qualified for the EITC and the average annual benefit available to eligible beneficiaries was $2046.

Table 1: Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum	% observations equal to 0
hours	1479	951.7	0	5824	19.9
earn	26518	24373	0	302305	19.9
nonlabor	1172	6867	0	624000	72.6
dependents	1.06	1.29	0	9	46.6
preschchn	.31	.659	0	6	77.2
age	36.7	10.7	18	60	0
EITC	622.3	1205	0	6159	67.8
HS	.8	.4	0	1	19.9
twyr	.32	.46	0	1	68.4
bachelor	.151	0.358	0	1	84.9
graduate	.059	0.237	0	1	94.0

VII. **Results**

In the first subsection of this section, I examine the goodness of fit of the model regarding wages. In the second subsection I examine the goodness of fit of the model with respect to labor supply and use simulations to examine how labor supply will respond to a pure income grant and to the marginal wage rate, according to the model parameter estimates. In the third, fourth, and fifth subsections, I estimate the effects of the Federal EITC on labor supply, the effects of the EITC on income distribution after accounting for effects on labor supply, and a welfare maximizing EITC subject to a budget constraint. Parameter estimates are difficult to interpret individually and are left, with an explanation of their interpretation, to Tables A3, A4, A5, A6, and A7 in subsection (vii) of the Appendix.

Unless otherwise noted, all results reported here are for my preferred specification of the model. It is my preferred specification because it significantly outperformed all other models as indicated by the likelihood ratio test. That specification used the utility and wage model described in the empirical approach section of the paper, incorporated any SNAP benefits available in the budget constraint, and used my fullest set of wage and preference variables.

I tested several variations on the utility model described by equation (4), such as allowing preference variables to affect preferences through the parameters κ_1 and κ_2 rather than α, and dropping the parameter γ. The former two models significantly underperformed my preferred specification according to the Vuong test, and the latter model significantly underperformed my model as evaluated by the likelihood ratio test and are not reported here.

In the section on the estimated effects of the EITC on labor supply, I do report results from a model that uses fewer wage and labor supply bins to show that I use enough bins for results to not be sensitive to the number of bins. I also address the criticism of the uncertainty in SNAP benefit eligibility by showing that results do not change substantially when I do not include SNAP benefits in the budget constraint. In addition, I address the potential endogeneity of state level unemployment and labor force participation by showing that results do not change substantially when I include only national level unemployment and labor force participation as wage variables.

Also, although model parameters were estimated using all observations between 1987 and 2012, and those parameter estimates were used to produce all simulation results presented in this section, except where otherwise noted those simulation results used only the *observations* for the years 2006-2012. Those years were the four most recent waves of PSID data as of this writing, and I chose them to simulate as nearly as possible the effect of the EITC on labor supply given our *present-day* tax and transfer policies and wage distribution.

While labor supply simulation results from the period 2006-2012 might seem questionable because they include the Great Recession years, I find that the employment rate of the single female heads of household in my data averages only one percentage point lower over the period 2006-2012, at 80.1%, than over the whole period from 1987 to 2012. It is 1.5% higher over 2006-2008 and 3.3% lower over the period 2010-2012. Furthermore, whatever effect this choice of time period has on simulated labor supply, any bias on the simulated *effect of the EITC* on labor supply will be smaller to the extent that the choice of time period has the same effect on labor supply without the EITC as with the EITC.

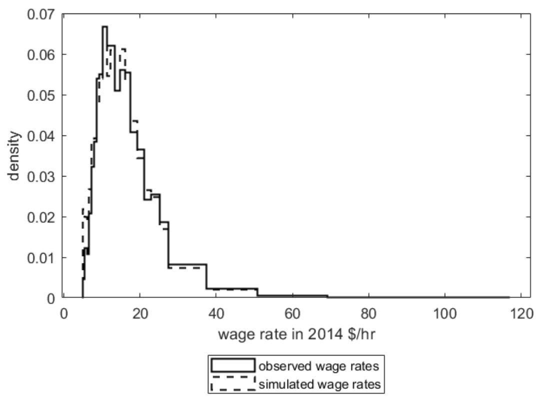
i. Goodness of Fit of the Wage Model

Since wage predictions affect labor supply predictions in the model, I start with the goodness of fit of the model with respect to wages. For the results reported in this subsection, I used data and simulations results for the last six years of observations, 2006-2012. As discussed in the empirical section and in more detail in Appendix (iii), the wage model used throughout the paper uses a discrete hazard model with covariates to assign probabilities to each wage bin, with each bin having an associated real wage.

I ran the following simulation to test how well accepted wages in the model match observed wages. I started by randomly assigning one of the heterogeneity types to each individual in the data. Wage variables and the parameters of the wage model associated with that heterogeneity type then gave a probability distribution over wage offers for each observation. Each observation receives a wage offer drawn randomly from its wage distribution, which determines the observation's budget constraint. The utility of each possible labor supply choice for each observation is then determined by the household budget constraint, preference variables, and the utility parameters associated with its type, according to the utility function given by equation (4). Those utilities determine the probability of not working from the value of equation (3) when hours of labor supply, L_{it}, equals 0. Each observation is also assigned an independent draw from the uniform (0,1) distribution that determines her employment decision in that year. She rejects the wage offer by choosing the zero hours bin if her uniform number draw is less than her probability of not working, and works otherwise. If she works, her wage offer is an accepted wage. The distribution of accepted wage offers from the simulation is expected to match the distribution of observed wage rates, since we only observed the wage rates of people who work.

Figure 3 plots the probability densities of wages observed versus wages accepted in that simulation, using all observations with observed wages over the period 2006-2012. Observed wages were rounded to the value associated with the bin that they fell into. Except for the lowest hourly wage rates, the distribution of predicted wages matches that of observed wages closely. The average wage offer in the simulation was $16.28, the average accepted wage offer in simulation was $17.66, and the average observed wage rate was $18.26. The median accepted wage in simulation was $15.35, as compared to a median observed wage of $15.89. I performed a Kolmogorov-Smirnov test of difference between the simulated and observed distributions, and the maximum difference between the cumulatives of the observed and simulated wage distributions was .03. This difference in distributions was statistically significant because the use of over 6,000 household year observations made the test very powerful, but is not economically significant.

Figure 3: Histogram of Observed Wage Rates and Wage Rates Accepted in Simulation, All Single Female Heads of Household



It is also important for the model to predict variation in wage rates, since that prediction of wage rates is used to predict the budget constraints of non-workers who will be most affected by the EITC. To test that predictive ability, I calculated the expected value of every observation's wage offer, conditional on the head of household choosing to work at that wage, as predicted by the model. This is calculated from each observation's probability distribution over accepted wages implied by model parameters and wage covariates, without taking random draws from that distribution. That is, I calculated

$$\hat{w}_{it}^{MLE} = \sum_{k=1}^{K} \mathbf{w_k} * pr(L_{it} > 0 | w_{it}, x_{it}) * pr(w_{it} = w_k | x_{it})$$

I found that work conditional expected wages $\hat{w}_{it}^{MLE}$ was a highly significant predictor of observed wages, with an R^2 of 27.2%. Since the discrete points of support of the wage distribution are defined in logs, I also tested how well the expected value of the log of accepted wages matched the log of observed wages. The model predicted the log of observed wages with an R^2 of 31.5%.

I also examined the fit of the wage model with respect to two variables that have interactive effects on wages, age and education. I did this by comparing the mean accepted wage in simulation to the mean observed wage, for each combination of five levels of highest degree level [15], and three year age intervals.[16] Since age and education combinations can have few observations, I simulated wage offers 750 times for each observation, with a different random number draw for wage offer, heterogeneity type, and labor supply choice each time.

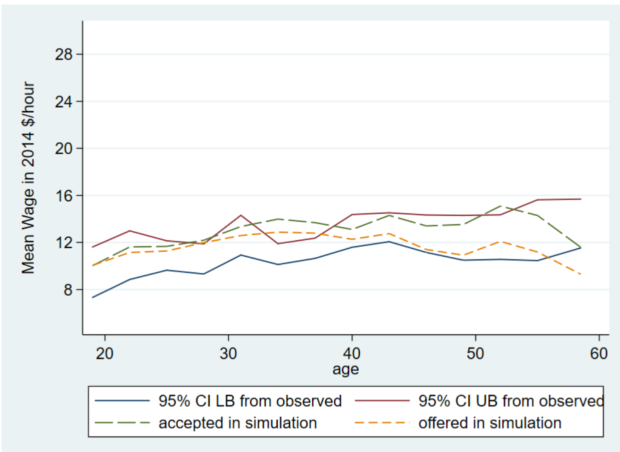
In figures 4, 5, and 6 I compare simulated and observed wages for the three most common levels of education in the data, high school dropouts, high school diploma but less than two years of college, and at least two years of college but no bachelor's degree. I plot the resulting mean offered and mean accepted wage in simulation, together with the upper and lower bounds for a 95% confidence band on observed wages. Those confidence bands were calculated for each age range and education level from the sample mean wage and the standard error on that sample mean, as calculated from the number of observations and their sample variance. Only the average **accepted** wage in simulation should closely match the mean observed wage and stay within the confidence bands, since only accepted wage offers are observed in data. I also plot the mean of all wage offers, though it has no

[15] No HS diploma, HS diploma only, at least 2 years of college but no bachelor's degree, bachelor's degree, and some graduate education

[16] Those three year intervals began with ages 18-20 for HS dropouts, start two years later for each step up in highest degree level, and end with the last two or three year interval that ends before age 60

observable counterpart. The first plot is for high school dropouts, who represent 12.6% of observations in the simulation data.

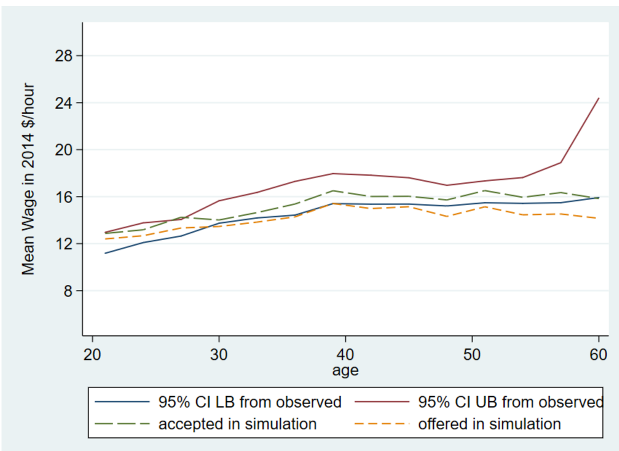
Figure 4: Mean Wage Offers in Simulation, Accepted Wages in Simulation, and Observed (accepted in data) Wages for High School Drop Outs



Note that in simulation, mean accepted wage offers are consistently greater on average than the set of all wage offers. This happens because one is more likely to accept a job if the wage offered is higher. Another feature of the model across all education categories is that the gap between the average observed and accepted wage offer grows with age, implying that economic agents become more selective about the wage rates that they are willing to work for. The model captures the way wages are low but increasing in age for high school dropouts.

In Figure 5, I graph the same relationship between wage rates and age for single female heads of household with a high school diploma but less than two years of college. They represent 43.8% of observations in the simulation data.

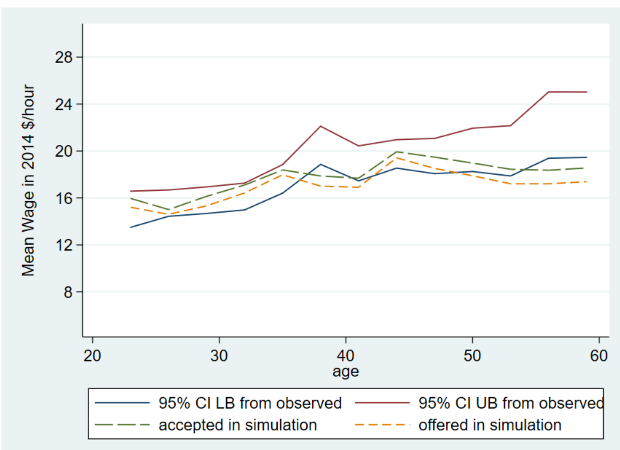
Figure 5: Mean Wage Offers in Simulation, Accepted Wages in Simulation, and Observed (accepted in data) Wages as a Confidence Interval, for High School Graduates



Unsurprisingly, average observed and predicted wages are higher than for high school dropouts. Except for the spike in observed wages at age 60, observed wages show an increasing and concave relationship with age that is captured by the model. That spike in wages at age 60 could easily be due to sampling variability, since the confidence band widens and the lower bound on wages does not change. For single female heads of household with exactly a high school education, and for female heads with two years of college, which we will see in the next graph, the confidence bands on observed wages get wider with age because there are fewer observations at those older ages.

In Figure 6, I present the same results for single female heads of household with at least two years of college but no bachelor's degree. They represent 21.8% of observations in the simulation data. The model fits the data well except possibly between the ages of 55-60. However, mean wage estimates become more uncertain for older ages due to a scarcity of observations. The model captures the relationship between wages and age and education well.

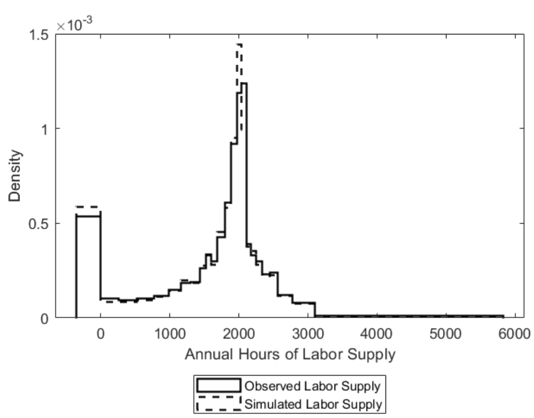
Figure 6: Mean Wage Offers in Simulation, Accepted Wages in Simulation, and Observed (accepted in data) Wages as a Confidence Interval, for Women with Two to Three Years of College



ii. Labor Supply Model Fit and Implications

Now I turn to labor supply. I start by comparing the distribution of hours predicted in the model simulation for years 2006-2012 to the data for those same years. Simulated labor supplies were obtained by first drawing wage draws for each observation in the years 2006-2012, by the same procedure described above for the wage simulations. The wage draws, the tax code in the year of observation, and nonlabor income give a budget constraint over hours and income. Preference parameters and variables then determine the probability distribution over hours choices for each observation, from which a random draw is taken. This procedure is repeated five times for each observation. At that number of simulations per observation, little of the deviation of an observation's average simulated labor supply from its observed labor supply could be attributed to the random variance incorporated into the simulation. Most of the remaining deviation of observations' average simulated and observed labor supplies could be attributed to sampling variability and parameter uncertainty, which can not be reduced by simulating labor supply for the same observations more times.

Figure 7: Probability Densities of Observed and Simulated Labor Supply



Since most of the variation in EITC benefits act through the interaction of the number of children in the household and time, it is important to control for the effects of children on labor supply. To test how well the model captures the effects of children on labor supply, I plotted histograms of simulated and observed labor supply separately for households with no dependents, 1 dependent, 2 dependents, or 3 or more dependents in Figures A1, A2, A3, and A4 in subsection v of the appendix.[17] Since the greatest EITC expansions were in the 1990s, I used all observations from 1987 to 2012 rather than only 2006 to 2012 for those four histograms. The histograms show that work hours differ substantially by family size, but the model captures the distribution of work hours for each family size well.

I then tested how well variation in expected hours of work in the model predict variation in actual hours of work, for the same observations. I calculated the expected value of hours of work for each observation, defined as

$$\hat{L}_{it}^{MLE} = \sum_{j=1}^{J} pr(\pi_j) \sum_{k=1}^{K} pr(w_{it} = w_k | x_{it}, \pi_j) * \sum_{L_{it}=L_1}^{L_H} \mathbf{L_{it}} * pr(L_{it} | w_{it}, x_{it}, \pi_j) \tag{12}$$

Expected annual hours of work were calculated from the predicted distribution over wages, even for observations with observed wage rates. When I regressed observed hours on expected hours, $\hat{L}^{MLE}$, the R^2 was 33.5% and $\hat{L}_{it}^{MLE}$ was significant at the 1% level. The model predicts variation in labor supply well.

