The General Equilibrium Incidence of the Earned Income Tax Credit

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Abstract

The Earned Income Tax Credit is a $67 billion tax expenditure that subsidizes 20% of all workers. Yet all prior analysis uses partial equilibrium assumptions on gross wages. I derive the general equilibrium incidence of wage subsidies and quantify the importance of EITC spillovers in three ways. I calculate the GE incidence of the 1993 and 2009 EITC expansions using new elasticity estimates. I contrast the incidence of counterfactual EITC and Welfare expansions. I quantify the effect of equalizing the EITC for workers with and without children. In all cases, I find spillovers are economically meaningful.

JEL: H22, H23, H24, H31, I32, J22

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1 Introduction

The Earned Income Tax Credit (EITC) is one of the largest anti-poverty programs in the United States. Over 20% of all workers and 40% of single parent workers receive a share of the $\$67$ billion expenditure. At the end of the 'phase-in' portion, the EITC yields a 19%-34% subsidy on gross earnings for workers with children. Lawmakers and policy advocates often propose expansions of EITC benefits and eligibility.

Yet essentially all prior research has assumed away the possibility of gross wage distortions when analyzing policy effects on labor supply. Since the EITC amount is based on gross earnings, if the program feeds-back into market wages – e.g., decreasing wages for low-income workers – then the anti-poverty policy goals will be undermined. With each expansion that increases benefits or expands eligibility, using partial equilibrium assumptions seems less tenable. Given the scope of the EITC, its place in anti-poverty policy discussions, and the importance of labor market earnings on its overall efficacy, this oversight looms large.

I model and evaluate the EITC by deriving a general equilibrium incidence equation that relates changes in average tax rates to changes market wages and labor supply.[1] My approach allows me to decompose wage changes into the direct and indirect effects on both the treated and untreated workers. I parameterize the incidence equation by estimating EITC specific labor supply and substitution elasticities and then perform four quantitative evaluations. I calculate the empirical incidence of the 1993 expansion for different demographic groups. I compare counterfactual marginal expansions of the pre-reform (1992) EITC and social safety-net 'Welfare' programs to compare how different tax incentives affect incidence and spillovers. Using the estimated elasticities to parameterize a structural labor supply model, I calculate the incidence of the out-of-sample 2009 EITC expansion, and I conduct a counterfactual EITC reform that equalizes the credit schedule for workers with and without children.

To conduct these exercises, I estimate labor supply elasticities for different demographic groups and a labor substitution elasticity that governs the curvature of labor demand. I use EITC policy variation tied to the 1993 Omnibus Budget Reconciliation Act (OBRA) on labor market data from the Current Population Survey. I assign workers to demographic-based labor market cells and estimate the cell-specific expected EITC policy reform exposure via a simulated instrument approach that uses a fixed distribution of worker characteristics from the 1990 Census. This approach uses all possible EITC policy information but purges endogenous behavioral responses from the policy changes. My estimation strategy allows me to avoid the assumption that women with and without children respond the same way to wage changes, as in typical difference-in-differences based analysis of the EITC. [2] Because the incidence depends on the wage responsiveness of different labor markets, capturing granular differences in supply responsiveness is important for accurately measuring incidence effects.[3]

[1] I refer to pre/post-tax wages as gross/net wages. I reference EITC tax rates as subsidies are 'negative taxes.' I define a 'partial equilibrium effect' as the direct effect of a policy change holding all else equal; a 'general equilibrium effect' as the total policy effect allowing all endogenous variables to adjust.

[2] Section C.3 shows how ignoring worker heterogeneity and/or spillovers affects identification.

[3] Section E shows that a constant labor supply elasticity of 0.75 for all groups implies larger (in magnitude) wage declines and net earnings increases relative to baseline results.

My primary theoretical contribution formalizes the labor market forces that generate 'spillover effects' from targeted wage taxes between treated and untreated workers and across labor market segments.[4] A policy that increases the quantity of one worker group increases the marginal product of complementary workers and decreases that of substitutable workers. These changes in marginal product cause labor demand shifts that I interpret as spillover effects. I show that spillover effects have 'first order' importance in market wages changes, and positive marginal product spillovers attenuate the negative direct wage effect. The partial equilibrium incidence (or direct effect) is the *upper bound* for treated workers and the *lower bound* for untreated workers relative to the general equilibrium gross wage incidence. Because the behavior of all *other* economic agents is held fixed in PE, the marginal product changes and thus wage spillover effects are ignored. Since the spillover effects are 'first-order' and opposite the direct effects, the general equilibrium incidence is theoretically ambiguous.

For example, suppose there are two sets of workers, $\{A, B\}$, that are complementary to each other in the production process, and we treat group A to a work subsidy. The labor supply increase of the *treated* set of workers will increase the marginal product of the *untreated* set; this causes labor demand to increase for the *untreated* workers; the resulting quantity increase in *untreated* workers will then increase the marginal product of the *treated* workers; and so on... Figure 1 displays these forces graphically using a two factor model with a targeted labor subsidy.

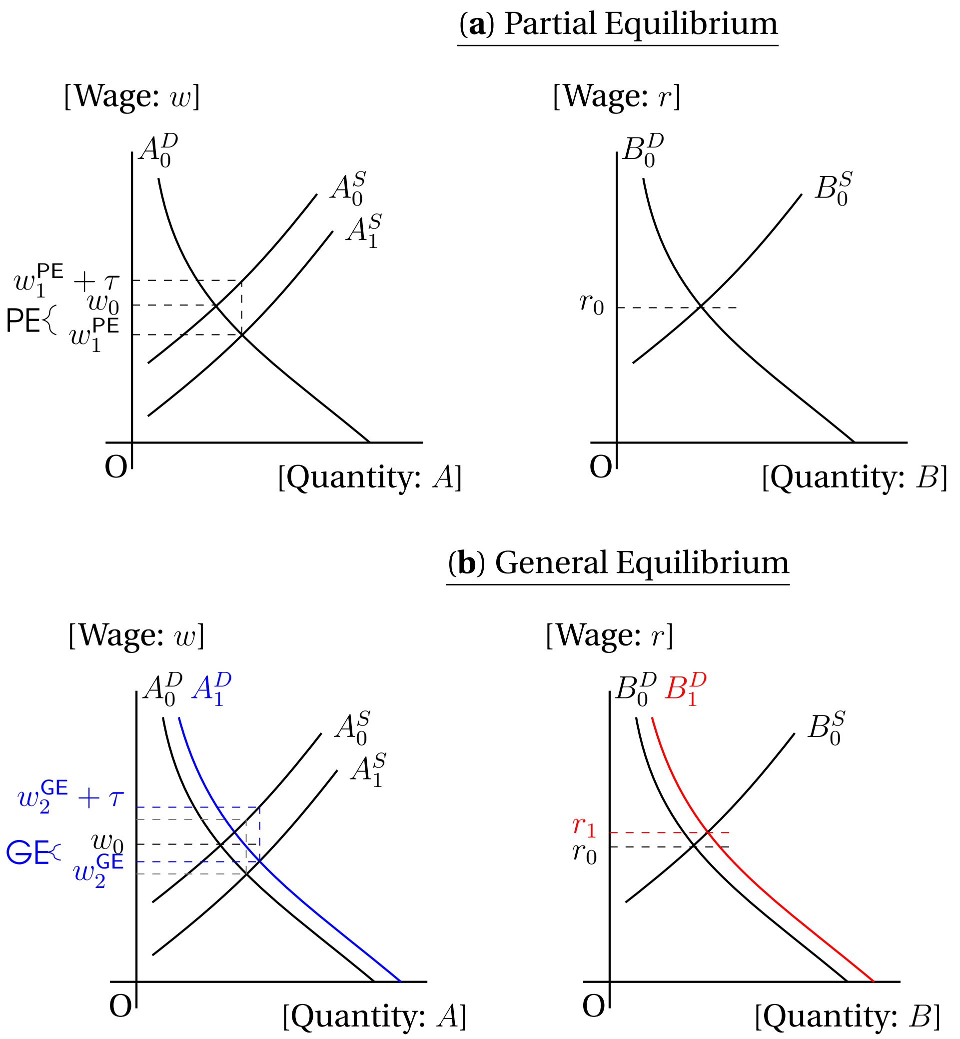
My primary empirical contribution quantifies the magnitude of EITC induced spillovers using four policy evaluations. Spillovers are small relative to the direct effects for an individual, but because spillovers affect every worker, they are economically important when aggregated. I find spillovers increase aggregate net earnings by about 22.2% for the 1993 OBRA EITC expansion and by 17.6% for the 2009 ARRA expansion. When comparing the EITC vs Welfare, the superiority of an EITC expansion relative to a Welfare expansion in terms of net-earnings becomes 21% larger when accounting for spillovers. Equalizing the EITC for workers with and without children would cause a 395% increase in net earnings change of unmarried women without children but at the expense of 88% *decrease* for unmarried mothers. I also calculate wage changes, labor supply changes, and the fiscal externality of EITC reforms across education, marriage, and parental status that highlights the heterogeneous distributional effects of the EITC.

My results highlight important features of the EITC and labor market programs in general. First, inducing labor supply mechanically expands the economy's possibilities frontier, while programs that incentivize leaving the labor force will contract the frontier. Thus, policies that expand the labor force, such as the EITC, have additional pro-growth benefits, while policies that subsidize leisure have additional costs to the economy. Second, the positive spillovers onto higher-income workers seems like an unintended transfer; however, with progressive taxation, these workers have a positive tax rate and the spillovers are taxed back. Thus, the EITC can help 'pay for itself' by indirectly increasing the tax-base, in addition to the direct effect of moving workers to employment (Bastian and Jones, 2018). These forces are omitted in Rothstein (2010) whose partial equilibrium approach shows the EITC in its worst light.[5] Finally, untreated-substitute workers face downward pressure on wages while untreated-complementary workers, who are already

[4] Agrawal and Hoyt (2018) study GE tax incidence in a multi-product consumer goods markets and applies results to cigarette taxation, while I consider multi-factor *input* markets taxes applied to the EITC.

[5] Section 8 and Appendix E replicate Rothstein (2010) in alternate ways with each finding the EITC superior to either a parameterized AFDC or NIT expansion in general equilibrium.

Figure 1 – Labor Subsidy Incidence in Two Factor Model: $\{A, B\}$



In (**a**), a supply subsidy shifts A^S to the right. In (**b**), assuming worker complementarity, the resulting marginal product spillovers cause *both* labor demands to shift right, which attenuates the PE gross wage decline for A-market.

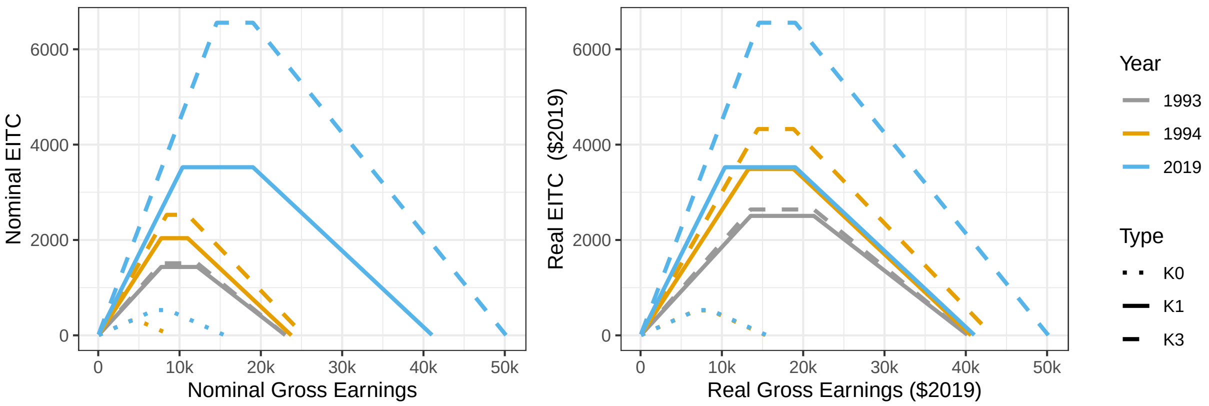
have higher wages, get a wage bump. In the medium to long run, this may incentivize the untreated-substitute workers to either become eligible (have children) or to up-skill out of the low-wage market.

An additional empirical contribution is that by isolating EITC specific policy variation, I allow for a more fine-tuned estimate of the treatment effects of the 1993 EITC expansion. Recently work by Kleven (2018) points out that Welfare reform during the 1990's potentially contaminates estimates of the EITC expansion effects. Partially, this is because prior analysis has used 'difference-in-differences' techniques where treatment is simply group membership interacted with year indicators which relies on strong assumptions about macro-trends. My estimates imply that labor supply for unmarried women with children increased 1.27% due to the 1993 EITC expansion, which is lower by a third to a tenth of the estimates summarized by Hotz and Scholz (2003). This supports the claim that prior EITC estimates were contaminated by macroeconomic conditions while also showing that the EITC *did* increase women's labor supply and thereby affected the market wages of the economy.

2 Overview of the EITC and Related Literature

This work is part of a long running effort to understand and quantify the economic and social effects of the Earned Income Tax Credit. The EITC is a $67 billion federal tax expenditure program designed to encourage work by subsidizing earned income through a refundable tax credit using a non-linear benefit schedule. Figure 2 shows how the program has expanded in real and nominal terms since the early 1990's to the present.

Figure 2 – EITC Schedule by Year and Number of Children



EITC schedules for single filing for years 1993, 1994, and 2019 by zero, one, and three children (Tax Policy Center, 2019). Joint filers have an extended plateau and phase out regions. Both nominal and real ($2019) values plotted.

The defining feature of the EITC is the phase-in region of the schedule, which increases the subsidy as earnings increase, and unambiguously promotes greater labor supply (Hotz and Scholz, 2003; Nichols and Rothstein, 2016). The phase-in differentiates the EITC from a Negative Income Tax or traditional Welfare program, which start at a high level and decrease with earnings.

Roughly 40% of all single parent families and 25% of married parent families are eligible for the EITC, and 40% of all families where the primary earner has less than a high school degree are EITC eligible (Nichols and Rothstein, 2016).

The EITC successfully encourages labor force participation and increases employment rates for eligible groups – primarily unmarried women workers with children and low levels of education. Two comprehensive survey articles – Hotz and Scholz (2003); Nichols and Rothstein (2016) – or two specific applications of the labor supply effects – Eissa and Liebman (1996); Eissa and Hoynes (2004) – provide a general overview of prior EITC studies.[6] Given the size of the EITC as a labor market intervention, we should expect wage and price distortions. However, most papers in the EITC labor literature assume that the EITC has had no effect on gross wages (Dickert et al., 1995; Eissa and Liebman, 1996; Saez, 2002; Eissa and Hoynes, 2004; Chetty et al., 2013). As noted by Hotz and Scholz (2003), this assumption had never been tested in first decade of EITC research.[7]

[6] More recent papers on labor market effects include Fitzpatrick and Thompson (2010); Chetty et al. (2013); Jones (2017); Kasy (2017); Hoynes and Patel (2018); Bastian (forthcoming). See also the impact of the EITC on non-labor-market outcomes – health (Dahl and Lochner, 2012; Evans and Garthwaite, 2014; Hoynes et al., 2015); education (Maxfield, 2015; Bastian and Michelmore, 2018); and marriage & fertility (Dickert-Conlin and Houser, 2002; Baughman and Dickert-Conlin, 2003).

[7] Some are explicit (Eissa and Liebman, 1996; Saez, 2002; Chetty et al., 2013) and others are implicit (i.e., holding wages fixed when simulating labor market effects) (Dickert et al., 1995; Eissa and Hoynes, 2004). In

Leigh (2010) and Rothstein (2010) study the gross wage incidence of the EITC in partial equilibrium.[8] Leigh (2010), using state and federal variation, finds that a 10% increase in the maximum EITC amount leads to a 5% decrease in the real wages of high school dropouts, and, using predicted labor supply within gender-age-education labor market cells, finds that 10% increase in cell labor supply leads to a 9% decrease in real wages within the labor market cell. Rothstein (2010) simulates a hypothetical EITC expansion change and reports that for every dollar of intended transfer real wages decrease by $\$0.34$. These results imply that the EITC is not *as effective* a program as policy makers may believe and may be an unintended transfer to non-targeted groups, such as business owners and wealthier households. My contribution is to allow for labor market spillovers that affect both treated and untreated workers, to derive an analytical formula that allows me to estimate the empirical incidence of the EITC rather than its maximum credit or hypothetical expansion, and to create a framework to predict and evaluate out-of-sample expansions.

In terms of general equilibrium effects of the EITC, this work is part of a small group. Lee and Saez (2012) allow for endogenous wages and argue that an EITC combined with an optimal minimum wage policy can prevent some of the incidence effect; however, the authors do not actually attempt to calculate the GE incidence. To build on their work, I incorporate spillover effects between labor markets and firm entry decisions allowing for an arbitrary number of factors with heterogeneous supply responses and tax changes. Kasy (2017) develops a novel estimation procedure using maximum EITC amounts to calculate the change in gross wages and labor supply along age, education, gender, and income distribution cells and finds negative earnings effects that dominate the credit, as if labor demand were completely inelastic – similar to Leigh (2010); Rothstein (2010). Because I do not rely on a difference-in-difference strategy between those with and without children, I allow for labor supply heterogeneity along parental status.[9] In addition, because I used empirical tax rates, I can compute both gross and net earnings effects. Froemel and Gottlieb (2019) develop a macroeconomic model to analyze consumption, savings, and wage determination, and find that both the gross earnings and wealth gap increase but the net earnings gap shrinks due to the EITC. These authors use a two skill model, focus solely on married households, approximate a EITC policy function, and ignore the distinction between workers with and without children. My work is able to account for most of these forces while maintaining a rich degree of individual heterogeneity in skills and wage responsiveness and exactly model the EITC.

Finally, my results rationalize a startling null-finding by Kleven (2019). The author uses every state and federal EITC reform since the program's inception and only finds "clear employment increases" from the OBRA expansion, which he notes occurred along with confounding macroeconomic and policy forces. I contribute to his work by estimating labor supply elasticities using purely EITC policy variation and by calculating the

Chetty et al. (2013), their model's the production function implies workers are perfect substitutes (thus no spillovers) and their empirical results depend on the stable unit treatment assumption. One potential reason for the absence is a greater interest in the individual policy treatment effects rather than aggregate labor market effects.

[8] Hoynes and Patel (2018) look at after-tax income distributional effects of the EITC and show that indirect effects increase net-income of workers near the poverty threshold. Azmat (2019) studies the partial equilibrium incidence of the Working Families Tax Credit, a conceptually similar program in the UK, and finds that, due to differences in salience unique to the program, gross wages fall by 7% for claimants and 1.7% for non-claimants.

[9] One reason that his estimates are similar to partial equilibrium analysis could be that common policy-shock effects are omitted through use of year indicator variables.

incidence by a structural approach that holds these confounding variables constant. Additionally, by separately calculating the labor market effects of the OBRA and ARRA expansion, I show that most EITC expansions likely do not generate economic forces large enough to be observed using difference-in-difference methods.

3 Model

In this section, I describe a general equilibrium labor market model to investigate the effect of targeted labor subsidies. The primary assumptions are that worker utility is quasi-linear in a composite consumption good, production technology has constant elasticity of substitution between factors and is constant returns to scale, and worker characteristics are observed by all market participants. To make analysis simpler, I abstract from other taxation issues by assuming the subsidy is financed by lump-sum taxes on workers, except I allow for an unemployment benefit.

For exposition, I present a model with only two labor skill levels. In Appendix A, I derive welfare measures for the model, show that the model easily generalizes to arbitrary labor types with type-specific tax changes, and discuss two extensions: allowing labor market 'switching' and two output sectors.

3.1 Workers

Let there be a mass N of workers, where each is defined by a skill level, $e \in \{0, 1\}$, a parental status, $c \in \{0, 1\}$, and a continuous and stochastic disutility of labor, $\nu \sim F_{e,c}(\nu)$. Suppose that only skill determines worker productivity, so wages are positively related to skills but unrelated to parental status conditional on skill. Given perfect information and perfect labor competition, all workers with the same skill earn the same wage.

Each worker has preferences over a homogeneous consumption good, X, and labor, L, representable by a quasi-linear utility function, $U(X, L; \nu) = X - \nu \cdot L$. Workers maximize utility by choosing a labor-consumption bundle given wages (w) and the tax system:

$$\max_{X,L}\{X - \nu \cdot L\} \quad \text{s.t. } X \leq T_c(w_e \cdot L) \quad \& \quad L \in \{0, 1\}, \tag{1}$$

where $T_c(w_e)$ is post-tax earnings, which depends on gross earnings and parental status.[10] By substituting the constraints, the problem becomes a discrete choice problem:

$$\max_{L=\{0,1\}} \left\{ \underbrace{T_c(0)}_{L=0}, \underbrace{T_c(w_e) - \nu}_{L=1} \right\}. \tag{2}$$

The solution yields worker output demand and labor supply functions, X_i^D and L_i^S. Let $\mathsf{v}_{e,c} = T_c(w_e) - T_c(0)$, then by definition $\Pr(\nu \leq \mathsf{v}_{e,c} \mid e, c) = F_{e,c}(\mathsf{v}_{e,c})$. With specific density functions the labor supply probability of each type of worker is known; e.g., with Type-1 Extreme Value draws, labor supply has a logit form: $F_{e,c}(\mathsf{v}) = \mathsf{e}^{\mathsf{v}}/(1 + \mathsf{e}^{\mathsf{v}})$.

[10] In this section I ignore non-labor income as there are no income effects; however, in the empirical sections I incorporate non-labor income when calculating effective tax rates.

Thus, the demographic, skill, and total aggregate labor supply functions are:

$$L^S_{e,c} = F_{e,c}(\mathsf{v}_{e,c}) \cdot N_{e,c} \quad \& \quad L^S_e = \sum_{c \in \mathcal{C}} L^S_{e,c} \quad \& \quad L^S = \sum_{e \in \mathcal{E}} L^S_e. \tag{3}$$

The labor supply elasticity for demographic group (e, c) is:

$$\frac{\partial L^S_{e,c}}{\partial w} \frac{w_e}{L_{e,c}} = \left[\frac{\partial T_{e,c}}{\partial w} f_{e,c}(\mathsf{v}_{e,c})\right] \cdot \frac{w_e}{L_{e,c}} := \varepsilon^L_{e,c}. \tag{4}$$

Using the logit example, $\varepsilon^L_{e,c} = \frac{\partial T_{e,c}}{\partial w} w_e(1 - F_{e,c}(\mathsf{v}_{e,c}))$. As there are no income effects for labor supply, the Marshallian and Hicksian elasticities are equivalent.

3.2 Production

Let there be mass J of producers indexed by $j \in \mathcal{J}$, each endowed with one unit of capital (K), that hires labor to produce the consumption good. Firms draw a capital supply cost (or entry cost), ξ_j, from a continuous distribution, $G(\xi)$. Technology is represented by a nested constant elasticity of substitution (CES) production function:

$$\begin{aligned} q^S_j = Q(\{L_{e;j}\}_e, K_j) &= A_j \left[\left(\sum_{e \in \mathcal{E}} \vartheta_e (L^D_{e;j})^{\frac{1+\rho}{\rho}}\right)^{\frac{\rho}{1+\rho}}\right]^{\alpha} K_j^{(1-\alpha)} & (5) \\ &= A_j \cdot \mathbf{L}_j^{\alpha} K_j^{(1-\alpha)}, & (6) \end{aligned}$$

where A_j is a Hicks-neutral productivity term, $L^D_{e;j}$ is the firm-j type-e labor demand, and $\mathbf{L}_j$ denotes the aggregate labor index for the firm. The elasticity of substitution between labor skill-groups is parameterized by:

$$\rho = \mathsf{d} \ln[L_{e''} \;/\; L_{e'}] / \mathsf{d} \ln[w_{e''}/w_{e'}] < 0, \text{ for } e', e'' \in \mathcal{E}. \tag{7}$$

This technology features constant returns to scale (CRS) and assumes fixed substitution elasticities between factors.[11] Firms maximize profits: $\pi_j = p \cdot Q(\{L_{e;j}\}_{e \in \mathcal{E}}, K_j) - \sum_{e \in \mathcal{E}} w_e L_{e;j} - rK_j$. Aggregate output is defined as $q^S = \int_j q^S_j \mathsf{d}j$. Price taking, zero profits, and identical production functions imply all firms choose the same factor input bundle, so by CRS the aggregate production function is also nested CES. I normalize the output price to one, $p = 1$, so wages and capital rents are in terms of the final good.

