The Mid-1990s EITC Expansion: Aggregate Labor Supply Effects and Economic Incidence

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Abstract

I propose a new approach to estimating the incidence of federal income taxes, using variation across the wage distribution in exposure to tax changes to provide identifying variation in the impacts of these changes on labor markets for workers of different skill levels. Taking as my application the mid-1990s expansion of the Earned Income Tax Credit, I extend the approach of DiNardo, Fortin, and Lemieux (1996) to permit fully nonparametric estimation of labor supply and wage schedule changes for female workers during this period. I find compelling evidence that the EITC expansion caused substantial increases in the labor supply of low– and mid-skill single women with children. Both the margin of increase–large changes in participation and no changes in hours conditional on participation–and its distribution across tax brackets indicate that reductions in average tax rates were far more important than changes in marginal rates. Estimates of changes in wages are much less precise, but generally indicate that wages increased slightly and insignificantly with labor supply, consistent with perfectly elastic labor demand. I find suggestive evidence, however, that EITC-eligible women's wages fell relative to those of similarly-skilled but ineligible women. This is not consistent with standard incidence models, but I speculate about possible explanations.

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1 Introduction

The Earned Income Tax Credit (EITC) is an increasingly important part of the U.S. income redistribution policy toolkit. EITC payments–including credits that offset other income tax liabilities–amounted to \$31.5 billion in 2000, about 70% more than was spent on on traditional welfare under the Temporary Assistance to Needy Families program (Hotz and Scholz 2003). One of the most attractive features of the EITC is that it promises to avoid the disincentives to work that are thought to plague traditional welfare programs with high implicit tax rates. Instead, the EITC aims to encourage employment by subsidizing the first dollar of earnings. Targeting this subsidy to low earners requires positive tax rates for some workers, and families with earnings above a threshold (around \$10,300 in 1992 dollars for a two-child family) face positive EITC-related marginal tax rates (MTRs) as their credits phase out with income. This has been found to reduce employment among secondary earners (Eissa and Hoynes 2004), and the net labor supply effects of the EITC are a subject of considerable research activity. One goal of this paper is to provide estimates of the impact of an EITC expansion on the total quantity of labor that women supply to market.

The incidence of EITC taxes has received less attention, though it is of equal policy importance.[1] One wants of an income transfer program not just that it minimize labor supply distortions but also that it successfully transfer income to the intended recipients. With positive labor supply elasticities and negative demand elasticities, negative tax rates will lower the equilibrium pre-tax wage. If one effect of the EITC is to reduce wages for the lowest-skilled workers, a portion of EITC expenditures go to subsidize low-wage employers, and the EITC is a less cost-effective transfer program than might otherwise be expected.

The theory of tax incidence in competitive markets is clear (Fullerton and Metcalf 2002): Income taxes–both positive and negative–tend to be borne by workers when supply is inelastic and demand is elastic; in the converse cases, most of the tax is borne by employers. There is substantial uncertainty about the elasticities of both supply and demand of labor, however,

[1] Hotz and Scholz (2003), for example, write that "We can think of no major EITC-related topic that has not received at least some attention from serious scholars, possibly with the exception of the economic incidence of the credit" (p. 192).

making it difficult to compute incidence directly from these parameters. Even with good estimates, plug-in calculations would be undesirable, as it seems nearly certain that both elasticities depend crucially on the source of the intervention. Finally, although economists typically assume that workers can choose their hours of work continuously, producing the typical labor supply function's dependence on the marginal tax rate and on the zero-labor-supply "virtual" income, it is also possible that for many workers the primary decision is about participation. If this decision is discrete–if one cannot participate at one hour per week–average tax rates may be more relevant than are marginal rates, at least in one-worker families. The EITC has substantially different effects on average and marginal rates, with opposite signs for most single-earner families, so this distinction is particularly important. Thus, to evaluate incidence one wants a measure of the direct effects of a particular tax on the quantity and price of taxed labor.

In a review of the literature on tax incidence, Fullerton and Metcalf (2002) note that most analyses of the distribution of tax burdens (e.g. Pechman and Okner 1974, Pechman 1985) assume that workers bear the full weight of income taxes, though "this assumption has never been tested" (p. 29). One reason is that "natural experiment"-style empirical approaches are difficult to apply to the estimation of general equilbrium responses like those implicated in tax incidence. Those that exist primarily leverage geographic variation in tax regimes.[2] Leigh's (2003) study of the EITC's incidence–providing the only estimates in the literature–is an example. He uses variation across states in the presence and generosity of a state EITC add-on to generate cross-sectional variation in the average tax rate faced by women with children. One drawback to this approach is that state EITCs are small relative to the federal program, and many recipients may not be aware of their existence. A more general problem is that by eschewing the use of within-state variation in EITC parameters for estimation, Leigh misses much of the information that might be used to identify the EITC's effect on the offered wage. Finally, to the extent that labor or capital are mobile across state borders, federal taxes may have different incidence than do state add-ons.

[2] See, for example, Gruber's (1994) study of the incidence of employer benefit mandates, as well as Gruber and Krueger (1991). Kubik (2004) uses variation in median wages across occupations to study the incidence of the 1986 Tax Reform Act.

This paper uses variation across family types and across the wage distribution in the implications of the mid-1990s federal EITC expansion, in which some families' total credits and EITC-related marginal tax rates approximately doubled over a three year period, to identify the EITC's effects on women's aggregate labor supply and on the female wage schedule.[3] Many single mothers earning around \$5 per hour saw reductions of as much as 20 percentage points in their EITC-related marginal tax rates from this reform, while a substantial fraction of single mothers with wages around \$10 saw their tax rates rise. Both groups saw substantial increases in their credits (i.e. more negative average tax rates); by contrast, few childless women or women with wages above \$15 were affected by the program at all. To the extent that \$5, \$10, and \$15 workers are imperfect substitutes, incidence effects can be identified from the contrast among them, with added power deriving from the differential treatment of women with zero, one, or two or more children.[4]

Changes in both labor supply and wage schedules are estimated semiparametrically, using the re-weighting technique proposed by DiNardo, Fortin, and Lemieux (1996) to account for changes in the distribution of skill among labor force participants. This technique permits estimation of aggregate changes in labor supply and of changes in wages at each skill level using data from repeated cross-sectional surveys.

I find that labor force participation increased for low- and mid-skill single mothers in the mid-1990s, relative both to single mothers whose earnings were too high for EITC eligibility and to single, childless women earning comparable wages, with the largest effects seen among the lowest-skilled workers. Although the probability of employment conditional on participation fell slightly among the same groups of women, overall employment rates rose substantially. By contrast, I find no effect whatsoever on weekly hours conditional on em-

[3] I focus on women because they are far more likely to be single, custodial parents and because their wages tend to be lower, each of which increases exposure to the EITC. Of course, to the extent that men and women are substitutes in production, I may overstate the absolute demand elasticity by treating women as a distinct labor market.

[4] Comparisons across groups require some care, as if married and single women are perfect substitutes in production a tax on one group should affect both groups' pre-tax wages equally. On the other hand, wage premia associated with marriage or the absence of children may indicate that the law of one price does not hold across these groups. I assume that workers from each group who earn the same hourly wage before the EITC expansion have similar skills, even if their observable characteristics differ. The results indicate some divergence of the groups' wage schedules with the reform, perhaps a sign of imperfect substitutability.

ployment. The mid-1990s EITC expansion lowered average tax rates (ATRs) throughout the EITC eligibility range but had substantially different impacts on the marginal tax rates (MTRs) facing low- and mid-skill mothers. My results thus indicate that the EITC's primary labor supply effects were on the extensive rather than the intensive margin. This is consistent with earlier results (Eissa and Liebman 1996, Eissa and Hoynes 2004).

By contrast, I find little evidence that the increased labor supply affected pre-tax wages. Skill groups whose tax rates were lowered the most tended to see declines in their wages, the opposite sign of the effect that would obtain were demand downward-sloping. Structural estimates of elasticity parameters indicate a large, positive demand elasticity. Given this, and as the standard errors are large on the wage effects, it seems unreasonable to reject the hypothesis of elastic demand.

My estimation strategy requires strong assumptions: That the distribution of skill among net new labor force entrants mirrors that among existing workers with the same observable characteristics, and that any changes in the wage schedule over the mid-1990s that are not due to the EITC can be absorbed with a smooth (log linear) relationship with the initial wage. These assumptions may be plausible for intervals of three to five years like that considered here. To test the sensitivity of my results to the assumptions, I re-estimate the model on a subset of states for which the welfare reform of the mid-1990s is least likely to have induced endogenous selection into the labor force and on intervals in which the EITC was not changed. I find no indication that the primary results are driven by violations of the assumptions.

The remainder of the paper proceeds as follows. Section 2 describes the EITC program. Section 3 develops a simple model of tax incidence in a labor market composed of several skill and demographic groups with a discriminatory tax schedule. Section 4 describes the estimation strategy, first for wage and labor supply schedule changes over the mid-1990s and second for testing the relationship of these changes to the tax reform. Section 5 describes the data, and Section 6 presents graphical results on various dimensions of labor supply and on pre-tax wages. Section 7 presents estimates of the effect of the EITC expansion on tax rates experienced by women of different skill groups. Section 8 presents parametric estimates of the tax effects and uses these to fit the supply and demand elasticities of the incidence model. Section 9 concludes.

2 The EITC Program

The EITC is a tax credit available to families with positive but low annual earnings. It was first introduced in 1975, with eligibility restricted to families with children but no further allowance for family size. The program grew slowly from its introduction in 1975 until 1993, with an important expansion in 1986 (see Eissa and Liebman 1996). In 1991, a separate and somewhat more generous credit schedule was introduced for families with two or more children. Expanding the EITC was a central component of Bill Clinton's "Making Work Pay" economic program during his 1992 presidential campaign, and the program's generosity nearly doubled between 1993 and 1996. At the same time, a small credit was introduced for childless families with extremely low incomes. These last changes–primarily the increasing generosity for families with children–provide the variation used in this paper. Importantly, the EITC has never distinguished between single-parent and married-couple households, and is based simply on total family earnings.

Four parameters define the EITC: A phase-in rate τ_1; a maximum credit C; an income level p at which the credit begins to phase out; and a phase-out rate τ_2. If $y_i \geq 0$ is the earnings of family i, the credit is

$$c_i = \begin{cases} \tau_1 y_i & \text{if } y_i < C/\tau_1 \\ C & \text{if } C/\tau_1 < y_i < p \\ C - \tau_2 (y_i - p) & \text{if } p < y_i < p + C/\tau_2 \\ 0 & \text{if } p + C/\tau_2 < y_i. \end{cases} \tag{1}$$

[5]

Earned income credits are refundable: Families whose credit brings the net tax liability below zero receive checks from the IRS. Take-up rates are estimated at 80% or more (Kopczuk and Pop-Eleches 2004).

Figure 1 graphs the EITC budget constraint in earnings-consumption space. Other taxes are neglected, and parameters are exaggerated for visual effect. As can be seen from the figure or from equation (1), the family faces a negative marginal tax rate of $-\tau_1$ on earnings up to C/τ_1; zero marginal tax on earnings from there to p, a positive marginal tax rate of τ_2 on the next C/τ_2 dollars of earnings, and zero MTR above that point. Virtual income, indicated by dashed lines extending each segment of the tax schedule to the zero-earnings intercept, is highest for families in the phase-out range, then for families in the zero-MTR "plateau," and is equal to non-labor income for families in the phase-in range and for those ineligible for the credit.

Table 1 presents the program parameters for the years 1991-1999, in constant 1992 dollars. Note the substantial expansion of the program between 1993 and 1996. The EITC's generosity and associated tax rates roughly doubled for two-child families during this three-year period. While the one-child credit was also expanded, the change was less dramatic.

2.1 Effects on labor supply

Consider an EITC expansion characterized by proportionate increases in τ_1, C, and τ_2, such that C/τ_1, p, and $p+C/\tau_2$ are all left unchanged. Because an increase in τ_2 increases virtual income, income and substitution effects reinforce in the phase-out range, and we expect that the expansion will lead to reductions in labor supply among families whose earnings already lie between p and $p+C/\tau_2$. Moreover, some families who previously chose high labor supply and earnings above $p + C/\tau_2$ may decide to reduce labor supply and relocate into the phase-out range. Finally, although marginal tax rates are unchanged in the plateau region $[C/\tau_1,\ p]$, virtual income is increased, and if leisure is a normal good labor supply should fall here as well. On the other hand, the increase in τ_1 may lead some families whose earnings previously fell in $[0,\ C/\tau_1)$ to increase labor supply, earnings, and after-tax income. Predicted labor supply responses are thus positive among families with low earnings and negative among families with higher earnings, though there should be zero response from families with earnings well above $p + C/\tau_2$ (except insofar as other taxes are raised to pay for the expansion).

The standard analysis assumes that individuals choose their labor supply continuously.

This may not be accurate: 58% of working women report working between 38 and 42 hours per week, and 82% of women who worked at all in 1992 reported having worked at least 48 weeks. Furthermore, as I show below, average annual earnings of unmarried women track quite closely what would be obtained if every woman worked either full time (and full year) or not at all. As there is little reason to suspect such a concentrated distribution of preferences, it seems likely that employers are unwilling to hire workers for other than full-time work. If the primary labor supply decision is about participation, workers should respond to average tax rates–the additional tax charged when a woman participates divided by her earnings–rather than to MTRs. The EITC amounts to a negative ATR for anyone who is eligible, and expansions should unambiguously increase participation for any eligible worker whose earnings, if she participates, would be below the $p + C/\tau_2$ threshold.

Early evidence on labor supply responses to taxation came from nonlinear income tax models (Moffitt 1990, Hausman 1985). Saez (2002), who notes that these models imply "bunching" in the income distribution around points where MTRs increase (like $C/\tau_1$and p) but finds evidence of bunching only around the zero-income kink point, is in this tradition.[6] Another approach, more common in recent years, is to use natural experiment methods to study the responses of specific groups to changes in taxes (Eissa and Liebman 1996, Eissa and Hoynes 2004, Meyer and Rosenbaum 2001, Dickert, Houser, and Scholz 1995). The consensus view (see, e.g., Hotz and Scholz 2003) seems to be that the EITC's primary labor supply effects are on the participation margin, with increased participation of single parents and reduced participation of secondary earners.

2.2 Wage distribution of EITC recipients

There is no direct relationship between the hourly wage rate and the credit, which depends on the product of wages and hours of work (as well as on the husband's earnings, if any). Columns I, J, and K of Table 1 list the wage rates (in constant 1992 dollars) at which a full-time, full-year breadwinner would reach the plateau, the beginning of the phase-out range,

[6] Saez finds clear evidence of bunching around the first EITC kink point (i.e. around C/τ_1 in my notation) among the small subpopulation of families with substantial self employment income. This appears to indicate manipulation of reported earnings. My analysis below excludes the self employed.

and the exhaustion of the credit. The most striking feature of these columns is the low hourly wage associated with the first kink. Even at the minimum wage (the federal minimum is shown in Column L), full-time, full-year, single workers reach the plateau portion of every schedule. Workers without children are well into the phase-out range, and even workers with children would not need to earn much more than the minimum to enter this range. Married women with working husbands, of course, will need substantially lower wages than those listed to reach the kinks. Thus, the phase-out region is likely to be a more important determinant of labor market outcomes, at least for full-time, full-year workers, than is the phase-in.

I investigate the relationship between hourly wage rates and total family earnings before the EITC expansion, separately by marital status and the number of children, using women from the 1993 and 1994 March Current Population Survey (CPS) samples for whom I can compute both.[7] Figure 2 shows kernel estimates of average annual family earnings in the CPS data for working women at various hourly wage rates, separately for groups defined by marital status and the presence or absence of children. It indicates that the average single mother with a wage rate below about \$4.45 earned less than \$7,525 (each measured in constant 1992 dollars), so was in the phase-in range under the 1993 schedule; between \$6.50 and \$11.15, the average was in the phase-out range. For married mothers–most of whose husbands work–at all wages the average family's income was too high to be eligible for the EITC.

Additional series in Figure 2 show what one- and two-worker families would earn, assuming that each worker earned the indicated wage for 2080 hours of work. The one-worker series is nearly identical to the observed averages among single women, consistent with the large fraction of working women who are full-time, full-year workers. The two-worker series, however, is notably below those for married women (particularly at lower wages), suggesting that most married women who work have spouses with higher wage rates.

Finally, note that average family earnings for both married and single women, as a function of the hourly wage, do not vary substantially with the presence or number of children,

[7] Only families with a woman aged 16 to 64 are included. Because the CPS is a rotating panel survey, I exclude women from the 1993 survey with month-in-sample 1 through 4: These women are also included in the 1994 sample if they have not moved in the interim. The sample construction is described in greater detail below.

suggesting that childless women may be a reasonable control group for women with children– or women with one child for those with two or more–once differences in participation and hourly wages are accounted for.

There is, of course, considerable heterogeneity of earnings around the conditional mean. Using the same CPS data, I simulate credit eligibility and marginal tax rates from the federal EITC program.[8] Figure 3 depicts the distribution of women with children across EITC tax brackets by wage level, separately for married and unmarried mothers. A substantial fraction–approaching half–of the very lowest wage single mothers are in the phase-in range, where marginal tax rates are negative. The importance of this tax bracket declines quickly, however, as wages rise, with only about a quarter in this range at wages around \$5.80. Above about \$6.50 per hour, the vast majority are in the phase-out range, and EITC eligibility declines quickly at wages around \$10-11 per hour. (This is consistent with the earlier evidence on the frequency of full-time, full-year workers: The threshold for eligibility in 1992 and 1993 was \$22,380, and a full-time, full-year worker would reach this earnings level with an hourly wage around \$11.) Among married women, even at the lowest wages only a third are EITC-eligible, with the bulk of these in the phase-out range, and essentially no one with an hourly wage above \$5.50 is in the phase-in range.

Figures 4, 5, and 6 offer yet another look at the distribution of EITC benefits. Figure 4 presents average total EITCs by wage rate, separately for married and unmarried mothers; Figure 5 presents average EITC-related MTRs; and Figure 6 presents total (EITC and non-EITC) ATRs.[9] Among single mothers, average MTRs are negative at wages below about \$6 per hour, and large and positive as wages rise above that until most women lose eligibility around a wage of \$10-\$11. Total credits, not surprisingly, increase somewhat with the wage below the point where average MTRs become positive, then shrink until they again approach

[8] Here and throughout I neglect state EITC programs, which are generally small and usually proportional to the federal credit. My calculations agree almost perfectly with those generated by the NBER TAXSIM calculator, `http://www.nber.org/~taxsim` (Feenberg and Coutts 1993), on which I rely below. The TAXSIM program, however, does not separately report EITC-related and other marginal tax rates.

[9] I compute the ATR as the difference between the state, federal, and FICA tax burden that Taxsim calculates for each family's actual income and a counterfactual tax burden computed using the family's income minus the woman's earnings, expressed as a share of those earnings. This is the relevant tax rate for participation decisions if hours and weeks of work are not choice variables.

zero around \$11. Among married mothers, the picture is quite different: Average MTRs are always positive but quite small, and average total credits never exceed about \$250. ATRs are near zero for the lowest-wage single mothers, as the EITC subsidy offsets payroll taxes. Above about \$10 per hour, single mothers' ATRs resemble those of single, childless women.

Below, I present estimates of changes in taxes and in marginal tax rates over the period of the mid-1990s EITC expansion, averaged over workers with the same pre-reform hourly wage. As the expansion was roughly proportional to the preexisting schedule (i.e. it can be approximated as an increase in τ_1, τ_2, and C), one might expect that MTRs would fall for single mothers with very low pre-expansion wages and rise for single mothers with wages between about \$5 and about \$11 and, to a much lesser extent, for married mothers at all wages below about \$10. ATRs should be expected to fall for low-wage single mothers and rise slightly for married mothers. In each case, the changes should be more dramatic for women with two or more children than for one-child mothers. In the absence of panel data, however, estimating the distribution of tax rate changes requires an estimate of the change in the wage schedule: It is not reasonable to assume that a woman whose real wage was \$10 in 1993 had an identical wage four years later, if nothing else because mean female wages grew by several percent over this period. I thus defer presentation of estimates of the change in the tax parameters faced by women at different wage levels until after discussion of my estimates of wage schedule changes over the period.