The model performed much better on the extensive margin than on the intensive margin but was a highly significant predictor of labor supply on both margins. I tested

[17]EITC benefits do not change for additional dependents beyond three

model fit on the extensive margin by regressing an indicator for working positive work hours on the probability of working positive work hours predicted by the model. This predicted probability was calculated as the sum of the probabilities of all type, wage, and labor supply combinations in equation (11), only with those combinations involving the 0 hours bin removed. The R^2 was 40.9% and the predicted probability was significant at the 1% level. Since working positive hours is a binary outcome, I also calculated Negelkerke's pseudo-R^2 for that outcome, which was 46.3%. Nagelkerke's (1991) pseudo-R-squared is defined as $\frac{1-(L_0/L_1)^{2/n}}{1-L_0^{2/n}}$, where L_0 is the likelihood of a constant only model and L_1 is the likelihood of the model evaluated. I then calculated expected hours conditional on working as expected hours, or equation (11), divided by the predicted probability of working. When I regressed observed hours on expected hours conditional on working for those households with positive observed hours, the R^2 was 5.9% but the coefficient on expected hours conditional on working was still significant at the 1% level.

Now I turn to implications of the model for labor supply. Marginal changes in labor supply due to the EITC or other changes in the tax code are equal to the sum of income and substitution effects on labor supply. I will therefore illustrate the magnitude of income and substitution effects on labor supply, according to model estimates. This allows me to make predictions about the effects of EITC parameters on labor supply.

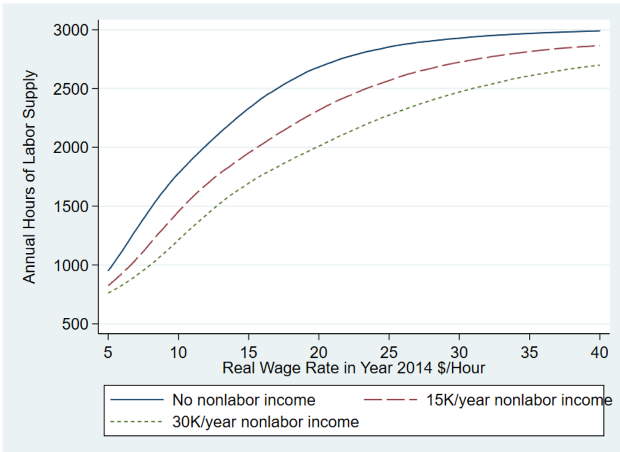
In this exercise I simulate the effect on labor supply of a lump sum income grant and a constant after-tax marginal wage rate, which assigns every household the following budget constraint

$$c_{it} = g_j + L_{it} * w_k \tag{13}$$

where c_{it} is annual household income, g_j is the annual income grant, L_{it} is a possible level of annual hours of labor supply, and w_k is the real after-tax hourly wage rate. Although a realistic budget constraint would be more complex than this, any piecewise-linear budget constraint can be broken into segments described by equation (12). Each segment has a marginal after-tax wage rate, w_k, and a virtual income, g_j. g_j represents how much more income one has compared to a world where one worked the same number of hours, but there is no non-labor income, and every hour of labor, no matter the budget segment, paid w_k. The substitution effect of a tax policy change is caused by the change in w_k, while g_j represents a pure income effect.

I randomly assigned heterogeneity types to each household before simulating labor supply and held them constant across simulations. For each combination of 3 levels of the income grant, $g_j \in \{0, \$15000, \$30000\}$, and every ten-cent increment in the after-tax wage rate, w_k, between \$5 and \$40, I assigned each household the same budget constraint defined by equation (12) and simulated labor supply. Results are displayed in figure 8.

Figure 8: Mean Simulated Labor Supply as a Function of the Wage Rate and a Nonlabor Income Grant, Conditional on Working Positive Hours

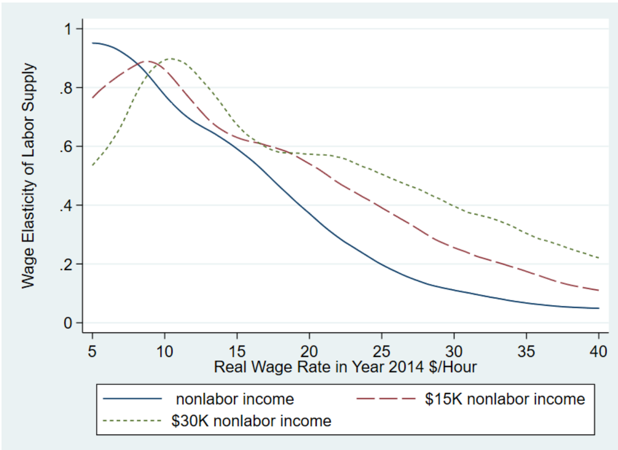


Labor supply falls with non-labor income, which is consistent with leisure being a normal good. That means the EITC will reduce labor supply for a tax filer in the plateau earnings range, as predicted by theory. The fact that the effect of non-labor income on labor supply is smaller for lower wages partly reflects that employment is lower the lower the wage rate, giving hours less room to decrease on the intensive margin. Many potential workers' labor supplies are already at the zero hours lower bound at those wages. The fact that income effects peak at intermediate wages and become smaller at higher wages reflects that the income grant becomes smaller relative to what one earns from working at higher wages.

What is more interesting is that labor supply increases with the wage rate, from a wage rate of \$5 an hour to at least \$40 an hour. This is true even when households are assigned no nonlabor income. In the case of no nonlabor income, equation (12) implies that an increase in the wage rate raises the marginal wage rate and income, before labor supply changes, by the same proportion. This suggests that for a policy that increases one's marginal wage rate by at least the same percentage as one's income, the substitution effect will dominate, and labor supply will increase. Therefore, an increase in the subsidy rate of the EITC is expected to increase labor supply on the intensive margin, for households whose earnings put them in the phase-in region and who have negligible non-labor income. Likewise, a reduction in the first marginal income tax rate is expected to raise the labor supply of filers in that tax bracket, and a reduction in the tax rate in the phase-out region of the EITC is expected to raise labor supply for tax filers in that range of earnings.

It is convenient to graph labor supply in terms of wage rate elasticities for ease of interpretation and to compare to existing labor supply literature. Since my model is flexible enough to allow the wage rate elasticity of labor supply to vary by the wage rate and non-labor income, I plotted the wage elasticity of labor supply as a function of wage rates and non-labor income in figure 9, using the same range of wage rates and non-labor income used in figure 8. This wage rate elasticity is defined for each simulation as $\frac{dL}{L}/\frac{dw}{w}$, where L is the average annual hours of labor supply in the simulation, dL is the change in L from the simulation with a ten cent lower hourly wage rate, w is the hourly wage rate used in the simulation, and dw is the ten cent increase in the wage rate from the previous simulation. It is unsurprising that the elasticity of labor supply is less than one and declines with the wage rate.

Figure 9: Mean Simulated Wage Elasticities of Labor Supply as a Function of the Wage Rate and a Nonlabor Income Grant



iii. The Effect of the EITC on Labor Supply

Next, I turn to the effects of the Federal EITC on the labor supply of single mothers. I estimated the effects of the Federal EITC on the labor supply of single mothers by taking the difference in labor supply between two simulations. The first simulation included in the budget constraint the Federal EITC, any applicable state EITCs, and all other tax credits and liabilities as figured by TAXSIM for the household in the year of observation. I then simulated labor supply using the same budget constraint, only with the Federal EITC subtracted out, and estimated the effect of the EITC from the change in labor supply from the first to the second simulation. I did this using my most recent four waves of data, 2006-2012, to better estimate the effect that EITC presently has on the labor supply of single mothers.

In Table 2, I report labor supply effects for my preferred specification. That model had 33 labor supply bins, including the zero hours bin, and 23 wage bins. It incorporates the estimated value of SNAP benefits the household is eligible for, if any, in the budget constraint. How I estimated the amount of SNAP benefits that each household is eligible for is detailed in subsection (iv) of the Appendix. As noted earlier, single mothers are here defined broadly to include women with any dependents in their household, with results for all other observations reported under the row of Table 2 labeled "childless single women".

In the first column, *LFP* is the effect on the labor force participation rate of single mothers. The EITC caused some single workers not in the labor force to enter, but did not cause any single workers in the workforce to exit. That is consistent with the model and standard utility theory, since the income and utility of the zero hours bin is unchanged by the EITC while the utility of each positive hours bin is either unchanged or increased. Moving towards the right of Table 2, *entrant hours* is an estimate of the average hours worked by single mothers induced into the workforce by the EITC. It is calculated from the average hours worked by single mothers in the simulation with the EITC, for single mothers who were predicted to work positive hours in the simulation with the EITC but not in the simulation without the EITC. *Incumbent hours* measures the intensive margin effect of the EITC. It is the effect on the average annual hours of labor supply of single mother beneficiaries who would work with or without the existence of the EITC. It is estimated from the difference in average hours worked in the simulation with the EITC minus average hours worked in the simulation without the EITC, for single mothers predicted to work positive hours even in the simulation without the EITC. Hours is the effect on the average annual hours of labor supply over all single mothers, employed or not.

The Federal EITC increased the labor force participation of single mothers by about seven and a half percentage points relative to what it would be had there been no Federal EITC. Since about 20% of single mothers were not in the labor force, this implies that without the EITC, the proportion of single mothers who are not in the labor force would be about 37.5% higher. Single female heads of household induced into the workforce by the EITC worked an average of 1600 hours a year, which is fairly close to the average among all employed single female heads of household in the data, 1815. It is not surprising that single mothers induced into the workforce by the EITC would work fewer hours than the average working single mother. The fact that they would not work in the absence of the EITC suggests that they have a lower propensity to work than the average worker. Therefore, the literature estimating the effect of the EITC on employment left open the possibility of a very small effect on labor supply if those single women induced into the workforce by the EITC only worked, for example, 500 hours a year. The fact that their hours are only somewhat less than the average hours of all working single mothers is highly favorable to the EITC if the goal is to raise the labor supply of single mothers.

The effect on the average hours of single mothers who are already employed is fairly small and not statistically different from zero. This is unsurprising, since some workers are most likely incentivized to increase their hours, while some workers are incentivized to reduce their hours. The large positive average effect on the hours of single mothers who would not otherwise be working and the small negative effect on the hours of single mothers already working sum to a substantial and statistically significant positive effect on the hours worked by single mothers.

Table 2: Simulated Effects of the EITC on the Labor Supply of Single Mothers, Change From no EITC to 2012 EITC, Preferred Specification

	LFP, % points	Entrant Hours	Incumbent Hours	Hours
Single Mothers	7.52*** (.93)	1,599*** (656)	-16.5 (20.4)	108.7*** (20.4)
Childless Single Women	.39 (.45)	1,138** (657)	-2.3 (10.7)	2.6 (9.43)

Standard errors are in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels. Significance tests employed a one-sided test that the coefficient was greater than 0 for LFP and entrant hours, and a two-sided test that the coefficient was different from 0 for incumbent hours and hours

In the second row, the same labor supply effects are presented for childless female heads of household. As expected, labor supply effects on childless female heads of household are very small, because they are only eligible for a small fraction of the benefits that single mothers are eligible for.

Table A2 in Section (vi) of the Appendix reports simulated labor supply effects of the next four highest likelihood models together with my preferred specification as robustness checks, with the number of parameters and the log likelihood of the model to compare model performance. Each specification or robustness check occupies a row. The row labeled “second fullest” is nearly identical to the preferred specification, it is only missing two preference variables that can affect the fixed cost of employment and shift the marginal valuation of each hour of leisure. Those two preference variables are interactions of the time trend with the indicators for at least one and at least two children. Those two variables were later added to the second fullest model to produce the preferred specification because they produced a substantial and statistically significant improvement in the likelihood as indicated by the likelihood ratio test.

The model labeled “no state level unemployment” is identical to the simpler model except that the variables state level labor force participation rate and the state level unemployment rate are removed. All interactions of variables with the state level unemployment rate were replaced with interactions of those variables with the national unemployment rate. Results for that model are displayed to show that concerns about the potential endogeneity of state level labor market variables are misplaced, since removing those variables does not substantially change results. The model labeled no food stamps used the same budget constraint as in the second fullest model, only with the SNAP benefits that the household is eligible for subtracted out from the budget constraint. Results are substantially unchanged. The cruder bins model is identical to the simpler model only it used about half as many labor supply bins (16) and wage bins (13). Although this produced the largest difference in results from the preferred specification, particularly in the labor force participation effect, that effect is still in a neighborhood of the preferred specification and effects on entrant and incumbent hours are not significantly different.

iv. Redistributional Impacts of the EITC

A major policy motivation of the EITC was to boost the income of poor single mothers with children, both directly through benefits and by increasing the single mothers' labor supply. For that reason, I turn now to the distributional impact of EITC benefits on single mothers. Define the total income increase as after-tax income with the EITC minus after-tax income without the EITC, accounting for expected differences in labor supply without the EITC. This total income increase consists of two components, the change in after-tax earnings before the EITC caused by the labor supply incentives in the EITC, and the EITC benefits. For every wage bin between $5 and $24 an hour, I performed a set of simulations in which I assigned every household observed over the period 2006-2012 the same wage rate, simulated labor supply with and without the Federal EITC in the budget constraint five times and recorded average EITC benefits, the increase in earnings, and the total income increase each time. Results are plotted in Figure 10.

Figure 10: EITC Benefits and their Effect on Earnings and Household Income for all Single Mothers, by Offered Wage Rate

Mean earnings increase for single mothers who make less than $18 an hour because of the labor supply incentives of the EITC. Those positive labor supply effects result from the fact that single mothers with lower wage offers are more likely to be in the phase-in earnings range. This is especially true of beneficiaries who would not work without the EITC, since the EITC is a pure substitution effect at the first hour of work. That causes family income in those households to increase by more than the benefits paid. The mean earnings and income increases seem to both be greatest for single mothers who earn around $11 an hour. The average EITC benefit seems to be greatest for single mothers who earn very slightly more than $11 an hour.

For single mothers who earn more than $18 an hour, the EITC reduces labor supply, thereby increasing family income by less than the benefits paid. That results from the fact that those single mothers are more likely to be in the plateau or phaseout earnings ranges.

Earnings fall the most for single mothers who earn around $20 an hour. At wages greater than $20 an hour, earnings fall less because single mothers who receive those wage offers are less likely to be affected by the EITC.

Another conclusion from this is that a $15 an hour minimum wage would destroy much of the benefit of the EITC. Workers whose wage offers are between $5 and $15 an hour could be left unemployed by the policy, since their market wage is below the price floor of $15 an hour. If they lose their jobs, they no longer benefit from the EITC as well, when they presently benefit the most from the EITC judging from simulation results in Figure 10.

Even among single mothers who earn the same wage rate, the total income increase has a very skewed distribution. Labor force entrants, who are defined as single mothers who benefit from the EITC and would not work without the EITC, have a much larger increase in household income than other beneficiaries, who are labor force incumbents. Partly that is because they tend to receive more benefits, as we see from figure 11, but one can see from figure 12 that the difference in total income change is too large to be mainly accounted for by differences in benefits. Most of that difference is from the greater increase in the earnings of labor force entrants, since by definition the EITC caused them to enter the workforce. Although this greater increase in income for entrants is arguably justified by their greater increase in labor supply, if the goal is to increase income in poor households with children it is worth considering that two equally poor households with children as measured by the head of household's wage rate can differ greatly in their EITC benefit.

