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TAXES, DEADWEIGHT LOSS AND INTERTEMPORAL FEMALE LABOR SUPPLY: EVIDENCE FROM PANEL DATA

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Abstract

Very few existing studies have estimated female labor supply elasticities using a U.S. panel data set, though cross-sectional studies abound. Also, most existing studies have done so in a static framework. I make an attempt to fill the gap in this literature, by estimating a lifecycle-consistent specification with taxes, in a limited dependent variable framework, on a panel of married females from the PSID. Both parametric random effects and semiparametric fixed effects methods are applied. I find evidence of larger substitution effects than found in female labor supply literature with taxes, suggesting considerable distortionary effects from income taxation. The uncompensated wage elasticity is estimated at 1.4, which is comparable to estimates found in other labor supply studies with taxes. The income effect in a lifecycle-consistent specification is negative and very small. The estimate of compensated elasticity for females in the sample is 1.4 using random effects estimator and 1.35 using semiparametric fixed effect estimator. I estimate exact deadweight loss from taxes and find that deadweight loss from a 20% increase in the marginal tax rate is about 30% of tax revenue collected, evaluated at the sample mean. The deadweight loss from taxation of wife's labor income from 1980-1987, for a median household is estimated to be 57% of tax revenue as opposed to 49% for a switch to a revenue-neutral proportional tax system. Finally, the intertemporal preference parameters are estimated using GMM.

*Department of Economics, and Research Associate, Center for Policy Research, Syracuse University. I thank Gary Engelhardt, Tom Kniesner, Dan Black, Duke Kao, Jeffrey Kubik and Jan Ondrich for valuable comments. I am fully responsible for any errors.

1. Introduction

Due to a sustained increase in female labor force participation and proliferation of tax and transfer policies targeted at their labor market behavior, the estimation of female labor supply elasticities is an important focus of research in public finance and labor economics. There is a very large literature on female labor supply, but little consensus on elasticity estimates. For example, the estimates of compensated wage elasticities range from -0.12 (Nakamura and Nakamura, 1981) to as large as 15.35 (Dooley, 1982). However, there is little disagreement that female elasticities are much larger than those for males, implying bigger deadweight loss from taxation (Hausman, 1981a; Triest, 1990; Kimmel and Kniesner, 1998). In this paper, I estimate female labor supply elasticities in the presence of taxes in a lifecycle-consistent framework, using a panel of married females from the Panel Study of Income Dynamics (PSID), and then calculate the economic cost of taxation.

The paper makes five contributions to the literature. First, I empirically estimate a lifecycle-consistent secondary earner female labor supply model without imposing separability in the intertemporal budget constraint. I fully take into account the nonlinearities in the budget set induced by the tax system by using the differentiable budget constraint methodology proposed by MaCurdy, Green, and Paarsch (1990).[1] Second, I am one of the first to apply semiparametric techniques to account for fixed effects in the context of female labor supply on a U.S. panel dataset. Third, this is one of the first attempts to estimate a panel selection-bias-corrected wage equation in a Type III Tobit framework.

[1] I do not use maximum likelihood with a kinked budget set implemented in the path-breaking works of Hausman (1981a) and Burtless and Hausman (1978). This method has been the subject of much controversy and debate over the last decades. Besides imposing theoretical restrictions at the kink points (MaCurdy *et. al,* 1990), this method is susceptible to nonlinear measurement error problems, and also to errors in specifying the

Fourth, I use the labor supply parameter estimates to estimate exact deadweight loss and simulate the impact of alternative tax regimes on female labor supply. Finally, I estimate the parameters of the intertemporal Euler equation and intertemporal labor supply elasticity.

I have five primary findings. First, the labor supply estimates are sensitive to the method used to predict wages for non-workers. Second, I estimate a compensated wage elasticity of 1.4, which translates into a sizeable substitution effect. Third, my estimates of the uncompensated wage elasticity at the intensive margin are between 0.8 and 0.9; on the participation margin, the estimated elasticity is 0.7, somewhat lower. Thus, I find evidence of substantial response on both margins. The large estimated substitution effect has implications for tax policy, and creates potential for large efficiency costs of income taxation. Fourth, the exact deadweight loss (at the sample mean) from a 20% tax imposition in most specifications is close to 30% of the tax revenue raised. My simulations indicate that the tax system that existed between 1980 and 1987 could have resulted in a deadweight loss of 57% of tax revenue collected, for the median married household. On the other hand, a revenue-neutral switch to proportional taxation would reduce deadweight loss from taxation to 49% of tax revenue. Finally, my estimate of the Frisch elasticity of 1.5 is very close to the compensated elasticity, which suggests that *intratemporal* elasticities provide a good approximation for evaluation of the intertemporal impact of an anticipated wage change.

The analysis proceeds in three steps. First, I estimate a selectivity-bias-corrected wage equation to predict wages for non-workers in the sample. I use both a standard probit

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budget set. Moreover, Saez (2000) argues that there is lack of clustering of individuals, except at the first kink point of the tax system, a situation that is not particularly conducive to maximum likelihood estimation.

and a Type III Tobit model that uses more information by specifying a censored selection variable based on hours.[2] Next, I estimate a lifecycle-consistent labor supply equation based on two-stage budgeting, treating the after-tax wage and virtual income as endogenous. I use the parametric random effects estimator and semiparametric estimators proposed by Honore (1992) and Kyriazidou (1997). Finally, I use the intratemporal labor supply parameter estimates to recover the intertemporal preference parameters. Specifically, I follow Blundell, Meghir, and Neves (1993) and Ziliak and Kniesner (1999) and parameterize a monotonic transformation of the indirect utility function, allowing the underlying preference parameters to vary with demographics. All the variables in the model are treated as endogenous, and the parameters of a log transformation of the Euler equation are estimated using lagged values of economic and demographic variables in the information set as instruments. I apply iterative GMM to estimate the intertemporal preference parameters efficiently. This step enables me to recover the Frisch elasticity.

This paper is organized as follows. Section 2 presents the theoretical framework for married female labor supply in the presence of joint non-linear capital and labor income taxation, and outlines the reasons for the use of two-stage budgeting. Section 3 outlines the econometric specification. Section 4 provides a brief description of the data and construction of these key variables: wage, income, assets and taxes. Section 5 describes the estimation of the selection-bias-corrected wage equation. The estimation of the labor supply equation is discussed in Section 6. The results on deadweight loss are presented in Section

[2] The usual selection equation uses a binary selection indicator as the dependent variable, which leads to a Type II Tobit Model. A Type III Tobit model uses more available information by specifying a censored selection variable. For an excellent taxonomy of Tobit models, see Amemiya (1985).

7. The estimation of the intertemporal preference parameters is discussed in Section 8. There is a brief conclusion.

2. Background and Theoretical Framework

Most female labor supply studies accounting for taxes have adopted a static framework. Even though I use a dynamic framework to study the effect of taxes, the static model serves as a useful starting point to describe the theory.

2.1 The Static Model with Taxes

Let $U(C_t, H_t, X_t)$ be a strictly quasiconcave utility function in which C_t is consumption in period t, H_t is hours worked, and X_t is a vector of exogenous taste shifters. In a standard static labor supply model with taxes, the consumer maximizes the utility function in period t, $U(C_t, H_t, X_t)$, subject to the budget constraint:

$$C_t = W_t H_t + y_t - T(I_t, D_t, E_t), \tag{1}$$

where W_t is the gross wage, y_t is the unearned income, I_t, the taxable income of the individual, D_t, the tax deductions, E_t, exemptions and $T(.)$ is a function determining tax liability. Graduated tax rate and bracket structures create a piecewise linear budget set with kinks at the points where the marginal tax rate changes. Figure 1 presents the budget set for a typical individual under a hypothetical progressive income tax with three tax brackets. Earnings up to WH_1 are exempt from taxes. From WH_1 to WH_2, earnings are taxed at the marginal tax rate of τ_1, and from WH_2 to $W\overline{H}$, a marginal tax rate of τ_2 applies. This tax system creates three budget set segments with slopes W, $W(1-\tau_1)$, and $W(1-\tau_2)$, respectively, and two kinks at H_1 and H_2. Virtual income is the income associated with

zero hours on each budget segment. In Figure 1, for the first budget segment with no taxes, the virtual income is y_1, which is just the unearned income. However, the second and third segments yield virtual incomes y_2^v and y_3^v, respectively. The intuition behind using virtual income is that the consumer's last-dollar marginal tax rate (in the case of progressive taxation) is higher than marginal tax rate she faces on other parts of her budget set. Virtual income appropriately adds a lump-sum transfer to the consumer's actual unearned income to account for the nonlinear taxation of labor income.

Utility maximization yields a solution for a labor supply that is a function of the individual's after-tax wage, ω_t, and virtual income, y_t^v:

$$H_t = f(\omega_t(H_t), y_t^v(H_t), X_t). \tag{2}$$

Because the tax rate the individual faces is a function of hours, the after-tax wage and virtual income are functions of hours worked and in the estimation need to be treated as endogenous.

There are three approaches to the estimation of the static model. One approach to estimating the labor supply function is to linearize the budget constraint at observed hours (Hall, 1973). To account for the fact that taxes are endogenous, one can use an appropriate instrumental variable procedure to recover the parameters of the labor supply function. A more efficient approach is to use maximum likelihood to estimate the labor supply function while fully accounting for the probability of observing an individual on the budget segments or the kinks (Burtless and Hausman, 1978; Hausman, 1980; Hausman, 1981a; Hausman, 1985a; Hausman, 1985b). The maximum likelihood approach imposes the requirement of exact knowledge of the budget set and all the tax parameters and is particularly vulnerable to

measurement error in income. A third approach is to construct a smooth and differentiable budget constraint, as proposed by MaCurdy, Green and Paarsch (1990) and used among others by Ziliak and Kniesner (1999), Blomquist (1996), Aaronson and French (2002), that provides a reasonable approximation of the tax schedule facing the individual and facilitates the use of instrumental variable methods to estimate the labor supply function.

The static model imposes myopic behavior on the part of consumers and assumes perfectly constrained capital markets. This means that if the labor supply decision is taken in a multi-period setting then static regressions can confuse shifts of wage profiles with movements along wage profiles, and, thus, yield parameter estimates that lack precise economic meaning. The elasticities derived from the static specification can be placed in an intertemporal setting but are economically meaningful only under strong assumptions of either complete myopia or perfectly constrained capital markets (Blundell and MaCurdy, 1999). I relax both of these restrictions by estimating a dynamic model with taxes.