3 A Simple Tax Incidence Model

The basic tax incidence model is most easily illustrated in a simple economy, in which production depends only on capital and on homogeneous, taxed labor. My empirical strategy, however, relies on variation in the tax treatment of workers at different wages. Workers earning different wages can be seen as having different skills, and for most tasks one cannot replace one hour of a skilled worker's labor with two hours from lower-skilled workers. Thus, after developing the basic framework in the one-type case, I extend it to an economy with multiple types of labor. In the single-type case, elasticities of supply and demand are identified only if aggregate demand is assumed constant. With multiple labor types and elasticities that are constant across types, however, variation in the tax treatment of different types can identify both elasticities without assumptions on aggregate demand. Finally, I develop an extension of the model in which each skill group contains members of demographic groups whose tax treatments differ but whose labor is perfectly substitutable. This permits even stronger identification of the elasticity of labor suply, though not of that of demand.

3.1 A single type of labor

Suppose that homogeneous labor is supplied and demanded with constant elasticity:

$$\begin{aligned} L^S(w) &= \alpha w^{\sigma},\ \sigma > 0, \text{ and} && (2) \\ L^D(w) &= \beta w^{\rho},\ \rho < 0. && (3) \end{aligned}$$

The equilibrium wage satisfies $L^S(w) = L^D(w)$, or

$$w^* = \left(\beta \alpha^{-1}\right)^{\frac{1}{\sigma-\rho}}. \tag{4}$$

A tax, τ $(0 < \tau < 1)$, introduces a wedge between supply and demand. The new equilibrium condition is $L^S(w(1-\tau)) = L^D(w)$, so the wage is

$$w^* = \left(\beta \alpha^{-1} (1-\tau)^{-\sigma}\right)^{\frac{1}{\sigma-\rho}}. \tag{5}$$

The quantity of labor is

$$L^* = L^D(w^*) = L^S(w^*(1-\tau)) = \left(\beta^{\sigma} \alpha^{-\rho} (1-\tau)^{-\sigma\rho}\right)^{\frac{1}{\sigma-\rho}}. \tag{6}$$

Both σ and ρ are identified from a single tax change. This is in contrast to the usual case with supply-demand systems, in which identification of both supply and demand requires an instrument for each: An instrument for supply causes the supply curve to shift, producing a movement along the demand curve and identifying demand parameters, and vice versa. The key to identification here is that the instrument is a direct change in price, so the size of the supply shift in response to the tax change is informative about the parameters: For any $(L,\ w)$ on the untaxed supply curve, the taxed supply curve passes through $(L,\ w(1-\tau))$.[10] Formally,

$$d\ln w^* = \frac{-\sigma}{\sigma-\rho} d\ln(1-\tau) \approx \frac{\sigma}{\sigma-\rho} d\tau \tag{7a}$$

$$d\ln L^* = \frac{-\rho\sigma}{\sigma-\rho} d\ln(1-\tau) \approx \frac{\rho\sigma}{\sigma-\rho} d\tau \tag{7b}$$

As equations (7a) and (7b) indicate, ρ and σ provide all the information that is needed to compute incidence. Employers bear a share $\frac{\sigma}{\sigma-\rho}$ of taxes, while workers bear the remaining $\frac{-\rho}{\sigma-\rho}$ share. A negative tax rate, as is implicit in the EITC's phase-in region, will thus more effectively transfer income to workers when σ is smaller and when ρ is larger (more negative).

3.2 Several types of labor

The above analysis considered an economy with a single type of homogenous labor, and was not particularly useful for study of tax policies that treat skill groups differentially. To see that the basic ideas are more general, consider an economy with S imperfectly substitutable skill groups, $\{s_1,\ s_2,\ \ldots,\ s_S\}$. Suppose that the supply of type s is as above, $L_s^S = \alpha_s w_s^{\sigma_s}$, and that total effective labor supply is

$$L = \left(\sum_{s=1}^{S} b_s L_s^\theta \right)^{\frac{1}{\theta}},\ \theta < 1. \tag{8}$$

Suppose further that the aggregate production function is also of the Constant Elasticity of Substitution (CES) form:

$$Y = \left(L^\phi + cK^\phi \right)^{\frac{\lambda}{\phi}},\ \text{with } \phi < 1. \tag{9}$$

[10] As the model is developed here, a tax change causes a shift in supply and a movement along the demand curve. Equilibrium could equally well be written in terms of the after-tax wage, however, in which case the tax change would shift the demand curve and produce a movement along the supply curve.

Cost-minimization in production implies that, for any two skill groups s and t, $\frac{\partial Y/\partial L_s}{w_s} = \frac{\partial Y/\partial L_t}{w_t}$, or

$$\frac{L_s}{L_t} = \left(\frac{w_s/b_s}{w_t/b_t}\right)^{\frac{1}{\theta-1}}. \tag{10}$$

Labor demand is thus

$$L_s^D = \psi\beta_s w_s^\rho, \tag{11}$$

where $\rho = \frac{1}{\theta-1} < 0$, $\beta_s = b_s^{-\rho}$, and ψ is a parameter, determined by the economy production level, that is constant across skill groups. Equilibrium satisfies

$$w_s^* = \left(\psi\beta_s\alpha_s^{-1}\right)^{\frac{1}{\sigma_s-\rho}}. \tag{12}$$

Tax rates for each skill group are $\tau = \{\tau_1,\ \tau_2,\ \ldots,\ \tau_S\}$. Pre-tax wages satisfy

$$w_s^* = \left(\psi(\tau)\,\beta_s\alpha_s^{-1}\,(1-\tau_s)^{-\sigma_s}\right)^{\frac{1}{\sigma_s-\rho}}, \tag{13}$$

where the notation $\psi = \psi(\tau)$ indicates that the economy-wide production level varies with taxes. With CES production, cross-price effects appear only through the aggregate production level, so τ_t does not enter the expressions for w_s^*, $s \neq t$, except through ψ. The response to changes in the tax price vector is

$$d\ln w_s^* \approx \frac{1}{\sigma_s-\rho}d\ln\psi + \frac{\sigma_s}{\sigma_s-\rho}d\tau_i \tag{14a}$$

$$d\ln L_s^* \approx \frac{\sigma_s}{\sigma_s-\rho}d\ln\psi + \frac{\rho\sigma_s}{\sigma_s-\rho}d\tau_i. \tag{14b}$$

Without restrictions on the σ_s, this model is identified only from changes in the aggregate production level, as these are the only source of information that can distinguish $\frac{1}{\sigma_s-\rho}$ from $d\ln\psi$. The assumption, implicit in the one-type model considered earlier, that tax policy is the only determinant of output is unattractive. If, however, one imposes the restriction that supply elasticities are constant across skill groups (i.e. that $\sigma_s = \sigma$ for all s), a tax change that affects groups differentially identifies both supply and demand elasticities. In this case, the effect of tax policy on aggregate production is absorbed by the intercepts in regressions of changes in wages and labor supply for the s skill groups on changes in tax rates. The tax rate coefficients from the two regressions can be solved for the elasticity parameters.[11]

3.3 Heterogeneous tax schedules

The EITC does not treat all similarly-skilled workers identically, but discriminates based on the number of children and, implicitly, on marital status. It is helpful to expand the model above to allow for several demographic groups, indexed by g, competing in the same labor market but each facing a different tax rate. Labor supply at each skill level in each group is

$$L_{sg}^S = \alpha w_s^\sigma \left(1 - \tau_{sg}\right)^\sigma . \tag{15}$$

Equation (11) may be transformed into the inverse labor demand function. The relevant quantity for labor demand is the sum of supply across all groups, $L_s = \Sigma_g L_{sg}$:

$$w_s^D = \left(\frac{L_s}{\psi\beta}\right)^{1/\rho} = \left(\frac{\Sigma_g L_{sg}}{\psi\beta}\right)^{1/\rho} . \tag{16}$$

We can find the response to a change in taxes by differentiating (15) and (16) in logs:

$$\begin{aligned}
\partial \ln L_{sg} &\approx \sigma \partial \ln w_s - \sigma \partial \tau_{sg} && \text{(17a)} \\
\partial \ln w_s &= -\frac{1}{\rho}\partial \ln \psi + \frac{1}{\rho}\sum\nolimits_k \frac{L_{sk}}{L_s}\partial \ln L_{ik} \\
&\approx \frac{1}{\rho}\left[-\partial \ln \psi + \sigma\left(\partial \ln w_s - \sum\nolimits_k \frac{L_{sk}}{L_s}\partial \tau_{sk}\right)\right] && \text{(17b)}
\end{aligned}$$

The quasi-reduced form of these (neglecting to solve out the effects of $\partial\tau$ on the economy-wide

[11] An alternative estimate of σ can be obtained from the ratio of the labor supply intercept to that from the wage models. This, however, would rely on unattractive assumptions (for example, that there are no shifts in aggregate demand that are unrelated to changes in taxes), and the intercepts are best treated as nuisance parameters.

production level, ψ) is

$$\begin{aligned}
\partial \ln w_s &\approx \frac{1}{\sigma-\rho}\partial \ln \psi + \frac{\sigma}{\sigma-\rho}\textstyle\sum_k \frac{L_{sk}}{L_s}\partial \tau_{sk} \\
&= \frac{1}{\sigma-\rho}\partial \ln \psi + \frac{\sigma}{\sigma-\rho}\overline{\partial \tau_s} \qquad (18a) \\
\partial \ln L_{sg} &\approx \frac{\sigma}{\sigma-\rho}\partial \ln \psi + \frac{\sigma^2}{\sigma-\rho}\textstyle\sum_{k\neq g} \frac{L_{sk}}{L_s}\partial \tau_{sk} + \frac{\sigma\rho}{\sigma-\rho}\partial \tau_{sg} \\
&= \frac{\sigma}{\sigma-\rho}\partial \ln \psi + \frac{\sigma^2}{\sigma-\rho}\textstyle\sum_k \frac{L_{sk}}{L_s}\partial \tau_{sk} - \sigma\partial \tau_{sg} \\
&= \frac{\sigma}{\sigma-\rho}\partial \ln \psi + \frac{\sigma^2}{\sigma-\rho}\overline{\partial \tau_s} - \sigma\partial \tau_{sg}, \qquad (18b)
\end{aligned}$$

where $\overline{\partial \tau_s} = L_s^{-1}\Sigma_k L_{sk}\partial \tau_{sk}$ is the weighted average of changes in the tax rate applicable to the different types of workers at skill s, with weights equal to each group's share of labor supply at that skill. Thus, the supply of labor from group g depends positively on the across-group average tax treatment of similarly-skilled workers, but negatively on the own-group tax rate. Wages, on the other hand, are invariant to the own-group rate, rising with the average tax rate across groups. It is helpful to note that if supply of each type is not observed, the equation for the total supply is similar to that found earlier:

$$\partial \ln L_s = \partial \ln \left(\Sigma_k L_{sk}\right) = \frac{\sigma}{\sigma-\rho}\partial \ln \psi + \frac{\sigma\rho}{\sigma-\rho}\overline{\partial \tau_s}. \qquad (19)$$

3.4 Identification

The models above suggest two sources of variation that can identify the elasticity parameters of interest. First, because low-skill (low-wage) workers are treated differently than high-skill workers, one can compare changes in labor supply and wages of workers at different skill levels when the EITC expands. This strategy is more plausible for responses to MTRs, which changed quite heterogeneously over the wage distribution, than for responses to ATRs, which vary more smoothly. Figure 6 shows that the pre-reform average ATR for single women with exactly one child is very nearly a linear function of the log wage. A proportionate expansion of the EITC thus produces ATR changes that are linearly related with the initial log wage.

Any change in supply or demand–such as, for example, skill-biased technical change that reduces the demand for low-skill labor–that is approximately linear in the base log wage will have effects that are indistinguishable from those of the EITC.

A more promising strategy takes advantage of differences in tax parameters facing similarly-skilled workers from different demographic groups. Consider two groups, g and h, facing different tax schedules. Equation (18b) indicates that

$$\partial \ln L_{sg} - \partial \ln L_{sh} = -\sigma \left(\partial \tau_{sg} - \partial \tau_{sh} \right) \tag{20}$$

eliminates the term describing aggregate demand responses. As noted earlier, identical workers with different numbers of children are treated quite differently by the EITC. I use this fact to estimate labor supply elasticities that are robust to arbitrary shocks to labor supply at each skill level. The same strategy cannot be used, however, to identify demand-side parameters, as only the average tax rate over all demographic groups enters into the expression for wage changes in (18a), so $\partial \ln w_{sg} - \partial \ln w_{sh} = 0$.

In practice, of course, things are more complicated than in the simple models above. First, I work with repeated cross-sections, so am unable to compute the change in any single worker's wage, tax rate, or labor supply. Instead, I work with the change in average tax rates among workers of the same skill-demographic group. By equations (19) and (18a), these are sufficient statistics for the effects of the tax change on the group's aggregate labor supply and wage rate.

Second, I do not observe skill directly. I identify skill groups from their positions in the wage distribution, assuming a monotonic relationship between skill and wage at any point in time. Over time, a worker at a given percentile of the wage distribution in one period has the same skills as a worker at the same percentile in another period *once changes in the composition of the labor force are accounted for*. I discuss how this is done below, in Section 4.1.

Third, the tax system does not "tag" specific skill groups; tax parameters are functions of earnings (i.e. of wL). As a result, observed tax changes for a given worker or skill group are potentially endogenous to changes in wages and hours. I construct an instrument for the actual tax change experienced by workers of a given skill and demographic group from the intended tax change, that which would have been experienced absent any change in wages or quantities.

Finally, individual labor supply decisions may depend on parameters other than the marginal tax rate. Traditional empirical implementations allow labor supply to respond both to the marginal tax rate and to so-called virtual income, the zero-hours intercept (in earnings-consumption space) of the relevant straight-line segment of the budget constraint. I ignore this issue in most of my analysis, focusing instead on whether average or marginal rates appear to best predict the observed changes in labor supply and wages, but I do present tables in the appendix that include changes in virtual income as an explanatory variable.

4 Empirical Framework

There are two components to my empirical strategy. First, I estimate changes in wage schedules and in labor supply during the mid-1990s. Ideally, this would use a panel data set, in which individual workers' changes in supply and earnings could be observed directly. Unfortunately, while a few panel data sets (e.g., the Survey of Income and Program Participation, the National Longitudinal Study of Youth) bracket the mid-1990s EITC expansion, sample sizes are very small. As an alternative, I use an approach proposed by DiNardo, Fortin, and Lemieux (1996; hereafter *DFL*) that permits use of repeated cross-section data.[12] Second, I use the changes in labor supply and wage schedules estimated in the first stage as dependent variables in simple models, motivated by the discussion in Section 3, with changes in tax parameters as explanatory variables.

[12] This approach has also been fruitfully applied by Lee (1999) to study the impact of changing real minimum wages.

4.1 Changes in Labor Supply and Wage Schedules

Let $t = 0$ denote the period before the expansion and $t = 1$ the period afterward.[13] Assume that the skill of worker i, $s_i \in S \subset \mathfrak{R}$, satisfies $s_i = h_t(X_i, \varepsilon_i)$, for $h_t(\cdot)$ a function with arbitrary scale; X_i a vector of observables with distribution function $\lambda_t(X)$ in the labor market at time t; and ε_i an unobserved component with conditional distribution $\varphi_t(\varepsilon \mid X)$.

I make two strong assumptions:

- The function h_t translating observables and unobservables into skill is constant over time: $h_1(X, \varepsilon) = h_0(X, \varepsilon) = h(X, \varepsilon)$ for all X, ε.
- The distribution of ε conditional on X is also constant: $\varphi_1(\varepsilon \mid X) = \varphi_0(\varepsilon \mid X) = \varphi(\varepsilon \mid X)$ for all X, ε.

The second assumption amounts to selection-on-observables: Unobserved skill components have the same distribution (conditional on X) in among period-0 and period-1 workers. Alternatively, I might write the two assumptions as a single one about the conditional distribution of skill among workers: $g_1(s \mid X) = g_0(s \mid X)$. Of course, there may be changes in the distribution of observables. If $\lambda_t(\cdot)$ varies with t, in general $g_1(s) \neq g_0(s)$, and indeed the change in g_t–interpretable as the change in labor supply by skill–is one of the outcomes of interest.

A wage schedule is a function $\Lambda_t : S \to \mathfrak{R}$ that translates skill into log wages. I make an additional assumption on the wage schedule, which should be uncontroversial:

- Higher-skill workers earn higher wages: $\Lambda_t'(s) > 0$ for all s and t.

We are interested in estimating the changes in the wage schedule and in labor supply between time 0 and 1:

$$D^w(s) \equiv \Lambda_1(s) - \Lambda_0(s) \text{ and} \tag{21a}$$

$$D^L(s) \equiv \frac{g_1(s) - g_0(s)}{g_0(s)}. \tag{21b}$$

[13] This section draws heavily on DiNardo, Fortin, and Lemieux (1996) and on Section 11.4.2 of Johnston and DiNardo (1997).

Because s is an arbitrary index, it is convenient to work in terms of the period-0 wage. With the change of variables $s = \Lambda_0^{-1}(w)$, equation (21) becomes

$$\begin{aligned} \Delta^w(w) &\equiv D^w\left(\Lambda_0^{-1}(w)\right) = \Lambda_1\left(\Lambda_0^{-1}(w)\right) - w \text{ and} && \text{(22a)} \\ \Delta^L(w) &= D^L\left(\Lambda_0^{-1}(w)\right) = \frac{g_1\left(\Lambda_0^{-1}(w)\right) - g_0\left(\Lambda_0^{-1}(w)\right)}{g_0\left(\Lambda_0^{-1}(w)\right)}. && \text{(22b)} \end{aligned}$$

The distribution function for wages in time t can be written as

$$\begin{aligned} F_t(w) &= \int\left(\int_{\Lambda_t(s)\leq w} g_t(s \mid X)\, ds\right)\lambda_t(X)\, dX \\ &= \int\left(\int_{h(X,\ \varepsilon)\leq\Lambda_t^{-1}(w)} \varphi(\varepsilon \mid X)\, d\varepsilon\right)\lambda_t(X)\, dX. \qquad (23) \end{aligned}$$

Under the above assumptions, there are only two time-varying components in (23): The inverse wage schedule, Λ_t^{-1}, and the distribution of X, λ_t. To describe counterfactual distributions that modify either labor supply or the wage schedule, one can simply replace these terms with the counterfactual functions. Thus, the distribution that would have been observed had the period-1 wage schedule applied with labor supply as in period 0 is

$$\begin{aligned} \widetilde{F}_1(w) &= \int\left(\int_{h(X,\ \varepsilon)\leq\Lambda_1^{-1}(w)} \varphi(\varepsilon \mid X)\, d\varepsilon\right)\lambda_0(X)\, dX \\ &= \int\left(\int_{h(X,\ \varepsilon)\leq\Lambda_1^{-1}(w)} \varphi(\varepsilon \mid X)\, d\varepsilon\right)\lambda_1(X)\frac{\lambda_0(X)}{\lambda_1(X)}dX. \qquad (24) \end{aligned}$$

Note that the terms inside parentheses in the expressions given in (23), as applied to $F_1(w)$, and (24) are identical; the expressions differ only in the "weighting function" $p(X) \equiv \lambda_0(X)/\lambda_1(X)$ in (24). We can therefore compute $\widetilde{F}_1$ as the distribution of wages in reweighted period-1 data, where the reweighting factor is $p(X)$. This function is easily estimated: In data pooling random samples of workers from both periods,

$$\Pr\{\text{observation } i \text{ came from period } 0 \mid X\} = \frac{\lambda_0(X)}{\lambda_0(X)+\lambda_1(X)} = \frac{p(X)}{1+p(X)}, \qquad (25)$$

which can be estimated using binary dependent variable models. Using the fitted values from a probit model for (25) to compute $p_i = p(X_i)$, I compute

$$\widehat{F}_0(w) = \frac{1}{N_0}\sum_{t=0} \mathbf{1}(w_i \leq w) \text{ and} \tag{26a}$$

$$\widehat{\widetilde{F}}_1(w) = \sum_{t=1} p_i \mathbf{1}(w_i \leq w) \ / \ \sum_{t=1} p_i \tag{26b}$$

where the indices of summation indicate that the first is over the period-0 data and the second over the period-1 data.