Figure 11: Average EITC Benefits for Single Mothers who are Labor Force Entrants and Single Mothers who are Labor Force Incumbents, by Offered Wage Rate

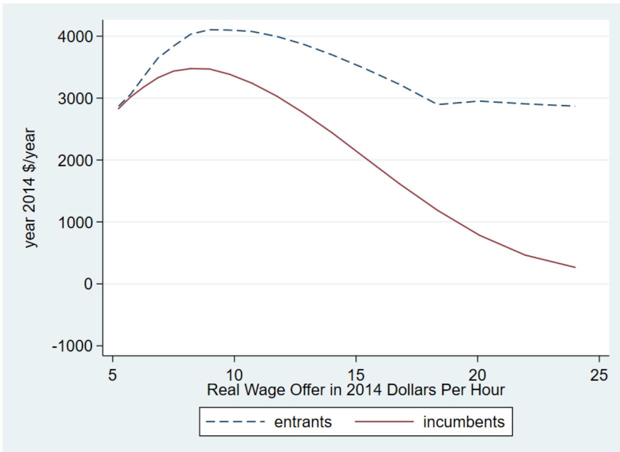
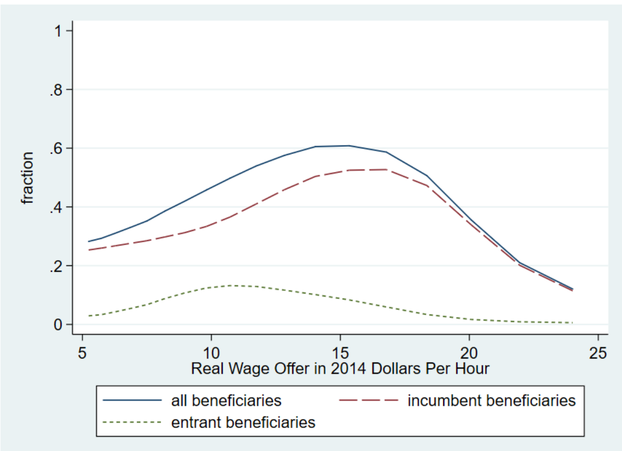


Figure 12: The Average Effect of EITC Labor Supply Incentives on Earnings, for Single Mothers who are Labor Force Entrants and Single Mothers who are Labor Force Incumbents, by Offered Wage Rate

Figure 13 shows the fraction of single mothers who benefits from the EITC at different wage rates, divided into entrant and incumbent beneficiaries. Dividing the fraction that are entrant beneficiaries by the fraction represented by all beneficiaries shows that entrant beneficiaries are never more than 30% of all beneficiaries, although I have found that they receive more than half of the income gains to the EITC at some wage rates.

Figure 13: EITC Recipients as a Fraction of All Single Mothers, Labor Force Entrants and Incumbents



v. An Optimal EITC Program

The EITC is designed to improve the welfare of poor households with children. If the goal was to produce the greatest increase in the utility of single mothers for a given level of EITC spending, and that utility increase was measured with consumer surplus, however, single mothers would simply receive a lump sum payment. Intuitively, that is because if beneficiaries could receive the same level of EITC benefits that they do now at any possible level of labor supply, beneficiaries would prefer a different level of labor supply. Beneficiaries in the phase-in earnings range would reduce their labor supply because the loss of earnings would no longer cost them benefits, while beneficiaries in the phase-out earnings range would increase their labor supply because the gain in earnings would no longer cost them benefits. To the extent that we value utility or income gains to the poor more heavily than the rich, benefits would fall with earnings but would not rise with earnings.

Since EITC benefits do rise with earnings for poorer beneficiaries, one might interpret the goal of the EITC as maximizing the household income of single mothers rather than their utility. Maximizing the average income of single mothers, however, would not weigh gains to a poorer single mother any more than an equivalent gain to a richer single mother. For that reason, I consider how the EITC can most cost-effectively maximize the consumption component of utility, or $\alpha sign(\delta_1)(\kappa_1 + c_{it})^{\delta_1}$, for single mothers. The consumption component of utility is the part of equation (4) that depends on consumption and not leisure, after removing the parameters A and γ. The parameters A and γ are monotonic transformations of utility that do not alter one's rate of substitution between consumption and leisure. The objective, then, is to optimize the EITC parameters to maximize $\alpha sign(\delta_1)(\kappa_1 + c_{it})^{\delta_1}$, averaged over all households i with dependents in year $t \in (2006, 2012)$, subject to an upper limit on average EITC benefits per single head of household. Since parameter estimates make this function concave in consumption, the objective will give greater weight to an income gain to a poor household than an income gain of equal magnitude to a better-off household.[18]

The objective function and spending constraint assume complete take-up of all benefits available to the household. For this exercise I defined household consumption as household income divided by the number of people in the household and weighted the utility of every female head of household equally, only with no weight on childless heads of household. The number of people in the household is defined as one plus the number of dependents in the household.

My procedure was as follows: For every single mother observation in the years 2006-2012, I randomly drew a heterogeneity type and associated wage bin five times. I treated each combination of a household and its five associated pairs of type and wage bin draws as five observations. I then maximized the objective function over the four EITC parameters that determine benefits, subject to the spending limit. Those parameters are the subsidy rate, s, at which benefits rise with earnings in the phase-in earnings range; the level of earnings in which the phase-in range ends and the flat or plateau range begins, th_1; the level of earnings in which the flat range ends and the phase-out range begins, th_2; and the rate at which benefits are lost, t, for each dollar beyond the flat range.[19] These parameters can take separate values for households with 1, 2, or 3 dependents. Based on my data for the years 2006-2012 and TAXSIM output, the average single female head of

[18] one could simply maximize average income over single mothers, though I find that results in a phase-out rate of essentially 0

[19] The end point of the phaseout range and of EITC eligibility is determined by the other four parameters as $th_2 + \frac{s*th_1}{t}$. That is because the maximum benefit, received for earnings between th_1 and th_2, is $s*th_1$. Since the maximum benefit declines at rate t beyond th_2, the benefit reaches 0 at $th_2 + \frac{s*th_1}{t}$.

Table 3: Optimal EITC Estimates

33% less spending	1 child	2 children	3 children
subsidy rate (%)	8.72	13.8	25
for earnings up to ($)	15,100	16,400	18,600
maximum benefit ($)	1,317	2,263	4,650
for earnings from ($)	15,100	16,400	18,600
to ($)	35,600	36,800	3,6700
tax rate (%)	-49.3	-49.6	-48.9
for earnings beyond ($)	35600	36800	36,700
same spending			
subsidy rate (%)	12.2	19.4	34.1
for earnings up to ($)	15,400	16,800	18,900
maximum benefit ($)	1,879	3,259	64,45
for earnings from ($)	15,400	16800	18,900
to ($)	36,000	37,200	37,200
tax rate (%)	-49.4	-49.6	-49
for earnings beyond ($)	36,000	37,200	37,200
33% more spending			
subsidy rate (%)	16	25	41.5
for earnings up to ($)	15,600	16,900	19,100
maximum benefit ($)	2,496	4,225	7,927
for earnings from ($)	15,600	16,900	19,100
to ($)	36,200	37,300	37,400
tax rate (%)	-49.4	-49.5	-49
for earnings beyond ($)	36,200	37,300	37,400

household was eligible for about $753 in EITC benefits in 2014 dollars, counting heads that are not eligible for any benefits. I therefore take that as the current level of EITC spending. In Table 3, I report results for three spending limits, one 33% less than the current average level of spending per single female head of household, another equal to current spending per single female head of household, and another 33% higher than the current level of spending per single female head of household.

Given the above described objectives, there are four broad conclusions for how the EITC should be changed relative to how it is now. Three of those conclusions regarding an optimal program are the same regardless of whether one considers the optimal program subject to a spending limit 33% smaller than current spending, the optimal program subject to current spending, or the optimal program allowing for up to 33% higher spending. I will start with those three conclusions.

One conclusion is that the tax rate should be higher. It should be near 50%; it is about 20% under current law. The benefit of a higher tax rate is that less money is spent on households in the phase-out earnings range, leaving more money to spend on beneficiaries in the phase-in or plateau earnings range, where the marginal utility of consumption is higher. Although in theory that would disincentivize labor supply for beneficiaries in the phase-out earnings range, it is not surprising that this effect was not big enough to make the optimal tax rate lower rather than it is under current law. The tax rate effects labor supply on the intensive rather than extensive margin, since it does not affect the maximum EITC benefit or the marginal wage rate at zero hours of work. The simulation results in Table 2 suggest that labor supply is not very responsive to the EITC on the intensive margin.

A second conclusion is that the phase-in and especially the plateau earnings ranges should be longer, with the phase-in earnings range flatter. The plateau earnings range should be longer than the phase-in earnings range when it is shorter than the phase-in earnings range under current policy.

A third result from the optimization is that the program should be more generous to households with more children, and especially more generous to households with three children relative to households with two children. Presently, the program treats households with two and three children about the same. Each optimal program remained substantially more generous to households with three dependents than households with two dependents, and more generous towards households with two dependents than households with one dependent. This optimization of course does not reflect the extent to which such a policy might incentivize fertility.

I decided to test whether this third conclusion resulted from defining consumption (c) in terms of income per household member rather than total household income, which defines households with more children as poorer and causes the objective to put more weight on their household income. I did this by estimating an optimal EITC program with the same assumptions and nearly the same objective as the optimal EITC reported in Table 3, only with consumption defined as total household income rather than income per family member. The difference in generosity towards families of different sizes was reduced in the case of the 33% lower spending and equal spending program relative to the case where consumption was defined as income per family member. In the case of a 33% more generous program, however, the optimal program was similar whether consumption was defined as total family income or income per family member.

A fourth conclusion can be made regarding how optimal programs with more and less generous spending limits would differ from one another. The more generous the spending limit, the higher the optimal subsidy rate is, even though the optimal value of other EITC parameters are largely constant with respect to the spending limit. This might reflect the fact that an increase in the subsidy rate will raise benefits not-only in the phase-in earnings range, but will raise benefits in the plateau and phase-out earnings range as well because it will increase the maximum benefit. A reduction in the tax rate will only increase income in the phase-out earnings range.

Therefore, putting these four conclusions together, one can say that regardless of spending level, the EITC should have longer phase-in and plateau earnings ranges, with a steeper tax rate in the phase-out earnings range. The subsidy rate should be much flatter for a less generous program, somewhat flatter to maintain the same level of spending, and about the same in the case of a more generous program.

VIII. **Conclusions**

I draw three major conclusions about the EITC. One conclusion is that the EITC raises the labor force participation of single mothers by about 7.5 percentage points. That means that about a third of all non-working single mothers under a regime without the EITC work as a result of the EITC. Another conclusion is that those single mothers induced into the workforce by the EITC work hours that are substantially close to that of the average single mother, 1600 hours. The existing literature that estimated an effect on labor force participation but not hours left open the possibility that workers induced into the workforce by the EITC were working few hours, producing only a small increase in labor supply and a small benefit to the poorest households. When the above two conclusions are combined with a small and statistically insignificant effect of the EITC on the hours of single mothers already in the labor force, the net effect of the EITC on the hours of single mothers is positive. This is an important result because the net effect on labor supply of other social programs is theoretically and empirically negative. Finally, I conclude that relative to the existing program, an optimal EITC program would feature a longer and flatter phase-in region, and a steeper phase-out region.

There are general equilibrium effects that threaten the interpretation of these results as causal effects. One is that by increasing the supply of low-skilled labor, the EITC can lower offered wage rates before accounting for the EITC. For example, Rothstein (2015) finds that every dollar in benefits to eligible households reduces the wages paid to ineligible workers by 43 cents. That will tend to cause the labor supply and welfare effects of the

EITC on poorer households overstated, although it also means there are benefits to employers of low-skilled labor from the EITC.

Therefore, the ideal model compares the observed labor supply of single mothers to what their labor supply would be without EITC benefits *or* the general equilibrium effects of the EITC on their wage rates before taxes. This is tricky because the EITC also affects the wage offers of ineligible workers, who fall into the control group in a DID approach. My model mitigates this problem because labor supply without the EITC is predicted using a wage offer model that is likely to be largely independent of the EITC, since it does not include EITC parameters. Still, it would be useful to include the maximum EITC benefit as a wage variable, and allow the EITC to effect labor supply not only through benefits but through wage offers in simulations estimating the effect of the EITC on labor supply.

Another general equilibrium effect is that by increasing the supply of low-skilled labor, the EITC lowers the relative prices of goods that use low-skilled labor intensively. That could also have welfare effects if different groups allocate greater or smaller budget shares to those goods. Although this has not been addressed in this thesis or any part of the labor supply literature to my knowledge, it also needs to be addressed in future research.

A productive area for future research might be what activities single mothers allocate less time towards if the EITC incentivizes them to allocate more time towards work. A major purpose of the EITC was to improve the welfare of children in poor families. If the EITC incentivizes single women to allocate more time towards work and less time towards pure leisure activities, then surely that improves the welfare of children in those families.

One can imagine, however, that a single mother might have little time for pure leisure and that the EITC causes her to allocate more time towards work at the expense of time with her children. In that case, the improvement in child welfare depends on how one weighs the income of single parents against their time with their children. The American Time Use Survey can provide data on the time allocation of single parents.

The labor supply modeling approach in this paper can also be easily extended to married and cohabiting couples. To describe how to do this in the simplest terms, I will refer to one able-bodied adult in the household as the husband and the other as the wife, though they need not be legally married or opposite sex. The labor supplies of both spouses or partners in the household can be modeled as jointly maximizing a utility function with three goods: husband's leisure time, wife's leisure time, and total household income. To allow for complementarity or substitutability between husband and wife's leisure time, each can be an input to a composite good simply called leisure. Leisure could then be defined as $l = sign(\delta_3)l_1^{\delta_3} + sign(\delta_3)l_2^{\delta_3}$, where l is leisure, l_1 is the husband's leisure, l_2 is the wife's leisure, and δ_3 is a parameter to be estimated. With consumption defined as total household income, utility can be defined by equation (4).

One interesting application of this model would then be to the effect of the EITC on the labor supply of married couples and what an optimal EITC for married couples might look like. The effect of the EITC on the employment of married people is theoretically ambiguous, in contrast to its effect on the employment of single workers. That is because EITC benefits increase the income effect of one's spouse's earnings, and can lower the marginal wage rate of one's first hour of work if your spouse's earnings put you in the phase-out earnings range. Eissa and Hoynes (2004) find that the EITC expansions over the period from 1984 to 1996 lowered the employment of married women by 1.1 percentage points while raising the employment of married men by only .2 percentage points, but a different EITC policy might reduce or reverse those negative labor supply effects.

