# The General Equilibrium Incidence of the Earned Income Tax Credit

C. Luke Watson*

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**Abstract**

The Earned Income Tax Credit is the *de facto* largest anti-poverty program in the US, utilized by 20% of the labor force, yet all prior policy analysis has used partial equilibrium assumptions on gross wages. I derive the general equilibrium incidence of targeted wage subsidies allowing for elastic labor supply and imperfect labor substitution across labor markets and apply this to the EITC. To quantify spillover effects, I estimate the general equilibrium incidence of the 1993 OBRA EITC expansion by combing new labor supply elasticity estimates with tax changes during the 1990s. To highlight how the spillover effects alter policy recommendations between programs, I simulate the partial versus general equilibrium incidence of two equal sized tax reforms: an expansion of the EITC and of a hypothetical Negative Income Tax. In both situations, I find that spillovers are economically meaningful.

*Watson: Department of Economics, Michigan State University, email: watso220@msu.edu. I am grateful for the advice and support from my advisors Leslie Papke, John D. Wilson, and Oren Ziv. All mistakes are my own.

# Contents

# 1 Introduction

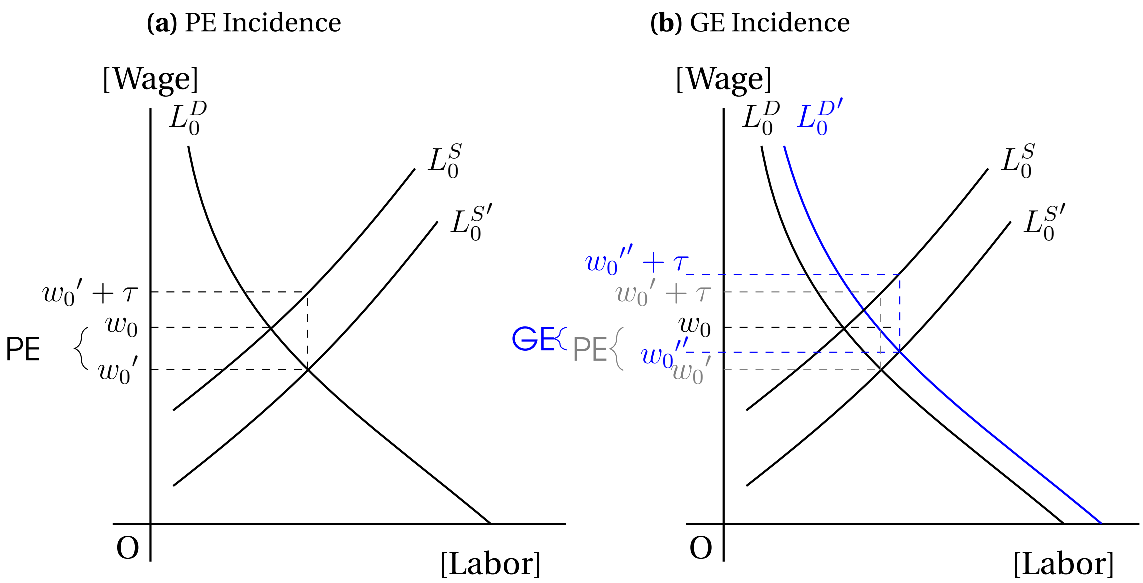
The Earned Income Tax Credit is the *de facto* largest anti-poverty program in the United States, with over 20% of all workers receiving some share of the $\$67$ billion expenditure, yet essentially all prior studies have assumed away the possibility of gross wage responses when analyzing policy effects on labor supply. 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.

Considered as a government intervention in the labor market, if the EITC causes meaningful wage distortions, then the anti-poverty policy goals will be undermined. Lawmakers occasionally propose expansion of EITC benefits and several think-tanks have proposals to expand eligibility. However, the EITC is not the only policy option available for increasing the income of the working poor. The closest substitutes are a Negative Income Tax or Universal Basic Income. The goal of this paper is to understand the magnitude and importance of spillovers when determining the most cost effective public policy to alleviate poverty.

I revisit the effect of the EITC on gross wages and earnings by deriving the general equilibrium incidence of targeted wage subsidies. 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 spillover terms are first order terms and do not disappear as market size shrinks. Because of these spillovers, the net effect on wages is theoretically ambiguous due to cascading feedback across labor markets. The mechanism is simple. A subsidy that increase labor supply of some *initial* set of workers will increase the marginal product of all *other* workers; this causes labor demand to increase for the *other* workers; the resulting quantity increase in *other* workers will increase the marginal product of the *initial* workers; and so on...

My primary theoretical contribution is to show general equilibrium incidence effects are conceptually and quantitatively important to consider in assessing large conditional wage subsidies due to two channels. First, when all tax changes are in the same direction, the partial equilibrium incidence is the *upper bound* on the magnitude of the gross wage changes. Intuitively, this is because the behavior of all other economic agents is held fixed so wage spillover effects are ignored. I show that these two general equilibrium terms are in the opposite direction of the partial effect; e.g., if a subsidy increase causes a positive labor supply shock that puts downward pressure on wages, then spillovers will pull the wages back up. With a two factor model with a labor subsidy, this can be seen graphically in figure 1. Similar to Agrawal and Hoyt (2018), I show that general equilibrium incidence is the sum of the partial incidence and two other 'first order' terms that incorporate labor market spillovers.

**Figure 1** – Labor Subsidy Incidence in Two Factor Model




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 demand to shift right, attenuating the PE gross wage decline.

Second, I show that if workers may switch factor markets (such as from high to low skill), there are additional spillover effects of incentivising low wage work through subsidies. In short, a low wage subsidy will encourage low wage work, both by new workers entering the labor force and incumbent workers switching from high wage work. Past EITC work has only considered intensive *hours* choices but not *skill* / *sector* choices.

Because the spillover magnitude is ambiguous, my primary empirical contribution is to quantify the importance. First, I calculate the empirical general equilibrium incidence of the 1993 OBRA expansion of the EITC. This expansion created the largest single change in EITC incentives in the programs history. I find that the spillovers were economically meaningful, especially for workers who were not primarily targeted by the EITC. For all unmarried women, gross wages fell by $0.62\%$ with a spillover magnitude of $14\%$. For married women, gross wages increased by $0.05\%$ with a spillover magnitude of $61\%$. For every dollar that went to unmarried women, net-earnings increased by $\$1.27$ for those with children but those without children saw net-earnings fall by $\$0.58$. For every dollar that went to married women, net-earnings increased for the two groups by $\$1.00$ and $\$0.12$ respectively. In aggregate, a one dollar increase in EITC spending led to a $\$0.93$ increase in net-labor-earnings with an equivalent variation of $\$0.72$. 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 contribution is to highlight how the spillovers of different wage subsidy policies will manifest to affect policy recommendations. I consider a hypothetical policy goal of transferring $100million to workers through an EITC expansion versus a Negative Income Tax. Thus, I offer a general equilibrium extension to Rothstein (2010), who compares these hypothetical reforms in partial equilibrium. My simulation finds that spillovers are economically meaningful when anticipating aggregate policy effects. Depending on the parameterization, I find that spillovers are important enough to reverse a policy recommendation from an NIT to an EITC. In my preferred general equilibrium specification, an intended dollar of EITC spending delivers $\$1.28$ of net-earnings to workers while the NIT delivers only $\$1.08$ 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 NIT 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.

To calculate the incidence terms, I estimate labor supply elasticities for different demographic groups and a labor supply elasticity that governs the curvature of labor demand. I use state-year policy variation in the EITC during the 1990s *within* demographic-based labor markets to estimate labor supply elasticities that vary education, marriage, and parental status. Because the incidence depends on the wage responsiveness of different labor markets, capturing granular differences in supply responsiveness is important for accurately measuring incidence effects. My estimation strategy allows me to avoid the assumption that women with and without children respond the same way to wage changes. Additionally, I estimate the labor substitution elasticity, which governs how much firms are willing to adjust wages, using policy variation *between* labor markets.

My results contrast with the partial equilibrium analysis of Rothstein (2010) who finds that the NIT is the unambiguously more cost effective program. This is for two reasons. First, because I model the GE spillovers, I show that spillovers attenuate the 'bad' effects of the EITC as well as the 'good' of the NIT. Second, I use a more empirically relevant estimate of the substitution elasticity that is closer to the literature consensus. Rothstein's main specification use a substitution elasticity of $\rho = -0.3$ while I estimate a value of $-2.5$.[1] Mechanically, this choice will exaggerate the effects of tax changes, as the theory shows.[2] Using my estimate of the substitution elasticity, I find that the EITC increases net-earnings more than the NIT in *both* partial and general equilibrium.

The overarching message of this paper is that the impact of general equilibrium spillovers of conditional wage subsidies, such as existing EITC or proposed UBI, 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 alle-

[1]Rothstein's estimate is based on a value estimated in Rothstein (2008) using a novel labor market definition, but the labor market definitions used in Rothstein (2010) are closer to the immigration literature which consistently estimates a larger elasticity Borjas et al. (2012).

[2]This is becuase the substitution elasticity enters the incidence through the denominator, so dividing by an inelastic versus an elastic value can dramatically affect the effect.

viating the burden 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.

[EITC BENEFIT SCHEDULE TO GO HERE]

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 effect 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. See either 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) – for a general overview of prior EITC studies.[3] However, few papers have studied the EITC's effect on gross wages due to the supply shifts. As a large labor market intervention, we should expect distortionary effects on labor allocations in potentially unpredictable ways. 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).[4] As noted by Hotz and Scholz (2003), this assumption had never been tested in first decade of EITC research.

[3]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; Han, 2016; Bastian and Michelmore, 2018); and marriage & fertility (Dickert-Conlin and Houser, 2002; Baughman and Dickert-Conlin, 2003, 2009).

[4]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).

The works closest to my own are Leigh (2010) and Rothstein (2010), who study the wage incidence in partial equilibrium.[5] In partial equilibrium, we expect that a supply increase with fixed demand should cause wages to fall, with the amount governed by the relative supply and demand elasticities. The fall in gross wages reduces the overall cost effectiveness of the EITC as a means of transferring income to low-income workers. Leigh (2010), using state and federal variation, finds that a 10% increase in EITC generosity leads to a 5% decrease in the real wages of high school dropouts, and, using a simulated instrument 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 an 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-targetted groups. Lee and Saez (2012) allow for endogenous wages and argue that combined with an EITC with optimal minimum wage policy can prevent some of the incidence effect; however, the authors do not actually attempt to calculate the incidence.[6] I build on their work to incorporate spillover effects between labor markets and firm entry decisions allowing for heterogeneous supply responses and tax changes.

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 equilibrium wage incidence and discuss the assumptions needed. In section 4, I derive the general equilibrium wage incidence in a two type model, a model that allows workers to switch sectors, and a model with heterogeneous tax changes and arbitrary number of types. In section 5, I estimate the general equilibrium incidence of the 1993 EITC expansion. In section 6, I simulate the hypothetical EITC vs NIT policy reforms. Finally, I conclude by briefly summarizing the results and describing how these results affect considerations of the EITC.

[5] 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.

[6] This is despite using a general equilibrium argument elsewhere in the paper when designing the optimal minimum wage policy.

## 2 Model

In this section, I layout a general equilibrium model of the labor market to investigate the effect of targeted labor subsidies. The primary assumptions are that worker utility is quasi-linear in consumption, production technology 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. I initially analyze a three factor model – two labor types and capital – to show the economic forces involved; however, I later generalize to an arbitrary number of labor types.

### 2.1 Labor Supply

Let there be workers $i \in \mathcal{N}$ with utility defined over a composite consumption good and labor, $u_i : \mathcal{X} \times \mathcal{L} \to \mathbb{R}$. 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. I assume that utility is quasi-linear with respect to final good consumption. Without loss of generality, the labor supply choice can be represented by:

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

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

where $T_i(\cdot)$ is a mapping from wages, unearned income, and transfers to final good consumption implied by the worker's budget set, $b_i$ is the unemployment benefit, and $v_i$ combines the disutility of effort and any potential opportunity cost of *not* participating in the labor force.

Let $v_i$ be drawn from some distribution, $F_i(\mathsf{v})$, which potentially depends on other fixed 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 $L_i^S(w_i)$.[7] The

[7]With specific distributional assumptions on $F(\mathsf{v})$ the expected labor supply of each worker is continuous; e.g., with Type-1 Extreme Value, $\Pr(L_i = 1 \mid \chi) = \mathsf{e}^{T_i}/(\mathsf{e}^{b_i} + \mathsf{e}^{T_i})$.

model implies a threshold labor supply strategy:

$$L_i = 1 \iff v_i \leq \tilde{v}_i(w_i) = T_i(w_i, m_i) - b_i, \tag{3}$$

where the threshold depends on the market wage, net unearned income, and unemployment benefit for the worker.

Let worker $i$ be described by a vector of demographics, $d_i = (e_i, k_i) \in \mathcal{E} \times \mathcal{K} = \mathcal{D}$, which can be partitioned into a subvector that determines productivity, $e$, and one that is unrelated to productivity (conditional on $e$), $k$. For example, suppose workers are described by education levels and parental status, but only education affects marginal product.[8] Given perfect information and perfect labor competition, all workers with the same $e$ will earn the same wage, $w$.

By integrating over workers of the same demographic, the aggregate labor supply functions are:

$$L_d^S = F_d(\tilde{v}_d)N_d \quad \& \quad L_e^S = \sum_{k \in \mathcal{K}} L_{(e,k)}^S \quad \& \quad L^S = \sum_{e \in \mathcal{E}} L_e^S. \tag{4}$$

Using the above, I define the labor supply elasticity as:

$$\frac{\partial L^S}{\partial w}\frac{w}{L} = \sum_{d \in \mathcal{D}} \left(\frac{F_d(\tilde{v}_d)N_d}{L}\right)\left(\frac{w \cdot f_d(\tilde{v}_d)}{F_d(\tilde{v}_d)}\right) \equiv \sum_{d \in \mathcal{D}} \left(\theta_d \cdot \varepsilon_d^S\right), \tag{5}$$

which is a labor supply weighted sum of the market specific labor supply elasticities.[9]

## 2.2 Production

Suppose that there are $j \in \mathcal{J}$ potential producers, each endowed with one unit of capital[10] and can hire labor to produce a homogeneous consumption good. Firms face

[8] I maintain throughout the assumption that $(e_i, w_i)$ are monotone.

[9] Returning to the T1EV example, this would imply an elasticity $\varepsilon_d^S = \frac{\partial T_d}{\partial w_d} w_d F_d(\tilde{v}_d)(1 - F_d(\tilde{v}_d))$.

[10] That is, $k_j = 1$ for all producers.

heterogeneous costs of supplying their unit of capital, $c_j$,[11] that is drawn from some distribution, $G(\mathsf{c})$.