2.2 The Dynamic Model with Taxes

The consumer maximizes the expected present discounted value of utility:

$$\max_{\{C_t, H_t\}} E_t \sum_t (1+\rho)^{-t} U(C_t, H_t, X_t) \qquad (3)$$
$$t = 0,1,2,...,T$$

where r_t is the stochastic rate of return and E_t is the expectation operator conditional on the information set Ω_{t-1}, subject to the asset accumulation constraint

$$A_t = (1+r_t)A_{t-1} + W_t H_t - C_t - T(I_t, D_t, E_t), \qquad (4)$$

where A_t represents assets in period t. I_t is adjusted gross income, such that

$$I_t = W_t H_t + r_t A_{t-1}, \qquad (5)$$

where $T(I_t, D_t, E_t)$ is a twice continuously differentiable tax function that takes as arguments tax deductions, D_t, and tax exemptions, E_t.[3]

In general in intertemporal models, the current choices of consumption and hours can affect future choices in three ways: first, through a wealth effect (i.e., what assets are transferred to next period); second, by changing the utility in the next period as it is affected by current period consumption (i.e., if preferences are not time separable); or, third, by changing next period's relative prices (i.e., if the budget set is not time separable). Most female labor supply studies have assumed a time-separable budget constraint and thereby limited linkages of periods through the wealth effect. However, Blomquist (1985) showed that a nonlinear joint capital and labor income tax system has important implications for behavior in an intertemporal labor supply model. In particular, if the tax system is sufficiently progressive, individuals may work more in periods in which before-tax wage rate is low and vice versa.

Notice that I can write adjusted gross income as

$$I_{t+1} = W_{t+1}H_{t+1} + r_{t+1}A_t . \tag{6}$$

Substituting (4) into (6) for A_t I get

$$I_{t+1} = W_{t+1}H_{t+1} + r_{t+1}[(1+r_t)A_{t-1} + W_tH_t - C_t - T(I_t, D, E)] . \tag{7}$$

Noting that C_t and H_t appear in the period $t+1$ asset accumulation constraint, the Lagrangean for the maximization problem can be written as:

[3] The model presented here takes into account the realities of joint labor and capital income taxation and imposes no restrictions on the separability of the intertemporal budget constraint.

$$L = (1+\rho)^{-t} U(C_t, H_t, X_t) - \lambda_t (A_{t+1} - [(1+r_{t+1})[(1+r_t)A_{t-1} + W_t H_t - C_t - T(I_t, D, E)] + W_{t+1} H_{t+1} - C_{t+1} - T(I_{t+1}, D, E)]). \tag{8}$$

The first-order conditions are

$$C_t : \left(\frac{\partial U}{\partial C_t}\right) = \lambda_t (1+\rho)^t \left\{1 - \left[\frac{r_{t+1}}{1+r_{t+1}}\right] \frac{\partial T(I_{t+1})}{\partial I_{t+1}}\right\} \tag{9}$$

and

$$H_t : \left(\frac{\partial U}{\partial H_t}\right) = \lambda_t (1+\rho)^t W_t \left(1 - \frac{\partial T(I_t)}{\partial I_t}\right)\left\{1 - \left[\frac{r_{t+1}}{1+r_{t+1}}\right] \frac{\partial T(I_{t+1})}{\partial I_{t+1}}\right\}, \tag{10}$$

where $\frac{\partial T(I_t)}{\partial I_t}$ is the marginal tax rate.

If the tax function is nonlinear, from (9) and (10) and using the implicit function theorem, one gets the λ- constant consumption and hours demand functions (Heckman and MaCurdy (1980), MaCurdy (1981)). Estimating the λ- constant labor supply function is a key method for empirical implementation in panel data, where λ is treated as a individual-specific fixed effect. In the presence of joint nonlinear labor and capital income taxation, this function depends on λ and current as well as future prices and tax rates. In this scenario, λ, the marginal utility of wealth, ceases to be a sufficient statistic for extra-period information. Also, one can see from (9) and (10) that future taxes enter the opportunity cost for today's consumption and leisure through the term

$$\left\{1 - \left[\frac{r_{t+1}}{1+r_{t+1}}\right] \frac{\partial T(I_{t+1})}{\partial I_{t+1}}\right\} \tag{11}$$

This is because capital income on A_t is taxed in period $t+1$. Thus, there is intertemporal non-separability in the budget constraint induced by joint nonlinear capital and labor income taxation that creates a link between today's actions and tomorrow's relative prices. Note that if joint labor and capital income taxation is ignored, the portion in the curly brackets in (9)

and (10) disappears, giving consumption and hours demand functions that have no between-period dependence, and λ becomes a valid sufficient statistic for extra-period information. One gets an empirically tractable labor supply function of the form:

$$H_t = H(\lambda_t, W_t, X_t). \tag{12}$$

Indeed, with intertemporal separability of the budget set, (9) and (10) collapse to the usual within-period marginal rate of substitution condition:

$$-\frac{\frac{\partial U}{\partial H_t}}{\frac{\partial U}{\partial C_t}} = W_t[1 - T'(I_t, D, E)]. \tag{13}$$

Even though non-separability in the intertemporal budget constraint does not change the relative allocation within period, one can no longer use λ-constant labor supply function to get the *levels* of demand.

As an alternative, I use two-stage budgeting, proposed by Gorman (1959), to solve the consumer's problem. In particular, Blomquist (1985) showed that in the presence of nonlinear taxation, the λ-constant labor supply function fails to account for the nonseparabilities in the budget constraint, but two-stage budgeting continues to be valid. In the first-stage, the consumer allocates total expenditure across periods to equate the marginal utility of wealth. In the second-stage, she takes the allocation of wealth between periods as given, and allocates between consumption and hours, like a standard static intratemporal problem, conditional on A_t and A_{t-1}. In this framework, A_{t-1} contains information on the past decisions and A_t represents the effect of future prices. Thus, A_t and A_{t-1} can be treated as sufficient statistics that capture the adjustment in the level of assets by the end of

the period. Other functions of A_t and A_{t-1} like full income or consumption-based full income also can function as sufficient statistics in the labor supply function.

I choose to condition on full income, defined in Blundell and MaCurdy (1999) as

$$Y_t^C = r_t A_{t-1} + \Delta A_t + B_t - T(I_t, D, E), \tag{14}$$

where B_t is unearned non-asset income in period *t*. This measure can be derived as follows. We can write the full income as

$$M_t \equiv C_t + W_t L_t = r_t A_{t-1}^* + \Delta A_t + B_t + W_t \overline{L} - T(I_t, D, E), \tag{15}$$

where $\overline{L}$ is the total time endowment, B_t, the unearned non-asset income, and other components are as defined before. Rearrange to yield

$$C_t = r_t A_{t-1}^* + \Delta A_t + B_t + W_t H_t - T(I_t, D, E). \tag{16}$$

In this framework, the consumer's problem in the first stage of the two-stage budgeting framework can be written as:

$$\max_{\{C_t, H_t\}} U(C_t, H_t, X_t) \tag{17}$$

subject to

$$C_t = Y_t^{*C} + W_t H_t \tag{18}$$

where $Y_t^{*C} = r_t A^*_{t-1} + \Delta A^*_t + B_t - T(I_t, D, E)$ is the full income measure that captures the capability to transfer funds between periods through ΔA_t, a component that is ignored in the static model.

In a labor supply model with taxes and a piecewise-linear budget constraint, the after-tax wage is the slope of the budget segment on which the individual locates, and is the

appropriate price of leisure. In this set up, the coefficient on the after-tax wage can be interpreted as the Marshallian elasticity, and compensated elasticities can be derived using the Slutsky equation (Blundell and MaCurdy, 1999).

3. Econometric Specification

I assume a linear specification of the life-cycle consistent labor supply function,

$$H_{it}^{*} = \alpha\omega_{it} + \beta Y_{it}^{Cv} + X_{it}\delta + \vartheta_i + \mu_t + \varepsilon_{it}, \tag{19}$$

where the hours worked, H_{it}^{*}, is a latent variable that is observed only for females who choose to work, ω_{it} is the after-tax wage, Y_{it}^{Cv}, is the virtual full income, ϑ_i is an individual-specific effect, μ_t is a time-specific effect and ε_{it} is the error term that varies with both individuals and time. In a model with nonlinear income taxation, both ω_{it} and Y_{it}^{Cv} are endogenous variables that may be correlated with either ϑ_i or ε_{it} or both.[4] The choice of a linear specification allows comparability of results to an overwhelming majority of labor supply studies that have found (19) to be a good first-order linear approximation to the labor supply function. This labor supply function is consistent with the following underlying indirect utility function (Hausman (1981c)):

$$v(\omega, Y^{Cv}) = \exp\{\beta\omega\}\left[Y^{Cv} + \frac{1}{\beta}\left(\alpha\omega - \frac{\alpha}{\beta} + X\delta\right)\right]. \tag{20}$$

In the labor supply equation (19), X_{it} is a vector of exogenous taste shifters, which consists of children and other demographic factors.[5] In the context of female labor supply,

[4] The virtual income is computed as $Y_t^{Cv} = Y_t^{Cv} + [\tau(I_t) * I_t - T(I_t)]$ where $\tau(I_t)$ is the marginal tax rate, I_t is the adjusted gross income and $T(I_t)$ is the actual taxes calculated at I_t by integrating the marginal tax function.

[5] Mroz (1987) finds evidence that children are not endogenous in a female labor supply equation with taxes.

(19) is a censored regression model. If the reservation wage is above the offered wage rate, the female does not work, resulting in a corner solution.[6] If $\varepsilon_{it} \sim N(0,\sigma^2)$, then (19) is the well known Tobit model with a limited dependent variable

$$H_{it} = H_{it}^{*} \text{ if } H_{it}^{*} > 0 \tag{21}$$

$$= 0 \qquad \text{otherwise.} \tag{22}$$

4. Data

The Panel Study of Income Dynamics (PSID) began in 1968, and is a longitudinal study of a representative sample of U.S. individuals (men, women, and children) and the family units in which they reside. The sample consists of wives. Women belonging to Survey of Economic Opportunity (SEO) subsample were excluded from the analysis sample. The final sample consists of 6,288 person-years of wives from the 1980-1987 PSID, for women who were in the sample for at least two years. Table 1 gives the descriptive statistics on selected variables.