IX. **Appendix**

i. Earned Income Tax Credit Parameters, 1988-2012

Table A1: Earned Income Tax Credit Parameters, 1988-2012 (Dollar amounts unadjusted for inflation)

Calendar year	Credit rate (percent)	Minimum income for maximum credit	Maximum credit	Phaseout rate (percent)	Phaseout range [1] Beginning income	Phaseout range [1] Ending income
2012						
No children	7.65	6,210	475	7.65	7,770	13,980
One child	34	9,320	3,169	15.98	17,090	36,920
Two children	40	13,090	5,236	21.06	17,090	41,952
Three children	45	13,090	5,891	21.06	17,090	45,060
2011						
No children	7.65	6,070	464	7.65	7,590	13,660
One child	34	9,100	3,094	15.98	16,690	36,052
Two children	40	12,780	5,112	21.06	16,690	40,964
Three children	45	12,780	5,751	21.06	16,690	43,998
2010						
No children	7.65	5,980	457	7.65	7,480	13,460
One child	34	8,970	3,050	15.98	16,450	35,535
Two children	40	12,590	5,036	21.06	16,450	40,363
Three children	45	12,590	5,666	21.06	16,450	43,352
2009						
No children	7.65	5,970	457	7.65	7,470	13,440
One child	34	8,950	3,043	15.98	16,420	35,463
Two children	40	12,570	5,028	21.06	16,420	40,295
Three children	45	12,570	5,657	21.06	16,420	43,279
2008						
No children	7.65	5,720	438	7.65	7,160	12,880
One child	34	8,580	2,917	15.98	15,740	33,995
Two children	40	12,060	4,824	21.06	15,740	38,646
2007						
No children	7.65	5,590	428	7.65	7,000	12,590
One child	34	8,390	2,853	15.98	15,390	33,241
Two children	40	11,790	4,716	21.06	15,390	37,783

Earned Income Tax Credit Parameters, 1988-2012 (continued) (Dollar amounts unadjusted for inflation)

Calendar year	Credit rate (percent)	Minimum income for maximum credit	Maximum credit	Phaseout rate (percent)	Phaseout range [1] Beginning income	Ending income
2006						
No children	7.65	5,380	412	7.65	6,740	12,120
One child	34	8,080	2,747	15.98	14,810	32,001
Two children	40	11,340	4,536	21.06	14,810	36,348
2005						
No children	7.65	5,220	399	7.65	6,530	11,750
One child	34	7,830	2,662	15.98	14,370	31,030
Two children	40	11,000	4,400	21.06	14,370	35,263
2004						
No children	7.65	5,100	390	7.65	6,390	11,490
One child	34	7,660	2,604	15.98	14,040	30,338
Two children	40	10,750	4,300	21.06	14,040	34,458
2003						
No children	7.65	4,990	382	7.65	6,240	11,230
One child	34	7,490	2,547	15.98	13,730	29,666
Two children	40	10,510	4,204	21.06	13,730	33,692
2002						
No children	7.65	4,910	376	7.65	6,150	11,060
One child	34	7,370	2,506	15.98	13,520	29,201
Two children	40	10,350	4,140	21.06	13,520	33,178
2001						
No children	7.65	4,760	364	7.65	5,950	10,710
One child	34	7,140	2,428	15.98	13,090	28,281
Two children	40	10,020	4,008	21.06	13,090	32,121
2000						
No children	7.65	4,610	353	7.65	5,770	10,380
One child	34	6,920	2,353	15.98	12,690	27,413
Two children	40	9,720	3,888	21.06	12,690	31,152
1999						
No children	7.65	4,530	347	7.65	5,670	10,200
One child	34	6,800	2,312	15.98	12,460	26,928
Two children	40	9,540	3,816	21.06	12,460	30,580

Earned Income Tax Credit Parameters, 1988-2012 (continued) (Dollar amounts unadjusted for inflation)

Calendar year	Credit rate (percent)	Minimum income for maximum credit	Maximum credit	Phaseout rate (percent)	Phaseout range [1] Beginning income	Ending income
1998						
No children	7.65	4,460	341	7.65	5,570	10,030
One child	34	6,680	2,271	15.98	12,260	26,473
Two children	40	9,390	3,756	21.06	12,260	30,095
1997						
No children	7.65	4,340	332	7.65	5,430	9,770
One child	34	6,500	2,210	15.98	11,930	25,750
Two children	40	9,140	3,656	21.06	11,930	29,290
1996						
No children	7.65	4,220	323	7.65	5,280	9,500
One child	34	6,330	2,152	15.98	11,610	25,078
Two children	40	8,890	3,556	21.06	11,610	28,495
1995						
No children	7.65	4,100	314	7.65	5,130	9,230
One child	34	6,160	2,094	15.98	11,290	24,396
Two children	36	8,640	3,110	20.22	11,290	26,673
1994						
No children	7.65	4,000	306	7.65	5,000	9,000
One child	26.3	7,750	2,038	15.98	11,000	23,755
Two children	30	8,425	2,528	17.68	11,000	25,296
1993						
One child	18.5	7,750	1,434	13.21	12,200	23,050
Two children	19.5	7,750	1,511	13.93	12,200	23,050
1992						
One child	17.6	7,520	1,324	12.57	11,840	22,370
Two children	18.4	7,520	1,384	13.14	11,840	22,370
1991						
One child	16.7	7,140	1,192	11.93	11,250	21,250
Two children	17.3	7,140	1,235	12.36	11,250	21,250
1990	14	6,810	953	10	10,730	20,264
1989	14	6,500	910	10	10,240	19,340
1988	14	6,240	874	10	9,840	18,576

http://www.taxpolicycenter.org/statistics/eitc-parameters, July 2016

ii. Properties of $\hat{u}$

The first criterion states that the share of time devoted to paid work can be the entire time endowment, none of the time endowment, or any fraction in between. I will show that this is the case if $\kappa_1 > 0$, $\kappa_2 > 0$, $\delta_1 < 1$, and $\delta_2 < 1$. The first two inequalities are necessary. I do not believe that the last two are, but they will simplify the proof.

To see that the criterion is satisfied, take expected utility as given by equation (4), and take the marginal rate of substitution between consumption (c_i) and leisure (l_i)

$$MRS = \frac{\left(l_i + \kappa_2\right)^{\delta_2 - 1}}{\alpha\left(c_i + \kappa_1\right)^{\delta_1 - 1}} \tag{14}$$

Note that positive values of κ_1 and κ_2 and the non-negativity of l_i and c_i guarantee that the MRS is defined, even if l_i or c_i are 0. The lowest possible rate of substitution of consumption for leisure is when leisure is at its maximum, which is the full time endowment E, and consumption is at its minimum, 0. Then the MRS equals $\frac{(E+\kappa_2)^{\delta_2-1}}{\alpha\kappa_1^{\delta_1-1}}$, and if the wage rate is below that, the agent does not gain enough income from an additional unit of time working for the utility gain from that income to be greater than the utility loss from lost leisure. She can only be worse off consuming less leisure than the maximum possible, so the choice that maximizes expected utility is to work zero hours.

Now consider values of leisure consumption less than the maximum, with the rest of the time endowment devoted to paid work. The time devoted to paid work is $E - l_i$, where E is the time endowment. The worker's total consumption is therefore $c = w_{it}(E - l_i) + g_i$, where w_{it} is her wage rate and g_i is all non-labor income person i receives. Substituting this equation for consumption into (13) yields

$$MRS = \frac{\left(l_i + \kappa_2\right)^{\delta_2 - 1}}{\alpha\left(w_{it}(E - l_i) + \kappa_1\right)^{\delta_1 - 1}} \tag{15}$$

Since the numerator and denominator are both strictly positive and finite for leisure consumption between 0 and E, the MRS is defined for all possible levels of leisure consumption. Therefore, for any level of leisure consumption, l*, there is a wage w* such that the MRS equals the wage. Since the MRS falls monotonically in leisure consumption, that equality implies that any choice of leisure consumption l* is a utility maximizing choice for some wage rate w*. If the MRS were greater than the wage, utility could be increased only by consuming more leisure. If the MRS were less than the wage, utility could be increased only by consuming less leisure. That the MRS equals the wage means that utility can not be increased.

As leisure consumption falls, the numerator of equation (14) rises and the denominator of equation (14) falls, so the MRS increases. Leisure is more valued on the margin because it is rarer, while consumption is less valued on the margin because it is more abundant. The MRS reaches a maximum of $\frac{\kappa_2^{\delta_2 - 1}}{\alpha(w_{it}E + \kappa_1)^{\delta_1 - 1}}$ when leisure consumption is 0. If the wage rate is greater than this maximum, utility is maximized with no leisure consumption and the entire time endowment is devoted to paid work.

Criterion 2 states that leisure and consumption can be perfect complements as δ_1 and δ_2 approach -∞, perfect substitutes as δ_1 and δ_2 approach 1, and anything in between. One can see this by taking the marginal rate of substitution given by equation 13 and imposing the condition that it equals the wage rate, which will be true if optimal leisure consumption is not equal to one of the two possible corner solutions of 0 or the entire time endowment. Log linearize that condition to obtain

$$\Delta(w_i) = (\delta_2 - 1)\Delta(l_i + \kappa_2) - (\delta_1 - 1)\Delta(c_i + \kappa_1) \tag{16}$$

Where $\Delta(x)$ indicates a percentage change in x. Leisure can be transformed into income at the rate of w, the wage rate, and at an optimal labor supply the marginal rate of substitution between leisure and income is equal to w.

First consider the case where δ_1 and δ_2 approach $-\infty$. A large percentage increase in w_i requires a small percentage decrease in l_i, inversely proportional to $\delta_2 - 1$, to restore the MRS to be equal to the wage rate. Since Hicksian demand necessitates that a fall in leisure is accompanied by a rise in consumption to remain on the same indifference curve, leisure consumption falls by a percentage less than the inverse of $\delta_2 - 1$ for each percentage increase in w. As δ_2 goes to $-\infty$, therefore, that percentage change in leisure consumption must go to 0. That implies zero substitutability between leisure and consumption, so leisure and consumption are perfect complements.

That substitutability must increase as δ_1 and δ_2 increase because $\delta_1 - 1$ and $\delta_2 - 1$ become smaller monotonically in absolute value up until δ_1 and/or δ_2 equal 1. When δ_1 and δ_2 equal 1, leisure and consumption are perfect substitutes because any given change in the wage rate requires an infinite change in leisure consumption to restore the condition that the MRS equals the wage rate.

Criterion (3) states that out of your maximum possible income, $E * w_{it} + g_{it}$, the fraction that you give up to consume leisure can vary by the size of that maximum income. To see that criterion (3) is met, consider the effect on the MRS of increasing both consumption and leisure by an equal proportion without a change in the wage rate. This is possible if non-labor income, g_{it}, increases. This is also possible if one's earnings are in the plateau region, but the subsidy rate in the phase-in region is increased, providing a pure income effect. Unless $\delta_2 = \delta_1$, the MRS would change. If $\delta_2 > \delta_1$ the marginal rate of substitution of consumption for leisure would increase, so if the wage rate were not changed you would choose to consume still more leisure. The budget share devoted to leisure would increase. If $\delta_2 < \delta_1$, the marginal rate of substitution of consumption for leisure would decrease, so if the wage rate were unchanged, leisure would increase by a smaller proportion than income. The budget share of leisure would decrease. A constant elasticity of substitution utility function imposes $\delta_1 = \delta_2$, as does a Cobb-Douglas utility function, since it is a special case of a CES utility function.

To see that criterion (4) is satisfied, expand (14) and consider how the parameters κ_1 and κ_2 become less important while δ_1 and δ_2 have more influence asymptotically.

$$\Delta(w_i) = (\delta_2 - 1)\Delta(l_i)\frac{l_i}{l_i + \kappa_i} - (\delta_1 - 1)\Delta(c_i)(\frac{c_i}{c_i + \kappa_i}) \tag{17}$$

Suppose I gain nonlabor income to spend on consumption and leisure while the price of leisure is unchanged, so $\Delta(wi) = 0$.

$$\frac{\Delta(c_i)}{\Delta(l_i)} = \frac{(\delta_2 - 1)\frac{l_i}{l_i+\kappa_i}}{(\delta_1 - 1)\frac{c_i}{c_i+\kappa_i}} = \frac{(\delta_2 - 1)(1 + \frac{\kappa_1}{c_i})}{(\delta_1 - 1)(1 + \frac{\kappa_2}{l_i})} \tag{18}$$

If and only if this fraction is greater than 1, will consumption take an increasing fraction of the budget as we grow wealthier. If and only if this fraction is less than 1, will leisure take an increasing fraction of the budget as we grow wealthier. Whatever the values of δ_1 and δ_2, this fraction can be greater than 1 if κ_1 is large enough relative to κ_2 and less than 1 in the reverse case. However, as consumption and leisure increase, the fraction gets closer to $\frac{\delta_2 - 1}{\delta_1 - 1}$, allowing it to change from less than 1 to greater than 1 or vice versa.

iii. A Discrete Hazard Model in the Context of Wages, and the Choice of Wage Bins

A discrete model over wage bins defines the probability of being in any given wage bin by first estimating the **hazard** of being in any given wage bin, where the hazard of being in any wage bin k is defined as follows:

$$\lambda_k = pr(\text{in bin k, given one is in bin k or higher}) = \frac{\text{pr(in bin k)}}{\sum\limits_{j=k}^{K} \text{pr(in bin j)}}$$

Where the bins are numbered from the lowest range of wages (1) to the highest range of wages (capital K) and pr denotes probability. If we denote by p_k the probability of being in some bin k, note that

$$p_1 = \lambda_1 \tag{19}$$

$$\begin{aligned} p_j &= pr(\text{bin k or higher}) * pr(\text{bin k, conditional on being in bin k or higher}) \\ &= pr(\text{not in any bin lower than k}) * pr(\text{bin k, if in bin k or higher}) \\ &= \lambda_k \prod_{j=1}^{k-1} (1-\lambda_j) \end{aligned} \tag{20}$$

Where Π denotes a product and the hazard rate over the highest bin, λ_K, equals one.

That means a set of K-1 hazard rates over the first K-1 bins, each between 0 and 1, gives a probability over each of the K bins. To ensure that the hazard rates are between 0 and 1, the hazard rates over each bin k are defined as

$$\lambda_j = \frac{exp(x_{it} * b_j)}{1 + exp(x_{it} * b_j)} \tag{21}$$

Where x_{it} is a set of covariates.[20] Included in $x_{it} * b_j$ is the log of the unconditional hazard rate in each bin. The fact that the λ_j are between 0 and 1 guarantees that the probabilities are between 0 and 1 and sum to 1. Intuitively, this is because the first hazard rate merely splits the probabilities into two bins that sum to 1, with probabilities p_1 and $1 - p_1$. A second hazard rate merely splits the probability of the second bin into two bins, a probability of bin 2 and a probability greater than bin two, to give a total of three bins. The logic applies to any additional hazard rates and bins.

I defined wage bins as follows. Except for those wage bins that begin at a level greater than $30 an hour, all wage bins were defined so that the difference between the logs of the upper limits of any two consecutive bins were the same. In other words, the second wage bin, $5.49 to $5.99 an hour, was about 9% wider than the first wage bin, and the third wage bin was about 9% wider than the second, etc. Wage bins beyond $30 an hour were defined differently to be even wider because otherwise the low density of observations would make some of them empty. Observations of wage in the first K-1 wage bins were assigned a wage equal to the midpoint of the wage bin that they fell into. Wages in the last wage bin were assigned the mean of observations in that bin, because the midpoint would not be very accurate due to the right skewness of wages in the highest wage bin. The cutoffs for the wage bins in year 2014 dollars per hour were defined as follows

[5 5.48 5.99 6.55 7.16 7.84 8.57 9.37 10.25 11.21 12.26 13.41 14.66 16.03 17.53 19.18 20.97 22.94 25.08 27.43 37.32 50.78 69.09 117];

[20] In my specification, some b_j are the same across bins, while others are an interaction term of a covariate with the bin number or a constant specific to the given bin

For the specification that used cruder labor supply and wage bins, they were [5 5.99 7.17 8.57 10.25 12.26 14.66 17.53 20.97 25.08 34.9 48.55 67.53 117];

iv. Food Stamps

The law governing the Food Stamp (SNAP) program is laid out in title 7, section 273 of the Code of Federal Regulations. I determined eligibility and benefit determination for each year of data by downloading and reading subsections 8 through 10 of that code for each year in 1987 through 2012. For any given individual, SNAP benefits at each possible level of labor supply were calculated assuming that only earnings would differ at different levels of labor supply. It is assumed that asset holdings and other variables that can affect SNAP benefits would not differ from their observed value at other levels of labor supply.

Households are eligible for SNAP benefits if their assets, gross income, and net income are below certain limits. Gross income is defined for the purposes of the program as essentially all cash income outside of the EITC. Net income is defined as gross income minus certain deductions that I detail below.

Gross income limits are more generous for households with elderly (over 60) or disabled members. The net and gross income limits are also more generous for larger families, taking different values for every number of people in the household between 1 and 8 inclusive. These limits increase by a constant amount for each additional household member beyond 8. For every level of labor supply, gross income was calculated using what income would be in the budget constraint without SNAP or EITC benefits. This measure of annual income was divided by twelve because SNAP benefits are allotted monthly and calculated based on monthly income.

