The General Equilibrium Incidence of the Earned Income Tax Credit

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Abstract

The Earned Income Tax Credit is the US's largest anti-poverty program, used by 20% of workers. Yet all prior analysis uses partial equilibrium assumptions on gross wages. I derive the general equilibrium incidence of wage subsidies and apply this to the EITC. I quantify the importance of 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 parameterize a structural model to show 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 the *de facto* largest anti-poverty program in the United States, with over 20 percent of all workers receive some share of the $67 billion expenditure, 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 affects market wage rates – e.g., decreasing targeted workers' wages – then the anti-poverty policy goals will be undermined. 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.

The EITC is a refundable tax credit that depends on a tax unit's gross earnings, marital status, and number of young dependents. Initially designed as payroll taxes rebate, the EITC is now an anti-poverty program in the form of a low wage subsidy for workers with children. Receiving the maximum credit yields a 20%-45% subsidy on gross earnings for workers with children. Lawmakers and policy advocates often propose expansions of EITC benefits and eligibility. With each expansion, the scope for unintended consequences which ripple across the economy increases.

The primary goals of this paper are to understand and quantify both the importance of EITC induced spillovers on the rest of the economy and the trade-offs from large scale interventions into the labor market. I do this using three evaluations. First, I estimate new labor market elasticities and calculate the empirical incidence of the 1993 and 2009 EITC expansions by using a general equilibrium incidence result that allows for heterogeneous tax changes and labor market responsiveness. Second, I compare counterfactual marginal expansions of the 1992 EITC versus the 1992 social safety-net 'Welfare' programs to compare how different labor market incentives affect the incidence. Third, I use the estimated elasticities to parameterize a structural labor supply model that allows me to calculate the effect of implementing an EITC reform that equalizes the credit schedule for workers with and without children.

To understand the EITC's effect on gross wages and earnings, I derive the general equilibrium incidence of targeted wage subsidies in a single output economy with imperfectly substitutable factors of production.[1] I show that the general equilibrium incidence can be expressed as a function of elasticities, market shares, and tax rate changes. Importantly, I show that GE spillover effects are 'first order terms' and do not disappear even as market size shrinks. Because of these spillovers, I show that the net effect on wages is theoretically ambiguous due to cascading feedback across labor markets.

The mechanism is simple. A policy that increases labor supply of a *treated* set of workers will increase the marginal product of *untreated* workers; 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 labor subsidy.

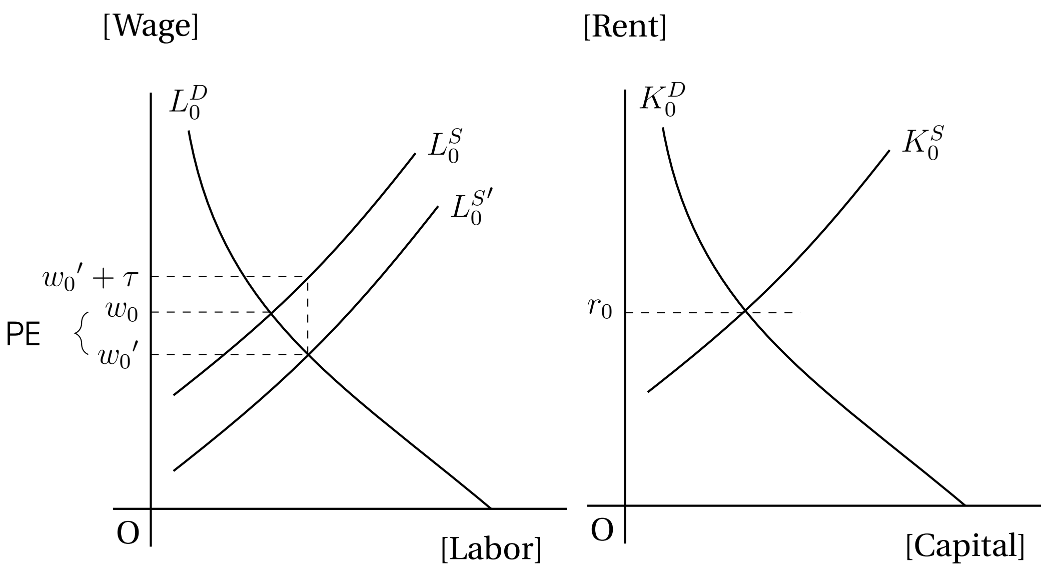
My primary theoretical contribution is to formalize the economic forces that generate spillover effects from targeted wage taxes. I show that when all tax changes are in the same direction, the partial equilibrium incidence is the *upper bound* for treated workers and the *lower bound* for untreated workers relative to the general equilibrium gross wage incidence (as Figure 1 shows). Intuitively, because the behavior of all *other* economic agents is held fixed in PE, the marginal product changes are ignored so wage spillover effects are also ignored. Since the spillover effects are 'first order' and opposite relative to the direct effects, the general equilibrium incidence is theoretically ambiguous.

My primary empirical contribution is to quantify the magnitude of the spillovers caused by the 1993 and 2009 EITC expansions as well as the two counterfactual policy experiments. First, I calculate the empirical general equilibrium incidence of two EITC expansions: the 1993 Omnibus Budget Reconciliation Act (OBRA) and the 2009 American Recovery and Reinvestment Act (ARRA). The OBRA expansion was the largest single increase in EITC subsidies in the program's history, with the ARRA being the second largest. I find that the spillovers were economically meaningful relative to the direct effects, especially for workers who were not primarily targeted by the EITC, but only the OBRA

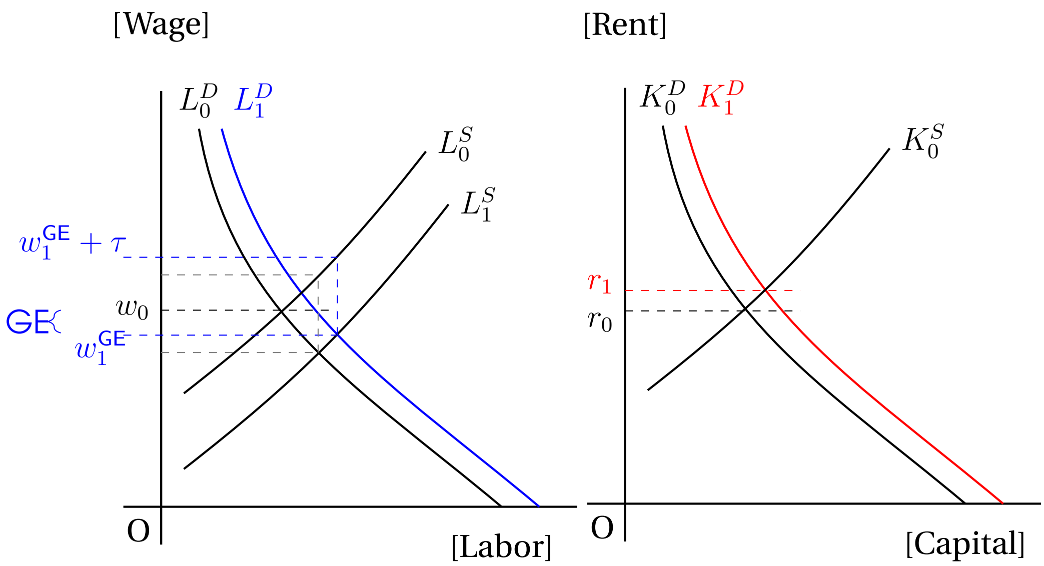
[1] In Appendix A I derive a two sector model and several other generalizations.

Figure 1 – Labor Subsidy Incidence in Two Factor Model

(**a**) Partial Equilibrium



(**b**) General Equilibrium



These drawings are based on the two factor model of Lee and Saez (2012) which incorporates an equilibrium in the capital market. In (**b**), marginal product spillovers cause labor and capital demand to shift right, attenuating the PE gross wage decline.

expansion had large labor market effects. For the OBRA expansion, I calculate that gross wages declined by an average 0.4% (roughly 10% less decline due to positive spillovers) for unmarried women with children, by 0.2% (17% less decline) for unmarried without children, increased by 0.03% (roughly 60% greater due to spillovers) for unmarried with children, and did not change for unmarried women without children. In aggregate, for every new dollar of EITC spending net-labor-earnings increased by $\$0.55$ (17% greater than PE) with an equivalent variation of $-\$0.02$ (33% smaller than PE), implying a small overall increase in government spending. For the ARRA expansion, I calculate that gross wages declined by 0.12% (7%) for unmarried women with children, by 0.06% (13%) for unmarried without children, increased by 0.01% (29%) for unmarried with children, and did not change for unmarried women without children. A one dollar increase in EITC spending led to an aggregate $\$0.20$ increase in net-labor-earnings with an equivalent variation of $\$0.00$ in aggregate. This implies that the EITC expenditures were successful at transferring (at least) a dollar to workers with children, but caused significant spillover effects for other groups.

My second empirical exercise highlights how different policies' labor incentives affect spillovers and overall policy efficacy. I consider a hypothetical policy goal of transferring \$100 million to workers through an EITC expansion versus an expansion of 'Welfare' programs. Thus, I essentially offer a general equilibrium extension to Rothstein (2010), who compares an EITC expansion to a hypothetical Negative Income Tax expansion. I find that an intended dollar of EITC spending delivers $\$0.61$ of net earnings to workers ($\$1.21$ with fixed taxes and transfers) while a equal-sized Welfare expansion delivers $-\$0.41$ ($\$0.90$) of intended dollars! This result is driven by different policy consequences that policy-makers must decide how to balance. Foremost, the EITC increases welfare because there of positive marginal product spillovers on higher skill workers which feeds back to increase labor demand for the low-skill EITC workers despite their labor supply increase. The Welfare expansion increases welfare because the government is transferring consumption from *other* markets and allowing the subsidized workers to decrease labor supply (which drives up their wages), but that ultimately decreases market output and causes negative marginal product spillovers for all other workers. My results contrast with the partial equilibrium analysis of Rothstein (2010) who finds that the NIT is the unambiguously more cost-effective program relative to the EITC.[2]

[2] In Appendix E, I replicate and update the analysis of Rothstein (2010). Our conclusions differ for two reasons. First, I allow for spillover effects and show these are quantitatively important. Second, I estimate an elastic labor substitution elasticity, in line with the labor literature (Katz and Murphy, 1992; Goldin

My third exercise calculates the effect of equalizing the EITC schedule for workers without children and those with one child. A complaint about the EITC is the credit is quite small relative to workers with children. The current maximum childless worker credit is \$538 versus \$3,584 for unmarried workers with one child. Further, as I show in the exercises above, expanding EITC generosity for workers with children causes gross and net wage decreases for childless workers. Using a general equilibrium structural model, I calculate the effect of the 1993 OBRA expansion that instituted the childless worker schedule to a counterfactual OBRA that made the childless worker credit equal to the schedule for families with one child. I find that increasing the generosity for childless workers, through equilibrium gross wage changes, creates a diminished pro-work incentive for workers with children. Labor supply for unmarried women with children decreases by roughly one-third: from a 2.1% increase to a 1.3% percent increase. For unmarried women without children, labor supply increases from 0.8% percent to 8.3% percent! Thus, when considering whether to increase the generosity of the EITC for workers without children, policymakers will need to consider the large effects of this on workers with children.

To calculate labor market effects in the exercises summarized above, I estimate labor supply elasticities for different demographic groups and a labor substitution elasticity that governs the curvature of labor demand. I use state-year policy variation in the EITC during the 1990s along with initial labor market exposure to the EITC to estimate labor supply elasticities that vary education, marriage, and parental status.[3] I isolate EITC policy variation by creating simulated instruments by calculating tax parameters for each year in the sample with the same fixed distribution of worker characteristics from the 1990 Census.[4] My estimation strategy allows me to avoid the assumption that women with and without children respond the same way to wage changes, as in difference-in-difference based analysis. Because the incidence depends on the wage responsiveness

and Katz, 2009; Borjas et al., 2012), rather than the inelastic parameter used in the main specification of Rothstein (2010). Figure 3 in Appendix A shows how important different substitution elasticities are for the incidence calculation.

[3]The primary policy variation comes from the 1993 OBRA expansion of the EITC, but a hand-full of states provide additional policy variation.

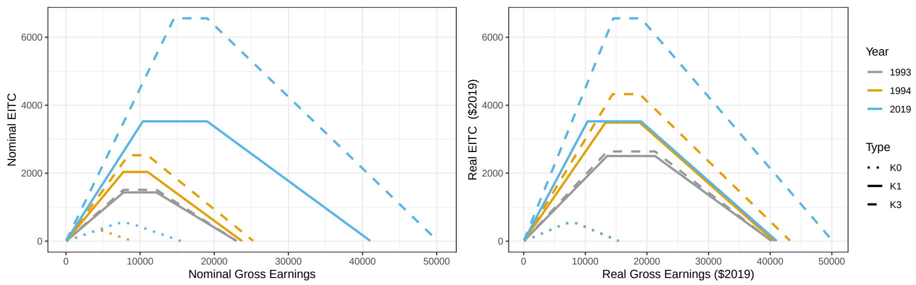
[4]Importantly, this approach combines all possible information in EITC parameters but purges the variables of the endogenous behavioral responses from the policy changes.

of different labor markets, capturing granular differences in supply responsiveness is important for accurately measuring incidence effects.