Firm entry is endogenously determined by capital supply costs and the price of capital, such that firm j will enter if $\xi_j \leq r$. In equilibrium, this determines the aggregate capital supply function, $K^S(r)$, and the aggregate capital supply elasticity, $\varepsilon^S_K = r \cdot \frac{g(r)}{G(r)}$.

3.3 Tax and Transfer System

For simplicity, suppose that initially the government raises revenue using lump-sum taxation at the level n, provides an unemployment benefit at level b, and balances its budget. The government then reforms the tax system to provide a small labor subsidy for low skill workers with children, $\tau_{(0,1)}$, but not for other workers and is paid for by lump-sum tax changes. Because there is no subsidy for other types of workers, I refer to $\tau_{0,1}$ simply as τ.

[11] When there are more than two skill groups, ρ is the *partial* elasticity of substitution.

3.4 Equilibrium

An equilibrium in the economy is a wage and rent schedule such that the factor market clears and firms make zero profits (thus clearing the output market) given the tax system. The economy is in equilibrium when no worker wishes to adjust her labor supply and no firm wishes to adjust its input bundle.

The CRS assumption implies the scale of factor demands cannot be determined. Fortunately, the model can be solved in terms of equilibrium demand ratios:

$$\frac{L_0^D}{L_1^D} = \left(\frac{w_0/\vartheta_0}{w_1/\vartheta_1}\right)^{\rho}. \tag{8}$$

While the labor-aggregate and capital demand bundle must satisfy:

$$\frac{\mathbf{L}^D}{K^D} = \left(\frac{\bar{w}/\alpha}{r/(1-\alpha)}\right)^{-1}, \tag{9}$$

where $\bar{w} = \left(\vartheta_0 \left(w_0/\vartheta_0\right)^{1+\rho} + \vartheta_1 \left(w_1/\vartheta_1\right)^{1+\rho}\right)^{\frac{1}{1+\rho}}$ is a labor cost index.

I find the the model's equilibrium conditions by equating the factor demand and supply functions and enforcing zero profits using the unit cost function, with output price normalized to one.[12] Thus, the general equilibrium of the economy is any set of prices, $\{w_0, w_1, r\}$, that solve the following equations:

$$\text{Labor Clearing} \quad \frac{L_0^S}{L_1^S} = \left(\frac{w_0/\vartheta_0}{w_1/\vartheta_1}\right)^{\rho} \tag{10}$$

$$\text{Factor Clearing} \quad \frac{L_0^S + L_1^S}{K^S} = \left(\frac{\bar{w}/\alpha}{r/1-\alpha}\right)^{-1} \tag{11}$$

$$\text{Zero Profits} \quad 1 = c(w_0, w_1, r). \tag{12}$$

4 Incidence

In this section, I present the partial and general equilibrium incidence of targeted labor subsidies for the two skill model which provides all necessary economic intuition. At the end, I present the incidence result for the full model that allows for arbitrary labor types which I use in the empirical applications.

4.1 Partial Equilibrium

I find the partial equilibrium incidence by totally differentiating the labor clearing condition (equation 10) while holding $\{L_1, K, w_1, r\}$ constant. In the limit when the market size of subsidized group goes to zero, this result is equivalent to the general equilibrium result, discussed next. This yields (when $\hat{\tau} > 0$):

$$\hat{w}_0^{\mathsf{PE}} = \left(\frac{\varepsilon_{0,1}^L}{\varepsilon_0^L - \rho}\right) \cdot \theta_{0,1} \cdot \hat{\tau} := \gamma_0 \cdot \hat{\tau} < 0, \tag{13}$$

[12]The unit cost function has the following form: $c(w_0, w_1, r) = (1/A)\left(\bar{w}/\alpha\right)^{\alpha}\left(r/1-\alpha\right)^{1-\alpha}$.

where $\hat{x}_e = x_e/w_e$ is the percent of wage change for the e-group, $\theta_{e,c} = L_{e,c}/L_e$ is the within skill share of subsidized workers, and ε_e^L and $\varepsilon_{e,c}^L$ are the group and sub-group supply elasticities, respectively, where $\varepsilon_e^L = \theta_{e,1}\varepsilon_{e,1}^L + (1-\theta_{e,1})\varepsilon_{e,0}^L$. Note that the numerator uses the elasticity of the subsidized group while the denominator uses the aggregate supply elasticity for the low skill market.

Interestingly, the model implies that the partial equilibrium labor demand elasticity for labor is constant, equivalent for all labor types, and equal to the labor elasticity of substitution. To see why this is the case, consider the following:[13]

$$L_0^D(w_0) = L_1^S(w_1(w_0)) \cdot \left(\frac{w_0/\vartheta_0}{w_1(w_0)/\vartheta_1}\right)^{\rho} \implies \eta_0^D = \rho + \frac{\partial w_1}{\partial w_0}\left(\varepsilon_1^L - \rho\right). \tag{14}$$

When $\frac{\partial w_1}{\partial w_0} = 0$ by partial equilibrium assumption, the demand elasticity equals the substitution elasticity between factors.[14] Holding w_1 and r fixed is equivalent to holding those factors' marginal product constant, but this is invalid when L_0 increases (except when the low skill group is infinitesimal).

4.1.1 Implication and Interpretation for Policy

The PE assumptions require that for any specific labor group no other group adjusts its supply, which creates a set of mutually exclusive assumptions. With multiple labor types and heterogeneous subsidy changes, aggregating the PE results yields an 'employment weighted average partial equilibrium effect.' This is not of theoretical or practical interest unless one knows *ex-ante* that spillover effects will be negligible.

Rothstein (2010) implies that decreases in gross wages are a transfer to *firms* at the expense of workers: "this implies that employers of low-skill labor capture a portion of the intended EITC transfer" and "...targeted work subsidies produce unintended transfers to employers...". While Rothstein's partial equilibrium analysis is technically correct, the interpretation of his result does not necessarily follow for two reasons.

First, with zero profits, there are no explicit profits for firms only returns to factors. With CRS technology, if one factor price goes down, then some other factor(s) must increase. Second, assuming entrepreneurs own some other factor (such as capital), then entrepreneurs may 'capture' the wage subsidy if their own factor payments increase.[15] However, the 'all else equal' for the PE incidence requires the prices and quantities of all other factors be held *fixed*, which means that owners of other factors *cannot* actually realize any factor price increases.

Thus, a partial equilibrium story is incapable of yielding Rothstein's conclusion about transfers to firms at the expense of workers. In order to render the conclusion about firm owners benefiting from changes in gross wages, one must use a general equilibrium analysis.

[13] In the two factor CRS case, Lee and Saez (2012) show that in equilibrium, the supply responses of the second factor can be used to pin down the first factor's demand and second factor's price as only a function of the first factor's price, despite the unknown scale of production.

[14] Another way to see this is that: $\eta_e^D = \frac{\mathsf{d}\ln[L_e^D]}{\mathsf{d}\ln[w_e]} = \frac{\mathsf{d}\ln[L_e^D/L_{e'}^D]}{\mathsf{d}\ln[w_e/w_{e'}]} = \rho$ if $\mathsf{d}\ln[L_{e'}^D] = \mathsf{d}\ln[w_{e'}] = 0$.

[15] The production function in Rothstein (2010) only includes labor factors, so there is no possible factor to be owned by entrepreneurs, though a pre-published version of his analysis did include capital.

4.2 General Equilibrium

To calculate the incidence, I totally differentiate equations 10, 11, and 12 with respect to $\{w_0, w_1, r, \tau\}$. Since the two type model system has three equations and three unknowns $(\mathrm{d}w_0, \mathrm{d}w_1, \mathrm{d}r)$, I can solve the for a change in low skill wages using iterative substitution. Use the zero profits condition to solve $\mathrm{d}r = f(\mathrm{d}w_0, \mathrm{d}w_1)$, use the labor clearing condition to solve $\mathrm{d}w_1 = g(\mathrm{d}w_0, \mathrm{d}\tau)$, and then substitute into the factor clearing condition for $\mathrm{d}w_0 = h(\mathrm{d}\tau)$. This yields:

$$\hat{w}_0^{\mathsf{GE}} = \left(\frac{-\varepsilon^L_{0,1}\theta_{0,1}}{(\varepsilon^L_0 - \rho)} + \frac{s_{L0}\left(\frac{\varepsilon^L_{0,1}\theta_{0,1}}{(\varepsilon^L_0-\rho)}\right)\left(\frac{\varepsilon^K+1}{s_K} + \frac{1+\rho}{s_L}\right)}{(\varepsilon^L_0 - \rho)\left(1 + \left(\frac{\varepsilon^K+1}{s_K} + \frac{1+\rho}{s_{L0}+s_{L1}}\right)\left(\frac{s_{L0}}{(\varepsilon^L_0-\rho)} + \frac{s_{L1}}{(\varepsilon^L_1-\rho)}\right)\right)} \right)\hat{\tau} \tag{15}$$
$$:= (\gamma_0 + \Gamma_0)\cdot\hat{\tau},$$

where γ_0 is the PE gross wage effect and Γ_0 is the GE spillover term, and s_h are factor cost shares. Thus, the GE incidence is the direct (PE) effect plus a weighted sum of cross-factor effects.[16] Since $\Gamma_0 \geq 0$, a subsidy increase for low skill labor implies that the spillover effects attenuate the PE wage effects, so workers retain more of the subsidy than is implied by the PE analysis.

Solving for the other price effects (when $\hat{\tau} > 0$): $\hat{w}_1^{\mathsf{GE}} = \left(\frac{\varepsilon^L_0-\rho}{\varepsilon^L_1-\rho}\right)\Gamma_0\hat{\tau} \;\; \geq 0$ and $\hat{r}^{\mathsf{GE}} = -\left(\frac{s_{L0}}{s_K}\hat{w}_0^{\mathsf{GE}} + \frac{s_{L1}}{s_K}\hat{w}_1^{\mathsf{GE}}\right)$.[17] With only a low skill labor subsidy, the PE analysis provides an upper bound for the low skill labor market wage effect, but PE is completely uninformative about the magnitude of the other input price effects since these depend on GE spillover terms.

As alluded to before, $\hat{w}_0^{\mathsf{PE}} = \hat{w}_0^{\mathsf{GE}}$ only if $s_{L0} = 0$, which is a small-market assumption that makes little sense in a two type model.[18] Figure 3 provides a visual comparison of PE and GE incidence for a 1% effective subsidy increase for L_0 as implied by different endogenous cost shares.

Figure 3 also shows the importance of the substitution elasticity, ρ. When inelastic, as in Rothstein (2010), the PE incidence implies large wage effects; however, when more elastic, as in my estimates presented in Section 5, the wage effects are smaller. This pattern is because a larger elasticity implies a firm can more easily adjust its factor demand bundle to take advantage of cost savings.

4.2.1 General Equilibrium Incidence with Many Labor Markets

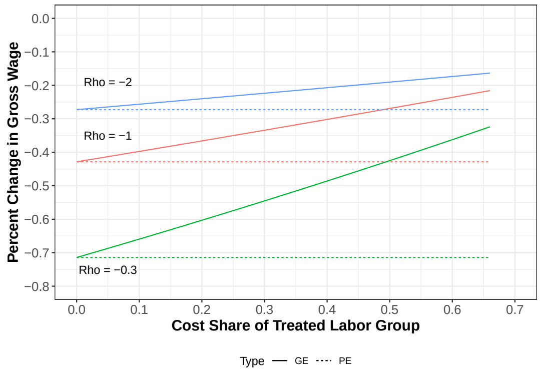
Adding additional types of labor in this context is relatively simple given the symmetry of the model. Let skills be indexed by $e \in \{0, 1, 2, \ldots, E\} = \mathcal{E}$. I allow arbitrary skill-specific subsidies $(\hat{\tau}_e)$, and then solve the equations in the same manner as before using iterative substitution after totally differentiating. Full details are in Appendix A.

[16]Equation 15 resembles the result in Agrawal and Hoyt (2018) in that the general equilibrium incidence is a linear function of the PE incidence and GE spillover effects.

[17]See that $\hat{r}^{\mathsf{GE}} > 0$ if $(s_L/s_K)\varepsilon^K + (1/s_K) > -\rho$. For $s_K = 0.33$ and $\varepsilon^K = 1$, $\hat{r}^{\mathsf{GE}} > 0$ if $\rho > -5$, which other authors and I find empirically (Katz and Murphy, 1992; Goldin and Katz, 2009; Borjas et al., 2012).

[18]Recall, 20% of tax units (40% of workers with children) receive the EITC (Nichols and Rothstein, 2016).

Figure 3 – Incidence Comparison Across Labor Substitutions



This plots the percent change in gross wages for low skill workers from a 1% subsidy increase at different substitution elasticities and cost shares. Other parameters: $\varepsilon_0^L = 0.75,\ \varepsilon_1^L = 0.6,\ \varepsilon^K = 1$. Details in Appendix A.

The general equilibrium incidence for type e' labor is:

$$\hat{w}_{e'}^{\mathsf{GE}} = \frac{-\varepsilon_{e',1}^L \theta_{e',1}\hat{\tau}_{e'}}{\varepsilon_{e'}^L - \rho} + \frac{\Lambda\left(\sum_e \frac{s_e \varepsilon_{e,1}^L \theta_{e,1}\hat{\tau}_e}{\varepsilon_e^L - \rho}\right)}{(\varepsilon_{e'}^L - \rho)\left(1 + \Lambda\left(\sum_e \frac{s_e}{\varepsilon_e^L - \rho}\right)\right)} \tag{16}$$

$$= (\gamma_{e'} + \Gamma_{e'})\,\hat{\tau}_{e'} + \Psi_{e'}(\{\tau_e\}_{e\in\mathcal{E}\setminus e'}), \tag{17}$$

where $\Lambda = \left(\frac{\varepsilon^K+1}{s_K} + \frac{1+\rho}{s_L}\right)$. Equation 16 shows three first order terms with respect to a tax reform: the direct effect, the own-supply induced marginal product spillovers, and the received marginal product spillovers from other tax changes.

Generally, one cannot sign equation 16 without knowing the magnitude of each $\{\tau_{e'}\}_e$. For example, if the tax change for one group is small *but* all other changes are large and positive, then the GE spillovers may dominate, so the wage change would be positive. Only if both spillover terms are small will $w^{\mathsf{GE}} \approx w^{\mathsf{PE}}$; e.g., if the cost share weighted average tax change is zero: $\mathsf{E}[s_e\tau_e\theta_{e,1}] = 0$.[19]

5 Estimating Labor Market Elasticities

In this section, I describe how I estimate labor supply and substitution elasticities: $(\{\varepsilon_{e'}\}, \rho)$, which are used in the empirical applications in sections 7- 11. In summary, I combine two data sets to calculate the labor market variables: the 1986-2000 Current Population Surveys (Flood et al., 2018) and the 1990 US Census 5% sample, (Ruggles et al., 2018). Next, I use NBER's TAXSIM (Feenberg and Coutts, 1993) to create EITC induced average tax rate changes as the empirical analogue of $\hat{\tau}$. Finally, I use a two-step efficient GMM to estimate the supply and substitution elasticities. Additional details and results are in Appendices B-D.

[19] Agrawal and Hoyt (2018) make this point by supposing that the market share of taxed goods is small relative to a composite consumption good.

5.1 Data

I use the 1986 to 2000 CPS Outgoing Rotation Group (ORG) samples for labor market information by state and year. The sample asks detailed employment, earnings, and household structure information from roughly 100k households per month. I pool the monthly samples for annual level labor market variables.[20]

I assign workers to their labor skill levels based on observable demographic characteristics. Labor skill levels are defined by four education categories, nine age groups, and marriage status – this implies 72 skill levels. I assign workers to a labor markets based on the worker's skill level, state, and year. Additionally, I assign workers to demographic groups by dividing the labor market between workers with and without children. This yields $72 \times 51 \times 15$ labor market cells – $e \in \mathcal{E}$– and $2 \times 72 \times 51 \times 15$ demographic cells – $(e, c) = d \in \{\mathcal{E} \times \{0, 1\}\}$.[21]

For labor market quantities, I use total hours worked divided by total potential workers at the labor market level.[22] For labor market prices, I calculate a worker's real effective wage as earnings per week divided usual weekly hours deflated using the the BLS CPI All Items Research Series (Bureau of Labor Statistics, 2019). Appendix B includes additional details and summary statistics.

I use the 1990 US Census 5% sample to calculate demographic-specific simulated instruments for the EITC policy changes.[23] Specifically, I calculate EITC tax parameters for every tax year using NBER's Internet TAXSIM for the fixed 1990 worker population. The primary EITC tax parameter is the average tax rate associated with the EITC (EITC ATR), defined as $\tau^{\text{EITC ATR}} = \frac{\text{EITC(Actual)} - \text{EITC(No Work)}}{\text{True Earnings}}$. I also calculate an indicator for if a worker is eligible for the EITC and the change in EITC amount from one tax-year to the next holding earnings constant.

I further describe the instrument construction and formalize the exogeneity requirements in Section 5.3 and Appendix C, but the virtue of using the Census is that by using the fixed population, all variation in the tax parameters is due to policy reforms over time and space and initial exposure levels of the EITC to these reforms.[24] That is, the variation in the simulated tax parameters is *not* due to any endogenous behavioral response to the policy reforms – see Figure 5 below.

5.2 Summary Statistics

Table 1 displays the difference in labor market variable means before and after tax year 1993 conditional on marriage and parental status to highlight the identification using

[20] I drop individuals who were in group quarters or not interviewed, variable values that were allocated, married workers with absent spouse, full-time students out of the labor force, and households with more than 10 members (due to the difficulty in assigning children for complex households).

[21] This follows the main market definition in Rothstein (2010) with added geographic dimension.

[22] This measure captures both extensive and intensive margin responses that are relevant for labor market equilibrium. Appendix D displays results using only the extensive margin response.

[23] Simulating tax parameters to generate instruments is also used in numerous prior studies such as: Dickert-Conlin and Houser (2002); Gruber and Saez (2002); Rothstein (2008); Leigh (2010); Bastian and Michelmore (2018).

[24] In this way, the tax instruments are similar to 'shift-share' instruments. See Adao, Kolesár and Morales (2018); Borusyak, Hull and Jaravel (2018); Goldsmith-Pinkham, Sorkin and Swift (2018).

EITC policy tax changes. The first two rows are the labor market variables from the CPS ORG sample, and the third is the simulated EITC average tax rate using the 1990 Census.

Labor supply increased for unmarried women with children and married women but decreased slightly for unmarried women without children. Contemporaneously, there are meaningful wage increases for every group in this period. While the wage growth is lowest for unmarried mothers, the summary statistics show that the labor demand must dominate the supply increases to result in positive wage growth.[25] For this reason, I use EITC-specific policy variation that is unrelated to demand shocks to untangle these competing forces. The change in the EITC ATR is largest for unmarried women with children, small for unmarried women without children, and effectively no change for married women.

Table 1 – Summary Statistics for Estimation Sample

	Unmarried No Children	Unmarried w/ Children	Married No Children	Married w/ Children
Log Hours/Person	-0.03	0.09	0.02	0.06
	(0.01)	(0.01)	(0.01)	(0.01)
Log Real Wage	0.04	0.02	0.05	0.05
	(0.01)	(0.01)	(0.01)	(0.01)
EITC ATR	-0.01	-0.07	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Obs	9,816	5,594	10,041	9,213

All data from 1990-1993 & 1995-2008 CPS ORG samples and 1990 US Census. Each observation is a demographic-state-year cell. EITC ATRs calculated using TAXSIM. Values are from univariate regression of the outcome on a post-EITC indicator for each demographic group separately with robust standard errors.

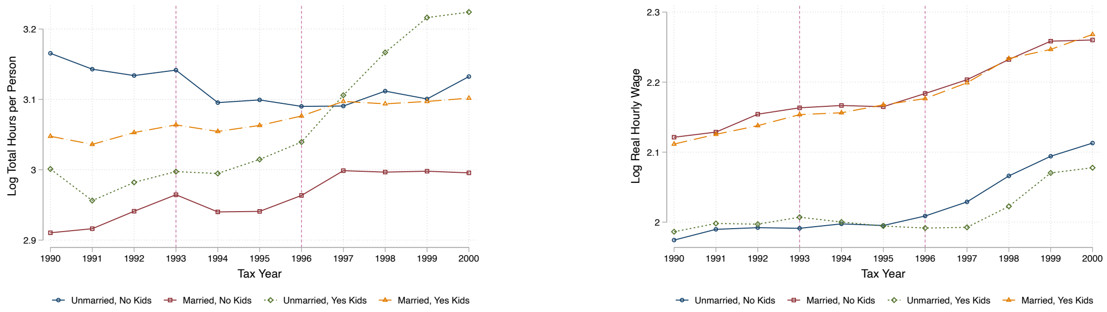
Figure 4 plots the time series variation for log total hours per worker and mean log gross wages by demographic groups during the 1990's. These are the primary outcome and and endogenous explanatory variable in the empirical specification, respectively.

In Figure 5, I plot the simulated EITC ATRs and EITC take-up shares against the empirical measures from the ASEC. The primary policy change for unmarried mothers occurred over tax years 1993 to 1996, while the only policy change for unmarried women without children was in tax year 1993. For unmarried mothers, the true ATR is less than the simulated ATR that holds labor supply fixed, which is consistent with workers entering the labor force at lower earnings. The simulated share predicts that fewer unmarried mothers would claim the EITC starting in tax year 1996 due to an added income test.

Many empirical EITC studies assume that the EITC policy changes for workers without children is not enough to affect behavior. The figures show this is a reasonable assumption because I can predict the the EITC ATR and share using only the 1990 distribution of labor supply and inflation.

[25] The 1990s were a time of technological change and favorable macroeconomic conditions which can exaggerate EITC effects on labor supply and confound the wage effects (Nichols and Rothstein, 2016; Kleven, 2019).

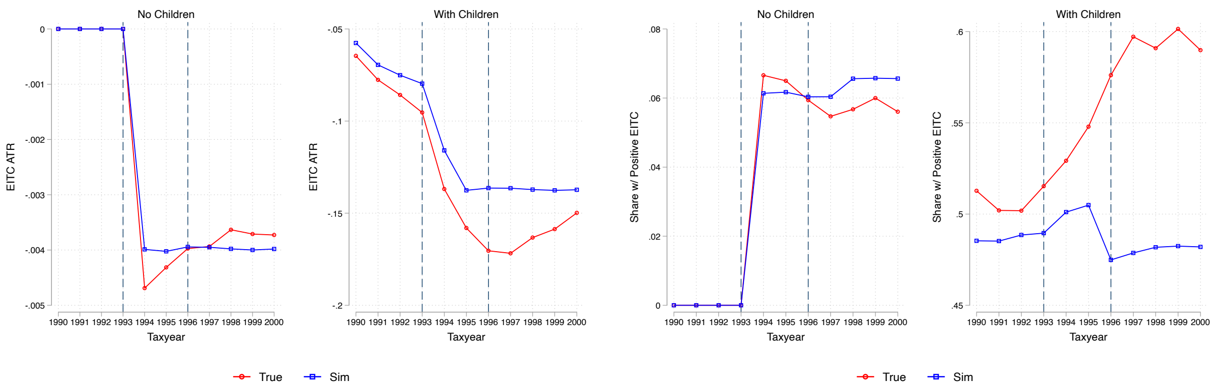
Figure 4 – Labor and Wages Across Demographic Groups



(a) Log Hours per Worker **(b)** Log Wage

This plots log total hours per worker (**a**) and mean log real wage (**b**) using CPS ORG samples of women (1990-2000) by marriage and parental status. Log total hours per worker is used as the measure of labor quantity and mean log real wage as labor prices.