Wages

The PSID contains more than one measure of the wage rate. One measure can be formed by dividing annual real earnings by the annual hours worked. This measure has been found in the literature to induce division bias in labor supply estimates, yielding parameter estimates inconsistent with theory (Ziliak and Kniesner, 1999).[7] I use a self-reported measure of the hourly wage, using the methodology in Ziliak and Kniesner (1999),

[6] Blundell and Meghir (1993) show that the Euler equation for consumption holds even in the presence of nonparticipation and nonseparability between consumption and leisure, provided the wages are replaced by the shadow value.

[7] A similar incidence of division bias has also been found in Engelhardt and Kumar (2003).

that does not require dividing annual labor income with annual hours, and is relatively free of division bias.

Taxes

I use NBER's TAXSIM calculator to compute the marginal tax rate for each individual given her filing status, number of exemptions, and itemization status. The marginal tax rate function is smoothed using a cubic polynomial.[8] This marginal tax function is integrated to infer the actual taxes paid for every individual. The details of the construction of the differentiable budget constraint using the smooth marginal tax rate function are described in the appendix.

Income

Non-labor income of the wife is estimated as the difference between family money income and the labor income of the wife. Thus, wives' non-labor income includes labor income of their husbands. The total labor income of the household is defined as the sum of head's and wife's labor income. The adjusted gross income for the purposes of calculating the marginal tax rate is computed as the sum of total labor income of the household and the capital income. This paper assumes that the wife, as the secondary earner in the household, chooses her labor supply after the husband has made his decision. In a household with head and wife filing joint returns, the marginal tax rate faced by the wife is the tax on the joint labor and capital income of the household.

Assets

I use the methodology adopted by Ziliak and Kniesner (1999) to construct the asset measures for all the individuals in the sample. Assets consist of liquid and illiquid assets.

Liquid assets are the capitalized rent, interest, and dividend income, which are regularly collected by PSID. The illiquid assets are computed from the difference between the house value and remaining principal amount. The full income measure uses the asset variable as an input.

5. Estimation of the Wage Equation

The hours equation in (19) is estimated over the full sample of wives, and has hourly wage as an explanatory variable. Wages are observed only for women who work. Following the literature, I calculate wages for women out of the labor force as follows.[9] To estimate the wage equation, I write the following two-equation system

$$W_{it} = x_{it}\beta + \alpha_i + u_{it} \tag{23}$$

and

$$d_{it}^{*} = x_{it}\ \delta + \xi_i + a_{it} \tag{24}$$

$$d_{it} = 1 \ \text{ if } \ d_{it}^{*} > 0 \tag{25}$$

$$= 0 \text{ otherwise} \tag{26}$$

where W_{it} is the gross wage rate of the individual, α_i and ξ_i are individual-specific fixed effects, and u_{it} and a_{it} are mean zero and homoscedastic error terms, respectively. Let x_i represent the vector of all the leads and lags of x_{it} i.e. $x_i = (x_{i1}, x_{i2}, x_{i3}, ..., x_{iT})$. This

[8] The details of this procedure are described in the Appendix.

[9] Using predicted wages for non-workers is standard in the literature on female labor supply with taxes. The primary condition for consistency is consistent estimates of the wage equation parameters (Wales and Woodland (1980). Some earlier researchers used OLS to estimate the wage equation (Hall, 1973; Rosen, 1976). This strategy has been criticized on grounds of selectivity-bias in the wage equation. (Killingsworth and Heckman, 1986; Wales and Woodland, 1980). Many other studies use selectivity-bias adjusted wage predictions (Hausman, 1980; Bourgiugnon and Magnac, 1990; Colombino and Del Boca, 1990; Triest, 1990; Kaiser et al., 1992; van Soest et al., 1990).

approach allows for arbitrary correlation between u_{it} and x_i. d_{it}^* is a latent variable that determines labor force participation.

Wages are observed if $d_{it} = 1$. In a standard two-step selectivity-bias-correction procedure, the selection equation is estimated using Probit in the first step, and the wage equation is estimated with the inverse Mills ratio as a regressor in the second step (Heckman (1980)). This is a Type II Tobit representation of the wage equation. However, there is no *a priori* reason to ignore the information on hours of work. A Type III Tobit model uses all available information on hours. In this framework, the selection equation (24) is written with a censored dependent variable, such that the model becomes

$$H_{it}^* = x_{it}\,\delta + \xi_i + a_{it} \tag{27}$$

$$H^*_{it} = H_{it} \quad \text{if } H_{it}^* > 0 \tag{28}$$

$$=0 \text{ otherwise} \tag{29}$$

I correct for selection bias in the wage equation, using a correlated random effects approach suggested by Woolridge (1995).[10] In this framework, the wage equation has the following form.

$$E(W_{it} \mid x_i, \upsilon_{it}, d_{it} = 1) = x_i\psi + x_{it}\beta + (\rho_t + \phi_t)\upsilon_{it} \tag{30}$$

[10] Kyriazidou (1997) uses differencing under a conditional exchangeability assumption on the error term to eliminate the fixed effect as well as the selection bias term from the wage equation. Under certain regularity conditions, a two-step method gets rid of both the effects. In the first step, ϕ in the participation equation is estimated using conditional fixed effects logit or any other consistent estimator. In the second step, ψ is estimated semiparametrically, using a kernel-weighted least squares on first differences. Using this estimator, one can get all the slope parameters but the constant is not identified. Therefore, I do not use this method to correct for selection bias to get the wage prediction because I need the constant to get the correct wage level.

Where $(\rho_t + \phi_t)\upsilon_{it}$ is the term arising due to a possible selection bias. I use the Type III Tobit because it uses more information than a Type II Tobit model, which assumes that the selection indicator is unobserved. An estimate of υ_{it} comes from the Tobit residuals by estimating (24). A requirement for the correction of standard errors due to estimated regressors applies.[11]

I estimate a selectivity-bias-corrected log wage equation with the following variables as controls: non-labor income, a spline in age with knots at 35 and 45, a spline in education with knots at 7 and 11 years of education, a race dummy and city size. This specification is in line with other female labor supply studies.[12] The unobserved effect in the selection equation and the wage equation were modeled as a linear function of time-varying characteristics, which, in this case, happen to be non-labor income and children under six.

For identification, I need an exclusion restriction. I use children under six years of age. Specifically in accordance with much of the existing literature in labor supply, I assume that children under six years of age have a strong effect on female labor force participation, but, conditional on participation, are uncorrelated with the female's wage.

The estimates are presented in Table 2. Column 1 presents the results using Type II Tobit and column 2 has the results for Type III Tobit. Some differences in signs and magnitudes of coefficients are noticeable between columns 1 and 2. Age after 45 has a

[11] In several studies, the wage equation for females, estimated on a sample of workers, has been found to be relatively insensitive to selection bias (Heckman (1980), Hausman (1981)). So, first I tested for selection bias in the sample based on a procedure applicable to panel data, suggested in Wooldridge (1995). The coefficient on the estimated residuals is statistically significant with a t-statistic of 4.9. Thus, I rejected the null hypothesis that the estimates of the wage equation on the working sample will not be affected by selection bias. This test entails estimating the second- stage wage equation with fixed effects. The coefficients on the residuals follows a t-distribution under the null.

[12] I also estimated a wage equation with a quartic in age, education and all nonredundant interactions. The results did not change.

positive effect using the Type II Tobit while it has a negative effect in the Type III Tobit. High school education has much stronger effect using Type III. Bad health has a negative effect on wage using Type III Tobit while a positive effect using Type II Tobit. Table 2 clearly shows that the results using the two models are quite different.[13]

6. Estimation of the Hours Equation

6.1 Identification

Estimation of the hours equation is plagued by problems of endogeneity. First, in a nonlinear budget set framework, the marginal tax rate is endogenous to the choice of hours of work. Second, as noted by Eissa (1995), the marginal tax rate is a nonlinear function of income and family size, and may be correlated with underlying tastes for work which also may be correlated with income and family size. Third, the gross wage itself may be endogenous, because it may be correlated with unobserved tastes for work.

Most previous studies on taxes and labor supply have used cross-sectional variation in marginal tax rates to identify the effect of taxes. Because the marginal tax rate depends on choices that are correlated with labor supply, there may be insufficient independent cross-sectional variation in tax rates to identify the tax effect on labor supply. Plausibly exogenous time-series variation generated by the tax reforms in the 1980s is relatively underexploited in studies that employ nonlinear budget set techniques. There were two major tax policy reforms in the 1980's: the Economic Recovery Act of 1981 (ERTA) and the Tax Reform Act of 1986 (TRA86). Specifically, Eissa (1995) estimated a reduced-form specification in a difference-in-difference framework using cross-sectional and time-series

[13] I interpret the coefficients assuming that the individual effects are correlated only with the lags and leads of time-varying regressors. If this restriction is not imposed, the coefficients on time invariant regressors are not

variation in marginal tax rates from TRA86. However, this study did not explicitly take into account the nonlinear budget set faced by individuals. Eissa (1995) used the TRA86 in a natural experiment framework to identify the labor supply effects of taxes on wives married to husbands at or above 99th percentile of the income distribution. She used two different control groups; wives married to husbands between the 75th and 80th percentiles of the income distribution; and those married to husbands between 90th and 95th percentiles of the income distribution. [14]

Using panel data, this paper circumvents these problems by using both cross-sectional and time-series variation in tax rates over the 1980s to identify the effect of taxes on labor supply. To get a sense of the time-series variation in the 1980s, Figure 2 graphs the federal marginal tax rates by real adjusted gross income for a household filing married jointly, with two children and no age exemption from 1980 to 1987. It can be seen that there was substantial variation in marginal tax rates during this period.

One pitfall of the natural experiment approach is that the behavioral parameters are not identified. In particular, the best one can do is to identify a weighted substitution-income effect (Blundell and MaCurdy, 1999). Therefore, I follow a structural approach where I explicitly seek to identify the parameters of the indirect utility function (20) by estimating the labor supply equation (19). I treat both the after-tax wage and virtual full income as endogenous. Also, the virtual income is constructed using a lump-sum transfer that depends on the marginal tax rate, which is endogenous. I instrument for them using the

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separately identified from the individual specific effect (Wooldridge, 1995).