By assumption, the skill distribution generating F_0 is identical to that generating $\widetilde{F}_1$; all that differs is the wage schedule. Because wage schedules are assumed monotonic, the change in the wage schedule can be estimated by comparing the wages of workers at the same percentile:

$$\Delta^w(w) = \widetilde{F}_1^{-1}(F_0(w)) - w. \tag{27}$$

The weighting function $p(X)$ also provides the information needed to compute changes in labor supply. Notice that $g_0(s) = \int g(s \mid X)\lambda_0(X)\,dX$ and that $g_1(s) = \int g(s \mid X)\lambda_1(X)\,dX = \int \frac{1}{p(X)} g(s \mid X)\lambda_0(X)\,dX$. As a result,

$$D^L(s) = \frac{g_1(s)}{g_0(s)} - 1 = \frac{\int \frac{1}{p(X)} g(s \mid X)\lambda_0(X)\,dX}{\int g(s \mid X)\lambda_0(X)\,dX} - 1, \tag{28}$$

or, more simply,

$$D^L(s) = E_0\left[\frac{1}{p(X)} \mid h(X,\ \varepsilon) = s\right] - 1, \tag{29}$$

where the notation E_0 indicates that the expectation is to be computed over the period-0 X distribution. Expressed in terms of period-0 wages, this is even simpler:

$$\begin{aligned}
\Delta^L(w) &= D^L\left(\Lambda_0^{-1}(w)\right) = E_0\left[\frac{1}{p(X)} \mid h(X,\ \varepsilon) = \Lambda_0^{-1}(w)\right] - 1 \\
&= E_0\left[\frac{1}{p(X)} \mid \Lambda_0(h(X,\ \varepsilon)) = w\right] - 1 \\
&= E_0\left[\frac{1}{p_i} \mid w_i = w\right] - 1.
\end{aligned} \tag{30}$$

That is, $\Delta^L(w)$ is simply the mean of p^{-1} over all period-0 individuals earning wage w, less one. I compute the conditional mean using a kernel regression, with an Epanechnikov kernel and a bandwidth of 0.05 log points.

4.2 Margins of labor supply

The discussion thus far treats individual labor supply as a single, continuous variable. It is useful, however, to distinguish several components of the change in labor supply: Changes in labor force participation, changes in the probability of employment conditional on participation, and changes in hours conditional on employment. I estimate equation (25) separately for each margin, producing three separate estimates of $p(X)$, each conditional on the previous. The estimate for changes in hours conditional on employment, for example, comes from fitting

$$X_i\beta_3 = \Pr\{\text{observation } i \text{ came from period } 0 \mid X, i \text{ is employed}\}$$

to data that have been weighted by $p_1(X_i)\, p_2(X_i)\, h_i$, where p_1 and p_2 describe labor force participation and conditional employment rates (so $p_1 p_2$ describes unconditional employment) and h_i is the weekly hours worked. $p_3(X_i)$ is then the solution to $X_i\beta_3 = \frac{p_3(X_i)}{1+p_3(X_i)}$. The interpretation is as follows: Suppose that we take samples of workers from each period such that the distribution of X_i is the same in each period's sample. If we pool these two samples, what is the probability that a given hour came from the period-0 sample, conditional on X_i?

Each p, or combinations of them, can be used for the computation of $\Delta^L(w)$, to describe changes in different components of labor supply. The counterfactual wage distribution $\widehat{\widehat{F}}_1(w)$ is computed by reweighting the period-1 data by $p_1 p_2 p_3$.[14]

[14] In practice, I use five components of labor supply, with the additional components being two that are not germane to the study of tax incidence. First, changes in the skill distribution of the population as a whole would alter the distribution of skill supplied to market with no changes in average supply decisions, but do not depend (at least in the short- to medium-run) on tax parameters. Second, changes in the relationship between skill and the propensity to not report a valid wage, leading to "allocation" of a wage. Since I discard allocated wages from my analysis, such changes could produce spurious changes in the estimated wage distribution. Although allocation rates rose substantially in the mid-1990s, this change appears unrelated to the wage level. I discuss this in further detail in the appendix. The population-reweighting is carried out before estimating labor supply changes, and the allocation-reweighting afterward; both are incorporated in the counterfactual wage distribution.

4.3 Relating changes in the tax schedule to changes in labor supply and wages

The above procedure provides estimates of changes in labor supply and wages as functions of the initial wage, $\Delta^L(w)$ and $\Delta^w(w)$. I carry it out separately for each of six demographic groups: Single and married women, with zero, one, and two or more children. The next task is to relate these to the tax schedule. The change in taxes experienced by a worker from group g whose skill earned her a wage of w $(= \Lambda_{g0}(s))$ in period 0 is

$$\begin{aligned}\Delta_g^{\tau}(w) &= \tau_{g1}\left(\Lambda_{g1}\left(\Lambda_{g0}^{-1}(w)\right)\right) - \tau_{g0}(w) \\ &= \tau_{g1}\left(w + \Delta_g^w(w)\right) - \tau_{g0}(w). \end{aligned} \tag{31}$$

I estimate average tax parameters as a function of g and w from pre- and post-reform March CPS data. (The pre-period schedule, $\tau_{g0}(w)$, is graphed in Figures 4, 5, and 6 for different definitions of τ.) I then use my first-stage estimate of $\Delta_g^w(w)$ to relate points in the time-0 and time-1 wage schedules. It is also useful to have notation for the average of (31) across demographic groups: $\Delta^{\tau}(w) = \Sigma_g f_g \Delta_g^{\tau}(w)$, where f_g is the fraction of pre-period hours worked at wage level w that were supplied by workers of group g.

I form a data set by estimating $\Delta_g^L(w)$, $\Delta_g^w(w)$, $\Delta_g^{\tau}(w)$, and $\Delta^{\tau}(w)$ at 199 points corresponding to half-percentiles of the pre-reform female wage distribution, then stacking the six demographic groups. I estimate two sorts of models using these data. First, I attempt to ascertain the reduced-form response of labor supply to the own-group tax rate. This suggests a model of the form

$$y_{gs} = \alpha_g + \beta_s + \Delta_g^{\tau}(w_s)\gamma + w_s\theta_g + \varepsilon_{gs}, \tag{32}$$

where y_{gs} is a measure of the change in labor supply at a particular margin at skill level s among workers of group g, $\Delta_g^L(w_s) = \Delta_g^L(\Lambda_{g0}(s))$; α_g and β_s are demographic group and skill level fixed effects; $\Delta_g^{\tau}(w_s) = \Delta_g^{\tau}(\Lambda_{g0}(s))$ is the change in tax rates (computed as either the change in marginal or average rates) among skill-s workers from group g; and $w_s = \Lambda_{g0}(s)$ is a term, linear in the initial (log) wage, mean to absorb group-specific changes in y that are unrelated to taxes. (Note that the β_s effects absorb any shocks to skill-s labor supply that are common across demographic groups.) Standard errors are estimated by drawing 600 bootstrap samples from the original CPS microdata, re-estimating changes in labor supply, tax, and wage schedules on these samples, and estimating (32) on these samples.

This model is a way of estimating (20), and $\gamma = -\sigma$. I also estimate identical models where y is the change in wages, $\Delta_g^w(w_s)$. Perfect substitutability of the demographic groups implies that $\gamma = 0$ in this model, as wages of all groups respond similarly to changes in the average tax rate over all groups. β_s absorbs these changes, and there should be no further response to the own-group change in tax rates.

An important problem with estimating equation (32) is endogeneity bias: Because the tax schedule is nonlinear, the actual tax parameters experienced by a worker depend on her total earnings, so are influenced by other determinants of either the wage or labor supply. As a result, $\Delta_g^\tau(w_s)$ is endogenous in (32). I form an instruments from the change in average tax rates that would have been experienced in the absence of any change in the wage schedule or in labor supply. This is computed by applying the tax schedules from each of the two periods to data from period 0.[15] As shown below, the resulting simulated change (denoted $\widetilde{\Delta}_g^\tau(w)$ or $\widetilde{\Delta}^\tau(w)$) is strongly related to the actual change in tax rates.

After establishing the basic reduced-form relationships, I move to more structured models that identify the demand elasticity as well as supply. This requires replacing the skill fixed effects, β_s, in (32) with the average of $\Delta_g^\tau(w_s)$ over demographic groups at skill s, $\Delta^\tau(w_s)$. I also loosen restrictions in (32), allowing both γ and the coefficient on the average tax rate to vary across demographic groups. The resulting model is:

$$y_{gs} = \alpha_g + \Delta^\tau(w_s)\beta_g + \Delta_g^\tau(w_s)\gamma_g + w_s\theta_g + \varepsilon_{gs}. \tag{33}$$

I estimate (33) for two dependent variables: The total change in hours supplied and the

[15] In practice, I inflate period-0 earnings and wages by the inflation rate between 1992 or 1993 and 1995, then assume 3% annual growth on top of that generated by inflation.

change in wage. From the model in Section 3, the resulting parameters are

$$\Pi_g = \left(\beta_g^L,\ \gamma_g^L,\ \beta_g^w,\ \gamma_g^w\right)' = f\left(\sigma,\ \rho\right) = \left(\frac{\sigma^2}{\sigma-\rho},\ \ -\sigma,\ \frac{\sigma}{\sigma-\rho},\ 0\right)'. \tag{34}$$

I use an optimal minimum distance (OMD, Abowd and Card 1989, Chamberlain 1984) estimator for σ and ρ. This minimizes

$$\left(\Pi - f\left(\sigma,\ \rho\right)\right)' \left[Var\left(\Pi\right)\right]^{-1} \left(\Pi - f\left(\sigma,\ \rho\right)\right), \tag{35}$$

and has variance

$$Var\left(\hat{\sigma}_{omd},\ \hat{\rho}_{omd}\right) = \left[J\left(\hat{\sigma}_{omd},\ \hat{\rho}_{omd}\right)' \left[Var\left(\Pi\right)\right]^{-1} J\left(\hat{\sigma}_{omd},\ \hat{\rho}_{omd}\right)\right]^{-1}, \tag{36}$$

where J is the Jacobian matrix of f evaluated at $\left(\hat{\sigma}_{omd},\ \hat{\rho}_{omd}\right)$. Under the hypothesis that (34) is correctly specified, the OMD objective function (35) has a χ^2 distribution, with degrees of freedom equal to the number of overidentifying restrictions (Newey 1985). Equation (34) yields two overidentifying restrictions when β_g and γ_g are not permitted to vary across groups. When they are permitted to vary, there are more: Six when just single mothers with one child or with two or more are used, or ten when all single women are used.

5 Data

I use repeated cross sections assembled from the merged outgoing rotation groups (MORGs) of the Current Population Survey (CPS), which ask about work and earnings in the previous week, for estimation of the DFL model. These surveys provide observations on hourly wages and hours of work for roughly 3-5,000 female workers each month. My pre-reform sample consists of women aged 16-64 from the pooled 1992 and 1993 MORG files, while my post-reform sample is drawn from the 1995 (September through December), 1996, and 1997 (January through August) files.[16] One hazard is that the CPS questionnaire–particularly

[16] Each household appears in the MORG files twice, at an interval of one year. To ensure a sample of unduplicated respondents, I use only observations in their 8th month-in-sample (i.e. the second MORG appearance)

questions needed to compute weekly hours and hourly wages–changed substantially in 1994, as did the population estimates on which the sampling weights are based; I must rely on the assumption that any resulting changes in wage schedules do not vary systematically with EITC exposure. I measure labor supply as usual weekly hours and wages as the hourly wage rate. For analyses of labor supply and wages, I exclude the self employed, observations with hourly wages (in real January 1992 dollars) below $1 or above $100, and observations with allocated earnings.[17]

As discussed above, I rely on the March CPS survey to estimate the average tax parameters faced by workers at each wage level. This survey asks respondents about their income by category (i.e. wage and salary earnings, dividends, etc.) in the previous calendar year, which I use to simulate EITC eligibility and tax rates. I confirm my EITC simulations by checking them against the full tax simulation provided by the National Bureau of Economic Research's TAXSIM program (`http://www.nber.org/~taxsim`; Feenberg and Coutts 1993); there are unexplained discrepancies between the two simulations in only a very small fraction of cases. I form hourly wages in the March data by dividing total annual wage and salary earnings by the product of weeks worked and usual weekly hours. Again, wages are set to missing for the self-employed, those with hourly wages below $1 or above $100, and those with allocated wages.

I use the 1993 and 1994 March CPS surveys (describing earnings in the 1992 and 1993 tax years) for the pre-reform distribution of family income and the 1996 and 1997 surveys for the post-reform distribution. I also simulate the effect of the tax reform by applying the post-reform schedule to the pre-reform observations. The resulting estimates of tax parameters are free of endogeneity introduced by individual responses to the changing budget constraint–e.g. individuals in the EITC phase-out range who reduce labor supply in order to increase

from 1992, and only observations in their 4th month from the September 1996 to August 1997 period. The mid-year beginning of the post-reform sampling window is chosen because the CPS survey was changed substantially in September 1995. A later post-reform sampling window would allow for a lag in the EITC's effect, but I use the early window to minimize the potentially contaminating effects of welfare reform, which was implemented nationwide in late 1996 and early 1997 and which I discuss in greater detail in Section 6.1.

[17] Individuals with allocated wages are used in estimating the $p(X_i)$ functions for changes in labor supply; as noted earlier, an additional $p_4(X_i)$ is estimated to absorb changes in allocation rates between periods. See Lemieux (2004) and Hirsch and Schumacher (2004) for more on wage allocation in the CPS.

their credit eligibility–and thus provide an instrument for the actual change in tax parameters experienced by a given skill group.

6 Estimates: Changes in Labor Supply and Wage Schedules

As noted earlier, I estimate changes in labor supply sequentially for several margins of supply. As a preliminary step, I re-weight the data to balance the population distribution of demographic characteristics between the pre- and post-periods.[18] Once this is accomplished, I move on to estimate changes in labor force participation, using the algorithm described above in Section 4.1. Pooling all observations, workers and non-workers alike, from the pre- and post-reform samples, I form an indicator for appearing in the earlier sample. I then estimate a flexible probit model for this "pre" indicator, using individual observable characteristics as explanatory variables.[19] Letting q_i^1 denote the predicted probability for observation i, I form a reweighting factor $p_i^1 = \frac{q_i^1}{1-q_i^1}$ for each observation in the post-reform sample. When this reweighting factor is applied, the distribution of X_i among labor force participants is similar in the pre- and post-reform samples. The reweighting factors may be interpreted as the inverse of the proportional change in the number of labor force participants in the (weighted) CPS sample with observables like individual i over the time period.

Figure 7A graphs the conditional expectation $E\left[\left(p_i^1\right)^{-1} - 1 \mid w_i\right]$ in the pre-period data, separately by marital status and number of children.[20] This can be interpreted as the

[18] To take one example, average education is nearly a quarter of a year higher among women in my 1995-1997 ORG sample than in the 1992-1993 sample. There are two sources of this shift. First, the population composition changed somewhat, as less-educated older individuals were replaced by younger cohorts with higher average education. Second, in 1994 and 1995 the Bureau of Labor Statistics introduced new sampling weights, based on the 2000 Census data, where earlier weights were intended to produce population characteristics predicted from the 1990 Census data. Regardless of the source, an increase in the educational distribution would tend to raise the wage at any particular percentile, even without changes in labor supply or demand. I use the same procedure described in the text to "reweight" the post-reform data to resemble that seen in the pre-reform period.

[19] This model includes the full interaction of four education dummies and eight potential experience categories; separate linear education terms and quadratics in potential experience terms for whites, blacks, Hispanics, and Asians; indicators for each of the latter three ethnicity categories; indicators for having exactly one or two or more children; a linear term in the number of children under age 6; and indicators for residence in a metropolitan area and in a central city of an MSA. The probit is estimated separately for each of the six demographic groups.

[20] Here and elsewhere in this paper, I estimate these conditional expectations as a kernel regression on the log real wage, with an Epanechnikov kernel and a bandwidth of 0.03. The figure also shows 90% confidence intervals

percentage change in the probability of participating in the labor force among workers whose skills would have earned a wage w_i in period 0. There are large differences in the change in labor force participation across demographic and skill groups. Married women's labor supply increased at all skill levels during the time period, with the largest changes seen among women with children but with little variation along the wage distribution. Labor force participation of single, childless women was essentially flat. For single women with children, however, there were dramatic increases in labor force participation, concentrated among the lowest-skill women. Moreover, the changes were largest for women with two or more children, with participation rates of the lowest-skilled women growing by upwards of 25 percent over the three year window. The pattern of results is entirely consistent with the predicted effects of the EITC expansion, as this expansion substantially increased the incentives for low- and mid-skilled single mothers to work and the incentive changes were largest for women with more than one child.

The next margin to consider is the probability of employment conditional on labor force participation. I use an identical technique to examine this. I begin with data re-weighted by p_i^1, but drop any observations who are not employed. I then estimate a set of probit models for appearance in the earlier period–using the same control variables as in the previous step–on the re-weighted data, and use the fitted probabilities from these models to form p_i^2. Finally, to estimate changes in hours conditional on employment, I re-weight the data again by the product of p_i^2 and weekly hours and compute a third set of probit models.

Figures 7B and 7C show the resulting estimates of changes in the probability of working conditional on being in the labor force and in mean weekly hours conditional on working in the reference week. Focusing first on Figure 7B, there were declines in the employment rate among low-skill women of all demographic groups, with the largest declines seen among single women with two or more children. Thus, to some extent the increased labor force participation in this group resulted in increased unemployment rather than increased employment. On the other hand, the changes in employment conditional on participation are much smaller in

for the conditional expectations, estimated as the pointwise 5th and 95th percentiles from 600 replications of the procedure on bootstrap samples drawn with replacement from the original ORG sample.

magnitude than those in participation, so this is unlikely to be the whole story. Figure 7C shows results for weekly hours conditional on employment. There is no clear pattern here, and all changes are small, uniformly below 6%. Thus, there is no indication of responses to the EITC expansion on the intensive margin.[21]

Figures 8A and 8B combine the earlier estimates into estimates of changes in total labor supply. Figure 8A shows changes in the unconditional probability of employment (i.e., without conditioning on labor force participation). These are computed as the kernel regression of $\left(p_i^1 p_i^2\right)^{-1} - 1$ on wages in the pre-reform data. The figure is quite similar to Figure 7A, as the changes in labor force participation depicted there are large enough to swamp the partially-offsetting changes in conditional employment rates. Again, we see large increases in employment among low-skill single women with two or more children; smaller but still substantial relative increases among low-skill single women with one child; and relatively little action among the other groups. (There does appear to be a small relative reduction in the employment of low-skill married mothers, perhaps reflecting the declines in the incentives to work for many of these women studied by Eissa and Hoynes, 2004.[22]) Figure 8B shows changes in the total number of weekly hours worked per woman, combining all three margins of response. Consistent with the small changes in weekly hours among those working, this figure is quite similar to the previous one.

Combining all of the re-weighting factors used in Figure 8B, the post-period data can be re-weighted so that the distribution of X (and, under the assumptions in Section 4.1, of s) in the labor market matches that seen in the pre-period data. When this is done, the difference in the (hours-weighted) qth percentile wage between the pre-period data and the re-weighted post-period data is the change in wages for workers at the qth percentile of the (hours-weighted) pre-period skill distribution, whose wages were $F_0^{-1}(q)$ in the pre-period and are $\widetilde{F}_1^{-1}(q)$ in the post-period. Figure 9 graphs the changes in wages as a function of the initial

[21] This requires a bit of caution: Because I rely on the CPS outgoing rotation groups for my analysis of labor supply changes, I cannot distinguish changes in participation from changes in the number of weeks worked per year. My discussion about "intensive" responses is thus solely about responses in the hours worked per week.

[22] Given the relatively low exposure to the EITC among even the lowest-wage married mothers, my approach–which does not distinguish between women with high- and low-wage husbands–does not have the power to detect effects of the size that Eissa and Hoynes find. I am motivated by the question of incidence, and small changes in labor supply are unlikely to have detectable effects on wages in any case.

wage (that is, $\Delta_g^w(w) = \widetilde{F}_1^{-1}(F_0(w)) - w$ against w), along with 90% confidence intervals. For comparison, it also graphs (with a dashed line) the raw change in wages obtained by matching percentiles of the pre- and post-period wage distributions without accounting for changes in labor supply or population characteristics, $F_1^{-1}(F_0(w)) - w$.[23]

Wages appear to have been stable for all six groups at the very bottom end of the distribution, though there are prominent spikes here. These spikes may reflect the evolving real minimum wage (Lee 1999) or spikes in the true nominal distribution at round numbers.[24] For married women, wages were essentially stable for all three groups in the \$6 to \$13 range, though the wages of married women with children seem to have grown more rapidly than those of women without children above about \$15. Turning our attention to single women, there is some indication that wages of mid-skill women with children fell relative to those of women without children, though standard errors are large. If women of different demographic groups were perfect substitutes in production, one would have expected similar wage schedule changes for all four groups. This prediction is clearly rejected by the data, though it is difficult to connect this with the EITC, as the maintained assumption of perfect substitutability implies that wages should move together for all substitutable groups.

