Lifecycle-Consistent Female Labor Supply with Nonlinear Taxes: Evidence from Unobserved Effects Panel Data Models with Censoring, Selection and Endogeneity

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Abstract

This paper uses the PSID from 1979-2007 to estimate lifecycle-consistent labor supply elasticities of U.S. females with nonlinear taxes, in a two-stage budgeting framework. The paper is the first to estimate U.S. female labor supply models using semiparametric unobserved effects panel data methods with censoring, selection and endogeneity. The paper finds that female labor supply elasticities, particularly on the intensive margin, are sensitive to both the method used to account for unobserved effects and to economic assumptions regarding lifecycle behavior. The estimated lifecycle-consistent uncompensated wage elasticity for U.S. females from the correlated random effects model with instrumental variables is 0.56 on the extensive margin and 0.31 on the intensive margin, implying an overall wage elasticity of 0.87. In comparison, fixed effects models yield an overall wage elasticity of 0.77, substantially smaller than pooled panel models.

Keywords: Taxes and Female Labor supply, Lifecycle labor Supply, Fixed Effects models with censoring, selection, and endogeneity

JEL Numbers: J22, H24, C14, C23, C24

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1. Introduction

Following a sustained increase since the 1970's, the recent decline in labor force participation of married women has led to concerns that they are opting out of the labor force (Juhn and Potter (2006), Macunovich and Pegula (2010)).[1] With looming retirement of baby boomers and a projected decline in the overall labor force participation rate, policies aimed at stemming the exit of married females from the labor force could soon assume added significance. Central to the design of such policies and evaluation of their welfare costs is the female labor supply elasticity which remains an active area of research in public finance and labor economics. Although there is broad agreement that female labor supply is more elastic than male's, consensus remains elusive on exactly how responsive females are to tax and wage changes. More accurate estimates of the female labor supply elasticity are also necessary to estimate the impact of fundamental tax reforms, back on the public policy agenda due to growing concerns about the long-term sustainability of the U.S. fiscal deficit.

There is a long literature on taxation and female labor supply but gaps remain. Much of the previous literature estimating within-period Marshallian labor supply elasticities for U.S. females, incorporating nonlinear taxes, has primarily estimated static models assuming myopic behavior and perfectly constrained capital markets.[2] Estimates of within-period elasticities from purely static models are not lifecycle-consistent and can be inaccurate if

[1] Unless otherwise indicated all references to female labor supply in this paper refers only to married women. For recent research on single women, see Meyer and Rosenbaum (2001), Eissa and Liebman (1996) among others.
[2] For example Hausman (1980), Hausman (1981), Moffitt (1984), Eissa (1995), Eissa (1995b), Eissa (1996) , Eissa and Hoynes (2004), Eissa and Hoynes (2005), Triest (1990), Blomquist and Hansson-Brusewitz (1990), van Soest et al. (1990), Heim (2007), Heim (2009), Kumar (2010) .

households can transfer assets across periods (Blundell and Macurdy (1999), Blundell and Walker (1986)).

Estimating lifecycle-consistent female labor supply specification also forms a crucial first step in the well-known two-stage budgeting framework to recover intertemporal preferences if taxes are nonlinear and the intertemporal budget constraint is nonseparable. Presence of nonlinear taxes can invalidate the widely used λ-constant labor supply specifications ((Blomquist (1985), Blundell and Macurdy (1999), Ziliak and Kniesner (1999)), while econometric specifications consistent with two stage budgeting remain valid and can be used to estimate life-cycle consistent within-period female labor supply following which intertemporal preference parameters can be recovered. Blundell and Walker (1986), Blundell et al. (1993), Blundell et al. (1998) used two-stage budgeting specifications to estimate lifecycle-consistent elasticities for British females. Aronsson and Wikström (1994) estimated lifecycle-consistent of family labor supply with nonlinear taxes using Swedish cross section data. Ziliak and Kniesner (1999) used the PSID to estimate lifecycle-consistent labor supply elasticities in the presence of nonlinear taxes for a sample of U.S. men. Papers that estimated lifecycle labor supply models for U.S. females, in general, ignored complications caused by nonlinear taxation.[3] Studies that accounted carefully for nonlinear taxes, did not estimate lifecycle-consistent two-stage budgeting specifications.