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

$$q_j^S = Q(\{L_{e',j}\}_e, K_j) = A\left[\left(\sum_e \vartheta_{e'}(L_{e',j}^D)^{\frac{1+\rho}{\rho}}\right)^{\frac{\rho}{1+\rho}}\right]^{\alpha} K_j^{(1-\alpha)} \tag{6}$$

$$= A \cdot \mathbf{L}_j^{\alpha} K_j^{(1-\alpha)}, \tag{7}$$

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 $\rho = d\ln[L_{e''}/L_{e'}]/d\ln[w_{e''}/r_{e'}] < 0$. The elasticity of substitution between aggregate labor and capital is $(-1)$ by assumption. This technology assumes these elasticities are constant and features constant returns to scale (CRS). The primary modeling benefit to this technology is that it allows for tractable solutions with indefinite numbers of different factors, which will come up later.[12] Firms hire labor to maximize profit, given prices, $\pi_j = p \cdot Q(\{L_{e',j}\}_e, K_j) - \sum_e w_{e'} L_{e'} - rK_j$. Aggregate output is defined as $q^S = \int_j q_j^S dj$. In order to solve the model, I choose to normalize $p := 1$.

Given price taking, zero profits, and identical CES production functions, all firms choose the same factor input bundle, and by CRS this implies that the aggregate production function is also CES:

$$q^S = Q(\{L_{e'}\}_e, K) = A\left[\left(\sum_e \vartheta_{e'}(L_{e'}^D)^{\frac{1+\rho}{\rho}}\right)^{\frac{\rho}{1+\rho}}\right]^{\alpha} K^{(1-\alpha)}. \tag{8}$$

In this set up, the firm capital supply is synonymous with firm entry, which is determined by firm capital supply costs, $c_j$. By zero profits, $Q(\{L_{e',j}\}_e, K_j) - \int_{i\in L_j} w_i L_i = r$, again where each firm only has one unit of capital. As with workers, firms will enter based on a

[11] Alternatively, firms have heterogeneous entry costs.

[12] Specifically I use the fact that the substitution effect between two factors only depends on the pair's factor prices. As shown in Matsuyama and Ushchev (2017), this property requires throwing out many potential homothetic demand systems.

threshold condition: $c_j \leq \tilde{c}(r)$. In equilibrium, this will determine the aggregate capital supply function, $K^S(r)$. A firm's 'producer surplus' is profit minus the cost of entry, $r - c_j$. The 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, $\tau_i$. The changes in lump-sum tax policy to pay for the subsidy have no behavoral effects, and there are no changes in the unemployment benefit. I model the subsidy as a unit excise tax/subsidy, $T_i(w_i \cdot L_i, m_i) = (w_i + \tau_i) \cdot L_i + (1 - L_i) \cdot b_i - n_i$. I suppose that the benefit and subsidy amounts are functions of earnings, which the government observes, and demographics conditions, which the government can verify. Thus, the benefit and the transfer function varies at the demographic level, $\{b_d, \tau_d\}$. In the EITC context, the subsidy is only for low income workers with children.[13]

In the analysis, I consider a differential change in the tax, $d\tau_d$, starting from a tax of zero.[14] To model the targeted aspect of the labor subsidies, let the set of demographics be partitioned into a condition that concerns labor market variables and one that concerns non-labor market variables: $d = (e, k)$. Let $k$ determine overall eligibility and let $e$ determine the size of the subsidy. For example, if $(e, k) \in \{0, 1\}^2$ proxy for education and parental status and the subsidy targets low income workers with children, then

$$d\tau_d = \begin{cases} \tau \text{ if } d = (0, 1) \\ 0 \text{ if } d \neq (0, 1). \end{cases}$$

[13]Technically, the EITC gives a small ($\leq$ \$500) subsidy to workers without children, but this is often assumed to have no behavoral effects on these workers.

[14]If there were no unemployment benefit, then this would imply the initial equilibrium is efficient. With the benefit, it is efficient conditional on the benefit.

Given the labor market assumptions above, this implies the following $e$-group labor supply function:

$$L_e^S(w_e, \tau_e) = L_{e,k_0}^S(w_e) + L_{e,k_1}^S(w_e + \tau_e). \tag{9}$$

## 2.4 Equilibrium in Three Factors

For exposition, I show equilibrium in three factors and then generalize to arbitrary factors. In equilibrium, the factor markets clear when all factors are paid their marginal product and firms make zero profits, which then clears the output market. Due to the CRS assumption, the scale of production cannot be determined so the scale of factor demands cannot be determined (without utilizing equilibrium relationships). Fortunately, the nested CES production function can be solved in terms of factor input and price ratios.

For the CES labor aggregator function, the factor demand ratios equal a function of the factor price ratio. For the two labor factors, $(L_0, L_1)$:

$$\frac{L_0^D}{L_1^D} = \left(\frac{w_0/\vartheta_0}{w_1/\vartheta_1}\right)^{\rho} \tag{10}$$

The labor aggregate and capital also have a CES relationship:

$$\frac{\mathbf{L}^D}{K^D} = \left(\frac{\bar{w}/\alpha}{r/(1-\alpha)}\right)^{-1}, \tag{11}$$

where $\bar{w}$ is a labor cost index.

Thus, the equilibrium conditions for the model can be derived by equating the factor demand for supply functions and enforcing zero profits using the unit cost function, with output price normalized to one:

$$\text{Labor Clearing} \quad \frac{L_0^S(w_0,\tau_0)}{L_1^S(w_1,\tau_1)} = \left(\frac{w_0/\vartheta_0}{w_1/\vartheta_1}\right)^{\rho} \tag{12}$$

$$\text{Factor Clearing} \quad \frac{L^S(w_0,w_1,\tau_0,\tau_1)}{K^S(r)} = \left(\frac{\bar{w}/\alpha}{r/1-\alpha}\right)^{-1} \tag{13}$$

$$\text{Zero Profits} \quad p = c(w_0,w_1,r) := 1 \tag{14}$$

with Labor Cost Index: $\bar{w} = \left(\vartheta_0\left(\frac{w_0}{\vartheta_0}\right)^{1+\rho} + \vartheta_1\left(\frac{w_1}{\vartheta_1}\right)^{1+\rho}\right)^{\frac{1}{1+\rho}}$.

**Definition 2.1** (General Equilibrium)**.** An equilibrium is an allocation of consumption goods and factor supplies and prices such that equations 12, 13, and 14 hold for the economy described above.

## 2.5 Equilibrium with Many Labor Factors

The above equilibrium only considers three factors of production, $L_0, L_1$ and $K$. A more general model allows for many more factors of production. Specifically, suppose that labor is much more differentiated in terms of marginal product so that there are $|\mathcal{E}|$ types of labor. This creates $(|\mathcal{E}|+1)$ different factors of production from the perspective of the firm.[15] However, suppose that the nested CES structure remains.[16]

Thus the equilibrium system becomes:

$$\text{Labor Clearing} \quad \frac{L_e^S(w_e,\tau_e)}{L_{e'}^S(w_{e'},\tau_{e'})} = \left(\frac{w_e/\vartheta_e}{w_{e'}/\vartheta_{e'}}\right)^{\rho}, \forall\, e' \in \mathcal{E} \tag{15}$$

$$\text{Factor Clearing} \quad \frac{L^S(\{(w_e,\tau_e)\}_{e\in\mathcal{E}})}{K^S(r)} = \left(\frac{\bar{w}/\alpha}{r/1-\alpha}\right)^{-1} \tag{16}$$

$$\text{Zero Profits} \quad P = c(\{w_e\}_{e\in\mathcal{E}}, r) := 1 \tag{17}$$

with Labor Cost Index: $\bar{w} = \left(\sum_e \vartheta_e \left(\frac{w_e}{\vartheta_e}\right)^{1+\rho}\right)^{\frac{1}{1+\rho}}$.

[15] I could additionally suppose that there are other material factors of production other than capital, and treat the aggregate capital as a material factor index.

[16] Thus, even though there are more types of labor there is still a single (partial) elasticity of substitution between labor types.

## 2.6 Welfare

The market surplus if worker $i$ participates, facing prices $\{T_d(w)\}$, is

$$S_{i,d} = U_{i,d}(L_i = 1) - U_{i,d}(L = 0) = \tilde{v}_d - v_i. \tag{18}$$

This implies the aggregate *participation* surplus is:

$$S_d = \left[ T_d(w)F(\tilde{v}_d) - \int_{\underline{v}}^{\tilde{v}_d} \mathsf{v} f(\mathsf{v}) d\mathsf{v} \right] N_d = \left(\tilde{v}_d - \mathsf{E}[\mathsf{v} \mid \mathsf{v} < \tilde{v}_d]\right) L_d^S \tag{19}$$

Total welfare is equal to the sum of non-participating workers consuming their non-labor income plus the sum of participating worker surplus:[17]

$$\begin{aligned} TW_d &= \left[ (m_d - n_d) + (b_d) \cdot (1 - F(\tilde{v}_d)) + w_d \cdot F(\tilde{v}_d) - \int_{\underline{v}}^{\tilde{v}_d} \mathsf{v} f(\mathsf{v}) d\mathsf{v} \right] N_d & (20)\\ &= \left[ (m_d - n_d) + b_d + (w_d - b_d - \mathsf{E}[\mathsf{v} \mid \mathsf{v} < \tilde{v}_d])F(\tilde{v}_d) \right] N_d & (21)\\ &= (m_d - n_d + b_d)(N_d) + (w_d - b_d)L_d^S & (22) \end{aligned}$$

Market aggregate surplus and welfare are given by $S = \sum_d S_d$ and $TW = \sum_d TW_d$. This states that total welfare in this model is the net-consumption of non-workers plus the net-consumption of workers minus the workers' disutility of labor.

# 3 Partial Equilibrium Incidence

In this section, I present the partial equilibrium incidence and show implications of the partial analysis. This section is lighter on details because it effectively replicates Rothstein (2010) using a more fleshed out model.

Return to the three factor model, where labor types are $d = (e, k) \in \{0, 1\}^2$. Suppose that the government is only subsidizing labor for the $(0, 1)$ group. I find the partial

[17] Here I assume that non-labor income can also be described demographically; extending this to individual idiosyncratic amounts is simple but adds unnecessary messiness.

equilibrium incidence by totally differentiating the labor clearing condition (equation 12) while holding $\{L_1, K, w_1, r\}$ constant.[18] This yields (when $\hat{\tau} > 0$):

$$\hat{w}_0^{\mathsf{PE}} = \left(\frac{\varepsilon_{0,1}^L}{\varepsilon_0^L - \rho}\right) \cdot \theta_{0,1} \cdot \hat{\tau} < 0, \tag{23}$$

where $\theta_{e,k}$ is the labor supply share of type $e$ workers with demographic $k$, $\hat{x}_e = x_e/w_e$ is the percent of wage change for the $e$-group, and $\varepsilon_e^L$ and $\varepsilon_{e,k}^L$ are the group and sub-group supply elasticity, respectively.[19]

This implies, as in Rothstein (2010), 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:[20]

$$L_0^D(w_0) = L_1^S(w_1(w_0)) \cdot \left(\frac{w_0/\theta_0}{w_1(w_0)/\theta_1}\right)^\rho \tag{24}$$

$$\implies \eta_0^D = \rho + \frac{\partial w_1}{\partial w_0}\left(\varepsilon_1^L - \rho\right). \tag{25}$$

When $\frac{\partial w_1}{\partial w_0} = 0$ by partial equilibrium assumption, then the demand elasticity is only the substitution elasticity between factors.

## 3.1 Implication of Partial Equilibrium Assumption

Suppose there are multiple labor types with heterogeneous subsidy changes, as in the Rothstein (2010) analysis. Suppose that one wants to use the partial equilibrium incidence formula to assess the impact of a targeted subsidy, as in Rothstein (2010). In a many

[18] Note, I ignore the factor clearing and zero profits condition because in partial equilibrium these equations cannot simultaneously be true given other fixed variables *and* have non-zero change in gross wages. For instance, the totally differentiating the zero profit condition, with the other variables fixed implies, that $L_0 \cdot dw_0 = 0$, which can only be true if $dw_0 = 0$, implying that the subsidy has no partial equilibrium effect at all!

[19] Note, $\varepsilon_e^L = \theta_{e,1}\varepsilon_{e,1}^L + (1-\theta_{e,1})\varepsilon_{e,0}^L$.

[20] In the CRS context, the scale of production and thus factors is unknown. In the two factor 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.

labor factor model, this implies the partial equilibrium labor demand elasticity is:

$$\eta_e^D = \frac{d\ln[L_e^D]}{d\ln[w_e]} = \frac{d\ln[L_e^D/L_{e'}^D]}{d\ln[w_e/w_{e'}]} = \rho,\ \forall\, e' \in \mathcal{E}. \tag{26}$$

The above is true for $e$ only when $d\ln[L_{e'}^D] = d\ln[w_{e'}] = 0$ for every other labor factor, but this can never be simultaneously true with multiple markets. Calculating the partial incidence for multiple labor markets is problematic since this requires a set of mutually exclusive conditions, especially when allowing for heterogeneous subsidies for different labor markets. In this case, using the Rothstein (2010) type analysis yields an 'employment weighted average partial equilibrium effect', which is not an object of theoretical or practical interest.

Note, if one wanted to describe the PE incidence as the GE under a set of assumptions, it is **not** sufficient to assume that $\varepsilon_{e'}^L = 0$ for some set of factors. The sufficient assumption is that the wage of all other factors must be held fixed. Since the wage equals (value) marginal product, this implies that the despite changes in ratios of labor types – e.g., the supply of low wage labor – the marginal product of the high wage labor must be held fixed to arrive at 23. But this is mechanically impossible.

## 3.2 Interpretation of Partial Equilibrium Results

In his analysis, Rothstein implies that decreases in gross wages are in effect 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..." (Rothstein, 2010).[21] While Rothstein's partial equilibrium analysis is technically correct, the interpretation of his result, given the model and analysis he conducts, does not follow.

First, with zero profits, there are no explicit profits for firms. Rather, with CRS technology, if one factor price goes down, then another factor price must increase, so the

[21]This is similar to the social critique that low wage firms, such as 'big-box' retail firms, are able to take advantage of anti-poverty programs such as SNAP and Medicaid.

analysis points to the *owners* of the other factors benefiting. Else, with marginal cost pricing, then the output price must decrease (but price is held fixed).

But, if one believes that entrepreneurs are themselves the owners of some other factors (such as capital in the model from the previous section), then firms/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 firms.[22]

Nevertheless, the 'all else equal' for the partial incidence for a specific factor 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.

# 4 General Equilibrium Incidence

In this section, I lead with the simple three factor model and then show the generalized version. For the three factor model, I will only consider a subsidy for the low income labor group, but in the generalized version I allow for each labor type to have its own group specific subsidy. Finally, for the three type model, I consider an extension where workers additionally have group-specific preferences, where the high income group have the option of working in either the low or high income group.[23]

I all models, I show that the general equilibrium incidence includes other 'first order' terms, some of which do not go to zero as the market size becomes infinitesimal. Thus, partial equilibrium analysis cannot be justified on 'second order' spillover effects nor small open, market assumptions.

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

[23] This is similar to the model used in Saez (2002).

## 4.1 General Equilibrium Incidence with Three Factors

In this section, I use a three factor general equilibrium model to show how targeted labor subsidies affect the labor market equilibrium. Specifically, I show that the partial and general equilibrium incidence results are different because changing the relative supplies of labor – by initially incentivising low wage labor supply – causes changes in the relative marginal products and wages of all factors, so firms reoptimize their factor demands. This causes a cascade of labor supply and demand changes until equilibrium is achieved. In the end, the general equilibrium incidence formula is the partial equilibrium incidence plus a weighted sum of market responses for all other factors.