To provide a clearer picture of the variation of interest, Figure 10 shows differences between the labor supply and wage changes seen among single mothers and those seen among single women without children. As seen earlier, low-skill single mothers' employment rates and overall average hours rose substantially, relative both to higher-skilled single mothers and to similarly-skilled single women without children, with the largest changes for women with two or more children. By contrast, there is no relative change in hours conditional on employment. There is some indication that mid-skill single mothers with two or more children experienced

[23] Note that the naive estimates overstate the growth in wages for all groups except single mothers with two or more children. The reason is that there was skill upgrading in the population, independent of labor supply, in all groups (see Appendix Figure 1). This tends to bias upward estimates of the change at any particular percentile, but is offset among single women with multiple children by the increase in labor supply among low-skill women, which biases raw percentile changes in the opposite direction.

[24] The minimum wage was \$4.25 from 1991-1995, then rose to \$4.75 in 1996 and \$5.15 in 1997. In 1992 dollars, however, it never rose above about \$4.50. There are also large spikes in the nominal wage distriibution at \$5 and \$10, which move slightly in real terms as inflation erodes the value of a dollar. These are visible as dips just below each value in each group. Evidence of similar but smaller spikes can also be seen at other round numbers (e.g. \$15).

relative wage declines, perhaps a sign of imperfect substitutability, though this effect is hardly seen among women with just one child.

The remainder of this section presents several tests designed to ensure that the basic labor supply and wage results are not an artifact of the entrance of unobservably low-skilled workers leaving the welfare rolls in response to welfare reform nor due to long-run trends in the wage structure. Section 7 uses the wage schedule changes to derive estimates of the change in average tax parameters experienced by each skill group, and Section 8 explores the elasticities of supply and demand implied by the tax, labor supply and wage estimates.

6.1 Are these effects due to welfare reform?

The strategy taken for identifying changes in the wage schedule rests on the assumption that the distribution of unobservable skill conditional on observed characteristics in the labor market is unchanged over the period studied. If, for example, there were a substantial inflow into the labor force in the mid-1990s of single mothers who were observably similar to women earning around $8 per hour but who had unobservably lower skill, this could account for the apparent decline in single mothers' relative wages around that point in the distribution without any changes in actual wage schedules.

One potential source of such an inflow is welfare reform, which was implemented on a national level shortly after the EITC expansion, with several states implementing reforms over the years preceeding passage and implementation of the federal law. One of the key goals of these reforms was to encourage welfare recipients to transition quickly into employment, with incentives created via time limits on the receipt of benefits and binding work requirements. Although there is some dispute about the causality, welfare caseloads declined sharply in 1996 and, even more so, in 1997.[25] It seems reasonable to expect that welfare recipients in 1993 were of lower skill than were workers with similar observable characteristics, which would violate the selection-on-observables assumption.

Fortunately, the EITC expansions were not exactly contemporaneous with welfare reform.

[25] Moffitt (2003) reviews welfare reform, caseload trends, and state waivers. For contrasting estimates of the effect of reform on caseloads, see Wallace and Blank (1999) and Figlio and Ziliak (1999).

Although some states had waivers from the federal government that permitted welfare reforms beginning in 1992, many did not, and in the latter states reform was gradually implemented between the third quarter of 1996 and mid-1997. Thus, under the assumption that welfare reform did not have important effects on labor force participation before it was implemented, I can avoid bias by constructing a sample drawn only from pre-implementation time periods. To do this, I drop all observations from the 1997 ORG files–using only October 1995 through December 1996 as the "post" period–as well as all observations from any year from 14 early-adopter states, then reestimate labor supply and wage responses on the shrunken data set.[26] The first row of Figure 11 shows estimated changes in total labor supply and wages for single women in the main sample, while the second row shows estimates from the pre-welfare-reform sample. There are no substantial differences, suggesting that neither the large labor supply impacts nor the apparent lack of wage impacts seen earlier can be attributed to the influence of welfare reform.

6.2 Estimates from periods without tax changes

Another possible explanation for the results is that they reflect a long-run trend that would have occurred regardless of any changes in tax and transfer policy. Although this hypothesis cannot be disproven, it does suggest that we should observe similar changes in wage structures during periods when there was no EITC expansion. Unfortunately, it is difficult to find a period in which macroeconomic conditions resembled those in the mid-1990s and there were no large-scale policy shifts affecting low-wage workers. From a business cycle perspective, the mid-1980s are attractive. The drawback of this period as a counterfactual is that the Tax Reform Act of 1986 may have had its own effects on labor supply and wage schedules, though its primary effects were on higher-income families (Eissa 1995). I consider two counterfactual periods, neither perfect: The period from 1983/4 to 1986/7 (hopefully before any TRA86 effects appear), and from 1997/98 to 2000/01 (during which we might see the effects of an

[26] The early adopters are Arizona, California, Connecticut, Illinois, Iowa, Massachusetts, Montana, North Carolina, South Dakota, Utah, Virginia, Vermont, Washington, and Wisconsin; each implemented a major waiver to impose time limits or stricter-than-usual work requirements before September 1996 (Bitler, Gelbach, and Hoynes forthcoming, Crouse 1999).

overheated business cycle and delayed impacts of welfare reform). During each period, EITC parameters were essentially stable (Table 1).[27] Estimates of labor supply and wage schedule changes from each period are shown in the bottom rows of Figure 11.

In the mid-1980s sample, there is no indication of large shifts in labor supply, nor that any changes varied either by the presence of children or by the initial wage. Similarly, wage schedules appear to show a stable increase in inequality, with real wage declines among the lowest-skilled workers (perhaps reflecting the erosion of the real minimum wage over this period), but no variation across groups.

The late-1990s sample looks notably different. First, labor supply trends are similar to those seen in the mid-1990s samples, with large relative increases in the supply of low-skill women with children. This most likely reflects three factors: The delayed impacts of the EITC expansion, the effects of welfare reform, and the extremely low unemployment rate during the late 1990s, which drew many previously unemployable individuals into the labor force. Turning to changes in wage schedules, these are again similar to those seen in the base sample, with slight hollowing-out in the middle of the distribution. The spike at the very bottom is much less prominent here, and there are essentially no differences by the number of children.

Taking the estimates in Figure 11 together, it seems clear that there were large increases in the relative labor supply of low-skill single mothers beginning in the mid-1990s and continuing into the later part of the decade. These do not appear to reflect a pre-existing trend, so can be plausibly attributed to the EITC. Similarly, it would be difficult to argue that there was a long-run trend toward higher wages for low-skill workers that was interrupted by the EITC reform; the results seem to indicate that the EITC expansion failed to produce any substantial downward pressure on wages at the bottom of the distribution. There is some indication, however, that the mid-1990s period saw divergence between the wages of women with and without children–with relative declines of those with children, particularly at low- and mid-level wages–that are not seen in other periods. The model above ruled out this sort

[27] The mid-1980s is an exception: The EITC was expanded in 1985. By the standards of the mid-1990s, however, the expansion was small, changing marginal tax rates by only 4 percentage points and increasing the maximum credit by only $50.

of response with its assumption of perfect substitutability.

7 Estimates of changing tax parameters

In order to connect the changes in labor supply and wage schedules estimated above to the EITC expansion, I require estimates of the changes in tax rates experienced by each skill group. Using March CPS data from the pre- and post-period, I can estimate the wage-tax parameter relationships in each period, as are presented for the pre-period in Figures 4-6. Let $\tau_{gt}(w)$ be the average tax rate experienced by a worker of wage w from group g in period t. The change in average tax rates experienced by group-g workers of skill s (with pre-period wage $w = \Lambda_{g0}(s)$) is

$$\Delta_g^{\tau}(w) \equiv \tau_{g1}\left(w + \Delta_g^{w}(w)\right) - \tau_{g0}(w). \tag{37}$$

The dashed lines in Figure 12 present estimates of $\Delta_g^{\tau}(w)$ for each demographic group. Figure 13 repeats the exercise for marginal tax rates (MTRs) and Figure 14 for average tax rates (ATRs).

The measured tax change has three components: Changes in the tax schedule, changes in the wage schedule–which might shift a worker to a different segment in the tax schedule even if labor supply were unchanged–and changes in hours of work. The latter two mean that $\Delta_g^{\tau}(w)$ is clearly endogenous to the outcomes of interest. I isolate an exogenous component of the tax change by estimating the change in tax parameters assuming no change in labor supply and a constant 3% per year growth in real wages and earnings. In practice, this involves calculating $\tilde{\tau}_{g1}(w)$ by applying the post-expansion (1995) schedule to data from the pre-reform March CPS, assuming that real wages and incomes grew 3% per year between 1992/3 and 1995. I then compute $\tilde{\Delta}_g^{\tau}(w) \equiv \tilde{\tau}_{g1}(w) - \tau_{g0}(w)$, the portion of changes in tax rates that derives directly from the EITC reform. These series are graphed as solid lines in Figures 12-14.

Not surprisingly, given the extremely low earnings threshold for the zero-child EITC that was introduced in 1994, the solid lines are nearly flat at zero for both married and unmarried childless women, with only slight changes in average tax parameters for the lowest-wage single women. The EITC expansion had slightly more of an effect on low-wage married women with children, increasing average credits by about \$250 at the very bottom of the wage distribution and increasing marginal tax rates by about 2.5 percentage points. The bulk of the EITC's effect, however, appears for single mothers, for whom the increase in the credit amounted to over \$700 at wages below about \$7 per hour. Simulated marginal tax rates fell by about five percentage points at the bottom of the wage distribution, rose by nearly as much in the middle of the distribution, and were flat among the highest-wage women. By contrast, average tax rates fell for all single mothers with wages below about \$11 and were essentially flat above that point.

There is clearly a strong relationship between the simulated and actual series in Figures 12-14, both across and within groups defined by marital status and presence of children. The EITC expansion accounts for most of the sizable changes in tax parameters experienced by single mothers over this period.[28] There is little variation in either marginal or average tax rates for the other demographic groups. Appendix Table 1 presents regression models relating the simulated and actual tax parameters; these models are the first stages for the instrumental variables models for wages and labor supply below.

8 Estimates of Supply and Demand Elasticities

The graphical evidence in Figures 7, 8, 9, and 10 certainly appears consistent with a substantial labor supply response among single mothers to the EITC expansion and, perhaps a bit less convincingly, with a decline in these women's wages relative to those of other groups. In this section, I formalize this somewhat, presenting regression models fit to the estimated changes in tax parameters, labor supply, and wage schedules. Specifically, I form a data set by taking each half-percentile of the initial female wage distribution as a distinct skill group, discarding

[28] The largest divergence between simulated and actual changes is for the MTRs of single mothers earning around \$5-\$6 in 1992. Recall (Figure 3) that this is the range where many women transition from the phase-in to the plateau region of the credit. As seen in Figure 9, real wages for single mothers at this skill level grew quickly over my sample period, and the resulting "bracket creep" meant rising MTRs for many of them. The simulation assumes constant nominal wages, so misses this effect.

the top and bottom three percentiles. For each skill group I measure the change in tax rates (marginal and average), labor supply, and wages experienced by each of six demographic groups: Single and married women, with zero, one, and two or more children. I use these data to estimate models like (32) and (33).

Computation of standard errors for regressions estimated from this data set is not straightforward. The estimated changes in labor supply and wage schedules that form the dependent variables are clearly not independent across adjacent percentiles of the initial wage distribution. Relatedly, the relevant sampling is not of percentiles but of the original CPS data used to compute the labor supply, tax, and wage changes at each percentile. Thus, to compute standard errors I use the bootstrap samples used earlier to produce confidence intervals for the nonparametric estimates. I re-estimate each regression on each bootstrap sample, and report the standard deviation of the resulting coefficients across the 600 samples as the standard errors for coefficients estimated from the primary sample.

8.1 Reduced-form estimates

I begin with estimates of the reduced-form equation (32), relating the tax change experienced by workers of skill s in group g to changes in labor supply and wages for those workers. Table 2 presents estimates of models that take as the dependent variable the change in labor force participation rates. Panel A presents OLS estimates, and Panel B IV estimates that use the simulated tax change as an instrument for the observed change in tax rates. In each panel, I consider three models, characterized by different definitions of tax rates, and nine specifications. In "Model 1," τ is the marginal tax rate, so $\Delta_g^{\tau}(w_s)$ is the change in average MTRs experienced by skill-s workers from group g. In "Model 2," τ is the ATR, and in "Model 3" both the change in average MTRs and the change in average ATRs are included.

Focus first on the OLS estimates in Panel A. Columns A-C are estimated using data on all women, with fixed effects for each group (married and single crossed with zero, one, and two or more children). Column A also includes a single base log wage term that takes a common coefficient across the six groups. The estimate for Model 1 indicates that for each percentage point increase in MTRs, labor force participation falls 0.38%. Model 2 indicates much larger responses to ATRs, with a decline in labor force participation of 1.1% for each percentage point increase in ATRs. When both MTRs and ATRs are included, in Model 3, the ATR effect is essentially unchanged, but the MTR effect disappears, with a positive point estimate that is not significantly different from zero.

Column B adds to the specification fixed effects for each skill group (identified by the pre-period wage). In this column, tax effects are identified only from the covariance along the skill distribution between between-group contrasts in tax changes and between-group contrasts in participation. Estimates are quite similar to those in column A. Column C adds separate base log wage effects for each of the six groups, to absorb any unobserved determinants of each group's labor supply that are linearly related to the log wage. This shrinks the ATR coefficient by about two thirds, though it remains significantly different from zero.

The remaining columns repeat these specifications on more restricted samples. In Columns D-F, the sample consists of the three groups (zero, one, and two or more children) of single women, while in Columns G-I only single mothers are included, with identification coming from the contrast between women with one and two or more children. Estimates are quite similar to those seen in A-C, though the coefficients are less precisely estimated. As a result, the ATR coefficient in the most saturated models ceases to be significant.

Panel B presents instrumental variables estimates of each specification. These are generally similar to those estimated by OLS. The pattern is clear: There appear to be substantial effects of ATRs on labor force participation rates, though these are somewhat sensitive to the inclusion of group-specific trends. (This should not be particularly surprising: The changes in ATRs are very nearly linear in the log wage within each group, so the mid-1990s expansion cannot be used identify their effects distinct from linear trends.) By contrast, there appear to be no effects of changes in MTRs on participation. Although standard errors are sometimes large, point estimates generally have the wrong sign.

Table 3 repeats the exercise with the change in hours conditional on working as the dependent variable. Neither of the tax variables has a coefficient that is significantly different from zero in any specification, and point estimates are nearly uniformly quite small. There appears to be no relationship of the change in taxes with labor supply responses on the intensive margin.

Table 4 presents estimates for total labor supply, combining participation, employment, and hours. Estimates are similar to those seen in Table 2, though point estimates are somewhat smaller. In my preferred specification, the OLS estimate of Model 3 in Column E, a one percentage point increase in ATRs leads to a 0.85% reduction in hours worked.

Table 5 presents estimates for hourly wages. In the first two columns, there appears to be a negative relationship between ATRs and wages–the opposite of the sign predicted by incidence theory, which suggests that a tax increase should lower labor supply and raise wages–but this is not at all robust to discarding married women from the sample.

Finally, Table 6 presents a summary of models for various dimensions of labor supply, estimated by OLS from the sample of single women. The dependent variables considered thus far are presented in rows 1, 4, 5, and 6. The remaining rows present estimates for employment conditional on labor force participation (row 2, with tax increases associated with increases in employment), for total employment rates (row 3, with a negative relationship between taxes and employment), and for two variables, non-allocation of wages and population composition, that are discussed in the Appendix. In each case, the estimated effects are consistent with those shown earlier in the Figures 7, 8, and 9. Each effect is robust to the inclusion of skill-level fixed effects, though none are robust to the addition of group-specific base log wage controls.

8.2 Structural estimates of supply and demand elasticities

The models in Tables 2, 3, 4, and 6, particularly those including skill group fixed effects, provide estimates of the elasticity of labor supply: The coefficients on tax rates estimate $-\sigma$. The results thus indicate a substantial elasticity of labor force participation, employment, and total hours with respect to the average tax rate, albeit one that is somewhat sensitive to the addition of group-specific inequality trends. On the other hand, the wage estimates in Table

5 do not estimate the demand elasticity, as demand responses to tax increases should be seen in all groups' wages equally, and are therefore absorbed by the skill group fixed effects.

To make progress on this parameter, I turn to more restrictive models, like (33), that replace the skill group fixed effects with the average tax rate experienced by workers of skill s across groups, which in my linear specification summarizes the effect of the tax change on labor supply. Table 7 presents estimates of several such models, all estimated by OLS. Standard errors for regression coefficient estimates are computed as the standard deviation of the coefficients across bootstrap estimates, while inference for optimal minimum distance (OMD) estimates of the elasticity parameters uses formula (36) together with the bootstrap variance matrix for the regression coefficients.

Recall that labor supply is predicted to be negatively responsive to the own-group tax rate, but when this is held constant to be positively responsive to the average tax rate across groups. (The logic is that a high tax rate on another group competing in my labor market lowers labor supply of members of that group, raising the equilibrium wage, and the wage increase induces me to increase my labor supply.) Wages are responsive only to the average tax rate across groups, and are predicted to rise with increases in taxes. Column A of Table 7 presents the parametric responses predicted by the model.

Column B presents estimates from a panel combining labor supply and wage changes of all three groups (no children, one child, and two or more children) of single women, with the coefficients on the tax variables constrained to be the same across groups. The specification includes fixed effects for each group (in changes) and a single base log wage effect that is constant across groups. The response of labor supply to the own-group change in tax rates is large and negative, consistent with the earlier estimates. The response to the across-group average change, however, is positive, as predicted, but much smaller. Turning to models for the change in wages, the coefficient on the own group ATR change is essentially zero. The coefficient on the across-group average wage change, however, is large, negative, and significant, where the predicted effect of this variable is positive.

The next three columns (C1-C3) present a second set of estimates in which the tax parameters are allowed to have different coefficients in each of the three groups. Results are generally similar to those in Column B, though the regression coefficients are more variable across groups than might have been expected. The remaining columns of the table repeat the specifications on a sample restricted just to single mothers, with identification coming from the differential treatment of women with one and with two or more children. (These models implicitly assume that the relevant labor market excludes childless women, so that tax rates averaged across single mothers are sufficient statistics for the total impacts of the EITC expansion on labor supply.) In each case, the coefficients on the across-group average tax rate in the wage model are large and negative, the opposite of the predicted effects.

Panel B presents optimal minimum distance estimates of the elasticity parameters, computed from each set of regression coefficients. It also presents test statistics and p-values from overidentification tests, which fail to reject in three out of four cases. (The exception derives from the inclusion of single women without children in Column C, as the regression coefficients are substantially different for this group, whose taxes essentially didn't change, than for the other groups.) The estimated supply elasticities are quite stable across specifications, ranging from 0.4 to 0.5 with reasonably small standard errors. Demand elasticities, however, are uniformly large, positive, and significantly different from zero. All are much larger than the supply elasticities. This cannot be correct, as it implies that any labor market equilibrium is unstable: A small positive perturbation to labor supply would cause large increases in both wages and labor supply.

The only reasonable conclusion that one can draw from these results is that the simple model presented earlier cannot account for the observed changes in labor supply and wages. Given the large negative coefficients on the across-group average tax rate, nearly all of which are significant, it does seem safe to conclude as well that the expansion of labor supply induced by the EITC–and well-identified in the reduced-form models above–did not lead to a reduction in wages for the affected women.

9 Discussion

This paper has investigated the aggregate labor supply impacts and the wage effects of the mid-1990s EITC expansion. I extend methods proposed by DiNardo, Fortin, and Lemieux (1996) to permit a semiparametric analysis of wage and labor supply changes among women of different skill groups, exploiting variation across the wage distribution in exposure to the EITC to generate variation in the change in tax rates. This approach shows promise for the empirical evaluation of the incidence of federal taxes, which are otherwise quite difficult to study given their uniformity across space and their spillover effects on untaxed participants in the same labor market as those facing the tax.

The clearest result of my investigation is that the EITC expansion lead to substantial increases in the labor force participation rates of low-skill single mothers, but had no effect on weekly hours conditional on participation. Implied elasticities of total hours worked with respect to the after tax average wage are reasonable, in the 0.5 - 1.0 range.

Unfortunately, the dependence of supply on average tax rates reduces the power of my approach to estimate wage effects, as there is substantially less variation of average than of marginal tax rates across workers with different wages. Thus, I am unable to obtain precise estimates of the effect of the EITC expansion on wage rates. I find no evidence, however, that the effect was to reduce wages in the relevant labor markets. Rather, reductions in average tax rates are associated with *increases* in hourly wages. The data are not consistent with a simple model of the labor market, but seem to indicate that the elasticity of labor demand is, if anything, positive. Given the inability of simple models to explain the observed results, it would be premature to place much confidence on the positive estimated elasticity. However, it does seem reasonable to conclude, tentatively, that employers were unable to capture the benefit of the EITC expansion, and that workers may even have obtained more than 100 percent of the benefits.