The overarching message of this paper is that the impact of general equilibrium spillovers of conditional wage subsidies – such as the EITC, social safety-net programs, or proposed Universal Basic Income – on labor market outcomes are of first order importance. Further, because the labor market is central to the distribution of goods and services in the economy, tax policy aimed at ameliorating the financial hardships of the working poor can nevertheless have unintended consequences across all sectors of the economy.

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 Earned Income Tax Credit is a large federal tax expenditure program designed to encourage work by subsidizing earned income using a non-linear benefit schedule. Figure 2 shows how the program has expanded since the early 1990's to the present.

Figure 2 – EITC Schedule by Year and Number of Children



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

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). This massive intervention in the labor market should have economically meaningful effects on labor market sorting and equilibrium.

Previous studies have consistently found that the EITC benefit structure 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.[5] 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).[6] As noted by Hotz and Scholz (2003), this assumption had never been tested in first decade of EITC research.

The research closest to my own are those by Leigh (2010) and Rothstein (2010), who study the wage incidence in partial equilibrium.[7] 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 cell real wages. As mentioned earlier, Rothstein (2010) simulates a hypothetical EITC expansion change and finds that for every dollar of intended transfer real wages decrease by $\$0.34$ (in partial equilibrium). 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 to these papers is to allow for labor market spillovers that affect both

[5]More recent papers on labor market effects and net-income distributions include Fitzpatrick and Thompson (2010); Chetty et al. (2013); Jones (2017); Kasy (2017); Hoynes and Patel (2018); Bastian (forthcoming). In addition, there are many papers that assess the social impact of the EITC on various 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).

[6]Some of these papers are explicit (Eissa and Liebman, 1996; Saez, 2002; Chetty et al., 2013) and others are implicit in by holding wages fixed when simulating labor market effects (Dickert et al., 1995; Eissa and Hoynes, 2004).

[7]Azmat (2019) studies the incidence, also in partial equilibrium, of a conceptually similar Working Families Tax Credit program in the UK. She finds that, due to differences in salience unique to the UK program, gross wages fall by 7% for claimants and 1.7% for non-claimants. Also, 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.

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.

Agrawal and Hoyt (2018) study general equilibrium tax incidence in a multi-product consumer goods markets. They find that tax rate overshifting is possible when related goods are substitutes and find that spillovers are empirically important in alcohol markets. My paper considers taxes in multi-factor *input* markets, applies this to empirically to the EITC and Welfare programs, and also finds spillovers are empirically important.

In terms of general equilibrium effects on 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.[8] In addition, because I used empirical tax rates, I can compute both gross and net earnings effects. Finally, 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. To come to these conclusions, the authors use a two skill model, focus solely on married households, use an approximated 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

[8]Additionally, the author omits common-policy-shock effects by using year indicator variables in his empirical specification. This may be one reason that his empirical estimates are similar to partial equilibrium analysis.

maintaining a rich degree of individual heterogeneity in skills and wage responsiveness and exactly modeling the EITC.

Finally, my results are able to 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 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.

The rest of the paper is organized as follows. In Section 2, I describe the labor market model and its assumptions. In Section 3, I derive the partial and general equilibrium wage incidence and discuss the two. In Section 4, I describe the data I use to estimate the labor market elasticities, the methods that I use, and the elasticity results. In Sections 5-8, I use these estimates to calculate the general equilibrium incidence and labor market effects of the policy evaluations described above. Finally, I conclude by briefly summarizing the results and describing how these results affect considerations of the EITC.

2 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.[9]

2.1 Labor Supply

Let $i \in \mathcal{N}$ index workers who have preferences over a composite consumption good and labor that is representable by a utility function, $U_i \colon \mathcal{X} \times \mathcal{L} \to \mathbb{R}$. Let utility be quasi-linear with respect to final good consumption. Workers maximize utility by making a discrete labor supply choice over whether to participate in the labor market or not, given prices and non-labor income.[10] After substituting the budget constraint, the utility maximization problem is:

$$\arg\max_{L=\{0,1\}} \{V_i(b_i, m_i; L_i = 0), V_i(w_i, m_i; L_i = 1)\} \tag{1}$$

$$= \arg\max_{L=\{0,1\}} \{0,\ T_i(w_i \cdot L_i, m_i) + v_i\}, \tag{2}$$

where $T_i(\cdot)$ is a mapping from gross earnings and unearned income to net total income and v_i is the net disutility of labor. Let v_i be drawn from some distribution, $F_i(\vee)$, that can depend on worker attributes. Taking prices, the transfer function, and v_i as given, the problem yields worker output demand and labor supply functions, $X_i^D(w_i, m_i)$ and $L_i^S(w_i)$. [11]

Let worker i be described by a skill level, $e \in \{0,1\}$, and a parental status $k \in \{0,1\}$, where $d = (e,k)$ is the worker's 'demographics.' Suppose that only skill determines worker productivity, so that 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 will earn the same wage.

[9] 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 include several extensions.

[10] Non-labor income includes spousal earned income for married workers, a $\varsigma^i \in (0,1)$ share of capital assets, and some exogenous income level.

[11] Note: $L_i = 1 \iff v_i \le \tilde{v}_i(w_i)$, so $\Pr(L_i = 1 \mid \chi) = F_i(\tilde{v}_i)$. With specific distributional assumptions on $F_i(\vee)$ the expected labor supply function of each worker is known; e.g., with Type-1 Extreme Value draws labor supply has a logit form: $\Pr(L_i = 1 \mid \chi) = \mathrm{e}^{\tilde{v}_i(w_i)}/(1 + \mathrm{e}^{\tilde{v}_i(w_i)})$.

By integrating over workers of the same demographic, the aggregate labor supply functions are: $L_d^S = F_d(\tilde{v}_d)N_d,\ L_e^S = \sum_{k\in\mathcal{K}} L_{(e,k)}^S$, and $L^S = \sum_{e\in\mathcal{E}} L_e^S$. The labor supply elasticity for market e is: $\frac{\partial L_e^S}{\partial w_e}\frac{w_e}{L_e} = \sum_{k\in\mathcal{K}}\left(\frac{F_{e,k}(\tilde{v}_{e,k})N_{e,k}}{L_e}\right)\left(\frac{w_e\cdot f_{e,k}(\tilde{v}_{e,k})}{F_{e,k}(\tilde{v}_{e,k})}\right) \equiv \sum_{k\in\mathcal{K}}\left(\theta_{e,k}\cdot\varepsilon_{e,k}^S\right)$, which is a labor weighted sum of the demographic specific labor supply elasticities. [12] Under these assumptions, the Marshallian elasticity is equal to the Hicksian compensated elasticity, so there are no income effects for labor supply.

2.2 Production

Suppose that there are $j \in \mathcal{J}$ potential producers, each endowed with one unit of capital,[13] that can hire labor to produce a homogeneous consumption good. Firms face heterogeneous costs of supplying their unit of capital, c_j, that is drawn from some distribution, $G(\mathsf{c})$.

Technology is represented by a nested constant elasticity of substitution (CES) production function:

$$q_j^S = Q(\{L_{e,j}\}_e, K_j) = A\left[\left(\sum_{e\in\mathcal{E}}\vartheta_e(L_{e,j}^D)^{\frac{1+\rho}{\rho}}\right)^{\frac{\rho}{1+\rho}}\right]^\alpha K_j^{(1-\alpha)} \tag{3}$$

$$= A\cdot\mathbf{L}_j^\alpha K_j^{(1-\alpha)}, \tag{4}$$

where $L_{e,j}^D$ is the type e labor demand for producer j and $\mathbf{L}_j$ is the labor aggregate. The elasticity of substitution between labor types is parameterized by:

$$\rho = \mathsf{d}\ln[L_{e''}\ /\ L_{e'}]/\mathsf{d}\ln[w_{e''}/w_{e'}] < 0. \tag{5}$$

This technology features constant returns to scale (CRS) and assumes the substitution elasticity is the same between all types.[14] Firms maximize profits: $\pi_j = p\cdot Q(\{L_{e,j}\}_{e\in\mathcal{E}}, K_j) - \sum_{e\in\mathcal{E}} w_e L_e - rK_j$. Aggregate output is defined as $q^S = \int_j q_j^S \mathsf{d}j$. Price taking, zero profits,

[12] Using the logit example, $\varepsilon_{e,k}^S = \frac{\partial T_{e,k}}{\partial w_e} w_e(1 - F_{e,k}(\tilde{v}_{e,k}))$.

[13] That is, $K_j = 1$ for all producers.

[14] The primary modeling benefit to this technology is that it allows for tractable analytic solutions with an arbitrary number of labor types, as I use in the generalized model for the empirical applications. The substitution elasticity between $\mathbf{L}_j$ and K_j is (-1) by the Cobb-Douglas assumption.

and identical production functions imply all firms choose the same factor input bundle, so by CRS this implies that the aggregate production function is also nested CES. To solve the model, I normalize all wages and capital rents by the final good price – effectively this sets $p = 1$. I define a factor's cost share as $s_{L_e} = w_e L_e / (\bar{w}\mathbf{L} + rK)$, with $s_L = \sum_{e \in \mathcal{E}} s_{L_e}$ and $s_K = rK/(\bar{w}\mathbf{L} + rK)$.

In this set up, the firm capital supply is synonymous with firm entry that is determined by firm capital supply costs, c_j. By zero profits, $Q(\{L_{e,j}\}_{e \in \mathcal{E}}, K_j) - \int_{i \in L_j} w_i L_i = r$, again where each firm only has one unit of capital. As with workers, firms will enter based on a threshold condition: $c_j \leq \tilde{c}(r)$. In equilibrium, this will determine the aggregate capital supply function, $K^S(r)$, and a capital supply elasticity, $\varepsilon_K^S = r \cdot \frac{g(\tilde{c})}{G(\tilde{c})}$.

2.3 Transfer System

For simplicity, I assume that the government initially uses lump-sum taxation, n_i, with an unemployment benefit, b_i, and then imposes a targeted labor subsidy, τ_i. I assume the government balances its budget and finances any subsidy change using lump sum tax changes. I model the subsidy as a unit excise tax/subsidy, $T_i(w_i \cdot L_i, m_i) = (w_i + \tau_i) \cdot L_i + (1 - L_i) \cdot b_i - n_i$.[15] I suppose that the subsidy and unemployment benefit amounts depend on gross income and worker demographics that the government can verify. Given the assumption about wages and skills, the subsidy and benefits both vary at the demographic level.[16]

2.4 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). The market is in

[15] A subsidy can be considered a negative tax, so I refer to τ as a tax or subsidy based on context.

[16] In the EITC context, despite a small subsidy to workers without children, the subsidy is typically modeled as only for low income workers with children. This implies the following e-group labor supply function: $L_e^S(w_e, \tau_e) = L_{e,k_0}^S(w_e) + L_{e,k_1}^S(w_e + \tau_e)$.

equilibrium when no worker wishes to adjust her labor supply and no firm wishes to adjust its input bundle.

Due to the CRS assumption, the scale of production cannot be determined so the scale of factor demands cannot be determined (without using equilibrium relationships). Fortunately, the model can be solved in terms of quantity and price ratios. In equilibrium, the labor demand bundle must satisfy:

$$\frac{L_0^D}{L_1^D} = \left(\frac{w_0/\vartheta_0}{w_1/\vartheta_1}\right)^{\rho} \tag{6}$$

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

$$\frac{\mathbf{L}^D}{K^D} = \left(\frac{\bar{w}/\alpha}{r/(1-\alpha)}\right)^{-1}, \tag{7}$$

where $\bar{w} = \left(\vartheta_0\left(\frac{w_0}{\vartheta_0}\right)^{1+\rho} + \vartheta_1\left(\frac{w_1}{\vartheta_1}\right)^{1+\rho}\right)^{\frac{1}{1+\rho}}$ 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. Thus, the general equilibrium of the economy is any $\{w_0, w_1, r\}$ that solves the following equations:

$$\text{Labor Clearing} \quad \frac{L_0^S(w_0,\tau_0)}{L_1^S(w_1,\tau_1)} = \left(\frac{w_0/\vartheta_0}{w_1/\vartheta_1}\right)^{\rho} \tag{8}$$

$$\text{Factor Clearing} \quad \frac{L^S(w_0,w_1,\tau_0,\tau_1)}{K^S(r)} = \left(\frac{\bar{w}/\alpha}{r/1-\alpha}\right)^{-1} \tag{9}$$

$$\text{Zero Profits} \quad 1 = c(w_0,w_1,r). \tag{10}$$

3 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. The partial equilibrium section essentially replicates Rothstein (2010) using the above model notation.

3.1 Partial Equilibrium

Suppose that the government is only subsidizing low skill labor for workers with children: $d = (0, 1)$. I find the partial equilibrium incidence by totally differentiating the labor clearing condition (equation 8) while holding $\{L_1, K, w_1, r\}$ constant.[17] This yields (when $\hat{\tau} > 0$):

$$\hat{w}_0^{\mathsf{PE}} = \left(\frac{\varepsilon_{0,1}^L}{\varepsilon_0^L - \rho}\right) \cdot \theta_{0,1} \cdot \hat{\tau} := \gamma_0 \cdot \hat{\tau} < 0 \tag{11}$$

where $\hat{x}_e = x_e / w_e$ is the percent of wage change for the e-group, and ε_e^L and $\varepsilon_{e,k}^L$ are the group and sub-group supply elasticity, respectively.