Define the demographic sub-group specific labor supply elasticity as $\varepsilon^L_{e,k}$ for $k \in \{0,1\}$, the capital supply derivative as $dK^S/dr = \kappa$, and the the cost shares $w_e L_e/(\bar{w}\mathbf{L}+rK) = s_{L_e}$ and $s_K$ similarly. Define the percent changes in wages and tax rates as $\hat{w} = dw/w$ and $\hat{\tau} = d\tau/w$, and define the demographic employment share as $\theta_{e,k} = L_{(e,k)}/L_e$.

To calculate the incidence, totally differentiate equations 12, 13, and 14 with respect to $\{w_0, w_1, r, \tau\}$. The system features three equations and three unknowns $(dw_0, dw_1, dr)$. Use Zero Profits to solve $dr = f(dw_0, dw_1)$, use Labor Clearing to solve $dw_1 = g(dw_0, d\tau)$, and then substitute into Factor Clearing for $dw_0 = h(d\tau)$. This yields (when $\hat{\tau} > 0$):

$$\hat{w}_1^{\mathsf{GE}} = \left( \frac{-\varepsilon^L_{0,1}\theta_{0,1}}{(\varepsilon^L_0 - \rho)} + \frac{\left(\frac{\varepsilon^L_{0,1}\theta_{0,1}}{(\varepsilon^L_0-\rho)}\right) s_0 \left(\frac{\varepsilon_K+1}{s_K} + \frac{1+\rho}{s_L}\right)}{(\varepsilon^L_0 - \rho)\left(1 + \left(\frac{\varepsilon_K+1}{s_K} + \frac{1+\rho}{s_L}\right)\left(\frac{s_0}{(\varepsilon^L_0-\rho)} + \frac{s_1}{(\varepsilon^L_1-\rho)}\right)\right)} \right)\hat{\tau} \leq 0 \tag{27}$$

$$= (\mathsf{p}_0 + \Gamma_0)\cdot\hat{\tau} \leq 0 \tag{28}$$

$$\implies \mathsf{p}_0 \leq -\Gamma_0 \leq 0 \tag{29}$$

As in Agrawal and Hoyt (2018), the general equilibrium incidence as a linear function of the partial equilibrium incidence and general equilibrium effects. Note, only in the case that $s_0 = 0$ are $\hat{w}_0^{\mathsf{PE}} = \hat{w}_0^{\mathsf{GE}}$, which is a infinitesimal markets scenario that makes little sense in a two labor type model.

The most important aspect of equation 27 is that there are **two** 'first order' effects and understanding the reason for each. Partial equilibrium analysis is often justified on the basis of capturing the 'first order' effect while other effects are 'second order'; however, this is not the case above. For this reason, the general equilibrium effects can *theoretically* be similar in magnitude as the partial equilibrium effect.

Note also that $\hat{w} < 0$, $\mathsf{p} < 0$, and $\Gamma > 0$. This implies that the partial equilibrium incidence is the *upper bound* in the gross wage change, so the general equilibrium effects offset the partial equilibrium effects of the subsidy.

Intuitively, the partial equilibrium formula omits firm reoptimization (by demanding more capital and high wage labor) and factor reoptimization (by supplying more), and thus the *benefits* to the subsidized factor of these reoptimizations (increases in other factors increase the subsidized labor's marginal productivity) are not present. Figure 2 provides a graphical comparison of the market outcomes.

The relative size of the two *opposing* wage effects depends on $s_L$, the curvature of factor demand $\rho$, and the behavoral supply responses of all factors. Thus, determining the magnitudes of the general and partial equilibrium effects is ultimately an empirical question. In table 1, I show that for various parameters, the general equilibrium incidence result can be quite far from the partial incidence. The relevant set of parameters are: $\big(\{(\varepsilon^L_{e,k},\ \tau_d)\}_d,\ \varepsilon_K, \rho,\ s_L\big)$.

### 4.1.1 Visual Incidence Comparison

Here, I compare the gross wage incidence from a labor subsidy based on the two factor model with an exogenous, 1% tax change.[24] This shows the importance of different elasticity assumptions when calibrating the labor market effects, particularly the substitution elasticity. I use equation 23 for the partial equilibrium incidence and I use equation 27 for the general equilibrium incidence.

[24] 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.

In table 1, I present the main parameters I use in the calibration and a summary of incidence results. 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 $\rho \in \{-0.3, -1.4, -2.5\}$, based on Rothstein (2010), Katz and Murphy (1992); Goldin and Katz (2009), and my empirical analysis presented later. I set $s_L = 0.66$ based on the labor share of total input costs for the economy in the 1990s. 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 subsidied $(\hat{\tau}_{1,1}/\hat{\tau}_{0,1} = 0)$, but in the third panel I allow for a smaller subsidy on the high wage workers.

**Table 1** – Summary:
Percent Change in Gross Wage for Low Wage Market

| | Partial Equilibrium (%) | General Equilibrium (%) |
|---|---|---|
| | Using Baseline Supply Elasticities | |
| $\rho = -0.3$ | -0.714 | -0.645 |
| $\rho = -1.4$ | -0.349 | -0.319 |
| $\rho = -2.5$ | -0.231 | -0.216 |
| | Other Elasticities with $\rho = -2.5$ | |
| $\varepsilon^L_0 = 1.0$ | -0.286 | -0.269 |
| $\varepsilon^L_1 = 0.3$ | -0.231 | -0.217 |
| $\varepsilon^L_1 = 0.9$ | -0.231 | -0.215 |
| $\varepsilon^K = 2$ | -0.231 | -0.212 |
| | Allowing $\hat{\tau}_{1,1} > 0$ with $\rho = -2.5$ | |
| $\frac{\hat{\tau}_{1,1}}{\hat{\tau}_{0,1}} = 0.1$ | -0.231 | -0.207 |
| $\frac{\hat{\tau}_{1,1}}{\hat{\tau}_{0,1}} = 0.2$ | -0.231 | -0.198 |

Baseline: $\varepsilon^L_0 = 0.75, \varepsilon^L_1 = 0.6, \varepsilon_K = 1, \frac{\hat{\tau}_{1,1}}{\hat{\tau}_{0,1}} = 0$
Incidence results computed at $s_{L_1} = 0.125, s_L = 0.66$

The table results show that the general equilibrium incidence always attenuates the PE incidence, especially as market size grows. The results highlight that the labor substitution elasticity appears to dictate the magnitude of the incidence effect. Using the value $\rho = -0.3$ from Rothstein (2010) implies a PE incidence of $-0.71\%$ while a $\rho = -2.5$ implies only a $-0.23\%$ change in gross wages.

In figure 2, 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 partial equilibrium incidence and the upward sloping lines are the general equilibrium incidence. As can be seen, only at $s_L = 0$ are the PE and GE effects equivalent. The graph shows that the PE incidence can overstate the GE incidence by over $100\%$ depending on the share of workers who are subsidized. The graph additionally shows that an inelastic substitution parameter can imply a large divergence between the PE and GE wage effects, while an elastic parameter implies that the PE and GE effects are relatively similar in absolute value.

### 4.1.2 Change in Net-Earnings

Since net-earnings for workers in market $j$ are $Z_j = (w_j + \tau_j)L_j$, then for a subsidy increase the general equilibrium change in net-earnings for that market is:

$$\frac{\mathsf{d}Z_j}{Z_j} = \frac{\mathsf{d}w_j + \mathsf{d}\tau_j}{w_j} + \frac{\mathsf{d}L_j}{L_j} := (\hat{w}_j + \hat{\tau}_j) + \hat{L}_j \tag{30}$$

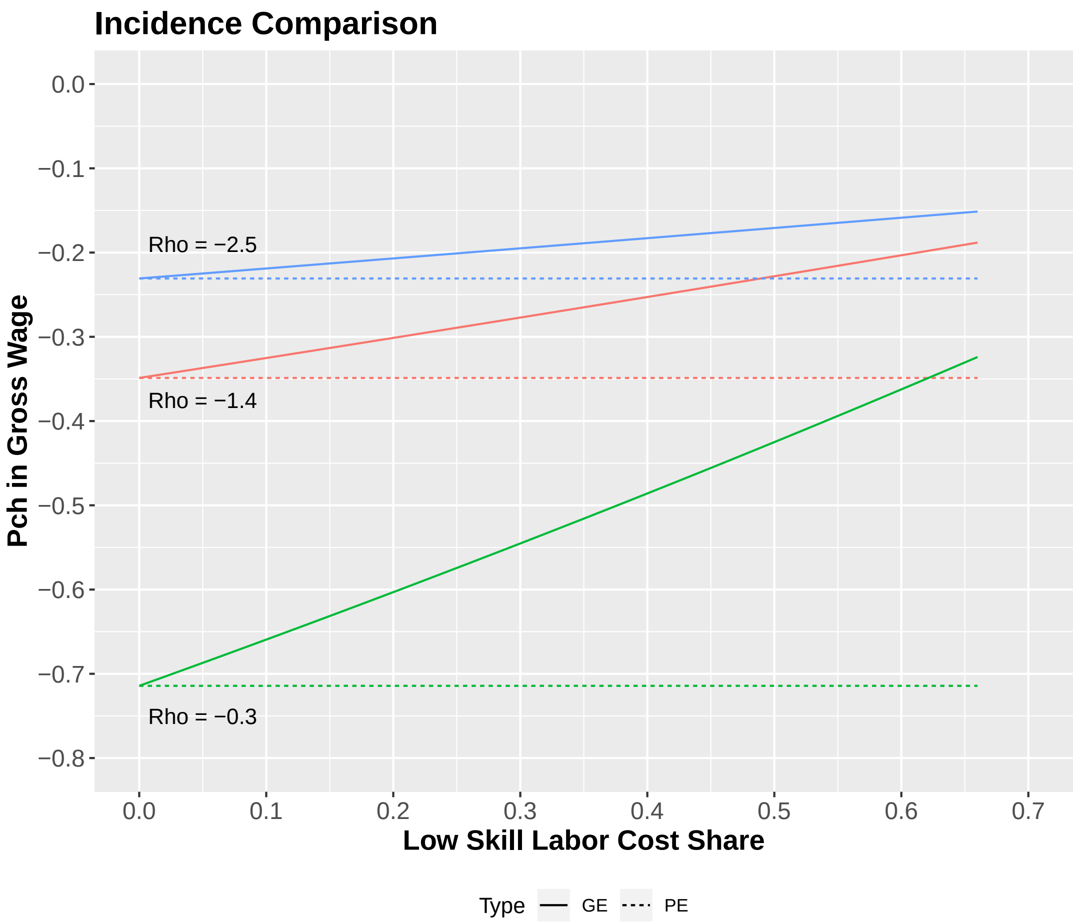
$$= (\mathsf{p}_j + \Gamma_j)\hat{\tau}_j + \hat{\tau}_j + \varepsilon_j^L \left( (\mathsf{p}_j + \Gamma_j)\hat{\tau}_j + \hat{\tau}_j \right) \tag{31}$$

$$= \Gamma_j \left( \hat{\tau}_j + \varepsilon_j^L \right) + \hat{\tau}_j \cdot \left( \frac{\rho(\varepsilon_j^L + 1)}{\varepsilon_j^L - \rho} \right) > 0, \tag{32}$$

where $\Gamma_j$ is the GE spillover effect on gross wages for market $j$. The GE increases in net-earnings increase in proportion with supply responsiveness ($\varepsilon^L$) and in the size of the subsidy change. For the unsubsidized market, since $\hat{\tau}_1 = 0$, then

$$\hat{Z}_1 = \varepsilon_1^L \Gamma_1 = \varepsilon_1^L \hat{L}_1 = \varepsilon_1^L \hat{w}_1 > 0.$$

**Figure 2** – 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 low skill labor cost shares. Other parameters: $\varepsilon_0^L = 0.75,\ \varepsilon_1^L = 0.6,\ \varepsilon_K = 1,\ \frac{\hat{\tau}_{1,1}}{\hat{\tau}_{0,1}} = 0$

### 4.1.3 Equivalent Variation

Since utility is quasi-linear, the equivalent variation is exactly equal to the change in worker surplus. Nevertheless, I show this below.

The change in total welfare for group $d$ is (again evaluated at initial $\tau_d = 0$):

$$\begin{aligned} dTW_d =& \Bigg[(dw + d\tau_d)F(\tilde{v}_d) + (w_d - b_d)\left((dw + d\tau_d)\left(\frac{\partial \tilde{v}}{\partial w}\right) f(\tilde{v}_d)\right) \\ & - \tilde{v}_d\left((dw + d\tau_d)\left(\frac{\partial \tilde{v}}{\partial w}\right) f(\tilde{v}_d)\right)\Bigg] \cdot N_d \qquad (33) \\ =& (dw_d + d\tau_d)\left(F(\tilde{v}_d) - \left(\frac{\partial \tilde{v}}{\partial w}\right) f(\tilde{v}_d)\left(w_d - b_d - \tilde{v}_d\right)\right) \cdot N_d \qquad (34) \\ =& (\hat{w}_d + \hat{\tau}_d)(w_d \cdot L_d^S), \qquad (35) \end{aligned}$$

where $\tilde{v}_d = w_d - b_d$. As before, the aggregate welfare change is the size weighted sum of the group changes: $dTW = \sum_d dTW_d$.

The welfare change is equal to the net income effect on incumbent workers. The change is intuitive. Since utility is quasi-linear the change in consumption is equal to the change in utility. This is due to an envelope condition where the disutility of effort by the *entrants* is offset by their consumption change, so only effects on the incumbent workers contribute to the welfare changes.

As noted at the start, since preferences are quasi-linear, the change in total welfare is equal to the equivalent variation for the policy. The goal is to find for each worker the amount to make the worker *ex ante* indifferent to the policy change: $U_{i,t_0} + EV_i = U_{i,t_1}$. Before and after the policy, these are the worker's choices:

$$\max_{L=\{0,1\}} \{b_d, w - v_i\} \qquad (36)$$

$$\max_{L=\{0,1\}} \{b_d, w + dw_d + d\tau_d - v_i\}. \qquad (37)$$

There are four possible behavoral responses:

$$0 \to 0 : EV_i = 0 \tag{38}$$

$$0 \to 1 : EV_i = w_d + dw_d + d\tau_d - v_i - b_d = \tilde{v}_{d,t_1} - v_i = \tilde{v}_{d,t_0} + dw_d + d\tau_d - v_i \tag{39}$$

$$1 \to 0 : EV_i = b_d - w_d + v_j = v_i - \tilde{v}_{d,t_0} \tag{40}$$

$$1 \to 1 : EV_i = dw_d + d\tau_d \tag{41}$$

For a differential change in the subsidy, marginal entrants $(0 \to 1)$ and exiters $(1 \to 0)$ are indifferent in the two regimes, so the $EV$ for these two cases is also $0$. A non-differential change in the subsidy will cause these terms to be non-zero for some measure of the switchers.