[14] Blundell *et al.* (1998) explicitly took into account kinks in the budget set and used education and cohort interacted with year, as exclusion restrictions to identify the parameters of the labor supply equation with British data. Both these studies have been conducted using repeated cross-sections.

net wage and virtual income constructed from a synthetic tax rate.[15] The identifying assumption is that this synthetic marginal tax rate is correlated with the observed marginal tax rate but is uncorrelated with hours of work. Four types of synthetic tax rates were used to construct the instruments for the after-tax wage rate: (1) the husband's first-dollar tax rate on earnings; (2) the husband's last-dollar tax rate on earnings; (3) the maximum state marginal tax rate for a synthetic tax payer (earning $350,000); and, (4) the maximum total of federal and state tax rate for a synthetic tax payer (earning $350,000). To make the instrument for after-tax wage and virtual full income, I also replaced the gross wage and full income with the twice lagged value of gross wage and full income, respectively.[16] After constructing the synthetic marginal tax rates, I instrument ω_t with a synthetic after-tax wage rate ω_t^{syn}, where

$$\omega_t^{syn} = \hat{W}_{t-2}(1-\tau_t^{syn}) \ , \tag{31}$$

with $\hat{W}_{t-2}$, the twice lagged predicted gross wage rate and, τ_t^{syn}, the synthetic marginal tax rate.

Analogously, I instrument Y_t^{Cv} with $Y_t^{Cv^{syn}}$, which is constructed by replacing the corresponding marginal tax rates and taxes with the synthetic counterparts and using a synthetic twice lagged value of full income in place of contemporaneous full income

$$Y_t^{Cv^{syn}} = \hat{Y}_{t-2}^{C} + [(\tau_t^{syn} * I_t^{syn}) - T(I_t^{syn}) \ ], \tag{32}$$

[15] In the literature on nonlinear budget set estimation with taxes using maximum likelihood, gross wage and full income are treated as exogenous. However, both of these could be endogenous in a lifecycle model due to human capital accumulation factors.

[16] Under the assumption of rational expectations, everything in the information set at time $t-1$ and before is exogenous. So the twice-lagged value of the gross wage and full income are considered exogenous are valid for making instruments.

where I_t^{syn} is the synthetic adjusted gross income and $\hat{Y}_{t-2}{}^{C}$, the twice lagged synthetic full income.[17] These synthetic tax rates do not depend on choice of hours of work and hence can be treated as exogenous.[18]

6.2 Estimation

The hours equation (19) is estimated using both random-effects and fixed-effects estimation techniques. The choice of estimation technique depends upon the assumptions regarding the correlation between the individual-specific effects and other regressors. In uncorrelated random effects models, the fixed effects are assumed to be uncorrelated with the regressors, i.e., $Cov(\vartheta_i, x_{it}) = 0$. In models that have come to be described as correlated random effects models, $Cov(\vartheta_i, x_{it}) \neq 0$, and the correlation between ϑ_i and other regressors is modeled as a linear projection on all the lags and leads of x_{it}. However, in the latter framework, the regressors x_{it} are treated as strictly exogenous. The most promising way to account for the individual specific fixed effects is to difference them away, but in nonlinear models it is not possible to apply simple differencing techniques to get rid of the fixed effects.[19] This leads to semiparametric estimators derived in Honore (1992) that use a clever trimming to difference away the fixed effects.

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[17] I call $\hat{Y}_{t-2}{}^{C}$ synthetic because I removed the supposedly endogenous components from this measure of full income, e.g., taxes paid and transfer income.

[18] I test for the existence of weak instruments by doing a partial F-test on the instruments in the reduced form regression. The null of weak instruments is consistently rejected. The partial F-statistic on instruments in the after tax wage regression is 241.83 and that in Y^{Cv} regression is 527.67. Both these statistics pass the rule of thumb tests presented in Bound, Jaeger and Baker (1994) and Stock, Wright and Yogo (2002). As a note of caution, both these results may not apply to nonlinear models.

[19] In nonlinear models, differencing to get rid of the fixed effects is not a viable alternative. A sufficient statistic for Logit and Poisson models is available. However, for the Tobit model a sufficient statistic to condition out the ϑ_is is not available. The only way to deal with fixed effects is to estimate them as

6.3 Cross Section Results

Table 4 presents estimates of the labor supply parameters treating 8 years of data on married females as independent cross sections and ignoring the individual-specific effects. Table 4 uses the predicted wage from the Type III Tobit model. The Amemiya Generalized Least Squares (AGLS) estimator of Newey (1987) is used to estimate the Tobit hours model with instrumental variables. In addition to after-tax wage and virtual full income, other controls include the number of children between one and two years old, number of children between three and five years old, number of children between six and thirteen years old, a dummy for self-reported bad health, and a quartic in age.

The results are quite consistent with theory. In particular, the Slutsky restrictions are satisfied in each year. The uncompensated wage elasticity is estimated between 1.8 and 2.5. These estimates are close to the higher end of results found in the existing literature, which primarily uses a Type II Tobit model to predict wages. [20] The income elasticity ranges from -0.21 to -0.31. Leisure appears as a normal good in each cross-section. The compensated elasticities are between 1.8 to 2.5. On the intensive margin, compensated elasticities range from 1.2 to 1.8.[21]

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parameters. In datasets where the time dimension is fixed, these parameters grow with sample size, giving rise to incidental parameters problem as found by Neyman and Scott (1948). The inconsistency induced in estimating the ϑ_i s, due to incidental parameters problem is transmitted to γ due to the nonlinearities. However, the amount of inconsistency decreases as $T \to \infty$ so that at least for larger panels the amount of inconsistency will not be large. This approach has been adopted in Heckman and MaCurdy (1980) and Jakubson (1988) to estimate labor supply functions.

[20] At the intensive margin, these elasticities are between 1.2 to 1.8. The elasticities on the participation margin range from 0.6 to 1.

[21] These estimates can be compared with static specifications estimated in the literature on estimation of female labor supply tax effects in a nonlinear budget set environment, using the PSID. Hausman (1981) estimated wage and income elasticities for females working full time of 1 and -0.5 respectively. Triest (1990) estimated uncompensated wage elasticities of 0.9 and 1.12 for one error and two error model respectively, using Maximum Likelihood. The income elasticities estimated here are much closer to the estimates of Triest (1990), whose estimates were between -0.15 to -0.31. Rosen (1976) estimated an uncompensated elasticity of

6.4 Random Effects Estimation with Instrumental Variables

In column 1, of Table 5 I present results for the pooled Tobit model with instrumental variables. The results of random effects model with instrumental variables are presented in column 2 of Table 5.[22] The pooled Tobit and the random effects results are very similar. From the random effects model, the parameter estimates for α and δ are 453 and -0.0018, respectively. The uncompensated wage elasticity evaluated at the sample mean is 1.37. The signs of the wage and income elasticities are as expected, with leisure appearing as a normal good. The Slutsky restrictions are satisfied in all specifications. The compensated elasticity at the sample mean is 1.37. Random effects estimation with instrumental variables yields remarkably robust estimates of the effects of children and health on labor supply.[23]

6.5 Semiparametric Fixed Effects Estimation Results

The incidental parameters problem can induce inconsistency in the estimates of parameters of interest in a parametric fixed effect model. The maximum likelihood estimation of Tobit models is also susceptible to biases from heteroscedasticity and nonnormality of the true error distributions. Some semiparametric estimators deal with both

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2.3 and an income elasticity of -0.42. Hausman and Ruud (1986) estimated wage and income elasticities of 0.76 and -0.36, respectively. Thus, my estimates obtained from estimating a static model using the cross-sections are qualitatively similar to the previous literature. I also attempted to replicate Triest (1990) for the 1983 cross-section. A 95% confidence band around my parameter estimates substantially overlaps the confidence band around estimates in Triest (1990). So using cross-section in a static framework, I am broadly able to replicate the estimates found elsewhere.

[22] See Appendix 2 for details of estimation

[23] The coefficient on children between 1-2 years old ranges from -303 to -346. This translates into a reduction of 140 annual hours of work for each additional child between 1-3 years of age. An additional child between 3-5 years old reduces labor supply by about 100 hours in the richest specification. A child between 6-13 years of age reduces hours worked by much smaller 36 hours. As expected, I find evidence of an effect on labor supply that is declining in the age of children. Conditional on the number of children in these three age ranges, the effect of total number of children is not statistically significant. On average, bad health status reduces labor

of these problems by using a trimming mechanism to restore the symmetry of the error distribution that is spoiled by censoring or truncation, and then use a least squares or a least absolute deviation estimator. The distribution of the error term is left unspecified.

In this paper, I apply the trimmed least squares (TLS) estimator and trimmed least absolute deviation (TLAD) estimators proposed in Honore (1992).[24] The estimates are presented in column 3 and 4 of Table 5. The coefficient on after-tax wage is estimated at 344.6 using TLS estimator and 360.2 using TLAD estimator. Leisure is estimated as a normal good.[25] The implied compensated elasticities are 1.04 and 1.11 from TLS and TLAD, respectively. There is no obvious way to deal with endogeneity in Honore's estimator. One of the shortcomings of this estimator is that regressors are treated as strictly exogenous.[26] Nevertheless, if the endogeneity of net wage and virtual income operates only through the time invariant individual specific effect, the estimates will be consistent. Again, the semiparametric estimates confirm the finding of a strong wage effect.

6.6 Semiparametric Selection Corrected Hours Equation using Kyriazidou (1997)

Female labor supply estimates have been found to be sensitive not only to the estimates of the wage equation and the use of the instrument set but also to the type of Tobit model. In particular, selection-bias-corrected or truncated specifications are known to yield results different from censored specifications (Killingsworth and Heckman, 1986; Triest, 1990). I also estimate a selection-bias-corrected specification. In the following estimation procedure, I do not assume any distribution for the individual effect or the time varying error

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supply by 110 hours. I include health as a control as most other studies do e.g. Triest (1990). I recognize that it may be endogenous in a labor supply equation.

[24] The estimation of TLS was carried out using a GAUSS program available from Honore's website.

[25] The coefficients on children entered significantly and with expected negative signs. The wage coefficient was quite robust to different specifications and to addition of time and region dummies in the model.

term and hence avoid problems due to heteroscedasticity or nonnormality of the error term which contaminates the estimates in a Tobit model. This procedure has been found to be sensitive to the choice of bandwidth constant h.[27] I employ the plug-in method to choose h. I use a second-order bias-reducing kernel. For the kernel function, I use the Gaussian kernel.