Figure 5 – Simulated vs True EITC Parameters



(a) EITC ATR **(b)** Share w/ EITC

This plots the average EITC ATR (**a**) and share with EITC (**b**) for unmarried women-headed tax units calculated using ASEC ('true') or 1990 Census ('sim') samples and NBER TAXSIM. The 1990 Census values are uses as simulated IVs for labor market outcomes.

5.3 Identification

The incidence model – summarized in Figure 1 – illuminates that the EITC creates both supply and demand variation in wages that can be used to identify labor supply and labor substitution elasticities:

$$\underbrace{\mathrm{d}w_{est}}_{\text{Wage Variation in the Data}} = \underbrace{\underbrace{\gamma_e \mathrm{d}\tau_{est}}_{\text{Supply Shift}} + \underbrace{\Psi_{est}(\{\tau_{e'st}\}_{e'})}_{\text{Demand Shift}}}_{\text{Incidence Model}} + \underbrace{v^w_{est}}_{\text{Unobserved Variation}}. \tag{18}$$

As discussed in Watson (2020), supply elasticities are identified using spillover based demand variation and conditioning on the own tax rate that controls for supply shifts; whereas, demand elasticities are identified using the tax reform supply shock and conditioning on the demand spillovers.

A sufficient set of identifying assumptions for both labor supply and substitution elasticities is that:

$$\mathsf{E}[\tau_{est} \cdot u^D_{e'st} \mid \Psi_{est}, X] = 0, \; \forall\, e, e' \in \mathcal{E} \tag{19}$$

$$\mathsf{E}[\Psi_{est} \cdot u^S_{e'cst} \mid \tau_{ecst}, X] = 0, \; \forall\, e, e' \in \mathcal{E}, \tag{20}$$

where $\tau_{est} = \theta_{e0st}\tau_{e0st} + \theta_{e1st}\tau_{e1st}$.[26] In words, tax rate variation is uncorrelated to both unobserved non-spillover demand shocks – e.g., skill biased technical change or changes in hiring costs – and to unobserved supply shocks – e.g., employment opportunity costs. See Appendix C.1 for more details and derivation.

To empirically implement this, I create two sets of IVs using the 1990 Census sample, which I call the own-market IVs and the substitute-market IVs. The own-market IVs are calculated using a simple average of simulated individual EITC variables within a given demographic-skill state-year group. These variables measure the direct effect of the EITC on a given market group. This is what is plotted in Figure 5.

The substitute-market IVs are calculated using two sets of 'leave-out' averages in the same state-year. The first set is based on similar education groups and the second is based on similar age group. For example, consider the group 'young, unmarried women with less than a high school degree,' then the first IV set is based on averaging across all women with less than a high school degree but leaving out the young, unmarried group in that average. Further, by conditioning on the own-market EITC parameters, the remaining variation is orthogonal to the direct tax shock to any particular group. These IVs use EITC exposure, but not responsiveness, of close-substitute workers. I describe this argument in greater detail in Appendix C.1.

Thus the supply elasticities are identified using the spillover variation *within* demographic cells across state-years, and the substitution elasticity is identified using the direct EITC variation *between* skill levels across state-years.

5.4 Estimating Equations

To estimate the labor supply and substitution elasticities, $(\{\varepsilon_{e'}\}, \rho)$, I use two-step efficient GMM with standard errors clustered at the labor market level. I estimate the parameters in two separate steps (Zoutman et al., 2018; Watson, 2020).[27]

To estimate the heterogeneous labor supply elasticities while controlling for market conditions via fixed effects, I specify the coefficient on log market wage as function of marriage, parental, and education status. This leads to the following estimation equations:

$$\begin{aligned} \ln[W]_{dst} = {} & \pi_0 + Z_{dst}\Pi_1 + [Z_{dst} \cdot \mathsf{g}_d]\,\Pi_d + \pi_2\tau_{dst} + \pi_3 \ln[P_{dst}] \\ & + \mathsf{d}_d + \mathsf{d}_{st} + \mathsf{d}_{w_0^{\%},t} + \mathsf{d}^{\mathsf{BMW}}_{lst} + \mathsf{d}^{\mathsf{waiver}}_{kst} + e^w_{dst} \end{aligned} \tag{21}$$

$$\begin{aligned} \ln[L]_{dst} = {} & \beta_0 + \varepsilon^L_1 \ln[W]_{dst} + \varepsilon^L_g\,[\ln[W]_{dst} \cdot \mathsf{g}_d] + \beta_2\tau_{dst} + \beta_3 \ln[P_{dst}] \\ & + \mathsf{d}_d + \mathsf{d}_{st} + \mathsf{d}_{w_0^{\%},t} + \mathsf{d}^{\mathsf{BMW}}_{lst} + \mathsf{d}^{\mathsf{waiver}}_{kst} + e^L_{dst} \end{aligned} \tag{22}$$

[26] These assumptions are slightly stronger than necessary; see Appendix C.1.

[27] The supply and demand parameters could be estimated jointly for efficiency, but separating the estimation allows for the parameters to be transparently identified and more robust to misspecification.

where Z are market level simulated EITC instruments from the 1990 Census, τ_{dst} is the own EITC ATR simulated from the 1990 Census, $\ln[P_{dst}]$ is log cell population, g_d are indicator variables for marriage, parental, and education status, d_d are demographic group fixed effects (FEs), d_{st} are state-year FEs, $\mathsf{d}_{w_0^{\%},t}$ are FEs for initial (1989) wage percentiles interacted with year indicators, $\mathsf{d}_{lst}^{\mathsf{BMW}}$ are FEs for deciles of workers in 1990 that have wages at or below the prevailing state minimum wage interacted with year indicators, and $\mathsf{d}_{dst}^{\mathsf{waiver}}$ are FEs for state welfare waivers interacted with parental status indicators. The implied elasticity for a given labor market is $\varepsilon_d^L = \varepsilon_1^L + \varepsilon_{g(d)}^L$.

The controls are meant to absorb any demand or supply shocks other than the EITC policy changes that may affect labor supply. The demographic group FEs, d_d, control for any time invariant correlation between wages and labor supply that is specific to a demographic group; e.g., demographic level tastes for working. The state-year FEs, d_{st}, control for any state-year level correlations across demographic groups; e.g., a state policy change that affect the cost of working for all workers. The initial wage percentile FEs, $\mathsf{d}_{w_0^{\%},t}$, control for any correlations at specific to a market's wage segment before the EITC expansions; e.g., mean-reversion in wages or skill biased technological change. The binding-minimum-wage FEs, $\mathsf{d}_{lst}^{\mathsf{BMW}}$, control for the degree to which supply responses are limited by binding minimum wages[28], Finally, the waiver FEs, $\mathsf{d}_{dst}^{\mathsf{waiver}}$, control for correlations that are due to state welfare changes prior to the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA), provided by Kleven (2019).

To estimate the substitution elasticity, I use the following equation:

$$\begin{aligned} \widetilde{\ln[W]}_{est} &= \gamma_0 + \gamma_1 \tilde{\tau}_{est} + \gamma_2 \tilde{Z}_{est} + \gamma_3 \widetilde{\ln[P]}_{est} \\ &\quad + \mathsf{d}_{et} + \mathsf{d}_{st} + \mathsf{d}_{w_0^{\%},t} + u_{est}^{w} \end{aligned} \tag{23}$$

$$\begin{aligned} \widetilde{\ln[L]}_{est} &= \alpha_0 + \rho \widetilde{\ln[W]}_{est} + \alpha_2 \tilde{Z}_{est} + \alpha_3 \widetilde{\ln[P]}_{est} \\ &\quad + \mathsf{d}_{et} + \mathsf{d}_{st} + \mathsf{d}_{w_0^{\%},t} + u_{est}^{L}, \end{aligned} \tag{24}$$

where $\tilde{x}_{est} = x_{est} - x_{0st}$, the log difference. I use controls analogous to the supply model but with interpretation based on relative quantities and wages.[29] I make one important change in FEs: the market level FE d_{et} pools married and unmarried markets (i.e., only interacts age and education) and is additionally interacted with year to absorb skill-specific shocks to labor demand.[30]

5.5 Elasticity Estimates

Table 2 displays the estimated elasticities. The results show that labor supply responsiveness decreases with education, that having children makes one less responsive to wages, and that married women are more responsive than unmarried women.

My estimate for the labor supply elasticity for unmarried mothers with low education attainment is quite similar to other estimates. I estimate the value 0.82 while Rothstein

[28]A binding-minimum-wage limits the degree of price responsiveness which in turn limits the changes in market quantities underlying the general equilibrium forces.

[29]I do not use state Welfare Waivers in this specification because at the market level they are perfectly colinear with the state-year FEs. I do not use binding-minimum-wage FEs, but unreported robustness tests show no meaningful change in elasticity estimates.

[30]Omitting marriage status in the FE is of necessity as its inclusion absorbs too much variation in the instruments and causes the covariance matrix to be nearly singular. See Appendix D.

(2008) estimates a value of 0.75 and Meyer and Rosenbaum (2001) estimate 0.83 for participation for work in an average week.[31] I find that unmarried women without children and less than a high school degree have an elasticity of 1.16, and I can reject that the labor supply elasticities for unmarried women with and without children are equal. This can imply a violation of "parallel trends" when using difference-in-difference methods because workers will respond differently to labor market effects on gross wages.

My estimates for married women with low education are higher than previous estimates. I estimate the value 0.89 while Eissa and Hoynes (2004) estimate 0.27 for similarly educated married women.[32] Bargain and Peichl (2016) survey labor supply elasticities across countries and show estimates for married women range from almost perfectly inelastic to 1.50 for the United States.

Table 2 – Labor Supply Elasticity Estimates by Labor Groups: ε_d^L

	Hours per Worker			
	w/o Children		w/ Children	
	Unmarried	Married	Unmarried	Married
Less HS	1.16	1.36	0.82	0.89
	(0.07)	(0.07)	(0.08)	(0.08)
HS	0.85	1.05	0.51	0.58
	(0.06)	(0.05)	(0.06)	(0.06)
Some College	0.82	1.02	0.48	0.55
	(0.05)	(0.05)	(0.05)	(0.05)
BA Plus	0.53	0.73	0.19	0.26
	(0.05)	(0.04)	(0.6)	(0.05)
	Obs	AR F	KP rk Wald F	MOP Effective-F
	47,339	39.84	39.76	16.68

All data from MORG 86-00, 1990 Census; EITC ATRs calculated using TAXSIM. Standard errors clustered by (144) demographic groups. Weighted by number of observations in each labor market. Model controls: log cell population, FEs for demographics, State-Year, Initial-Wage-Pct-Year, BMW-Year, and Welfare waivers. KP rk Wald F is cluster robust Cragg-Donald stat; AR is cluster robust F stat of IVs on structural equation residuals. MOP Effective-F is weak-IV F-statistic (Olea and Pflueger, 2013).

Table 3 presents estimates of the labor substitution elasticity between labor markets for the two relative labor supply measures. Column (1) is just identified using the 'relative' EITC ATR and column (2) is overidentified using the 'relative' EITC ATR, change in EITC amount, and share in with EITC. For each estimate I report the cluster robust standard error in parentheses. Additionally, I report the Weak IV Robust confidence interval based on Andrews (2018). For both specifications, I can reject that the substitution elasticity is inelastic, which is in line with the immigration literature estimates around -1.4 (Katz

[31] Additionally, Dickert et al. (1995) calibrate a labor supply estimate of 0.85 and the difference-in-differences result from Eissa and Liebman (1996) implies an elasticity of 1.16.

[32] Eissa and Hoynes (2004) estimate a joint labor supply decision at the individual level while I hold constant the married partner's labor supply and treat this an non-labor income for the wife; also, they use a longer time series of policy variation while my variation linked to the 1993 OBRA expansion only.

and Murphy, 1992; Goldin and Katz, 2009; Borjas et al., 2012). A more inelastic estimate of ρ will tend to imply larger magnitude incidence effects since ρ is in the denominator of equations 13 and 16.

Table 3 – Labor Substitution Elasticity Estimates Across Labor Markets

	Hours per Worker	
	(1)	(2)
ρ	-1.81	-1.57
Wald SE	(0.30)	(0.45)
WIVR CI	[-2.43,-1.29]	[-3.11,-1.38]
KP rk Wald F	67.28	13.77
Anderson-Rubin F	39.47	5.68
MOP Effective-F	110.08	15.74
# IVs	1	3
Obs	19,501	19,501

All data from MORG 86-00, 1990 Census; EITC ATRs calculated using TAXSIM. Column (1) is just identified using relative EITC ATRs; (2) uses additional IVs. Weighted by geometric mean of labor market observation pairs. Standard errors clustered by (63) labor market groups. Weak IV Robust CIs based using AR (1) or LC test (2,3) (Andrews, 2018; Sun, 2018). Model controls: log relative cell population, FEs for Edu-Age-Year, State-Year, and Initial-Wage-Quintile-Year. KP rk Wald F is cluster robust Cragg-Donald stat; AR is cluster robust F stat of IVs on structural equation residuals. MOP Effective-F is weak-IV F-statistic (Olea and Pflueger, 2013).

6 Empirical Policy Evaluation Methodology

In this section, I outline how I combine the incidence model, estimated elasticities, and data to derive the policy evaluation results. I present three types of results: gross wage changes, labor changes, and per dollar effects (multipliers). The wage and labor changes are based on estimates elasticities and tax/subsidy changes. The per dollar effects closely follow Rothstein (2010) but incorporate spillovers and update formulas to allow for changes in welfare program usage and tax payments given earnings changes.

6.1 Data

I use the Annual Social and Economic sample from the March CPS as this sample contains employment and income information in the previous calendar year that is necessary to calculate Federal average tax rates and EITC specific ATRs (Flood et al., 2018). Specifically, I use the 1994 ASEC for the 1993 OBRA expansion and the 2009 ASEC for the 2009 ARRA expansion. I use the same definition of skills and demographics as in the estimation section. However, for the policy evaluations, I no longer distinguish between states and only use Federal EITC variation due to the ASEC being one tenth the sample size as the ORG samples in the estimation section. While the ASEC sample asks about welfare program usage, I combine this sample with the output of the Urban Institute's Transfer Income Model 3 (Urban Institute, 2020) to complement the reported amount.[33] The TRIM3 simulates household and family level transfer program amounts that is analogous to the NBER's TAXSIM model for tax rates and credits. For more details about the sample, see Appendix B.2.

6.2 Model Wage and Labor Changes

To calculate model implied wage and labor changes, I combine the data described above and the elasticities from the Section 5 results. I calculate and report the model implied wages percent changes, $\hat{w}_e$, using the general incidence formula in equation 16. I calculate the model implied labor percent changes as: $\hat{L}_{e,c} = \varepsilon_{e,c}\left(\hat{w}_e - \hat{\tau}_{e,c}\right)$. I then report the percentage point changes in labor force participation as $\mathsf{d}L_{e,c} = \hat{L}_{e,c} \cdot L_{e,c}$.

6.3 Per Dollar Effects

I calculate per dollar effects by summing the changes in total income for the economy divided by the change in EITC expenditure. By defining gross earnings as $Z^G = w \cdot L$ and net earnings as $Z^N = (1-\tau) \cdot Z^G$, I can look at sources of change in total income from the EITC reforms by totally differentiating the income measures. The total change in gross earnings is $\mathsf{d}Z^G = w\mathsf{d}L + \mathsf{d}wL + \mathsf{d}w\mathsf{d}L$ and the total change in net earnings is $\mathsf{d}Z^N = (1-\tau)\mathsf{d}Z^G - \mathsf{d}\tau(Z^G + \mathsf{d}Z^G)$.

I report the change in gross earnings due to labor changes ($w\mathsf{d}L$), the change due to wage changes ($\mathsf{d}wL$), the total gross earnings change ($\mathsf{d}Z^G$), and the total net earnings change ($\mathsf{d}Z^N$). I additionally include what Rothstein (2010) refers to as the change in net-transfers ($\mathsf{d}Z^G + \mathsf{d}\tau Z^G$) and the net-earnings ($\mathsf{d}Z^G + \mathsf{d}\tau Z^G$), which hold all other taxes and transfers constant rather than allowing them to adjust given the gross earnings changes. Finally, the table reports the *ex post* 'fiscal externality' that measures the policy reform's effect on the government budget constraint incorporating extensive labor supply effects, $\mathsf{dFE} = \tau w\mathsf{d}L$ (Hendren, 2016; Kleven, 2018).[34,35] To put these in per dollar terms, I divide the measures by the total new EITC expenditure.

6.4 Caveats

There are two caveats to the empirical exercises I wish to make salient. First, I hold workers' market designation fixed, which could be interpreted as a short-run assumption.

[33] I find self-reported amounts are less than the TRIM model (Meyer and Mittag, 2019). For the Empirical 1993 Incidence results, I average the two measures for welfare usage. For the EITC vs Welfare counterfactuals, I only use the TRIM3 model as I am altering the program's parameters directly.

[34] I calculate the extensive margin change in Welfare usage, B, as $\mathsf{d}B = (B\mid_{L=0}) \cdot \frac{\mathsf{d}\Pr(L=1)}{1-\Pr(L=1)} + (B\mid_{L=1,\text{Phase-In}}) \cdot \frac{\mathsf{d}\Pr(L=1)}{\Pr(L=1)}$ that assumes new workers, who originally received zero-earnings welfare benefit, enter into the EITC Phase-In earnings region and use Welfare programs at this income level.

[35] Assuming a utilitarian social welfare function with a unit marginal value of cost of government revenue, one can interpret this as Consumer Welfare measure. See Section A.2.2 for a derivation of this result

That is, while I allow for wages ('skill prices') to adjust, I do not allow workers to respond to the price adjustment other than through staying or leaving the labor market. This ignores human capital investment responses, such as through education (Maxfield, 2015; Bastian, forthcoming), health (Dahl and Lochner, 2012), and marriage and fertility (Dickert-Conlin and Houser, 2002). However, incorporating these responses is outside the scope of this paper. See Appendix A for theoretical extension allowing this adjustment.

Second, my model ignores potential frictions in the wage-labor adjustment process. The most obvious example is the minimum wage. Recall the two type model as presented earlier, where group A is subsidized. The incidence model supposes that as the labor supply for A increases, the gross wage for A falls, so labor demand for the B market shifts outward. Suppose that A is the low-wage group with and that there is a binding minimum wage. If firms cannot absorb additional workers at the binding wage, then unemployment rises rather than employment and so there is no increase in labor demand for the B market.

While the model is silent about this, I make two points about how the results incorporate this potential friction. First, the elasticity estimates are ultimately local average treatment effects (LATEs) for the effect of the 1993 EITC expansion on wages. Thus, any market frictions that existed with the EITC should be captured in the elasticity estimates. Because I am ultimately interested in the effects of this program, the LATEs exactly provide the variation I wish to use in estimating program effects. Next, unlike in the elasticity estimation, the incidence results pool workers nationally. Thus, while imperfect, if nationally market frictions 'wash-out', then the results can be trusted. Exactly dealing with this issue is beyond the scope of the paper, and I am currently unaware of any study empirically dealing with this issue.[36]

7 Incidence of 1993 EITC Expansion

The 1993 OBRA expansion created a credit for workers without children and increased the maximum credit for workers with children leaving the terminal income the same (see Figure 2). To calculate the general equilibrium incidence of the expansion, I use the estimated elasticities and data from the 1994 Annual Social and Economic Supplement (ASEC) of the CPS that includes labor market information for tax year 1993 (Flood et al., 2018). In Appendix B, I describe the variable construction and present summary statistics for this sample. I report aggregate effects, but in Appendix E I report individual level effects and alternative specifications.

7.1 1993 Incidence Results

Table 4 presents the the gross wage incidence effects of the 1993 OBRA expansion. Specifically, it displays the own EITC ATR change, PE Incidence (direct effect), GE Incidence (direct + spillover), and the relative magnitude ('Size') of the spillover and direct effects. Note, the incidence effects are *not* normalized by a 1% tax change since the incidence effects depend on multiple tax changes across skill groups. Unmarried women without

[36] Lee and Saez (2012) theoretically consider an optimal EITC with a minimum wage, but do not empirically test any results.

a high school degree, which had the largest tax decrease, see the largest gross wage changes. In aggregate, spillovers represent between 11-18% of the total gross wage effects for unmarried women and 56-60% for married women.

Table 4 – Empirical Incidence of the 1993 EITC Expansion on 1993 Gross Wages

	Unmarried No Children				Unmarried w/ Children			
(%)	dτ	PE	GE	Size	dτ	PE	GE	Size
Less HS	-1.47	-0.41	-0.39	7.20	-2.98	-0.95	-0.93	4.30
HS	-1.16	-0.28	-0.25	10.20	-1.73	-0.41	-0.38	7.20
Some College	-0.71	-0.15	-0.12	19.30	-1.11	-0.24	-0.21	12.30
BA +	-0.25	-0.04	-0.01	47.30	-0.29	-0.04	-0.01	44.00
Total	-0.94	-0.23	-0.21	18.70	-1.70	-0.45	-0.43	11.70
	Married No Children				Married w/ Children			
(%)	dτ	PE	GE	Size	dτ	PE	GE	Size
Less HS	-0.42	-0.16	-0.13	19.40	-0.04	-0.02	0.01	34.10
HS	-0.05	-0.02	0.00	53.10	0.05	0.01	0.04	66.50
Some College	0.05	0.01	0.04	63.50	0.12	0.03	0.06	50.20
BA +	0.06	0.01	0.04	79.80	0.08	0.01	0.04	74.30
Total	-0.06	-0.03	0.00	56.50	0.06	0.01	0.04	59.60

All data from 1994 March CPS, Women from Tax Units, and TRIM3 model. Note: GE = PE + Spillover; Size = abs(Spillover) / (abs(PE) + abs(Spillover)). Values are average percent changes. Labor supply elasticities from Table 2 and column 1 in Table 3.

Table 5 translates the net wage changes into percentage point labor supply effects using the estimated labor supply elasticities. As expected, unmarried women with children and low levels of education increase their labor supply, but other groups have marginal labor supply changes.

Figure 6 visually shows the model implied GE change in labor force participation by demographic group and compares it to three alternative empirical strategies, Dickert et al. (1995); Meyer and Rosenbaum (2001), and a simple difference in difference model, described in Appendix D.1. This figure supports the claim by Kleven (2018) that prior EITC elasticity estimates may have been contaminated by concurrent factors and biased up. Using my simulated IV and model based estimate, I find attenuated (but clearly positive, non-zero) labor supply effects that are below all other estimates.

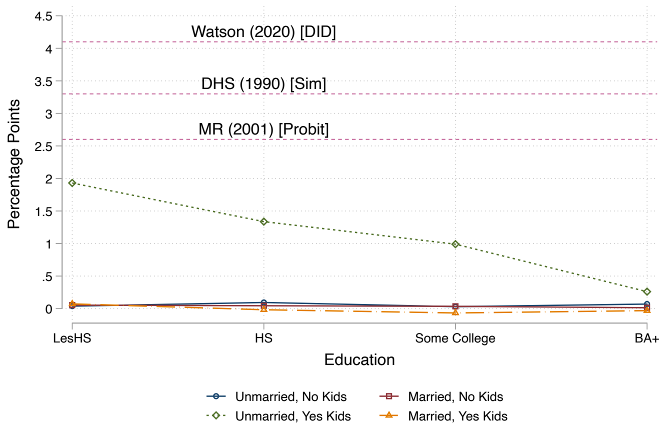
Table 6 displays the incidence effects in terms of aggregate earnings changes per dollar of new EITC expenditure to make the effects. The expansion's effect on earnings is dominated by the labor supply effect. The aggregate change in gross earnings increases by $\$0.14$ in partial equilibrium and $\$0.24$ accounting for spillover effects, which is a 71% increase. The aggregate GE effect on net earning holding taxes constant is $\$1.24$ but is

Table 5 – Empirical Incidence of the 1994 EITC Expansion on Labor Supply

	Total		Unmarried No Children		Unmarried w/ Children		Married No Children		Married w/ Children	
dL	PE	GE	PE	GE	PE	GE	PE	GE	PE	GE
Less HS	0.31	0.33	-0.01	0.01	2.11	2.12	0.04	0.06	0.06	0.07
HS	0.17	0.18	0.06	0.07	1.37	1.38	0.03	0.05	-0.02	-0.01
Some College	0.10	0.12	-0.01	0.01	1.11	1.12	0.02	0.04	-0.06	-0.05
BA+	0.01	0.02	0.04	0.06	0.16	0.17	-0.01	0.01	-0.02	-0.01
Total	0.15	0.16	0.02	0.04	1.35	1.36	0.02	0.04	-0.02	-0.01

Note: $\%\Delta L_{e,k} = \varepsilon^L_e\left(\%\Delta w_e - \mathrm{d}\tau_{e,k}\right)$. All data from 1994 March CPS, Women from Tax Units, and TRIM3 model. Values are average percentage point changes. Labor supply elasticities from Table 2 and column 1 in Table 3.