The aggregate EV for the economy is going to be the weighted sum of the different EV amounts, where the weights are based on the number of workers in each behavoral category. Note, for any group $d$, $\tilde{v}_{d,t_1} > \tilde{v}_{d,t_0}$ iff $dw_d + d\tau_d > 0$; else, the opposite. This means that for any $d$, there are only switchers in one direction, $0 \to 1$ or $1 \to 0$.

For any group, the total $EV_d$ is the summation of the remaining incumbent workers and the switcher group:

$$EV_d = (dw_d + d\tau_d)L_d + (\tilde{v}_{d,t_0} - \mathsf{E}\left[\mathsf{v} \mid \mathsf{v} \in [\tilde{v}_{d,t_0}, \tilde{v}_{d,t_1}]\right])dL_d^S \tag{42}$$

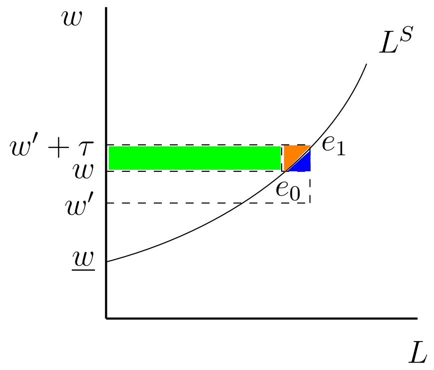
$$= (\hat{w}_d + \hat{\tau}_d)(w_d \cdot L_d^S) \tag{43}$$

Again, only if there is a differential subsidy change does the second term disappear. Equation 42 abuses some notation because it may be the case that $\hat{v}_{d,0} > \hat{v}_{d,1}$, but this only requires understanding that the sign of the second term is implied by the direction.

As stated, the equivalent variation in equation 43 is equal to the change in total welfare in equation 35. Graphically, these ideas are quite simple to represent, see figures 3 and 4.

For the case when there is a subsidy, the *ex ante* worker surplus is the area $(\underline{w} : w : e_0)$, and the *ex post* surplus is the area $(\underline{w} : (w' + \tau) : e_1)$. The subsidy causes overall worker surplus to increase, but there is also an increase in labor effort from new entrants. With quasi-linear utility, the change in surplus can be expressed in terms of expenditure amounts. The dotted box $(w' : e_1)$ is the entire expenditure by the government. The green box is the net increase in earnings by incumbent workers. The orange area is the added surplus of entrant workers, and the blue area is the additional labor effort by these workers.

**Figure 3** – Surplus of Group with Subsidy

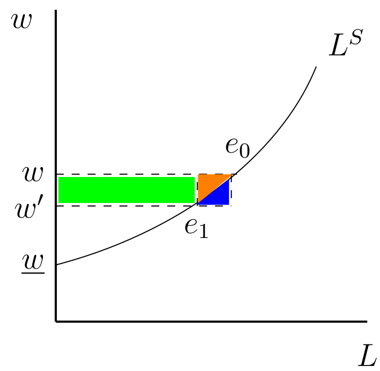



Boxes:
Green: $(dw + d\tau) \cdot L_0$
Orange: $(dw + d\tau) \cdot dL/2 + \delta$
Blue: $(dw + d\tau) \cdot dL/2 - \delta$

When aggregate labor supply is linear, then the orange and blue area will cancel each other out. With a differential change in the subsidy, the aggregate labor supply elasticity will be roughly linear. With a discrete subsidy change, when aggregate labor supply is non-linear, and *concave-up* (i.e., positive second derivative, traditional textbook case), then the orange area will be slightly larger than the blue area. In this case, the green expenditure is a lower bound on the aggregate equivalent variation.

In figure 4, I show the change in worker surplus change for a group that experiences a wage fall without a subsidy. The orange and blue areas will cancel out for a small enough change in the wage. This leaves only the income change for the incumbent workers who continue to participate because the worker who leave the market are (almost) exactly compensated by their decreased labor effort.

**Figure 4** – Surplus of Group without Subsidy: Wage Fall




Boxes:
Green: $(dw) \cdot L_0$
Orange: $(dw) \cdot dL/2 + \delta$
Blue: $(dw) \cdot dL/2 - \delta$

## 4.2 General Equilibrium Incidence with Many Worker Types

Adding additional types of labor in this context is relatively simple. Here, I allow for each labor type to have a heterogeneous tax change, and I solve the equations in the same manner as before using substitution after totally differentiating. Let worker types be indexed by $e \in \{0, 1, 2, \ldots, E\} = \mathcal{E}$.[25] I solve the general equilibrium wage change for type $0$ labor group, and can the labor-group clearing condition (equation 15) to solve for any other group.

The general equilibrium incidence for type $0$ labor is:

$$\hat{w}_0^{\mathsf{GE}} = \frac{-\varepsilon^L_{(0,1)}\theta_{0,1}\hat{\tau}_0}{\varepsilon^L_0 - \rho} + \frac{\Lambda\left(\sum_e \frac{s_e \varepsilon^L_{(e,1)}\theta_{e,1}\hat{\tau}_e}{\varepsilon^L_e - \rho}\right)}{(\varepsilon^L_0 - \rho)\left(1 + \Lambda\left(\sum_e \frac{s_e}{\varepsilon^L_e - \rho}\right)\right)} \tag{44}$$

$$= (\mathsf{p}_0)\hat{\tau}_0 + \Psi_0(\{\tau_e\}_{e\in\mathcal{E}}) \tag{45}$$

$$\text{where } \Lambda = \left(\frac{\varepsilon_K + 1}{s_K} + \frac{1 + \rho}{s_L}\right). \tag{46}$$

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

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

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. Now one needs to assume that $\mathsf{E}[s_e \theta_{e,1} \tau_e] \approx 0$.

## 4.3 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.[26]

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):

$$\text{Labor Clearing} \quad \frac{L^0_{0,0} + L^1_{0,0} + L^0_{0,1} + L^1_{0,1}}{L^1_{1,0} + L^1_{1,1}} = \left(\frac{w_0/\theta_{0,1}}{w_1/\theta_{1,1}}\right)^{\rho} \tag{47}$$

$$\text{Factor Clearing} \quad \frac{L^0_{0,0} + L^1_{0,0} + L^0_{0,1} + L^1_{0,1}}{K^S(r)} = \left(\frac{\bar{w}/\alpha}{r/1-\alpha}\right)^{-1} \tag{48}$$

$$\text{Zero Profits} \quad P = c(w_0, w_1, r) := 1 \tag{49}$$

The general equilibrium incidence for this model is:

$$\hat{w}_0^{\mathsf{GE}} = \frac{-(\varepsilon^L_{0,1} - \tilde{\chi}_1^{1,0})\hat{\tau}_0}{(\varepsilon^L_0 - \tilde{\chi}^{1,0} - \rho)} + \frac{\Lambda\left(\sum_d \left(\frac{s_d \hat{\tau}_d(\varepsilon^L_{d,1} - \tilde{\chi}_1^{\neg d,d})}{(\varepsilon^L_d - \tilde{\chi}^{\neg d,d} - \rho)}\right)\right)}{1 + \sum_d \left(\frac{s_d \Lambda + \tilde{\chi}_1^{\neg d,d}}{(\varepsilon^L_d - \tilde{\chi}^{\neg d,d} - \rho)}\right)} \tag{50}$$

$$= (\mathsf{p}_0 + \Gamma_0 + \mathcal{X}_0)\hat{\tau}_0 + \Psi_0(\hat{\tau}_2) + \mathfrak{X}_0(\hat{\tau}_2) \tag{51}$$

where $\varepsilon^L_{d,1}$ and $\tilde{\chi}_k^{g,g'}$ incorporate the relevant share of workers based on $\theta^e_{g,k}$. 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.

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

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.

# 5 Empirical Incidence of the EITC

In this section, I connect the theory to data to calculate the general equilibrium incidence of the 1993 OBRA expansion of the EITC. The key ingredients are the observed tax changes and market shares along with the labor market elasticities that govern responsiveness. Below, I describe my estimation of the elasticities, and then I calculate the partial incidence using equation 23 and the general incidence using equation 44.[27]

In subsection 5.1, I describe the identification of the elasticities, the data I use, the variable definitions, summary statistics, and finally the estimation equations. Then, in subsection 5.2 I show the elasticity results and in subsection 5.3 I show the main empirical incidence results.

## 5.1 Estimating Labor Market Elasticities

I estimate the parameters using two separate two-stage least squares models. I use labor market data from the Current Population Survey and calculate EITC based average tax rates using the 1990 Census and TAXSIM. I specifiy demographic based labor markets to create market level variables for labor quantity, wage, and EITC based average tax rate variables for each state and year. My calculation of market-state-year specific EITC-ATRs function as simulated instrument in the spirit of Gruber and Saez (2002). Despite using a single source of tax induced variation, Zoutman et al. (2018) show that imposing knowledge about which side of the market is tax/subsidized allows researchers to alternatively

[27] I focus on the general equilibrium incidence without market switching since at this time there are not well known cross-sector net-wage elasticities.

estimate supply and demand parameters using the same set of instruments. I augment this by using variation within and between markets to identify the different parameters.

By specifying labor markets and using a simulated instrument at the market level, I am able to allow the labor supply elasticity to vary with based on worker characteristics. I estimate labor market elasticities that vary by parental, marriage, and education status.[28] This allows me to avoid assumptions such as parallel trends and to capture greater flexibility in supply responses than previous estimates in the EITC literature.

### 5.1.1 Identification of Elasticities

Based on equations 5 and 44, I identify the labor supply elasticities using the following linear simultaneous system:

$$\ln[w]_{dst} = \rho_d \tau_{dst} + \Psi_d\left(\{\tau_{d'st}\}_{d' \in \mathcal{D}}\right) + e^{w}_{dst} \tag{52}$$

$$\ln[L]_{dst} = \varepsilon^{L}_{d}\left(\ln[w]_{dst} + \tau_{dst}\right) + e^{L}_{dst}, \tag{53}$$

The identifying variation is tax changes *within* a labor market across state-year observations that differentially shift labor supply.

Based on equations 15 and 44, I identify the labor substitution elasticity using the following linear simultaneous system:

$$\ln[w]_{dst} - \ln[w]_{d_0st} = \left[\rho_d \tau_{dst} - \rho_{d_0} \tau_{d_0st}\right] + \Psi_d\left(\{\tau_{d'st}\}_{d' \in \mathcal{D}}\right) - \Psi_{d_0}\left(\{\tau_{d'st}\}_{d' \in \mathcal{D}}\right) + u^{w}_{dst} \tag{54}$$

$$\ln[L]_{dst} - \ln[L]_{d_0st} = \rho\left[\ln[w]_{dst} - \ln[w]_{d_0st}\right] + u^{L}_{dst}, \tag{55}$$

for some base labor market $d_0$. The identifying variation is relative tax changes *between* a labor market across state-year observations that differentially shift relative labor supply.

While the parameters *could* be estimated non-linearly using a numerical method of moments search, in practice, I separate the estimation based on which labor market parameters I am targeting. This will be less efficient but is more robust to misspecification

[28] Using four education levels – less than HS, HS only, some college, and college graduate – this makes 12 labor supply elasticities.

and ensures that the model is estimated transparently using linear instrumental variable models. Thus, I separately estimate $\varepsilon_d^L$ using the first pair of equations (group level) and then estimate $\rho$ using the second equations (group differences).

### 5.1.2 Estimation Data

I combine two sets of information to estimate the elasticities, the Current Population Survey and the 1990 US Census 5% sample, (Flood, King, Ruggles and Warren, 2018; Ruggles, Flood, Goeken, Grover, Meyer, Pacas and Sobek., 2018).

First, I use the CPS Merged Outgoing Rotation Group (MORG) samples and the Annual Social and Economic (ASEC) samples for labor market information by state and year. The MORG is roughly 100k households per month while the ASEC is roughly 100k in March of every year. These two samples ask detailed employment, earnings, and household structure information. Second, I use the 1990 US Census 5% sample to calculate labor market specific simulated EITC tax instruments. For the ASEC and Census, I use the NBER Internet TAXSIM to calculate tax parameters (Feenberg and Coutts, 1993).[29]

The MORG sample does not ask detailed information about non-labor earnings but does as about labor supply and wage information. This data is techincally at the monthly level and is pooled for annual analysis.[30] I use this dataset for market wages and labor quantities. The ASEC sample is much smaller but the detailed non-labor income information allows for calculating average tax rates. I use this dataset to calculate 'true' EITC based ATRs that vary by state and year, along with the other statistics such as percent of labor market with positive EITC.

For the Census, I use earnings information to calculate the same EITC statistics as in the ASEC sample for each year. As I am using the same fixed demographics, the time-series variation within labor markets is entirely due to policy changes. The cross-sectional variation between labor markets is due to initial conditions before the 1993

[29]Assuming that TAXSIM calculates an accurate adjusted-gross-income which is necessary for EITC calculations, I can replicate NBER TAXSIM's EITC results using a hand collected EITC parameter database.

[30]See for example Leigh (2010); Rothstein (2008).

expansion and state reforms. In this way, the tax instruments are similar to 'shift-share' instruments.[31]

#### 5.1.3 Estimation Variable Definitions and Construction

Labor markets segments are defined by four education categories, eight age groups, and marriage status — this makes 72 markets.[32] Each segment pools workers with and without children. For every market, $d$, I have a state-year panel.[33]

I define labor supply as the sum of all hours divided by the sum of all persons:

$$L_{dst} = \frac{\sum\limits_{i \in (dst)} a_i h_i}{\sum\limits_{i \in (dst)} a_i}, \tag{56}$$

where $a_i$ is the sample weight and $h_i$ is the usual hours worked for worker $i$. This corresponds to the average units of labor supplied to the market per worker in terms of hours. Alternative measures include: total workers in the labor force, labor force participation rates, employment totals or rates, and full time equivalent units.

I define market level log real wages as the mean log real wage for all workers:

$$\mathtt{w}_{dst} = \frac{\sum\limits_{i \in (dst)} \mathtt{h}_i \ln[w_i]}{\sum\limits_{i \in (dst)} \mathtt{h}_i}, \tag{57}$$

where $\mathtt{h}_i = a_i \cdot h_i$ is the product of hours worked and the sample weight, as is standard in wage regressions, and $w_i$ is the real wage. This value can be interpreted as a geometric mean wage, which corresponds to an hours weighted productivity index Borjas et al. (2012). I calculate the real wage by dividing weekly earnings by hours worked and then deflate this using the the BLS CPI All Items Research Series (U.S. Department of Labor, 2019).

[31] 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).

[32] That is, 72 markets for each gender, but I will only focus on women workers for my empirical analysis.

[33] Other than the splitting the markets by state, this follows the definition used in the baseline specification of Rothstein (2010).

The main EITC tax parameter that I use is the average tax rate associated with EITC benefits. I calculate this as the hypothetical difference in EITC benefits from actual labor supply versus no labor supply, divided by actual earned income:

$$\tau_i = \frac{E_i^{\text{act}} - E_i^{\text{cf}}}{w_i \cdot h_i}. \tag{58}$$

I calculate $\tau_{dst}$ using the sample weighted mean. I describe exactly how this is calculated after introducing the data.

I also use other EITC statistics as instruments, such as the EITC marginal tax rate, the portion of the labor market in the 'phase-in' region, and the overall share of workers receiving EITC benefits.