This 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:[18]

$$L_0^D(w_0) = L_1^S(w_1(w_0)) \cdot \left(\frac{w_0/\theta_0}{w_1(w_0)/\theta_1}\right)^\rho \implies \eta_0^D = \rho + \frac{\partial w_1}{\partial w_0}\left(\varepsilon_1^L - \rho\right). \tag{12}$$

When $\frac{\partial w_1}{\partial w_0} = 0$ by partial equilibrium assumption, the demand elasticity equals the substitution elasticity between factors.[19] Holding w_1 and r fixed is equivalent to holding the factors' marginal product constant, but this is invalid when L_0 increases.

3.1.1 Implication and Interpretation for Policy

When there are multiple labor types with heterogeneous subsidy changes, using the PE analysis an 'employment weighted average partial equilibrium effect.' This is not of

[17] Note, I ignore equations (9, 10) because these cannot simultaneously hold with non-zero change in gross wages but other variables fixed. For example, totally differentiating equation 10 with other variables fixed implies $L_0 \cdot \mathsf{d}w_0 = 0$, which is only true if $\mathsf{d}w_0 = 0$, but then the incidence is not shared!

[18] 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.

[19] 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 $\mathsf{d}\ln[L_{e'}^D] = \mathsf{d}\ln[w_{e'}] = 0$.

theoretical or practical interest unless it is *ex-ante* known that spillover effects will be negligible. The PE assumptions require that for any specific labor group there is no effect on any other group, which creates a set of mutually exclusive assumptions.

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...".[20] 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. With CRS technology, if one factor price goes down, then another must increase, so the *owners* of the other factors benefit if low skill wages fall.[21] Second, if entrepreneurs own some of the other factors (such as capital), then entrepreneurs may 'capture' the wage subsidy because their own factor payments increase. However, the production function in Rothstein (2010) only includes labor factors, so there is no possible factor to be owned by entrepreneurs.[22]

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.

3.2 General Equilibrium

To calculate the incidence, I totally differentiate equations 8, 9, and 10 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 intuitively solve the for a change in low skill wages using iterative

[20] Kasy (2017) makes a similar claim.

[21] Alternatively, holding other wages and rents constant, the output price must decrease which benefits consumers – especially low income – rather than firm owners.

[22] In an earlier working paper, Rothstein's production function did include capital but this was omitted in the published version.

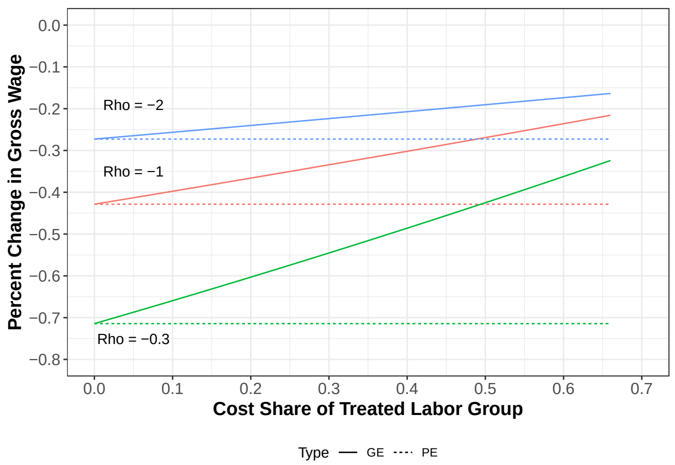
substitution.[23] Use the zero profits condition to solve $\mathrm{d}r = f(\mathrm{d}w_0, \mathrm{d}w_1)$, use the labor clearing condition to solve $\mathrm{d}w_1 = g(\mathrm{d}w_0, \mathrm{d}\tau)$, and then substitute into the factor clearing condition for $\mathrm{d}w_0 = h(\mathrm{d}\tau)$. This yields:

$$\hat{w}_0^{\mathsf{GE}} = \left(\frac{-\varepsilon_{0,1}^L \theta_{0,1}}{(\varepsilon_0^L - \rho)} + \frac{s_{L_0}\left(\frac{\varepsilon_{0,1}^L \theta_{0,1}}{(\varepsilon_0^L - \rho)}\right)\left(\frac{\varepsilon_K + 1}{s_K} + \frac{1+\rho}{s_L}\right)}{(\varepsilon_0^L - \rho)\left(1 + \left(\frac{\varepsilon_K+1}{s_K} + \frac{1+\rho}{s_L}\right)\left(\frac{s_{L_0}}{(\varepsilon_0^L - \rho)} + \frac{s_{L_1}}{(\varepsilon_1^L - \rho)}\right)\right)} \right) \hat{\tau} \tag{13}$$
$$:= (\gamma_0 + \Gamma_0) \cdot \hat{\tau},$$

where γ_0 is the PE gross wage effect and Γ_0 is the GE spillover term. Thus, the GE incidence is the direct (PE) effect plus a weighted sum of the all direct and cross-factor effects.[24]

Since $\Gamma_0 \geq 0$, a subsidy increase for low skill labor implies that $\hat{w}_0^{\mathsf{GE}} \in \left[\hat{w}_0^{\mathsf{PE}},\, 0\right]$. That is, the spillover effects attenuate the PE wage effects, so workers retain more of the subsidy than is implied by the PE analysis. Note, $\hat{w}_0^{\mathsf{PE}} = \hat{w}_0^{\mathsf{GE}}$ only if $s_{L_0} = 0$, which is a small-market assumption that makes little sense in a two type model.[25] Figure 3 provides a for a visual comparison of PE GE incidence for a 1% effective subsidy increase for L_0.

Figure 3 – Incidence Comparison Across Labor Substitutions



Plots 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.

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[23] Alternatively, Cramer's Rule can be used to solve the resulting linear system of equations.

[24] Equation 13 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.

[25] As noted earlier, around 20% of tax units receive the EITC and 40% of all workers with children (Nichols and Rothstein, 2016).

Solving for the other price effects (when $\hat{\tau} > 0$): $\hat{w}_1^{\mathsf{GE}} = \left(\frac{\varepsilon_0^L - \rho}{\varepsilon_1^L - \rho}\right) \Gamma_0 \hat{\tau} \geq 0$ and $\hat{r}^{\mathsf{GE}} = -\left(\frac{s_{L0}}{s_K}\hat{w}_0^{\mathsf{GE}} + \frac{s_{L1}}{s_K}\hat{w}_1^{\mathsf{GE}}\right)$.[26] When there is only the tax change for low skill labor, the PE analysis can only provide a lower bound for the wage effect for low skill labor market but is uninformative about the input price effects for other factor markets.

3.2.1 General Equilibrium Incidence with Many Labor Markets

Adding additional types of labor in this context is relatively simple given the symmetry of the model.[27] I allow skill-specific tax changes, and then solve the equations in the same manner as before using iterative substitution after totally differentiating. Full details are in Appendix A. The general equilibrium incidence for type e' labor is:

$$\hat{w}_{e'}^{\mathsf{GE}} = \frac{-\varepsilon_{(e',1)}^L \theta_{e',1} \hat{\tau}_{e'}}{\varepsilon_{e'}^L - \rho} + \frac{\Lambda \left(\sum_e \frac{s_e \varepsilon_{(e,1)}^L \theta_{e,1} \hat{\tau}_e}{\varepsilon_e^L - \rho}\right)}{(\varepsilon_{e'}^L - \rho)\left(1 + \Lambda \left(\sum_e \frac{s_e}{\varepsilon_e^L - \rho}\right)\right)} \tag{14}$$

$$= (\gamma_{e'} + \Gamma_{e'})\, \hat{\tau}_{e'} + \Psi_{e'}(\{\tau_e\}_{e \in \mathcal{E} \setminus e'}) \tag{15}$$

$$\text{where } \Lambda = \left(\frac{\varepsilon_K + 1}{s_K} + \frac{1 + \rho}{s_L}\right). \tag{16}$$

Generally, one cannot sign the expression without knowing the magnitude of each $\{\tau_{e'}\}_e$. For example, if the tax change for a specific market is small *but* all other changes are large and positive, then the GE spillovers may dominate, so the expression would be positive.

Equation 14 shows that generally there will be 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. Only if both spillover terms are small will $w^{\mathsf{GE}} \approx w^{\mathsf{PE}}$. With multiple tax changes, a (almost) sufficient condition is that the cost share weighted average tax change is zero ($\mathsf{E}[s_e \theta_{e,1} t\hat{a}u_e] \approx 0$), essentially that the policy reform has no meaningful effect on the tax rates.

[26] A sufficient condition for $\hat{r}^{\mathsf{GE}} > 0$ is that $(s_L/s_k)\varepsilon^K + (1/s_K) > -\rho$. If $s_L = 0.67$ and $\varepsilon^K = 1$, then $\hat{r}^{\mathsf{GE}} > 0$ when $\rho > -5$, which other authors and I find empirically (Katz and Murphy, 1992; Goldin and Katz, 2009; Borjas et al., 2012).

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

4 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 5- 8. 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).[28] 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 two-stage least squares to estimate the supply and substitution elasticities. Additional details and results are in Appendices B-D.

4.1 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.[29]

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.[30] 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 – $(e, k) = d \in \{\mathcal{E} \times \{0, 1\}\}$.[31]

[28] I use two subsamples from the CPS: the Outgoing Rotation Groups (ORG) and the Annual Social and Economic (ASEC) samples.

[29] I drop individuals who were not interviewed or in group quarters, variable values that were allocated, married workers without a cohabitating spouse, full time students out of the labor force, and households with greater than 10 members because of the difficulty in assigning children for complex family structures (less than 0.5 percent of the sample).

[30] That is, 72 skill levels for each gender though I focus only on women workers for my empirical analysis.

[31] This follows the baseline market definition in Rothstein (2010), except I add geographic delineation by state. The benefit to this definition is that I 'observe' the skill level of unemployed workers.

For labor market quantities, I use total hours worked divided by total potential workers at the labor market level.[32] 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, 2019a).[33] 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.[34] 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). Let a worker's EITC ATR be the sum of the actual credit received minus the credit if not working divided by total earned income.[35] I describe the instrument construction and formalize the exogeneity requirements in Appendix C, but the virtue of this procedure 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.[36] That is, the variation in the simulated tax parameters is *not* due to any endogenous behavioral response to the policy reforms – see Figure 4 below.

4.2 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 EITC policy tax changes. The first two variables are averages of the EITC Average Tax Rates, where the first is the instrument calculated from the 1990 Census and the second

[32]This measure captures both extensive and intensive margin responses that are relevant for labor market equilibrium. In Appendix D, I present results using the total number of workers that captures only the extensive margin response.

[33]This variable is the log geometric mean wage, which interpretable as an hours weighted productivity index (Borjas et al., 2012).

[34]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).

[35]Further details on the EITC ATR and other constructed EITC variables are in Appendix C.

[36]In this way, the tax instruments are similar to 'shift-share' instruments. See the following on recent analysis concerning the general identifying assumptions of these instruments: Adao, Kolesár and Morales (2018); Borusyak, Hull and Jaravel (2018); Goldsmith-Pinkham, Sorkin and Swift (2018).

use values from the ASEC samples (described later), which incorporate endogenous behavioral responses. Before the reform, the true and simulated tax rates are similar, but post-OBRA the true tax rates are lower (implying a larger credit). This is due to endogenous labor supply increases in the true rates but not the simulated rates, as the instrument calculation fixes labor supply decisions.[37]

Next, the table shows that labor supply increased for unmarried women with children and married women but decreased slightly for unmarried women without children. Despite these supply increases, there are meaningful wage increases for every group in this period. The summary statistics show that the labor demand must dominate the supply increases to result in positive wage growth.[38] For this reason, I use EITC-specific policy variation that is unrelated to demand shocks to untangle these competing forces.

In Figure 4, 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.

[37]This could be due to earnings decreases (from lower wages or less supply) causing workers to qualify for more credits, but this is unlikely given Table 1 shows wage and labor supply increases.

[38]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).