Figure 6 – Model Implied Change in LFP by Demographic Group



This plots the GE change in LFP by marriage, parental, and education group from the incidence model as well as the estimated change from alternative empirical strategies, Dickert et al. (1995); Meyer and Rosenbaum (2001), and a simple difference in difference model, described in Appendix D.1.

$\$0.55$ after accounting for changes in taxes and transfers due to earnings changes. Note, this difference is almost entirely due to lower net earnings for married mothers, who are more likely to be higher income workers with positive tax rates, rather than unmarried women who are lower income workers.

The fiscal externality is a $\$0.09$ increase per dollar of new EITC spending, implying a small net increase in government spending despite the large EITC expansion! This result complements the empirical finding by Bastian and Michelmore (2018) that the EITC 'pays for itself' as unmarried mothers who do not work tend to receive the maximal welfare benefits which is larger than the maximal EITC credit amount. Thus, moving an unmarried mother from non-work to the phase-in region of the EITC schedule results in a net positive position for the government budget.[37]

[37] Hendren (2016) uses labor supply elasticities from the EITC literature to calculate a fiscal externality of $-\$0.09$ potentially due to holding constant welfare expenditure changes. If I hold welfare program expenditure constant, then I find a fiscal externality of -0.03 that is now negative but still smaller, which likely due to the smaller labor supply elasticities that I estimate.

Across demographic groups there is considerable heterogeneity. Gross earnings decline for unmarried women without children but rise for other groups of women because the former group faces gross wage losses with essentially no increase in transfers. Net earnings decrease only for married women with children for three reasons. First and foremost, the OBRA reform implemented an asset test that *decreased* EITC amounts for higher income tax units, which tend to be married workers. Additionally, a large portion of married workers with positive EITC also face positive tax rates due to spousal earnings, so the EITC is 'taxed back.' Finally, since many married tax filers are in the phase-out region, increased gross earnings due to spillovers decreases the EITC amounts even more.

Interestingly, although wages fall for unmarried women without children, I find that *in GE* net earnings actually rise for this group. While the change is quite small, given that the PE net earnings effect is negative, the positive GE forces counteract the incidence effects which was one of the principal concerns of EITC expansions.

Table 6 – Empirical Incidence Results: Change Per Dollar of New Expenditure

	Total		Unmarried No Children		Unmarried w/ Children		Married No Children		Married w/ Children	
Dollars	PE	GE	PE	GE	PE	GE	PE	GE	PE	GE
Labor	0.32	0.36	0.05	0.06	0.29	0.29	0.01	0.03	-0.03	-0.02
Wages	-0.18	-0.12	-0.12	-0.10	-0.07	-0.07	-0.00	0.01	0.01	0.03
Gross Earnings	0.14	0.24	-0.07	-0.04	0.22	0.23	0.01	0.04	-0.02	0.02
Net Transfer, Fixed Taxes	0.82	0.88	-0.06	-0.05	0.32	0.33	0.02	0.03	0.54	0.56
Net Earn, Fixed Taxes	1.14	1.24	-0.02	0.01	0.61	0.62	0.03	0.06	0.51	0.55
Net Earnings	0.45	0.55	-0.01	0.02	0.58	0.59	0.01	0.03	-0.12	-0.09
Fiscal Externality	0.09	0.09	0.01	0.01	0.08	0.08	0.00	0.00	-0.00	-0.00

Units in table are changes in dollars of earnings summed across demographic groups. Note: $Z^G = w \cdot L$, $Z^N = (1-\tau) \cdot w \cdot L$. All data from 1994 March CPS, Women from Tax Units, and TRIM3 model. Labor elasticities from Table 2 and column 1 in Table 3.

8 Comparing EITC and Welfare Reforms

In this section, I compare three hypothetical policy reforms based on the OBRA and PRWORA reforms in the mid-1990's. The first is an exogenously funded \$100 million dollar expansions of the 1992 EITC. The second is equal sized expansion of the combined 1992 ADFC and Food Stamps programs (which I refer to as simply 'Welfare').[38] The third experiment, which I call the Net EITC reform, simultaneously expands the EITC and contracts Welfare benefits to create an *ex ante* revenue neutral EITC expansion with no distortions on higher wage markets.[39] This allows me to ignore the distortionary effects

[38] This reform is roughly the same as the hypothetical Negative Income Tax reform Rothstein (2010) considers. In Appendix E, I replicate his experiments and find qualitatively similar results.

[39] Because the experiment is a 'marginal reform,' taking the negative of the values reported for the Net EITC reform would be the same as conducting a Net Welfare expansion.

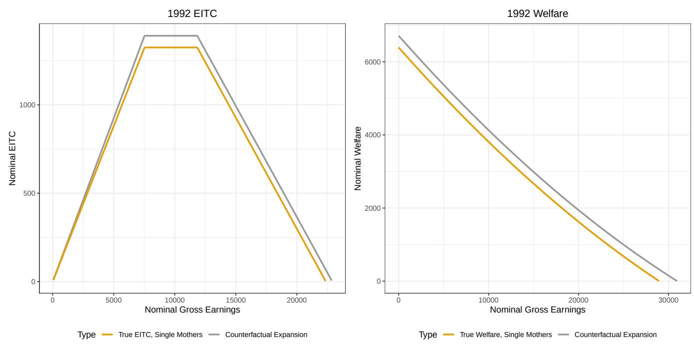
of financing the expansion as well as mirroring the tax and transfer system policy reforms of the 1990s.

8.1 Simulating the Tax Reforms

The baseline for the simulation is the 1992 pre-OBRA EITC and Welfare schedules. I calculate transfer inclusive average tax rates, calculated using the reported income data, NBER TAXSIM, and the Urban Institute's TRIM3 welfare simulator (Feenberg and Coutts, 1993; Urban Institute, 2020). For each reform, I suppose that the government wishes to increase the generosity of its tax and transfer system for low income tax units by $100 million through either an EITC expansion or Welfare expansion, but does not consider behavioral changes in response to the reforms.

To implement the EITC expansion, I solve for the new maximum credit amount holding fixed the existing 'kink points' such that the total expenditure equals the targeted amount. To implement the welfare expansion, I approximate the existing welfare system as a fixed benefit and a rate at the benefit is taxed away, and then solve for the change in the benefit such that total new expenditure equals the targeted amount while keeping the same rate. The Net EITC reform implements the EITC expansion above and the *negative* of the welfare expansion to make the reform *ex-ante* revenue neutral. Figure 7 visually shows the reform transfer programs.

Figure 7 – True and Counterfactual 1992 Transfer Programs



Plots EITC and Composite Welfare for single women with one child in 1992 using data from CPS ASEC 1993, NBER TAXSIM, and Urban Institute's TRIM3. The counterfactual EITC expansion raises the max credit holding the first two kink points fixed; the counterfactual Welfare expansion increases the base transfer amount holding the effective marginal tax rate constant.

8.2 Simulation Results

Tables 7 and 8 display the incidence results for the EITC, Welfare, and Net EITC simulated tax reforms at the aggregate and demographic level, respectively, and are interpreted the same as Table 6. For both tables, columns (1-3) show the partial equilibrium results and columns (4-6) incorporate spillovers. The upshot is that the 'bad' aspects of the EITC expansions (gross wage decreases) and the 'good' aspects of Welfare expansions (gross wage increases and positive welfare) are attenuated by the GE forces.

For the EITC, the dollar change due to wages is $-\$0.12$ in PE but only $-\$0.04$ in GE, but for the Welfare reform the $\$0.06$ wage growth in PE becomes $\$0.02$ in GE. For the

Net EITC reform, the wage decline goes from $-\$0.18$ to $-\$0.06$, a two-thirds decrease due to spillover effects. Aggregate gross earnings increase for the EITC and Net EITC programs but decrease for the Welfare expansion. This is because the Welfare expansion incentivizes workers to exit the labor force, and this source of earnings loss dominates the scarcity induced wage increases.

The difference between Net Earnings with Fixed Taxes, which Rothstein (2010) reports, and Net Earnings is that the latter measure accounts for the fact that the increase in gross wages will be taxed. If one holds taxes fixed, then the whole intended transfer is added to gross earnings, which overestimates the net earnings gain. The net earnings measure reported allows for additional earnings to be taxed (holding the ATR constant), so the some of the intended transfer goes to taxes as well as incidence effects. For the Welfare expansion, net earnings with fixed taxes is $\$0.89$ in GE but allowing for tax changes net earnings actually decrease by $-\$0.41$! For the EITC reforms, both measures of net earnings are positive.

As noted earlier, the welfare measure is the *ex post* fiscal externality of the reform. In GE, the EITC and net-EITC reforms increase revenues by $\$0.04$ and $\$0.06$, respectively, while the Welfare expansion decreases revenues by $\$0.02$. As before, the EITC expansions increase economic activity leading to a positive revenue externality. The Welfare expansion decreases economic activity by allowing workers to leave the labor force and lowering wages of other workers, which decreases revenue.

Table 7 – Incidence Results:
Aggregate Effects: All Women

Dollars	"PE"			GE		
	EITC	Welfare	Net EITC	EITC	Welfare	Net EITC
	(1)	(2)	(3)	(4)	(5)	(6)
Intended	1.00	0.65	0.35	1.00	0.65	0.35
Labor	0.22	-0.10	0.32	0.27	-0.13	0.40
Wages	-0.12	0.06	-0.18	-0.04	0.02	-0.06
Gross Earnings	0.10	-0.05	0.14	0.23	-0.11	0.34
Net Transfer, Fixed Taxes	0.88	1.06	-0.18	0.96	1.02	-0.6
Net Earn, Fixed Taxes	1.10	0.95	0.14	1.23	0.89	0.34
Net Earnings	0.50	-0.36	0.21	0.63	-0.41	0.39
Fiscal Externality	0.03	-0.02	0.05	0.04	-0.02	0.06

Table shows changes in dollars of earnings summed across demographic groups. Note: $Z^G = w \cdot L$, $Z^N = (1-\tau) \cdot w \cdot L$. All data from 1993 March CPS, Women from Tax Units. Labor supply elasticities from Model 1 in Table 2 and column 1 in Table 3.

Table 8 decomposes the aggregate effects by demographic groups for each reform. The EITC reform GE net earnings change for unmarried women with children is $\$0.79$ and 0.04 for married women with children, while net earnings fall for married and unmarried women without children by $-\$0.10$, since the latter groups receive almost no subsidy but are exposed to wage decreases. The Welfare reform GE net earnings change is negative for women with children and effectively zero for women with children.

The aggregate fiscal externality changes are almost entirely due to changes from unmarried women with children. Because the EITC and Welfare reforms primarily affect unmarried mothers' labor supply, this group drives the fiscal externality.

Table 8 – Incidence Results:
Aggregate Effects: Subgroups of Women

Dollars	"PE"			GE		
	EITC	Welfare	Net EITC	EITC	Welfare	Net EITC
	(1)	(2)	(3)	(4)	(5)	(6)
	Unmarried Mothers					
Net Earn, Fixed Taxes	0.72	0.66	0.07	0.74	0.65	0.08
Net Earnings	0.78	-0.26	0.38	0.79	-0.27	0.40
Fiscal Externality	0.04	-0.02	0.06	0.04	-0.02	0.06
	Unmarried Women					
Net Earn, Fixed Taxes	-0.15	0.03	-0.19	-0.12	0.02	-0.13
Net Earnings	-0.14	0.03	-0.17	-0.11	0.02	-0.12
Fiscal Externality	-0.01	0.00	-0.01	-0.01	0.00	-0.01
	Married Mothers					
Net Earn, Fixed Taxes	0.52	0.25	0.27	0.55	0.23	0.32
Net Earnings	-0.14	-0.14	0.01	-0.11	-0.15	0.06
Fiscal Externality	0.00	-0.01	0.00	0.00	-0.01	0.00
	Married Women					
Net Earn, Fixed Taxes	0.01	0.01	-0.01	0.04	0.00	0.04
Net Earnings	0.01	0.01	-0.01	0.04	0.00	0.04
Fiscal Externality	0.00	0.00	0.00	0.00	0.00	0.00

Table shows changes in dollars of earnings summed within demographic groups. Note: $Z^G = w \cdot L$, $Z^N = (1-\tau) \cdot w \cdot L$. All data from 1993 March CPS, Women from Tax Units. Labor supply elasticities from Model 1 in Table 2 and column 1 in Table 3.

9 Structural Model Parameterization

The previous results were all derived using only the assumption of quasi-linearity of the utility function. In this section, I add a distributional assumption about the worker specific disutility of labor that allows me to parameterize demographic specific labor supply functions to calculate general equilibrium results for non-marginal and out-of-sample reforms. Specifically, I use labor participation probabilities and my elasticity estimates to parameterize a standard 'logit' binary choice model.

9.1 Structural Model

The utility problem for workers is the following discrete choice:

$$\max_{L=\{0,1\}} \{\underbrace{u_i\left(T_c(0,m_i)\right)-\nu_i(0)}_{L=0},\ \underbrace{u_i\left(T_c(w_i,m_i)\right)-\nu_i(1)}_{L=1}\}, \tag{25}$$

where ν_i is the idiosyncratic disutility of labor drawn from some distribution, $F_{e,c}(\nu)$. Initially, I assumed that $u_i(x)=x$, but now suppose that $u_i(x)=\beta_{e,c}\cdot x$, where $\beta_{e,c}$ can be interpreted as type-specific marginal utility of consumption. Additionally, suppose $\nu_i(0)-\nu_i(1)=\delta_{e,c}+\epsilon_i$, where ϵ_i distributed independent Type 1 Extreme Value ($F(\epsilon)=\mathrm{e}^{-\mathrm{e}^{-\epsilon}}$) and $\delta_{e,c}$ is interpreted as an unobserved utility cost of labor (a supply 'shifter'). Then, demographic-specific labor supply probability is:

$$\Pr(L^i=1\mid w_e,m_{e,c},T_c)=\frac{\mathrm{e}^{\beta_{e,c}T_c(w_e,m_{e,c})+\delta_{e,c}}}{\mathrm{e}^{\beta_{e,c}T_c(0,m_{e,c})}+\mathrm{e}^{\beta_{e,c}T_c(w_e,m_{e,c})+\delta_{e,c}}}:=\pi_{e,c}. \tag{26}$$

9.2 Recovering Structural Parameters

Defining $\mathsf{v}_{e,c}:=T_{e,c}(w_e,m_{e,c})-T_{e,c}(0,m_{e,c})$ as the net wage, the model implies that:

$$\text{Gross Wage Elasticity:}\quad \varepsilon^L_{e,c}=\frac{\partial\pi_{e,c}}{\partial w_e}\frac{w_e}{\pi_{e,c}}=\beta_{e,c}\frac{\partial\mathsf{v}_{e,c}}{\partial w}w_e(1-\pi_{e,c}) \tag{27}$$

$$\text{Net Wage Elasticity:}\quad \eta^L_{e,c}=\frac{\partial\pi_{e,c}}{\partial\mathsf{v}_{e,c}}\frac{\mathsf{v}_{e,c}}{\pi_{e,c}}=\beta_{e,c}\mathsf{v}_{e,c}(1-\pi_{e,c}). \tag{28}$$

If the transfer function is $T_{e,c}(w_e,m_{e,c})=(1-\tau_{e,c})(w_eL)+b_{e,c}(1-L)+t(m)$, so that the net wage is $(1-\tau_{e,c})(w_e)$, then $\frac{\partial\mathsf{v}_{e,c}}{\partial w}w_e=\mathsf{v}_{e,c}$ so that $\varepsilon^L_{e,c}=\eta^L_{e,c}$. Thus, I can recover the marginal utility of consumption parameters using the following:

$$\frac{\varepsilon^L_{e,c}}{(\mathsf{v}_{e,c}(1-\pi_{e,c}))}=\beta_{e,c}. \tag{29}$$

With an estimate of $\beta_{e,c}$, I can then recover the unobservable net supply shifters using a Berry (1994) style inversion technique:

$$\ln\left[\pi_{e,c}\right]-\ln\left[(1-\pi_{e,c})\right]-(\beta_{e,c}\mathsf{v}_{e,c})=\delta_{e,c}. \tag{30}$$

With the estimated structural utility parameters $\{(\widehat{\beta}_{e,c},\widehat{\delta}_{e,c})\}_{(e,c)\in\mathcal{D}}$, I can simulate non-differential EITC reforms. Note, I estimate these parameters based on the elasticities estimates from the 1990's, so the underlying assumption of these parameters is that β is a fixed utility parameter and any changes over time (conditional on the net wage) occur through the shifter, δ.

10 Childless Worker Reform

Advocacy groups encourage policymakers to reform the EITC schedule such that workers without children are treated the same as workers with children.[40] Advocates cite issues related to horizontal equity on the basis of skill as well as lifting more workers out of poverty. Another reason is, given that there are negative earnings effects for childless workers who are close substitutes, expanding the EITC for these workers can offset the incidence effects just like for unmarried women with children.

To quantify the effects of this reform, I equalize the 1994 EITC schedule for workers without children and workers with one qualifying dependent.[41] That is, I create a counterfactual OBRA expansion where the credit for workers without children was equalized rather than set with a max of $306. My model based approach can describe the labor supply and earnings effects of this and predict any additional take-up that may occur.

Note, the structural model results below and the incidence model results above do not yield the same quantitative values for two reasons. First, the incidence results use analytic results for changes in ATRs, while the structural results numerically solve for market clearing prices. Second, the incidence results, based on marginal changes in ATRs, hold constant other features of the tax and transfer system, while the structural results incorporate tax liability changes when calculating labor supply. Thus, the incidence model describes how the EITC expansions are shared between workers and the structural model shows the total effect of equalizing the EITC schedules on market equilibrium incorporating spillovers.

10.1 Childless Worker Reform Results

In Tables 9 and 10, I display the results of the policy reform. To make comparisons as close as possible, I solve the model using the actual EITC schedule in tax year 1993 as a baseline, next solve the model using the actual 1994 schedule, and then solve the model using the counterfactual 1994 schedule. This holds all non-labor-market variables constant, such as labor supply shifters, aggregate productivity or demand shifts, and capital supply shifts. I then calculate the changes for each expansion from the baseline.

There are two striking elements from the results. First, equalizing the credit schedules would substantially increase labor supply for unmarried workers without children – an 4.8 percentage point (ppt) increase in aggregate. This is because these workers have a greater labor supply elasticity than workers with children and the expanded credit substantially increases their net income. Second, equalization creates a countervailing effect on unmarried mothers' the labor supply – from 1.5 to 1.0 ppts in aggregate and 2.5 to 1.4 ppts for those without a high school degree. This is due the same gross wage

[40] See discussions in Nichols and Rothstein (2016); Marr et al. (2016); Maag et al. (2019). Nichols and Rothstein (2016) note that both former President Obama and then former House Ways and Means committee chairman Ryan both advocated for increasing the generosity for childless workers.

[41] My reform is larger than many existing proposals. Maag et al. (2019) use the 2016 American Community Survey to parameterize an equalization reform that triples the childless worker maximum credit and doubles the kink-point thresholds, but hold gross wages and labor supply constant, which ignores behavioral responses or incidence effects. President Obama's proposal doubled the maximum credit and extended the second kink-point by half Executive Office of the President and US Department of Treasury (2014).

incidence effects from the much larger labor supply shock that advocates cite when promoting a childless worker expansion. Gross wages for unmarried workers initially decrease by about $0.6 - 0.7\%$ under the actual expansion but decrease between $2.4 - 3.6\%$ under the expansion regime.[42]

Table 9 – Empirical Incidence Results:
1994 EITC Expansion + Equalization of Credit Schedule

Percent Change in Wages

$\%\Delta w$	Unmarried No Children Act	Cft	Diff	Unmarried w/ Children Act	Cft	Diff	Married No Children Act	Cft	Diff	Married w/ Children Act	Cft	Diff
LessHS	-2.33	-7.63	-5.44	-2.10	-6.21	-4.21	-0.10	-1.87	-1.78	-0.30	-0.42	-0.13
HS	-0.17	-2.35	-2.19	-0.25	-1.79	-1.54	0.05	0.31	0.26	0.05	0.33	0.28
Some College	-0.36	-3.03	-2.69	-0.19	-0.98	-0.90	0.05	0.31	0.26	0.05	0.33	0.28
BA+	0.05	-0.09	-0.15	0.06	0.27	0.21	0.06	0.36	0.30	0.06	0.38	0.32
Total	-0.76	-3.55	-2.84	-0.65	-2.41	-1.79	0.03	0.01	-0.02	0.01	0.25	0.24

Percentage Point Change in Labor Supply

dL	Unmarried No Children Act	Cft	Diff	Unmarried w/ Children Act	Cft	Diff	Married No Children Act	Cft	Diff	Married w/ Children Act	Cft	Diff
LessHS	1.54	7.94	6.17	2.52	1.38	-1.07	-0.06	1.45	1.52	0.49	0.51	0.02
HS	-0.12	4.98	5.11	1.46	1.02	-0.42	0.03	0.19	0.16	0.02	0.14	0.12
Some College	0.40	5.93	5.47	1.05	0.82	-0.22	0.04	0.25	0.21	0.02	0.14	0.12
BA+	0.02	0.94	0.92	0.07	0.13	0.06	0.03	0.20	0.17	0.01	0.08	0.06
Total	0.50	5.33	4.76	1.45	0.96	-0.47	0.02	0.39	0.37	0.08	0.17	0.10

'Act' : Actual EITC schedules; 'Cft' : Counterfactual EITC schedule where workers with no children get same credit as workers with one child; 'Diff' : Equalization specific effects All data from 1994 March CPS, Women from Tax Units. Values are average percent changes, weighted population.

Table 10 puts the effects in terms of dollars of planned new expenditure and shows three important facts. First, neither the actual or counterfactual reform has much effect on married women mostly because these workers have household earnings that are too high to be affected by the policy. Second, the reforms have similar aggregate effects in terms of earnings and welfare measures. Third, the reforms have similar aggregate effects because the labor supply effects of the policy are almost exactly reversed for the unmarried women. Those without children supply more labor but those with children become much less likely to join the labor force.

While equalizing the EITC schedule may be more 'fair' and certainly will help many low income workers, these results imply that such a reform does not come without a cost. Policymakers wishing to reform the EITC face a dilemma: the current structure disadvantages workers without children but reforming the EITC may harm workers with children (and through secondary effects their children). Just as policymakers should

[42]The wage changes in Table 9 are slightly different between unmarried workers with and children because workers do not perfectly overlap in demographic-skill based markets.