### 5.1.4 Empirical Tax Instruments

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; 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). 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 dirstribution 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, $E_i^{\text{act}}$, by using TAXSIM on the actual data, where $E$ is the federal and state EITC benefit. To calculate the counterfactual benefits, $E_i^{\text{cf}}$, I set the worker's labor earnings equal to zero but leaving all else equal and rerun TAXSIM.[34] Finally, I calculate the EITC Average Tax Rate as the difference in the actual minus the counterfactual benefits over earned income using equation 58.

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, $\tau_{dst}$. 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 $\Psi_{dst}$ terms, but this depends on the parameters that I wish to estimate – see equation 44. 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:

$$\Psi_{dst} = H\left(\{\tau_{d'st}\}_{d' \in \mathcal{D}}\right) \approx \left(\sum_{f=1}^{6} \gamma_f \bar{\tau}_{g_f(d),st}\right) + \nu_{dst}. \tag{59}$$

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. I also create these two averages for the expected share of women / unmarried mothers receiving EITC in a cell.

[34] 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.

#### 5.1.4.1 Labor Supply Instruments

Thus, for every group $\tilde{d}$, I have up to 10 simulated instruments:

1. the EITC ATR for $\tilde{d}$: $\tau_{\tilde{d}st}$
2. the portion of $\tilde{d}$ workers with positive EITC: $z_{\tilde{d}st}$

3-8. six EITC ATR approximation averages: $\{\bar{\tau}_{g_{(\cdot)}(\tilde{d})st}\}$

9,10. two additional approximation averages: $\{\bar{z}_{g_3(\tilde{d})st}, \bar{z}_{g_6(\tilde{d})st}\}$.

My main specification uses all 10 IVs; however, I additionally use a 'light' version that only includes $\{\tau_{\tilde{d}st}, z_{\tilde{d}st}, \bar{\tau}_{g_3(\tilde{d})st}, \bar{\tau}_{g_6(\tilde{d})st}, \bar{z}_{g_3(\tilde{d})st}, \bar{z}_{g_6(\tilde{d})st}\}$.

#### 5.1.4.2 Labor Substitution Instruments

Note, the labor substitution elasticity depends on the relative wage, $\ln[w_{dst}/w_{d_0st}]$. The identifying variation must also come from tax changes across markets. Thus, I use 'relative EITC ATRs' to instrument for relative wages:

$$\tau_{(\tilde{d},d_0)st} = \frac{\tau_{\tilde{d}st}}{\tau_{d_0st}}. \tag{60}$$

Similarly, I construct relative instruments using the other instruments $\{z_{\tilde{d}st}, \bar{\tau}_{g_3(\tilde{d})st}, \bar{\tau}_{g_6(\tilde{d})st}\}$.

### 5.1.5 Estimation Summary Statistics

In this section, I show summary statistics for the primary estimation variables for the empirical models; see appendix A for additional summary details. Table 2 features the difference in means before and after 1994 (tax year 1993) for the labor supply, wages, and the tax changes divided by 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 is the actual tax changes using the ASEC samples for comparison. In the initial period, both tax rates are quite similar; however, in the post period, the true tax rates are lower (implying a larger credit). This is due to endogenous labor supply increases reacting to the tax rates in the true rates

**Table 2** – Summary Statistics for Estimation Sample

| | 1990 - 1994 | | 1996-2000 | | 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

but not the simulated rates, as the instrument calculation does not alter labor supply decisions.[35] This can also be seen in figures 6 and 5, which I describe below.

Next, I show the change in log total hours per person in the submarket-state-year cell. This can be thought of as the average number of 'labor units' supplied. For unmarried women with children and married women labor supply increased over the 1990s, but decreased slightly for unmarried women without children. We see the largest increase for unmarried women with children.

Finally, I show the change in log real wages in the market-state-year cell.[36] Despite labor supply increases for most labor groups, there are meaningful wage increases for every group in this period. This seems counterintuitive unless rightward shifts in labor demand caused the labor quantity increases. To untangle these forces, I use the changes in tax policy that should only directly affect the worker's incentive to supply labor to estimate the labor supply elasticities.

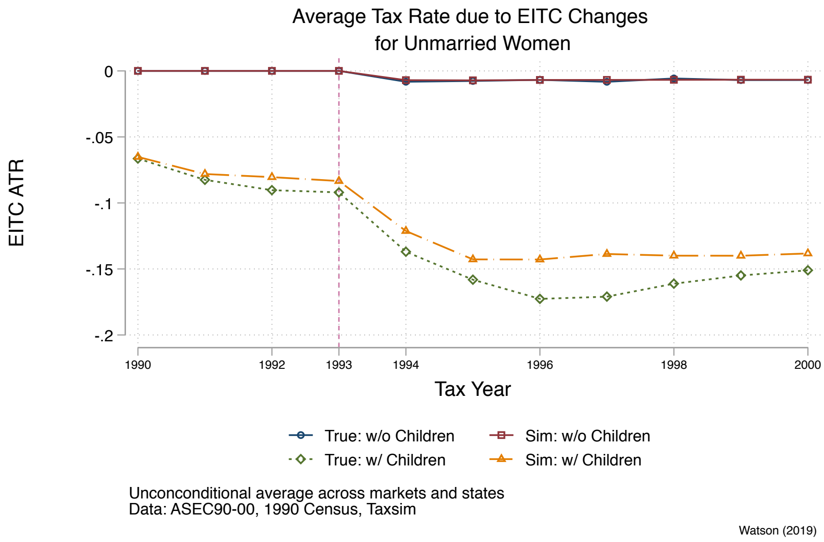
Returning to the claim that the tax rates change due to endogenous labor supply decisions, in the next to figures I plot simulated EITC ATRs and the share of workers receiving positive EITC benefits against their true counterparts. In figure 5, I plot the EITC ATRs. The primary policy change for unmarried mothers occurred over the period from tax-year 1993 to 1996, while for unmarried women without children, there was effectively only the one-time change in tax year 1993. For unmarried mothers, the empirical average ATR is unambiguously less than the simulated that holds labor supply fixed. Given that we know from above that gross-wages and labor supply increased, this is consistent with workers entering the labor force at low wages.

Next, in figure 6, I plot the simulated share of unmarried workers with positive EITC relative to the true share, that shows a large increase in the share with positive EITC relative to the simulated around the time of the EITC expansion for women with children

[35]While, this could be due to earnings decreases (from lower wages or less supply) causing workers to qualify for more credits, but given that table 2 shows across the board wage and labor supply increases, this is unlikely.

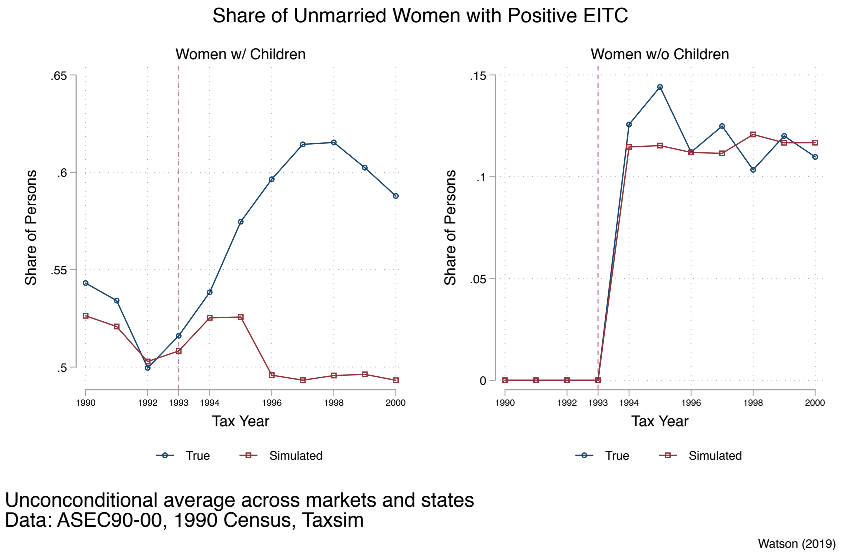
[36]Thus, the wage changes are the same for workers with children and without, as the model implies. In table 11 in appendix A, I show the wage change by submarket, where the there are level differences but the per/post differences are essentially the same for both groups.

**Figure 5** – Simulated vs True Share Receiving EITC




but not those without. An often made assumption is that the change in EITC policy towards workers without children is not enough to affect behavior. The figure shows this is a reasonable assumption because we are able to predict average ATRs and the EITC share for workers without children only using the 1990 distribution of labor supply and inflation.

**Figure 6** – Simulated vs True Share Receiving EITC



### 5.1.6 Estimating Equations

For a given set of tax instruments, $Z$, which I will describe after the data is introduced, I use the following empirical specifications. Given that each model is potentially overidentified, I use Two-Step Efficient IVGMM routines for my primary specifications. I use asymptotic standard errors clustered at the market level.

The labor supply elasticities, $\varepsilon_d^L$, are estimated using variation *within* labor markets and across state-years:

$$\mathtt{w}_{dst} = \pi_0 + Z_{dst}\Pi_1 + [Z_{dst} \cdot \mathtt{g}_d]\,\Pi_d + \pi_3 \mathsf{d}_d + \pi_4 \mathsf{d}_{st} + \pi_5 \mathsf{d}_{w_0^{\%},t} + e_{dst}^w \tag{61}$$

$$\ln[L]_{dst} = \beta_0 + \varepsilon_1^L \mathtt{w}_{dst} + \varepsilon_g^L [\mathtt{w}_{dst} \cdot \mathtt{g}_d] + \beta_3 \mathsf{d}_d + \beta_4 \mathsf{d}_{st} + \beta_5 \mathsf{d}_{w_0^{\%},t} + e_{dst}^L \tag{62}$$

where $\mathtt{g}_d$ are dummies for marriage, parental, and education status, $\mathsf{d}_d$ are labor market FEs, $\mathsf{d}_{st}$ are state-year FEs, and $\mathsf{d}_{w_0^{\%},t}$ are FEs for initial (1988) wage percentiles interacted with year dummies. The implied elasticity for a given labor market is $\varepsilon_d^L = \varepsilon_1^L + \varepsilon_{g(d)}^L$.

Conversely, the substitution elasticity, $\rho$, is estimated using variation *between* labor markets across state-years:[37]

$$\mathtt{w}_{dst} - \mathtt{w}_{d_0st} = \gamma_0 + [Z_{dst} - Z_{d_0st}]\,\Gamma_1 + \gamma_3 \mathsf{d}_d + \gamma_4 \mathsf{d}_{st} + \gamma_5 \mathsf{d}_{w_0^{\%},t} + u_{dst}^w \tag{63}$$

$$\ln[L]_{dst} - \ln[L]_{d_0st} = \alpha_0 + \rho\,[\mathtt{w}_{dst} - \mathtt{w}_{d_0st}] + \alpha_3 \mathsf{d}_e + \alpha_4 \mathsf{d}_{st} + \alpha_5 \mathsf{d}_{w_0^{\%},t} + u_{dst}^L. \tag{64}$$

Because the labor supply model is non-linear in the endogenous variable, $w$, I additionally consider a two-step control function approach. Under the additional assumption that

$$\mathsf{E}[e^L \mid w, Z] = \mathsf{E}[e^L \mid e^w] = g(e^w), \tag{65}$$

for some $g(\cdot)$, then the control function will be more efficient. In practice, I specify $g(e^w) = \varrho \cdot e^w$, which can be interpreted as the linear projection of the structural error on

[37] For this specification, I use similar fixed effects but they have a different interpretation because the regressions use relative quantities and relative wages; additionally, the market level FE $\mathsf{d}_e$ pools married and unmarried markets because the full market level FE $\mathsf{d}_d$ absorbs too much variation.

the first stage residual.[38] Since the control function is estimated, I bootstrap the standard errors with clustering by markets.

## 5.2 Elasticity Estimates

Table 3 displays estimated elasticities. I present three sets of results: Model 1 with ten instruments, Model 2 with six, and Model 3 using a control function approach.[39] I estimate the first two models using two-step efficient GMM with clustered standard errors at the labor-market and parental-status level. I estimate Model 3 using the same instruments as Model 1, but save the first stage residuals, and then estimate the structural equation with the residual as an additional regressor and use clustered bootstrap standard errors.

Models 1 and 2 both show that labor supply responsiveness decreases with education, that having children makes one more responsive to wages, and that married women are more responsive than unmarried women.

I prefer Model 1 because it has the strongest first stage and the estimates seem the most plausible. The main difference between the estimates is that Model 1 is *less* elastic than Model 2, and Model 3 has less variation in the elasticities with a relatively flat education gradient. In practice, less elastic estimates should yield the more conservative incidence effect estimates.

My estimate for the labor supply elasticity for unmarried mothers with low education attainment is quite similar to other estimates. I estimate the values $\{0.72, 0.91, 0.94\}$ 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.[40] In all three models, I can reject that the labor supply elasticities for unmarried women are the same for workers with and without children. This can imply a violation of "parallel trends" when using difference in

[38] Additonally, I have considered semiparametric approaches such as Robinson (1988)'s estimator, a fractal polynomial approach with an AIC model selection criterion, and a penalized spline regression; all three yield nearly identical elasticity results as the linear specification.

[39] Section 5.1.4 describes the instruments used.

[40] 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 $1.16$.

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 values $\{0.87, 0.99, 1.04\}$ while Eissa and Hoynes (2004) estimate $0.27$ for similarly educated married women.[41] 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 4 presents estimates of the labor substitution elasticity between labor markets. Each column uses different sets on 'relative' instruments, as discussed in section 5.1.4 in equation 60. Each specification yields a statistically significant elasticity with a consensus estimate of about $-2.55$. 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). Under all specification, I can reject that the substitution elasticity is inelastic, which is in line with the immigration literature (Katz and Murphy, 1992; Goldin and Katz, 2009; Borjas et al., 2012). It is worth noting that the main specification of Rothstein (2010) uses a value of $\rho = -0.3$, which is far from the consensus estimates.[42] A more inelastic estimate of $\rho$ will tend to imply larger magnitude incidence effects since $\rho$ is in the denominator of equations 23 and 44.

## 5.3 Incidence of 1993 OBRA EITC Expansion

In table 5, I present my estimates of the empirical incidence of the 1993 OBRA EITC expansion which affected 1994 labor market outcomes. I show the PE Incidence, which is the direct effect of the expansion for a given labor market holding fixed all other markets; the GE Incidence, which add the spillover effects on a given market, and the relative magnitudes of the spillover and direct effects. For these variables, I presents two sets of estimates.

[41] One reason for the difference could be that Eissa and Hoynes (2004) estimate a joint labor supply decision while I hold constant the married partner's labor supply and treat this an non-labor income for the wife.

[42] Also worth emphasizing is that Rothstein (2010) uses multiple different values of $\rho$ in additional robustness calculations.