Table 1 – Summary Statistics for Estimation Sample

Tax Years	1989 - 1993		1995-1999		Difference	
	Mean	SD	Mean	SD	b	t
	Unmarried Women w/ Children					
EITC ATR - 1990 Census	-0.08	0.04	-0.14	0.08	-0.06***	-40.86
EITC ATR - ASEC	-0.08	0.06	-0.16	0.11	-0.08***	-34.20
Log Hours Per Person - MORG	3.08	0.54	3.19	0.44	0.11***	8.55
Log Real Wage - MORG	2.15	0.31	2.47	0.33	0.32***	39.09
Observations	2560		3854		6414	
	Unmarried Women w/o Children					
EITC ATR - 1990 Census	0.00	0.00	-0.01	0.01	-0.01***	-69.49
EITC ATR - ASEC	0.00	0.00	-0.01	0.01	-0.01***	-32.69
Log Hours Per Person - MORG	3.32	0.37	3.28	0.35	-0.05***	-5.01
Log Real Wage - MORG	2.15	0.31	2.47	0.33	0.32***	39.47
Observations	2589		3864		6453	
	Married Women w/ Children					
EITC ATR - 1990 Census	0.00	0.00	0.00	0.01	0.00***	14.72
EITC ATR - ASEC	0.00	0.01	0.00	0.02	0.00	1.92
Log Hours Per Person - MORG	3.03	0.40	3.10	0.34	0.07***	8.34
Log Real Wage - MORG	2.23	0.30	2.58	0.32	0.35***	54.45
Observations	3809		5349		9158	
	Married Women w/o Children					
EITC ATR - 1990 Census	0.00	0.00	0.00	0.00	-0.00***	-7.65
EITC ATR - ASEC	0.00	0.00	0.00	0.00	-0.00***	-4.53
Log Hours Per Person - MORG	3.27	0.39	3.29	0.34	0.02**	2.68
Log Real Wage - MORG	2.23	0.30	2.58	0.32	0.35***	54.49
Observations	3844		5336		9180	

All data from CPS Samples 1990 to 2000 and 1990 US Census
EITC ATRs calculated using TAXSIM

4.3 Estimating Equations

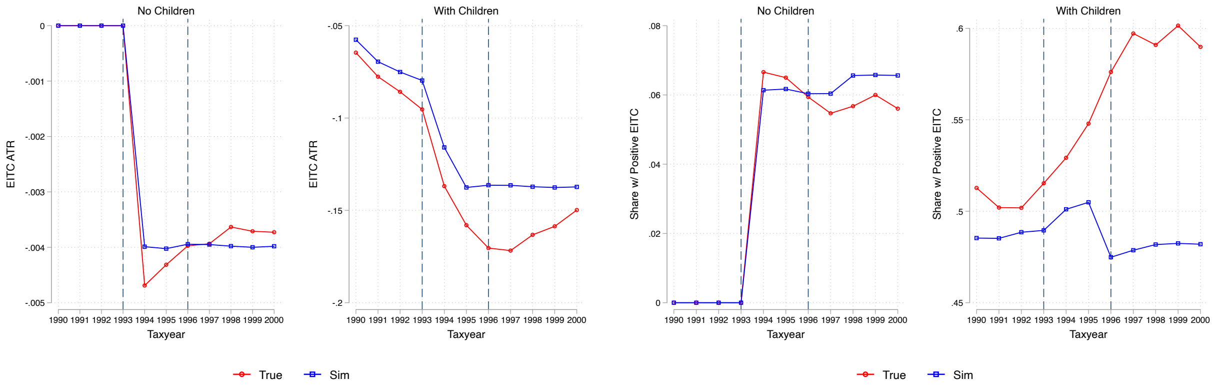
To estimate the labor supply and substitution elasticities, $(\{\varepsilon_{e'}\}, \rho)$, I use two-stage least squares with standard errors clustered at the labor market level.[39] While theoretically possible to estimate the supply and substitution elasticities jointly, I estimate the parameters in two separate steps.[40]

I estimate the labor supply elasticities, ε_d^L, using variation *within* demographic cells across state-years. That is, identification comes from the differences in EITC induced

[39]Alternatively, I could use a two-step efficient IVGMM method; however, because the problem is overidentified, estimating the second-stage weighting matrix can be problematic in finite samples (Doran and Schmidt, 2006). In practice, I find that the IVGMM yields more elastic results; see Appendix D additional empirical specifications.

[40]The linearized deviations from equilibrium, used to arrive at equation 14, forms a linear system of equations that can be estimated using GMM, similar to Suárez Serrato and Zidar (2016). Separating the estimation tasks allows for the parameters to be transparently identified, but the estimates are not efficient given the assumptions of the model.

Figure 4 – Simulated vs True EITC Parameters



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

Calculated using ASEC vs 1990 Census samples using NBER TAXSIM.

wage changes within a demographic group due to differential exposure to EITC reforms in a given state-year. For example, suppose in state A relative to B there are more unmarried mothers, then state A has greater exposure to EITC reforms, which should predict wage and labor supply responses.

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

$$\begin{aligned}\ln[W]_{dst} &= \pi_0 + Z_{dst}\Pi_1 + [Z_{dst}\cdot \mathsf{g}_d]\,\Pi_d + \pi_2 \ln[P_{dst}] \\ &\quad + \mathsf{d}_d + \mathsf{d}_{st} + \mathsf{d}_{w_0^{\%},t} + \mathsf{d}_{kst}^{\text{waiver}} + e_{dst}^{w} \qquad (17)\end{aligned}$$

$$\begin{aligned}\ln[L]_{dst} &= \beta_0 + \varepsilon_1^L \ln[W]_{dst} + \varepsilon_g^L\left[\ln[W]_{dst}\cdot \mathsf{g}_d\right] + \beta_2 \ln[P_{dst}] \\ &\quad + \mathsf{d}_d + \mathsf{d}_{st} + \mathsf{d}_{w_0^{\%},t} + \mathsf{d}_{kst}^{\text{waiver}} + e_{dst}^{L} \qquad (18)\end{aligned}$$

where Z are simulated EITC instruments, $\ln[P_{dst}]$ is log cell population, g_d are indicator variables for marriage, parental, and education status, d_d are demographic group FEs, d_{st} are state-year FEs, $\mathsf{d}_{w_0^{\%},t}$ are FEs for initial (1989) wage percentiles interacted with year indicators, and $\mathsf{d}_{kst}^{\text{waiver}}$ 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.[41] 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 correlations across demographic groups that constant within a state-year; e.g., state policy changes that affect the cost of working for all workers. The initial wage percentile FEs, $\mathsf{d}_{w_0^{\%},t}$, control for any correlations that due to the wage percentile that a market was before the EITC expansions; e.g., mean-reversion in wages or skill biased technological change. Finally, the waiver FEs, $\mathsf{d}_{kst}^{\text{waiver}}$, 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).

I estimate the substitution elasticity using variation *between* skill levels across state-years:

$$\begin{aligned} \ln[W]_{est} - \ln[W]_{e_0st} &= \gamma_0 + [Z_{est} - Z_{e_0st}]\,\Gamma_1 + \gamma_2\,[\ln[P_{est}] - \ln[P_{e_0st}]] \\ &\quad + \mathsf{d}_e + \mathsf{d}_{st} + \mathsf{d}_{w_0^{\%},t} + u_{est}^{w} \end{aligned} \tag{19}$$

$$\begin{aligned} \ln[L]_{est} - \ln[L]_{e_0st} &= \alpha_0 + \rho\,[\ln[W]_{est} - \ln[W]_{e_0st}] + \alpha_2\,[\ln[P_{est}] - \ln[P_{e_0st}]] \\ &\quad + \mathsf{d}_e + \mathsf{d}_{st} + \mathsf{d}_{w_0^{\%},t} + u_{est}^{L}. \end{aligned} \tag{20}$$

For this specification, I use similar FEs as the supply model but the interpretation is different because the regressions use relative quantities and wages.[42] The identification is based on the relative differences in EITC induced wage changes within a skill level across state-years.

[41] I discuss identification in much greater detail in Appendix C.1.

[42] I do not use state Welfare Waivers in this specification because at the market level they are perfectly colinear with the state-year FEs. Additionally, the market level FE d_e pools married and unmarried markets.

4.4 Elasticity Estimates

Table 2 displays the estimated elasticities.[43] 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 0.85 while Rothstein (2008) estimates a value of 0.75 and Meyer and Rosenbaum (2001) estimate 0.83 for participation for work in an average week.[44] I find that unmarried women without children and less that a high school degree have an elasticity of 1.35, 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 0.93 while Eissa and Hoynes (2004) estimate 0.27 for similarly educated married women.[45] Bargain and Peichl (2016) survey labor supply elasticities across countries and show estimates for married women range from almost perfectly inelastic to 1.5 for the United States.

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, EITC MTR, and share receiving the 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 and Murphy, 1992; Goldin and Katz, 2009; Borjas et al., 2012). A more inelastic estimate

[43] In Appendix D, I present additional specification results, including alternative dependent variables.

[44] 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.

[45] One reason for the difference could be that 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.

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

	Hours per Worker			
	Unmarried		Married	
	w/o Children	w/ Children	w/o Children	w/ Children
Less HS	1.35	1.38	0.85	0.93
	(0.15)	(0.16)	(0.17)	(0.18)
HS	0.96	0.99	0.47	0.54
	(0.12)	(0.13)	(0.11)	(0.12)
Some College	0.92	0.94	0.42	0.49
	(0.13)	(0.13)	(0.11)	(0.12)
BA Plus	0.69	0.72	0.20	0.27
	(0.14)	(0.13)	(0.13)	(0.12)
	Obs	AR F	KP rk Wald F	MOP Effective-F
	67,043	70.52	43.77	33.75

All data from MORG 86-00, 1990 Census; EITC ATRs calculated using TAXSIM. Standard Errors clustered by (144) demographic groupings. Weighted by number of observations in each labor market. Model controls: log cell population, FEs for demographics, State-Year, Initial-Wage-Pct-Year, and Welfare Reforms. AR is cluster robust F stat on first stage coefs; KP rk Wald F is cluster robust Cragg-Donald stat. MOP Effective-F is an alternative weak-IV F-statistic, calculated using a linear function of wages (Olea and Pflueger, 2013; Pflueger, 2015)

of ρ will tend to imply larger magnitude incidence effects since ρ is in the denominator of equations 11 and 14.

5 Incidence of 1993 EITC Expansion

In this section, I use the estimated elasticities and the empirical average tax changes to calculate the general equilibrium incidence of the 1993 EITC expansion. I use 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). The ASEC includes labor and non-labor income information that allows me to calculate tax parameters necessary for estimating the effect of the 1993 expansion. In Appendix B, I describe the variable construction and present summary statistics for the empirical incidence sample.

Table 3 – Labor Substitution Elasticity Estimates Across Labor Markets

	Hours per Worker	
	(1)	(2)
ρ	-1.95	-1.91
Wald SE	(0.32)	(0.31)
WIVR CI	[-2.61,-1.58]	[-2.80,-1.46]
KP rk Wald F	99.92	42.07
Anderson-Rubin F	46.29	20.01
MOP Effective-F	73.26	27.85
# IVs	1	3
Obs	10,339	10,339

All data from MORG 86-00, 1990 Census; EITC ATRs calculated using TAXSIM. Weighted by geometric mean of labor market observation pairs. Standard Errors clustered by (63) labor market groupings. Weak IV Robust CIs based using AR test (Andrews, 2018; Sun, 2018). Model controls: log relative cell population, FEs for Edu-Age-Year, State-Year, and Initial-Wage-Pct-Year. KP rk Wald F is cluster robust Cragg-Donald stat; AR is cluster robust F stat on first stage coefs. MOP Effective-F is an alternative weak-IV F-statistic (Olea and Pflueger, 2013; Pflueger, 2015).

5.1 Incidence Results

In Table 4, I present my estimates of the gross wage incidence effects of the 1993 OBRA EITC expansion. The table displays 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 markets. Unmarried women without a high school degree, which had the largest tax decrease, see the largest gross wage changes. In aggregate for unmarried women, spillovers represent between 10-17% of the total gross wage effects. For unmarried women, either this is essentially no wage change or wage growth due to the EITC.

Table 5 translates the net wage changes into 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.