[3]Heckman and Macurdy (1980) and Kimmel and Kniesner (1998) estimated intertemporal elasticities for US females using a lifecycle model but ignored taxation. Other papers that have estimated lifecycle models for U.S. females ignoring taxes include Eckstein and Wolpin (1989), Jakubson (1988), Johnson and Pencavel (1984), Lilja (1986), Lundberg (1988), Zabel (1997) also estimated λ-constant female labor supply models without taxes.

In estimating static specifications, previous literature on taxes and female labor supply in the U.S. used primarily cross-sectional rather than panel data.[4] It is difficult to account comprehensively for unobserved heterogeneity in female labor supply behavior using cross-section data.[5] Estimating unobserved effects models of female labor supply with censoring and selection, has additional challenges, as simple fixed effects models do not work due to incidental parameters problems; first differencing to remove the fixed effects is not possible since the model is nonlinear (Neyman and Scott (1948)).

This paper makes two contributions to the existing body of work on female labor supply. First, it uses the PSID from 1979-2007 to estimate within-period lifecycle consistent labor supply elasticities of US females, in the presence of nonlinear taxation, in a two-stage budgeting framework, in the spirit of papers such as Ziliak and Kniesner (1999) for US males and (R Blundell et al., 1993) for British females.[6] Second, the paper is the first to estimate U.S. female labor supply models employing a variety of panel data estimation methods including semiparametric fixed effects panel data methods with censoring, selection and endogeneity, combining econometric approaches in Honoré (1992),

[4]Although panel data facilitates life-cycle consistent estimation, it is by no means absolutely necessary. Such specifications can be estimated even using cross-section data (see MaCurdy (1983), Blundell and Walker (1986)).

[5]Among recent papers on female labor supply elasticity, Devereux (2004) used repeated cross-section data from the Census IPUMS and used a grouping strategy to estimate static specifications of female labor supply with group fixed effects. Blau and Kahn (2007) and Heim (2007), who find compelling evidence that female labor supply elasticities are in a long term decline and converging towards men, estimated static models using a time series of cross-section data from the CPS. Gelber and Mitchell (2011) used fixed effects panel data model to estimate the hours elasticity with respect to net-of-tax-rate for single women of 0.53 using PSID 1975-2004.

[6] In line with most other studies on female labor supply with nonlinear taxes, this paper estimates a secondary earners female labor supply model, in a unitary rather than collective framework, where wives, being secondary earners, make labor supply decisions conditional on husbands having made their labor supply choices. See Chiappori (1988), Fortin and Lacroix (1997), Apps and Rees (1997), Blundell et al. (2007) , Cherchye and Vermeulen (2008), Donni (2003), among others, for collective models of labor supply.

Kyriazidou (1997), Blundell and Powell (2007), Blundell and Powell (2004), (Charlier et al., 2001), Papke and Wooldridge (2008), Wooldridge (2009) and Semykina and Wooldridge (2010).

In many respects this paper is similar in spirit to three other papers which carefully examined the sensitivity of female labor supply estimates to a variety of different specifications: Mroz (1987), Jakubson (1988), and Zabel (1997). This paper differs from all these three papers. While Mroz (1987) restricted analysis to just 1975 wave of the PSID, Jakubson (1988), and Zabel (1997) used panel data from the PSID but estimated λ-constant random and fixed effects Tobit models without taxes, ignoring the potential bias due to the incidental parameters problem as well as complications due to nonlinear taxation.

There are three primary findings. First, female labor supply elasticity estimates, particularly on the intensive margin, are sensitive to estimating unobserved effects specifications. Fixed effects models yield participation wage elasticity of 0.43 compared with 0.56 from both simple pooled panel models without unobserved effects and Correlated random effects (CRE) specifications.[7] Intensive margin elasticities, however, are more sensitive to accounting for unobserved effects; fixed effects models and CRE specifications produce much smaller and insignificant hours elasticities than pooled panel models.