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Figure 1. EITC Tax Schedule (Parameters Exaggerated for Readability)

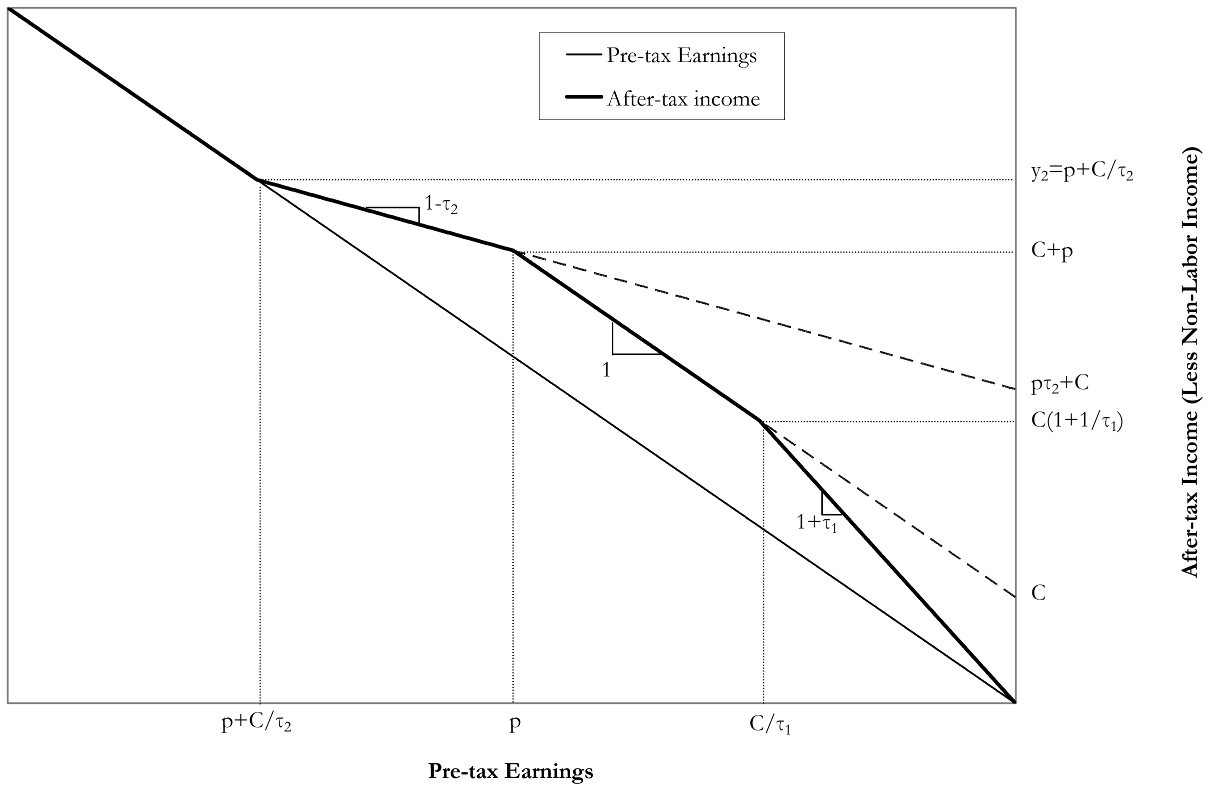


Figure 2. EITC Schedule, 1992 and 1996

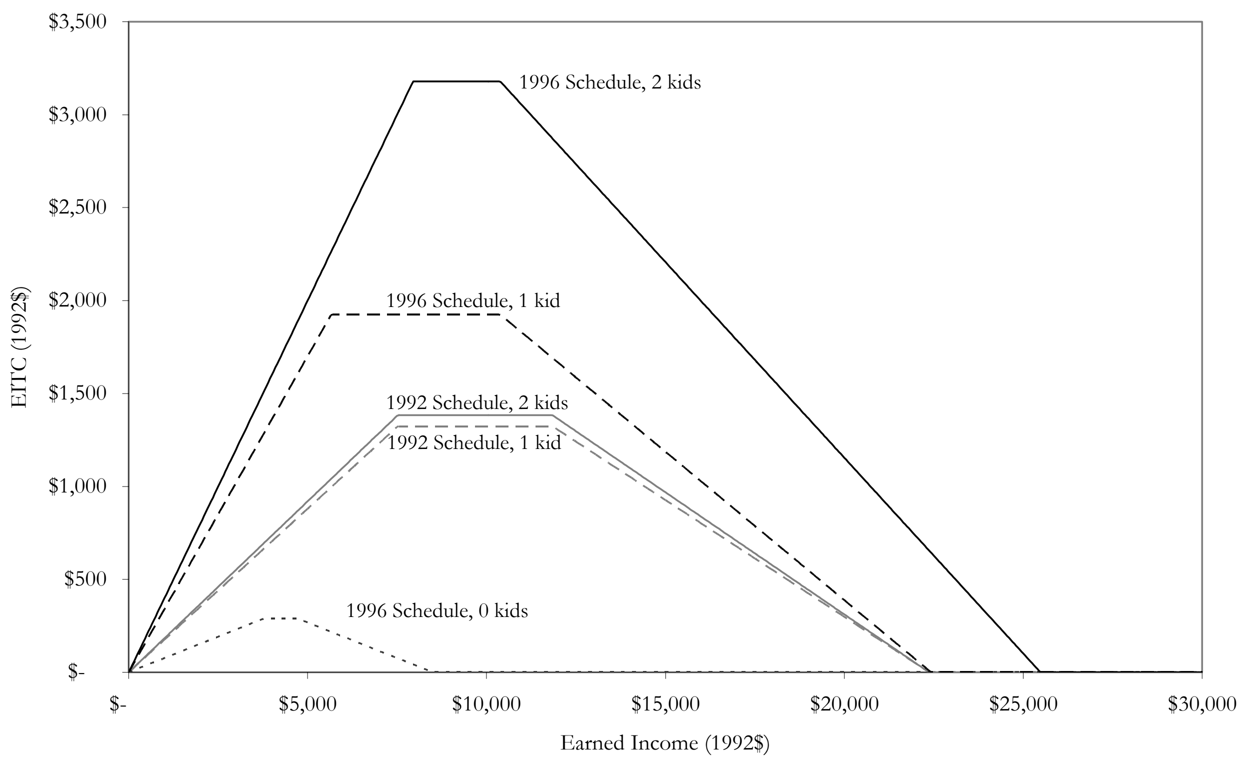
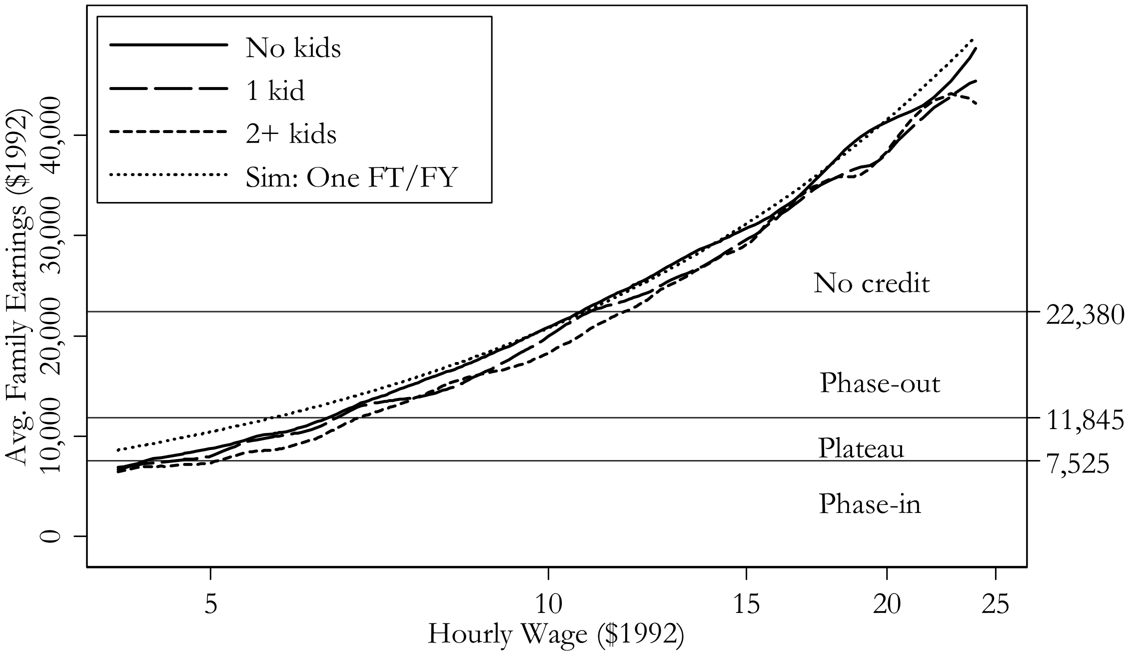
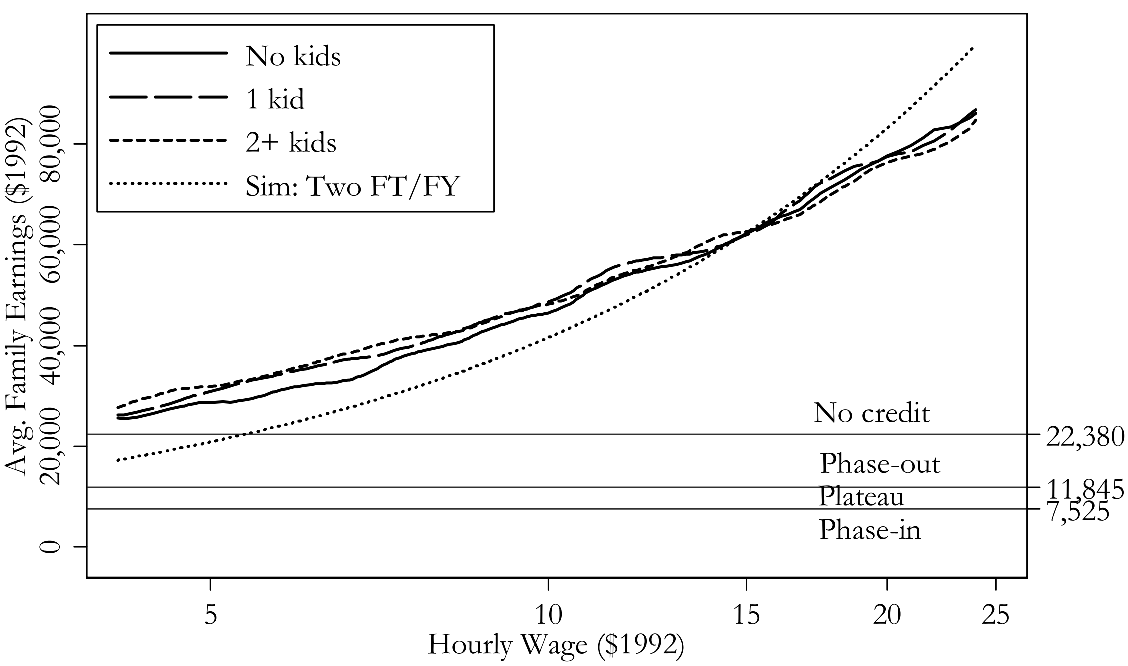


Figure 2A.
Avg. family earnings as a function of women's hourly wage, 1992/3, unmarried women



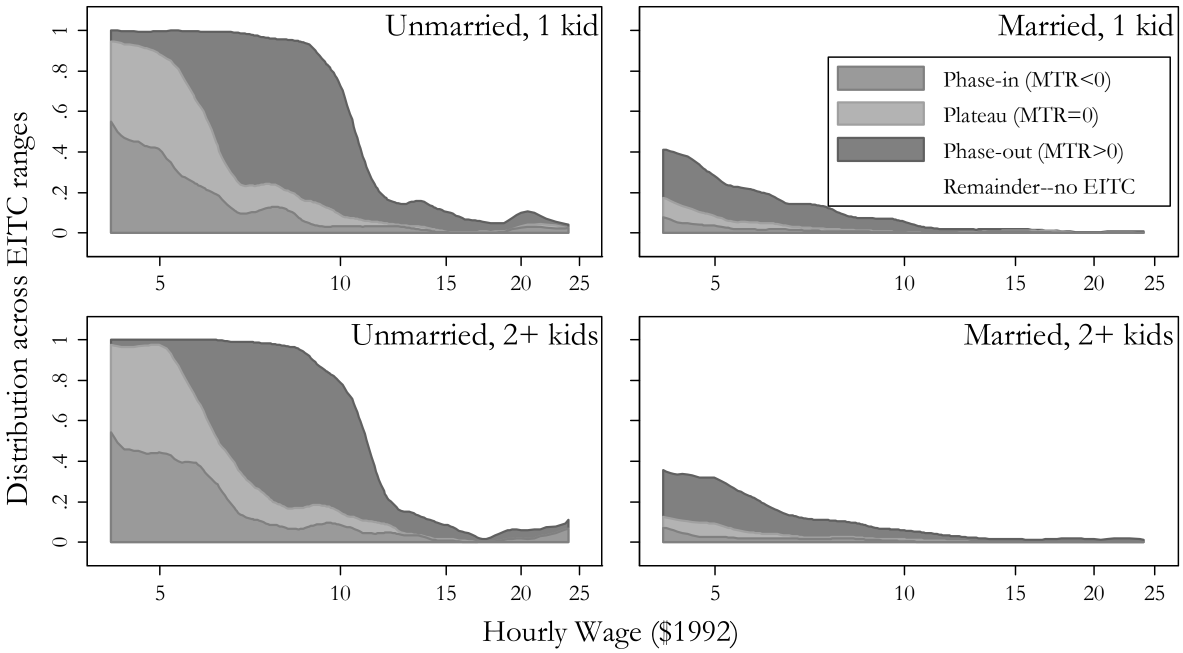
Source: Author's analysis of 1993 (MIS 5-8 only) and 1994 March CPS.

Figure 2B.
Avg. family earnings as a function of women's hourly wage, 1992/3, married women



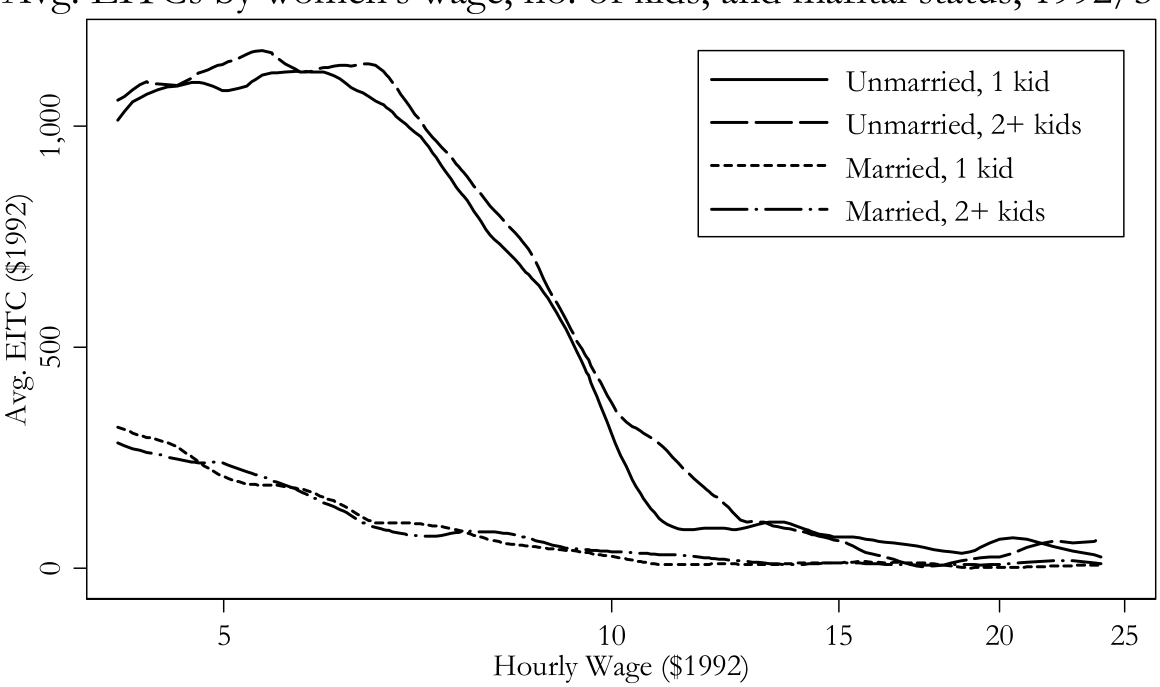
Source: Author's analysis of 1993 (MIS 5-8 only) and 1994 March CPS.

Figure 3.
Distribution of women with children across EITC schedule brackets, 1992/3, by marital status and # of children



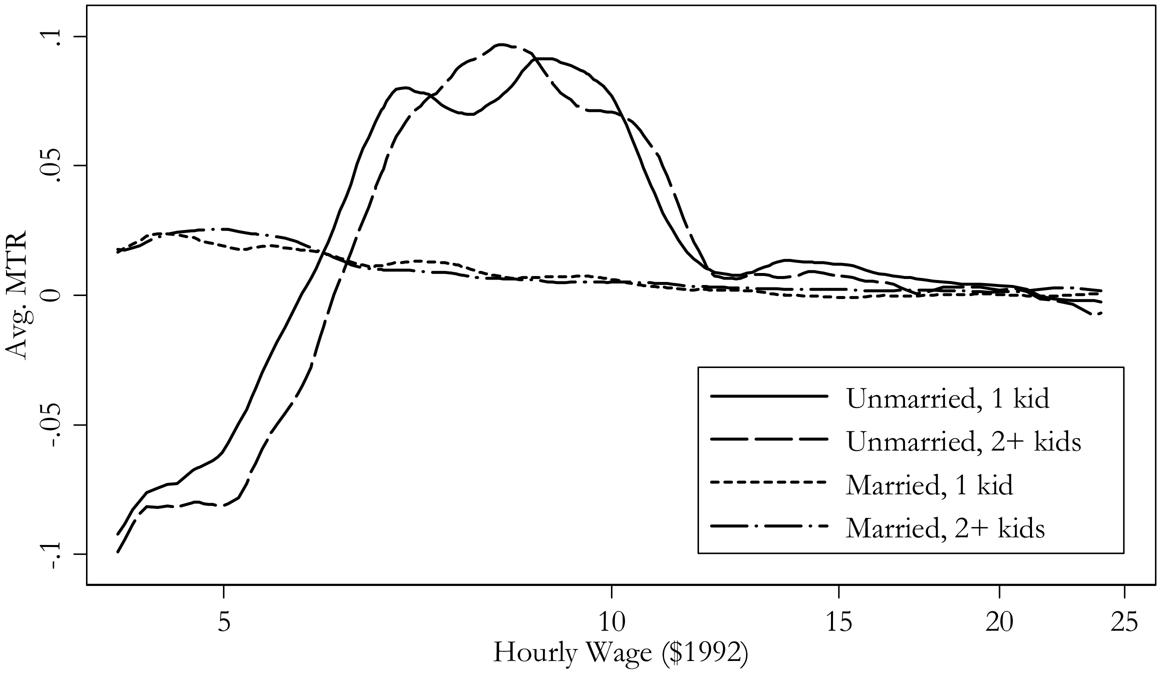
Source: Author's analysis of 1993 (MIS 5-8 only) and 1994 March CPS. Credits are simulated, and averages estimated by kernel regression on log hourly wage, with Epanechnikov kernel and bandwidth of 0.05.