In calculating net income, all potential beneficiaries get to subtract what is called a standard deduction from their gross income. They also get to subtract 20% of all earned income, reflecting the cost of payroll taxes.[21]. The earned income deduction was calculated by taking 20% of the level of labor income implied by each wage and labor bin. The cost of dependent care necessary to maintain employment outside of the home is also subtracted up to a limit per dependent, which is more generous for dependents under the age of two. The dependent care deduction was calculated using the level of child care expenses reported in the PSID, censored at the deduction cap for their family size and composition. Starting in 1994, legally obligated child support payments to children outside of the beneficiary's home also became deductible. Child support deductions were calculated using child support payments reported in the PSID.[22] [23] Earned income, child care costs, and child support payments were all converted into monthly averages by dividing annual data from the PSID by twelve.

The above deductions must be subtracted from gross income first to obtain *net income before shelter*. Net income is then defined as net income before shelter minus *excess shelter expense*, where excess shelter expense is any housing cost in excess of one half of net income before shelter but up to a shelter deduction limit. In other words, the deduction for excess

[21] This was 18% of all earnings prior to 1988

[22] This was treated as 0 for 2003, 2005, and 2007 because it was missing from the PSID

[23] out of pocket medical expenses of elderly or disabled household members in excess of $35 month are also deductible. The medical expenses deduction was ignored because the PSID data does not specify what medical expenses are for elderly or disabled members vs other members, and because only 12% of the households on SNAP with senior or disabled household members claimed it.Jones (2014)

shelter expense is calculated as housing cost minus one half of *net income before shelter*, then left censored at 0 and right censored by the shelter deduction limit. Mathematically, if the head of household's housing expenses are H and the law sets the shelter deduction limit as E-bar ($\bar{E}$), the deduction for excess shelter expense, or E, is calculated as

$$E = Min\Big(\bar{E}, Max(0, H - .5 * \textit{net income before shelter})\Big) \tag{22}$$

and *net income* is *net income before shelter* minus the variable E defined above. Housing costs were measured with the annualized cost of rent in the year of interview from the PSID, divided by twelve. For even years after 1997 and in 1988, rent was imputed with its one-year lag since the rent variable was not available in those years.

Assets include cash and anything that can be readily converted into cash such as stocks and retirement accounts, as well as the value of vehicles in excess of what is owed on them beyond a certain limit. Variables measuring the value of checking accounts, vehicles minus what is owed on them, and stocks minus what is owed on them, were available from the PSID in the years 1989, 1994, and odd (interview) years for 1999-2011. Values of these variables in other years were imputed with their nearest lead. A variable for IRA value was available for odd years from 1999 to 2012. To account for all assets in an IRA if one existed, without double counting the value of stocks in an IRA, the value of stocks was replaced with the IRA variable if both were observed and the IRA variable was greater. All values of stocks, checking accounts, and vehicles were imputed as 0 if missing and added together to get an asset measure. If this asset measure was greater than the asset limit, predicted benefits were 0.

Finally, SNAP benefits for households that meet the gross income, net income, and asset limits are calculated as follows. The law specifies a maximum monthly household benefit that depends on the number of people in the household. The household's benefit is the maximum benefit minus thirty cents for every dollar of net income, as defined above. If this calculation produces a benefit below $15 a month, but the household is otherwise eligible, the household receives the minimum benefit of $15 a month.

A change in the law came in 1996, in which benefits were reduced for households with able bodied adults without dependents (ABAWDs). ABAWDs are defined as people between the ages of 18 and 50 who are not disabled and have no dependents. They were unable to claim benefits for more than three months in any 36-month period, except for a provision that allowed states to keep up to 15% of otherwise eligible ABAWDs on the benefit rolls. This was modeled by reducing the benefits of observations in the model without dependents and within that age who did not claim to be a limited "a lot" or "somewhat" by disability in the PSID by the fraction .15+(1/12) of what they would otherwise be, for all observations in the year 1997 and later.

Historical data on the shelter deduction cap, standard deduction, and maximum benefits, asset limits, and net income limits by family size over the study time period were provided by email from the USDA. Over a limited set of years, SNAP benefits were reported directly by PSID respondents. For those observations, predicted Food Stamps benefits predicted the Food Stamps benefits reported in the data with an R^2 of .5.

v. Histograms of Labor Supply by the Number of Dependents in the Household

Figure A1: Probability Densities of Observed and Simulated Labor Supply: No Dependents, Model with Food Stamps

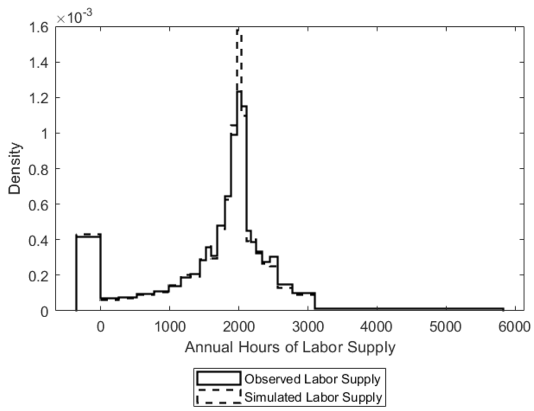


Figure A2: Probability Densities of Observed and Simulated Labor Supply: One Dependent, Model with Food Stamps

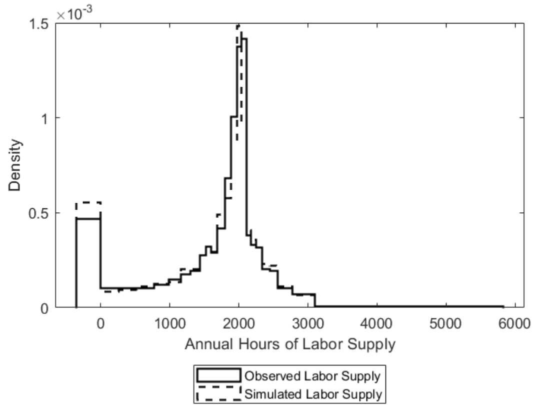


Figure A3: Probability Densities of Observed and Simulated Labor Supply: Two Dependents, Model with Food Stamps

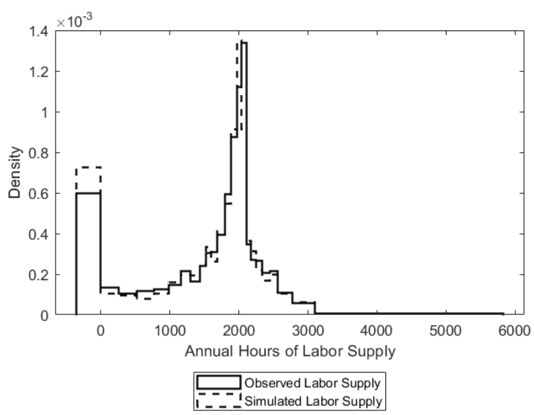
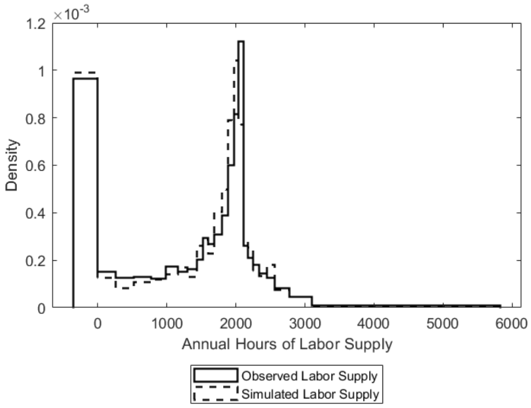


Figure A4: Probability Densities of Observed and Simulated Labor Supply: Three Dependents, Model with Food Stamps



vi. EITC Labor Supply Effects: Robustness Checks

Table A2: Simulated Effects of the EITC on the Labor Supply of Single Mothers, Change from no EITC to 2012 EITC, Robustness Checks

	LFP	entrant hours	incumbent hours	hours	log likeilihood	# of parameters
preferred specification	7.52 (0.93)	1599 (656)	-16.5 (20.4)	109 (20.4)	-127,339.6	308
second fullest	7.68 (1.51)	1545 (679)	-1.4 (8.5)	118 (32.5)	-127,367.5	300
no food stamps	7.53 (1.96)	1617 (454)	-1.4 (11.7)	121 (29.6)	-127,402.5	300
no state level unemployment	6.79 (1.04)	1595 (537)	-0.5 (4.8)	108 (22.8)	-127,619.2	288
cruder bins	11.2 (1.62)	1568 (107)	1.5 (3.27)	177 (25.4)	-99,043.7	300

*,**, and *** indicate signficance at the 10%, 5%, and 1% levels. Significance tests employed a one sided test that the coefficient was greater than 0 for LFP and entrant hours, and a two-sided test that the coefficient was different from 0 for incumbent hours and hours

vii. Tables of Parameter Estimates and their Interpretation

To describe how to interpret parameter coefficients, I will use table A3 below as an example. This gives parameter estimates for the preferred specification. First note that there are three sets of parameter estimates in the table, separated by vertical lines, each with a probability expressed in log odds associated with it and an estimate and standard error for each parameter. These are the types or discrete factors discussed in the introduction, and we can think of the model as a mixture model of these 3 separate models. For some parameters, such as for "ext log odds" and "int log odds", the entries for types 2 and 3 are blank. That means this parameter could take only one value over all types, the value under type 1. Since each type has the same parameters, only with different values, I will describe parameter interpretation using the first type as an example.

Starting from the top of the table and working down, *ext log odds* is the log odds of the head of household incorporating the EITC into the budget constraint in the decision of whether to work. It is how much probability weight is placed on the model of employment that incorporates the EITC in the work decision, or p_1 in equation (6). It is estimated as a log odds, or the natural log of $\frac{p_1}{1-p_1}$, because that insures that the implied value of p_1 is bound between 0 and 1. Converting the estimated log odds to a probability, it equals .831. [24]

After the probability of working is calculated, the probability of choosing any labor supply bin other than the zero hours bin is calculated as the probability of working times

[24] take the exponential of the estimate and divided it by one plus the exponential of the estimate

the probability of choosing each non-zero hours bin, conditional on working. Those work conditional probabilities are calculated from a mixture model or weighted average of a model that incorporates the EITC in the budget constraint and an otherwise identical model that does not. The log odds on the model with the EITC on the budget for calculating work conditional probabilities is given by the row *int log odds*. When *int log odds* is converted to a probability, it is .51.

The row for the *type log odds* gives the log odds of each type, relative to the baseline or first type. For example, the odds that any given individual is type 2, conditional on being either type 1 (baseline) or type 2 is exp(-.21)=.811. This also reduces to the ratio of probabilities of type 2 to type 1, making the probability of type 2 about 81% as likely as type 1. Likewise, the odds of type 3 relative to the baseline are exp(-.33)=.719, making the third type about 72% as likely as the first type.

The meaning of parameter estimates α through γ are given by equation (4) and the labor supply subsection of section V. Alpha can be interpreted as the valuation of income relative to each hour of leisure in utility, but two values of α can only be compared holding other utility parameters constant. Other parameters and characteristics equal, a larger value of α means you will tend to work more.

To interpret parameters δ_1 through κ_2, consider that the marginal utility of income is proportional to $(w * L + E + \kappa_1)^{\delta_1 - 1}$, where w is the wage rate, L is labor supply, and E is non-labor income. The fact that $\delta_1 < 1$ indicates diminishing marginal utility of income. An increase in the wage rate will reduce labor supply if the marginal utility of income falls by a greater percentage than the wage increases, and increase labor supply in the opposite case. When E and κ_1 are negligible compared to earned income w*L, which will be the case for higher wage earners, one can say that a wage increase will reduce labor supply if $\delta_1 < 0$ and increase labor supply if $\delta_1 > 0$. Thus, my negative estimates for δ_1 imply that for very high wage earners with little non-labor income, labor supply will fall with the wage rate. This could be reversed if non-labor income is larger relative to labor income. In that case, the same increase in the wage rate will produce a smaller fall in the marginal utility of income because income increases less from the wage change in percentage terms. Large estimates for κ_1 mean that the marginal utility of income diminishes much less for a given percentage increase in the wage rate for low wages. Therefore, my negative estimates for δ_1 and large estimates of κ_1 mean that labor supply rises with the wage rate for low incomes and falls with the wage rate for high incomes.

FCL is the fixed cost in leisure time of working any positive number of hours, it could represent time lost to commuting or finding employment. The parameters uscaler and γ are monotonic transformations of utility, where the parameter uscaler is the parameter A in equation 4. A smaller value of uscaler will make each possible labor supply choice more similar in likelihood, while a larger value will increase the difference in likelihood assigned to more and less likely choices.

Below those estimates there are a list of parameter estimates with a heading of “FCU” for Fixed Cost in Utility to the left, a list of estimates with the heading MU (marginal utility) of leisure to the left, and a list of estimates with the heading “wage hazard model” to the left. Those are estimates of how explanatory variables affect behavior through fixed utility costs of work, a constant shift in the marginal utility of each hour of leisure, and the wage distribution, respectively. The same variable can appear in more than one of these lists because it can affect more than one of those aspects of the model.

Under FCU is the linear effect of various variables on the utility penalty of the first hour of work. It represents the effect of those variables on the probability of working, relative to the baseline of a white, non-hispanic, high school dropout. Positive numbers indicate that the condition makes you less likely to work, while negative values mean that the condition makes you more likely to work. 1 ch is an indicator for having *at least* 1 child, 2 ch is an indicator for having *at least* 2 children, HS only is an indicator for having only a high school diploma in educational attainment, while twyr is an indicator for having completed *at least* two years of college. In this way, 3 ch can only equal 1 if 2 ch can only equal one if 1 ch equals 1. That way each estimate is of the additive effect of additional children in the household, rather than the effect relative to having no children.

The set of coefficient estimates under ”MU of leisure”, for marginal utility of leisure, describe how the function f in equation (4) depends linearly on various variables. The positive coefficient on age indicates that older women value leisure more than younger women, for example. A negative coefficient on a given variable means that variable is correlated with a lower valuation of each hour of leisure, or higher labor supply for a given wage. Age and the year of observation are normalized to be between 0 and 1 as follows $age = \frac{age-16}{48}$, $trend = \frac{year-1987}{48}$, since years of observation range from 1987 to 2012.

On the next page, below the heading "wage bin hazards", you see the wage variables and how they affect the wage offer distribution. These variables determine the hazard odds of each wage bin, where the hazard odds of a wage bin k is defined as the probability of being in wage bin k, conditional on being in wage bin k or higher. Since these hazard odds are expressed in logs, we can think of coefficients as approximately fractional or percentage changes. All coefficients are changes in the wage hazard relative to the unconditional wage hazard over all observed wages. Therefore, negative coefficients mean that when this variable is larger or equal to "true", wages are higher or right-shifted, while positive coefficients mean that this variable makes wages lower or left-shifted.

The coefficient on imptwg estimates the effect on wages when the wage rate is not reported directly by the respondent. In those cases, the wage rate was calculated as reported earnings divided by reported hours, and the predicted value of those wages after all wages were regressed on an individual fixed effect, age, age-squared, year dummies, and a dummy variable for division wages was then used as the wage to reduce division bias in the wage variable. Unemployment is the unemployment rate, expressed as a fraction, times ten. The education variables HS, twyr, bach, and grad, indicate having *at least* a high school diploma, *at least* two years of college, *at least* a bachelor's degree, and *at least* some graduate education, respectively. In this way, if any of these education indicators are equal to one, all lower indicators are equal to one, and estimates represent the additional effect on wages of reach that degree level relative to the degree level just below it. Note the contrast between the variable HS and the variable HS only used in the fixed cost of employment and marginal utility of leisure equations, since HS only indicates having exactly a high school diploma as one's highest degree level.