Second, estimates of wage elasticity are somewhat sensitive to the choice of a more general lifecycle-consistent framework applicable under nonlinear taxes versus a static model, underscoring the need to account for lifecycle factors in female labor supply. In the CRE specification with instrumental variables, the estimated lifecycle-consistent wage

[7] This is different from the results for single women in Gelber and Mitchell (2011) who found that elasticities from fixed effects models were 50% larger than those without fixed effects.

elasticity on the extensive margin is 0.56, compared with 0.46 from the static model. On the intensive margin, estimated lifecycle-consistent wage elasticity is 0.31 from the CRE specification, while the static model yields a much smaller elasticity of 0.13. However, given the large standard errors, the estimates are statistically indistinguishable.

Finally, the paper does not find evidence of significant difference in estimated elasticities across lifecycle-consistent models applicable to linear taxes that condition on net saving vis-à-vis models consistent with joint nonlinear labor and capital income taxes.[8] Overall, the results indicate that the choice of econometric specification and economic assumptions regarding lifecycle behavior can have implications for the estimated impact of tax and transfer policies on female labor supply. The lifecycle-consistent wage elasticity from the correlated random effects (CRE) model with instrumental variables is 0.56 on the extensive margin and 0.31 on the intensive margin, implying an overall wage elasticity of 0.87. Fixed effects models yield an overall wage elasticity of 0.77 compared with an elasticity of greater than one from pooled panel models.

This paper is organized as follows. Section 2 presents a brief 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 describes the econometric specification. Section 4 provides a brief description of the data and construction of the key variables: wage, income, assets and taxes. Section 5 discusses the results. There is a brief conclusion.

2. Theoretical Framework

[8] Ziliak and Kniesner (1999) found negative wage elasticity when conditioning on net saving.

In the benchmark static model labor supply model with taxes, the consumer maximizes the current period utility function with respect to consumption C_{it} and hours of work H_{it}

$$U(C_{it}, H_{it}; \boldsymbol{X}_{it}) \tag{1}$$

subject to the static budget constraint,

$$C_{it} = W_{it}H_{it} + Y_{it} - T(I_{it}, D_{it}, E_{it}), \tag{2}$$

where i indexes individuals and t indexes time, $\boldsymbol{X_{it}}$ is a vector of exogenous taste shifters that include other demographic and economic characteristics, W_{it} the hourly wage rate, Y_{it} the nonlabor income. $T(I_{it}, D_{it}, E_{it})$ is the nonlinear tax function with adjusted gross income $I_{it} = W_{it}H_{it} + r_{it}A_{it-1}$; $r_{it}A_{it-1}$ is the capital income from end of period $t-1$ assets A_{it-1} at an interest rate of r_{it}, D_{it} deductions and E_{it} the number of exemptions. Consumer's optimization problem yields a labor supply equation as a function of after-tax wage rate ω_{it} which equals $W_{it}(1-\tau_{it})$ with τ, the marginal tax rate, and virtual income R_{it}:[9]

$$H_{it}^{*} = f(R_{it}, \omega_{it}; \boldsymbol{X}_{it}) \tag{3}$$

In the lifecycle model, the consumer chooses consumption and hours of work to maximize the expected present discounted value of utility:

$$E_t \sum_{t=1}^{T} \beta^t \, U(C_{it}, H_{it}; X_{it}) \tag{4}$$

subject to the asset accumulation constraint

$$A_{it} = (1+r)A_{it-1} + W_{it}H_{it} - C_{it} - T(I_{it}, D_{it}, E_{it}) \tag{5}$$

where A_{it} and A_{it-1} represents assets in period t and $t-1$, respectively.

[9] More specifically $R_{it} = Y_{it} + \{(\tau_{it} \times W_{it} \times H_{it}) - T_{it}\}$ where T_{it} is the actual tax liability and $\tau_{it} \times W_{it} \times H_{it}$ is what it would have been if the entire earnings were taxed at the marginal tax rate.