Kyriazidou's estimator uses consistent first-stage parameter estimates from the selection equation. I estimate a selection equation for the probability of labor force participation assuming that the errors in the selection equation are distributed i.i.d. logistic and adopt a fixed effect conditional ML estimation method.[28] In the selection equation, the after-tax wage and virtual full income should be treated as endogenous. Estimators for a binary choice selection equation with endogenous regressors are not readily available, so I use ω_{fd} and Y_{fd}^{Cv} as regressors in the selection equation.[29] Identification in this model also requires an exclusion restriction that appears in the selection equation but is absent from the main equation. Finding an exclusion restriction in the labor supply context can be very hard. I experiment with family size and union dummy as potential exclusion restrictions. The results were similar using either.[30]

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[26] An instrumental variable estimator of this type is Honore and Hu (2001).

[27] The details of the estimation procedure are available from the author on request. A STATA program to implement the estimator is also available.

[28] I have a choice between the conditional maximum likelihood approach (Chamberlain, 1984), the semi parametric maximum score estimator (Manski, 1987). While the conditional ML approach assumes a distribution for the error term and is $\sqrt{n}$ - consistent and asymptotically normal, the semiparametric estimator converges at a rate slower than $\sqrt{n}$. Chamberlain (1992) shows that with bounded support of the variables in the selection equation, identification of the selection equation parameters is possible only in the logistic case. Even if we assume unbounded support, $\sqrt{n}$ consistency is achieved only in the logistic case.

[29] This method is also adopted in Charlier, Melenberg and van Soest (1997).

[30] The estimation of the selection equation yielded positive and statistically significant coefficient on first-dollar net wage ω_{fd}. The coefficient on first-dollar virtual full income Y_{fd}^{Cv} was negative and statistically

The results for the hours equation are presented in columns 5 and 6 of Table 5. Column 5 presents the parameter estimates without using instrumental variables for net wage and virtual full income and just estimating the selection-bias-corrected labor supply equation by weighted least squares, using the kernel density estimate of the selection index, as weights. The uncompensated wage elasticity is estimated at 1.24. The estimate of the income elasticity is -0.002. Column 6, presents estimates using instrumental variables for net wage and virtual income. The uncompensated wage effect is about 451. The coefficient on virtual full income is -0.0002 and statistically insignificant. Slutsky condition is satisfied and leisure appears as a normal good. The compensated elasticity is estimated at 1.35. The estimates are moderately sensitive to the bandwidth constant h.[31] The estimated net wage and full income coefficients are close to the estimates from random effects Tobit model with instrumental variables. This suggests that the random effects Tobit model may not be misspecified.

6.7 Sensitivity to Instruments, Functional form, and Wage Measure

In the results discussed so far, I have used the husband's last-dollar marginal tax rate as an instrument for the wife's observed marginal tax rate. The estimates will be inconsistent if husband's last-dollar marginal tax rate itself is endogenous. Therefore, I estimated the labor supply elasticities using the maximum state marginal tax rate and maximum federal plus state marginal tax rate as instruments for the observed marginal tax

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insignificant. The signs on other variables like children and health were as expected. Children and bad health had a negative effect on probability of labor force participation. Overall, I find theoretically consistent estimates in the selection equation.

[31] I experimented with a grid of possible values. However, I present the results for the bandwidth constant, which gave me the best bias standard error tradeoff for the estimates. Over a range of bandwidth constants, I found that point estimates declined with the value of bandwidth while the precision increased. I subjectively

rate. These instruments were constructed by running the sample through NBER's TAXSIM by assigning an adjusted gross income of $350,000 to every individual. I also constructed a more synthetic version of this instrument by running a hypothetical individual who is married with two children, filing jointly, and with no age exemption. This addresses the concern that family size may be endogenous with the marginal tax rate. The results presented in Table 6 are fairly robust to the use of these instruments. Both parametric and semiparametric results did not change by much.

Many researchers have used predicted wages only for non-workers, while using observed gross wages for workers in their estimation. I examine the sensitivity of estimates due to this methodology. The results are presented in Table 7. I find that the results are sensitive to using this method. The estimated compensated elasticities are now lower. Also, the parameter estimates are not robust across estimators. The estimated compensated elasticity from the random effects estimator with instrumental variables is 0.67. Using the semiparametric TLS and TLAD, estimators the estimates of compensated elasticities go down to about 0.4. This may be due the endogeneity of observed gross wage. Kyriazidou's estimator did not yield statistically significant estimates for a broad range of bandwidth constant h. However, leisure is still estimated as a normal good and the Slutsky condition is satisfied across all estimators.

I also checked the sensitivity of the results with respect to functional form assumptions for the labor supply function. In particular, I used a quadratic labor supply function. The top panel of Table 8 presents the comparison using predicted wages from the

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chose the value that yielded sufficient precision. The estimates remain practically unchanged for bandwidth constant higher than 5. The results did not vary with the choice of the order of kernel.

wage equation for everybody in the sample. The estimated elasticities are about 20% larger than those estimated with a linear labor supply function. The compensated elasticity increased from 1.67 to 2.03. The bottom panel uses predicted wages only for non-workers. These results did not change by much. The compensated elasticity using both the functional forms are close to 1.

7. Deadweight Loss from Taxes

I now use the parameter estimates to estimate deadweight loss from taxes. In the nonlinear budget set estimation with taxes, Triest (1990) found that taxes reduce labor supply by 30% in the censored specifications he estimated. Hausman (1981) found that the tax system reduces labor supply by 8.5%. He found a mean deadweight loss as a percentage of tax revenue of 28.7% for husbands. For wives, he estimated deadweight loss from 4.6% for a mean wage of 2.11 dollars to 35.7% for a mean wage of 5.79 dollars. He found that the estimated deadweight loss rises with the market wage rate. For wives he found a deadweight loss of 18.4% of the tax revenue. Hausman (1981) noted that tax treatment of married persons creates substantial deadweight loss for working wives. A wife who worked full time at $4 an hour and whose husband's income in 1975 was $10,000 would face a deadweight loss of 58.1% of tax revenue. From these calculations, it appears that the deadweight loss for wives is very strongly related to husband's income. The higher the husband's income – for a wife filing jointly – the higher the marginal tax rate and higher the potential for deadweight loss as it rises with the square of the tax rate.

For the linear labor supply equation (19), the compensating variation can be written as (Hausman, 1981):

$$CV(\omega^0,\omega^1,Y^{Cv_0},e(\omega,Y^{Cv}) = \exp\{\beta(\omega^1-\omega^0)\}\left[Y^{Cv}+\frac{1}{\beta}\left(\alpha\omega^0+\frac{\alpha}{\beta}+X\delta\right)\right]-\frac{1}{\beta}\left(\alpha\omega^1+\frac{\alpha}{\beta}+X\delta\right)-Y^{Cv}. \tag{33}$$

The exact deadweight loss is easily calculated after subtracting the tax revenue from the compensating variation.

First, I use estimates from the random-effects instrumental variables estimator presented in Table 5 to calculate the exact deadweight loss from an across-the-board 20% tax imposition.[32] This gives us an estimate of the magnitude of potential distortion caused by taxes. From a 20% tax imposition, I estimate a compensating variation (CV) of 625 dollars.[33] The change in consumer surplus (CS) is marginally higher than the compensating variation as expected from theory. Indeed the difference between CV and CS is extremely small which is contrary to what was found in Hausman (1981). In this paper, it is small because of the inconsequential size of the income effect. The magnitude of the deadweight loss as a fraction of tax revenue raised gives us a measure of the economic costs of taxation (Hausman, 1981).[34]

Next, I compare the efficiency of the existing progressive tax system and proportional tax system which yields the same tax revenue. Because deadweight loss is

[32] Specifically I measure the deadweight loss from a 20% increase in the current price of leisure. This follows standard practice in this literature.

[33] This means that a consumer will be required to be compensated $625 to keep her at the same level of utility as before a 20% tax imposition. At the sample means of hours, income and other explanatory variables, it implies a deadweight loss of 186.57 dollars.

[34]The validity of the exact deadweight loss calculations using the indirect utility function approach depends upon the existence of the said utility function. Vartia's (1983) method does not rely on the existence of such indirect utility function and calculates the required compensation by numerically solving the first order differential equation obtained from the Roy's Identity. To check the sensitivity of the results, I also applied Vartia's approach. The results were almost identical.

proportional to the square of the tax rate, a progressive tax system is likely to create substantially higher deadweight loss than a proportional tax system.[35]

Column 1 of Table 9 presents estimates of the effect of the existing tax system on the deadweight loss. I find that deadweight loss varies a great deal in the sample. Due to the presence of outliers, I focus on the median estimates. Under the progressive tax system, the median compensating variation is $4951. Thus the median household would need to be compensated $4951 to achieve the pre-tax level of utility under the progressive tax system. The deadweight loss for the median household is $1588 – about 57% of tax revenue. Column 2 of Table 9 shows the calculations for a new tax regime in which the same revenue was collected using a much simpler and proportional tax structure. My simulations suggest that this switch would lead to efficiency gains. The compensating variation for the median household is $4821. This implies a deadweight loss of $1458, i.e., 49% of tax revenue.

8. Intertemporal Preference Parameters

So far in the paper, I have concentrated on within-period elasticities. It is well known that an anticipated or evolutionary wage change with constant marginal utility of wealth (λ), induces a larger labor supply response than Hicksian or Marshallian elasticities (MaCurdy, 1981; Browning, 1985). This is because with λ being constant, a change in wages is only due to a movement along the given life-cycle profile, known at the beginning of the lifetime, and, hence, there is no wealth effect associated with a λ-constant wage change. On the contrary, the income- or utility-constant wage changes contain a wealth

[35] I calculated the actual tax paid on wife's labor income by assuming that she makes the decision to work after the decision of the husband, based on a secondary earner model. I could easily get an estimate of the taxes paid by running the income of every household through TAXSIM, first before adding wife's labor income and then after adding her labor income. The difference between the taxes paid estimates from the two runs gives us the taxes paid on wife's income.

effect. Therefore, λ-constant (also known as Frisch) elasticities are important for analysis of the effect of anticipated change in wage (Browning, 1985). The Frisch elasticity can be obtained from intertemporal preference parameters.