Figure 4.
Avg. EITCs by women's wage, no. of kids, and marital status, 1992/3



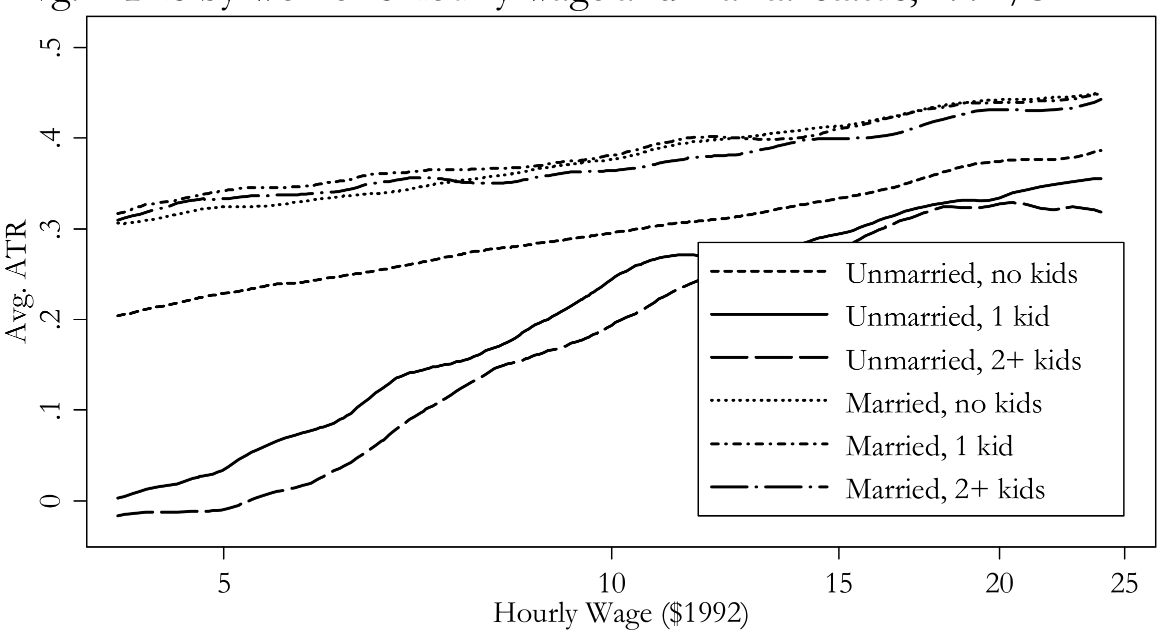
Source: Author's analysis of 1993 (MIS 5-8 only) and 1994 March CPS. Credits are simulated, and averages estimated by kernel regression on log hourly wage, with Epanechnikov kernel and bandwidth of 0.05.

Figure 5.
Avg. EITC MTRs by women's hourly wage and marital status, 1992/3



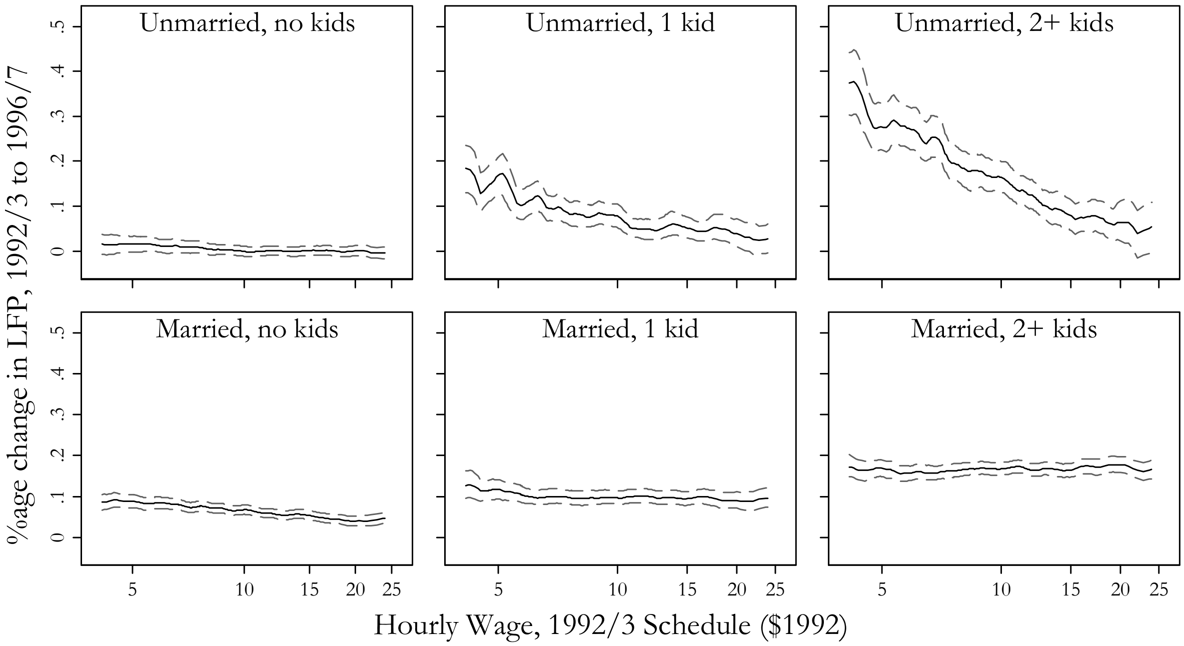
Source: Author's analysis of 1993 (MIS 5-8 only) and 1994 March CPS. Credits are simulated, and averages estimated by kernel regression on log hourly wage, with Epanechnikov kernel and bandwidth of 0.05.

Figure 6.
Avg. ATRs by women's hourly wage and marital status, 1992/3



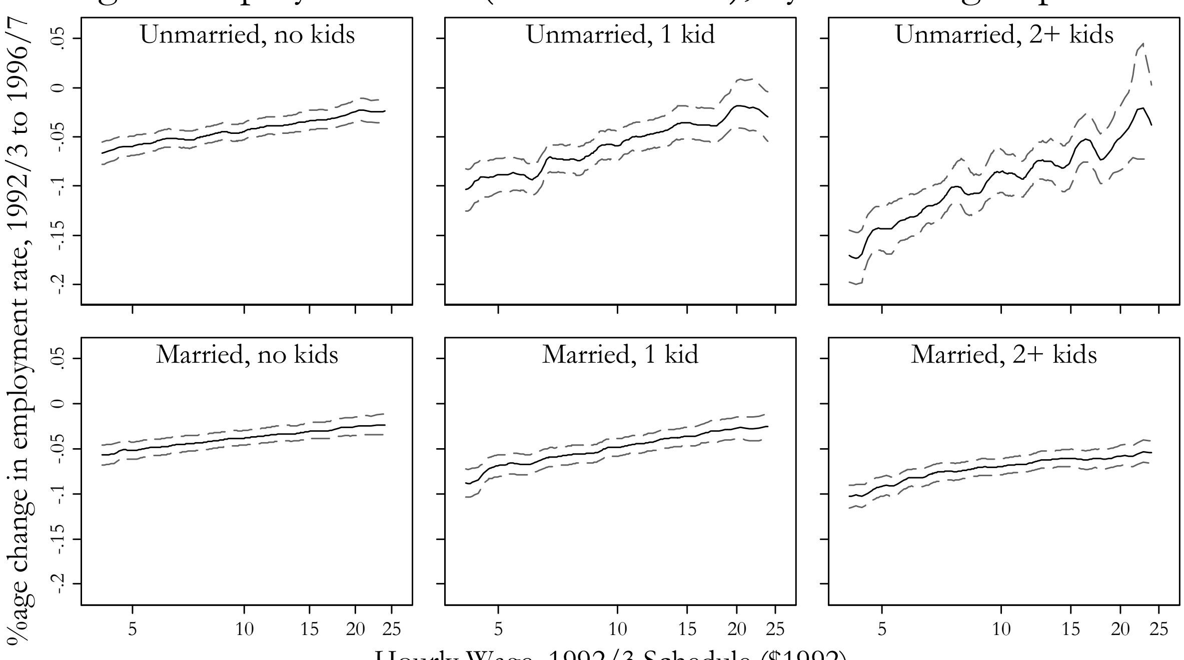
Source: Author's analysis of 1993 (MIS 5-8 only) and 1994 March CPS. ATRs include payroll taxes and federal and state income taxes, as computed by TAXSIM, and are average tax rates over female earnings. Averages are estimated by kernel regression on the log hourly wage, with Epanechnikov kernel and bandwidth of 0.05.

Figure 7A.
Change in labor force participation, by skill and group



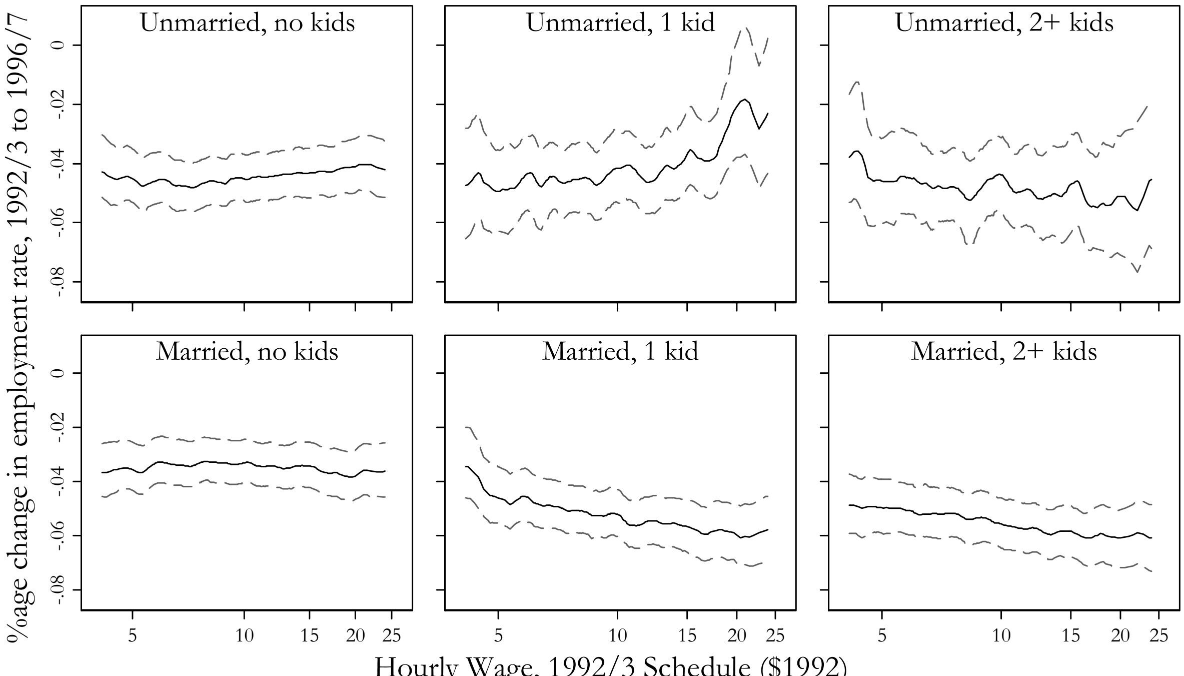
Source: Author's analysis of 1992/3 and 1995-7 CPS ORG. Participation rate is fraction of women who worked, had a job, or looked for work. 90% confidence intervals, indicated by dashed lines, are computed by sampling from the underlying microdata (with replacement) and feeding bootstrap samples through the DFL algorithm; see text for details.

Figure 7B.
Change in employment rate (of those in LF), by skill and group



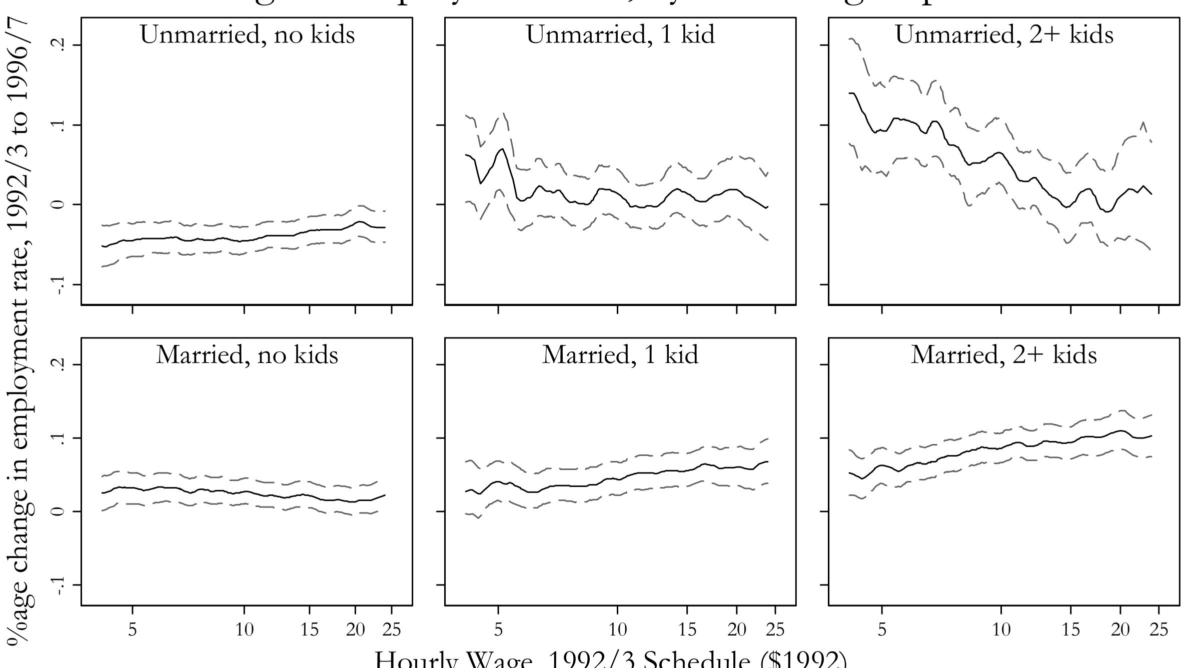
Source: Author's analysis of 1992/3 and 1995-7 CPS ORG. Employment rate is fraction of women in LF who worked some hours during the year. 90% confidence intervals, indicated by dashed lines, are computed by sampling from the underlying microdata (with replacement) and feeding bootstrap samples through the DFL algorithm; see text for details.

Figure 7C.
Change in avg. hours conditional on employment, by skill and group



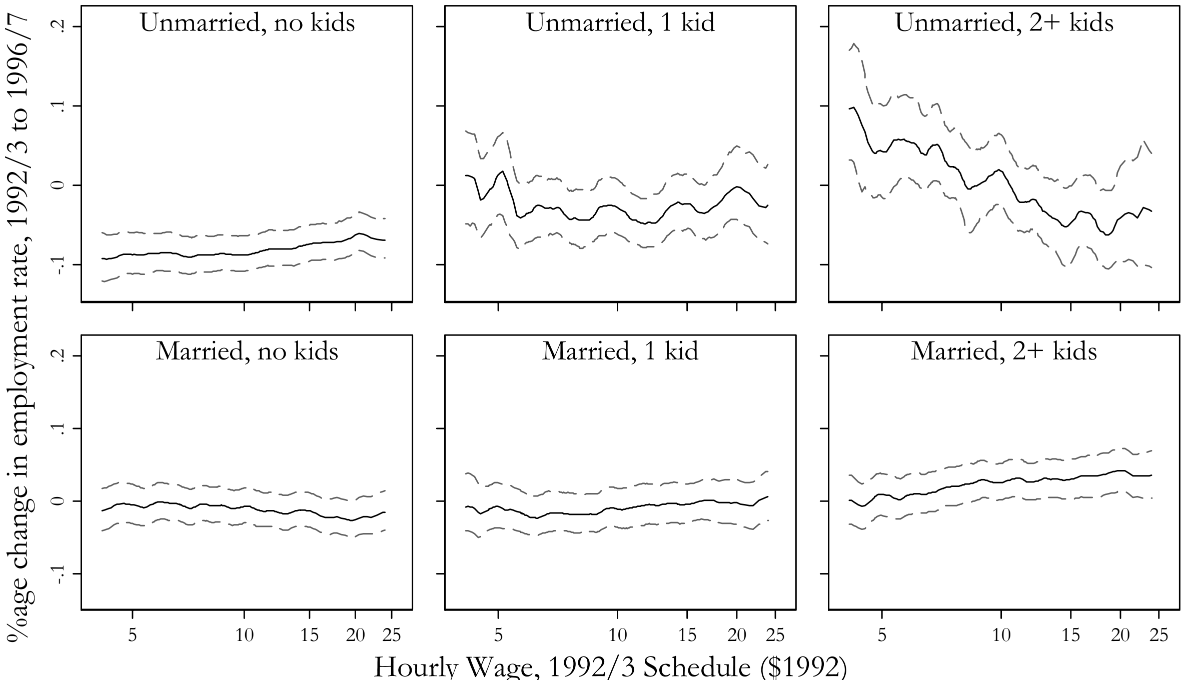
Source: Author's analysis of 1992/3 and 1995-7 CPS ORG. 90% confidence intervals, indicated by dashed lines, are computed by sampling from the underlying microdata (with replacement) and feeding bootstrap samples through the DFL algorithm; see text for details.

Figure 8A.
Net change in employment rate, by skill and group



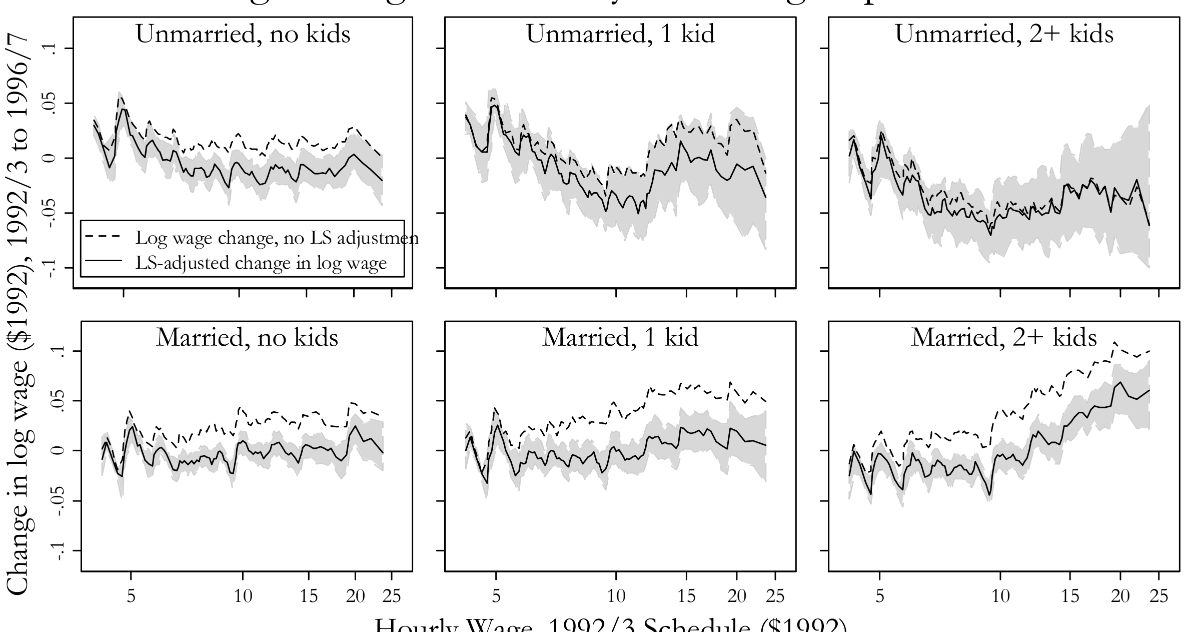
Source: Author's analysis of 1992/3 and 1995-7 CPS ORG. Employment rate is fraction of women who worked some hours during the year. 90% confidence intervals, indicated by dashed lines, are computed by sampling from the underlying microdata (with replacement) and feeding bootstrap samples through the DFL algorithm; see text for details.