Table 10 – Empirical Incidence Results:
1994 EITC Expansion + Equalization of Credit Schedule
Change Per Dollar of New Planned Expenditure

	Total		Unmarried No Children		Unmarried w/ Children		Married No Children		Married w/ Children	
Dollars	Act	Cft	Act	Cft	Act	Cft	Act	Cft	Act	Cft
Labor	0.62	0.65	0.11	0.51	0.42	0.05	0.03	0.05	0.05	0.03
Wages	-0.12	-0.11	-0.14	-0.16	-0.07	-0.04	0.04	0.04	0.05	0.06
Gross Earnings	0.50	0.51	-0.03	0.33	0.35	0.01	0.07	0.08	0.11	0.09
Net Transfer, Fixed Taxes	0.88	0.89	0.12	0.70	0.64	0.07	0.04	0.05	0.08	0.06
Net Earn, Fixed Taxes	1.50	1.51	0.23	1.19	1.06	0.12	0.07	0.10	0.14	0.09
Net Earnings	1.37	1.41	0.23	1.14	0.97	0.12	0.05	0.08	0.11	0.07
Welfare	-0.10	-0.09	-0.01	-0.06	-0.07	-0.01	-0.01	-0.01	-0.01	-0.01

'Act' : Actual EITC schedules; 'Cft' : Counterfactual EITC schedule where workers with no children get same credit as workers with one child. Units in table are changes in dollars of earnings summed across demographic groups. Note: $Z^G = w \cdot L$, $Z^N = (1-\tau) \cdot w \cdot L$. All data from 1994 March CPS, Women from Tax Units.

consider the spillover effects from the current EITC structure, they should be sure to understand the trade-offs in terms of families from a structural reform of the EITC.

11 Incidence of the 2009 EITC Expansion

In this section, I consider the labor market effects of the 2009 EITC expansion that was part of the American Recovery and Reinvestment Act of 2009. The reform made the credit schedule more generous for workers with three or more qualifying children as well as for married workers by extending the 'max credit' portion of the EITC to reduce 'marriage penalties' (Nichols and Rothstein, 2016).[43] The reform was intended to provide counter-cyclical income support for low wage workers rather than strengthening labor force attachment.[44] Nevertheless, because the expansion is the second largest EITC reform after the 1993 expansion, the reform gave economists an opportunity to revisit the EITC's labor market effects. In short, Iribarren (2016) and Kleven (2019) find no statistically significant effect from this reform.

There are three potential explanations for this. First, there was no effect, which is a conjecture recently advanced by Kleven (2019). Second, there were prevailing forces that dominated any EITC effect and a clean experiment is not possible. The existing papers rely on treatment and control group based estimates that should purge the overall economic forces during the recession period, so the results depend on appropriateness of these grouping decisions. Third, the reform was too small to see a large labor supply effect, even holding economic conditions constant. The expansion increased the maximum

[43] The expansions were set to expire in 2017 but have since been made permanent.

[44] It is theoretically ambiguous how the EITC fares in a recession since the laid-off worker will likely lose eligibility whereas workers with reduced hours may become eligible. Jones (2017) uses linked CPS-IRS data to show that unmarried mothers with low education had a higher likelihood of losing eligibility and lower likelihood of gaining eligibility through lost earnings.

credit by $600, which may not be enough to create large labor supply changes, and the targeted groups – workers with 3+ children, married workers – are a small proportion of the EITC claimers.

My incidence analysis allows me to provide a benchmark estimate of the 2009 expansion effects. If the labor market effects are small even when I am able to hold all other economic conditions constant, then this implies that standard difference-in-difference evidence may simply be under-powered to detect an effect. However, if the effects of the expansion are comparable to the larger 1993 expansion, then the a change in labor market fundamentals is necessary to explain the empirical null findings. Additionally, the results provide insight into *why* EITC expansion may have different effects over time. If labor supply elasticities are falling or costs increasing, then larger and larger EITC expansions are necessary to achieve the same labor supply effects.

11.1 2009 Incidence Results

Compared to Table 4, Table 11 shows that the tax rate change for unmarried women was less than a third of the 1993 EITC expansion but the expansions were similar for married women. As such, the 2009 direct and spillover effects are much smaller than the 1993 case; in fact, the spillover effects are effectively zero.

Table 12 shows that unmarried mothers' aggregate labor supply should have increased by 0.6% while other groups show essentially no change, compared with 1.4% for the 1993 expansion. Despite the fact that the 2009 expansion reduced the two earners 'marriage penalty,' there is essentially no effect for married workers. The aggregate general equilibrium labor supply change effect is only 0.05%.

Finally, in Table 13, I show the per dollar effect of the 2009 expansion. Again, the direct and spillover effects are much smaller than the 1993 expansion, with essentially no scope for spillovers. The aggregate gross and net earnings changes are both less than half of the 1993 per dollar effects. This implies near zero fiscal externality because there was little behavioral change.

12 Conclusion

I evaluate the Earned Income Tax Credit allowing for general equilibrium interactions in the labor market and heterogeneous wage responsiveness. My approach allows one to evaluate any large scale program that affects average tax rates by mapping those changes to gross wages and labor supply as long as one has information on initial wages, quantities, and elasticities. When labor markets are imperfect substitutes, a tax induced supply change in one market will affect the marginal product of workers in other markets, creating cascading marginal product and wage spillovers across labor markets. Because the general equilibrium wage changes are theoretically ambiguous, I quantified the importance of general equilibrium effects in three ways.

First, I calculated the empirical incidence of the 1993 OBRA and 2009 ARRA EITC expansion. I find that spillovers represent about 15-30% of aggregate wage and net earnings effects in the direction of increasing dollars to workers. Second, to compare

Table 11 – Empirical Incidence of the 1993 EITC Expansion on 1993 Gross Wages

	Unmarried No Children				Unmarried w/ Children			
%	dτ	PE	GE	Size	dτ	PE	GE	Size
LessHS	-0.40	-0.12	-0.12	5.00	-0.85	-0.31	-0.31	2.90
HS	-0.38	-0.09	-0.09	8.60	-0.66	-0.15	-0.15	4.80
Some Col.	-0.23	-0.06	-0.05	13.60	-0.45	-0.11	-0.11	7.10
BA+	-0.08	-0.02	-0.01	34.40	-0.12	-0.02	-0.02	24.20
Total	-0.27	-0.07	-0.06	15.30	-0.53	-0.14	-0.14	8.40
	Married No Children				Married w/ Children			
%	dτ	PE	GE	Size	dτ	PE	GE	Size
LessHS	-0.19	-0.07	-0.07	15.80	-0.21	-0.08	-0.07	23.00
HS	-0.02	-0.01	0.00	35.80	0.04	0.01	0.02	33.20
Some Col.	0.04	0.01	0.02	49.70	0.13	0.03	0.04	20.30
BA+	0.05	0.01	0.01	49.40	0.10	0.01	0.02	33.20
Total	0.01	0.00	0.00	42.20	0.06	0.01	0.02	28.60

All data from 2009 March CPS, Women from Tax Units. Note: GE = PE + Spillover; Size = abs(Spillover) / (abs(PE) + abs(Spillover)). Values are average percent changes, weighed by population. Labor supply elasticities from structural model; equation 29.

Table 12 – Empirical Incidence of the 2009 EITC Expansion on Labor Supply

	Total		Unmarried No Children		Unmarried w/ Children		Married No Children		Married w/ Children	
dL	PE	GE	PE	GE	PE	GE	PE	GE	PE	GE
Less HS	0.11	0.11	-0.05	-0.05	1.00	1.00	0.00	0.01	0.10	0.10
HS	0.06	0.07	-0.06	-0.06	0.65	0.65	0.01	0.01	-0.02	-0.02
Some College	0.03	0.04	-0.04	-0.04	0.56	0.56	0.01	0.02	-0.07	-0.07
BA+	-0.00	0.00	-0.00	-0.00	0.18	0.18	0.01	0.01	-0.03	-0.03
Total	0.04	0.05	-0.04	-0.04	0.60	0.60	0.01	0.01	-0.03	-0.03

Note: $\%\Delta L_{e,k} = \varepsilon_e^L \left(\%\Delta w_e - \mathrm{d}\tau_{e,k}\right)$. All data from 2009 March CPS, Women from Tax Units. Values are average percent point changes, weighed by population. Labor supply elasticities from structural model; equation 29.

how different labor market policies affect spillovers, I simulated a $100 million expansion of the EITC, of the AFDC and Food Stamps programs, and a reform that pays for the EITC expansion by reducing Welfare benefits. For all three policy reforms experiments, the GE incidence is less than one-third the PE incidence – for the EITC reforms this implies

Table 13 – Empirical Incidence of the 2009 EITC Expansion: Change Per Dollar of New Expenditure

	Total		Unmarried No Children		Unmarried w/ Children		Married No Children		Married w/ Children	
Dollars	PE	GE	PE	GE.	PE	GE	PE	GE	PE	GE
Labor	0.12	0.14	-0.04	-0.04	0.21	0.21	0.01	0.02	-0.05	-0.05
Wages	-0.07	-0.05	-0.05	-0.05	-0.04	-0.04	0.00	0.01	0.02	0.03
Gross Earnings	0.05	0.09	-0.10	-0.09	0.17	0.17	0.02	0.03	-0.03	-0.02
Net Transfer, Fixed Taxes	0.93	0.95	-0.05	-0.04	0.21	0.21	0.02	0.03	0.75	0.75
Net Earn, Fixed Taxes	1.05	1.09	-0.09	-0.08	0.42	0.42	0.03	0.04	0.69	0.70
Net Earnings	0.17	0.20	-0.08	-0.07	0.43	0.43	0.01	0.02	-0.200	-0.19
Welfare	0.00	0.00	-0.00	-0.00	0.01	0.01	0.00	0.00	-0.01	-0.01

Units in table are changes in dollars of earnings summed across demographic groups. Note: $Z^G = w \cdot L,\ Z^N = (1-\tau) \cdot w \cdot L$. All data from 2009 March CPS, Women from Tax Units. Labor supply elasticities from structural model; equation 29.

more dollars go to workers while for the Welfare reform workers receive fewer dollars. Third, I used my elasticities to parameterize a structural labor supply model to consider the effect of equalizing the the EITC schedule for workers with and without children. I find that equalizing the EITC would have the opposite issue of current EITC expansions: gross wage decreases would causes marginal workers with children *not* to enter the labor market.

Overall, these results show that the EITC is a cost effective program in transferring income to low wage workers. In all cases, the fiscal externality of the EITC expansions is always quite small relative to the increases in net earnings. The 1993 expansion created large labor market direct and indirect effects; however, the 2009 expansion appears not to have caused labor market disruptions. The best explanation for this seems to be simply that the 2009 expansion was smaller, focused on a smaller group, and in an environment where many people were already working. When labor market disruptions are small, the program is primarily functioning as an immediate anti-poverty tool in that dollars go to low income workers without distorting untreated workers' behaviors. When they are large, the program is acting as a immediate and long-run anti-poverty tool by increasing the earnings potential of workers and the economy as a whole.

The above assessment of the EITC's cost effectiveness is not without some caveats. First, the EITC has a positive fiscal externality only because net transfers from non-employment to employment are positive rather than due to spillovers. Thus, while positive marginal product spillovers expand the economic capacity of the economy and tax base, ignoring this interaction with other transfers, the EITC would not 'pay for itself.' Second, the EITC has heterogeneous effects that may not yield horizontal equity. Similar skilled workers without children will be subject to gross earnings effects but will not receive the subsidy. I find that the welfare effects are ultimately small for these workers; nevertheless, proponents of expanding the EITC must accept that some workers will be financially hurt. As indicated, this also holds for those who want to expand the EITC for worker without children. Third, choosing an EITC expansion over a Welfare expansion – or any other policy that links benefit levels with non-employment – implies a judgement about the marginal value of leisure for workers on the margin of the labor supply threshold.

Finally, my approach still makes a number of simplifications worth pointing out. First, the production technology assumes a constant elasticity of substitution, so all factors are (imperfectly) substitutable in the same way. Second, the incidence is derived assuming frictionless labor market assumptions; e.g., perfect competition, price taking. Third, the model has abstracted from fully modeling the tax system or incorporating different industries or trade patterns. Incorporating and resolving these issues would be an interesting, informative, and potentially important contribution to understanding the incidence effects of government programs.

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A Theory Appendix

In this appendix, I describe additional theoretical details of the model in the main text as well as consider two theoretical extensions. First, I present the parameters for the numerical comparative statics from Figure 3 and describe how welfare is calculated within the model. Second, I present the equilibrium conditions that lead to the the many type model that is used in the empirical exercises. Adding additional types of labor in this context is relatively simple due to the symmetry of the modeling assumptions. Next, I return to the two skill model but now the high skill worker is able to switch between sectors. This extension is essentially a simplified version of Saez (2002) with endogenous wages. Finally, in the two skill model, I allow for two consumption goods producing industries that employ both high and low skill workers. This extension essentially 'stacks' the equilibrium conditions used in the single industry model in the main text.

A.1 Incidence Value Comparison

Here, I compare the gross wage incidence from a one percent tax change[45] between PE and GE and across labor market elasticities. I use equation 13 for the PE incidence and I use equation 15 for the GE incidence. The main takeaway is that the incidence effect magnitude depends primarily on the labor substitution elasticity, ρ, and the cost share of the subsidized market, s_{L0}.

In Table 14, I present incidence values for various parameter pairings. I use the following baseline parameters: $\varepsilon^L_{0,0} = \varepsilon^L_{0,1} = 0.75$, $\varepsilon^L_{1,0} = \varepsilon^L_{1,1} = 0.6$, and $\varepsilon_K = 1$, based on Rothstein (2010), Eissa and Hoynes (2004), and Goolsbee (1998), respectively. For the elasticity of substitution I use $\rho \in \{-0.3, -1, -2\}$, based on Rothstein (2010), my empirical analysis presented later ($\rho = -2$), and an intermediate value. I set $s_L = 0.66$ based on the approximate 1990s labor share of input costs. I set $s_{L0} = 0.125$ and $s_{L1} = 0.66 - s_{L0}$, based on the 1992 March CPS and my own calculations. For the first two panels I assume

[45] That is I plot $\hat{w}_0/(\theta_{0,1}\hat{\tau})$, so that these results are not affected by the share of eligible workers within a skill level.

that only the low wage market is subsidized ($\hat{\tau}_{1,1}/\hat{\tau}_{0,1} = 0$), but in the third panel I allow for a smaller subsidy on the high wage workers, $(\hat{\tau}_{1,1}/\hat{\tau}_{0,1}) > 0$.

Table 14 – Summary:
Percent Change in Gross Wage for Low Wage Market
from 1% Subsidy Increase

	Partial Equilibrium	General Equilibrium
	Using Baseline Supply Elasticities	
$\rho = -0.3$	-0.714	-0.645
$\rho = -1$	-0.429	-0.390
$\rho = -2$	-0.273	-0.252
	Other Elasticities with $\rho = -2$	
$\varepsilon_0^L = 1.0$	-0.333	-0.269
$\varepsilon_1^L = 0.3$	-0.273	-0.254
$\varepsilon_1^L = 0.9$	-0.273	-0.251
$\varepsilon^K = 2$	-0.273	-0.249
	Allowing $\hat{\tau}_{1,1} > 0$ with $\rho = -2$	
$\frac{\hat{\tau}_{1,1}}{\hat{\tau}_{0,1}} = 0.1$	-0.273	-0.240
$\frac{\hat{\tau}_{1,1}}{\hat{\tau}_{0,1}} = 0.2$	-0.273	-0.228

Baseline: $\varepsilon_0^L = 0.75, \varepsilon_1^L = 0.6, \varepsilon_K = 1, \frac{\hat{\tau}_{1,1}}{\hat{\tau}_{0,1}} = 0$
Incidence results computed at $s_{L0} = 0.125, s_L = 0.66$

Table 14 shows that the general equilibrium incidence always attenuates the PE incidence, especially as market size grows. The results highlight that the labor substitution elasticity appears to dictate the magnitude of the incidence effect. Using the value $\rho = -0.3$ from Rothstein (2010) implies a PE incidence of -0.71% while a $\rho = -2$ implies only a -0.25% change in gross wages.

Figure 3 is a graphical representation of Table 14. I plot the partial and general equilibrium incidence of the gross wage at different labor cost shares ($s_{L0} \in [0, 1]$) and different substitution elasticities. The flat lines are the PE incidence and the upward sloping lines are the GE incidence. The graphical representation shows that as more workers are subsidized the GE incidence effects can quickly diverge from the PE effects.

A.2 Welfare

Here, I describe the measure of welfare in the model and changes due to tax policy.

For this section, I adjust the notation. Let $i \in \mathcal{N}$ index each specific worker: $i = (e_i, c_i, \nu_i)$. Let each worker have some non-labor income, m_i. Let each worker own some share of the firms in the economy,$\varsigma_i \in [0,1]$, such that $\sum_{i \in \mathcal{N}} \varsigma_i = 1$.

A.2.1 Welfare

Total welfare in the economy is the sum of utility given the optimal decisions by workers and firms. In terms of Chetty (2009), with an added capital revenue equation,[46] the model is the following:

$$\text{Utility}: \quad U(X, L; \nu) = X + \nu \cdot L \tag{31}$$

$$\text{Tax Function}: \quad T_i(wL, m) = (w + \tau_i)L - b_i(1 - L) - n_i \tag{32}$$

$$\text{Capital Revenue}: \quad R = \int_j ((r - \xi_j) \cdot k_j) \, \mathsf{d}_j \tag{33}$$

$$\text{Budget Set}: \quad X + T_i(wL, m) - wL - m \leq 0 \tag{34}$$

Thus, aggregate welfare with a Utilitarian SWF is aggregate consumption plus the utility cost of labor for those that work:

$$\begin{aligned}
W &= \int_i \nu_i \mathsf{d}_i + \int_i (T_i) \, \mathsf{d}_i && (35)\\
&= \int_i ((w_i L_i - T_i) + \nu_i(L_i) + \varsigma_i R) \, \mathsf{d}_i + \int_i (T_i) \, \mathsf{d}_i && (36)\\
&= \int_i ((w_i L_i) + (\nu_i \cdot L_i) + \varsigma_i R) \, \mathsf{d}_i. && (37)
\end{aligned}$$

A.2.2 Welfare Changes

The change in welfare for the economy is determined by totally differentiating the aggregate welfare measure. I follow the methods specified in Chetty (2009) and Kleven (2018). That is, I totally differentiate equation 36 holding unemployment benefits constant but

[46] Recall that each worker has some $\varsigma_\nu \in (0, 1)$ share of capital revenue as part of unearned income that is taken as given in the labor supply choice.

adjusting the lump sum tax to finance the subsidy increase (and recall that $\tau_i = \mathsf{d}\tau_i = 0$ if $(e_i, c_i) \neq (0, 1)$):

$$\begin{aligned}
\mathsf{d}W^{\mathsf{GE}} &= \int_i \left((\mathsf{d}w_i + \mathsf{d}\tau_i)L_i + (w_i + \tau_i - b_i)\mathsf{d}L_i + \frac{\partial \nu_i}{\partial L_i}\mathsf{d}L_i + \varsigma_i \mathsf{d}R - \mathsf{d}n_i \right) \mathsf{d}_i \\
&\quad + \int_i (-\mathsf{d}\tau_i L_i - (\tau_i - b_i)\mathsf{d}L_i + \mathsf{d}n_i)\, \mathsf{d}_i && (38) \\
&= \int_i ((\mathsf{d}w_i)L_i + \varsigma_i \mathsf{d}R)\, \mathsf{d}_i + \int_i (-(\tau_i - b_i)\mathsf{d}L_i)\, \mathsf{d}_i && (39) \\
&= \int_i (-(\tau_i - b_i)\mathsf{d}L_i)\, \mathsf{d}_i = -\int_i \left((\tau_i - b_i)\varepsilon_i^L(\mathsf{d}w_i + \mathsf{d}\tau_i)\right) \mathsf{d}_i && (40) \\
&= -\int_i \left((\tau_i - b_i)\varepsilon_i^L((1+\gamma_i)\mathsf{d}\tau_i + \Gamma_i)\right) \mathsf{d}_i. && (41)
\end{aligned}$$

From equation 38 to 39, I use the envelope condition to remove $\frac{\partial \nu_i}{\partial L_i}$; from 39 to 40, I use the zero profit condition to show that $\mathsf{d}R = \int_i ((\mathsf{d}w_i)L_i)\, \mathsf{d}_i$; and from 40 to 41, I use the incidence result to characterize the "fiscal externality" in terms of elasticities (Hendren, 2016; Kleven, 2018). The welfare measure's negative sign because the behavioral fiscal externality implies that the government is paying more subsidies due to the extensive margin response. However, if $\mathsf{d}L_i > 0$, then the government is also paying less in unemployment benefits, as empirically shown in Bastian and Michelmore (2018).

The above supposes that lump sum taxation is used, so the fact that wages rise for other workers is not part of the fiscal externality; i.e., the fact that greater earnings lessen the need to change the lump sum tax. If instead an income tax was used (with individual rate t_i), then the change in welfare is the following:

$$\mathsf{d}W^{\mathsf{GE}} = \int_i (t_i w_i \mathsf{d}L_i)\, \mathsf{d}_i = \int_i \left(t_i w_i \varepsilon_i^L((1+\gamma_i)\mathsf{d}\tau_i + \Gamma_i)\right) \mathsf{d}_i. \tag{42}$$

See that high wage workers now contribute the following term to the welfare change: $t^H w^H \Gamma^H > 0$. Because tax revenues increase for the high wage group, the government's budget constraint is further loosened which lessens the negative fiscal externality. The welfare change in this case cannot be theoretically signed, so the welfare impact becomes an empirical to question.

A.3 Model with Many Worker Types

Here, I allow for each labor type to have a heterogeneous tax change, and then I solve the equations in the same manner as before using substitution after totally differentiating. Let worker types be indexed by $e \in \{0, 1, 2, \ldots, E\} = \mathcal{E}$.[47]

I use the following equilibrium system (suppressing labor supply arguments):

$$\text{Labor Clearing} \quad \frac{L_{\mathring{e},0} + L_{\mathring{e},1}}{L_{\tilde{e},0} + L_{\tilde{e},1}} = \left(\frac{w_{\mathring{e}}/\theta_{\mathring{e}}}{w_{\tilde{e}}/\theta_{\tilde{e}}}\right)^{\rho} \qquad \forall \tilde{e} \in \mathcal{E} \setminus \mathring{e} \tag{43}$$

$$\text{Factor Clearing} \quad \frac{\sum_e L_e}{K^S(r)} = \left(\frac{\bar{w}/\alpha}{r/1-\alpha}\right)^{-1} \tag{44}$$

$$\text{Zero Profits} \quad P = c\left(\{w_e\}_{e \in \mathcal{E}}, r\right) := 1 \tag{45}$$

The incidence is solved using by taking the total derivative to linearize the system and then either iterative substitution or Cramer's rule to solve for the factor price changes as a function of the tax change. By adjusting the labor clearing condition (equation 43), I can solve for any specific market's incidence.

The general equilibrium incidence for type 0 labor is:

$$\hat{w}_0^{\mathsf{GE}} = \frac{-\varepsilon^L_{(0,1)}\theta_{0,1}\hat{\tau}_0}{\varepsilon^L_0 - \rho} + \frac{\Lambda\left(\sum_e \frac{s_e \varepsilon^L_{(e,1)}\theta_{e,1}\hat{\tau}_e}{\varepsilon^L_e - \rho}\right)}{(\varepsilon^L_0 - \rho)\left(1 + \Lambda\left(\sum_e \frac{s_e}{\varepsilon^L_e - \rho}\right)\right)} \tag{46}$$

$$= (\gamma_0 + \Gamma_0)\hat{\tau}_0 + \Psi_0(\{\tau_e\}_{e \in \mathcal{E} \setminus e=0}) \tag{47}$$

$$\text{where } \Lambda = \left(\frac{\varepsilon_K + 1}{s_K} + \frac{1+\rho}{s_L}\right). \tag{48}$$

Generally, one cannot sign the expression without knowing the direction of each $\{\tau_d\}_d$. This is similar to Agrawal and Hoyt (2018) in the context of taxing multiple consumer goods. For example, if the own tax change is large but all other tax changes are small, then very likely the partial equilibrium term will dominate, so the expression is negative. However, if the own tax change is small but all other are large and positive, then the general equilibrium spillovers will dominate, so the expression is positive.