Notice that the tax function incorporates joint nonlinear taxation of labor and capital income. Three points to note about the lifecycle-consistent consumer's optimization problem are: (1) utility is intertemporally separable; (2) within period utility is weakly separable in consumption and leisure; (3) due to joint nonlinear taxation of labor and capital income, the budget constraint is nonseparable in goods and prices across periods.

2.1. Nonlinear Taxes Invalidate λ-Constant Labor Supply Function

As shown in Blomquist (1985), if both preferences and the budget constraint are intertemporally separable then the only way wages in one period change demand for leisure in another is through a wealth effect. If so, a common solution is to estimate λ-constant or Frisch labor supply functions, where λ, the individual specific time invariant marginal utility of wealth is a sufficient statistic for information in other periods and can be differenced away using fixed effects panel data models Heckman and Macurdy (1980).

However, when taxes are nonlinear and the budget constraint is nonseparable in goods and prices, wage changes in one period can affect labor supply in other periods by impacting wages in those periods, in addition to the wealth effect. In other words, labor supply in one period is a function of prices in other periods. Blomquist (1985) showed that in the presence of nonlinear taxes, the marginal utility of wealth λ is no more a sufficient statistic and λ-constant labor supply function fails to account for the nonseparabilities in the budget constraint, but two-stage budgeting remains valid. Ziliak and Kniesner (1999) used two-stage budgeting approach to estimate lifecycle-consistent labor supply elasticities for US males. Such an approach has not been used to model lifecycle-consistent elasticities for US married women.

2.2. Sufficient Statistics Under Two-Stage Budgeting

In a two stage budgeting framework, proposed by Gorman (1959), 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.

As shown in Blomquist (1985), in a two-stage budgeting framework, in the absence of taxes or in the presence of a linear capital income tax that result in time separable budget constraint, net saving $A_t - (1 + r^a)A_{t-1}$ is a sufficient statistic for incorporating information from other periods, where r^a is the after tax rate of interest.

Instead, if taxes are nonlinear as they are in the U.S., then A_t and A_{t-1} can be used as sufficient statistics that capture the adjustment in level of assets by the end of the period. Alternatively, saving $A_t - (1 + r)A_{t-1}$ and capital income $r_t A_{t-1}$ can also serve as sufficient statistics. Following Ziliak and Kniesner (1999) and using A_t and A_{t-1} as sufficient statistic, lifecycle-consistent labor supply is a function of the after-tax wage rate ω_{it}, A_t and virtual lagged asset A_{t-1}^v:[10]

$$H_{it} = f(\omega_{it}, A_{it}, A_{it-1}^v\,; \boldsymbol{X}_{it}) \tag{6}$$

3. Estimation and Identification

[10]Analogous to virtual income R_{it}, following Ziliak and Kniesner (1999), the virtual lagged assets are defined as $A_{t-1}^v = A_{t-1} + \{(\tau_{it} \times W_{it} \times H_{it}) - T_{it}\}/r_{it}$. The reason why this adjustment is made to lagged assets and not to current period assets is, as explained in Ziliak and Kniesner (1999), that income on previous period assets figure into tax calculations.

Writing the desired labor supply in (6) as a latent variable H_{it}^{*}, the baseline lifecycle-consistent female labor supply specification in a world with nonlinear taxes becomes: [11]

$$H_{it}^{*} = \beta_0 + \beta_1 \omega_{it} + \beta_2 A_{it} + \beta_2 A_{it-1}^{v} + X_{it}\gamma + \alpha_i + \epsilon_{it} \quad (7)$$

H_{it}^{*} equals actual hours H_{it} if $H_{it} \geq 0$ and 0 otherwise. α_i is an individual specific unobserved effect, ϵ_{it} is a mean zero error term.

What distinguishes the general lifecycle-consistent specification with nonlinear taxes in (7) from more restrictive specifications with a linear capital income tax or from a static model without possibility of transfer of assets across periods? If capital income taxes were linear or there were no taxes, then virtual net saving could be used instead of A_{it} and A_{it-1}^{v} in (7).[12] If, on the other hand, the objective is to estimate a static model, virtual income R_{it} replaces A_{it} and A_{it-1}^{v} in (7) above.