Figure 8B.
Change in average hours worked, by skill and group



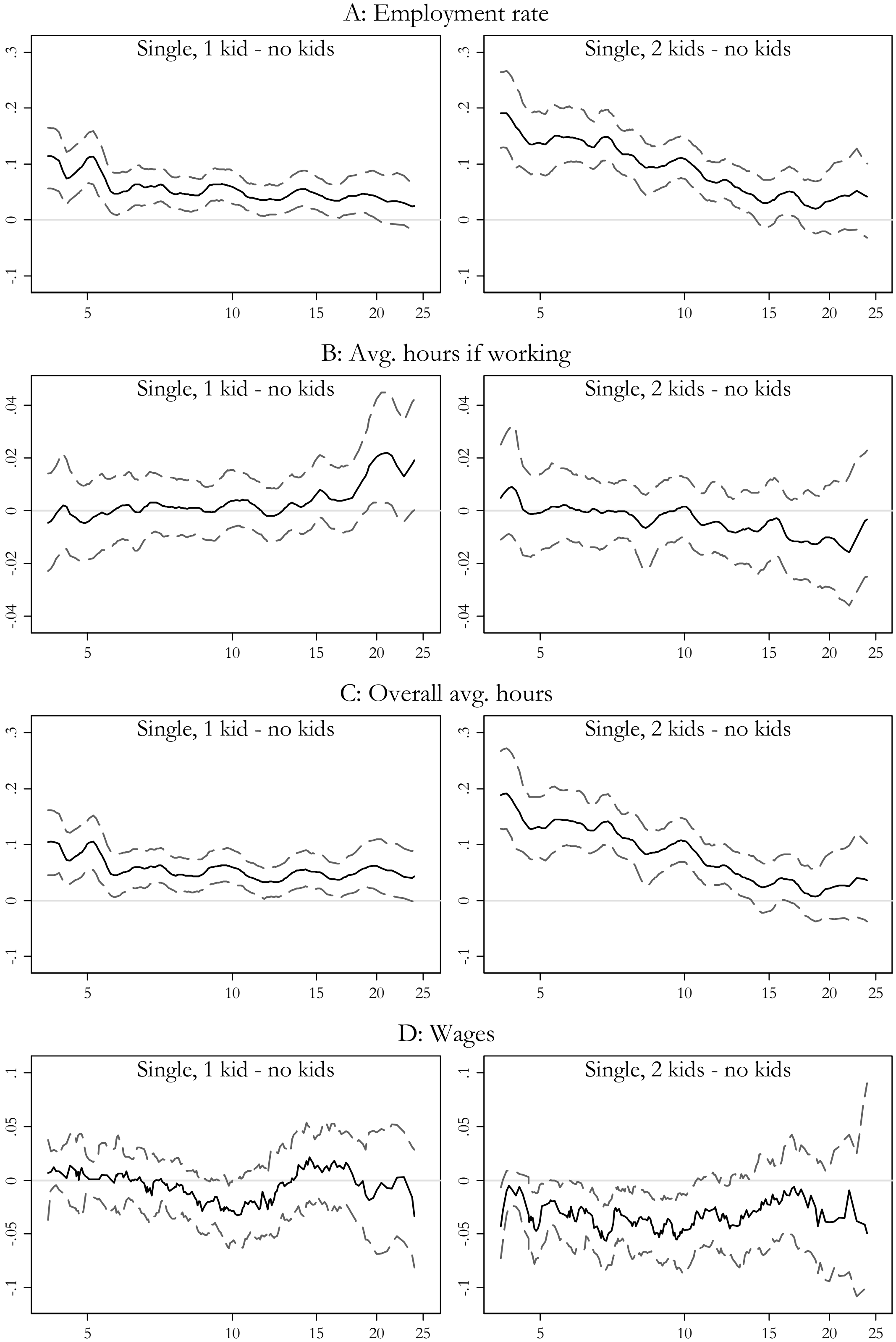
Source: Author's analysis of 1992/3 and 1995-7 CPS ORG. 90% confidence intervals, indicated by dashed lines, are computed by sampling from the underlying microdata (with replacement) and feeding bootstrap samples through the DFL algorithm; see text for details.

Figure 9.
Change in wage schedule by skill and group



Source: Author's analysis of 1992/3 and 1995-7 CPS ORG. 90% confidence intervals for labor-supply-adjusted series, shaded, are computed by bootstrapping the underlying microdata (with replacement) and feeding the bootstrap samples through the DFL algorithm; see text for details. Estimate without LS adjustment is the change at corresponding percentiles of the wage distribution, without adjusting for changes in the distribution of skill in the labor force.

Figure 10.
Difference-in-difference estimates of changes in labor supply and wage schedules, single mothers minus single women without children



Note: 90% confidence interval indicated by dashed lines

Figure 11.
Estimates of labor supply and wage schedule changes in four samples, Single women, by number of children

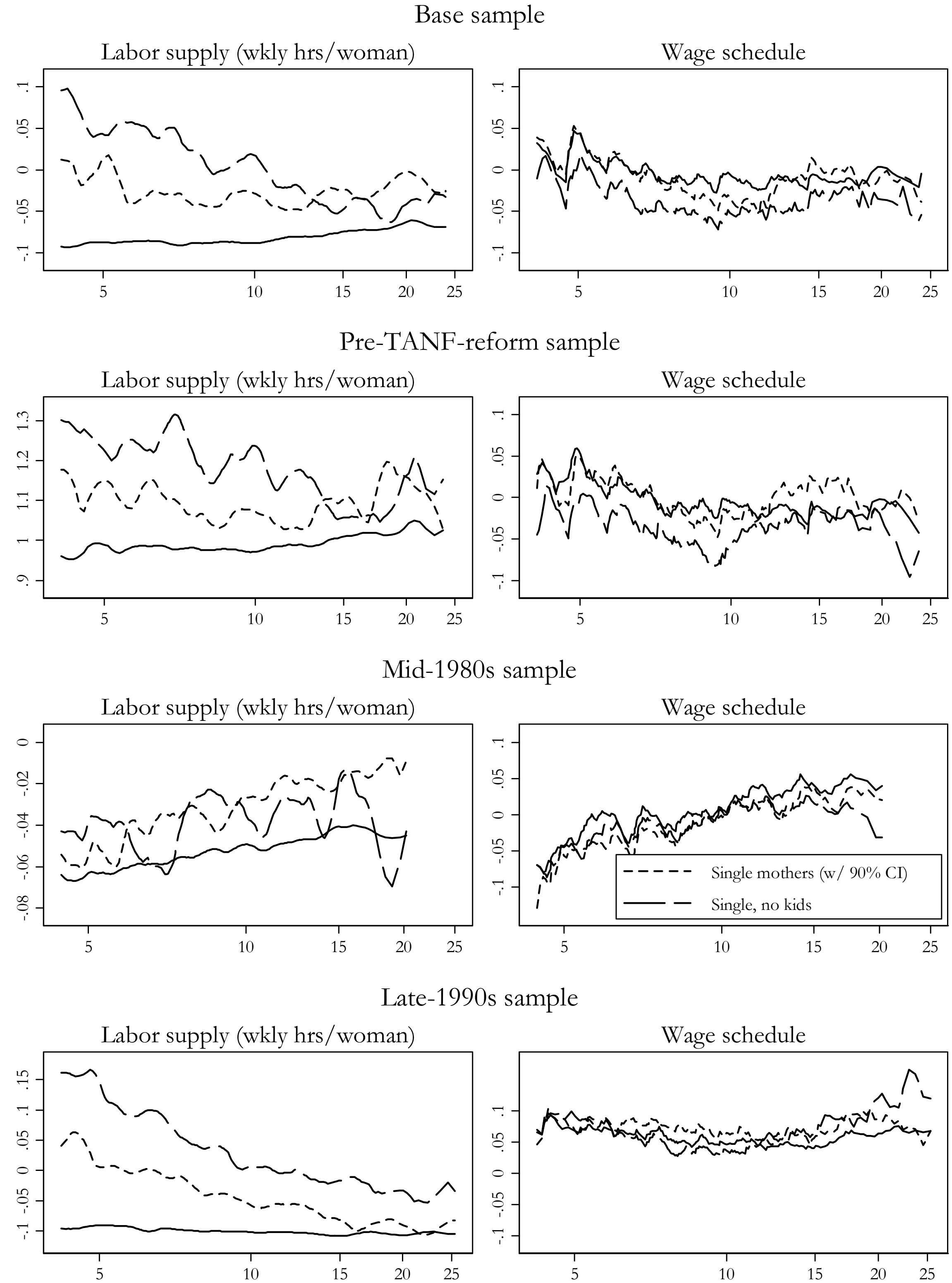
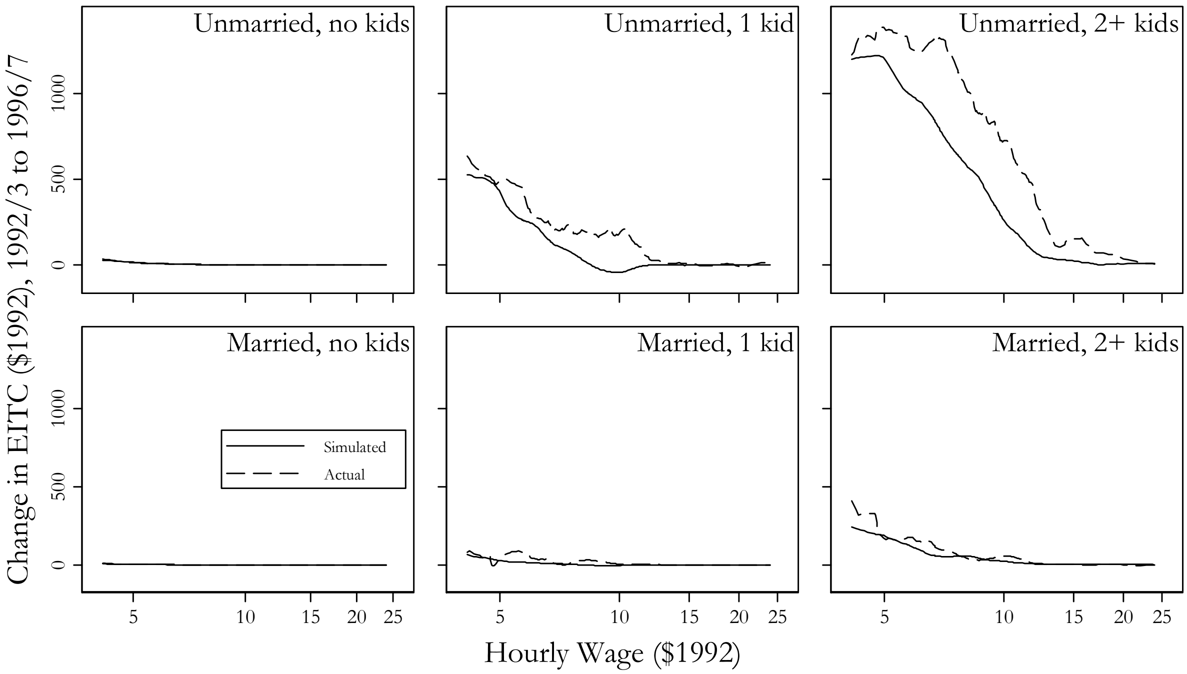
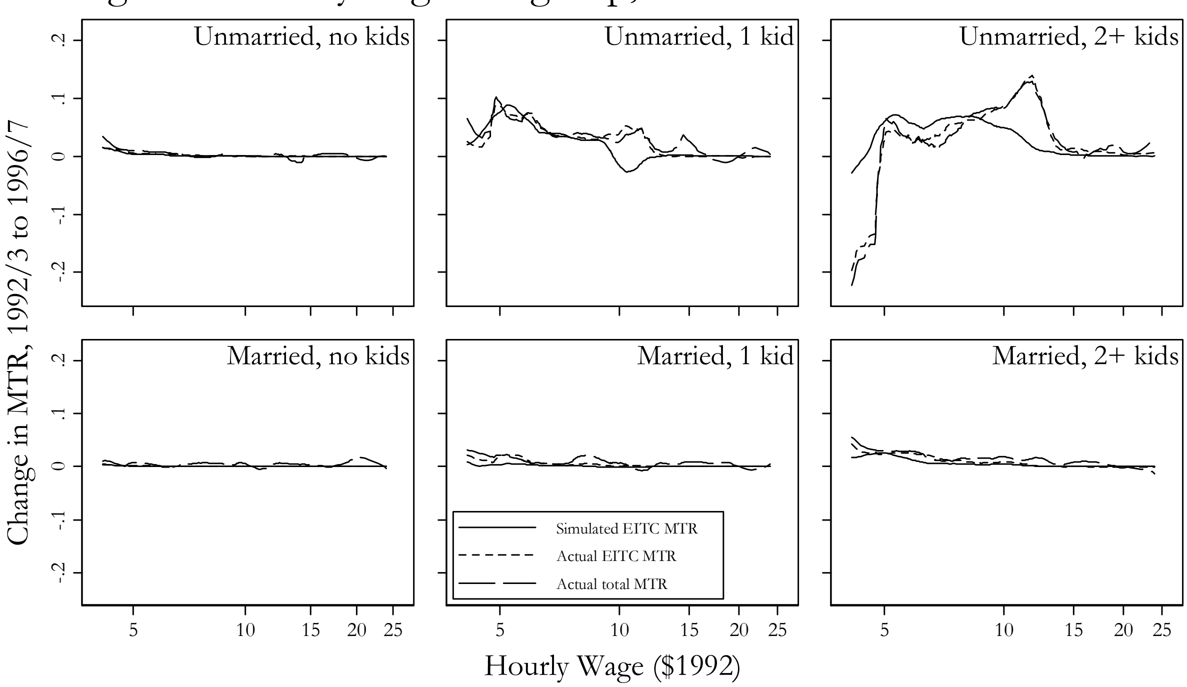


Figure 12.
Change in real EITCs by wage and group, actual and simulated



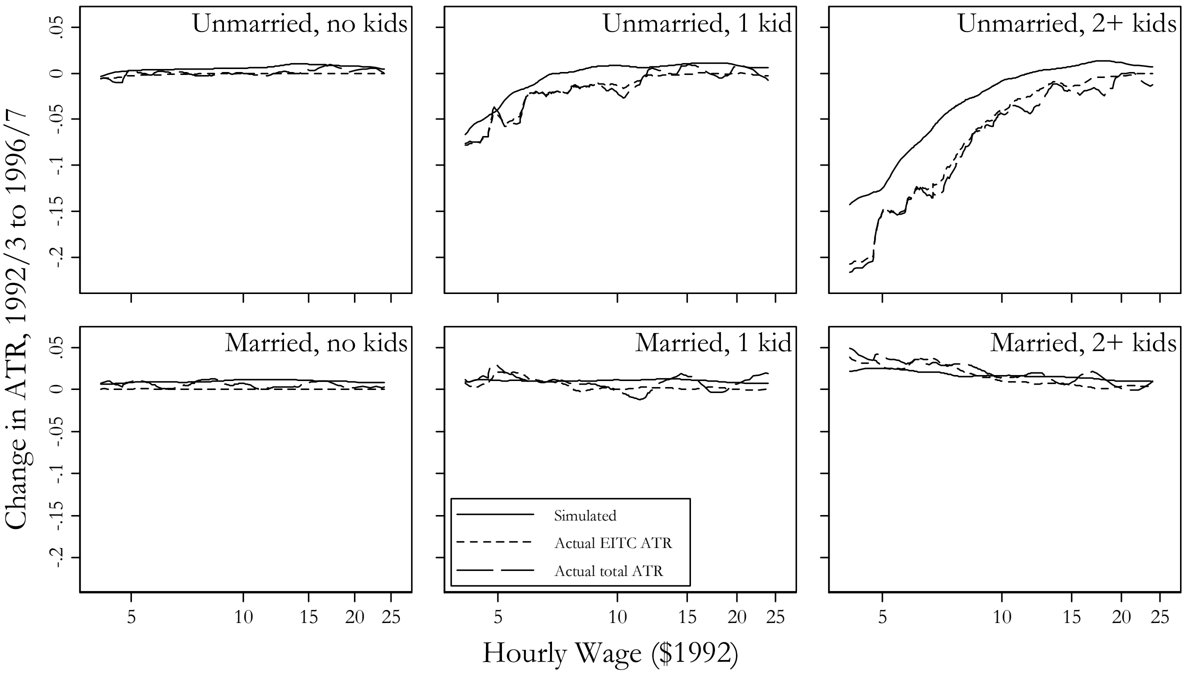
Source: Author's analysis of 1993/4 and 1997/8 March CPS. "Simulated" series applies change in EITC schedule to pre-change sample; "actual" series adjusts for changes in wage schedules to compare at similar points in a constant-skill wage distribution. See text (Section #) for details.

Figure 13.
Change in MTRs by wage and group, actual and simulated



Source: Author's analysis of 1993/4 and 1997/8 March CPS. "Simulated" series applies change in EITC schedule to pre-change sample; "actual" series compare workers at similar points in a constant-skill wage distribution. See text (Section #) for details.

Figure 14.
Change in ATRs by wage and group, actual and simulated



Source: Author's analysis of 1993/4 and 1997/8 March CPS. "Simulated" series applies change in tax schedule to pre-change sample; "actual" series compare workers at similar points in a constant-skill wage distribution. See text (Section #) for details.

Table 1. EITC parameters, 1987-2001 (in constant 1992 dollars)

# of children	Year	Marginal tax rates: Phase-in ($-\tau 1$)	Marginal tax rates: Phase-out ($\tau 2$)	Max. credit (C)	Kink points: 1) Phase-in to plateau	Kink points: 2) Plateau to phase-out (p)	Kink points: 3) Phase-out to no credit	Hourly wage for FT, FY worker to hit: Kink 1	Kink 2	Kink 3	Federal minimum wage
(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
One-child families											
	1983	-10.0%	12.5%	$704	$7,043	$8,452	$14,086	$3.52	$4.23	$7.04	$4.72
	1984	-10.0%	12.5%	$675	$6,752	$8,102	$13,503	$3.38	$4.05	$6.75	$4.52
	1985	-14.0%	12.2%	$717	$6,520	$8,475	$14,343	$3.26	$4.24	$7.17	$4.37
	1986	-14.0%	12.2%	$704	$6,401	$8,321	$14,081	$3.20	$4.16	$7.04	$4.29
	1987	-14.0%	10.0%	$1,051	$7,509	$8,546	$19,059	$3.75	$4.27	$9.53	$4.14
	1988	-14.0%	10.0%	$1,037	$7,400	$11,670	$22,031	$3.70	$5.83	$11.02	$3.97
	1989	-14.0%	10.0%	$1,030	$7,354	$11,586	$21,882	$3.68	$5.79	$10.94	$3.79
	1990	-14.0%	10.0%	$1,023	$7,310	$11,518	$21,752	$3.66	$5.76	$10.88	$4.08
	1991	-16.7%	11.9%	$1,228	$7,355	$11,589	$21,890	$3.68	$5.79	$10.94	$4.38
	1992	-17.6%	12.6%	$1,324	$7,520	$11,840	$22,370	$3.76	$5.92	$11.19	$4.25
	1993	-18.5%	13.2%	$1,392	$7,525	$11,845	$22,380	$3.76	$5.92	$11.19	$4.13
	1994	-26.3%	16.0%	$1,929	$7,337	$10,414	$22,489	$3.67	$5.21	$11.24	$4.02
	1995	-34.0%	16.0%	$1,928	$5,671	$10,394	$22,459	$2.84	$5.20	$11.23	$3.91
	1996	-34.0%	16.0%	$1,924	$5,660	$10,382	$22,425	$2.83	$5.19	$11.21	$4.25
	1997	-34.0%	16.0%	$1,932	$5,682	$10,429	$22,509	$2.84	$5.21	$11.25	$4.50
	1998	-34.0%	16.0%	$1,955	$5,750	$10,553	$22,786	$2.87	$5.28	$11.39	$4.43
	1999	-34.0%	16.0%	$1,947	$5,727	$10,493	$22,677	$2.86	$5.25	$11.34	$4.34
	2000	-34.0%	16.0%	$1,917	$5,638	$10,339	$22,335	$2.82	$5.17	$11.17	$4.20
	2001	-34.0%	16.0%	$1,923	$5,656	$10,370	$22,404	$2.83	$5.19	$11.20	$4.08
Two or more children											
	1983-1990: Same as one child										
	1991	-17.3%	12.4%	$1,272	$7,355	$11,589	$21,890	$3.68	$5.79	$10.94	$4.38
	1992	-18.4%	13.1%	$1,384	$7,520	$11,840	$22,370	$3.76	$5.92	$11.19	$4.25
	1993	-19.5%	13.9%	$1,467	$7,525	$11,845	$22,380	$3.76	$5.92	$11.19	$4.13
	1994	-30.0%	17.7%	$2,393	$7,976	$10,414	$23,948	$3.99	$5.21	$11.97	$4.02
	1995	-36.0%	20.2%	$2,863	$7,954	$10,394	$24,555	$3.98	$5.20	$12.28	$3.91
	1996	-40.0%	21.1%	$3,180	$7,949	$10,382	$25,480	$3.97	$5.19	$12.74	$4.25
	1997	-40.0%	21.1%	$3,196	$7,990	$10,429	$25,604	$3.99	$5.21	$12.80	$4.50
	1998	-40.0%	21.1%	$3,233	$8,082	$10,553	$25,904	$4.04	$5.28	$12.95	$4.43
	1999	-40.0%	21.1%	$3,214	$8,034	$10,493	$25,753	$4.02	$5.25	$12.88	$4.34
	2000	-40.0%	21.1%	$3,168	$7,919	$10,339	$25,381	$3.96	$5.17	$12.69	$4.20
	2001	-40.0%	21.1%	$3,175	$7,938	$10,370	$25,454	$3.97	$5.19	$12.73	$4.08
Families without children											
	1983-1993: No credit										
	1994	-7.7%	7.7%	$290	$3,787	$4,733	$8,520	$1.89	$2.37	$4.26	$4.02
	1995	-7.7%	7.7%	$289	$3,774	$4,723	$8,497	$1.89	$2.36	$4.25	$3.91
	1996	-7.7%	7.7%	$289	$3,774	$4,721	$8,495	$1.89	$2.36	$4.25	$4.25
	1997	-7.7%	7.7%	$290	$3,794	$4,747	$8,540	$1.90	$2.37	$4.27	$4.50
	1998	-7.7%	7.7%	$294	$3,839	$4,794	$8,633	$1.92	$2.40	$4.32	$4.43
	1999	-7.7%	7.7%	$292	$3,815	$4,775	$8,590	$1.91	$2.39	$4.29	$4.34
	2000	-7.7%	7.7%	$288	$3,756	$4,701	$8,457	$1.88	$2.35	$4.23	$4.20
	2001	-7.7%	7.7%	$288	$3,771	$4,714	$8,483	$1.89	$2.36	$4.24	$4.08