Again, this shows that generally there will be **two** first order terms with respect to the tax change. Only if the general equilibrium spillover term is small will $w^{\mathsf{GE}} \approx w^{\mathsf{PE}}$. Note,

[47] In the calibrated model, $|\mathcal{E}| = 72$ based on age, education, and marital status of women.

with multiple tax changes, it is no longer sufficient to suppose that $s_0 \approx 0$ for the GE terms to disappear. Rather, one needs to assume that the average cost share weighted tax change is equal to zero: $\mathsf{E}[s_e \theta_{e,1} \hat{\tau}_e] \approx 0$.

A.4 Model with Market Switching

Here, I return three factor model but I allow the high wage workers, $e = 1$, to switch between markets. Additionally, I allow for a differential tax change in both labor markets.

This set up is similar to the model used in Saez (2002), only simplified to fewer employment groups. This allows $e = 1$ workers to substitute between unemployment, low wage work, and high wage work. Workers with $e = 0$ are only able to adjust between unemployment and low wage work.

For example, in the EITC context, suppose that high wage mothers see the net low-wage sector wage increase relative to high-wage work, and if this worker is marginally attached to high wage work, then there she will switch to low wage work. Alternatively, if a $e = 1$ worker without children originally chose low-wage work, then the potential real wage decrease relative to the high-wage sector will cause this worker to choose high wage work.

In this framework notation can get messy because workers of the same (e, c) can earn different wages, so I need to track both worker type and worker labor choice for four different types of workers and three sectors. This is not conceptually difficult, but messy. I assume that $e = 1$ workers are paid equal to $e = 0$ if they participate in the low-wage sector. One foundation for this is that low-wage work involves some set tasks that cannot benefit from high-wage worker's skills, so workers of both e types will have the same marginal product.[48]

Let the labor supply of a type (e, c) worker be denoted as $L^e_{g,c}$, where $g \in \{0, 1\}$ designates low or high wage labor group. Let $\varepsilon^L_{e,g,c}$ be the extensive labor supply elasticity, and for type $e = 1$ workers let $\chi_c^{g \to g'}$ be the cross wage elasticity with respect to sector

[48] Note, this rules out pricing power by firms to create a separating equilibrium among worker types.

choice for workers. The latter elasticity is only concerned with incumbent workers who potentially switch sectors. I suppress the group conditional demographic shares, $\theta^e_{g,c}$, to ease notation.

This implies the following equilibrium system (suppressing labor supply arguments):

$$\text{Labor Clearing} \quad \frac{L^0_{0,0} + L^1_{0,0} + L^0_{0,1} + L^1_{0,1}}{L^1_{1,0} + L^1_{1,1}} = \left(\frac{w_0/\theta_{0,1}}{w_1/\theta_{1,1}}\right)^{\rho} \tag{49}$$

$$\text{Factor Clearing} \quad \frac{L^0_{0,0} + L^1_{0,0} + L^0_{0,1} + L^1_{0,1}}{K^S(r)} = \left(\frac{\bar{w}/\alpha}{r/1-\alpha}\right)^{-1} \tag{50}$$

$$\text{Zero Profits} \quad P = c(w_0, w_1, r) := 1 \tag{51}$$

The general equilibrium incidence for this model is:

$$\hat{w}_0^{\mathsf{GE}} = \frac{-(\varepsilon^L_{0,1} - \tilde{\chi}_1^{1,0})\hat{\tau}_0}{(\varepsilon^L_0 - \tilde{\chi}^{1,0} - \rho)} + \frac{\Lambda\left(\sum_d \left(\frac{s_d\hat{\tau}_d(\varepsilon^L_{d,1} - \tilde{\chi}_1^{\neg d,d})}{(\varepsilon^L_d - \tilde{\chi}^{\neg d,d} - \rho)}\right)\right)}{1 + \sum_d \left(\frac{s_d\Lambda + \tilde{\chi}_1^{\neg d,d}}{(\varepsilon^L_d - \tilde{\chi}^{\neg d,d} - \rho)}\right)} \tag{52}$$

$$= (\mathsf{p}_0 + \Gamma_0 + \mathcal{X}_0)\hat{\tau}_0 + \Psi_0(\hat{\tau}_2) + \mathfrak{X}_0(\hat{\tau}_2) \tag{53}$$

where $\varepsilon^L_{d,1}$ and $\tilde{\chi}^{g,g'}_c$ incorporate the relevant share of workers based on $\theta^e_{g,c}$. As before, $\Lambda = \left(\frac{\varepsilon_K+1}{s_K} + \frac{1+\rho}{s_L}\right)$.

The main difference is that the supply elasticities are more complicated, intuitively, because workers can make more choices and supply is not inelastic between markets. There are now **five** first order terms in the incidence analysis, each capturing a different supply responses to wages.

This shows an additional consequence of partial equilibrium analysis. If worker have the ability to switch between sectors, then a partial equilibrium analysis will hold the supply of the other markets fixed. This omits important equilibrium responses to subsidies even for the market being studied.

A.5 Two Sector Model

A.5.1 Model

Let there be two final goods, $\{X, Y\}$, for sale at market prices, $\{p_x, p_y\}$, produced using three factors, $\{L, H, K\}$, that are each elastically supplied given factor prices, $\{w_x, w_y, v_x, v_y, r_x, r_y\}$.

I refer to L as low-skill labor, H as high-skill labor, and K as capital (or any other factor which is elastically supplied), w as low-skill wages, v as high-skill wages, and r as capital rents. Let all agents that can supply L or H service (labor) be called 'workers' regardless of their labor force participation; e.g., a low-skill worker either participates in the labor force or does not participate.

Production + Capital

Let $X = F^{(X)}(g_x(L_x, H_x), K_x)$ and $Y = F^{(Y)}(g_y(L_y, H_y), K_y)$, where $F^{\cdot}(\cdot)$ are both CRS production functions with a CES subfunction that aggregates the two labor types. For production I use

$$F = \left((L^{\frac{1+\rho}{\rho}} + H^{\frac{1+\rho}{\rho}})^{\alpha\frac{\rho}{1+\rho}} \cdot K^{(1-\alpha)}\right), \tag{54}$$

which is a nested CES production function that satisfies the assumption. Profit for an industry j is defined as $\pi_j = p_j X_j - w_j L_j - v_j H_j - r_j K_j$, and in equilibrium $\pi_j = 0$.

Let K be supplied according to the function $K^S(r_x, r_y)$, where the suppliers of capital consider the two sectors perfect substitutes. For example, if $r_x > r_y$, then $K_x = K^S(r)$ and $K_y = 0$. Thus, in any equilibrium where both goods are produced, $r_x = r_y$, and we may only refer to r.

Utility

Let type s worker utility be $u^s = U^s(X, Y, L_x, L_y, L_o)$, where $L_o = \mathcal{L} - L_x - L_y$ is leisure time. Let utility be separable so that $u^s = C^s(X, Y) + n(L_x, L_y, L_o)$. Further, let $C^s(X, Y) = c(X/Y) \cdot Y$, so that utility is homothetic for goods. Since utility is quasi-linear with respect to aggregate consumption, the labor supply will not depend on relative output prices – this can be relaxed.

Importantly, the disutility of labor depends on the type of labor. Depending on the function form (and stochastic assumptions), this implies that two types of workers may make heterogeneous labor supply decisions given the same market prices. This can be micro-founded by assuming that workers draw a triple ($\{\epsilon_x, \epsilon_y, \epsilon_o\}$) from some distribution, then solve the following problem:

$$\max_{x,y,o}\{V^\star(x)+\epsilon_x, V^\star(y)+\epsilon_y, V^\star(o)+\epsilon_o\}, \tag{55}$$

where $V^\star(\cdot)$ is the optimal consumption choice given a labor supply decision and prices. This yields the probability that a worker will work in the respective sectors: p_j^s. This approach is very common in the labor supply literature as well as in Saez (2002).

For an individual, this can be interpreted as the amount of labor supply devoted to each sector, where $\sum_j \mathsf{p}_j^s = 1$. Or, one can assume that each worker truly chooses only one sector but that the aggregate employment is matched exactly: $L = N \cdot \mathsf{p}$.

Budget Constraint + Subsidy

The worker budget constraint is $p_x X + p_y Y \leq \mathcal{T}^s(w_x L_x, w_y L_y, L_o)$. Let $\mathcal{T}^s(\cdot) = (w_x + \tau_s)L_x^s + w_y^s L_y^s + b_s L_o^s - T^s$, where τ_s is a labor subsidy for sector X, b_s in an unemployment benefit, and T^s is a lump sum tax on all workers regardless of labor supply. Given that utility only depends on leisure, the net return to supplying labor in the two sectors implies that in any equilibrium with both goods being produced, $(w_x^s + \tau_s) = w_y^s$.

To pay for the subsidy to sector X and unemployment, the government must set the lump-sum taxes to cover this cost in equilibrium. Let the government budget constraint be $T^L + T^H = \tau_L L_x + b_L L_o + \tau_H H_x b_H H_o$.

A.5.2 Equilibrium

The following are the equilibrium conditions:

$$\text{X Labor Market Clearing:}\quad \frac{L_x^S(w_x+\tau_L, w_y, b_L)}{H_x^S(v_x+\tau_H, v_y, b_H)} - \psi_x(w_x/v_x) = 0 \tag{56}$$

$$\text{X Factor Market Clearing:}\quad \frac{L_x^S(w_x+\tau_L, w_y, b_L)}{K_x^S(r)} - \psi_x(w_x/v_x)\Psi_x(w_x/r) = 0 \tag{57}$$

$$\text{X Zero Profits:}\quad p_x - c_x(w_x, v_x, r) = 0 \tag{58}$$

$$\text{Y Labor Market Clearing:}\quad \frac{L_y^S(w_y, w_x+\tau_L, b_L)}{H_y^S(v_y, v_x+\tau_H, b_H)} - \psi_y(w_y/v_y) = 0 \tag{59}$$

$$\text{Y Factor Market Clearing:}\quad \frac{L_y^S(w_y, w_x+\tau_L, b_L)}{K_y^S(r)} - \psi_y(w_y/v_y)\Psi_y(w_y/r) = 0 \tag{60}$$

$$\text{Y Zero Profits:}\quad p_y - c_y(w_x, v_x, r) = 0 \tag{61}$$

The model has seven endogenous prices $\{w_x, w_y, v_x, v_y, p_x, p_y, r\}$ and there are six equations, so I normalize $p_y = 1$.[49] This system is essentially the same as in the main text, but with an extra output sector and additional prices.

A.5.3 Solving for Wage Incidence

In this section, I will solve the model for incidence terms by linearizing the system in terms of differential changes in the subsidy.

Let $\tau_H = 0$ and $\mathrm{d}b_s = 0$.

In matrix form, the equilibrium system $A\hat{z} = \nu \cdot \hat{\tau}$ is:

$$\begin{bmatrix} \varepsilon_x^L - \rho_x & -(\varepsilon_x^H - \rho_x) & \chi_x^L & -\chi_x^H & 0 & 0 \\ \varepsilon_x^L + 1 - (1+\rho_x)\frac{s_x^H}{1-s_x^K} & -(1+\rho_x)\frac{s_x^H}{1-s_x^K} & \chi_x^L & 0 & 0 & -(\varepsilon_x^K+1) \\ \chi_y^L & -\chi_y^H & \varepsilon_y^L - \rho_y & -(\varepsilon_y^H - \rho_y) & 0 & 0 \\ \chi_y^L & \varepsilon_y^L + 1 - (1+\rho_y)\frac{s_y^H}{1-s_y^K} & -(1+\rho_y)\frac{s_y^H}{1-s_y^K} & & 0 & -(\varepsilon_y^K+1) \\ s_x^L & s_x^H & 0 & 0 & 1 & s_x^K \\ 0 & 0 & s_y^L & s_y^H & 0 & s_y^K \end{bmatrix} \begin{bmatrix} \hat{w}_x \\ \hat{v}_x \\ \hat{w}_y \\ \hat{v}_y \\ \hat{p} \\ \hat{r} \end{bmatrix} = \begin{bmatrix} -\varepsilon_x^L\hat{\tau} \\ -\varepsilon_x^L\hat{\tau} \\ -\chi_x^L\hat{\tau} \\ -\chi_x^L\hat{\tau} \\ 0 \\ 0 \end{bmatrix}$$

[49] The endogenous quantities, $\{L_j, H_j, K_j, X, Y\}$, all depend on the endogenous prices.

A.5.4 Two 'Tricks' for Solving

If $Az = b$, then by Cramer's Rule:

$$\text{Cramer's Rule:} \quad z_i = \frac{\det(A \mid b)}{\det(A)} \tag{62}$$

$$\text{Laplace Expansion:} \quad = \frac{\sum_j b_{i,j} \det(A^{(j)})}{\det(A)} \tag{63}$$

$$= \frac{\sum_j \frac{b_{i,j}}{a_{i,j}} a_{i,j} \det(A^{(j)})}{\det(A)} \tag{64}$$

$$\text{Matrix Derivative:} \quad = \frac{\sum_j \frac{b_{i,j}}{a_{i,j}} a_{i,j} \left(\frac{\partial \det(A)}{\partial a_{i,j}}\right)}{\det(A)} \tag{65}$$

$$:= \sum_j \left(\left(\frac{b_{i,j}}{a_{i,j}}\right) \left(\gamma_{a_{i,j}}\right) \right), \tag{66}$$

where $\gamma_{a_{i,j}} = \left(\frac{\partial \det(A)}{\partial a_{i,j}} \frac{a_{i,j}}{\det(A)}\right)$ is the elasticity of the determinant with respect to the matrix element.

This parameter is geometrically interpretable as the percent change in the area of the n-dimensional parallelogram formed by the system of equations from a 1% elemental change. Economically, the closest interpretation is that γ summarizes the effect of the exogenous variation (b) through the system of equations (A) from each equilibrium channel (the other elements of z).

Additionally, using some algebra:

$$z_i = \frac{\sum_j \frac{b_{i,j}}{a_{i,j}} a_{i,j} \det(A^{(j)})}{\det(A)} \tag{67}$$

$$= \frac{\sum_j \frac{b_{i,j}}{a_{i,j}} a_{i,j} \det(A^{(j)})}{\sum_j a_{i,j} \det(A^{(j)})} \tag{68}$$

$$= \sum_j \frac{b_{i,j}}{a_{i,j}} \frac{a_{i,j} \det(A^{(j)})}{\sum_j a_{i,j} \det(A^{(j)})} \tag{69}$$

$$= \frac{b_{i,i}}{a_{i,i}} + \left[\sum_{j \setminus i} \left(\frac{b_{i,j}}{a_{i,j}} - \frac{b_{i,i}}{a_{i,i}} \right) \frac{a_{i,j} \det(A^{(j)})}{\sum_j a_{i,j} \det(A^{(j)})} \right] \tag{70}$$

$$= \frac{b_{i,i}}{a_{i,i}} + \left[\sum_{j \setminus i} \left(\frac{b_{i,j}}{a_{i,j}} - \frac{b_{i,i}}{a_{i,i}} \right) \gamma_{a_{i,j}} \right] \tag{71}$$

A.5.5 Low Wage X Sector Incidence

It can be show using Cramer's Rule, Laplace Cofactor Expansion, and some algebra that

$$\frac{\hat{w}_x^L}{\hat{\tau}} = \underbrace{\frac{-\varepsilon_x^L}{\varepsilon_x^L - \rho_x}}_{\text{Partial Equilibrium}} \underbrace{+ \gamma_{a_{2,1}} \left(\frac{(1+\rho_x)(1 - \frac{s_x^H}{1-s_x^K})}{\varepsilon_x^L + 1 - (1+\rho_x)\frac{s_x^H}{1-s_x^K}} \right) + \left(\gamma_{a_{3,1}} + \gamma_{a_{4,1}}\right) \left(\frac{\rho_x}{\varepsilon_x^L - \rho_x} \right)}_{\text{Spillover Terms}} \tag{72}$$

B Data Description and Summary Statistics

In this appendix, I provide additional descriptions and summary statistic information for the data used in the empirical sections. Broadly, I use the Current Population Survey from 1986 to 2010 (Flood et al., 2018) and the 1990 US Census 5% sample, (Ruggles et al., 2018). I additionally use the Urban Institute's Transfer and Income Model, which requires the following disclosure:

> Information presented here is derived in part from the Transfer Income Model, Version 3 (TRIM3) and associated databases. TRIM3 requires users to input assumptions and/or interpretations about economic behavior and the rules governing federal programs. Therefore, the conclusions presented here are attributable only to the authors of this report.

B.1 Outgoing Rotation Group Samples

The ORG samples come from the Current Population Survey. A CPS respondent household is surveyed in two waves for four months each with an eight month break. On months four and eight, the surveyors ask the respondent additional labor market questions, such as usual hours and weekly earnings. The month-in-sample is staggered across respondents, so about one-fourth of any monthly sample is in an ORG.

I use the ORG samples for labor market quantities: wages and labor supply.[50] In table 15, I provide the underlying sample of women in the CPS ORG that are aggregated for the main analysis. As described in the main text, I calculate hourly wages by dividing `usual weekly earnings` by `usual hours worked at main job`. I discard calculated wages from workers with imputed earnings and/or hours. I discard observations where the respondent says their usual hours vary, workers reporting less than one hour per week, workers workers with implied real \$1990 wages less than \$0.50 or greater than \$150.00, and finally

[50]The major issue in using the ORG sample is that cannot it does not have enough information to predict EITC usage, which is based on previous year income and living arrangements.

if the worker is out of the labor force *and* reports being in school full time over two-thirds of their CPS observations.[51]

Table 15 – Market State Year Observations for Estimation Sample

	1989-1994		1995-2000		Difference	
	Mean	SD	Mean	SD	Dif	t
Age	38.98	12.24	39.91	11.99	0.93***	(39.21)
Married	0.63	0.48	0.62	0.49	-0.01***	(-14.19)
White	0.83	0.37	0.82	0.38	-0.01***	(-19.13)
Black	0.12	0.32	0.13	0.34	0.01***	(9.69)
Less HS	0.15	0.36	0.13	0.33	-0.02***	(-35.49)
High School	0.39	0.49	0.34	0.47	-0.06***	(-59.15)
Some College	0.32	0.47	0.30	0.46	-0.02***	(-22.04)
BA+	0.14	0.35	0.24	0.43	0.10***	(130.04)
Qualifying Child	0.48	0.50	0.47	0.50	-0.01***	(-14.21)
Age of Youngest	7.74	6.07	7.93	5.95	0.19***	(11.18)
LFP	0.68	0.46	0.71	0.46	0.02***	(23.43)
EPOP	0.64	0.48	0.68	7.00	0.03***	(32.98)
Usual Hours Total	37.60	10.48	38.00	10.23	0.39***	(8.11)
Usual Hours Main	36.68	9.90	37.28	9.70	0.61***	(25.53)
Real H.Wage	8.84	4.83	12.47	6.64	3.62***	(188.06)
Real Wage	10.73	6.03	15.71	9.05	5.98***	(234.76)
Real Weekly Earnings	431.63	276.53	629.24	420.29	197.61***	(207.12)
Observations	706,747		612,463		1,319,210	

All data from 1989-2000 CPS MORG samples, only women ages 20-65, accessed from IPUMS. All demographic, employment variables weighted by CPS Basic Weight, real wage and earnings by Earnings Weight × Hours. Real wages and earings inflated to 2018 dollars by BLS CPS Research Series. Real wage based on weekly earnings divided by usual hours for main job. Qualifying child based on child age, school status, and family structure.

In table 16, I display the number of demographic cells by marriage and education group that are used in the incidence calculations. I only include market-state-year cells that have a minimum of five workers with children *and* five workers without children. This causes me to have an unbalanced panel of cells, but ensures that the market averages

[51] Additionally, I drop workers who are in group housing, who have no identified head of house, who are in households with greater than ten members (as it is too hard to form tax units), who are in the armed forces, and who are married with absent or separated spouses.

are calculated using a reasonable number of workers. The table itself also highlights demographic changes overtime. As can be seen, with population growth, the total number of cells goes from 14.2 thousand to 20.3 thousand. We can also see education attainment increasing, as there is a decrease in workers without a high school degree to those with a college degree. Interestingly, there is an increase in unmarried women with some college but a decrease for married women, as this latter group shifts towards attaining their college degree.

Table 16 – Market State Year Observations for Estimation Sample

	Less HS		HS		Some College		BA Plus		Total	
Year	Unmarried	Married	Unmarried	Married	Unmarried	Married	Unmarried	Married	Unmarried	Married
1990	246	282	572	714	386	660	46	172	1,250	1,828
1991	258	252	536	738	428	658	46	176	1,268	1,824
1992	268	240	496	680	378	572	166	500	1,308	1,992
1993	210	216	512	684	418	584	158	510	1,298	1,994
1994	186	182	506	634	430	572	142	494	1,264	1,882
1995	182	180	494	602	444	590	176	522	1,296	1,894
1996	158	162	496	580	454	542	152	514	1,260	1,798
1997	156	140	494	550	454	536	160	532	1,264	1,758
1998	144	138	490	544	458	556	190	530	1,282	1,768
1999	154	116	506	546	484	562	218	556	1,362	1,780
2000	156	126	520	532	470	566	204	550	1,350	1,774
Total	2,118	2,034	5,622	6,804	4,804	6,398	1,658	5,056	14,202	20,292

All data from 1993 March CPS, Women from Tax Units, Wage in $1993
All variables weighted by CPS March Supplement Wt × Hours

B.1.1 Assignment of Children in ORG

We do not observe who claims EITC qualifying children is the CPS, so children must be assigned by the researcher according to some (*ad hoc*) rules. I assign children based on who seems the most likely primary care-giver in the social role of a parent. While not perfect, I heavily use the fact that children typically follow their primary care-giver in the record layout, in addition to family unit and relationship pointer variables. For most cases, this is simple and there is no ambiguity; however, household living arrangements can be complex. The main consequence of my allocation rules can be stated in two examples.

First, consider a household with a 40 year old head of house (HoH), a 16 year old child of HoH, and a 1 year old grandchild of HoH who is directly related to the child. I assign the grandchild to the child rather than to the HoH. Another researcher may assign both to the HoH. Second, consider a household with a 40 year old HoH and a 20 year old non-relative "roommate" (so not a foster or adoptive child) who is unmarried and in school. I do not assign the non-relative to the HoH; although, another researcher may.

Note: IPUMS constructs family relationship information, such as number of own children (`nchild`), based on an their definition of a family. Their goal is a combination of accuracy *and* scalability for many millions of observations. However, I find that this definition is does not suit my purpose of matching children to their most likely care-giver. When Census family identifying variables are available (primarily in the ASEC samples, discussed below), I am able to find many examples of child assignment that are not intuitive. Nevertheless, using the IPUMS family definitions result is the same qualitative results with minimal quantitative differences.

B.2 Annual Social and Economic Samples

I use the ASEC samples from the Current Population Survey to perform the simulation exercises: 1993-1995 for the OBRA expansion, 2008-2010 for the ARRA expansion. The ASEC samples is based on the March CPS and an oversampling from other months to increase data quality. March is chosen to coincide with tax-filing season, the surveyors ask additional questions about income, insurance, and other issues from the previous year. To reduce sampling errors, the surveyors include additional households for the ASEC from February and April (starting in 2002) and oversample Hispanic households (starting in 1976) (Flood et al., 2018).

I use the ASEC samples for incidence calculations because the possibility of calculating EITC usage given the income and family variables. However, the wage information is not as good as the ORG sample, since wages must be imputed using previous year annual earnings and work information rather than weekly earnings.

I present summary statistics on the incidence samples of women for tax year 1992 in Table 19 and for 2008 in Table 18.[52] As described in the main text, I calculate hourly wages by dividing `annual earnings last year` (all types) by the product `usual hours worked at main job last year` times `weeks worked last year`. The incidence sample is restricted to women ages 16 to 65. I drop women who are full or part time students *and* have not participated in the labor force for over one year and women who have negative tax unit self-employment earnings.[53]

Because the labor market variables are based on annual information, I classify an individual as a 'worker' if she satisfies the following: at least 40hrs of work last year, an average of at least 8hrs per week, must earn at least \$100 per year (in \$1990 dollars), and must have an implied wage of at least \$0.50 (in \$1990 dollars). This essentially relabels extreme part-time workers as 'non-workers.'