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

	Unmarried No Children				Unmarried w/ Children				Married No Children				Married w/ Children			
%	dτ	PE	GE	Size	dτ	PE	GE	Size	dτ	PE	GE	Size	dτ	PE	GE	Size
LessHS	-1.47	-0.40	-0.38	6.3	-2.98	-0.93	-0.91	3.8	-0.42	-0.15	-0.13	17.8	-0.04	-0.02	0.00	31.3
HS	-1.16	-0.25	-0.23	9.4	-1.73	-0.37	-0.34	6.8	-0.05	-0.02	0.00	52.6	0.05	0.01	0.03	66.1
Some Col.	-0.71	-0.13	-0.10	19.3	-1.11	-0.21	-0.18	12.3	0.05	0.01	0.03	63.5	0.12	0.02	0.05	50.6
BA+	-0.25	-0.04	-0.02	41.3	-0.29	-0.04	-0.02	37.8	0.06	0.01	0.03	78.2	0.08	0.01	0.04	72.1
Total	-0.94	-0.22	-0.19	17.2	-1.70	-0.42	-0.40	10.82	-0.06	-0.03	-0.00	55.7	0.06	0.01	0.03	58.8

All data from 1994 March CPS, Women from Tax Units. 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 – Empirical Incidence of the 1994 EITC Expansion on Labor Supply

	Total		Unmarried No Children		Unmarried w/ Children		Married No Children		Married w/ Children	
$\%\Delta L$	PE	GE	PE	GE	PE	GE	PE	GE	PE	GE
Less HS	0.73	0.75	0.02	0.05	4.65	4.66	0.14	0.17	0.16	0.18
HS	0.22	0.24	0.12	0.14	1.64	1.65	0.05	0.07	-0.03	-0.02
Some College	0.12	0.13	0.01	0.03	1.18	1.19	0.02	0.04	-0.07	-0.06
BA+	0.01	0.03	0.06	0.08	0.19	0.19	-0.01	0.01	-0.03	-0.02
Total	0.24	0.26	0.05	0.07	2.08	2.09	0.04	0.06	-0.02	-0.01

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

Table 6 displays the incidence effects in terms of aggregate earnings changes per dollar of new EITC expenditure to make the effects. To interpret the table, define gross earnings as $Z^G = w \cdot L$ and net earnings as $Z^N = (1-\tau)\cdot Z^G$. The total change in gross earnings is $\mathrm{d}Z^G = w\mathrm{d}L + \mathrm{d}wL + \mathrm{d}w\mathrm{d}L$ and the total change in net earnings is $\mathrm{d}Z^N = (1-\tau)\mathrm{d}Z^G - \mathrm{d}\tau(Z^G + \mathrm{d}Z^G)$. The table reports the intended transfer ($\mathrm{d}\tau Z^G$), the change in gross earnings due to labor changes ($w\mathrm{d}L$), the change due to wage changes ($\mathrm{d}wL$), the total gross earnings change ($\mathrm{d}Z^G$), and the total net earnings change ($\mathrm{d}Z^G$). I additionally include what Rothstein (2010) refers to as the change in net-transfers ($\mathrm{d}Z^G + \mathrm{d}\tau Z^G$) and the net-earnings ($\mathrm{d}Z^G + \mathrm{d}\tau Z^G$), which hold all other taxes and transfers constant rather than allowing them to adjust given the gross earnings changes. Finally, the table reports the change in welfare after making the tax change revenue neutral: $\mathrm{d}W = \tau w \mathrm{d}L$ – see section A.2.2 for a derivation of this result.[46]

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	0.06	0.08	0.27	0.28	0.01	0.02	-0.02	-0.02
Wages	-0.17	-0.12	-0.11	-0.10	-0.07	0.06	-0.00	0.01	0.01	0.03
Gross Earnings	0.15	0.24	-0.05	-0.02	0.21	0.21	0.01	0.03	-0.01	0.01
Net Earn, Fixed Taxes	0.83	0.88	-0.05	-0.04	0.33	0.33	0.02	0.03	0.54	0.56
Net Transfer, Fixed Taxes	1.15	1.24	0.01	0.04	0.60	0.61	0.03	0.05	0.51	0.54
Net Earnings	0.47	0.55	0.01	0.04	0.57	0.58	0.00	0.03	-0.12	-0.09
Welfare	-0.03	-0.02	0.01	0.01	-0.04	-0.04	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. Labor supply elasticities from Model 1 in Table 2 and column 1 in Table 3.

Table 6 reveals that the 1993 EITC expansion effect on earnings is dominated by the labor supply effect. The aggregate change in gross earnings increases by $\$0.15$ in partial equilibrium and $\$0.24$ accounting for spillover effects, which is a 60% increase. The aggregate GE effect on net earning holding taxes constant is $\$0.88$ but is $\$0.55$ after accounting for changes in taxes due to earnings changes. The aggregate welfare effect implies a small $\$0.02$ welfare decrease per dollar of new EITC spending, implying only a small increase in government spending despite the large EITC expansion.[47] This is because the reform ultimately increases government expenditures in aggregate, so the welfare change is equal to the fiscal externality.

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 two reasons. First, the

[46]Note, this result is based on a utilitarian social welfare function with a unit marginal value of cost of government revenue.

[47]This result complements the empirical finding by Bastian and Michelmore (2018) that the EITC 'pays for itself.'

1993 OBRA reform implemented an asset test that decreased EITC amounts (increased tax rates) for higher income tax units. Second, since many married tax filers are in the phase-out region, increased gross earnings due to spillovers actually decreases the EITC amounts.

6 Comparing EITC and Welfare Reforms

In this section, I use my estimated labor market elasticities to compare three hypothetical policy reforms based on the 1990s US anti-poverty reforms. The first two are exogenously funded $100 million dollar expansions of the 1992 EITC and the combined 1992 ADFC and Food Stamps programs (which I refer to as simply 'Welfare'). These two experiments are roughly the same as Rothstein (2010).[48] 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.[49] This allows me to ignore the distortionary effects of financing the expansion as well as mirroring the tax and transfer system policy reforms of the 1990s.

6.1 Simulating the Tax Reforms

6.1.1 Data + Labor Market

For the simulations, I use survey responses from the 1993 March Current Population Survey (Flood et al., 2018), which correspond to the 1992 tax year labor market variables. I calculate EITC tax parameters using NBER TAXSIM (Feenberg and Coutts, 1993) and estimate ADFC and Food Stamp transfers using TRIM3 developed by the Urban Institute (Urban Institute, 2020). I use the sample criteria and labor markets as described earlier in the paper, except I do not split workers up by state – see Appendix B for more details.

[48] Rothstein (2010) compares the 1992 EITC to a hypothetical Negative Income Tax program; in Appendix E I replicate his experiments and find qualitatively similar results.

[49] 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 reform.

6.1.2 Parameters

The partial equilibrium analysis only requires two structural parameters, a supply elasticity (which may vary by labor market) and a elasticity of substitution. I use the labor supply elasticities estimated in the previous section, located in Table 2, which vary by marriage, parental, and education status. For the labor substitution elasticity, I use the value from the aggregate hours specification in Table 3 column 1, $\rho = 1.95$. This value is similar to the estimates in Katz and Murphy (1992) and Goldin and Katz (2009) that find $\rho \approx -1.4$.

The labor cost share in 1992 was roughly 68% of total cost (Bureau of Labor Statistics, 2019b). To calculate the labor market specific cost share, I sum total earnings plus employer contribution to health insurance by labor market, calculate the ratio of each market to the sum of all markets, and then multiply this by 0.68.[50] Because the cost shares appear in the numerator and denominator of the spillover terms, as long as the cost shares that I calculate are *proportional* to the true cost share, then spillover terms will be accurate under the other assumptions of the model.[51] I set the capital supply elasticity equal to 1, based on the estimate in Goolsbee (1998).[52]

6.1.3 Simulated Tax Reforms

To implement the simulation, I characterize the tax system with 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).[53] 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

[50]That is $s_{L_d} = \left(\frac{\sum_{i \in L_d} W_{id}}{\sum_j \sum_{i \in L_j} W_{ij}} \right) \cdot \left(\frac{\text{Total Labor Costs}}{\text{Total Factor Payments}} \right)$.

[51]An implicit assumption is that there are no other factors used by firms other than the labor factors as specified and a material factor index, called capital. This assumption is necessary to calculate the demographic based cost shares which are not available in any other statistical product that is produced.

[52]I have not found a definitive summary of aggregate capital supply elasticity estimates. I find that results are similar for capital supply elasticity values less than 5; additional results available upon request.

[53]I do not consider an intensive hours margin, so I do not consider marginal tax rates. This accords with the preferred specification in Rothstein (2010), and most empirical literature on the EITC.

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 (keeping the same rate). The third reform experiment implements the EITC expansion above and the *negative* of the above welfare expansion to make the reform *ex-ante* revenue neutral.[54]

6.2 Simulation Results

Table 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 main takeaway 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.

Table 7 shows there are meaningful differences between the programs and between PE and GE analysis. For the EITC, the dollar change due to wages is $-\$0.10$ in PE but only $-\$0.04$ in GE, but for the Welfare reform the $\$0.05$ wage growth in PE becomes $\$0.02$ in GE. For the Net EITC reform, the wage decline goes from $-\$0.15$ to $-\$0.05$, roughly a two-thirds decrease due to spillover effects. These plus the labor supply effects cause gross earnings to 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

[54] These reforms roughly mirror the actual reforms in the 1990s but at a smaller scale.

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 $\$0.90$ 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. The EITC and net-EITC reforms have decrease of $\$0.08$ and $\$0.09$, respectively, but the Welfare expansion essentially has no externality. This means the EITC expansions impose an additional cost to the government to balance the budget but the Welfare reform does not. However, this should be considered along-side the gross and net earnings effects. The EITC expansion increases aggregate gross earnings (analogous to GDP) and net earnings by shifting some economic resources to lower income workers. The Welfare expansion shows that the government could lower aggregate gross and net earnings without requiring additional budget expenditures.

Table 8 decomposes the aggregate effects by demographic groups. The net earnings for this unmarried women with children are positive at $\$0.78$, so the reason the aggregate net earnings are lower is due to the fact that net earnings fall for unmarried women without children by $-\$0.10$ (since this groups gets no subsidy yet faces the wage decreases) and married women with children by $-\$0.11$. For this latter group, the net earnings effect is negative because this group has the highest average tax rates on earned income due to spousal earnings.

The aggregate welfare effects are almost entirely due to changes from unmarried women with children, despite the fact that married mothers are also directly affected by the EITC and Welfare reforms. This is partially due to the fact that welfare changes do not depend on incidence (given zero profits and CRS assumptions) but on how behavior is affected. Because the EITC primarily affects unmarried mother's labor supply, this group drives the fiscal externality.

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	0.20	-0.10	0.30	0.25	-0.12	0.37
Wages	-0.10	0.05	-0.15	-0.04	0.02	-0.05
Gross Earnings	0.10	-0.05	0.15	0.21	-0.10	0.31
Net Earn, Fixed Taxes	1.10	0.95	0.15	1.21	0.90	0.31
Net Transfer, Fixed Taxes	0.90	1.05	-0.15	0.96	1.02	-0.05
Net Earnings	0.50	-0.36	0.22	0.61	-0.41	0.37
Welfare	-0.08	0.01	-0.09	-0.08	0.00	-0.09

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 from Model 1 in Table 2 and column 1 in Table 3.

7 1993 EITC Expansion + Childless Worker Reform

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 reforms. With the labor supply functions, I use the incidence model to solve for the market clearing wages and interest rate when the EITC schedule for workers with no children is the same as workers with one child. Specifically, I contrast the true 1994 EITC expansion with a counterfactual expansion that *also* equalized the credit schedule for workers with and without qualifying children.

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

Dollars	"PE" EITC (1)	Welfare (2)	Net EITC (3)	GE EITC (4)	Welfare (5)	Net EITC (6)
			Unmarried Mothers			
Net Earn, Fixed Taxes	0.72	0.66	0.05	0.73	0.66	0.07
Net Earnings	0.77	-0.26	0.37	0.78	-0.27	0.38
Welfare	-0.07	0.01	-0.08	-0.07	0.01	-0.08
			Unmarried Women			
Net Earn, Fixed Taxes	-0.14	0.03	-0.17	-0.11	0.01	-0.12
Net Earnings	-0.13	0.03	-0.16	-0.10	0.01	-0.11
Welfare	-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
Welfare	0.00	0.00	0.00	0.00	0.00	0.00
			Married Women			
Net Earn, Fixed Taxes	0.01	0.01	-0.01	0.04	0.0-	0.04
Net Earnings	0.01	0.01	-0.01	0.05	0.00	0.04
Welfare	0.00	0.00	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 1993 March CPS, Women from Tax Units. Labor supply elasticities from Model 1 in Table 2 and column 1 in Table 3.

7.1 Structural Model

Recall that the utility problem for workers is the following discrete choice:

$$\max_{L=\{0,1\}} \{0,\ u^i\left(T_i(w_i \cdot L_i, m_i)\right) + v_i\}, \tag{21}$$

where v_i is the idiosyncratic disutility of labor drawn from some distribution, $F(\mathrm{v})$. Initially, I assumed that $u^i(c) = c$, but now suppose that $u^i(c) = \beta^i \cdot c$, where β^i can be interpreted as a idiosyncratic marginal utility of consumption (or income). Additionally, suppose $v_i = \delta^i + \epsilon_1^i - \epsilon_0^i$, where ϵ_L^i distributed independent Type 1 Extreme Value

($F(\epsilon) = \mathrm{e}^{-\mathrm{e}^{-\epsilon}}$) and δ^i is interpreted as an unobserved utility cost of labor (a supply 'shifter'). Then, demographic-specific (expected) labor supply function is:

$$\Pr(L^i = 1 \mid w^d, m^d, T^d) := \pi^d = \frac{\mathrm{e}^{\beta^d T^d(w^d, m^d)+\delta^d}}{\mathrm{e}^{\beta^d T^d(0,m^d)} + \mathrm{e}^{\beta^d T^d(w^d,m^d)+\delta^d}}. \tag{22}$$

7.1.1 Recovering Structural Parameters

Defining $n^d = T^d(w^d, m^d) - T^d(0, m^d)$ as the net wage, the model implies that:

$$\text{Gross Wage Elasticity:} \quad \varepsilon_d^L = \frac{\partial \pi^d}{\partial w^d}\frac{w^d}{\pi^d} = \beta^d \frac{\partial n^d}{\partial w} w^d (1-\pi^d) \tag{23}$$

$$\text{Net Wage Elasticity:} \quad \eta_d^L = \frac{\partial \pi^d}{\partial n^d}\frac{n^d}{\pi^d} = \beta^d n^d (1-\pi^d). \tag{24}$$

If the transfer function is $T^d(w^d, m^d) = (1-\tau^d)(w^d L) + b^d(1-L) + t(m)$, so that the net wage is $(1-\tau^d)(w^d)$, then $\frac{\partial n^d}{\partial w} w^d = n^d$ so that $\varepsilon_d^L = \eta_d^L$. Thus, I can recover the marginal utility of consumption parameters using the following:

$$\frac{\varepsilon_d^L}{(n_d(1-\pi_d))} = \beta^d. \tag{25}$$

With an estimate of β^d, I can then recover the unobservable net supply shifters using a Berry (1994) style inversion technique:

$$\ln\left[\pi^d\right] - \ln\left[(1-\pi^d)\right] - \beta^d\left(T^d(w^d, m^d) - T^d(0, m^d)\right) = \delta^d. \tag{26}$$

With the estimated structural utility parameters $\{(\widehat{\beta^d}, \widehat{\delta^d})\}_{d\in D}$, I can simulate non-differential EITC reforms. Note, I estimate these parameters based on the elasticities estimates from the 1990s, 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.