Table 2. Reduced-form models for tax effects on labor force participation

	Sample								
	All women			Single women			Single mothers		
	(A)	**(B)**	**(C)**	**(D)**	**(E)**	**(F)**	**(G)**	**(H)**	**(I)**
Panel A: OLS									
Model 1									
Change in MTR	**-0.38**	**-0.39**	-0.10	**-0.34**	**-0.37**	-0.06	**-0.31**	**-0.37**	0.01
	(0.12)	(0.13)	(0.09)	(0.11)	(0.13)	(0.10)	(0.10)	(0.16)	(0.13)
Group dummies	5	5	5	2	2	2	1	1	1
Base log wage	y	n	n	y	n	n	y	n	n
Skill group fixed effects	n	y	y	n	y	y	n	y	y
Group-specific base log wage effects	n	n	5	n	n	2	n	n	1
Model 2									
Change in ATR	**-1.13**	**-1.14**	**-0.41**	**-1.17**	**-1.22**	-0.43	**-0.97**	**-1.05**	-0.24
	(0.14)	(0.15)	(0.17)	(0.18)	(0.20)	(0.24)	(0.22)	(0.29)	(0.32)
Model 3									
Change in MTR	0.12	0.14	0.00	0.16	0.19	0.04	0.08	0.15	0.07
	(0.10)	(0.11)	(0.10)	(0.11)	(0.13)	(0.12)	(0.11)	(0.17)	(0.15)
Change in ATR	**-1.20**	**-1.22**	**-0.40**	**-1.30**	**-1.37**	-0.50	**-1.07**	**-1.23**	-0.38
	(0.15)	(0.15)	(0.17)	(0.19)	(0.20)	(0.27)	(0.25)	(0.33)	(0.38)
Panel B: IV									
Model 1									
Change in MTR	**0.86**	**0.98**	-0.05	0.36	0.54	-0.03	-0.18	-0.14	0.05
	(0.40)	(0.43)	(0.15)	(0.23)	(0.28)	(0.16)	(0.16)	(0.20)	(0.19)
Model 2									
Change in ATR	**-1.20**	**-1.18**	-0.59	**-1.22**	**-1.25**	-0.52	**-1.05**	**-1.11**	-0.05
	(0.18)	(0.17)	(0.41)	(0.22)	(0.22)	(0.49)	(0.30)	(0.37)	(3.96)
Model 3									
Change in MTR	0.20	0.21	0.13	0.26	0.29	0.15	0.22	0.40	0.17
	(0.19)	(0.18)	(0.96)	(0.21)	(0.20)	(2.39)	(0.32)	(0.38)	(7.71)
Change in ATR	**-1.32**	**-1.30**	-0.85	**-1.47**	**-1.48**	-0.88	**-1.38**	**-1.59**	-0.55
	(0.20)	(0.19)	(3.88)	(0.26)	(0.24)	(5.63)	(0.59)	(0.59)	(35.40)

Table 3. Reduced-form models for tax effects on weekly hours conditional on working

	Sample								
	All women			Single women			Single mothers		
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
Panel A: OLS									
Model 1									
Change in MTR	-0.03	-0.03	0.00	-0.04	-0.04	0.01	-0.04	-0.04	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Group dummies	5	5	5	2	2	2	1	1	1
Base log wage	y	n	n	y	n	n	y	n	n
Skill group fixed effects	n	y	y	n	y	y	n	y	y
Group-specific base log wage effects	n	n	5	n	n	2	n	n	1
Model 2									
Change in ATR	0.01	0.02	-0.02	-0.08	-0.08	0.03	-0.14	-0.14	0.11
	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)	(0.10)	(0.10)
Model 3									
Change in MTR	-0.04	-0.04	0.00	-0.01	-0.01	0.01	0.02	0.04	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)
Change in ATR	0.04	0.04	-0.02	-0.07	-0.07	0.01	-0.16	-0.19	0.08
	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)	(0.09)	(0.11)	(0.10)
Panel B: IV									
Model 1									
Change in MTR	-0.08	-0.08	0.00	-0.02	0.00	0.02	-0.02	-0.01	0.03
	(0.08)	(0.08)	(0.04)	(0.06)	(0.07)	(0.05)	(0.04)	(0.05)	(0.06)
Model 2									
Change in ATR	0.00	0.01	-0.04	-0.09	-0.07	0.06	-0.15	-0.15	0.29
	(0.05)	(0.05)	(0.12)	(0.06)	(0.07)	(0.14)	(0.09)	(0.12)	(1.98)
Model 3									
Change in MTR	-0.06	-0.06	0.02	-0.02	-0.01	0.01	0.03	0.08	-0.12
	(0.05)	(0.05)	(0.33)	(0.05)	(0.06)	(0.60)	(0.09)	(0.10)	(3.29)
Change in ATR	0.04	0.04	-0.09	-0.07	-0.06	0.03	-0.20	-0.24	0.64
	(0.06)	(0.06)	(1.34)	(0.08)	(0.08)	(1.47)	(0.17)	(0.19)	(15.61)

Table 4. Reduced-form models for tax effects on unconditional total hours

	Sample								
	All women			Single women			Single mothers		
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
Panel A: OLS									
Model 1									
Change in MTR	-0.21	-0.22	-0.02	-0.19	-0.19	0.05	-0.17	-0.18	0.13
	(0.11)	(0.12)	(0.10)	(0.11)	(0.14)	(0.11)	(0.11)	(0.17)	(0.14)
Group dummies	5	5	5	2	2	2	1	1	1
Base log wage	y	n	n	y	n	n	y	n	n
Skill group fixed effects	n	y	y	n	y	y	n	y	y
Group-specific base log wage effects	n	n	5	n	n	2	n	n	1
Model 2									
Change in ATR	**-0.61**	**-0.62**	-0.28	**-0.71**	**-0.72**	-0.20	**-0.68**	**-0.74**	-0.03
	(0.15)	(0.15)	(0.18)	(0.19)	(0.21)	(0.25)	(0.24)	(0.33)	(0.34)
Model 3									
Change in MTR	0.06	0.07	0.08	0.12	0.16	0.14	0.14	0.25	0.20
	(0.11)	(0.11)	(0.11)	(0.11)	(0.13)	(0.13)	(0.12)	(0.17)	(0.16)
Change in ATR	**-0.65**	**-0.66**	**-0.41**	**-0.81**	**-0.85**	-0.49	**-0.88**	**-1.04**	-0.42
	(0.16)	(0.16)	(0.18)	(0.20)	(0.22)	(0.28)	(0.27)	(0.36)	(0.38)
Panel B: IV									
Model 1									
Change in MTR	0.45	0.49	0.06	0.25	0.36	0.11	-0.03	0.04	0.20
	(0.30)	(0.31)	(0.17)	(0.22)	(0.25)	(0.18)	(0.17)	(0.21)	(0.22)
Model 2									
Change in ATR	**-0.65**	**-0.64**	-0.39	**-0.73**	**-0.73**	-0.10	**-0.72**	-0.77	0.42
	(0.18)	(0.18)	(0.43)	(0.23)	(0.24)	(0.49)	(0.31)	(0.40)	(4.38)
Model 3									
Change in MTR	0.09	0.09	0.24	0.19	0.21	0.26	0.32	0.50	0.30
	(0.19)	(0.18)	(1.14)	(0.20)	(0.20)	(1.32)	(0.34)	(0.37)	(4.08)
Change in ATR	**-0.71**	**-0.69**	-0.89	**-0.91**	**-0.89**	-0.74	-1.19	**-1.37**	-0.47
	(0.20)	(0.19)	(4.60)	(0.26)	(0.25)	(3.93)	(0.62)	(0.61)	(18.98)

Table 5. Reduced-form models for tax effects on hourly wages

	Sample								
	All women			Single women			Single mothers		
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
Panel A: OLS									
Model 1									
Change in MTR	-0.11	-0.07	-0.05	-0.09	0.00	-0.02	-0.09	0.07	0.07
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.09)	(0.07)	(0.09)	(0.12)
Group dummies	5	5	5	2	2	2	1	1	1
Base log wage	y	n	n	y	n	n	y	n	n
Skill group fixed effects	n	y	y	n	y	y	n	y	y
Group-specific base log wage effects	n	n	5	n	n	2	n	n	1
Model 2									
Change in ATR	**-0.29**	**-0.29**	-0.15	-0.06	0.03	-0.02	-0.11	0.12	0.33
	(0.11)	(0.12)	(0.17)	(0.13)	(0.14)	(0.23)	(0.19)	(0.23)	(0.29)
Model 3									
Change in MTR	0.01	0.07	-0.03	-0.09	-0.01	-0.02	-0.10	0.04	0.02
	(0.09)	(0.09)	(0.07)	(0.09)	(0.09)	(0.09)	(0.10)	(0.12)	(0.11)
Change in ATR	**-0.29**	**-0.32**	-0.09	0.02	0.04	0.03	0.03	0.07	0.29
	(0.14)	(0.14)	(0.17)	(0.17)	(0.18)	(0.24)	(0.26)	(0.31)	(0.29)
Panel B: IV									
Model 1									
Change in MTR	0.28	0.30	0.03	0.00	0.04	0.03	-0.01	0.09	0.10
	(0.24)	(0.24)	(0.13)	(0.16)	(0.18)	(0.14)	(0.12)	(0.15)	(0.19)
Model 2									
Change in ATR	**-0.41**	**-0.31**	-0.47	-0.25	0.00	-0.31	-0.42	0.10	0.38
	(0.13)	(0.13)	(0.57)	(0.16)	(0.16)	(0.69)	(0.27)	(0.28)	(4.93)
Model 3									
Change in MTR	0.06	0.09	0.21	-0.01	0.04	0.20	0.20	0.10	0.03
	(0.17)	(0.16)	(2.74)	(0.16)	(0.16)	(3.79)	(0.33)	(0.30)	(7.39)
Change in ATR	**-0.45**	**-0.36**	-0.90	-0.24	-0.03	-0.79	-0.72	-0.01	0.28
	(0.18)	(0.18)	(11.49)	(0.23)	(0.21)	(8.84)	(0.65)	(0.53)	(30.30)

Table 6. Summary of reduced-form ATR effects on labor supply and wages

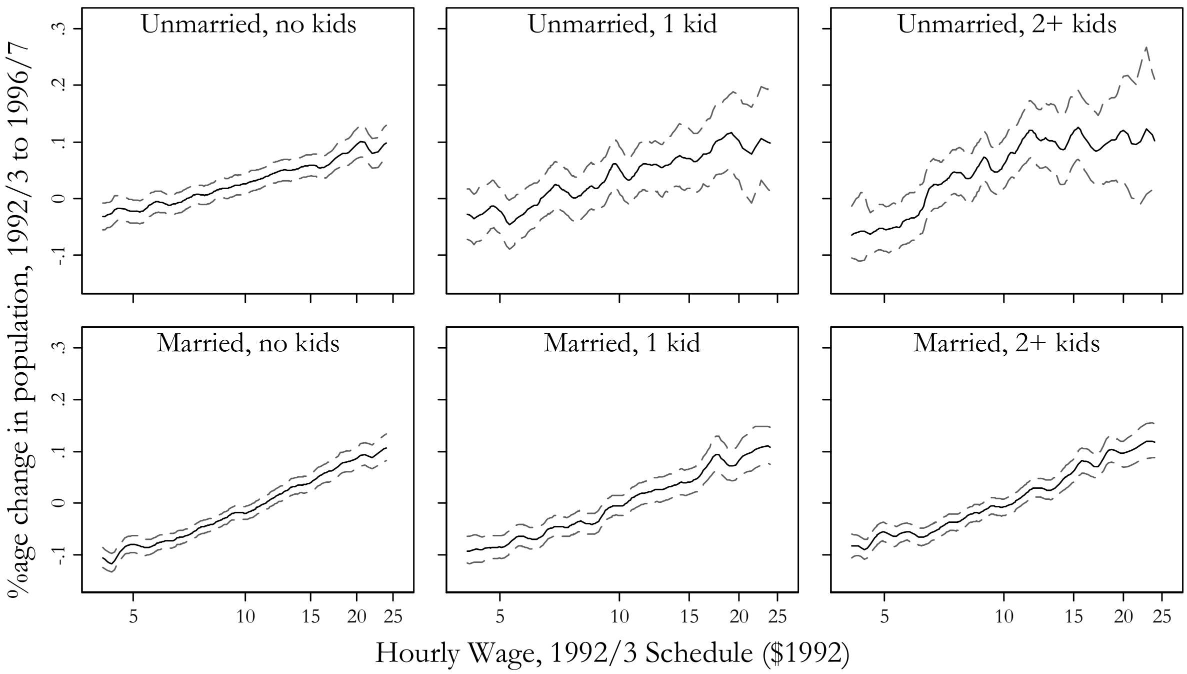
	Single women					
	OLS			IV		
	(A)	**(B)**	**(C)**	**(D)**	**(E)**	**(F)**
(1) Labor force participation	**-1.17**	**-1.22**	-0.43	**-1.22**	**-1.25**	-0.52
	(0.18)	(0.20)	(0.24)	(0.22)	(0.22)	(0.49)
Group dummies	2	2	2	2	2	2
Base log wage	y	n	n	y	n	n
Skill group fixed effects	n	y	y	n	y	y
Group-specific base log wage effects	n	n	2	n	n	2
(2) Employment conditional on LFP	**0.29**	**0.31**	0.05	**0.30**	**0.33**	0.14
	(0.09)	(0.10)	(0.13)	(0.10)	(0.11)	(0.26)
(3) Total employment (=1+2)	**-0.65**	**-0.68**	-0.23	**-0.67**	**-0.68**	-0.16
	(0.18)	(0.20)	(0.24)	(0.22)	(0.23)	(0.49)
(4) Hours conditional on employment	-0.08	-0.08	0.03	-0.09	-0.07	0.06
	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)	(0.14)
(5) Total hours (=3+4)	**-0.71**	**-0.72**	-0.20	**-0.73**	**-0.73**	-0.10
	(0.19)	(0.21)	(0.25)	(0.23)	(0.24)	(0.49)
(6) Wages	-0.06	0.03	-0.02	-0.25	0.00	-0.31
	(0.13)	(0.14)	(0.23)	(0.16)	(0.16)	(0.69)
(7) Non-allocation of wages conditional on hours	-0.19	-0.19	-0.08	-0.21	-0.20	-0.20
	(0.10)	(0.11)	(0.12)	(0.11)	(0.13)	(0.27)
(8) Population	**0.41**	0.41	0.58	**0.52**	**0.48**	1.24
	(0.19)	(0.21)	(0.31)	(0.21)	(0.23)	(0.80)

Table 7. Structural models for elasticities of labor supply and demand

	Predicted pattern	Sample 1: All single women				Sample 2: Single mothers		
		All together	Separate coeffs. for each group			All together	Separate coeffs. for each group	
			No kids	1 kid	2+ kids		1 kid	2+ kids
	(A)	(B)	(C1)	(C2)	(C3)	(D)	(E1)	(E2)
Panel A: Coefficient estimates								
Change in labor supply, group g, skill s								
Change in ATR within group	$-\sigma$	-0.72	0.78	-0.22	-0.86	-0.73	-0.48	-0.52
		(0.21)	(0.45)	(0.45)	(0.40)	(0.32)	(0.50)	(0.56)
Change in avg. ATR across groups	$\frac{\sigma^2}{\sigma - \varrho}$	0.12	-0.10	-0.40	0.45	0.15	0.06	-0.16
		(0.38)	(0.39)	(0.69)	(1.12)	(0.38)	(0.44)	(0.82)
Change in wage, group g, skill s								
Change in ATR within group	0	0.03	2.94	1.02	-0.03	0.12	1.17	-0.13
		(0.14)	(0.69)	(0.56)	(0.31)	(0.23)	(0.59)	(0.44)
Change in avg. ATR across groups	$\frac{\sigma}{\sigma - \varrho}$	-0.90	-1.12	-2.01	-0.76	-0.74	-1.33	-0.49
		(0.39)	(0.44)	(0.74)	(0.78)	(0.34)	(0.50)	(0.56)
Panel B: Elasticity estimates								
σ		0.51		0.39		0.43	0.43	
		(0.15)		(0.12)		(0.16)	(0.15)	
ϱ		1.21		0.92		1.19	1.23	
		(0.51)		(0.39)		(0.62)	(0.61)	
Overid test statistic (chi-sq.)		2.26		33.42		1.61	6.57	
DF		2		10		2	6	
p-value		0.32		0.00		0.45	0.36	

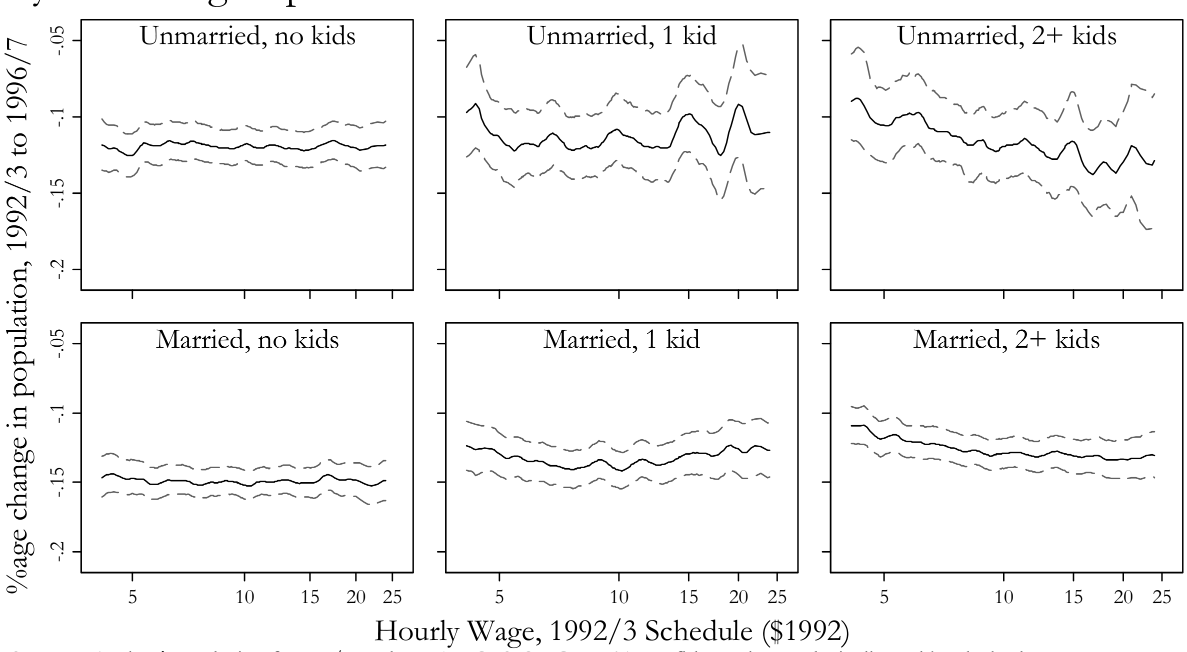
Notes: All models include group dummies and a single base log wage control that is constrained to have the same effect across groups. Elasticity estimates are obtained by optimum minimum distance, minimizing a weighted quadratic in the difference between the estimated coefficients and those predicted by the model, weighted by the inverse of the variance matrix of the coefficients (which is itself estimated via the bootstrap procedure discussed in the text).

Appendix Figure 1.
Change in population size by skill and group



Source: Author's analysis of 1992/3 and 1995-7 CPS ORG. 90% confidence intervals, indicated by dashed lines, are computed by sampling the underlying microdata (with replacement) and feeding bootstrap samples through the DFL algorithm; see text for details.

Appendix Figure 2.
Change in the probability of having a valid wage (conditional on hrs. worked), by skill and group



Source: Author's analysis of 1992/3 and 1995-7 CPS ORG. 90% confidence intervals, indicated by dashed lines, are computed by sampling the underlying microdata (with replacement) and feeding bootstrap samples through the DFL algorithm; see text for details.