A variety of approaches can be used to estimate the parameters of the labor supply equation (7). Some methods account comprehensively for piecewise-linear budget set underlying the derivation of the labor supply function (Burtless and Hausman (1978), Hausman (1981), Heckman and MaCurdy (1982), Blomquist and Newey (2002), Heim (2009), Kumar (2008), Kumar (2010), Liang (2011)). These methods, however, are not easily amenable to fixed effects estimation with panel data. Therefore, in line with other recent studies on female labor supply elasticities, this paper uses a simpler approach and

[11] Hereinafter ω denotes after-tax wage of workers as well as nonworkers with the nonworker's missing wages replaced by after tax predicted wage $\widehat{\omega}$.

[12] To account for nonlinear taxes virtual net saving was calculated as the sum of net saving and a lump sum transfer akin to one used for virtual income R_{it} i.e. $A_t - (1 + r^a)A_{t-1} + \{(\tau_{it} \times W_{it} \times H_{it}) - T_{it}\}$.

calculates the after-tax wage ω by linearizing the budget set at the observed marginal tax rate (Hall (1973)) and then treating ω as endogenous.[13]

Tobit can be used to estimate (7) if wages for all females were available. Tobit-type labor supply equations, however, are based on the premise of a continuous labor supply schedule that constrains the parameters of the participation decision and the hours of work decision to be identical and will be biased if participation and hours decisions are separate. The paper, therefore, also estimates participation elasticities using Probit/Logit models with an indicator for labor force participation, D^{LFP}, replacing H_{it}^{*} as the dependent variable in (7). Elasticities on the intensive margin are obtained by estimating selection-corrected hours equations, restricting the estimation sample to workers. Since Tobit/Probit/Logit model is based on the entire sample, imputed wages are required for females out of the labor force.

3.1 Selection-Corrected Wage Equation to Predict Wages

Following the previous literature, unobserved wages in the Probit/Logit/Tobit-type models are replaced by wage estimated from a selectivity-bias-corrected wage equation.[14] The two-step Heckman type selection-corrected wage equation can be written as:

$$D_{it}^{LFP} = X^{S}\pi_1 + e_{it} \tag{8}$$

$$LnW_{it} = X^{W}\pi_2 + \rho\psi(X^{S}\hat{\pi}_1) + u_{it} \tag{9}$$

[13]An alternative approach of imputing the effective marginal tax rate from a differentiable smooth budget constraint methodology proposed in MaCurdy et al. (1990) and Ziliak and Kniesner (1999) was also followed but the results were similar.

[14]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 (1980b); Bourguignon and Magnac (1990); Colombino and Del Boca (1990); Triest (1990); van Soest et al. (1990).

In the first step, a reduced form selection equation for labor force participation (8) is estimated as a linear regression on a vector of variables, X^S, consisting of power series in age, education, race, unearned income Y_{it} and a dummy for the presence children under seven years ($dkidsu7$), for each year, allowing the coefficients to vary by year. In the second step, for each year, the wage equation (9) is estimated by regressing log of real wage, LnW on a vector of regressors X^W consisting of all variables in X^S except unearned income Y_{it} and $dkidsu7$ - which act as exclusion restrictions- and inverse mills ratio term $\psi(\hat{\pi}_1 X^S)$, obtained from (8). The identifying assumption is, conditional on age, education and other demographics, Y_{it} and $dkidsu7$ are correlated with the labor force participation status but conditional on labor force participation, they are uncorrelated with wages.

3.2 Endogeneity, Instruments and Identification

Using panel data, this paper uses both cross-sectional and time-series variation in wages, assets, and tax rates from 1979-2007 to identify the effect of taxes on labor supply. The previous three decades spanned four major tax reforms in ERTA 1981, TRA 1986, 1993, and the Bush Tax Cuts of 2001. The time-series variation in marginal tax rates induced by these reforms helps identify the wage effects as well as the coefficient on virtual asset. The cross-sectional variation in after- tax wage, virtual income and assets, however is likely to be endogenous for three reasons.