Intertemporal preference parameters are estimated following the approach used in Ziliak and Kniesner (1999) and Blundell, Meghir and Neves (1993). Writing the Box-Cox transformation of the indirect utility as

$$F_t = \frac{v_t(\omega, Y^{Cv})^{1+\sigma_t} - 1}{1+\sigma_t} \tag{34}$$

Where $v_t(\omega, Y^{Cv})$ is the indirect utility function (20) and σ_t, the intertemporal preference parameter that is allowed to vary with a set of demographics, X_t, such that

$$\sigma_t = \sigma_0 + \sum_{j=1}^{k} \sigma_j X_{jt+1}. \tag{35}$$

From the maximization of the consumers lifetime expected utility, the Euler equation for the marginal utility of wealth can be written as:

$$\left(\frac{1+\bar{r}_t}{(1+\rho)}\right)\lambda_t = \lambda_{t-1}\varepsilon_t, \tag{36}$$

where $\bar{r}_t$ is the after-tax interest rate. This equation represents the first stage of the two-stage budgeting procedure and intuitively states that the consumer chooses consumption and labor supply such that marginal utility of wealth in period t equals the discounted value of marginal utility of wealth in period $t+1$. ε_t is the forecast error.

From taking a log of (36) and first differencing and substituting the marginal utility of wealth, by differentiating (20) and substituting for λ_t, we get the following equation,

$$\sigma_0 \Delta \ln \hat{v}_t(\omega, Y^{Cv}) \ + \sum_{j=1}^{k} \sigma_j \Delta\left(X_{jt} \ln \hat{v}_t(\omega, Y^{Cv})\right) + \Delta \ln \hat{v}_t'(\omega, Y^{Cv}) + \bar{r}_t - \rho = \ln \varepsilon_t \tag{37}$$

where

$$\Delta \ln \hat{v}_t'(\omega, Y^{Cv}) = \ln \frac{\partial \hat{v}_t(\omega, Y^{Cv})}{\partial Y_t^{Cv}} - \ln \frac{\partial \hat{v}_{t-1}(\omega, Y^{Cv})}{\partial Y_{t-1}^{Cv}} \tag{38}$$

Like Ziliak and Kniesner (1999) and Blundell *et al.* (1993), I estimate equation (37) using GMM. I allow the error to be serially correlated and use the Newey-West correction to the covariance matrix. I use iterative GMM where the variance-covariance matrix is re-estimated at each iteration.

In the intertemporal labor supply model I estimate, I allow the intertemporal preference parameters to vary with children, assets, and health. I treat all the regressors as endogenous and follow Ziliak and Kniesner (1999) and Blundell, Meghir and Neves (1993) in using the lagged values of gross wage, after-tax wage, virtual full income, asset, virtual assets, self-reported bad health, the net after-tax real interest rate, age, interactions between education and age, home ownership dummy, and number of children as instruments. I use the third and fourth lag of all these variables as instruments. The results of the estimation of the intertemporal preference parameters are presented in Table 10. I find that assets have a positive and economically significant effect on intertemporal preferences. Higher assets increase intertemporal substitution. I find that young children reduce intertemporal substitution. The effect of older children and the total number of children have a negative but statistically insignificant impact on intertemporal substitution. The effect of poor health on intertemporal substitution is negative and significant. The common discount rate is

estimated to be 0.05.[36] Even though the signs of the estimates of the intertemporal preference parameters are as expected, they imply an intertemporal labor supply elasticity that is very close to the compensated elasticity, i.e., 1.5.

Conclusion

I undertake lifecycle-consistent estimation of female labor supply parameters with taxes, in the presence of joint labor and capital income taxation. I account for corner solutions and censored outcomes by applying Tobit models to panel data with individual-specific effects. The nonlinear budget sets created by taxes are fully taken into account by constructing a differentiable budget constraint. Using a panel of married females from the PSID, this study finds that labor supply elasticities are sensitive to use of panel data as well the choice of estimators. I estimate both random effects and semiparametric fixed effects estimators using instrumental variables and find results consistent with theory. In particular, Slutsky restrictions are satisfied for practically every one in the sample. Random effects estimation with instrumental variables yields a compensated elasticity of 1.4, suggesting strong distortionary effects from taxation. Estimates from semiparametric panel selection-bias-corrected hours equation with instrumental variables yield compensated elasticity of 1.35. I calculate exact deadweight loss from income taxation and estimate economic cost of taxes of about 30% of tax revenue collected, for a 20% tax imposition. For the median household, the progressive tax system from 1980-1987 resulted in a deadweight loss of 57% of tax revenue. My simulations indicate that a revenue neutral proportional tax would reduce the deadweight loss to 49% of tax revenue. I use GMM to estimate intertemporal

[36] The Sargan statistic for the test of overidentification is 0.79 which under the null of valid orthogonality conditions has a chi-square distribution with degrees of freedom equal to the number of excluded instruments

preference parameters efficiently. My estimate of Frisch elasticity of labor supply is 1.5. The deadweight loss calculations do not take into account general equilibrium effects. I also do not model endogenous human capital formation which is an area of active research (Heckman, Lochner and Taber, 1998). These are possible extensions to be explored in future.

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which in this case is 13. I cannot reject the null that the orthogonality conditions are statisfied.

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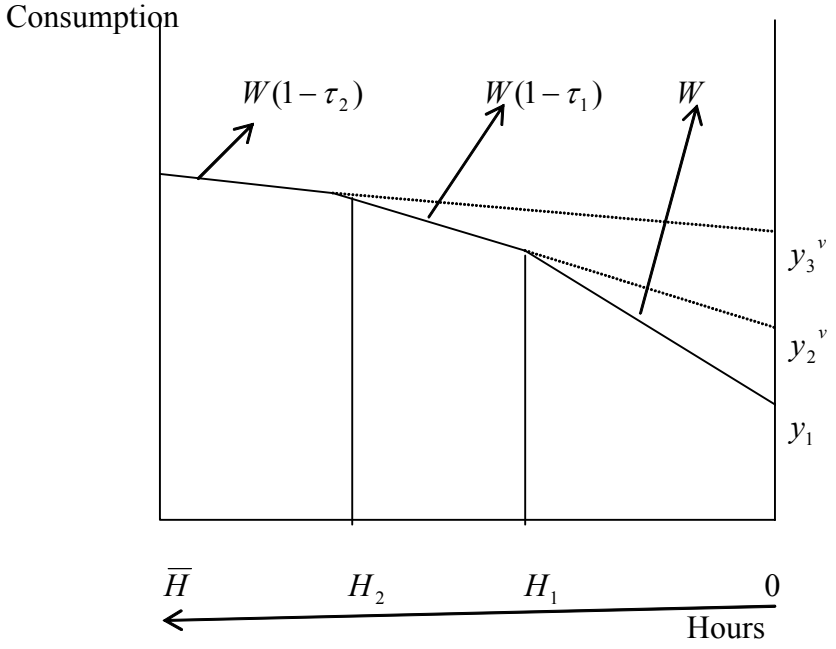
Figure 1


Consumption
$W(1-\tau_2)$
$W(1-\tau_1)$
W
y_3^v
y_2^v
y_1
$\overline{H}$
H_2
H_1
0
Hours

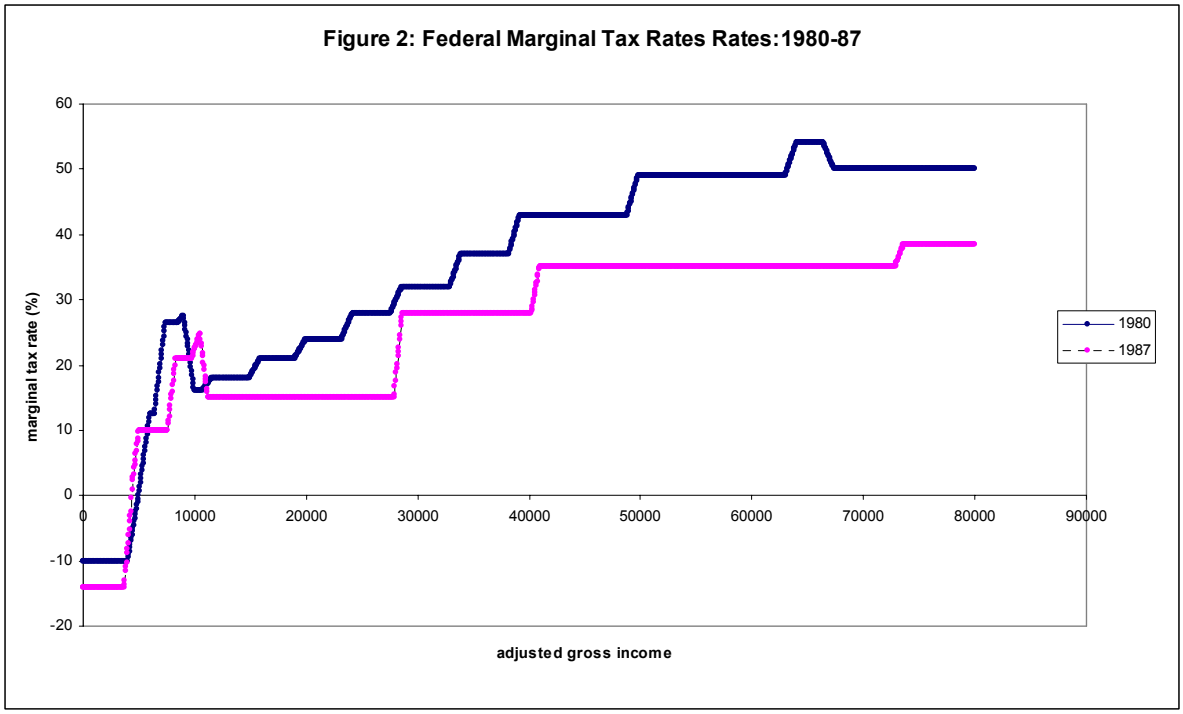


Figure 2: Federal Marginal Tax Rates Rates:1980-87
60
50
40
30
20
10
0
-10
-20
marginal tax rate (%)
0
10000
20000
30000
40000
50000
60000
70000
80000
90000
adjusted gross income
1980
1987

Table 1: Summary Statistics
(Standard deviation in parentheses, Median in square bracket)