**Table 3** – Labor Supply Elasticity Estimates by Labor Groups: $\varepsilon_d^L$

| | Model 1: Full | | | |
|---|---|---|---|---|
| | Unmarried | | Married | |
| | w/o Children | w/ Children | w/o Children | w/ Children |
| Less HS | 0.54 | 0.72 | 0.76 | 0.99 |
| | (0.10) | (0.09) | (0.09) | (0.09) |
| HS | 0.40 | 0.58 | 0.62 | 0.85 |
| | (0.08) | (0.07) | (0.07) | (0.07) |
| Some College | 0.40 | 0.58 | 0.62 | 0.86 |
| | (0.09) | (0.08) | (0.08) | (0.08) |
| BA Plus | 0.10 | 0.28 | 0.32 | 0.56 |
| | (0.09) | (0.09) | (0.08) | (0.08) |
| | **Model 2: Light** | | | |
| | Unmarried | | Married | |
| | w/o Children | w/ Children | w/o Children | w/ Children |
| Less HS | 0.70 | 0.91 | 0.89 | 1.04 |
| | (0.17) | (0.16) | (0.15) | (0.15) |
| HS | 0.56 | 0.77 | 0.75 | 0.90 |
| | (0.15) | (0.14) | (0.13) | (0.13) |
| Some College | 0.56 | 0.78 | 0.75 | 0.90 |
| | (0.16) | (0.14) | (0.14) | (0.14) |
| BA Plus | 0.17 | 0.38 | 0.35 | 0.50 |
| | (0.14) | (0.13) | (0.13) | (0.12) |
| | **Model 3: Control Function (Full)** | | | |
| | Unmarried | | Married | |
| | w/o Children | w/ Children | w/o Children | w/ Children |
| Less HS | 0.78 | 0.94 | 0.90 | 0.87 |
| | (0.20) | (0.21) | (0.20) | (0.20) |
| HS | 0.70 | 0.85 | 0.81 | 0.78 |
| | (0.20) | (0.20) | (0.19) | (0.20) |
| Some College | 0.73 | 0.88 | 0.84 | 0.81 |
| | (0.20) | (0.21) | (0.20) | (0.20) |
| BA Plus | 0.64 | 0.80 | 0.76 | 0.73 |
| | (0.21) | (0.22) | (0.21) | (0.21) |

| | Obs | KP rl LM | KP rk Wald F | MOP Effective-F |
|---|---|---|---|---|
| Model 1 | 33,902 | 104.4 | 57.314 | 23.530 |
| Model 2 | 33,902 | 88.396 | 23.135 | 30.028 |

All data from MORG 90-00, 1990 Census; EITC ATRs calculated using TAXSIM. Standard Errors clustered by (140) demographic groupings, Model 3 uses bootstrap. Model controls: log total cell size, FEs for demographics, State-Year, and Initial-Wage-Pct-Year. Model 1: 10 Instruments; Model 2: 6 Instruments, Model 3: CF based on 10 IVs. KP rk LM tests for underidentification of first stage; 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)

**Table 4** – Labor Substitution Elasticity Estimates Across Labor Markets

| | (1) | (2) | (3) |
|---|---|---|---|
| $\rho$ | -2.55 | -2.60 | -2.00 |
| Wald SE | (0.56) | (0.50) | (0.44) |
| WIVR CI | [-3.85,-1.58] | [-3.83,-1.70] | [-3.65,-1.60] |
| KP rk Wald F | 51.06 | 30.20 | 17.67 |
| Anderson-Rubin F | 28.39 | 19.33 | 10.36 |
| MOP Effective-F | 51.90 | 20.61 | 11.84 |
| # IVs | 1 | 2 | 4 |
| Obs | 9,674 | 9,674 | 9,674 |

All data from MORG 90-00, 1990 Census; EITC ATRs calculated using TAXSIM. Wald Standard Errors clustered by (140) demographic groupings. Weak IV Robust CIs based on Andrews (2018) and Sun (2018) . Model controls: log relative total cell size, FEs for Edu-Age-Year, State-Year, and Initial-Wage-Pct-Year. Models vary by instruments used, as discussed in text, 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).

The first panel uses the empirical labor supply and substitution elasticity estimated above in tables 3 and 4. The incidence results are intuitive. Unmarried women without a high school degree, which had the largest tax change, see the largest gross wage changes where the direct effects dominate the spillovers. Whereas, married women with a college degree have essentially no wage change due but 68% of the change in their gross wages is due to spillovers. In aggregate, for unmarried women spillovers represent about 13% of the total gross wage effects and 62% for married women.

The second panel, uses the empirical labor supply elasticities but then uses $\rho = -0.3$ from Rothstein (2010) for comparison. The comparison shows that the inelastic substitution elasticity causes much larger effect sizes in terms of magnitude. The GE effect goes from a -1.6% change when $\rho = -2.5$ to -5% when $\rho = -0.3$. The change also causes spillover effects to be much larger; e.g., compare the 13% for all unmarried women in panel one versus 27% in panel two.

**Table 5** – Empirical Incidence of the 1993 EITC Expansion on 1994 Gross Wages

| $\rho = -2.5$ | Unmarried | | | Married | | |
|---|---|---|---|---|---|---|
| | PE Incidence (%) | GE Incidence (%) | $\frac{\lvert\text{Spillover}\rvert}{\lvert\text{Spillover}\rvert+\lvert\text{PE}\rvert}$ (%) | PE Incidence (%) | GE Incidence (%) | $\frac{\lvert\text{Spillover}\rvert}{\lvert\text{Spillover}\rvert+\lvert\text{PE}\rvert}$ (%) |
| Less HS | -1.62 | -1.58 | 2.93 | -0.10 | -0.06 | 33.73 |
| HS | -0.81 | -0.76 | 6.49 | 0.01 | 0.06 | 68.18 |
| Some College | -0.68 | -0.63 | 7.85 | 0.05 | 0.09 | 54.89 |
| BA+ | -0.15 | -0.10 | 33.16 | 0.02 | 0.07 | 68.41 |
| Total | -0.68 | -0.63 | 13.21 | 0.02 | 0.06 | 61.81 |
| $\rho = -0.3$ | Unmarried | | | Married | | |
| | PE Incidence (%) | GE Incidence (%) | $\frac{\lvert\text{Spillover}\rvert}{\lvert\text{Spillover}\rvert+\lvert\text{PE}\rvert}$ (%) | PE Incidence (%) | GE Incidence (%) | $\frac{\lvert\text{Spillover}\rvert}{\lvert\text{Spillover}\rvert+\lvert\text{PE}\rvert}$ (%) |
| Less HS | -5.57 | -5.08 | 8.36 | -0.29 | 0.08 | 55.51 |
| HS | -3.12 | -2.54 | 17.13 | 0.03 | 0.45 | 85.73 |
| Some College | -2.69 | -2.11 | 20.10 | 0.14 | 0.55 | 76.49 |
| BA+ | -0.96 | 0.06 | 58.02 | 0.09 | 0.66 | 86.04 |
| Total | -2.67 | -1.99 | 27.42 | 0.06 | 0.51 | 80.89 |

All data from ASEC 1995; EITC ATRs calculated using TAXSIM. ASEC 1995 reports the 1994 earnings, which were the first market earnings affected by the 1993 OBRA EITC Expansion. Sample includes all women ages 16-59 who are not separated, full time students, or likely to have invalid wages. Labor market cells weighted by market size using CPS ASEC supplement weights. Note: GE = PE + Spillover.

**Table 6** – Empirical Incidence Results: Taxyear 1994
Aggregate Effects: All Women

| | Rothstein | $\rho = -0.3$ | | $\rho = -2.5$ | |
|---|---|---|---|---|---|
| | "PE" | "PE" | GE | "PE" | GE |
| Dollars | (1) | (2) | (3) | (4) | (5) |
| Labor | -1.47 | -0.42 | 0.18 | 0.15 | 0.21 |
| Wage | -2.25 | -1.48 | -0.41 | -0.37 | -0.28 |
| Earnings | -3.67 | -1.89 | -0.22 | -0.22 | -0.07 |
| NetEarn | -2.67 | -0.89 | 0.78 | 0.78 | 0.93 |
| EV | -1.25 | -0.48 | 0.59 | 0.63 | 0.72 |
| PE/GE | - | - | -0.81 | - | 0.88 |

Units in table are changes in dollars of earnings, LM changes summed across demographic groups. Earnings = Wage + Labor; Net Earnings = Earnings + Transfer, Equivalent Var. = Wages + Transfer. All data from 1995 March CPS, Women from Tax Units. Labor supply elasticities in table 8, except 'Rothstein' which uses $\varepsilon^L = 0.75$ for all.

# 6 Comparing EITC to NIT

In this section, I use my estimated labor market elasticities to compare two hypothetical policy reforms. I consider an equal sized expansion of the EITC versus an NIT program.[43] Using the two tax reforms, I calculate the partial incidence using equation 23 and the general incidence using equation 44.[44] This analysis allows me to compare the spillovers of the two programs.

Using my preferred specification, I find that for the EITC wages decrease by only a seventh of the PE amount and for the NIT wage only increase a seventh of the PE amount. This implies that for every dollar of new spending, the EITC increases net-earnings by $\$1.28$ while the NIT only increases by $\$0.63$. For the EITC, I find that the PE net transfer to workers is 88% of the intended amount but is 93% accounting for spillovers. For the NIT, I find that the PE net transfer is 115% of the intended amount, but is down to 108% after spillovers.[45]

Essentially, I come to nearly the opposite conclusion of Rothstein (2010) in that the EITC seems unambiguously more cost effective transfer program. This is because EITC labor supply increases in *other* markets provide a countervailing wage effect to the own market supply increase. This ends up increasing aggregate production, having a stimulative effect on the economy (holding output price fixed). For NIT, incentivising workers to exit the labor force causes widespread marginal product declines that dominates the transfer. This ends up decreasing aggregate output. The NIT is only able to increase wages because labor supply is decreased.

However, I find substantial heterogeneity among demographic groups and I find that the equivalent variation of the NIT is greater than the EITC. Most notably unmarried workers *without* children see net earning declines under an EITC expansion despite

[43] I follow the same outline as Rothstein (2010) for the simulations; this analysis has been greatly aided by his dedication to providing transparent research.

[44] I focus on the general equilibrium incidence without market switching since at this time there are not well known cross-sector net-wage elasticities.

[45] My PE results differ from Rothstein (2010) because of different sample creation and elasticity estimates; I am able to replicate his results when using his sample and parameterizations. Further details are in the data section below.

other groups clearly benefiting. Under the NIT, married workers *without* children see net earnings declines; however, these are not as large as the unmarried women.

The equivalent variation is greater under the NIT compared to the EITC. This is mechanical because the wage decreases for the EITC and increases for the NIT, and the reforms are created to have equal size. Nevertheless, because the partial equilibrium exaggerates the change in gross wages, the GE incidences shows that the programs are much closer in equivalent variation measures.

## 6.1 Simulating the Tax Reforms

### 6.1.1 Data

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.

The incidence sample is restricted to women ages 16 to 65 with reasonable labor market observations.[46] I drop women who are full or part time students and have not participated in the labor force for over one year, women who have negative tax unit self-employment earnings, and women who are in the armed forces.[47]

#### 6.1.1.1 Assignment of Children

I use Census coded family unit ID, household record numbers, and relationship pointers to link EITC eligible children to (most likely) parents. This process requires some subjectivity in assignment.

IPUMS constructs family relationship information, such as number of own children, based on its own definition of a family which differs from the Census definition. For very traditional, nuclear families there is no conflict. However, whenever there are any additional members of a family outside of a nuclear family, complications ensue. When creating tax units, the Census definition is closer to the spirit that researchers are aiming

[46] The main criterion is that wage (= Total Earnings / Total Hours) is between \$0.50 and \$100.

[47] I additionally drop married workers with absent, non-separated spouses because of missing income information, as well as women who are in group quarters.

to capture; however, the Census does not include any way of directly linking dependents to their care-givers, so the researcher must do this.

Thankfully, in almost all cases, children follow their parents in the record layout. I combine this fact along with household relationship pointers, family relationship pointers to assign children.

#### 6.1.1.2 Summary Statistics

In table 7, I present summary statistics on the incidence sample of women. There are two primary differences between my sample and that of Rothstein (2010), who uses nearly the same criteria. Summary statistics for his sample are in the appendix.

First, Rothstein drops all unmarried women below age 24 if these women do not have children, regardless of labor force / education status. This is sometimes done in the empirical literature in order to perform difference-in-difference estimation; however, it is not obvious that it should be done in the setting which is mostly theoretical. 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 $6,000$ workers and changes the average age of unmarried women without children from $41$ to $33$.

Second, I change the distribution of allocated qualified children compared to Rothstein. In the end, Rothstein assigns about two thousand more workers at least one EITC dependents than my procedure. Rothstein allocates children in a similar manner as I do, but at one point indiscriminately assigns children to the household head family in the household. Under the assumption that a the household head family would claim a child of another family, his procedure is correct.

The two changes I make, more workers in the sample and fewer EITC claimants, should mitigate the incidence effects. In an appendix, I use the Rothstein sample with my own tax incidence formulae and show this is the case. The effects of sample creation are noticeable, but not substantial.

**Table 7** – Summary Statistics for Incidence Sample

| | Age | Anykids | Married | Get Eic |
|---|---|---|---|---|
| Unmarried Women | 33.25 | 0.00 | 0.00 | 0.00 |
| Married Women | 47.54 | 0.00 | 1.00 | 0.00 |
| Unmarried Mothers | 34.51 | 1.00 | 0.00 | 0.66 |
| Married Mothers | 36.90 | 1.00 | 1.00 | 0.10 |
| Total | 37.99 | 0.45 | 0.57 | 0.11 |
| | Less HS | HS Only | Less BA | BA+ |
| Unmarried Women | 0.26 | 0.26 | 0.30 | 0.18 |
| Married Women | 0.15 | 0.42 | 0.23 | 0.21 |
| Unmarried Mothers | 0.25 | 0.39 | 0.26 | 0.10 |
| Married Mothers | 0.13 | 0.38 | 0.28 | 0.22 |
| Total | 0.19 | 0.35 | 0.27 | 0.19 |
| | Worker | Wage | Share of Workers | Cost Share |
| Unmarried Women | 0.73 | 10.09 | 0.30 | 0.19 |
| Married Women | 0.69 | 11.17 | 0.25 | 0.17 |
| Unmarried Mothers | 0.68 | 9.60 | 0.12 | 0.07 |
| Married Mothers | 0.72 | 10.83 | 0.33 | 0.22 |
| Total | 0.71 | 10.54 | 1.00 | 0.66 |

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

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.

### 6.1.2 Labor Markets

As before in the empirical section, labor markets segments are defined by four education categories, eight age groups, and marriage status — this makes 72 markets. Again, each segment pools workers with and without children, and across industry and occupations. However, for this simulation, I do not split the sample based on state of residence. I do this to allow for comparison to the baseline specification of Rothstein (2010).

#### 6.1.2.1 Two Assumptions

In addition to the economic environment, I need to use two strong assumptions for the simulation. First, there are no other factors used by firms other than the labor factors as specified and a material factor index, called capital. This assumption allows me to ignore other worker groups, such as men, and aggregate all other factor changes into a single variable. Second, the wage share of each labor market is also its cost share; this omits any non-wage labor costs. This assumption is necessary to calculate the demographic based cost shares which are not available in any other statistical product that is produced.

### 6.1.3 Parameters

The partial equilibrium analysis only requires two structural parameters, a supply elasticity (which may vary by labor market) and a elasticity of substitution.