First, if taxes are progressive, the current period marginal tax rate is endogenous to the choice of current period earnings and 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 that also may be correlated with income and family size. The endogeneity of the marginal tax rate renders key variables, after tax wage,

$\omega_{it} = W_{it}(1-\tau_{it})$ and virtual lagged real net assets, A^{v}_{t-1}, endogenous as they are functions of the marginal tax rate, τ_{it}. And finally, the gross wage W_{it} and current period assets A_{it} themselves may be endogenous as they may be potentially correlated with unobserved tastes for work.

Instrumental Variables

This paper accounts for the potential endogeneity of ω_{it}, A^{v}_{it-1}, and A_{it} using instrumental variables. After-tax real wage is instrumented with after-tax predicted real wage, $\widehat{\omega}^{z}_{it} = \widehat{W}_{it}(1-\tau^{z}_{it})$, where $\widehat{W}_{it}$ is the predicted wage from the wage equation (9) and τ^{z}_{it} is the first-dollar tax rate on household's earnings.[15] The identifying assumption is that the first-dollar tax rate is correlated with the observed marginal tax rate but is otherwise uncorrelated with hours of work.[16]

To further guard against potential endogeneity in contemporaneous values of $\widehat{\omega}^{z}_{it}$ the paper follows Ziliak and Kniesner (1999) in using the second lag of $\widehat{\omega}^{z}_{it}$ i.e. $\widehat{\omega}^{z}_{it-2}$ as instrument.[17] Analogously, the second lag of $A^{vz}_{t-1} = A_{t-1} + \{(\tau^{z}_{it} \times \widehat{W}_{it}) - T^{z}_{it}\}/r_t$ i.e. A^{vz}_{t-3} is used as instrument for A^{v}_{it-1}. With A_{t-3} used to construct the instrument for A_{t-1}, A_{it-4} is used as an instrument for current real assets A_{it}. In addition to $\widehat{\omega}^{z}_{it-2}, A^{vz}_{t-3}, and\ A_{it-4}$, the baseline instrument set also includes time dummies, the

[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. Also, first lags are not used as instruments due to potential first order serial correlation in the error term.

[16] Other plausible instruments for the tax rate e.g. marginal tax rate on husband's earnings based on 2000 hours a years were also used as instruments. The results were similar.

[17]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.

identifying assumption being that aggregate shocks are correlated with hours only through the after tax wage and asset variables (MaCurdy (1981); Altonji (1986); Angrist (1991); Ziliak and Kniesner (1999)).[18]

4. Data

The Panel Study of Income Dynamics (PSID) began in 1968, and is a longitudinal data on a sample of U.S. individuals and their family units, collected annually from 1968 to 1996 and every other year since 1997. The sample consists of an unbalanced panel of 2210 married women surveyed in the PSID between 1979 and 2007, for a total of 14303 observations.[19] Up to four lags of endogenous variables were used as instruments, and therefore, the PSID waves used in the estimation sample range from 1983 to 2007 with 1982 to 2006 as reference years. In addition to the PSID data directly available from the Survey Research Center, University of Michigan, the Cross-National Equivalent File for PSID (PSID-CNEF) available from the Department of Policy Analysis and Management at Cornell University were used to construct the key variables used in the paper ((Burkhauser et al., 2001)).

Measurement of Key Variables

[18] Analogously, $\widehat{\omega}_{it-2}^{z}$,the second lag of virtual net saving and time dummies are used as instruments in models applicable with linear capital income taxes and $\widehat{\omega}_{it-2}^{z}, R_{it-2}^{z}$ and time dummies are used as instruments in the static specifications, where R_{it-2}^{z} is constructed by replacing the actual marginal tax rate in R_{it} with the first dollar tax rate.