7.2 Counterfactual Reform for Childless Workers

Advocacy groups encourage policymakers to reform the EITC schedule such that workers without children are treated the same as workers with children.[55] 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 credit schedule for workers without children and workers with one qualifying dependent.[56] 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 these changes as earnings change to calculate labor supply. Thus, the incidence model describes how the EITC expansions are shared between workers and the structural model shows the overall effect of equalizing the EITC schedules on market equilibrium.

[55] 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.

[56] 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).

7.3 Childless Worker Reform Effects

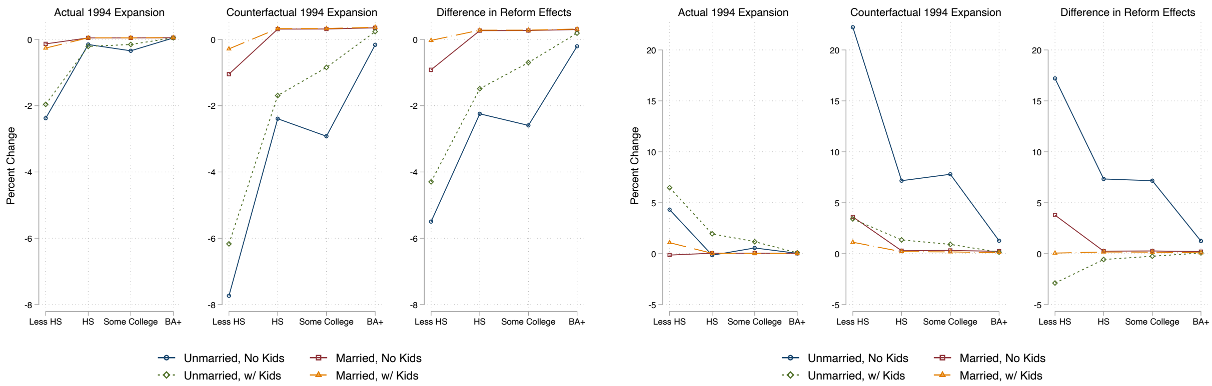
In Figure 5 and Tables 9 and 10, I display the results of the policy reform. To make comparisons as close as possible, I solve the model using the actual EITC schedule in tax year 1993 as a baseline, next solve the model using the actual 1994 schedule, and then solve the model using the counterfactual 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.

Figure 5 visually summarizes Table 9. There are two striking elements from the results. First, equalizing the credit schedules would substantially increase labor supply for unmarried workers without children – an 8.3% increase in aggregate but 22% for those without a high school degree. 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 2.1% to 1.3% in aggregate and 6.5% to 3.4% for those without a high school degree. This is due the same gross wage 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 $0.5 - 0.4\%$ under the actual expansion but decrease between $2.9 - 1.8\%$ under the expansion regime.[57]

Table 10 put the effects in terms of dollars of planned new expenditure similar 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.

[57] These values are slightly different because of the workers do not perfectly overlap in demographic-skill based markets.

Figure 5 – Empirical Incidence Results:
1994 EITC Expansion + Equalization of Credit Schedule



(a) Wages

(b) Labor Supply

Labor market effects from actual 1993 expansion relative to the counterfactual equalized 1993 expansion calculated from structural model.

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 have the wolf by the ears: 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 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.

8 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).[58] The reform was intended to provide counter-cyclical income support for low wage workers rather than strengthening labor

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

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

Percent Change in Wages : $\%\Delta w^{\mathsf{GE}}$

	Unmarried No Children			Unmarried w/ Children			Married No Children			Married w/ Children		
%	Act	Cft	Diff	Act	Cft	Diff	Act	Cft	Diff	Act	Cft	Diff
LessHS	-2.38	-7.74	-5.50	-1.96	-6.17	-4.30	-0.13	-1.05	-0.92	-0.26	-0.29	-0.03
HS	-0.15	-2.39	-2.24	-0.21	-1.69	-1.49	0.05	0.31	0.27	0.05	0.33	0.28
Some College	-0.34	-2.92	-2.59	-0.15	-0.85	-0.70	0.05	0.31	0.27	0.05	0.33	0.28
BA+	0.04	-0.16	-0.21	0.05	0.24	0.19	0.05	0.35	0.30	0.05	0.37	0.31
Total	-0.51	-2.89	-2.40	-0.41	-1.78	-1.39	0.03	0.20	0.17	0.02	0.29	0.26

Percent Change in Labor Supply : $\%\Delta L^{\mathsf{GE}}$

	Unmarried No Children			Unmarried w/ Children			Married No Children			Married w/ Children		
%	Act	Cft	Diff	Act	Cft	Diff	Act	Cft	Diff	Act	Cft	Diff
LessHS	4.32	22.23	17.20	6.48	3.41	-2.89	-0.14	3.61	3.78	1.08	1.12	0.05
HS	-0.15	7.16	7.33	1.94	1.35	-0.58	0.04	0.29	0.24	0.03	0.19	0.16
Some College	0.56	7.79	7.16	1.17	0.91	-0.26	0.05	0.31	0.26	0.03	0.17	0.15
BA+	0.03	1.26	1.23	0.08	0.14	0.06	0.03	0.23	0.19	0.01	0.10	0.08
Total	0.81	8.34	7.40	2.08	1.33	-0.71	0.02	0.57	0.54	0.11	0.24	0.13

'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.

force attachment.[59] 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 to purge the overall economic forces during the recession period, so the results depend on appropriateness of these grouping

[59]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.

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	0.70	0.14	0.57	0.40	0.05	0.03	0.05	0.05	0.03
Wages	-0.12	-0.12	-0.14	-0.17	-0.06	-0.04	0.03	0.03	0.05	0.06
Gross Earnings	0.49	0.55	-0.00	0.38	0.34	0.00	0.06	0.08	0.10	0.09
Net Earn, Fixed Taxes	0.88	0.88	0.12	0.70	0.65	0.07	0.03	0.05	0.08	0.06
Net Transfer, Fixed Taxes	1.49	1.55	0.26	1.24	1.05	0.12	0.06	0.10	0.13	0.09
Net Earnings	1.36	1.45	0.26	1.18	0.96	0.12	0.05	0.08	0.10	0.07
Welfare	-0.10	-0.09	-0.02	-0.07	-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.

decisions. Third, the reform was too small to see a large labor supply effect, even holding economic conditions constant. The expansion increased the maximum credit by $\$600$, which may not be enough to create large labor supply changes, and the target 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.

8.1 Incidence of 2009 Expansion

Compared to Table 4, Table 11 shows that the tax rate change for unmarried women is less than a third of the 1993 EITC expansion but the expansions are very similar for married women. As such, the direct and spillover effects are much smaller than the 1993 case. Table 12, show that unmarried mothers' aggregate labor supply should have increased by 0.7% while other groups show essentially no change, compared with 2.1% 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 0.06%.

Finally, in Table 13, I show the per dollar effect of the 2009 expansion. Again, the total effects as well as the spillover effects are much smaller than the 1993 expansion. The aggregate gross and net earnings changes are both less than half of the 1993 per dollar effects. This implies near zero aggregate welfare effects because there was little behavioral change.

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

	Unmarried No Children				Unmarried w/ Children				Married No Children				Married w/ Children			
%	dτ	PE	GE	Size	dτ	PE	GE	Size	dτ	PE	GE	Size	dτ	PE	GE	Size
LessHS	-0.40	-0.11	-0.11	4.1	-0.85	-0.30	-0.30	2.4	-0.19	-0.07	-0.07	14.7	-0.21	-0.08	-0.07	22.3
HS	-0.38	-0.08	-0.08	7.6	-0.66	-0.13	-0.13	4.3	-0.02	-0.01	-0.00	33.8	0.04	0.01	0.01	31.5
Some Col.	-0.23	-0.05	-0.04	13.0	-0.45	-0.09	-0.09	6.8	0.04	0.01	0.01	48.5	0.13	0.03	0.04	19.6
BA+	-0.08	-0.01	-0.01	29.1	-0.12	-0.02	-0.02	20.1	0.05	0.01	0.01	45.7	0.10	0.01	0.02	29.2
Total	-0.27	-0.06	-0.06	13.4	-0.53	-0.13	-0.12	7.35	0.01	-0.00	0.00	40.0	0.06	0.01	0.01	26.4

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. Labor supply elasticities from structural model implied by equation 25.

9 Conclusion

I revisited the incidence of the Earned Income Tax Credit using a general equilibrium framework. 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

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	
$\%\Delta L$	PE	GE	PE	GE	PE	GE	PE	GE	PE	GE
Less HS	0.32	0.32	-0.19	-0.18	1.74	1.74	0.02	0.02	0.20	0.21
HS	0.08	0.09	-0.07	-0.07	0.76	0.76	0.01	0.02	-0.03	-0.02
Some College	0.04	0.04	-0.06	-0.05	0.59	0.59	0.01	0.02	-0.09	-0.09
BA+	-0.00	0.00	-0.01	-0.00	0.21	0.21	0.01	0.01	-0.04	-0.04
Total	0.05	0.06	-0.05	-0.05	0.68	0.68	0.01	0.02	-0.04	-0.04

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 changes. Labor supply elasticities from structural model implied by equation 25.

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	0.13	-0.04	-0.03	0.20	0.20	0.01	0.02	-0.05	-0.05
Wages	-0.06	-0.04	-0.05	-0.04	-0.03	-0.03	0.00	0.01	0.02	0.02
Gross Earnings	0.06	0.09	-0.09	-0.08	0.16	0.17	0.02	0.02	-0.03	-0.03
Net Earn, Fixed Taxes	1.06	1.09	-0.08	-0.07	0.41	0.41	0.03	0.04	0.69	0.70
Net Transfer, Fixed Taxes	0.94	0.96	-0.04	-0.03	0.22	0.22	0.02	0.03	0.74	0.75
Net Earnings	0.17	0.20	-0.07	-0.06	0.42	0.43	0.01	0.02	-0.20	-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 implied by equation 25.

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 15-20% of aggregate wage and earnings effects in the direction of increasing dollars to workers. Second, to compare how different labor market policies affect spillovers, I simulated a $100million 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 this is an increases dollar to workers while for Welfare workers' net earnings decrease. 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 are always quite small relative to the increases in net earnings. The 1994 expansion created large labor market direct and indirect effects; however, the 2009 expansion appears not to have caused labor market disruptions. When labor market disruptions are small, the program is primarily functioning as an immediate anti-poverty tool in that dollars goes 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.

This conclusion is not without some caveats. First, while the EITC increases net earnings, neither the empirical 1993 expansion nor the simulated expansions 'pay for themselves' when workers respond to the increased generosity. The negative welfare results are due to a fiscal externality that must be incurred in order to balance the government budget. 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 harmed. As indicated, this also holds for those who want to expand the EITC for worker without children. Finally, 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. The EITC puts less weight on workers marginally out of the labor force while a Welfare policy weighs more on those marginally in the labor force.

This study highlights how using partial equilibrium analysis of large scale tax reforms can be misleading about cost effectiveness. However, the model still make 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 frictionless labor market assumptions – perfect competition, price taking – may not be realistic. 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 consider two theoretical extensions. First, 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. Second, 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.

A.1 Incidence Value Comparison

Here, I compare the gross wage incidence from a one percent tax change[60] between PE and GE and across labor market elasticities. I use equation 11 for the PE incidence and I use equation 13 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_{L_0}.

In Table 14, I present incidence values for various parameter pairings. I use the following baseline parameters: $\varepsilon^L_{0,k_0} = \varepsilon^L_{0,k_1} = 0.75$, $\varepsilon^L_{1,k_0} = \varepsilon^L_{1,k_1} = 0.6$, 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 $s_{L_0} = 0.125$ and $s_{L_1} = 0.66 - s_{L_0}$, based on the 1992 March CPS and my own calculations. For the first two panels I assume 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 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

[60] 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.

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 $s_{L_0} = 0.125, s_L = 0.66$

$\rho = -0.3$ 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 ($s_{L_0} \in [0, 1]$) 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.