#### 6.1.3.1 Labor Supply Elasticities

I use the labor supply elasticities estimated in the previous section. These vary by marriage, parental, and education status which yields twelve elasticities, as seen in table 8. I use values based on the results from Model 1 in table 3 from section 5.2. The main specification from Rothstein (2010) used the value $0.75$ for all women, regardless of demographic characteristics.

**Table 8** – Labor Supply Elasticity Estimates by Labor Groups: $\varepsilon_d^L$

| | Unmarried | | Married | |
|---|---|---|---|---|
| | w/o Children | w/ Children | w/o Children | w/ Children |
| Less HS | 0.54 | 0.72 | 0.76 | 0.99 |
| HS | 0.40 | 0.58 | 0.62 | 0.85 |
| Some College | 0.40 | 0.58 | 0.62 | 0.86 |
| BA Plus | 0.10 | 0.28 | 0.32 | 0.56 |

Elasticities from section 5.2 table 3 Model 1.

#### 6.1.3.2 Labor Substitution Elasticity

I present results using two different values: $-0.30$, $-2.50$. The first value is from Rothstein (2010), which is based on his 2008 working paper that used a wage-based labor market designation, and the second value is my estimate from the previous section. Note, $-0.30$ is considerably lower than estimates from the prior wage inequality literature as well as my own estimate when using demographic based labor markets, which Rothstein (2010) uses.[48] Thus, it is possible that prior partial equilibrium results are based on an outlier estimate of the substitution elasticity.

#### 6.1.3.3 Cost Shares

The labor cost share in 1992 was roughly 66% of total cost. To calculate the labor market specific cost share, I sum total earnings by labor market, calculate the ratio of each market to the sum of all markets, and then multiply this by $0.66$:

$$s_{L_d} = \left( \frac{\sum_{i \in L_d} W_{id}}{\sum_j \sum_{i \in L_j} W_{ij}} \right) \cdot \left( \frac{\text{Total Wages}}{\text{Total Factor Payments}} \right) \tag{66}$$

[48]Katz and Murphy (1992) and Goldin and Katz (2009) find $\rho \approx -1.4$ when basing their estimation on demographic groups, and Card and Lemieux (2001), who find substitution elasticities $< -2$ when substituting between education groups of similar aged (male) workers. See Borjas et al. (2012) for more discussion comparing methods.

I do not include worker benefits or other non-wage payments. If total compensation – thus cost – is a uniform percent mark-up over earnings which is roughly similar across labor groups, then the approximation will perform well, as the mark-up terms will cancel out.

#### 6.1.3.4 Capital Supply Elasticity

I have not found a definitive summary of the capital supply elasticity. As such, I use the value of 1 as a conservative estimate. Goolsbee (1998) estimates a short-run elasticity of about 1 and a medium run elasticity over three years of 2. For robustness, I also consider the value 2.

### 6.1.4 Simulated Tax Reforms

In the model presented earlier, I use a linear subsidy system and abstract from any other taxes. In reality, individual tax rates are highly complex and non-linear. To implement the simulation, I replace the excise taxes with average tax rates, calculated using the reported income data and NBER TAXSIM (Feenberg and Coutts, 1993).[49]

To get the initial tax parameters, I form tax units based on family living arrangements and use TAXSIM. I form tax unit status based on family living arrangements. Married workers with present spouses are always joint filers. Separated or married workers with absent spouses are always single filers. Non-married adults who are not EITC qualifying children are always single filers. All workers who are EITC qualifying children are dependents.

I follow Rothstein (2010) exactly in simulating two tax reforms. First, I use TAXSIM to estimate the initial vector of initial tax parameters. Second, for all tax units, I set the earned income of the tax-unit-head-woman – either the head of family for single women or the wife of a married household – with zero, and then I rerun TAXSIM. The primary output of these calculations are adjusted gross income, EITC amounts, and federal tax

[49]Currently, 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).

amounts. I then calculate the change in average tax of the woman choosing to work for those tax units where the head-woman works. Third, I use these variables to simulate an expenditure equivalent Negative Income Tax program.

Next, I suppose that the governments wish to increase the generosity of the EITC or NIT by $100 million. Governments do this by naively ignoring labor market and behavoral effects, and distribute the increase in expenditure based on the share of EITC/NIT each worker received prior:

$$\text{Subsidy}_{i,\text{Reform}} = \left(\frac{\$100m}{\sum_i \text{Subsidy}_{i,\text{Initial}}}\right) \cdot \text{Subsidy}_{i,\text{Initial}}. \tag{67}$$

This change in the subsidy for each worker is then aggregated to the worker's labor market to find the simulated tax change in the market to use in the incidence calculation:

$$\hat{\tau}_d = \sum_{i \in L_d} \left(\frac{\text{Subsidy}_{Reform} - \text{Subsidy}_{\text{Initial}}}{\text{Tax Unit Adj Gross Income}}\right)_i \tag{68}$$

### 6.1.5 Simulation Outputs

The simulation uses the hypothetical tax reforms to calculate labor market responses to the policy change. From the labor market changes, I calculate two main objects of interest: the change in net-earnings and the equivalent variation. The former is a measure of the change in aggregate economic activity due to the tax reform, as net-earnings equal overall output of the economy. The latter is an evaluative tool for cost-benefit analysis, which roughly is the necessary payment to make workers indifferent between receiving the payment and implementing the tax reform.

If the equivalent variation is positive, then the policy is worthwhile to consider; otherwise, workers would be willing to pay the government *not* to implement the policy. These measures differ because the net-earnings measure does not incorporate that the change in labor supply increases the aggregate disutility of labor effort.

To calculate these objects, I find the change in labor supply and the change in earnings due to the tax reform using the incidence formula in equation 27 and the labor supply elasticity. The change in net-earnings is calculated using the new wages, the new labor supply, and the transfer. I calculate the equivalent variation using equation 43. This measure uses the change in wages and transfer at the initial labor supply.

## 6.2 Simulation Results

Table 9 displays three sets of incidence results for the EITC and NIT simulated tax reforms for the aggregate labor market based on different parameterizations. Table 10 displays the aggregate effects for specific demographic groups. The first two columns replicate the partial equilibrium analysis of Rothstein (2010) on my sample.[50] Columns 3-9 use heterogeneous supply elasticities and compare between partial and general equilibrium incidence. I highlight columns 6-9 which use my preferred specification based on the estimated elasticities in section 5.2. The main takeaway from the table is that the dramatic difference between the programs in partial equilibrium is reversed in general equilibrium and somewhat exaggerated by a small labor substitution elasticity.

The main effects of interest are the change in wages, net-earnings (*NetEarn*), and the equivalent variation of the policy (*EV*). The change in wages shows the amount that wages fall per dollar of EITC transferred to workers based on the incidence formula. The change in net-earnings represents the *ex-post* policy consumption of the workers, which taken literally represents the impact on Gross Domestic Product. The equivalent variation is the payment required to make a worker indifferent between the *ex-post* policy allocation versus the *ex-ante* policy allocation plus the payment:

$$\{EV_i \,|\, V_i(p_0, m_0 + EV_i) = V_i(p_1, m_1)\}. \tag{69}$$

[50]The difference between columns (1,2) and table 5 column 1 in Rothstein (2010) are directly due to differences in our sample of workers, where Rothstein is using a strict sub-sample of my analysis.

If the aggregate equivalent variation is positive, then the policy passes the Hicks compensation test as the policy 'winners' would be willing and able to compensate the policy 'losers'.

**Table 9** – Incidence Results:
Aggregate Effects: All Women

| | Rothstein | | $\rho = -0.3$ | | | | $\rho = -2.5$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | "PE" | | "PE" | | GE | | "PE" | | GE | |
| Dollars | EITC | NIT | EITC | NIT | EITC | NIT | EITC | NIT | EITC | NIT |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Intended | 1.00 | 0.56 | 1.00 | 0.56 | 1.00 | 0.56 | 1.00 | 0.56 | 1.00 | 0.56 |
| Labor | 0.13 | -0.16 | 0.14 | -0.17 | 0.36 | -0.42 | 0.32 | -0.42 | 0.35 | -0.46 |
| Wage | -0.46 | 0.53 | -0.48 | 0.55 | -0.07 | 0.08 | -0.12 | 0.15 | -0.07 | 0.09 |
| Earnings | -0.34 | 0.37 | -0.34 | 0.38 | 0.29 | -0.34 | 0.20 | -0.26 | 0.28 | -0.37 |
| NetEarn | 0.66 | 1.37 | 0.66 | 1.38 | 1.29 | 0.66 | 1.20 | 0.73 | 1.28 | 0.63 |
| EV | 0.54 | 1.52 | 0.52 | 1.55 | 0.93 | 1.08 | 0.88 | 1.15 | 0.93 | 1.08 |
| PE/GE | - | - | - | - | 0.59 | 1.44 | - | - | 0.95 | 1.06 |
| NIT/EITC | - | 2.81 | - | 2.98 | - | 1.16 | - | 1.31 | - | 1.16 |

Units in table are changes in dollars of earnings, LM changes summed across demographic groups
Earnings = Wage + Labor; Net Earnings = Earnings + Transfer, Equivalent Var. = Wages + Transfer
All data from 1993 March CPS, Women from Tax Units
Labor supply elasticities in table 8, except 'Rothstein' which uses $\varepsilon^L = 0.75$ for all

In Table 9, I show the aggregate labor market effects across all demographic groups. There are several interesting and important differences between the columns; however, the most important is that the general equilibrium spillovers are economically meaningful for both reforms and that these spillovers make the EITC look better as a policy choice. For example, the PE difference between wages [columns (7,8)]is $\$0.27$ but the GE difference [columns (9,10)] is only $\$0.16$. This is because GE effects attenuate the gross wage changes.

An additional important insight is that the partial equilibrium results concerning the difference in net-earnings are dependent on the inelastic labor substitution elasticity in columns. The PE net-earnings in column (3) is only $\$0.66$ for every dollar of EITC but is $\$1.20$ in column (6); similarly the values are $\$1.55$ and $\$1.15$ for the NIT columns (4,7). Thus, using a more realistic labor substitution elasticity results in a complete reversal of the PE conclusions for net-earnings reported by Rothstein (2010).

Finally, the relative equivalent variation measures do *not* reverse from PE to GE; however, the differences are attenuated. The NIT still has a greater EV measure in GE because the EITC encourages labor force participation among those with relatively greater disutility of labor relative to the incumbent workers, while the NIT discourages labor supply among the incumbent workers with the relatively greater disutility. That is, since there is less 'leisure' in the economy, the EV cost of the EITC is greater than the NIT.

The conclusion from the partial equilibrium analysis is that a NIT is a better policy if the goal is to transfer income to low income workers. However, important to point out is that the EITC increases welfare by increasing consumption. Notice that net-total earnings increases by more than $\$1$ for every $\$1$ of additional EITC spending, and that the change in private earnings is positive. For the NIT, the net-total earnings are less than $\$1$ and the private earnings are actually negative! The NIT is only able to increase welfare by paying to keep some workers out of the labor force and causing firms to have to pay the remaining workers more. The overall effect is a decrease in private output from these markets.

Table 10 displays the aggregate effect on different demographic groups. For single mothers, the general equilibrium wage effects are similar to the partial equilibrium effects. In general equilibrium, net *earnings* increase for single mothers more from an EITC reform than the NIT reform; although, the welfare change is greater for the NIT than the EITC. As an anti-poverty program, the EITC does a better job at increasing net earnings for single mothers than the NIT but does so by also requiring greater labor supply and less leisure, as measured by the equivalent variation.

For single women without children, the EITC appears to create a greater spillover compared to the NIT. Only for this group is the EV for the EITC negative, implying these workers are actively hurt by the transfer program. These workers are unable to avoid the wage decreases due to the EITC but do not get any transfer. As before, the partial equilibrium effects are attenuated by the general equilibrium effects.

Married mothers and married women both do better from the EITC in terms of earnings and welfare. Only for married women without children is the NIT causing a welfare loss because the NIT is decreasing these worker's marginal product without any subsidy, which the married mothers receive.

**Table 10** – Incidence Results:
Aggregate Effects: Subgroups of Women

| | Rothstein | | $\rho = -0.3$ | | | | $\rho = -2.5$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | "PE" | | "PE" | | GE | | "PE" | | GE | |
| Dollars | EITC | NIT | EITC | NIT | EITC | NIT | EITC | NIT | EITC | NIT |
| | (1) | (2) | (3) | (4) | (5) | (6) | (6) | (7) | (8) | (9) |
| | Unmarried Mothers | | | | | | | | | |
| NetEarn | 0.73 | 0.54 | 0.64 | 0.61 | 0.71 | 0.52 | 0.88 | 0.47 | 0.89 | 0.36 |
| EV | 0.31 | 0.80 | 0.30 | 0.80 | 0.35 | 0.74 | 0.46 | 0.71 | 0.46 | 0.70 |
| | Unmarried Women | | | | | | | | | |
| NetEarn | -0.59 | 0.37 | -0.51 | 0.30 | -0.31 | 0.06 | -0.13 | 0.07 | -0.11 | 0.04 |
| EV | -0.32 | 0.20 | -0.34 | 0.20 | -0.18 | 0.02 | -0.09 | 0.05 | -0.07 | 0.03 |
| | Married Mothers | | | | | | | | | |
| NetEarn | 0.50 | 0.33 | 0.50 | 0.33 | 0.69 | 0.10 | 0.44 | 0.15 | 0.47 | 0.11 |
| EV | 0.53 | 0.45 | 0.54 | 0.47 | 0.65 | 0.34 | 0.50 | 0.37 | 0.52 | 0.35 |
| | Married Women | | | | | | | | | |
| NetEarn | 0.03 | 0.13 | 0.03 | 0.15 | 0.19 | -0.03 | 0.01 | 0.05 | 0.03 | 0.02 |
| EV | 0.02 | 0.07 | 0.02 | 0.08 | 0.11 | -0.02 | 0.01 | 0.03 | 0.02 | -0.01 |

Units in table are changes in dollars of earnings, LM changes summed across demographic groups
Earnings = Wage + Labor; Net Earnings = Earnings + Transfer, Equivalent Var. = Wages + Transfer
All data from 1993 March CPS, Women from Tax Units
Labor supply elasticities in table 8, except 'Rothstein' which uses $\varepsilon^L = 0.75$ for all

The analysis above emphasizes that the targeted nature of the program — subsidizing workers with children — can significantly affect the welfare of the untargeted workers. Single women without children see large welfare declines with the EITC because of decreases wages which reduce worker consumption. Married women without children see welfare increases from the EITC for the opposite reason. Interestingly, despite almost no NIT spillover on single workers without children, the NIT spillovers on married workers with children are very negative.

Overall, the results suggest that the partial equilibrium effects are vastly different from the general equilibrium effects. In partial equilibrium, the NIT appears to be the unambiguously better program at helping low income workers. However, allowing for cross market spillovers muddles the policy recommendation. In aggregate, the EITC is unambiguously more cost effective at transferring income, yet there is a great deal of heterogeneity in net earnings across labor markets. If policy-makers truly wish to increase the welfare of single mothers workers and are willing to decrease welfare to other workers, then the NIT is a more cost effective program. However, the EITC creates greater aggregate welfare improvements with fewer directly harmed groups.