Note that the first order wage variables also have interaction terms with the wage bin number. This is actually the wage bin number divided by the number of bins. Using the example of the variable bachelor, having a bachelor's degree changes the wage hazard by $-.93 + .49 * \frac{wagebin}{\text{total wage bins}}$. This means that a bachelor's degree lowers the wage hazard by -.93 in the lowest wage bin but only by .5 in the highest wage bin. With these bin interaction terms, the effect of a variable on the wage hazard can be negative for lower wage bins and positive for higher wage bins, compressing the wage distribution, or positive for lower wage bins and negative for higher wage bins, spreading it out.

A Dictionary of Variables

α-κ_2, γ: See equation (4). Paragraphs 5, 6, and 7 of this section give the interpretation.

age: age in years, minus 16 and divided by 48.

agesq: The square of the age variable defined above.

bach: An indicator that the respondent has at least a bachelor's degree.

black: respondent identifies as African-American

1 ch: An indicator for the presence of at least one child in the household

2 ch: An indicator for the presence of at least two children in the household

3 ch: An indicator for the presence of three or more children in the household

ext log odds: The log odds of incorporating the EITC in the budget constraint in the decision of whether or not to work.

FCL: The fixed reduction in leisure consumption from working more than zero hours for pay.

FCU: The fixed reduction in utility from working more than zero hours for pay.

female LFP: The national labor force participation rate of women aged 25-54

grad: An indicator for some postgraduate education.

high pay: An indicator for a respondent whose major of their highest degree had business, medicine, computing, or engineering in the title.

HS: The respondent has a high school diploma.

HS only: The respondent has a high school diploma, but no college education, or less than two years of college education.

hispanic: Respondent identifies as Hispanic.

imptwg: The wage was imputed using an individual fixed effect, year, age, and age squared. This is only for those observations who worked positive hours but did not directly report a wage, to avoid the division bias from using earnings divided by hours.

int log odds: The log odds of incorporating the EITC in the decision of how many hours to work, conditional on working and incorporating the EITC in the decision of whether to work.

male LFP: The national labor force participation rate of men aged 25-54.

st level LFP: The state level labor force participation rate.

st unempl: The state level of unemployment rate.

type log odds: The log odds of each type.

twyr: The respondent has at least two years of college education.

uscaler: A in equation (4). A scaler multiplier of utility that makes the labor supply decision more deterministic the larger it is.

yr: The year of observation, normalized to be from 0 to 1 as $\frac{year-1987}{25}$

yrsq: yr, defined above, squared.

yrc: The variable year cubed.

Table A3: Parameter Estimates for Preferred Specification

log likelihood=-127,339.6, n=25,329

		type 1 estimate	SE	type 2 estimate	SE	type 3 estimate	SE
ext log odds		1.59	3.08				
int log odds		0.04	2.83				
type log odds		baseline		-0.21	10.65	-0.33	8.38
α		14.76	4.66	9.84	0.51	13.65	2.47
δ_1		-0.4	0.67	-1.19	2.07	-0.25	0.38
δ_2		-1.68	0.24	-1.52	0.05	-1.29	0.79
$\ln(\kappa_1)$		1.43	1.13	0.99	1.51	0.82	2.17
$\ln(\kappa_2)$		2.45	0.36	1.8	0.12	1.7	1.54
FCL		-0.73	0.52	-0.2	2.03	-0.6	0.83
uscaler		13.14	3.39	6.98	0.23	11.76	0.16
γ		1.02	0.74	0.61	1.11	0.68	0.85
FCU	constant	-0.14	1.45	0.26	2.42	0.35	1.42
	HS only	-0.19	2.57				
	twyr	-0.75	2.08				
	1 ch	-0.29	1.83				
	1 ch*HS only	0.3	1.62				
	1 ch*twyr	0.06	1.73				
	2 ch	-0.35	1.73				
	2 ch*HS only	0.2	1.42				
	2 ch*twyr	1.22	1.39				
	3 ch	0.33	1.68				
	black	-0.2	2.32				
	hispanic	0.04	1.95				
	1 ch*yr	0.42	1.65				
	2 ch*yr	0.25	1.56				
MU of leisure	HS only	-0.09	1.58	-0.49	1.55	-0.04	1.7
	twyr	-0.01	2.81	-0.88	0.94	0.14	2.26
	1 ch	0.27	2.06	0.29	1.57	0.96	2.73
	1 ch*HS only	-0.02	2.35	0.08	1.29	-0.88	1.87
	1 ch*twyr	0.05	2.61	-0.22	2.36	-1.08	2.75
	2 ch	0.1	2.56	0.31	1.34	0.44	2.26
	2 ch*HS only	0.01	2.94	-0.69	0.84	-0.49	1.65
	2 ch*twyr	-0.17	3.18	-0.91	0.42	-0.69	2.03
	3 ch	-0.07	0.71	0.11	1.36	-0.09	1.89
	year	0.05	2.39	1.06	1.09	1.01	3.08

Parameter Estimates for Preferred Specification (continued)

		type 1		type 2		type 3	
		estimate	SE	estimate	SE	estimate	SE
	presch ch	0.06	0.3	0.46	1.82	0.47	3.45
	age	0.37	2.41	-0.57	0.91	1.15	2.35
	black	0.06	0.6	0.48	1.43	0.43	5.13
	hispanic	-0.01	1.13	0.21	1.65	0.26	3.45
	1 ch*yr	-0.14	2.77	0.06	0.2	0.17	1.64
	2 ch*yr	-0.09	2.87	-1.15	2.28	-0.31	2.69
wage hazard model	constant	11.05	1.34	8.57	1.62	6.57	1
	bin	2.42	1.43	4.12	2.01	3.45	1.92
	constant (last 3 bins)	0.52	0.19	-0.44	1.24	0.03	6.48
	yr	0.39	3.29	-0.44	2.01	-0.06	2.21
	yrsq	-0.01	1.13	-0.26	1.16	1.02	1.64
	yrc	0.09	1.63	-3.93	2.15	0.42	1.57
	imptwg	1.15	1.32	0.54	1.49	1.32	1.36
	HS	-3.2	3.28	-3.64	1.91	-5.69	3.58
	twyr	-1.6	3.12	-1.86	3.1	-2.16	2.6
	bach	-0.93	2.13	-0.77	2.03	-1.59	1.97
	grad	-1.45	2.49	-2.75	1.91	-1.66	2.8
	age	-0.58	1.91	-0.74	2.17	-0.47	1.83
	agesq	-5.81	2.76	-8.97	2.32	-8.05	4.22
	unempl	6.17	2.25	7.11	3.78	5.48	1.9
	st unempl	-1.74	1.39	-0.79	1.16	-2.7	0.97
	black	1.59	1.82	1.09	2.21	1.68	1.61
	hispanic	0.68	2.17	0.61	1.62	0.62	1.73
	high pay major	0.05	4.28	0.59	3.42	0.24	3.87
	female LFP	-1.1	1.49	-0.85	1.52	-0.54	1.64
	male LFP	0.91	1.06	1.94	1.23	1.45	0.83
	st level LFP	-3.07	1.24	-4.27	1.5	-2.7	0.99
	age*yr	-5.97	1.86	-5.44	2.91	-5.62	2.07
	age*imptwg	1.99	1.44	0.42	1.01	3.33	1.5
	age*HS	-2.78	2.36	-2.01	2.14	-3.31	2.51
	age*twyr	0.13	2.44	-0.31	2.23	-0.83	2.06
	age*bach	-0.77	1.6	-0.66	1.59	0.05	1.45
	age*grad	0.97	2.34	0.22	2.58	-0.51	1.21
	age*st unempl	0	1.19	-1.34	1.19	-1.12	1.68
	st unempl*yr	-1.08	1.66	-1.01	1.69	-1.38	1.62

Parameter Estimates for Preferred Specification (continued)

	type 1		type 2		type 3	
	estimate	SE	estimate	SE	estimate	SE
st unempl*imptwg	0.91	1.22	-0.19	1.19	1.51	1.07
st level unempl*HS	-0.93	1.84	0.69	1.21	-0.94	1.89
st level unempl*twyr	0.19	2.27	-0.23	2.12	0.15	2.43
st level unempl*bach	0.65	1.64	0.52	1.53	0.05	1.55
st level unempl*grad	0.46	2.12	0.72	1.19	0.69	1.66
st unempl2	-0.42	1.89	0.57	1.85	0.35	1.24
black*yr	-0.35	2.26	-0.02	1.9	-0.36	2.88
black*HS	-0.15	1.71	-0.64	1.19	-0.47	1.39
black*twyr	0.2	2.11	0.12	3.2	0.14	1.91
black*bach	-0.13	2.61	0.05	2.3	0.06	2.68
black*grad	-0.16	2.02	-0.17	1.8	0.38	2.14
black*age	-0.34	0.93	-1.25	1.14	-0.97	0.99
black*st unempl	0.03	1.49	0.51	2.05	0.59	1.58
hisp*yr	-0.32	1.25	0.72	1.66	-0.55	1.49
hisp*HS	-1.43	3.21	0.58	2.05	0.4	2.53
hisp*twyr	0.24	2.45	0.27	2.88	0.02	3.74
hisp*bach	-0.11	1.42	-0.34	1.65	0.03	3.49
hisp*grad	-0.13	1.55	-0.22	1.38	-0.37	1.19
hisp*age	0.42	1.52	-0.12	1.5	0.59	0.93
hisp*st unempl	0.44	2.21	1.62	2.36	0.66	1.76
year*HS	1.1	3.24	-0.01	2.41	-0.43	3.43
year*twyr	0.34	2.77	-0.21	1.91	0.3	1.67
year*bach	-0.01	1.39	-1.06	1.69	-0.66	1.92
year*grad	-0.15	1.71	-0.64	1.19	-0.47	1.39
bach*agesq	0.42	1.37	-0.28	1.07	0	0.93
yr*bin	-0.37	2.26	0.98	1.46	0.34	1.81
yrsq*bin	-3.64	1.98	1.27	2.24	-3.23	1.46
yrc*bin	-1.32	1.38	2.27	1.15	-0.93	1.36
imptwg*bin	-1.5	1	1.82	2.05	-1.4	1.62
HS*bin	10.01	3.21	6.26	1.44	7.96	3.17
twyr*bin	1.57	1.67	2.88	2	2.4	2.72
bach*bin	0.49	1.74	0.57	2.67	1.32	1.64
grad*bin	0.46	1.49	2.03	1.8	0.76	2.39
age*bin	0.6	1.15	1.42	1.38	0.42	1.71
agesq*bin	3.72	1.58	4.48	1.99	4.63	2.38

Parameter Estimates for Preferred Specification (continued)

	type 1		type 2		type 3	
	estimate	SE	estimate	SE	estimate	SE
unempl*bin	-3.64	1.14	-1.69	1.59	-1.83	3.29
st unempl*bin	3.58	0.94	0.89	1.4	3.24	1.01
black*bin	-2.89	1.02	-2.67	1.76	-1.36	1.13
hispanic*bin	-0.63	0.95	-0.97	1.97	0.01	1.68
high pay major*bin	0.6	1.36	-1.08	1.88	0.04	3.45
female LFP*bin	1.48	1.48	0.32	0.93	0.69	1.35
male LFP*bin	-2.02	1.16	-0.5	1.55	-1.29	1.37
st level LFP*bin	-4.13	1.33	-3.25	1.56	-3.21	1.74

Table A4: Parameter Estimates for Second Fullest Model

log likelihood=-127,367.5, n=25,329

		type 1 estimate	SE	type 2 estimate	SE	type 3 estimate	SE
ext log odds		2.29	2.9				
int log odds		-1.99	1.19				
type log odds		baseline		-0.2	10.48	-0.24	11.06
α		14.37	3.8	9.93	0.3	14.06	1.73
δ_1		-0.41	0.46	-1.45	2.13	-1.1	1.08
δ_2		-1.65	0.26	-1.54	0.15	-1.31	0.6
$\ln(\kappa_1)$		1.37	1.28	1.04	1.62	1.37	1.67
$\ln(\kappa_2)$		2.42	0.44	1.87	0.31	1.82	0.85
FCL		-0.83	0.75	-0.47	3.17	-0.61	0.99
uscaler		13.03	2.28	7.02	0.38	11.91	1.01
γ		1.01	0.99	0.61	0.8	0.8	0.64
FCU	constant	0.79	1.54	0.63	1.33	0.28	1.48
	HS only	-0.17	2.77				
	twyr	-0.65	1.84				
	1 ch	-0.28	2.27				
	1 ch*HS only	0.28	2.27				
	1 ch*twyr	0.03	1.32				
	2 ch	-0.31	1.91				
	2 ch*HS only	0.22	1.6				
	2 ch*twyr	1.14	1.34				
	3 ch	0.37	1.71				
	black	-0.14	2.5				
	hispanic	0.17	1.74				
MU of leisure	HS only	-0.07	2.31	-0.51	1.87	-0.25	2.46
	twyr	0.05	2.45	-0.89	1.2	-0.16	3.16
	1 ch	0.23	1.81	-0.07	1.55	0.56	3.97
	1 ch*HS only	-0.04	2.48	-0.02	1.61	-0.55	2.39
	1 ch*twyr	0	2.44	-0.41	1.19	-0.75	4.04
	2 ch	0.11	2.11	0.27	1.63	0.29	3.31
	2 ch*HS only	-0.03	3	-0.72	1.18	-0.28	2.77
	2 ch*twyr	-0.28	2.72	-0.95	0.78	-0.39	2.89
	3 ch	-0.06	0.91	0.15	1.33	-0.13	3
	year	-0.01	1.16	0.67	1.03	0.61	4.48
	presch ch	0.09	0.55	0.54	2.26	0.24	3.03
	age	0.51	4.84	-0.7	0.92	0.77	2.54

Parameter Estimates for Second Fullest Model (continued)

		type 1		type 2		type 3	
		estimate	SE	estimate	SE	estimate	SE
	black	0.08	1	0.43	2.01	0.26	4.63
	hispanic	-0.04	1.19	0.09	1.66	0.16	3.79
wage hazard	constant	10.99	1.66	8.55	1.68	6.65	1.18
model	bin	2.66	1.39	4.13	2.15	3.39	1.58
	constant (last 3 bins)	0.53	0.15	-0.57	1.28	0.01	6.72
	yr	-0.72	1.32	-0.51	1.31	-0.4	2.11
	yrsq	-0.22	1.82	-0.21	2.05	1.27	2.19
	yrc	0.06	1.53	-3.93	3.28	0.74	2.87
	imptwg	1.18	1.49	0.48	1.13	1.54	1.78
	HS	-2.82	2.49	-3.69	1.89	-6.09	4.7
	twyr	-1.63	3.58	-1.82	1.87	-2.31	2.3
	bach	-0.83	2.1	-0.59	2.4	-1.4	1.69
	grad	-1.48	2.44	-2.78	2.05	-1.63	2.67
	age	-0.56	1.87	-0.66	2.78	-0.43	1.95
	agesq	-5.73	2.58	-8.95	2.31	-7.98	5.08
	unempl	6.25	2.77	6.96	4.37	5.3	2.58
	st unempl	-1.72	1.47	-0.85	0.98	-2.7	1.21
	black	1.65	2.12	1.05	1.52	1.66	1.25
	hispanic	0.6	1.91	0.51	1.23	0.74	1.33
	high pay major	0.04	4.15	0.56	3.45	0.13	3.79
	female LFP	-0.72	1.32	-0.51	1.31	-0.4	2.11
	male LFP	0.83	1.67	1.92	1.27	1.5	1.01
	st level LFP	-3.11	1.56	-4.31	1.34	-2.63	1.17
	age*yr	-5.99	1.69	-5.33	3.04	-5.51	2.53
	age*imptwg	1.99	1.36	0.39	1.44	3.56	2.3
	age*HS	-2.93	2.45	-2.12	2.05	-3.5	2.89
	age*twyr	0.12	3.27	-0.28	2.45	-0.63	2.3
	age*bach	-0.69	1.65	-0.82	1.34	0.02	1.35
	age*grad	1.03	1.98	0.42	2.9	-0.36	1.18
	age*st unempl	0.03	1.09	-1.38	1.21	-1.03	1.34
	st unempl*yr	-1.06	1.37	-0.95	1.61	-1.44	1.61
	st unempl*imptwg	0.7	1.53	-0.13	2.37	1.69	0.95
	st level unempl*HS	-0.82	1.66	0.68	1.19	-1.1	1.37
	st level unempl*twyr	0.21	2.46	-0.22	1.85	0.11	1.93
	st level unempl*bach	0.63	1.63	0.41	1.35	0.1	1.37