Variable	Full Sample	Workers	Non-workers
Hours	1007.99	1409.69	0.00
	(870.75)	(702.87)	(0.00)
	[1024.00]	[1540.00]	[0.00]
Gross Wage	5.91	8.22	0.00
	(6.07)	(5.70)	(0.00)
	[5.26]	[7.25]	[0.00]
After-Tax Wage	3.89	4.30	2.86
	(1.85)	(1.94)	(1.04)
	[3.57]	[4.10]	[2.70]
Virtual Full income	43434.89	41703.35	47779.82
	(45614.99)	(44604.80)	(47792.50)
	[39542.02]	[38542.77]	[42465.34]
Assets	80268.54	77769.98	86538.20
	(91226.67)	(84138.6)	(106730.91)
	[58840.77]	[57922.41]	[61823.80]
Number of Children 1-2 years	0.14	0.11	0.19
	(0.38)	(0.34)	(0.45)
	[0.00]	[0.00]	[0.00]
Number of Children 3-5 years	0.20	0.18	0.24
	(0.44)	(0.42)	(0.49)
	[0]	[0.00]	[0.00]
Number of Children 6-13 years	0.68	0.72	0.60
	(0.89)	(0.90)	(0.84)
	[0]	[0.00]	[0.00]
Total Number of children	1.38	1.40	1.35
	(1.22)	(1.20)	(1.25)
	[1.00]	[1.00]	[1.00]

Table 1: (continued)

Variable	Full Sample	Workers	Non-workers
Family Size	3.70 (1.24) [4]	3.70 (1.22) [4.00]	3.71 (1.28) [4.00]
Marginal Tax Rate	0.37 (0.10) [0.38]	0.38 (0.08) [0.39]	0.34 (0.13) [0.37]
First-Dollar Tax Rate	0.03 (0.01) [0.03]	0.03 (0.01) [0.03]	0.03 (0.01) [0.03]
Belongs to Union	0.09	0.13	0.01
Owns Home	0.89	0.89	0.89
Age	41.43 (8.42) [40.00]	40.80 (8.10) [39.00]	42.83 (9.00) [42.00]
White	0.92	0.92	0.92
Education	12.83 (2.31) [12.00]	13.00 (2.28) [12.00]	12.33 (2.20) [12.00]

Note: Gross wage is the observed gross wage. After-tax wage is the after tax predicted wage from wage equation. After-tax Wage, Virtual Full Income, and Assets are expressed in 1987 dollars.

Table 2: Parameter Estimates of the Correlated Random Effects Two-Step Selection-Corrected Wage Equation. (Dependent Variable: Gross Wage)

	(1)	(2)
	Type II Tobit Model	Type III Tobit Model
Non-labor Income	8.71e-06	3.93e-06
	(1.74)	(0.82)
Age	0.062	0.124
	(1.49)	(3.31)
Age35	-0.031	-0.070
	(0.52)	(1.28)
Age45	0.005	-0.108
	(0.10)	(2.26)
Education	-0.196	0.072
	(0.51)	(0.20)
Education7	0.232	0.016
	(0.54)	(0.04)
Education11	0.730	0.926
	(5.34)	(7.08)
Self –Reported Health Status	0.649	-0.400
	(2.28)	(1.56)
R- Squared	0.13	0.20

Note: The dependent variable is gross wage per hour. The standard errors are not corrected for two-step estimation so should be viewed as lower bound. The regression was estimated on 6342 person-years of observations from years 1978-1987. Estimation was done using correlated random effects estimator of Wooldridge (1995). Other controls in the second-step regression include the inverse Mills ratio, time interacted inverse Mills ratio, all leads and lags of non-labor income, city size, and race. Age and education variables were included as spline. Accordingly Age35=Age-35 if Age>35 and =0 if Age<35. Age 45, Educ7 and Ecuc11 are defined analogously.

Table 3. Married-Women Labor Supply Results
(Dependent Variable: Labor Supply)

Authors	Uncompensated Wage elasticity	Income Elasticity	Compensated Elasticity
Ashworth/Ulph (1981)	0.19	–0.14	
Hausman (1981)	0.91	–0.50	
Nakamura/Nakamura (1981), United States	–0.16	–0.05	
Nakamura/Nakamura (1981), Canada	–0.3	–0.19	
Rosen (1976)	2.3	–0.42	
Hausman/Rudd (1984)	0.76	–0.36	
Triest (1990)	Censored:0.86-1.12 Truncated:0.21-0.28	-0.31--0.33 -0.15--0.17	
Heckman (1980)	2.00-6.61		
Mroz (1987)	1.09-1.97		
Zabalza (1983) (ordered Probit)	1.59	0.23	
Arufat and Zabalza (1986)	2.03	-0.21	
Moffitt (1984)	0.43	-0.28	
Blundell, Ham and Meghir (1998)	Workers:0.307 Nonworkers:		0.81 0.17
Blundell, Duncan and Meghir (1998)	No children:0.14 Y Child 0-2:0.2 Y Child 3-4:0.37 Y Child 5-10:0.13	0 -0.19 -0.17 -0.1	0.14 0.30 0.43 0.17
Eissa (1995)	Participation: 0.4-0.6 Hours:0.8-1		

Table 4: Cross-sectional Instrumental Variable Tobit Estimates using Cross Section 1980-1987
(Dependent Variable: Annual Hours of Work)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	1980	1981	1982	1983	1984	1985	1986	1987
(a) Parameter Estimates								
After Tax Wage	466.52	556.56	618.06	565.25	453.20	445.25	434.31	423.69
	(18.66)	(20.73)	(18.57)	(20.56)	(18.77)	(20.75)	(19.72)	(19.38)
Virtual Non-labor Income	-0.006	-0.008	-0.007	-0.007	-0.006	-0.008	-0.007	-0.009
	(4.20)	(5.55)	(4.84)	(5.19)	(6.32)	(9.09)	(7.15)	(7.60)
Number of Children 1-2 Years	-934.52	-1,234.78	-1,200.31	-1,395.02	-1,179.31	-1,039.70	-829.96	-578.34
	(10.70)	(12.93)	(11.17)	(12.76)	(11.70)	(10.14)	(8.02)	(4.55)
Number of Children 3-5 Years	-546.36	-550.01	-549.92	-1,021.77	-979.08	-986.45	-1,077.43	-1,072.62
	(7.16)	(6.86)	(5.91)	(11.61)	(11.41)	(12.08)	(11.53)	(10.53)
Number of Children 6-13 Years	55.84	17.42	-96.33	-301.60	-267.85	-268.86	-359.99	-408.67
	(0.95)	(0.29)	(1.42)	(4.99)	(4.69)	(5.00)	(6.43)	(6.49)
Total Number of Children	36.13	58.32	107.59	187.09	160.15	135.93	99.16	70.27
	(0.76)	(1.21)	(1.95)	(3.69)	(3.34)	(2.96)	(2.14)	(1.37)
Health	-665.69	-669.61	-594.32	-576.75	-420.43	-565.58	-661.13	-596.76
	(6.05)	(5.87)	(4.76)	(5.70)	(4.74)	(7.35)	(7.57)	(6.92)
(b) Elasticities								
Uncompensated Wage Elasticity	2.24	2.35	2.53	2.32	1.82	2.14	1.78	1.90
Income Elasticity	-.27	-.30	-.28	-.27	-.21	-.37	-.26	-.36
Compensated Elasticity	2.26	2.39	2.56	2.35	1.84	2.18	1.81	1.94

Note: Absolute value of z statistics in parentheses. The number of observations range from 872-892 in different years. All columns include a quartic in age and family size as controls. Elasticities are evaluated at sample means.

Table 5: Parameter Estimates from Panel Data estimation
(Dependent Variable: Annual Hours of Work)

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled Tobit With IV	Random Effects With IV	TLS	TLAD	Semiparametric (OLS)	Semiparametric (IV)
(a) Parameter Estimates						
After tax wage	477.40	453.00	344.60	360.20	415.20	451.40
	(51.71)	(33.56)	(28.63)	(35.47)	(50.4)	(4.87)
Virtual full income	-0.0051	-0.0018	-0.00001	-0.0009	-0.00001	-0.0002
	(-2.84)	(-0.98)	(-0.0093)	(-0.0018)	(0.95)	(0.35)
Number of Children 1-2 years	-451.60	-458.80	-329.10	-352.70	-140.00	-155.90
	(-13.96)	(19.5)	(7.36)	(6.2)	(2.78)	(2.78)
Number of Children 3-5 years	-322.87	-331.02	-220.30	-249.00	-241.66	-126.36
	(-11.38)	(16.22)	(6.13)	(4.2)	(6.56)	(2.05)
Number of Children 6-13 years	-77.09	-68.58	-35.07	-42.35	34.00	-28.52
	(-3.95)	(5.22)	(3.79)	(2.2)	(1.65)	(1.13)
Total Number of children	30.04	30.02	-31.23	-43.91	10.40	-31.47
	(1.25)	(0.26)	(1.82)	(2.88)	(0.56)	(1.4)
Self –Reported Health Status	-251.08	-357.50	-396.3	-367.7	-237.71	-173.15
	(-7.76)	(15.83)	(4.5)	(5.08)	(5.26)	(2.74)
(c) Elasticities						
Uncompensated elasticity	1.64	1.37	1.04	1.11	1.24	1.35
Income elasticity	-.13	-.066	-0.0013	-0.0013	-.002	-.008
Compensated Elasticity	1.67	1.37	1.04	1.11	1.24	1.35

Note: Dependent Variable is annual hours of work. *t* statistic is reported in parenthesis. Other controls include a quartic in age, family size and year dummies. Column (5) does not include family size and quartic in age but includes interaction of year dummies with the children variables and health. The estimates are based on 6462 person years of observations. For trimmed least squares and trimmed least absolute deviation estimators, the optimization of the objective function was carried out using Powell's algorithm. Parameter estimates were almost identical for a number of different starting values. Family Size was used as the exclusion restriction in all specifications. Note that Semiparametric estimator in column 5 is the estimator proposed by Kyriazidou (1997) and in column 6, results are presented from the instrumental variable extension of this estimator by Charlier, Melenberg and van Soest (1997).

Table 6: Sensitivity of the Wage and Income Elasticity to the Instrument for the Net Wage, by Estimator
(Dependent Variable: Annual Hours of Work)

	(1)	(2)	(3)	(4)	(5)
	Husband's last dollar MTR	Maximum State MTR	Maximum Federal plus State MTR	Maximum State MTR for Synthetic Tax Payer	Maximum Federal plus State MTR for Synthetic Tax Payer
Pooled Tobit Estimator					
Uncompensated elasticity	1.64	1.92	1.90	1.92	1.90
Income elasticity	-.13	-.27	-.27	-.27	-.27
Compensated Elasticity	1.67	1.94	1.93	1.94	1.93
Kyriazidou's Estimator					
Uncompensated elasticity	1.35	1.28	1.23	1.28	1.23
Income elasticity	-.008	-.023	-.038	-.023	-.037
Compensated Elasticity	1.35	1.29	1.24	1.29	1.24

Note: Maximum State MTR instrument was created by calculating the state marginal tax rate for the sample by assigning an adjusted gross income of $350,000 to everybody. Maximum Federal plus State MTR is the sum of state and federal marginal tax rates calculated by using similar methodology. Maximum State MTR for Synthetic Tax Payer instrument was created for a synthetic individual with 2 dependents, filing jointly and with an income of $350,000. Maximum Federal plus State MTR for Synthetic Tax Payer is the sum of state and federal marginal tax rates calculated by using similar methodology.