The most notable feature of the data is that the EITC is heavily concentrated in the unmarried women with children segment, but this segment is also the smallest in labor cost terms and labor supply term. This implies that since their market share is reasonably small, that the GE effects are likely to be closer to the PE incidence, all else equal.

B.2.1 Assignment of Children in ASEC

As discussed above, the assignment of EITC qualifying children is up to the researcher. I use Census coded family unit ID, household record numbers, and relationship pointers to link EITC eligible children to (most likely) parents. Again, for creating tax units, the Census definition is closer in spirit to what researchers are aiming to capture rather than IPUMS definitions.

[52] Note, for the empirical exercise in Section 8, I also use the 1993 ASEC, but the sample is marginally different due to simulating the Welfare program measures. There is effectively no impact on the summary statistics in Table 19.

[53] Additionally, I drop workers who are in group housing, who have no identified head of house, who are in households with greater than ten members (as it is too hard to form tax units), who are in the armed forces, and who are married with absent but non-separated spouses.

Table 17 – Summary Statistics for Simulation Incidence Sample
Tax Year 1992

	Age	Anykids	Married	Get Eic
Unmarried Women	33.00	0.00	0.00	0.00
Married Women	47.62	0.00	1.00	0.00
Unmarried Mothers	34.29	1.00	0.00	0.50
Married Mothers	36.90	1.00	1.00	0.18
	Less HS	HS Only	Less BA	BA+
Unmarried Women	0.26	0.26	0.30	0.18
Married Women	0.15	0.41	0.23	0.21
Unmarried Mothers	0.23	0.39	0.27	0.10
Married Mothers	0.12	0.38	0.28	0.22
	Worker	Wage	Share of Workers	Cost Share
Unmarried Women	0.72	10.14	0.32	0.20
Married Women	0.67	11.18	0.24	0.18
Unmarried Mothers	0.68	9.79	0.10	0.07
Married Mothers	0.70	10.86	0.35	0.23

All data from 1993 March CPS, Women from Tax Units, Wage in $1992. Demographic variables weighted by CPS March Supplement Wt, Wage by Supplement Wt × Usual Hours Last Year.

B.2.2 Sample Differences between Rothstein (2010)

There is primary difference between my ASEC sample and that of Rothstein (2010), who uses nearly the same criteria labor market criteria. Rothstein drops from the initial sample any person who is not labeled as the head of a family unit. This is roughly 36% of the initial sample, 13% of the initial 18 or older sample, and 6% of the initial 25 or older sample, who would not be dependents (sample proportions are unweighted). These individuals have roughly $4000 less in wage and salary income (conditional on age, education, race, marital status, and gender) meaning they are more likely to qualify for the EITC based on income.[54]

[54] They are also younger, more likely to have a high school degree or less, less likely to be white, more likely to be men, and much less likely to be or have been married.

Table 18 – Summary Statistics for Simulation Incidence Sample
Tax Year 2009

	Age	Anykids	Married	Get Eic
Unmarried Women	34.16	0.00	0.00	0.05
Married Women	50.20	0.00	1.00	0.04
Unmarried Mothers	35.98	1.00	0.00	0.55
Married Mothers	39.54	1.00	1.00	0.20
	Less HS	HS Only	Less BA	BA+
Unmarried Women	0.23	0.23	0.31	0.23
Married Women	0.08	0.33	0.28	0.31
Unmarried Mothers	0.17	0.32	0.35	0.16
Married Mothers	0.10	0.25	0.28	0.37
	Worker	Wage	Share of Workers	Cost Share
Unmarried Women	0.65	18.13	0.33	0.19
Married Women	0.69	20.19	0.25	0.17
Unmarried Mothers	0.76	16.75	0.12	0.07
Married Mothers	0.71	21.49	0.31	0.21

All data from 2009 March CPS, Women from Tax Units, Wage in \$2008. Demographic variables weighted by CPS March Supplement Wt, Wage by Supplement Wt $\times$ Usual Hours Last Year.

The effect of this is that in Rothstein's analysis there are only *three* women under the age of 24 without children. Such a sample makes sense in the empirical literature in order to perform difference-in-difference estimation (this is because the need for parallel trends pushes one to remove these young workers). However, it is not obvious that it should be done in the incidence calculation, which is mostly theoretical simulation exercise. Because I believe many of these workers are within-market rivals of unmarried women with children, I include them in my simulations. This increases the women in the sample by roughly six thousand individuals and changes the average age of unmarried women without children from 41 to 33.

Additionally,Rothstein essentially assigns all individuals who potentially qualify as EITC dependents (based on age and education enrollment) to the head of household. In the end, Rothstein assigns about two thousand more workers at least one EITC dependents than my procedure (that is his procedure yields more workers with a qualifying dependent than my sample procedure).

The two changes I make – more workers in the sample and fewer EITC claimants – should *mitigate* the incidence effects.

B.3 1990 US Census 5% Sample

I use the 1990 US Census 5% Sample (Ruggles et al., 2018) to create the simulated tax instruments.

Table 19 – Summary Statistics for Simulation Incidence Sample
1990 Census

	Age	Anykids	Married	Get Eic
Unmarried Women	32.68	0.00	0.00	0.00
Married Women	47.29	0.00	1.00	0.00
Unmarried Mothers	35.15	1.00	0.00	0.49
Married Mothers	36.43	1.00	1.00	0.15
	Less HS	HS Only	Less BA	BA+
Unmarried Women	0.30	0.24	0.28	0.12
Married Women	0.20	0.36	0.25	0.13
Unmarried Mothers	0.26	0.34	0.31	0.07
Married Mothers	0.16	0.34	0.30	0.14
	Worker	Wage	Share of Workers	Cost Share
Unmarried Women	0.75	9.29	0.33	0.21
Married Women	0.66	10.26	0.23	0.18
Unmarried Mothers	0.73	9.10	0.09	0.06
Married Mothers	0.70	9.70	0.34	0.22

All data from 1990 US Census, 5% Sample March CPS, Women from Tax Units, Wage in $1989. Demographic variables weighted by Census sample weight, Wage by sample weight × Usual Hours Last Year.

C Empirical Tax Instruments

C.1 Identification of Elasticities

To identify the labor supply and labor substitution elasticities, there are two sets of exclusion restrictions. The first set are used for the supply elasticities and the second for the substitution elasticity. The incidence model results imply an identification strategy. Direct changes in the own EITC ATR, τ, shift supply that allows me to identify the labor substitution elasticity that governs labor demand. GE spillover effects shift demand curves that allows me to identify the labor supply elasticities. Below, I formalize this using arguments from Watson (2020).

Consider the following simultaneous equations model [SEM]:

$$l_{it}^D = \alpha_0 + \alpha_1 w_{it} + u_{it}^D \qquad l_{it}^S = \beta_0 + \beta_1 w_{it} + \beta_1 \tau_{it} + u_{it}^S \qquad l_{it}^S = l_{it}^D. \tag{73}$$

This implies the following first stage and reduce form equations:

$$w_{it} = \frac{\alpha_0 - \beta_0}{\beta_1 - \alpha_1} + \frac{-\beta_1}{\beta_1 - \alpha_1}\tau_{it} + \frac{u_{it}^D - u_{it}^S}{\beta_1 - \alpha_1} := \pi_0 + \pi_1 \tau_{it} + v_{it}^w, \tag{74}$$

$$l_{it} = \frac{\alpha_0\beta_1 - \alpha_1\beta_0}{\beta_1 - \alpha_1} + \frac{-\alpha_1\beta_1}{\beta_1 - \alpha_1}\tau_{it} + \frac{\beta_1 u_{it}^D - \alpha_1 u_{it}^S}{\beta_1 - \alpha_1} := \mu_0 + \mu_1 \tau_{it} + v_{it}^L, \tag{75}$$

where all variables are in logs and $\ln[(1+\tau)] \approx \tau$. I assume that labor demand depends on the gross-wage while labor supply depends on the net-wage, and I suppress any dependence on covariates, X.

Now, I use the theoretical results from the main text imply the following wage incidence equation:

$$\underbrace{\mathrm{d}w_{it}}_{\text{Wage Change in Data}} = \underbrace{\gamma_1 \mathrm{d}\tau_{it} + \Psi_{it}}_{\text{Incidence Induced Change}} + \underbrace{\gamma_0 + v_{it}}_{\text{Unobs Wage Change}}, \tag{76}$$

where Ψ_{est} is a theoretical measurement of the GE spillover effect.

Combining the SEM with the incidence equation, the following equivalence must hold in the post period:

$$\underbrace{\gamma_0 + v_{it} + \gamma_i \mathrm{d}\tau_{it} + \Psi_{it}}_{\text{Incidence + Unobs}} = \underbrace{\mathrm{d}w}_{\text{Data}} = \underbrace{\frac{\alpha_0 - \beta_0}{\beta_1 - \alpha_1} + \frac{-\beta_1}{\beta_1 - \alpha_1}\mathrm{d}\tau_{it} + \frac{\mathrm{d}u_{it}^D - \mathrm{d}u_{it}^S}{\beta_1 - \alpha_1}}_{\text{SEM}}. \tag{77}$$

One obvious way to reconcile the two equations is the following:

$$v_{it} = \frac{-1}{\beta_1 - \alpha 1} \mathsf{d}u_{it}^S \qquad \Psi_{it} = \frac{1}{\beta_1 - \alpha 1} \mathsf{d}u_{it}^D \qquad \gamma_0 = \frac{\alpha_0 - \beta_0}{\beta_1 - \alpha_1} \qquad \gamma_1 = \frac{-\beta_1}{\beta_1 - \alpha_1}. \tag{78}$$

The above implies that if $\mathsf{Cov}(\tau, Z) \neq 0$, then $\mathsf{Cov}(\tau, u^D) \neq 0$, so τ is technically an invalid instrument in the SEM above. However, using the RF equation, the own tax change and spillovers can be used in tandem to estimate the elasticities:

$$\frac{\partial l}{\partial \Psi} = \frac{\beta_1}{\beta_1 - \alpha_1} \frac{\partial u^D}{\partial Z} \quad \& \quad \frac{\partial w}{\partial \Psi} = \frac{1}{\beta_1 - \alpha_1} \frac{\partial u^D}{\partial \Psi} \quad \implies \frac{\partial l / \partial \Psi}{\partial w / \partial \Psi} = \beta_1. \tag{79}$$

It is straight-forward to show: $\frac{\partial w}{\partial \Psi} = \frac{\partial [w+\tau]}{\partial \Psi}$ and $\frac{\partial l / \partial u^S}{\partial w / \partial u^S} = \alpha_1$. Additionally, I can allow for orthogonal demand unobservable changes: $v_{it} = u_{it}^S + u_{it}^{D,2}$, where $\mathsf{Cov}(\tau_{it}, u_{it}^{D,2}) = 0$ and $\mathsf{Cov}(\Psi_{it}, u_{it}^{D,2}) = 0$.

The main conclusion of Watson (2020) is that "in the context of the labor market SEM, we can use the tax reform treatment as a supply shifter and a measure of spillovers as a demand shifter." Let $\dot{y}_x$ be the residual from from a regression of y on x.

Proposition 1.
If τ is exogenous with the above SEM, then $\frac{\widehat{\mathsf{Cov}}(\dot{l}_\tau, \dot{Z}_\tau)}{\widehat{\mathsf{Cov}}(\dot{w}_\tau, \dot{Z}_\tau)} \to_p \beta_1$ and $\frac{\widehat{\mathsf{Cov}}(\dot{l}_Z, \dot{\tau}_Z)}{\widehat{\mathsf{Cov}}(\dot{w}_Z, \dot{\tau}_Z)} \to_p \alpha_1$, where 'exogenous' means that $\mathsf{Cov}(\tau, u^S) = 0$.

Thus, to identify β_1, I need a measure of the demand spillovers, which proxy for demand shifters, and to condition on the own tax rate as a proxy for supply shifters. The exclusion restriction is that the EITC tax reform and its spillovers are uncorrelated to unobservable differences in labor supply (conditional on the model controls):

$$\mathsf{E}\left[\tau_{ecst} \cdot u_{e'cst}^S \mid X\right] = 0, \ \forall e, e' \in \mathcal{E}. \tag{80}$$

This assumption would be violated if the EITC policy changes across demographic groups and state-years were chosen because the policymakers knew certain groups were more likely to systemically change their labor supply. Because the OBRA expansion was done at the national level (federal EITC rules are uniform across states), this would require that policymakers were able to precisely design the national change to take advantage of sub-state trends. More plausible is that state policy makers strategically implemented state-EITC reforms.[55] However, prior studies find that state EITC introductions and

[55] Nine states had a state program by 1995 and eighteen by 2000.

policy changes appear plausibly exogenous to local economic conditions (Leigh, 2010; Buhlmann et al., 2018).

Alternatively, if there are social program reforms that are correlated with EITC reforms, then I will misattribute to the EITC wage effects that are actual to due other program changes. The most obvious example is PRWORA that replaced Aid to Families with Dependent Children (AFDC) with Temporary Assistance for Needy Families (TANF) in 1996. This reform "was the culmination of state-led welfare reform efforts starting in the late 1980s ... implemented under the heading of welfare waivers, permissions from the federal government allowing states to experiment with their welfare programs Kleven (2019)." To account for this possibility, I interact an indicator for having children with indicators for implementation of state 'welfare waivers'.[56] Given that I include state-year FEs, these variables will control for any variation in EITC ATRs, wages, and supply that are due to differential effects of welfare reforms by parental status.

To identify the substitution elasticity, I rely on a similar argument as for α_1 in the above SEM. I now need to condition on the spillovers and use the direct EITC change as a supply instrument:

$$\mathsf{E}\left[\frac{\tau_{est}}{\tau_{0st}} \cdot u^{D}_{(e,0),st} \mid X, \Psi_{est}\right] = 0. \tag{81}$$

That is, the relative tax change between skills is uncorrelated with the relative demand unobservables conditional on covariates and spillovers.

This assumption would be violated if the EITC was implemented in a way that was complementary to underlying skill biased technical change where firms were demanding more low skill labor just as the EITC was expanding labor supply. To the extent that this occurred, I interact 1990 wage deciles with year indicators to capture any wage trends across states and skills.

[56]These are provided by Kleven (2019) in online replication material accessed on the author's personal website.

C.2 Construction

There are two ways of using EITC policy variation as an instrument for market variables. First, one can use the EITC policy parameters directly, such as maximum EITC benefit given number of children which varies at the state-year level (Leigh, 2010; Kasy, 2017; Bastian and Michelmore, 2018). This variable is very simple to implement but is constant across all labor markets in a state.

The second method is using a simulated tax instrument, similar to Gruber and Saez (2002); Rothstein (2008), for each demographic group across states.[57] Here I describe the construction of the EITC average tax rate in detail. I additionally calculate IVs using the share of a market with positive EITC and the change in EITC based on tax code changes in an analogous way.

Using a fixed distribution of worker characteristics from the 1990 Census, I calculate average tax rates due to the EITC over multiple years of policy changes. By fixing the distribution of workers, endogenous changes in ATRs due to changes in labor market variables are purged. This construction allows the instrument to vary at the labor market-state-year level.

To calculate this, I need to estimate the true EITC benefits and the counterfactual EITC benefits if the worker did not work. I calculate the true EITC benefits, E_i^{act}, by using TAXSIM on the actual data, where E is the federal and state EITC benefit. To calculate the counterfactual benefits, E_i^{cf}, I set the worker's labor earnings equal to zero but leaving all else equal and rerun TAXSIM.[58] Finally, I calculate the EITC Average Tax Rate as the difference in the actual minus the counterfactual benefits over earned income:

$$\tau_i^{\mathsf{EITC}} = \frac{E_i(L = L_i) - E_i(L = 0)}{w_i \cdot h_i}. \tag{82}$$

I use the market level sample weighted mean to calculate τ_{ecst}.

[57] Leigh (2010) and Bastian and Michelmore (2018) both also use this type of approach secondary analysis.

[58] In married couple tax units, the counterfactual is with respect to the wife's labor supply decision. I assume the husband's earned income remains unchanged.

As stated above, I use the 1990 Census to calculate the tax instrument. I replicate the data for each tax year and send the data to Internet TAXSIM. To avoid issues of 'bracket-creep', I inflate monetary values by the BLS CPI All Items Research Series but do not change any other quantity.

The above only calculated the EITC ATR for a specific labor market, τ_{ecst}. However, the total incidence also depends on a weighted sum of tax changes in *other* labor markets within a state-year, $\Psi_{ec}(\{\tau_{e,c'}\}_{e,c'\in\mathcal{D}})$. Thus, I need an empirical counterpart for the Ψ_{ecst} terms, but this depends on the parameters that I wish to estimate – see equation 46.

I approximate the function by creating two different 'leave-out' averages of the tax change across labor markets matched to a given market. Under the assumption that:

$$\Psi_{ecst} = H\left(\{\tau_{e'cst}\}_{ec'\in\mathcal{D}}\right) \approx \mathsf{a}_1\bar{\tau}_{g_1(e),cst} + \mathsf{a}_2\bar{\tau}_{g_2(e),cst} + \nu_{ecst}, \tag{83}$$

for observed $(\bar{\tau}_{g_1(e),cst}, \bar{\tau}_{g_2(e),cst})$, then I can use these observed variables as approximations to the true spillover.

The first match-group is based on age groups and the second match group is based on education groups. I create the leave-out averages by excluding the specific market-segment when creating the averages. For example, if $(\tilde{e}, c)$ is married women with some college between ages of 25 and 30, then $\bar{\tau}_{g_1(\tilde{e}),cst}$ equals the average EITC ATR for women with some college pooled across age groups excluding the specific group, $\bar{\tau}_{g_2(\tilde{e}),cst}$ equals the average EITC ATR for women between ages of 25 and 30 pooled across education groups also excluding the specific group.

Recall, because I include the own EITC ATR as a control variable in both the first stage and structural equation, the variation in these leave-averages is by construction orthogonal to direct EITC variation.

As stated above, I use the EITC ATR and two other simulated EITC statistics as instruments: the share of workers receiving EITC benefits and the mean change in expected real EITC amounts. Below I specify the IVs used in the main results. In Appendix D, I show that the elasticity estimates are robust to various combinations of the instruments.

C.2.1 Labor Supply Instruments

For every group $\tilde{d} = (e, c)$, I have nine market level simulated instruments for wages:

1. the EITC ATR: $\{\tau^{\mathsf{ATR}}_{\tilde{d}st}$
2. the portion of $\tilde{d}$ workers with positive EITC: $\{z^{\mathsf{Sh}}_{\tilde{d}st}\}$
3. the mean change in ETIC amount for $\tilde{d}$: $\{z^{\mathsf{dE}}_{\tilde{d}st}\}$

4,5. two EITC ATR approximation averages: $\{\bar{\tau}_{g_{(\cdot)}(\tilde{d})st}\}$

6,7. two positive EITC approximation averages: $\{\bar{z}^{\mathsf{Sh}}_{g_1(\tilde{d})st}, \bar{z}^{\mathsf{Sh}}_{g_2(\tilde{d})st}\}$

8,9. two mean changes in expected real EITC amounts approximation averages: $\{\bar{z}^{\mathsf{dE}}_{g_1(\tilde{d})st}, \bar{z}^{\mathsf{dE}}_{g_2(\tilde{d})st}\}$.

Based on the identification arguments above, I condition on the demographic specific simulated EITC ATR, share with EITC, and average change in EITC: $\{\tau_{ecst}, z^{\mathsf{sf}}_{ecst}, z^{\mathsf{dE}}_{ecst}\}$.

C.2.2 Labor Substitution Instruments

The labor substitution elasticity depends on the relative wage, $\ln[w_{est}/w_{e_0st}]$. My main specification uses a just identified model using the 'relative EITC ATRs' to instrument for relative wages:

$$\tau_{(\tilde{e},e_0)st} = \frac{\tau_{\tilde{e}st}}{\tau_{e_0st}}. \tag{84}$$

I also construct relative share of EITC claimants and the relative change in real EITC amounts to estimate an overidentified model. For the substitution elasticity, I only use the education based averages because, when I create the relative variables for the regressions, I match workers based on age so the age-group leave-out averages are absorbed into other fixed effects.

C.3 Comparison with Traditional Approaches

Here, I quickly describe the issues using more traditional approaches in the EITC literature to estimating relevant parameters when allowing worker heterogeneity and general equilibrium effects.

C.3.1 Labor Supply Difference in Difference

Previous authors have estimated labor supply responses using difference-in-difference style assumptions for unmarried women with and without children – see Eissa and Liebman (1996); Hotz et al. (2002) for an early example and a review of the empirical literature list of examples. This assumption supposes that these workers face similar market forces, such as being perfectly substitutable conditional on age and education (and experience), so that in a narrow window around EITC expansions the only change between these workers is the difference in EITC policy effects. Such assumptions lead to expecting "parallel trends" before the reform and using the post-reform dynamics of women without children to form a counterfactual baseline for women with children.

To see the implications of these assumptions, consider the following model, where $\tau_{e,c,t} = 0$ if $t = 0$ and $\tau_{e,c,t} = 0$ if $c = 0$:

$$\mathsf{E}[l^S_{ect}] = \beta_0 + \beta_{e,c}(w_{e,t} + \tau_{e,c,t}) + \lambda_e \tag{85}$$

$$\implies \mathsf{E}[l^S_{ec,1}] - \mathsf{E}[l^S_{ec,0}] = \beta_{e,c}(w_{e,1} - w_{e,0} + \tau_{e,c,1} - \tau_{e,c,0}) \tag{86}$$

$$\implies \left(\mathsf{E}[l^S_{e,1,1}] - \mathsf{E}[l^S_{e,1,0}]\right) - \left(\mathsf{E}[l^S_{e,0,1}] - \mathsf{E}[l^S_{e,0,0}]\right) =$$

$$\underbrace{(w_{e,1} - w_{e,0})}_{\text{Incidence Effects}} \cdot \underbrace{(\beta_{e,1} - \beta_{e,0})}_{\text{Elasticity Differences}} + \underbrace{\beta_{e,1}\tau_{e,c,1}}_{\text{ATET}} . \tag{87}$$

If one assumes that wages are fixed, $(w_{e,1} - w_{e,0}) = 0$, then the DiD estimates the ATET with no additional assumptions about behavioral responses to wages. If one allows for wage changes (via exogenous changes or incidence effects), then one needs to assume that the wage responsiveness of workers with and without children is equivalent; i.e., $(\beta_{e,1} - \beta_{e,0}) = 0$. This latter restriction is testable in the data with an appropriate empirical strategy.

Without either assumption, then the DiD estimate of the ATET is biases in an unknown direction unless one knows the parameters $\{\beta_{e,1}, \beta_{e,0}\}$, in which case estimation is not necessary. My approach allows for heterogeneous labor supply elasticities and uses wage and EITC variation across states and demographic groups to estimate the elasticities.

C.3.2 Log Wage Difference in Difference

The empirical literature on the EITC has not focused much on wage effects, due to typically assuming fixed wages. Leigh (2010) regresses log wages at the individual level on the maximum state EITC amount, but does not report incidence parameters directly.

To see how this fits with the incidence model, suppose we observe wages and tax rates for skill level e across states s and years t. The incidence results imply the following equation, where $\tau_{est} = \Psi_{est} = 0$ if $t = 0$:

$$\mathsf{E}[w_{est}] = \gamma_0 + \gamma_e \tau_{est} + \lambda_s + \Psi_{est} \tag{88}$$

$$\implies \mathsf{E}[w_{es1}] - \mathsf{E}[w_{es0}] = \gamma_e \tau_{es1} + \Psi_{es1} \tag{89}$$

$$\implies (\mathsf{E}[w_{e11}] - \mathsf{E}[w_{e10}]) - (\mathsf{E}[w_{e01}] - \mathsf{E}[w_{e-0}])$$

$$\gamma_e(\tau_{e11} - \tau_{e01}) + \underbrace{\Psi_{e11} - \Psi_{e01}}_{\text{GE Bias}}. \tag{90}$$

Unless one can control for GE spillovers or knows when they are negligible, then, even within a skill group, spillovers create a GE bias. If we compare across skill groups, $e \in \{0, 1\}$, in the same state where we know $\tau_{est} = 0$ for $e = 0$, then we still get GE bias unless skill group $e = 0$ has no exposure to skill group $e = 1$: $\gamma_1 \tau_{1st} + \Psi_{1s1} - \Psi_{0s1}$. However, if skill group $e = 0$ has no GE exposure, then we cannot trust that this is a valid control group. My approach deals with this GE bias by adding structural assumptions about labor demand and estimating labor market elasticities that compose the GE spillovers based on the incidence model.