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,[61] the model is the following:

$$\begin{aligned} \text{Utility}: &\quad u^i(C, L) = C + v^i(L) && (27) \\ \text{Tax Function}: &\quad T^i(wL, m) = (w + \tau^i)L - b^i(1 - L) - n_i && (28) \\ \text{Capital Revenue}: &\quad R = \int_j ((r - c_j) \cdot k_j)\, \mathsf{d}_j && (29) \\ \text{Budget Set}: &\quad C + T^i(wL, m) - wL - m \leq 0 && (30) \end{aligned}$$

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

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

$$W = \int_i V^i \mathsf{d}_i + \int_i \left(T^i\right) \mathsf{d}_i \tag{31}$$
$$= \int_i \left((w^i L^i - T^i) + v^i(L^i) + \varsigma^i R\right) \mathsf{d}_i + \int_i \left(T^i\right) \mathsf{d}_i \tag{32}$$
$$= \int_i \left((w^i L^i) + (v^i \cdot L^i) + \varsigma^i R\right) \mathsf{d}_i. \tag{33}$$

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 32 holding unemployment benefits constant but adjusting the lump sum tax to finance the subsidy increase (and recall that $\tau^i = \mathsf{d}\tau^i = 0$ if $(e^i, k^i) \neq (0, 1)$):

$$\begin{aligned}\mathsf{d}W^{\mathsf{GE}} &= \int_i \left((\mathsf{d}w^i + \mathsf{d}\tau^i)L^i + (w^i + \tau^i - b^i)\mathsf{d}L^i + \frac{\partial v^i}{\partial L^i}\mathsf{d}L^i + \varsigma^i \mathsf{d}R - \mathsf{d}n^i\right) \mathsf{d}_i \\ &\quad + \int_i \left(-\mathsf{d}\tau^i L^i - (\tau^i - b^i)\mathsf{d}L^i + \mathsf{d}n^i\right) \mathsf{d}_i \end{aligned} \tag{34}$$
$$= \int_i \left((\mathsf{d}w^i)L^i + \varsigma^i \mathsf{d}R\right) \mathsf{d}_i + \int_i \left(-(\tau^i - b^i)\mathsf{d}L^i\right) \mathsf{d}_i \tag{35}$$
$$= \int_i \left(-(\tau^i - b^i)\mathsf{d}L^i\right) \mathsf{d}_i = -\int_i \left((\tau^i - b^i)\varepsilon_i^L(\mathsf{d}w^i + \mathsf{d}\tau^i)\right) \mathsf{d}_i \tag{36}$$
$$= -\int_i \left((\tau^i - b^i)\varepsilon_i^L((1+\gamma^i)\mathsf{d}\tau^i + \Gamma^i)\right) \mathsf{d}_i. \tag{37}$$

From equation 34 to 35, I use the envelope condition to remove $\frac{\partial v^i}{\partial L^i}$; from 35 to 36, I use the zero profit condition to show that $\mathsf{d}R = \int_i \left((\mathsf{d}w^i)L^i\right) \mathsf{d}_i$; and from 36 to 37, 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:

$$\mathrm{d}W^{\mathsf{GE}} = \int_i \left(t^i w^i \mathrm{d}L^i\right) \mathrm{d}_i = \int_i \left(t^i w^i \varepsilon_i^L((1+\gamma^i)\mathrm{d}\tau^i + \Gamma^i)\right) \mathrm{d}_i. \tag{38}$$

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 $e \in \{0, 1, 2, \ldots, E\} = \mathcal{E}$.[62] I solve the general equilibrium wage change for type 0 labor group. Using the labor clearing condition (equation 39), I can easily solve for any other group's incidence.

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

$$\text{Labor Clearing} \quad \frac{L_{e_0,k_0} + L_{e_0,k_1}}{L_{e_j,k_0} + L_{e_j,k_1}} = \left(\frac{w_{e_0}/\theta_{e_0}}{w_{e_j}/\theta_{e_j}}\right)^{\rho} \qquad \forall e_j \in \mathcal{E} \setminus e_0 \tag{39}$$

$$\text{Factor Clearing} \quad \frac{\sum_e L_e}{K^S(r)} = \left(\frac{\bar{w}/\alpha}{r/1-\alpha}\right)^{-1} \tag{40}$$

$$\text{Zero Profits} \quad P = c\left(\{w_e\}_{e\in\mathcal{E}}, r\right) := 1 \tag{41}$$

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.

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

The general equilibrium incidence for type 0 labor is:

$$\hat{w}_0^{\mathsf{GE}} = \frac{-\varepsilon^L_{(0,1)}\theta_{0,1}\hat{\tau}_0}{\varepsilon^L_0 - \rho} + \frac{\Lambda\left(\sum_e \frac{s_e \varepsilon^L_{(e,1)}\theta_{e,1}\hat{\tau}_e}{\varepsilon^L_e - \rho}\right)}{(\varepsilon^L_0 - \rho)\left(1 + \Lambda\left(\sum_e \frac{s_e}{\varepsilon^L_e - \rho}\right)\right)} \tag{42}$$

$$= (\mathsf{p}_0)\hat{\tau}_0 + \Psi_0(\{\tau_e\}_{e\in\mathcal{E}}) \tag{43}$$

$$\text{where } \Lambda = \left(\frac{\varepsilon_K + 1}{s_K} + \frac{1+\rho}{s_L}\right). \tag{44}$$

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, 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, k) can earn different wages, so I would 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.[63]

Let the labor supply of a type (e, k) worker be denoted as $L^e_{g,k}$, where $g \in \{0, 1\}$ designates low or high wage labor group. Let $\varepsilon^L_{e,g,k}$ be the extensive labor supply elasticity, and for type $e = 1$ workers let $\chi_k^{g \to g'}$ be the cross wage elasticity with respect to sector choice for workers. The latter elasticity is only concerned with incumbent workers who potentially switch sectors. I suppress the group conditional demographic shares, $\theta^e_{g,k}$, to ease notation.

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

$$\text{Labor Clearing} \quad \frac{L^0_{0,0} + L^1_{0,0} + L^0_{0,1} + L^1_{0,1}}{L^1_{1,0} + L^1_{1,1}} = \left(\frac{w_0/\theta_{0,1}}{w_1/\theta_{1,1}}\right)^{\rho} \tag{45}$$

$$\text{Factor Clearing} \quad \frac{L^0_{0,0} + L^1_{0,0} + L^0_{0,1} + L^1_{0,1}}{K^S(r)} = \left(\frac{\bar{w}/\alpha}{r/1-\alpha}\right)^{-1} \tag{46}$$

$$\text{Zero Profits} \quad P = c(w_0, w_1, r) := 1 \tag{47}$$

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

The general equilibrium incidence for this model is:

$$\hat{w}_0^{\mathsf{GE}} = \frac{-(\varepsilon_{0,1}^L - \tilde{\chi}_1^{1,0})\hat{\tau}_0}{(\varepsilon_0^L - \tilde{\chi}^{1,0} - \rho)} + \frac{\Lambda\left(\sum_d \left(\frac{s_d \hat{\tau}_d(\varepsilon_{d,1}^L - \tilde{\chi}_1^{\neg d,d})}{(\varepsilon_d^L - \tilde{\chi}^{\neg d,d} - \rho)}\right)\right)}{1 + \sum_d \left(\frac{s_d \Lambda + \tilde{\chi}_1^{\neg d,d}}{(\varepsilon_d^L - \tilde{\chi}^{\neg d,d} - \rho)}\right)} \tag{48}$$

$$= (\mathsf{p}_0 + \Gamma_0 + \mathcal{X}_0)\hat{\tau}_0 + \Psi_0(\hat{\tau}_2) + \mathfrak{X}_0(\hat{\tau}_2) \tag{49}$$

where $\varepsilon_{d,1}^L$ and $\tilde{\chi}_k^{g,g'}$ incorporate the relevant share of workers based on $\theta_{g,k}^e$. 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

$$F = \left((L^{\frac{1+\rho}{\rho}} + H^{\frac{1+\rho}{\rho}})^{\alpha \frac{\rho}{1+\rho}} \cdot K^{(1-\alpha)}\right), \tag{50}$$

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:

$$\max_{x,y,o} \{V^\star(x) + \epsilon_x, V^\star(y) + \epsilon_y, V^\star(o) + \epsilon_o\}, \tag{51}$$

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:

$$\text{X Labor Market Clearing:} \quad \frac{L_x^S(w_x + \tau_L, w_y, b_L)}{H_x^S(v_x + \tau_H, v_y, b_H)} - \psi_x(w_x/v_x) = 0 \tag{52}$$

$$\text{X Factor Market Clearing:} \quad \frac{L_x^S(w_x + \tau_L, w_y, b_L)}{K_x^S(r)} - \psi_x(w_x/v_x)\Psi_x(w_x/r) = 0 \tag{53}$$

$$\text{X Zero Profits:} \quad p_x - c_x(w_x, v_x, r) = 0 \tag{54}$$

$$\text{Y Labor Market Clearing:} \quad \frac{L_y^S(w_y, w_x + \tau_L, b_L)}{H_y^S(v_y, v_x + \tau_H, b_H)} - \psi_y(w_y/v_y) = 0 \tag{55}$$

$$\text{Y Factor Market Clearing:} \quad \frac{L_y^S(w_y, w_x + \tau_L, b_L)}{K_y^S(r)} - \psi_y(w_y/v_y)\Psi_y(w_y/r) = 0 \tag{56}$$

$$\text{Y Zero Profits:} \quad p_y - c_y(w_x, v_x, r) = 0 \tag{57}$$

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 $p_y = 1$.[64] 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 is:

$$A\hat{z} = \nu \cdot \hat{\tau} \tag{58}$$

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

[64]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:

$$
\begin{aligned}
\text{Cramer's Rule:} \quad z_i &= \frac{\mathsf{det}(A \mid b)}{\mathsf{det}(A)} && (59)\\
\text{Laplace Expansion:} \quad &= \frac{\sum_j b_{i,j}\mathsf{det}(A^{(j)})}{\mathsf{det}(A)} && (60)\\
&= \frac{\sum_j \frac{b_{i,j}}{a_{i,j}} a_{i,j}\mathsf{det}(A^{(j)})}{\mathsf{det}(A)} && (61)\\
\text{Matrix Derivative:} \quad &= \frac{\sum_j \frac{b_{i,j}}{a_{i,j}} a_{i,j} \left(\frac{\partial \mathsf{det}(A)}{\partial a_{i,j}}\right)}{\mathsf{det}(A)} && (62)\\
&:= \sum_j \left(\left(\frac{b_{i,j}}{a_{i,j}}\right) \left(\gamma_{a_{i,j}}\right) \right), && (63)
\end{aligned}
$$

where $\gamma_{a_{i,j}} = \left(\frac{\partial \mathsf{det}(A)}{\partial a_{i,j}} \frac{a_{i,j}}{\mathsf{det}(A)}\right)$ 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:

$$
\begin{aligned}
z_i &= \frac{\sum_j \frac{b_{i,j}}{a_{i,j}} a_{i,j}\mathsf{det}(A^{(j)})}{\mathsf{det}(A)} && (64)\\
&= \frac{\sum_j \frac{b_{i,j}}{a_{i,j}} a_{i,j}\mathsf{det}(A^{(j)})}{\sum_j a_{i,j}\mathsf{det}(A^{(j)})} && (65)\\
&= \sum_j \frac{b_{i,j}}{a_{i,j}} \frac{a_{i,j}\mathsf{det}(A^{(j)})}{\sum_j a_{i,j}\mathsf{det}(A^{(j)})} && (66)\\
&= \frac{b_{i,i}}{a_{i,i}} + \left[\sum_{j \setminus i} \left(\frac{b_{i,j}}{a_{i,j}} - \frac{b_{i,i}}{a_{i,i}} \right) \frac{a_{i,j}\mathsf{det}(A^{(j)})}{\sum_j a_{i,j}\mathsf{det}(A^{(j)})} \right] && (67)\\
&= \frac{b_{i,i}}{a_{i,i}} + \left[\sum_{j \setminus i} \left(\frac{b_{i,j}}{a_{i,j}} - \frac{b_{i,i}}{a_{i,i}} \right) \gamma_{a_{i,j}} \right] && (68)
\end{aligned}
$$

A.5.5 Low Wage X Sector Incidence

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

$$\frac{\hat{w}_x^L}{\hat{\tau}} = \underbrace{\frac{-\varepsilon_x^L}{\varepsilon_x^L - \rho_x}}_{\text{Partial Equilibrium}} \underbrace{+ \gamma_{a_{2,1}} \left(\frac{(1+\rho_x)(1-\frac{s_x^H}{1-s_x^K})}{\varepsilon_x^L + 1 - (1+\rho_x)\frac{s_x^H}{1-s_x^K}} \right) + \left(\gamma_{a_{3,1}} + \gamma_{a_{4,1}}\right) \left(\frac{\rho_x}{\varepsilon_x^L - \rho_x} \right)}_{\text{Spillover Terms}} \tag{69}$$

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.[65] 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

[65]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.[66]

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

[66]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.

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

The ASEC samples also come from In March 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.[67] 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.[68]

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.

[67] Note, for the empirical exercise in Section 6, 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.

[68] 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.

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.

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.[69]

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.

[69]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.

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 Assumption

The exclusion restriction is that the EITC tax differences are uncorrelated to unobservable differences in labor supply (conditional on the model controls):

$$\mathsf{E}\left[\tau_{dst} \cdot e^{L}_{dst} \mid X\right] = 0. \tag{70}$$

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.[70] However, prior studies find that state EITC introductions and 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'.[71] Given that I include state-year

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

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

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.