Parameter Estimates for Second Fullest Model (continued)

	type 1		type 2		type 3	
	estimate	SE	estimate	SE	estimate	SE
st level unempl*grad	0.39	1.67	0.77	1.5	0.74	2
st unemplsq	-0.45	2.15	0.56	2.11	0.37	1.22
black*yr	-0.35	2.92	0.02	1.82	-0.34	2.5
black*HS	-0.13	1.53	-0.64	1.23	-0.42	1.44
black*twyr	0.21	2.1	0.1	2.18	0.07	1.76
black*bach	-0.21	2.49	0.07	2.23	0.06	2.81
black*grad	-0.22	1.76	-0.34	1.54	0.37	1.92
black*age	-0.31	0.91	-1.14	1.36	-0.87	1.24
black*st unempl	-0.1	1.96	0.37	1.66	0.52	1.51
hisp*yr	-0.18	1.38	0.7	1.44	-0.55	1.31
hisp*HS	-1.32	2.95	0.6	2.04	0.29	2.46
hisp*twyr	0.25	2.37	0.36	2.58	0.02	3.74
hisp*bach	-0.11	1.55	-0.34	1.95	0.01	3.39
hisp*grad	-0.15	1.23	-0.22	1.9	-0.37	0.94
hisp*age	0.5	1.59	-0.05	1.55	0.5	1.02
hisp*st unempl	0.33	1.88	1.4	2.54	0.58	1.71
year*HS	0.98	2.97	-0.04	2.5	-0.45	3.59
year*twyr	0.29	3.14	-0.29	1.83	0.57	1.99
year*bach	-0.01	1.99	-0.98	1.68	-0.6	1.73
year*grad	-0.13	1.53	-0.64	1.23	-0.42	1.44
bach*agesq	0.31	1.32	-0.39	1.04	0.06	0.97
yr*bin	1.05	0.87	0.32	0.87	0.5	1.66
yrsq*bin	-3.2	1.02	1.3	1.54	-3.75	3.9
yrc*bin	-1.11	1.15	2.31	0.76	-1.36	2.49
imptwg*bin	-1.45	1.18	1.83	1.45	-1.81	2.52
HS*bin	9.33	2.3	6.39	2.08	8.54	5.02
twyr*bin	1.58	1.74	2.94	1.68	2.42	2.43
bach*bin	0.36	1.03	0.53	1.43	1.17	2.05
grad*bin	0.39	1.32	1.92	1.96	0.63	2.46
age*bin	0.64	1.65	1.41	1.61	0.34	1.77
agesq*bin	3.54	1.61	4.6	1.82	4.68	2.67
unempl*bin	-3.89	1.24	-1.67	2.05	-1.93	3.62
st unempl*bin	3.48	1.1	0.84	1.41	3.19	0.95
black*bin	-2.98	1.3	-2.74	2.35	-1.41	1.77
hispanic*bin	-0.44	0.96	-0.68	1.57	0.01	1.34

Parameter Estimates for Second Fullest Model (continued)

	type 1		type 2		type 3	
	estimate	SE	estimate	SE	estimate	SE
high pay major*bin	0.82	1.27	-1.04	1.92	0.25	3.28
female LFP*bin	1.05	0.87	0.32	0.87	0.5	1.66
male LFP*bin	-1.81	1.01	-0.51	1.61	-1.37	1.27
st level LFP*bin	-3.93	1.25	-3.25	1.54	-3.25	1.45

Table A5: Parameter Estimates for Model Without Food Stamps

log likelihood=-127,402.5, n=25,329

		type 1		type 2		type 3	
		estimate	SE	estimate	SE	estimate	SE
ext log odds		2.88	1.23				
int log odds		-2.26	0.5				
type log odds		baseline		-0.21	9.18	-0.33	9.31
α		15.28	4.49	9.94	0.33	13.8	2.12
δ_1		-0.56	0.23	-0.81	2.37	-0.69	0.83
δ_2		-1.75	0.54	-1.55	0.03	-1.22	1.23
$\ln(\kappa_1)$		1.63	1.03	1.25	2.19	1.35	1.93
$\ln(\kappa_2)$		2.57	0.79	1.88	0.08	1.62	2.31
FCL		-0.84	0.38	-0.46	2.44	-0.65	0.63
uscaler		13.54	3.55	6.91	0.23	11.88	0.95
γ		1.05	0.57	0.57	0.71	0.72	0.7
FCU	constant	0.64	1.74	0.76	1.22	0.46	1.72
	HS only	-0.13	2.82				
	twyr	-0.51	2.07				
	1 ch	-0.39	2.14				
	1 ch*HS only	0.25	2.27				
	1 ch*twyr	0.03	1.58				
	2 ch	-0.3	2.11				
	2 ch*HS only	0.13	1.48				
	2 ch*twyr	1.13	1.19				
	3 ch	0.3	1.84				
	black	-0.25	2.35				
	hispanic	-0.04	1.95				
MU of leisure	HS only	-0.12	1.6	-0.71	1.43	-0.06	1.77
	twyr	-0.08	1.78	-1.36	0.75	0.07	2.6
	1 ch	0.27	1.8	0.15	1.31	0.83	3.45
	1 ch*HS only	-0.03	2.24	0.04	1.27	-0.76	1.97
	1 ch*twyr	0.01	2.37	-0.48	1.12	-1.01	3.25
	2 ch	0.09	1.45	0.41	1.27	0.55	2.48
	2 ch*HS only	0.02	2.13	-0.73	0.84	-0.49	1.99
	2 ch*twyr	-0.18	2.87	-0.88	0.31	-0.63	2.18
	3 ch	-0.01	0.41	0.3	1.15	-0.08	2.14
	year	0.04	0.51	0.57	1.3	0.81	3.08
	presch ch	0.07	0.19	0.64	1.97	0.42	3.6
	age	0.41	1.78	-1.03	0.88	1.01	2.56

Parameter Estimates for Model Without Food Stamps

		type 1		type 2		type 3	
		estimate	SE	estimate	SE	estimate	SE
	black	0.14	0.59	0.72	1.54	0.44	5.73
	hispanic	0.08	0.83	0.39	1.66	0.29	3.49
wage hazard	constant	11.04	1.66	8.57	1.17	6.61	1.36
model	constant*bin	2.44	1.39	4.18	2.16	3.41	1.98
	constant (last 3 bins)	0.59	0.42	-0.53	1.43	0.01	6.62
	yr	-0.78	1.41	-0.57	1.07	-0.36	2.04
	yrsq	-0.15	1.39	-0.34	1.32	1.35	1.65
	yrc	0.24	1.77	-4.1	2.68	0.85	2.44
	imptwg	1.21	1.38	0.53	1.34	1.65	1.71
	HS	-3.13	2.49	-3.51	2.06	-6.2	2.68
	twyr	-1.71	3.22	-1.85	1.33	-2.22	2.2
	bach	-0.81	2.1	-0.54	1.98	-1.43	2.02
	grad	-1.51	2.12	-2.84	1.72	-1.65	2.64
	age	-0.62	1.82	-0.54	2.39	-0.44	1.73
	agesq	-5.69	2.02	-8.94	2.63	-8.24	3.64
	unempl	6.1	3.21	7.18	2.89	5.27	1.72
	st unempl	-1.73	1.79	-0.74	1.27	-2.68	0.94
	black	1.73	1.9	1.15	2.03	1.72	1.72
	hispanic	0.73	1.56	0.58	1.22	0.74	1.71
	high pay major	0.2	4.38	0.66	3.24	0.31	4.9
	female LFP	-0.78	1.41	-0.57	1.07	-0.36	2.04
	male LFP	0.81	1.59	1.93	0.91	1.45	0.81
	st level LFP	-3.05	1.53	-4.33	1.17	-2.69	1.1
	age*yr	-5.88	1.64	-5.48	2.57	-5.45	2.86
	age*imptwg	2.16	1.35	0.39	1.06	3.47	1.91
	age*HS	-3.03	2.15	-1.93	1.97	-3.44	1.61
	age*twyr	0.17	2.8	-0.36	2.5	-0.73	2.18
	age*bach	-0.81	1.49	-0.91	2.27	0.02	1.33
	age*grad	1.17	2.37	0.49	1.8	-0.44	1.29
	age*st unempl	-0.03	1.17	-1.34	1.17	-1.12	1.12
	st unempl*yr	-0.98	1.37	-1.02	1.45	-1.33	1.78
	st unempl*imptwg	0.76	1.41	-0.25	1.31	1.72	1.25
	st level unempl*HS	-0.9	1.54	0.65	1.08	-1.12	1.64
	st level unempl*twyr	0.14	2.4	-0.29	1.57	0.09	2.12
	st level unempl*bach	0.7	1.85	0.35	1.4	0.09	1.7

Parameter Estimates for Model Without Food Stamps

	type 1		type 2		type 3	
	estimate	SE	estimate	SE	estimate	SE
st level unempl*grad	0.43	1.53	0.88	1.99	0.78	1.85
st unempl2	-0.52	1.73	0.5	1.93	0.35	1.17
black*yr	-0.39	2.2	0.02	1.65	-0.38	2.09
black*HS	-0.16	1.31	-0.67	1.43	-0.44	1.49
black*twyr	0.2	2.37	0.09	2.28	0.13	1.63
black*bach	-0.2	2.64	0.07	2.27	0.09	2.79
black*grad	-0.18	1.73	-0.29	1.87	0.34	2.35
black*age	-0.43	1.16	-1.3	0.97	-0.89	0.99
black*st unempl	-0.06	1.96	0.45	1.76	0.6	1.49
hisp*yr	-0.23	1.17	0.74	1.46	-0.56	1.32
hisp*HS	-1.42	3.26	0.58	1.96	0.34	2.75
hisp*twyr	0.33	2.21	0.3	2.93	0.06	4.36
hisp*bach	-0.36	1.79	-0.48	1.39	-0.02	3.75
hisp*grad	-0.06	1.19	-0.14	2.4	-0.36	0.86
hisp*age	0.53	1.25	-0.22	1.72	0.54	0.66
hisp*st unempl	0.46	2.2	1.57	2.36	0.71	1.99
year*HS	1.07	3.31	-0.02	2.34	-0.5	3.3
year*twyr	0.3	2.92	-0.19	1.54	0.48	1.32
year*bach	-0.06	1.45	-1.04	1.41	-0.64	1.74
year*grad	-0.16	1.31	-0.67	1.43	-0.44	1.49
bach*agesq	0.5	2.11	-0.33	0.94	-0.03	1.09
yr*bin	1.18	1.17	0.39	1.46	0.46	1.58
yrsq*bin	-3.55	1.1	1.53	1.99	-3.85	4.97
yrc*bin	-1.34	0.96	2.38	0.81	-1.42	3.15
imptwg*bin	-1.6	0.81	1.94	1.59	-1.87	2.94
HS*bin	10.17	2.84	6.11	1.97	8.7	5.55
twyr*bin	1.84	1.76	2.98	1.15	2.41	1.98
bach*bin	0.39	0.97	0.56	1.59	1.15	1.72
grad*bin	0.3	1.46	1.85	2.06	0.64	2.47
age*bin	0.86	1.98	1.38	1.55	0.42	1.63
agesq*bin	3.49	1.3	4.41	2.32	4.81	2.47
unempl*bin	-3.94	1.26	-1.76	1.38	-1.73	3.18
st unempl*bin	3.51	1.07	0.8	1.19	3.14	1.2
black*bin	-2.96	1.19	-2.81	1.4	-1.36	1.03
hispanic*bin	-0.72	0.78	-0.84	1.22	-0.05	1.6

Parameter Estimates for Model Without Food Stamps

	type 1		type 2		type 3	
	estimate	SE	estimate	SE	estimate	SE
high pay major*bin	0.6	1.34	-1.04	1.86	0.01	3.63
female LFP*bin	1.18	1.17	0.39	1.46	0.46	1.58
male LFP*bin	-2	1	-0.46	1.64	-1.38	1.94
st level LFP*bin	-4.12	1.24	-3.25	1.5	-3.23	1.84

Table A6: Parameter Estimates for Model Without State Level Labor Force Participation or Unemployment

log likelihood=-127,619.2, n=25,329

		type 1 estimate	SE	type 2 estimate	SE	type 3 estimate	SE
ext log odds		2	1.24				
int log odds o		-2.23	1.05				
type log odds		baseline		-0.26	0.73	-0.22	0.71
α		14.81	1.33	9.96	1	13.78	1.05
δ_1		-0.44	0.13	-1.23	1.01	-1.35	0.24
δ_2		-1.61	1	-1.52	1	-1.32	1
$\ln(\kappa_1)$		1.42	0.27	0.6	1.12	1.44	0.33
$\ln(\kappa_2)$		2.43	1.01	1.81	1	1.89	1
FCL		-0.8	0.07	-0.35	1.05	-0.61	0.21
uscaler		13.31	1.28	6.91	1	12.34	1.08
γ		0.97	0.09	0	0.44	0.89	0.12
FCU	constant	0.18	0.88	0.37	0.93	-0.07	1.06
	HS only	0.11	0.89				
	twyr	-0.43	0.94				
	1 ch	-0.08	0.86				
	1 ch*HS only	0.08	0.9				
	1 ch*twyr	-0.12	0.99				
	2 ch	-0.16	0.9				
	2 ch*HS only	0.11	0.94				
	2 ch*twyr	0.78	0.98				
	3 ch	0.45	0.97				
	black	0.05	0.78				
	hispanic	0.23	0.99				
MU of leisure	HS only	-0.03	0.43	-0.38	1.01	-0.68	0.7
	twyr	0.06	0.5	-0.41	1	-0.56	0.7
	1 ch	0.19	0.48	-0.08	1.01	0.17	0.59
	1 ch*HS only	-0.01	0.65	-0.18	1	-0.13	0.8
	1 ch*twyr	0.08	0.75	-0.74	1	-0.38	0.9
	2 ch	0.14	0.5	0.33	1	0.09	0.83
	2 ch*HS only	-0.06	0.62	-0.75	1	-0.07	0.91
	2 ch*twyr	-0.3	0.82	-0.56	1	-0.05	0.96
	3 ch	-0.07	0.21	-0.15	1	-0.14	0.91
	year	0.04	0.14	1.15	1.01	0.43	0.72
	presch ch	0.08	0.06	0.49	1	0.19	0.4
	age	0.42	0.34	0.82	1.01	0.72	0.89