D Additional Estimation Results

In Table 20, I provide additional elasticity estimates for labor supply. These specifications differ on five dimensions: method, weighting, sample, IVs, and dependent variable. The table displays the KP rk Wald F, a cluster robust Cragg-Donald statistic for first stage strength, the number of observations, and simple averages of the estimates elasticities.

A larger elasticity for unmarried women with children ('treated' workers) implies that that the spillover effect will be larger on the 'untreated' workers. A larger elasticity for untreated workers implies that spillovers will be larger on the treated workers.

The first line, model 0, is the baseline estimates used in the main text: I use two-step efficient GMM, weighted by the number of wage observations in a cell, using cells with at least five observations, using the baseline set of simulated tax instruments, as discussed in Appendix C.1.

The rest of models 1-14 vary some aspect of the empirical specification. Models 1,2 use more observations in the estimations by allowing sparser cells, which makes the elasticities more inelastic. Model 3 estimates the elasticities using two-stage least squares method, which tends to make the estimates more elastic. Models 4,5 use inverse wage variance weighting and no-weights respectively, which tend to make the empirical instrument strength weaker and thus larger elasticities.[59]

In models 6-9, I use different subsets of elasticities, which does not have a large effect on the estimated elasticities but does affect instrument strength. Because I am interacting the endogenous variable with demographic indicators, this is similar to estimating a non-linear model, so in models 10, 11 I use a control function approach. Model 10 uses a linear control function (first stage residual) approach while model 11 uses a cubic polynomial of the control function, but both estimates are effectively the same.

Models 12-15 estimate the elasticities in separate regressions based on parental and marriage status but using the same regression specification. The estimates for women

[59] Inverse wage variance weighting would be appropriate with measurement error in wages (Borjas et al., 2012) while unweighted treats sparser cells equally as cells with many observations, which cause bias if there is more measurement error in smaller cells.

with children are similar to baseline, but the estimates for women without children are much less elastic. Model 16 estimates the OLS relationship and finds near zero of negative labor supply elasticities, potentially due to the simultaneity bias that leads to use the instrumental variables method.

Finally, Models 17-20 use the (log) total number of workers in the labor force as the dependent variable. This measure is more coarse than the hours-per-worker variable that I use but is potentially subject to less measurement error. Because the hours based elasticities include the extensive and any potential intensive margin effects, the supply based elasticities are smaller. See that:

$$\mathsf{d}h_i\ell_i = \mathsf{d}h_i\ell_i + h_i\mathsf{d}\ell_i + \mathsf{d}h_i\mathsf{d}\ell_i \tag{91}$$

$$\Longrightarrow \varepsilon^L = \mu^h + \upsilon^\ell + \xi^{h\cdot\ell}. \tag{92}$$

Panel (C) in the table shows estimates of υ^ℓ while the parameter used in the main text and Panels (A) and (B) are ε^L.

In Table 21, I display alternative estimations for the labor substitution parameter. These specifications differ on five dimensions: method / FEs, weighting, sample, IVs, and dependent variable. The table also displays the number of observations and the KP rk Wald F, a cluster robust Cragg-Donald statistic.

Broadly, the overidentified models have lower first stage statistics and the estimates tend to be smaller in magnitude (towards zero). Additionally, the Employment based estimates of ρ tend to be larger than the Hours per Worker specification. This could be for two reasons. Given that $\rho = \mathsf{d}\ln[L_1/L_0]/\mathsf{d}\ln[w_1/w_0]$, either the numerator is larger or the denominator is smaller.

Approximately and using an equilibrium relationship with the supply functions, we can write this as $\rho \approx \frac{\mu_1^h+\upsilon_1^\ell+\xi_1^{h\cdot\ell}}{\mu_0^h+\upsilon_0^\ell+\xi_0^{h\cdot\ell}}$. If $\frac{\mu_1^h+\upsilon_1^\ell+\xi_1^{h\cdot\ell}}{\mu_0^h+\upsilon_0^\ell+\xi_0^{h\cdot\ell}} < \frac{\upsilon_1^\ell}{\upsilon_0^\ell}$, then this implies that the relative hours response is lower for the lower skill workers than the higher skill workers. Another possibility is that new entrant low skill workers work fewer hours than the incumbent workers, so $\xi_0 < 0$.

Table 20 – Additional Elasticity Specifications
Average within Demographic Groups

Model	Method	Weighting	Sample	IVs	Obs	KP rk F Stat	Total	Unmarried No Children	Unmarried w/ Children	Married No Children	Married w/ Children
(A)	Log Total Hours per Person: Baseline Elasticities used in Main Results										
0	GMM	Wage Obs	5,5	All	47339	40	0.74	0.84	1.04	0.50	0.57
(B)	Log Total Hours per Person										
1	GMM	Wage Obs	0,0	All	67,182	29	0.62	0.76	0.88	0.42	0.42
2	GMM	Wage Obs	3,3	All	57,379	33	0.71	0.79	0.99	0.50	0.55
3	2sls	Wage Obs	5,5	All	47,339	40	0.64	1.03	0.94	0.23	0.36
4	GMM	Inv W sd	5,5	All	47,339	16	1.00	1.16	1.23	0.93	0.66
5	GMM	Unwt	5,5	All	47,381	16	0.79	0.92	0.99	0.68	0.60
6	GMM	Wage Obs	5,5	Age	47,339	12	0.65	0.84	1.06	0.33	0.38
7	GMM	Wage Obs	5,5	Edu	47,339	25	0.78	0.87	1.08	0.52	0.64
8	GMM	Wage Obs	5,5	ATR	47,339	8	0.81	1.19	1.12	0.51	0.43
9	GMM	Wage Obs	5,5	Lite	47,339	21	0.56	0.82	1.00	0.12	0.32
10	CF Linear	Wage Obs	5,5	All	47,339	40	0.68	0.75	0.79	0.65	0.53
11	CF Poly	Wage Obs	5,5	All	47,339	40	0.69	0.76	0.80	0.66	0.54
12	GMM	Wage Obs	K0,M0	All	13,433	14	0.28	0.28	–	–	–
13	GMM	Wage Obs	K0,M1	All	13,623	18	0.58	–	0.58	–	–
14	GMM	Wage Obs	K1,M0	All	7,768	8	0.65	–	–	0.65	–
15	GMM	Wage Obs	K1,M1	All	12,515	16	0.54	–	–	–	0.54
16	OLS	Wage Obs	5,5	–	47,339	–	0.10	0.16	0.21	0.05	-0.05
(C)	Log Total Labor Supply										
17	GMM	Wage Obs	5,5	All	47,339	40	0.46	0.55	0.7	0.21	0.37
18	GMM	Wage Obs	0,0	All	67,178	29	0.53	0.69	0.72	0.3	0.4
19	GMM	Wage Obs	3,3	All	57,379	33	0.5	0.63	0.72	0.26	0.41
20	GMM	Inv W sd	5,5	All	47,339	16	0.67	0.8	0.9	0.41	0.56
21	GMM	Unwt	5,5	All	47,428	16	0.62	0.71	0.76	0.53	0.48
22	OLS	Wage Obs	5,5	–	47,339	–	0.03	0.07	0.11	-0.02	-0.04

Unmarried women not in school full time between the age of 20-55; CPS ORG samples 1990-2000. All regressions same controls as Table 2 the main text. I consider combinations of estimation methods (GMM, 2SLS, OLS, Control functions), weighting (by number of wage observations, inverse log wage variance, unweighted), different sample selections ($(\#_a, \#_b)$ refers to $\#_a$ observations in demographic-state-year cell and $\#_b$ wage observations in a skill-state-year cell; (K#, M#) refers to being a parent (K1) or not (K0) and being married (M1) or not (M0)), and of instruments (Age/Edu uses only spillover IVs based on Age/Edu, Tax only uses EITC ATR IVs, Lite uses only EITC ATR and Share w/ EITC IVs – see Section C.1).

As pointed out in the main text, the choice of FEs has a first order effect on the estimated elasticity. The baseline specification includes a fixed effect that is the interaction of education and age group indicator variables with year indicators, d_{et}, which is different than the labor supply specification that includes a fixed effect for education, age, marriage status, and parental status indicator interactions without year.[60] I add the year interactions based on the assumed parametric relationship:

$$\frac{L_t^A}{L_t^B} = \left(\frac{w_t^A/\vartheta_t^A}{w_t^B/\vartheta_t^B}\right)^\rho \implies \ln[L_t^A/L_t^B] = \rho\left(\ln[w_t^A/w_t^B] - \ln[\vartheta_t^A/\vartheta_t^B]\right). \tag{93}$$

[60]Dropping parental status is done because the substitution elasticity is estimated at the 'skill' level rather than demographic level.

I drop the marriage interaction because this absorbs too much variation.

To see how these choices affect the estimates, models 5-8 use alternative FEs. Models 5,7 use the interaction of education, age group, and marriage indicators, and the estimate seems similar to the main specification except the empirical instrument strength has gone down by an order of magnitude. Models 6,8 interact the above with year indicators, and this appears to raise instrument strength (although still less than baseline) but the estimates make less sense. For example, model 6 has a positive substitution elasticity (statistically indistinguishable from zero); although, model 8 is negative yet about a fourth as large in magnitude. Given that the first stage F statistic goes down, I interpret this as the FEs absorbing needed variation in the instrument.

D.1 Difference in Difference Regressions

To complement the model implied labor supply effects, I estimate a simple difference in difference specification. I use the 1990-1996 ASEC samples for the OBRA expansion and the 2006-2012 samples for the ARRA expansion. I regress an indicator for labor force participation during the previous year on an post indicator (1994-1996 and 2010-2012) times a parental status indicator. I include state-year indicators and demographic group indicators that interact age, education, marriage, parental status. I use robust standard errors clustered at the demographic group level and weight the regressions using the ASEC supplement weights.

In typical EITC DiD studies, one compares unmarried women with no qualifying children to those with qualifying children (Eissa and Liebman, 1996; Eissa and Hoynes, 2004; Bastian, forthcoming). One rationale for this is that unmarried workers who do not work definitely do not receive EITC benefits and these workers are thought to work in similar labor markets. As long as there is no other parental specific time-varying labor market changes around EITC expansions, then this should estimate the average treatment effect on the treated which is a measure of the direct labor supply effects of the EITC. Because the ARRA expansion was most generous specifically for workers with

Table 21 – Additional Elasticity Specifications
Average within Demographic Groups

Model	Method	Weighting	Sample	IVs	Obs	KP rk F Stat	ρ Hours per Worker	ρ Employment
(A)	Baseline in Main Results							
0	2sls	Wage Obs	5	JI-ATR	19,501	67.26	-1.81	-1.75
(B)	Just Identified							
1	2sls	Wage Obs	0	JI-ATR	29,604	63.66	-2.15	-2.00
2	2sls	Wage Obs	3	JI-ATR	25,773	63.61	-2.08	-1.93
3	2sls	Inv W sd	5	JI-ATR	19,501	47.91	-1.57	-1.40
4	2sls	Unwt	5	JI-ATR	19,501	58.03	-1.00	-0.71
5	2sls, FEs 1	Wage Obs	5	JI-ATR	19,501	6.54	-2.15	-3.41
6	2sls, FEs 2	Wage Obs	5	JI-ATR	19,501	21.89	0.15	-0.52
7	2sls, FEs 1	Wage Obs	3	JI-ATR	29,604	5.81	-4.29	-5.34
8	2sls, FEs 2	Wage Obs	3	JI-ATR	29,604	24.05	-0.55	-1.06
9	2sls	Wage Obs	5	JI-Pos	19,501	3.09	-1.83	-2.11
(C)	Over Identified							
10	GMM	Wage Obs	5	OvID	19,501	13.76	-1.57	-1.85
11	2sls	Wage Obs	5	OvID	19,501	13.76	-1.67	-2.06
12	GMM	Wage Obs	0	OvID	29,604	13.93	-2.30	-2.47
13	GMM	Wage Obs	3	OvID	25,773	13.46	-2.18	-2.35
14	GMM	Inv W sd	5	OvID	19,501	6.86	-1.54	-1.99
15	GMM	Unwt	5	OvID	19,501	8.74	-0.61	-0.54
(D)	OLS and Alternate Variable Constructions							
16	OLS	Wage Obs	5	–	19,501	–	0.06	0.01
17	2sls, alt 1	Wage Obs	5	JI-ATR	19,903	59.23	-1.81	-1.73
18	2sls, alt 2	Wage Obs	5	JI-ATR	12,288	88.8	-2.24	-2.20
19	2sls, alt 3	Wage Obs	5	JI-ATR	17,182	81.05	-1.97	-1.97
20	2sls, alt 4	Wage Obs	5	JI-ATR	5,239	61.23	-3.24	-3.19

Unmarried women not in school full time between the age of 20-55; CPS ORG samples 1990-2000. All regressions same controls as Table 3 the main text. I consider combinations of estimation methods (GMM, 2SLS, OLS; fixed effects and variable constructions), weighting (by number of wage observations, inverse log wage variance, unweighted), different sample selections ((#) refers to minimum value of the mean number of skill-state-year observations for the numerator and denominator group), and of instruments (Just Identifies using relative EITC ATRs or Share w/ EITC or Overidentified – see Section C.1).

three or more qualifying child, I include two additional specifications. In column (3), I compare workers with no qualifying children to workers with three qualifying children.

In column (4), I compare workers with one or two qualifying children to workers with three qualifying children.

Table 22 – EITC Difference-in-Difference Results

	OBRA	ARRA		
	(1)	(2)	(3)	(4)
Post $\times$ Parent Status	0.039	0.010	-0.006	-0.011
	(0.010)	(0.007)	(0.014)	(0.013)
Sub-Sample	-	-	$C \in \{0, 3\}$	$C \in \{1, 2, 3\}$
Obs	78,549	119,082	82,826	43,379
Clusters	64	64	64	32

Unmarried women not in school full time between the age of 20-55. All data from March CPS, ASEC samples, 1990-1996 & 2006-2012. All regressions include state-year indicators and demographic group indicators, as in the main text.

E Additional Incidence Results

E.1 Individual Level Effects of 1993 Expansion

In Table 23 I report individual level results rather than aggregate as in the main text. These results show how an individual's EITC amount is affected by incidence and behavioral responses. The change in the EITC is the naive change that holds all labor supply and wages constant. In Panel (A), unmarried mothers get roughly $\$417$ in expanded EITC but lose roughly a fourth of that amount due to wage incidence. For unmarried mothers, wage spillovers are less important, at roughly 21% of the wage effect, primarily because the direct effects dominate. For married mothers spillovers are 152% of the wage effect, while for women without children spillovers are only 8.4% of the wage effect.

E.2 EITC vs NIT

In Table 24, I present an EITC vs Negative Income Tax (NIT) simulation results using the labor supply elasticities from Table 2. This exercise compares the main specification of Rothstein (2010), as presented in Table 5, with the general equilibrium effects this paper describes.

In the table below, the 'Rothstein' specification replicates the first column of Table 5 of Rothstein (2010) using my incidence sample (where differences are described in Appendix B). For these columns, I use a homogeneous labor supply elasticity of $\varepsilon^L = 0.75$ and the labor substitution elasticity $\rho = -0.3$. The values closely correspond to the values in Rothstein. For example, I calculate a labor effect of $\$0.13$ for the EITC and $-\$0.18$ for the NIT while Rothstein calculates $\$0.09$ and $-\$0.16$, respectively.

The next set of columns (D-G) use the estimated labor supply elasticities from Table 2 but use the same $\rho = -0.3$. The heterogeneous labor supply elasticity changes the labor supply shocks, which amplifies and attenuates different labor market effects. For example, the EITC wage effects are $-\$0.42$ in column (B) but are only $-\$0.29$ in column (D).

Table 23 – Incidence Results: Individual Effects of 1993 Expansion

EDU	wL	ChEITC	$\mathrm{d}w^{\mathrm{PE}}L$	$\mathrm{d}w^{\mathrm{GE}}L$	$(\mathrm{d}w^{\mathrm{GE}}-\mathrm{d}w^{\mathrm{PE}})L$	$\frac{\mathrm{d}w^{\mathrm{GE}}L}{\mathrm{d}^{\mathrm{PE}}L}-1$	$\frac{\mathrm{d}w^{\mathrm{PE}}L}{\mathrm{ChEITC}}$	$\frac{\mathrm{d}w^{\mathrm{GE}}L}{\mathrm{ChEITC}}$
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
(A)	Unmarried Mothers							
LessHS	10,059	417	-117	-114	2.40	-3.4%	-28.6%	-29.3%
HS	17,637	314	-75	-70	4.70	-7.6%	-13.2%	-14.2%
SomeCol	18,259	260	-46	-41	4.90	-13.6%	-9.7%	-10.8%
BA+	30,936	99	-12	-3	9.30	-81.6%	-0.3%	-1.0%
Total	19,055	273	-60	-54	5.20	-20.8%	-11.7%	-12.7%
(B)	Married Mothers							
LessHS	10,796.2	162	-2.50	0.10	2.60	42.9%	-0.0%	-0.4%
HS	15,367.4	56	1.40	5.50	4.10	75.4%	0.2%	0.1%
SomeCol	19,334.3	35	5.30	10.50	5.20	118.7%	0.4%	0.2%
BA+	31,027.4	10	3.40	12.80	9.40	317.1%	0.1%	0.0%
Total	20,513.8	45	2.80	8.60	5.80	152.0%	0.2%	0.0%
(C)	Women without Children							
LessHS	11,196.2	20	-44	-42	2.60	-8.6%	-8.4%	-8.6%
HS	16,967.1	9	-26	-22	4.40	65.1%	-1.1%	-1.2%
SomeCol	18,859.6	4	-20	-15	4.90	45.3%	-0.7%	-0.8%
BA+	30,888.3	2	-5.30	3.80	9.10	-94.6%	-0.0%	-0.0%
Total	20,880.4	7	-20	-15	5.70	8.4%	-1.3%	-1.4%

All items are average across workers, weighted by hours $\times$ sample weights. All data from 1994 March CPS, Women from Tax Units Baseline labor supply elasticities in table 2 and $\rho = -1.8$.

The last set of columns (H-K) use the estimated labor supply elasticities and substitution elasticity from Table 2, $\rho = -1.8$. This has a pronounced effect on the PE labor market effects but less on the GE effects. For example, the EITC wage effects are $-\$0.42$ in column (B) but are now only $-\$0.12$ in column (H) but for columns (F) and (J) the effects much closer at $-\$0.04$ and $-\$0.03$.

One noteworthy point is that if Rothstein had used a general equilibrium analysis, then, comparing the differences in columns (D,E) to (F,G), the EITC would have fared far better.

Table 24 – Incidence Results:
Aggregate Effects: All Women
Rothstein (2010) Replication & Extension

Dollars	Rothstein		$\rho = -0.3$				$\rho = -2.00$			
	"PE"		"PE"		GE		"PE"		GE	
	EITC	NIT	EITC	NIT	EITC	NIT	EITC	NIT	EITC	NIT
	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)
Intended	1.00	0.56	1.00	0.56	1.00	0.56	1.00	0.56	1.00	0.56
Labor	0.13	-0.18	0.09	-0.12	0.24	-0.35	0.22	-0.30	0.27	-0.37
Wage	-0.42	0.60	-0.29	0.42	-0.04	0.06	-0.12	0.17	-0.04	0.05
Gross Earnings	-0.30	0.42	-0.20	0.29	0.20	-0.28	0.10	-0.13	0.23	-0.32
Net Transfer, Fixed Taxes	0.58	1.50	0.71	1.42	0.96	1.06	0.88	1.17	0.96	1.05
Net Earn, Fixed Taxes	0.70	1.42	0.80	1.29	1.20	0.72	1.10	0.87	1.23	0.68
Net Earnings	0.12	-0.35	0.20	-0.46	0.57	-0.99	0.50	-0.87	0.63	-1.04
Fiscal Externality	-0.10	0.05	-0.09	0.04	-0.07	0.02	-0.09	0.04	-0.08	0.03

Units in table are changes in dollars of earnings summed across demographic groups. Note: $Z^G = w \cdot L$, $Z^N = (1-\tau) \cdot w \cdot L$. All data from 1993 March CPS, Women from Tax Units Labor supply elasticities in table 2, except 'Rothstein' which uses $\varepsilon^L = 0.75$ for all.

First, note that Rothstein primarily used net earnings and transfers with fixed taxes to compare the programs. I have provided the additional columns of net earnings that allow taxes to change (given a fixed average tax rate) and the change in welfare assuming the expansions are revenue neutral.

Evaluating the programs based on Rothstein's criteria, in PE the EITC does worse on both measures, but in GE the measures give a mixed signal. Using the net earnings allowing for tax changes, fares better in both PE and GE. The net earnings for the EITC are always positive while are always negative for the NIT expansions. This is because the EITC expands production by bringing new workers into the labor force while the NIT decreases production by having workers leave. For some workers, the NIT drives wages up which causes this group to pay more in taxes, which can cause net earnings to decrease.

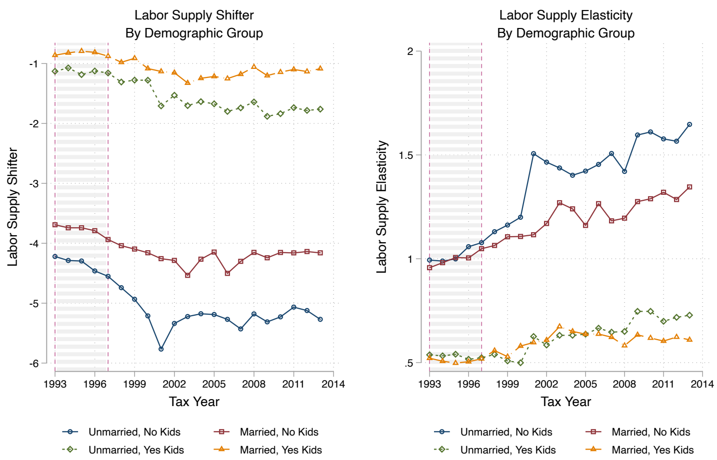
Finally, the welfare changes are always negative for the EITC and either positive or negative for the NIT depending on the parameterization. A negative welfare change here implies that the government expenditure increases (the welfare measure is the 'fiscal externality' – see Section A.2.2). For the EITC, the government is spending more because it is paying entering workers more in EITC. For the NIT, the government is spending more because it is paying exiting workers not to work. Balancing these two different reasons for increased government expenditure is a normative question.

F Structural Model Implied Parameters

Using the approach outlined in Section 9, I back-out the structural parameters and calculate the model implied elasticities for the out-of-sample period. In Figure 8 I plot the model implied average labor shifters and average supply elasticity by marriage and parental status over time.

The labor shifters appear to trend downward over time for unmarried women but constant for married women. This implies that the utility cost of labor supply is weakly increasing for unmarried women. For all groups, the elasticities are increasing since the late 1990's. Given equation 29, this is largely due to roughly stagnant real net wage growth and declining labor force participation in the 2000's. Together, for unmarried women this implies that the per dollar effectiveness of the EITC relative to the early 1990's is ambiguous, but should be more effective for married women.

Figure 8 – Model Implied Parameters



Supply shifter based on equation 30; elasticity based on equation 29; parameter β^d recovered from tax years 1993-1997 and estimated elasticities from Table 2 and tax and transfer inclusive real net wage.