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).[72] Using a fixed distribution of worker characteristics, one calculates 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.[73] Finally, I calculate the EITC Average Tax Rate as the difference in the actual minus the counterfactual benefits over earned income:

$$\tau_i^{\mathsf{EITC}} = \frac{E_i(L = L_i) - E_i(L = 0)}{w_i \cdot h_i}. \tag{71}$$

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

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

[73] 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_{dst}. However, the total incidence also depends on a weighted sum of tax changes in *other* labor markets within a state-year, $\Psi_d(\{\tau_{d'}\}_{d' \in \mathcal{D}})$. Thus, I need an empirical counterpart for the Ψ_{dst} terms, but this depends on the parameters that I wish to estimate – see equation 42. I approximate the function by creating six different averages of the tax change for across labor markets and then match this to a given market:

$$\Psi_{dst} = H\left(\{\tau_{d'st}\}_{d' \in \mathcal{D}}\right) \approx \left(\sum_{f=1}^{6} \gamma_f \bar{\tau}_{g_f(d),st}\right) + \nu_{dst}. \tag{72}$$

Three of the terms correspond to averages across all women and the other three are only across unmarried mothers, since this group experienced was most exposed to the tax change.

For example, if $\tilde{d}$ is married women with some college between ages of 25 and 30, then $\bar{\tau}_{g_1(\tilde{d})st}$ equals the average EITC ATR for women with some college pooled across age groups, $\bar{\tau}_{g_2(\tilde{d})st}$ equals the average EITC ATR for women between ages of 25 and 30 pooled across education groups, and $\bar{\tau}_{g_3(\tilde{d})st}$ equals the average EITC ATR for women with some college between ages of 25 and 30. Variables $4-5$, are similar except they are conditional averages for unmarried mothers. Thus $\bar{\tau}_{g_4(d),st}$ is the average EITC ATR for unmarried mothers with some college pooled across age groups, and so on.

Additionally, I use other simulated EITC statistics as instruments, such as the EITC marginal tax rate, the share of workers receiving EITC benefits, the mean change in expected EITC amounts, and the Federal Earnings average tax rate.

C.2.1 Labor Supply Instruments

For every group $\tilde{d}$, I have up to 13 simulated instruments:

1-3. the EITC ATR, EITC MTR, and Fed Earnings ATR for $\tilde{d}$: $\{\tau^{\mathsf{ATR}}_{\tilde{d}st}, \tau^{\mathsf{MTR}}_{\tilde{d}st}, \tau^{\mathsf{Fed}}_{\tilde{d}st}\}$

4. the portion of $\tilde{d}$ workers with positive EITC: $\{z^{\mathsf{Sh}}_{\tilde{d}st}\}$

5. the mean change in ETIC amount for $\tilde{d}$: $\{z^{\mathsf{dE}}_{\tilde{d}st}\}$

6-11. six EITC ATR approximation averages: $\{\bar{\tau}_{g_{(\cdot)}(\tilde{d})st}\}$

12,13. two additional approximation averages: $\{\bar{z}^{\mathsf{Sh}}_{g_3(\tilde{d})st}, \bar{z}^{\mathsf{Sh}}_{g_6(\tilde{d})st}\}$.

In Appendix D, I show that the elasticity estimates are robust to various combinations of the instruments.

C.2.2 Labor Substitution Instruments

The labor substitution elasticity depends on the relative wage, $\ln[w_{dst}/w_{d_0st}]$. My main specification uses a just identified model using the 'relative EITC ATRs' to instrument for relative wages:

$$\tau_{(\tilde{d},d_0)st} = \frac{\tau_{\tilde{d}st}}{\tau_{d_0st}}. \tag{73}$$

I construct relative share of EITC claimants and the relative EITC MTR to estimate an overidentified 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 is cluster robust Cragg-Donald statistic.

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

The first line is the baseline estimates used in the main text: I use two-stage least squares, weighted by the number of wage observations in a cell, over the whole sample, using the full set of simulated tax instruments. I additionally consider a two-step optimal GMM method, which tends to make the weighted estimates more elastic but the unweighted estimates less elastic.

I next consider the effect of weighting. The unweighted results have lower first stage estimates than the weighted estimates, and as such tend to amplify the estimated elasticities. Weighting by the sample size or the wage variance gives lower weight to the observations with more noise which helps in precision. I additionally create two subsamples: (1) with a lower bound of at least ten wage observations (which pools those with and without children) *and* at least five observations for each cell, and (2) which only requires the ten wage observations. These subsamples can be thought of as an additional discrete weighting.

I then look at the effect of different combinations of instruments – the set of IVs are described in more detail in Appendix C. The first stage statistics all decrease when I remove IVs implying that each IV provides some additional identification. As expected, a weaker first stage amplifies the elasticity estimates.

Finally, I consider using 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:

$$\mathsf{d}h_i\ell_i = \mathsf{d}h_i\ell_i + h_i\mathsf{d}\ell_i + \mathsf{d}h_i\mathsf{d}\ell_i \tag{74}$$

$$\implies \varepsilon^L = \mu^h + \upsilon^\ell + \xi^{h\cdot\ell}. \tag{75}$$

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

Table 20 – Additional Elasticity Specifications
Average within Demographic Groups

Obs	Method	Weighting	Sample	IVs	KP rk F Stat	Unmarried No Children	Unmarried w/ Children	Married No Children	Married w/ Children
(A)	Log Total Hours per Person								
67,043	2sls	Wage Obs	Baseline	Baseline	43.77	1.35	0.85	0.94	0.54
67,043	GMM	Wage Obs	Baseline	Baseline	43.77	1.42	1.17	1.05	0.71
67,043	2sls	Unweighted	Baseline	Baseline	31.60	1.54	1.06	0.95	0.77
67,043	GMM	Unweighted	Baseline	Baseline	31.60	1.37	1.08	0.80	0.25
33,305	2sls	Unweighted	Subsample 1	Baseline	24.15	0.98	0.59	1.06	0.86
33,305	GMM	Unweighted	Subsample 1	Baseline	24.15	0.56	0.43	1.07	0.62
41,620	2sls	Wage Obs	Subsample 2	Baseline	77.71	1.04	0.54	1.00	0.60
41,620	GMM	Wage Obs	Subsample 2	Baseline	77.71	1.12	0.83	1.21	0.80
41,564	2sls	Wage Variance	Subsample 2	Baseline	51.88	1.15	0.37	1.30	0.90
41,564	GMM	Wage Variance	Subsample 2	Baseline	51.88	0.99	0.45	1.16	1.01
67,043	2sls	Wage Obs	Baseline	Subset 1	39.01	1.33	0.62	0.95	0.46
67,043	2sls	Wage Obs	Baseline	Subset 2	29.86	1.33	0.59	1.02	0.50
67,043	2sls	Wage Obs	Baseline	Subset 3	18.00	1.55	1.06	1.27	0.83
67,043	2sls	Wage Obs	Baseline	Subset 4	20.20	1.78	1.29	1.24	0.83
67,043	2sls	Wage Obs	Baseline	Subset 5	12.44	1.69	1.18	1.15	0.76
67,043	2sls	Wage Obs	Baseline	Subset 6	38.80	1.26	0.74	0.88	0.49
67,043	2sls	Wage Obs	Baseline	Subset 7	10.94	1.62	0.70	1.09	0.61
67,043	2sls	Wage Obs	Baseline	Subset 8	12.44	1.69	1.18	1.15	0.76
67,043	2sls	Wage Obs	Baseline	Subset 9	16.21	1.41	0.92	1.19	0.72
(B)	Log Total Labor Supply								
67,039	2sls	Wage Obs	Baseline	Baseline	43.77	1.11	0.73	0.75	0.55
67,039	2sls	Unweighted	Baseline	Baseline	31.57	1.38	1.00	0.76	0.73
41,618	2sls	Unweighted	Subsample	Baseline	77.72	0.75	0.35	0.74	0.54
67,039	2sls	Wage Obs	Baseline	Subset 1	39.07	1.10	0.52	0.71	0.49
67,039	2sls	Wage Obs	Baseline	Subset 2	39.07	1.10	0.52	0.71	0.49
67,039	2sls	Wage Obs	Baseline	Subset 9	16.20	1.11	0.73	0.87	0.63

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.

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

Broadly, the overidentified models have lower first stage statistics and the estimates tend to be smaller in magnitude. Additionally, the Labor Supply based 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.[74]

From unreported results, there is not much qualitative or quantitative difference when the estimate of $\rho \in (-2.0, -1.8)$, but outside of this range there start to be noticeable quantitative differences (but no qualitative).

[74]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 21 – Additional Elasticity Specifications
Average within Demographic Groups

Method	Weighting	Sample	Obs	KP rk F Stat	ρ Hours per Worker	ρ Labor Supply
(A)	Just Identified					
2sls	Wage Obs	Full	10,339	99.92	-1.95	-2.48
2sls	Wage Obs	Subsample	5,210	72.32	-2.00	-2.56
2sls	Unweighted	Full	10,339	49.7	-1.80	-2.21
2sls	Unweighted	Subsample	5,210	60.57	-1.83	-2.20
2sls	Wage Variance	Full	10,318	86.85	-2.06	-2.53
2sls	Wage Variance	Subsample	5,210	71.48	-2.22	-2.59
(B)	Overidentified					
2sls	Wage Obs	Full	10,339	42.07	-1.91	-2.38
2sls	Wage Obs	Subsample	5,210	34.87	-1.91	-2.40
2sls	Unweighted	Full	10,339	28.49	-1.56	-2.00
2sls	Unweighted	Subsample	5,210	28.94	-1.61	-1.89
2sls	Wage Variance	Full	10,318	81.68	-1.77	-2.23
2sls	Wage Variance	Subsample	5,210	29.79	-2.04	-2.30
GMM	Wage Obs	Full	10,339	42.07	-1.86	-1.94
GMM	Wage Obs	Full	10,339	28.94	-1.59	-1.60

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.

E Additional Simulation Results

In Table 22, I present an EITC vs Negative Income Tax 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 $-\$0.37$ in column (D).

The last set of columns (H-K) use the estimated labor supply elasticities and substitution elasticity from Table 2. 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 only $-\$0.16$ in column (H) but for columns (F) and (I) the effects are $-\$0.06$ and $-\$0.05$.

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. 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.

Table 22 – Incidence Results:
Aggregate Effects: All Women
Rothstein (2010) Replication Extension

Dollars	Rothstein "PE" EITC (B)	Rothstein "PE" NIT (C)	$\rho = -0.3$ "PE" EITC (D)	$\rho = -0.3$ "PE" NIT (E)	$\rho = -0.3$ GE EITC (F)	$\rho = -0.3$ GE NIT (G)	$\rho = -1.95$ "PE" EITC (H)	$\rho = -1.95$ "PE" NIT (I)	$\rho = -1.95$ GE EITC (J)	$\rho = -1.95$ GE NIT (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	0.11	-0.15	0.33	-0.44	0.31	-0.40	0.38	-0.49
Wage	-0.42	0.60	-0.37	0.50	-0.06	0.08	-0.16	0.20	-0.05	0.07
Gross Earnings	-0.30	0.42	-0.26	0.35	0.27	-0.36	0.15	-0.19	0.33	-0.42
Net Earn, Fixed Taxes	0.70	1.42	0.74	1.35	1.27	0.64	1.15	0.81	1.33	0.58
Net Transfer, Fixed Taxes	0.58	1.50	0.63	1.50	0.94	1.08	0.84	1.20	0.95	1.07
Net Earnings	0.12	-0.35	0.17	-0.42	0.65	-1.07	0.58	-0.94	0.75	-1.15
Welfare	-0.10	0.05	-0.10	0.04	-0.10	-0.12	-0.12	0.05	-0.11	0.04

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.

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.

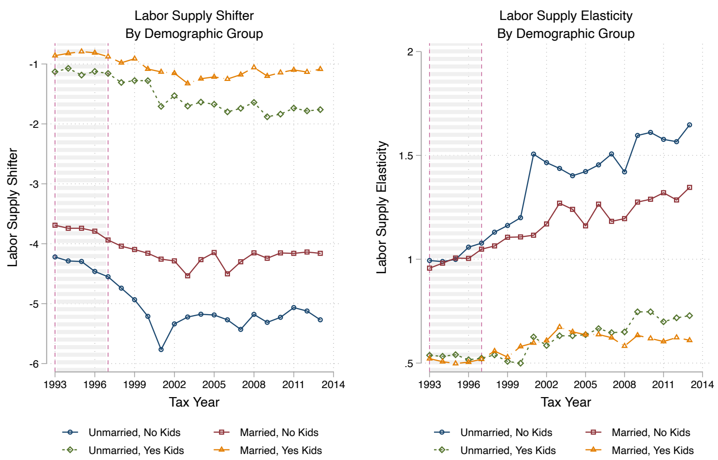
Finally, the welfare changes are always negative for the EITC and either positive or negative for the NIT depending on the parameterization. A negative welfare change here implies that the government expenditure increases (the welfare measure is the 'fiscal externality' – see Section A.2.2). For the 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 7.1, I back-out the structural parameters and calculate the model implied elasticities for the out-of-sample period. In Figure 6 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 25, 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 6 – Model Implied Parameters



Supply shifter based on equation 26; elasticity based on equation 25; parameter β^d recovered from tax years 1993-1997 and estimated elasticities from Table 2 and tax and transfer inclusive real net wage.