Parameter Estimates for Model Without State Level Labor Force Participation or Unemployment

		type 1		type 2		type 3	
		estimate	SE	estimate	SE	estimate	SE
	black	0.05	0.2	0.54	1.02	0.14	0.43
	hispanic	-0.03	0.32	0.09	1	0.13	0.93
wage hazard model	constant	11.58	0.88	8.6	0.89	7.49	0.96
	bin	1.7	0.95	2.78	1.02	2.15	1
	constant (last 3 bins)	0.44	1.01	-0.48	1	-0.01	0.89
	yr	-0.68	1	-0.39	1	-0.23	1.01
	yrsq	-0.29	0.94	0.04	0.96	1.6	1.06
	yrc	-0.02	0.94	-4.66	1.07	0.8	1.01
	imptwg	1.09	0.92	0.15	1.03	1.51	0.94
	HS	-2.44	0.79	-4.28	0.84	-6.19	1.17
	twyr	-1.14	0.75	-1.46	0.87	-2.83	0.97
	bach	-1.12	0.83	-0.87	0.86	-1.77	0.86
	grad	-1.65	0.92	-2.73	0.94	-1.61	0.94
	age	-0.7	0.98	-0.62	1.05	-0.41	0.99
	agesq	-4.57	1.12	-8.28	1.17	-6.57	1.2
	unempl	4.55	1.24	4.18	1.62	2.23	1.12
	black	0.59	0.95	0.31	0.96	1.51	0.97
	hispanic	0.79	0.79	0.68	0.82	0.83	0.87
	high pay major	0.28	0.98	0.73	1	0.22	0.98
	female LFP	-0.68	1	-0.39	1	-0.23	1.01
	male LFP	-2.98	0.92	-3.87	0.95	-2.11	0.96
	age*yr	-6.4	0.89	-4.26	0.91	-5.75	0.94
	age*imptwg	2.34	0.98	1.21	1.03	4.51	1.05
	age*HS	-2.9	0.97	-2.66	0.97	-4.24	1.11
	age*twyr	0.36	0.94	0.09	1.08	-1.09	0.99
	age*bach	-0.58	0.96	-0.86	0.94	0.03	0.96
	age*grad	0.53	0.98	-0.02	1.03	-0.59	1.01
	age*unempl	0.1	0.99	-1.38	1.04	-1.18	1.02
	unempl*yr	-0.99	1.01	0.06	1	-0.91	0.97
	unempl*imptwg	0.62	0.95	-0.22	0.99	1.63	0.97
	unempl*HS	-0.86	0.93	1.42	1.06	-1.52	0.95
	unempl*twyr	0.08	0.93	-0.17	0.98	-0.63	1.05
	unempl*bach	0.95	0.93	0.54	0.98	0.65	0.94
	unempl*grad	0.71	0.97	1.01	0.98	1.03	0.99
	unemplsq	-0.02	1	1.02	1	0.45	1

Parameter Estimates for Model Without State Level Labor Force Participation or Unemployment

	type 1		type 2		type 3	
	estimate	SE	estimate	SE	estimate	SE
black*yr	0.02	0.96	-0.15	0.97	0.4	0.97
black*HS	-0.05	0.97	-0.65	0.98	-0.46	0.98
black*twyr	0.22	0.78	0.17	0.81	0.11	0.85
black*bach	-0.04	0.93	0.36	0.92	0.15	0.92
black*grad	-0.14	0.99	-0.36	0.97	0.37	1
black*age	-0.38	1	-1.32	1.01	-1	1
black*st unempl	-0.43	0.92	0.11	0.97	0.61	0.97
hisp*yr	-0.13	0.9	0.66	1.01	-0.39	0.94
hisp*HS	-1.27	1	0.58	0.99	0.25	1.02
hisp*twyr	0.01	1.04	0.07	1.01	0.13	0.98
hisp*bach	0.1	1.04	0.09	1	0.08	0.99
hisp*grad	-0.46	1	-0.16	1.05	-0.28	1
hisp*age	0.17	1.07	-0.14	1.04	0.45	1.03
hisp*st unempl	0.29	1.03	1.68	1	0.71	1.02
year*HS	0.55	0.99	0.06	1	-0.58	1.03
year*twyr	0.06	0.92	-0.18	0.94	0.86	0.96
year*bach	-0.08	0.93	-0.89	0.98	-0.47	0.96
year*grad	-0.05	0.97	-0.65	0.98	-0.46	0.98
bach*agesq	0.12	0.99	-0.64	1	0.04	1
yr*bin	1.06	1.01	0.19	1	0.37	1.01
yrsq*bin	-2.97	0.98	1.69	0.99	-4.47	1.24
yrc*bin	-0.78	0.98	2.48	0.97	-1.61	1.04
imptwg*bin	-0.99	0.98	2.31	1.06	-1.71	1
HS*bin	8.75	1.1	6.98	0.94	9.26	1.27
twyr*bin	1.52	0.96	2.61	0.98	3.61	1.12
bach*bin	0.37	0.96	0.54	0.94	1.08	0.93
grad*bin	0.29	0.97	1.79	1	0.58	0.95
age*bin	0.55	1.02	1.24	1	0.32	0.99
agesq*bin	2.79	1.07	4.13	1.29	4.29	0.99
unempl*bin	-2.73	0.98	0.16	1.01	0.42	1.11
black*bin	-2.6	1.04	-3.31	1.05	-1.96	1.02
hispanic*bin	-0.56	0.96	-0.84	0.93	-0.29	0.9
high pay major*bin	1.01	1	-1.38	0.99	0.23	0.98
female LFP*bin	1.06	1.01	0.19	1	0.37	1.01
male LFP*bin	-2.52	0.97	-1.42	1.01	-2.38	1.04

Table A7: Parameter Estimates for Model With Cruder Wage and Labor Supply Bins

log likelihood=99,043.7, n=25,329

		type 1		type 2		type 3	
		estimate	SE	estimate	SE	estimate	SE
ext log odds		2.23	6.27				
int log odds		-2.37	15.45				
type log odds		baseline		-0.13	1.69	-0.22	1.67
α		14.72	8.97	9.69	2.23	13.7	0.87
δ_1		-0.43	0.54	-1.57	4.64	-1.17	13.07
δ_2		-1.57	3.13	-1.54	0.55	-1.13	0.06
$\ln(\kappa_1)$		1.39	1.21	0.89	2.69	1.36	7.48
$\ln(\kappa_2)$		2.35	3.3	1.83	1.17	1.55	0.08
FCL		-0.82	0.45	-0.49	5.14	-0.56	8.67
uscaler		12.89	8.39	6.77	2.08	11.98	1.29
γ		0.97	0.19	0.54	0.84	0.82	1.68
FCU	constant	0.27	9.25	0.15	14.65	-0.55	9.89
	HS only	-0.26	5.07				
	twyr	-0.64	8.84				
	1 ch	-0.33	4.14				
	1 ch*HS only	0.31	3.71				
	1 ch*twyr	0.14	3.11				
	2 ch	-0.22	1.61				
	2 ch*HS only	0.17	2.63				
	2 ch*twyr	0.91	1.99				
	3 ch	0.35	4.6				
	black	-0.2	2.83				
	hispanic	0.11	3.29				
MU of leisure	HS only	-0.04	13.11	-0.66	2.13	-0.28	1.59
	twyr	0.03	12.98	-1.43	12.01	-0.21	4.47
	1 ch	0.22	6.45	0.04	5.12	0.52	1.92
	1 ch*HS only	-0.04	8.76	-0.31	9.56	-0.46	7.95
	1 ch*twyr	-0.02	5.84	-0.65	6.41	-0.72	5.94
	2 ch	0.11	3.19	0.19	3.37	0.24	4.78
	2 ch*HS only	-0.04	2.13	-0.76	5.69	-0.23	5.61
	2 ch*twyr	-0.26	9.2	-1.15	7.06	-0.21	2.49
	3 ch	-0.06	7.86	0.14	6.49	-0.11	1.5
	year	-0.06	5.56	0.65	8.9	0.55	12.81
	presch ch	0.1	9.15	0.8	2.5	0.22	13.02
	age	0.52	18.01	-0.89	9.44	0.64	0.71

Parameter Estimates for Model With Cruder Labor Supply Bins (continued)

		type 1		type 2		type 3	
		estimate	SE	estimate	SE	estimate	SE
	black	0.13	3.19	0.8	6.76	0.19	1.34
	hispanic	0.01	7.21	0.29	1.82	0.15	1.97
wage hazard	constant	11.07	3.98	8.8	5.43	6.67	9.79
model	bin	3.09	7.45	4.38	9.88	3.58	5.13
	constant (last 3 bins)	0.94	1.65	-1.27	3.57	0.22	1.06
	yr	-0.87	5.64	-0.51	4.82	-0.42	12.17
	yrsq	-0.26	9.39	-0.52	21.44	1.45	15.27
	yrc	0.16	8.71	-4.52	11.11	1.19	12.91
	imptwg	1.18	1.83	0.25	3.35	2.14	29.43
	HS	-2.95	5.05	-4.1	12.85	-7.42	5.4
	twyr	-1.66	2.61	-1.98	3.63	-2.54	6.99
	bach	-0.58	8.57	-0.5	12.13	-0.85	6.52
	grad	-1.58	6.98	-2.87	9.36	-1.14	7.81
	age	-0.46	16.58	-0.59	15.11	-0.44	40.63
	agesq	-6.25	22.76	-9.82	25.97	-8.73	17.37
	unempl	6.86	11.6	7.5	4.67	5.75	6.84
	st unempl	-1.7	15.01	-0.82	12.25	-2.89	2.17
	black	1.91	3.95	1.07	3.65	1.6	6.48
	hispanic	0.62	4.97	0.73	9.14	0.64	21.07
	high pay major	0.09	7.44	0.59	14.85	0.12	3.88
	female LFP	-0.87	6.19	-0.51	8.65	-0.42	11.22
	male LFP	0.78	3.27	2.12	6.51	1.46	1.41
	st level LFP	-3.08	4.53	-4.17	11.59	-2.68	24.09
	age*yr	-6.32	13.1	-6.32	7.83	-5.36	47.29
	age*imptwg	2.42	11	0.77	8.03	4.6	16.85
	age*HS	-3.23	5.19	-1.96	4.84	-4.17	9.5
	age*twyr	0.2	4.66	-0.24	8.88	-0.56	24.13
	age*bach	-0.73	3.59	-0.9	4.28	0.16	10
	age*grad	0.71	8.91	-0.11	10.89	-0.64	5.94
	age*st unempl	-0.47	5.45	-3.19	2.14	-0.35	4.89
	st unempl*yr	-1.18	12.51	-0.99	6.05	-1.49	3.87
	st unempl*imptwg	0.6	5.16	-0.55	3.93	1.89	13.76
	st level unempl*HS	-0.93	1.85	0.85	1.84	-1.34	6.43
	st level unempl*twyr	0.05	1.47	-0.33	5.04	-0.02	5.89
	st level unempl*bach	0.46	6	0.12	2.97	-0.18	5.43

Parameter Estimates for Model With Cruder Labor Supply Bins (continued)

	type 1		type 2		type 3	
	estimate	SE	estimate	SE	estimate	SE
st level unempl*grad	0.29	6.06	0.75	1.82	0.91	4.86
st unempl2	-0.53	4.32	1	4.18	0.44	17.22
black*yr	-0.35	4.69	0.13	4.28	-0.03	7.07
black*HS	0.01	3.4	-0.62	5.45	-0.61	8.38
black*twyr	0.3	3.43	0.16	5.46	-0.03	10.17
black*bach	-0.24	3.74	0.27	3.55	0.07	7.49
black*grad	-0.22	2.07	-0.25	2.25	0.33	9.09
black*age	-0.09	3.88	-1.38	6.94	-0.21	2.44
black*st unempl	0.12	4.33	0.74	5.83	0.43	10.14
hisp*yr	-0.28	3.27	0.71	4.01	-0.47	24.73
hisp*HS	-1.72	4.51	0.09	5.11	0.27	5.01
hisp*twyr	0.37	4.97	0.47	12.5	-0.03	3.56
hisp*bach	-0.22	4.56	-0.39	5.62	-0.08	3.96
hisp*grad	-0.15	1.75	-0.48	1.1	-0.63	5.27
hisp*age	0.57	10.7	0.92	4.95	-0.08	4.48
hisp*st unempl	0.59	4.26	2.19	4.14	0.85	14.1
year*HS	1.06	4.62	-0.14	3.45	-0.68	5.83
year*twyr	0.43	3.12	-0.33	1.9	0.75	5.8
year*bach	0.08	2.18	-1.07	1.78	-0.47	4.09
year*grad	0.01	2.63	-0.62	3.04	-0.61	3.58
bach*agesq	0.05	2.94	0.33	2.61	-0.42	6.14
yr*bin	1.19	11.08	0.14	8.7	0.72	8.34
yrsq*bin	-3.29	4.43	2.12	8.53	-4.35	7.64
yrc*bin	-1.12	1.6	2.62	12.2	-1.91	9.35
imptwg*bin	-1.44	16.24	2.23	4.52	-2.26	33.39
HS*bin	8.99	3.37	6.25	9.4	9.82	25.03
twyr*bin	1.17	7.57	2.98	2.75	2.59	6.26
bach*bin	-0.14	5.68	0.6	6.41	0.44	5.28
grad*bin	0.5	3.45	1.7	5.59	0.14	5.83
age*bin	0.72	16.56	0.5	24.49	-0.06	17.49
agesq*bin	3.07	12.49	3.84	10.83	4.02	24.28
unempl*bin	-3.94	12.11	-1.53	2.65	-1.57	7.32
st unempl*bin	3.94	23.43	1.1	8.13	2.89	3.32
black*bin	-3.04	5.24	-2.67	7.53	-1.46	5.39
hispanic*bin	-0.17	5.25	-1.02	4.76	0.38	9.95

Parameter Estimates for Model With Cruder Labor Supply Bins (continued)

	type 1		type 2		type 3	
	estimate	SE	estimate	SE	estimate	SE
high pay major*bin	0.83	9.36	-1.17	6.7	0.57	5.02
female LFP*bin	1.19	7.36	0.14	9.45	0.72	9.86
male LFP*bin	-1.55	3.59	-0.26	2.3	-1.28	3.04
st level LFP*bin	-3.55	9.95	-3.14	7.17	-3.09	19.42

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XI. **Author Vita**

Michael Chennault Sikivie was born on July 14, 1986, in Gainesville, Florida. There, he attended Millhopper Montessori Elementary School, the magnet program at Howard Bishop Middle School, and Buchholz High School. His particular interest in math and social studies continued at Buchholz High School, from which he graduated in 2005 with the National AP Scholar Award. Another interest of his is cross country, which he participated in during both high school and college.

Michael was and is open-minded about living anywhere, and in the fall of that year he left Florida to attend Macalester College, a small liberal arts college in St. Paul, Minnesota. Michael took a variety of challenging courses in addition to his economics major at Macalester College, such as the three course chemistry sequence and two of the biology courses required of biology majors. He also studied Chinese, completing the third-year level of the language while studying abroad at Tsinghua University in Beijing. Ultimately, however, his strong interest in both math and social sciences led him to major in economics. In 2009, he graduated from Macalester College with a BA in economics and a minor in statistics.

Michael completed an MS in economics from the University of Illinois at Urbana-Champaign in 2011. While there, he became particularly interested in public economics, thanks to Dr. Gahvari's class on the economics of taxation and Dr. Polborn's class on political economy. Michael spent another summer in China after his first year at the University of Illinois, this time to intern at a branch of SPD Bank in Nanjing. There he learned a great deal about the role of letters of credit and SWIFT in facilitating international trade.

In 2012, Michael wrote the paper *Could Higher Gas Prices Speed Up Your Commute*, which was accepted at the Academy of Economics and Finance Conference (February 2014) at Chattanooga, TN. Having been accepted into the Doctoral program in economics at Georgia State University in the fall of 2013, however, he set aside efforts to publish the paper to focus on his doctoral studies. As a doctoral student in economics, he chose public economics as his major field and graduated in 2019.

He is particularly interested in the economics of taxation and labor and demographic economics. He is interested in a suitable journal to publish an abridged thesis, and has submitted an earlier version of it to the Journal of Labor Economics, where it was not desk rejected. He was also invited to present his doctoral research at the Wofford College Seminar in 2018. Other research ideas of his include extending the framework of this thesis to the situation of multiple (possible) earners in a household, the economics of fertility decisions, and the effect of state alimony laws on the labor supply and rates of remarriage of payer and payee.

While a doctoral student at Georgia State University, he received a graduate assistantship. Some of his jobs as a graduate assistant include research assistant, instructor of a class called *The Global Economy*, and teaching assistant. Outside of academia, he also earned money by renting his car out to others and betting money on election outcomes and other world events. Currently, while seeking a permanent job, Michael is tutoring in economics, calculus, and statistics. He continues to bet on world events today.