# 7 Conclusion

Conditional income transfers, such as the Earned Income Tax Credit, are a major anti-poverty tool that are relatively simple to implement since eligibility can be easily determined based on a few income and demographic variables. This has led to the EITC becoming the *de facto* largest anti-poverty program in the United States and a direct subsidy to roughly $20\%$ of the labor force (Internal Revenue Service, 2017). However, almost all prior EITC literature has implicitly or explicitly assumed way or used methods designed to purge general equilibrium gross wage effects. This is despite the fact that changes in gross wages directly affect policy efficacy.

I revisited the incidence of the Earned Income Tax Credit using a general equilibrium framework. I analyzed how targeted wage subsidies affect gross wages through direct effects and spillovers across labor markets. I found that when labor markets are imperfect substitutes, a tax induced supply changes in one market will affect the marginal product of workers in other markets. This creates a spillover feedback cycle of changes in marginal products and wages across labor markets. The result of these spillovers counteract any initial partial equilibrium wage effects, so the general equilibrium wage change is theoretically ambiguous.

Because theory is ambiguous, I quantified the importance of general equilibrium effects in two ways. First, I calculated the empirical incidence of the 1993 OBRA EITC expansion. I find that for every new dollar of EITC expenditure due to the 1993 expansion led to an increase in aggregate net-earnings of $\$0.93$, implying that firms were able to capture about $\$0.07$ of every new dollar. For every dollar that went to unmarried women, net-earnings increased by $\$1.27$ for those with children while those without children saw net-earnings fall by $\$0.58$. For every dollar that went to married women, net-earnings increased for the two groups by $\$1.00$ and $\$0.12$ respectively. Gross wages decreased by $0.62\%$ for unmarried women but increased by $0.07\%$ for married women. For unmarried women with children, the decrease in wage is more than offset by the increase in labor supply leading to overall wage increases for this group.

Second, I simulated a $100million expansion of the EITC versus an equal-sized expansion of a hypothetical NIT to contrast the spillovers that each policy generates. While in partial equilibrium the NIT *appears* more cost effective at increasing net-earnings, in general equilibrium the EITC *actually* is more cost effective policy. I my preferred general equilibrium specification, an intended dollar of EITC spending delivers $\$1.28$ of net-earnings to workers while the NIT delivers only $\$1.08$ of intended dollars. The difference in policy effectiveness is entirely due to marginal product spillovers that emerge in general equilibrium with imperfectly substitutable factors. Since the NIT *decreases* labor force participation in the low-wage labor market, the marginal product of all other workers *decreases*, which then *decreases* labor demand in the first market. Alternatively, when the EITC *increases* labor force participation in the low-wage market, the marginal product of all other workers *increases*, which then *increases* labor demand in the first market.

These results are driven by different factors that are important for policy makers 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 NIT increases welfare because the government is transferring consumption from *other* markets and allowing the subsidized workers to decrease labor supply to drive up their wages. This decreases market output and causes negative marginal product spillovers for all other workers.

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. This assumption is necessary for analytic results but is not necessary for the simulation which could be solved numerically. Second, the frictionless labor market assumptions – perfect competition, price taking – may not be realistic. In aggregate, these distortions may only matter marginally, but then the model obscures potentially important heterogeneity depending on firm concentration or anti-competitive behavior. Third, the model has abstracted from fully modeling the tax system or incorporating different industries or trade patterns. Modeling the tax system and requiring a balanced government budget (or debt policy) may remove some of the efficiency of the EITC if high productivity workers supply less labor. Only including a single output sector with no trading partners implies that there are no interesting output demand/price effects, which also may effect the efficiency of the EITC. For example, in a two sector model, factor intensity differences likely affect the tax incidence in the final goods market.

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 Additional Summary Statistics

In this appendix, I provide some additional summary statistic information for the estimation samples.

In table 11, I display the number of observations 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 worker cells, but ensures that the market averages 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 that the population acquired more education, 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 11** – 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 Additional Simulation Results

In table 12, I present the EITC vs NIT simulation results using the labor supply elasticities from Model 2 in table 3. The results are largely the same as with the main specification results in table 9.

**Table 12** – Incidence Results:
Aggregate Effects: All Women

| | Rothstein | | $\rho = -0.3$ | | | | $\rho = -2.5$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | "PE" | | "PE" | | GE | | "PE" | | GE | |
| Dollars | EITC | NIT | EITC | NIT | EITC | NIT | EITC | NIT | EITC | NIT |
| Intended | 1.00 | 0.55 | 1.00 | 0.55 | 1.00 | 0.55 | 1.00 | 0.55 | 1.00 | 0.55 |
| Labor | 0.13 | -0.16 | 0.15 | -0.17 | 0.43 | -0.48 | 0.41 | -0.48 | 0.46 | -0.53 |
| Wage | -0.46 | 0.53 | -0.53 | 0.58 | -0.08 | 0.09 | -0.16 | 0.18 | -0.09 | 0.10 |
| Earnings | -0.34 | 0.37 | -0.38 | 0.40 | 0.34 | -0.39 | 0.26 | -0.30 | 0.37 | -0.43 |
| NetEarn | 0.66 | 1.37 | 0.62 | 1.40 | 1.34 | 0.61 | 1.26 | 0.70 | 1.37 | 0.57 |
| EV | 0.54 | 1.52 | 0.47 | 1.58 | 0.92 | 1.09 | 0.84 | 1.17 | 0.91 | 1.10 |
| PE/GE | - | - | - | - | 0.84 | 1.45 | - | - | 0.92 | 1.06 |
| NIT/EITC | - | 2.81 | - | 3.36 | - | 1.18 | - | 1.39 | - | 1.21 |

Units in table are changes in dollars of earnings, LM changes summed across demographic groups
Earnings = Wage + Labor; Net Earnings = Earnings + Transfer, Equivalent Var. = Wages + Transfer
All data from 1993 March CPS, Women from Tax Units
Labor supply elasticities in table 8, except 'Rothstein' which uses $\varepsilon^L = 0.75$ for all

# C Very Specific Estimation Details

Here I describe in detail the estimation of the elasticities. This is here for review by my committee.

## C.1 Data

The labor quantity and wage data come from the Merged Outgoing Rotation Groups of the Current Population Survey. I use the years 1988 to 2000.

The average tax rates are based on using the 1990 Census 5% sample and calculating each individuals tax parameters for the EITC for taxyears 1990 to 2000 using the NBER Internet-TAXSIM software. I uses this to get exogenous EITC policy induced changes to average tax rates. Since the demographics are fixed, the only change from year to year is the tax policy. This is a form of simulated instrument.

## C.2 Labor Market Definitions

My demographic based labor markets are based on Age (9 levels), Education (4 levels), Marriage (2 levels), and Gender (2 levels) status for 72 levels per gender. I ignore effects on men. I pool women with and without children into the same market.

This definition is based on immigration-labor and inequality-labor literatures that want to test worker substitutability and how skill-biased-technological-change affects substitutability. I use these definitions to calculate the substitutability of women workers for between the different demographic-based labor markets. The key to the definition is that within a market firms consider all workers perfectly substitutable (elasticity equals infinity) and between markets I let the data tell me the degree of substitutability.

### C.2.1 Additional Notes

First, for each of the 72 labor markets for women, I observe that market in a particular state-year (potentially up to $50 \times 12$ observations for each market). I do this because

1. different states have different "inherent-potential" for EITC effects, by which I mean some states have a relatively greater amount of workers who are eligible for the EITC
2. tax policy for EITC amounts varies at the state level, so I get some additional policy variation this way

Second, I consider a sub-labor-market when I divide labor markets into the workers with children and those without children. This is important for identifying the difference in labor supply elasticities for workers with and without children, which is novel in my paper.

## C.3 Labor Supply Elasticity

I estimated these models at the sub-labor-market, state, year level using Two-Step-Efficient-IVGMM. For example of the observation level, a dependent variable observation in the regression is: `the log total labor supply of all women with a child, with a high school degree, between the ages of 20-25, who are unmarried, who live in Virginia, in 1994`. I would designate such terms as $\ln[L]_{dst}$. The 2Step-Efficient-IVGMM is a form of 2Stage-Least-Squares where I incorporate the first-step structural equation residual into the optimal weighting matrix. I cluster the standard errors at the sub-labor-market level: 72x2=144 levels.

To get capture the demographic differences in labor supply, I great two super-demographic indicators based on education (4 levels) and marriage-kid (4 levels) status. I interact these with the the log wage in the structural equation and with the instruments in the first stage. Thus, I model the heterogeneity of labor supply as a known function of the demographics.

I use three fixed effects. First, I use a fixed effect for the sub-labor-market. Second, I use state-year fixed effects. Third, I calculate the labor market initial wage percentile in 1988 and then interact this with year dummies. This last FE is meant to capture any skill biased technological change or mean reversion.

Based on prior papers, I also calculate the 'population' size of the labor markets, which is the total number of potential workers. This is potentially important because based on underlying changes in the distribution of population characteristics.

I limit the estimation sample to markets-state-years where I observe at least 5 workers with children and 5 workers without children (miniumum 10 obs) and have no missing observations.

### C.3.1 Regression Commands

```
ivreghdfe log_labor_quantity ///
log_population  ///
(log_wage c.log_wage#(i.edu_cat4 i.km4) ///
= ///
z1 c.z1_0#(i.edu_cat4 i.km4)   /// tax rate  - own
zbar1_1 c.zbar1_1#(i.edu_cat4 i.km4)  /// tax rate  - all  Edu
zbar1_2 c.zbar1_2#(i.edu_cat4 i.km4)  /// tax rate  - all Age
zbar1_3 c.zbar1_3#(i.edu_cat4 i.km4)  /// tax rate  - all Edu+Age
zbar1_4 c.zbar1_4#(i.edu_cat4 i.km4)  /// tax rate  - unmarried Edu
zbar1_5 c.zbar1_5#(i.edu_cat4 i.km4)  /// tax rate  - unmarried Age
zbar1_6 c.zbar1_6#(i.edu_cat4 i.km4)  /// tax rate  - unmarried Edu+Age
z2 c.z2#(i.edu_cat4 i.km4)  /// EITC_Share  - own
zbar2_3 c.zbar2_3#(i.edu_cat4 i.km4)  /// EITC_Share  - all  Edu+Age
zbar2_6 c.zbar2_6#(i.edu_cat4 i.km4)  /// EITC_Share  - unmarried Edu+Age
) ///
if woman1==1 & obsM5 & countsfortable, ///
absorb(pct_lwage88#year state#year DEMO) cluster(DEMO) gmm2s center
```

## C.4 Labor Substitution Elasticity

I estimated these models at the labor-market, state, year level using Two-Step-Efficient-IVGMM. These regressions use 'relative' variables using a base labor market as the relative variable. I always use unmarried, less than high school labor market and then match on state-year-age characteristics. For example of the observation level, a dependent variable observation in the regression could be:

$$\frac{\text{log Supply of women w/ HS degree, age 20-25, unmarried, in Virginia-1994}}{\text{log Supply of women w/o HS degree, age 20-25, unmarried, in Virginia-1994}} \tag{70}$$

or

$$\frac{\text{log Supply of women w/ some college, age 35-40, married, in Michigan-1992}}{\text{log Supply of women w/o HS degree, age 35-40, unmarried, in Michigan-1992}}. \tag{71}$$

I would designate such terms as $\frac{\ln[L]_{dst}}{\ln[L]_{d_0 st}}$. The 2Step-Efficient-IVGMM is a form of 2Stage-Least-Squares where I incorporate the first-step structural equation residual into the optimal weighting matrix. I cluster the standard errors at the sub-labor-market level: 72 levels. I estimate a single substitution elasticity.

I use three fixed effects, that while similar in construction are meant to capture relative trends between the markets. First, I use a fixed effect for the education (4 levels) interacted with the age groups (9 levels). Second, I use state-year fixed effects. Third, I calculate the labor market initial wage percentile in 1988 and then interact this with year dummies. This last FE is meant to capture any skill biased technological change or mean reversion.

Based on prior papers, I also calculate the 'population' size of the labor markets, which is the total number of potential workers. This is potentially important because based on underlying changes in the distribution of population characteristics.

I limit the estimation sample to markets-state-years where I observe at least 5 workers with children and 5 workers without children (miniumum 10 obs) and have no missing observations.

### C.4.1 Stata Commands

```
ivreghdfe log_labor_relative_quantity ///
log_relative_population  ///
(log_relative_wage  =  ///
z1_relative   /// relative tax rate - own
zbar1_3_relative  /// relative tax rate - all Edu-Age
zbar1_6_relative  /// relative tax rate - unmarried Edu-Age
z2_relative  /// relative EITC share - own
zbar2_3_relative  /// relative EITC share - all Edu-Age
```

```
zbar2_6_relative  /// relative EITC share - unmarried Edu-Age
) ///
if tag_labor_market & woman1==1 & obsM , ///
absorb(pct_lwage89#year state#year  edu_cat4#agegrp5y#year) cluster(LM) gmm2s center
```

## C.5 Robustness and WeakIV Tests

### C.5.1 Labor Supply Elasticity

I have run the labor supply regressions using Stata's `ivreghdfe`, `ivreg2`, `gmm` commands; in additon, I used a control function approach. I have also run the model using different subsets of the instruments. I find that eliminating IVs reduces the 'strength' of the first stage regressions, but typically does not meaningfully impact the estimates. I report the main specification, a version with fewer IVs, and the control function approach in the main text.

I have found that results are mostly stable except when I run `ivreghdfe, CUE`, where CUE is Continuously-Updating-Estimator using a numeric optimization algorithm. Using CUE, I get implausibly large elasticities. In theory, the CUE should have very good properties (especially in finite sample), but for this analysis it does not. My best guess is that this is due to the numerical search after partialling out the high-dimensional fixed effects. I do not report these estimates.

To check the strength of my IVs I use four diagnostic tools. I report the

- Kleibergen and Paap LM statistic: tests for underidentification of first stage
- Kleibergen and Paap rk Wald statistic: this is a robust version of the F-test of first stage
- Anderson-Rubin Wald statistic: tests for underidentification of first stage
- MOP Effective F Statistic: meant to be more robust to weak instruments

In all cases, the model passes the usual threshold conditions that authors of the various techniques provide. Thus, statistically speaking, the IVs are strong and the parameters of interest are identified.

### C.5.2 Labor Substitution Elasticity

I have run the labor supply regressions using Stata's `ivreghdfe`, `ivreg2`, `gmm` commands. I have also run the model using different subsets of the instruments. Unlike the above, adding more IVs reduces the 'strength' of the first stage. This is likely because I am attempting to instrument the relative wages using relative versions of the instruments, which may not be the most ideal.

To deal with this, in addition to the diagnostic tools mentioned above, I use Weak IV Robust Confidence Intervals (Andrews 2018). This is a two step procedure in the spirit of partial-identification when an equation is not exactly identified. (To be honest I am not exactly sure how it works.) However, in each case that I report, the model passes the usual threshold conditions that authors of the various techniques provide. Thus, statistically speaking, the IVs are strong and the parameter of interest is identified.