Table 7: Results Using Predicted Wages Only For Non-Workers
(Dependent Variable: Annual Hours of Work)

	(1)	(2)	(3)	(4)	(5)
	Pooled Tobit With IV	Random Effects With IV	TLS	TLAD	Semiparametric (IV)
Parameter Estimates					
After tax wage	255.73	214.01	115.70	117.20	517.75
	(50.56)	(21.73)	(10.59)	(16.43)	(0.9)
Virtual full income	-.0096	-.0041	-0.0002	-0.00001	-0.0050
	(-3.75)	(-0.82)	(-0.012)	(-0.003)	(0.009)
Elasticities					
Uncompensated elasticity	0.97	0.67	0.41	0.42	1.82
Income elasticity	-0.280	-0.100	-0.007	-0.003	-0.160
Compensated Elasticity	1.02	0.69	0.41	0.42	1.85

Table 8: Sensitivity to Functional Form
(Dependent Variable: Annual Hours of Work)

	(1) Linear Labor Supply	(2) Quadratic Labor Supply
Using Predicted Wage		
Uncompensated elasticity	1.64	2.02
Income elasticity	-0.130	-0.038
Compensated Elasticity	1.67	2.03
Using Predicted wage only for non workers		
Uncompensated elasticity	0.97	0.92
Income elasticity	-0.28	-0.16
Compensated Elasticity	1.02	0.95

Note: Pooled Tobit estimation was used for these results.

Table 9: Estimated Deadweight Loss from Revenue Neutral Proportional vs. Actual Progressive tax system from 1980-1987

	(1)	(2)
	Progressive	Proportional
Compensating variation	4951	4821
Exact Deadweight Loss	1588	1458
DWL/Tax Revenue	0.57	0.49

Note: Deadweight loss is reported for the median household. The values in different columns are based on Random Effects IV Estimates from Table 5. The actual tax rates for wives were calculated using TAXSIM. It was assumed that the first-dollar tax rate on wife's labor income is the last-dollar tax on husband's income.

Table 10: Parameter Estimates from GMM Estimation of Intertemporal Preference Parameters

Explanatory Variables	Estimates
Constant	1.78 (3.31)
Asset	.0025 (2.43)
Number of Children 1-2 years	-.056 (-2.53)
Number of Children 3-5 years	-.033 (-1.39)
Number of Children 6-13 years	-.015 (-1.15)
Total Number of children	.004 (0.51)
Self-Reported Health Status	-.062 (-2.13)
ρ	.053 (3.56)
Sargan Statistic	0.79

Note: t statistic in parenthesis

APPENDIX 1

Construction of Differentiable Budget Constraint

Marginal Tax Rates are calculated using NBER TAXSIM. We constructed a grid of adjusted gross incomes (AGI) from $50 to $350,000. We then use NBER's TAXSIM to generate marginal tax rates at every level of AGI in $50 interval conditional on tax status defined by any combination of tax marital status, number of dependents and age exemption. The individual's marginal tax rate τ was obtained from this grid.

The budget set can have multiple kinks depending on the tax status of the individual and can have multiple points of nondifferentiability, we constructed a differentiable budget constraint using a method suggested by MaCurdy, Green, and Paarsch (1990) and implemented by Ziliak and Kniesner (1999), to smooth the budget set around the kink points. First a lower bound and an upper bound was found from the TAXSIM grid below and above which the marginal tax rates do not change. Thus we explicitly took accounted for the first kink and the last kink in the budget set. The individual's budget sets around all the remaining kink points were approximated using a cubic polynomial. Because NBER TAXSIM does not report taxable income, we fitted a cubic polynomial of tax rates on adjusted gross income. Because the marginal rate is a smooth and continuously differentiable function of adjusted gross income, we can integrate the function back to obtain total tax payments. Using the coefficients from the polynomial regression, we were able to get the implicit tax rates at income levels corresponding to each contribution level in $50 intervals.

$$\hat{\tau}(I(H)) = \sum_{j=1}^{k} \left[\Phi_j\left(I(H)\right) - \Phi_{j+1}\left(I(H)\right)\right] b_i(I(H)) \qquad \text{(A.1)}$$

$\hat{\tau}$ is the smooth marginal tax rate. Separate parameter estimates were obtained for the cubic polynomial $b_i(I(H)$ depending upon the cells defined by marital status, number of dependents and age exemption[37].

Following Ziliak and Kniesner (1999) we added average state tax rate and payroll tax to the function. Then the Taxes paid were calculated by integrating the above function.

$$T(I_{it}) = \int (1-\Phi_{lb})\tau_{lb} + (\Phi_{lb} - \Phi_{ub})b_i(I(H) + \Phi_{ub}\tau_{lb} + \tau_{st} + \Phi_{fica}\tau_{fica} dI_{it} \qquad \text{(A.2)}$$

Where τ_{st} is the average state tax rate and τ_{fica} the payroll tax rate.

[37] Similar strategy has been applied in Cunningham and Engelhardt (2002)

APPENDIX 2

Random Effects Tobit with Instrumental Variables

In standard random effects Tobit specifications, the following assumptions are made with regard to labor supply equation (20).

$$\vartheta_i \sim IN(0, \sigma_\vartheta^{\ 2}) \tag{A.3}$$

$$\varepsilon_{it} \sim IN(0, \sigma_u^{\ 2}) \tag{A.4}$$

$$Cov(\vartheta_i, \varepsilon_{it}) = 0 \tag{A.5}$$

$$Cov(\vartheta_i, x_{it}) = 0 \tag{A.6}$$

$$Cov(x_{it}, \varepsilon_{it}) = 0 \tag{A.7}$$

In the random effects model that I estimate, I treat both after tax wage and virtual income as endogenous. Therefore, I relax assumptions (A.6)-(A.7), while retaining (A.3)-(A.5). For asymptotically efficient estimation with instrumental variables, I use an extension of the Amemiya Generalized Least Squares (AGLS) estimator of Newey (1987). This procedure requires consistent estimates of the structural parameters (α, β).[38] Estimation proceeds as follows. In the first step I estimate the following reduced form equations for after tax wage and virtual income assuming random effects.[39]

$$\omega_{it} = X_{it}\Pi_1 + \alpha_{1i} + v_{1it} \tag{A.8}$$

$$Y_{it}^{\ Cv} = X_{it}\Pi_2 + \alpha_{2i} + v_{2it} \tag{A.9}$$

[38] These are obtained using the method suggested by Smith and Blundell (1986). This approach has been extended to panel data by Vella and Verbeek (1999).

[39] I tested for the null of pooled OLS against random effects. The Breusch-Pagan test statistic soundly rejected the null of appropriateness of pooled OLS on this sample.

X_{it} contains the two instruments (first dollar after tax wage rate and first dollar virtual full income) and all the other exogenous variables in the model. Next, I estimate the residuals from the above regression i.e. $\hat{u}_{1it} = \hat{\alpha}_{1i} + \hat{v}_{1it}, \hat{u}_{2it} = \hat{\alpha}_{2i} + \hat{v}_{2it}$. I estimate the following hours equation using random effects Tobit with the residuals from the first stage included as regressors.[40]

$$H_{it}^{*} = \alpha\omega_{it} + \beta Y_{it}^{Cv} + X_{1it}\delta + \lambda_{11}\hat{u}_{1it} + \lambda_{12}\hat{u}_{2it} + \upsilon_{1i} + \upsilon_{2it} \qquad \text{(A.10)}$$

This is in the spirit of Vella and Verbeek (1999) who show that conditional on these residual terms, the error in the primary equation has an error component structure. Conditional on estimated residuals from the first stage, υ_{1i} is a random effect and (A.10) can be estimated using random effects Tobit procedure by integrating out the individual heterogeneity. This gives us consistent estimates of (α, β). In the next step I use AGLS estimator of Newey (1987) to obtain the asymptotically efficient estimates of all the structural parameters.[41]

[40] Vella and Verbeek (1999) suggested including the time means of residuals $\bar{u}_{1i}, \bar{u}_{2i}$. In the actual estimation adding $\bar{u}_{1i}, \bar{u}_{2i}$ to the regression made statistically indistinguishable difference to the estimates. So, I report results conditioning on just $\hat{u}_{1it}$ and $\hat{u}_{2it}$.

[41] A panel data application of Newey (1987) can be found in Schineller (1999). This procedure involves estimating a reduced form of the hours equation. From a consistent (but not efficient) estimate of (α, β) and the reduced form estimates, Newey's procedure uses minimum distance to recover asymptotically efficient estimates of the structural parameters. The procedure is also known as Amemiya Genralized Least Squares (AGLS) after the original suggestion of this approach by Amemiya (1978).

APPENDIX 3

Table A.1: Replication of Triest (1983) specification

	Triest (1983)	95% Confidence Interval		This Paper	95% Confidence Interval	
(a) Parameter Estimates						
After Tax Wage	306.6 (40.8)	225	388.2	269.262 (48.60)	173.99	364.53
Virtual Income	-.0219 (.0036)	-0.0291	-0.0147	-0.01 (.001)	-.013	-.006
Age-45 (45=0)	-66.6 (19.1)	-104.8	-28.4	-50.425 (13.9)	-77.75	-23.09
Children < 6	-374.3 (59.9)	-494.1	-254.5	-495.248 (73.46)	-639.23	-351.25
Family Size	-213.9 (37.0)	-287.9	-139.9	-40.667 (39.62)	-118.33	37.00
Bad Health	-350.8 (129.9)	-610.6	-91	-686.435 (142.06)	-964.88	-407.98
Constant	1003.6 (222.7)	558.2	1449	348.62 (300.63)	-240.60	937.85
Sigma	1010.6 (35.9)			1039.56		
(b) Elasticities						
Uncompensated Wage Elasticity	1.12			1.17		
Income Elasticity	-0.31			-0.35		
Compensated Elasticity				1.21		

Note: Absolute value of z statistics in parentheses. The number of observations range form 872-892 in different years. All columns include quartic in age and family size as controls. Elasticities evaluated at sample means.