[19] PSID collects most labor market information for the year before the survey year, so data 1979 to 2007 waves refer to years 1978 to 2006. Also since 1996, PSID surveyed individuals only once The main sample of PSID, i.e. excluding an oversample of low-income families, has 60368 observations on wives from 1979 and 2007. Restricting the age to 22-60 years olds resulted in 50675 observations. 14158 observations were dropped as wife or head was self-employed, head was a farmer, or household had own business, leaving 36517 observations. Further, 234 person years were excluded as they were deemed outliers using multivariate outlier detection criteria. 5899 observations from 1979-1982 were dropped as the instrument consisted of 4th lag of real asset. Finally 16089 person years were dropped due to missing data on one or more of the dependent variable, or the explanatory variables, or the instruments which consisted of 2nd, 3rd, and 4th lags of endogenous 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), Eklof and Sacklen (2000), Engelhardt and Kumar (2007)). Following the Ziliak and Kniesner (1999), a self-reported measure of wage is used, that does not require dividing annual labor income with annual hours, and is free of division bias. For hourly workers the hourly wage directly reported by workers was used. For salaried workers, the PSID asked the dollar amount they received in salary and the pay period i.e. once a month, twice a month, or weekly. Assuming that the salaried individual worked 40 hours a week, the dollar amount was divided by the respective number of hours worked during the pay period. Nominal hourly wages are then converted to real 2000 dollars by adjusting with the CPI (U). The log of real wage was used to estimate a selection-corrected wage equation to impute real wages for married women out of the labor force.

Nonlabor Income and Assets

Nonlabor income is calculated as the sum of head's labor income and the household's asset income obtained from PSID-CNEF data. The method proposed in Ziliak and Kniesner (1999) was used to calculate the assets at the household level. First, liquid assets were calculated by capitalizing the first $200 of annual household asset income using the one month CD rate while the amount above $200 was capitalized using the 3-month treasury bill rate. Liquid assets were then added to home equity to calculate total household asset. Home equity was calculated as the difference between self reported value of the house and the remaining mortgage and principal amount. The remaining mortgage and principal amount was not available for 1982; PSID-CNEF method was followed to impute the amount by adding half the difference between 1983 and 1981 value to the 1981 value.

Taxes

The adjusted gross income was calculated as the sum of household's pre-government income and government transfer income both available from the PSID-CNEF data. The pre-government income in PSID-CNEF is the sum of total family income from labor earnings, asset income, private transfers such as child support and alimony, and private pensions. Given the itemization status of the household from PSID, the dollar amount of itemized deduction was imputed as the average of itemized deduction for different categories of adjusted gross income from the NBER tax public use files obtained from IRS Statistics of Income. Information on year, filing status, number of dependents, number of age exemptions, household labor income, itemized deductions, and state was used to calculate the federal, state, and payroll tax rates and tax liabilities using the NBER-TAXSIM (Feenberg and Coutts (1993)). Federal, state, and payroll tax rates were then added to calculate the overall marginal tax rate for each individual, for each year.

5. Results from Panel Data Models with Censoring, Selection, and Endogeneity

The paper estimates three types of elasticities: (1) participation elasticity using Probit/Logit type model (2) intensive margin elasticities using selection-corrected hours equation by restricting sample to labor force participants, and (3) Tobit-type models with censoring to estimate total hours elasticity. All three labor supply models are estimated using: (1) Pooled panel data model, (2) Fixed Effects (FE) model, and (3) Correlated Random Effects (CRE) model. Further, each model is estimated first without instrumental variables (IV) and with IV. The estimation details of various models are presented in Appendix 1.

5.1 Participation Elasticities

Table 2 presents marginal effects and elasticities on the extensive margin with respect to the three key variables in the lifecycle-consistent specification: after-tax wage, virtual lagged asset and current asset. The upper panel contains the marginal effects while the lower panel of each table presents the estimated elasticities. Table 2 shows that IV estimates of marginal effects are larger than non-IV estimates. Among the three panel data models, FE-Logit-IV model yields the smallest elasticity of 0.43 compared with 0.56 from both the pooled panel and CRE-Probit-IV models, although, not statistically different..[20]

This pattern, however, does not apply to wealth elasticities as they are more or less similar across different models. Adding up the lagged and current assets elasticities yields a cumulative wealth elasticity of about -0.10 in both the pooled-Probit-IV and FE-Logit-IV specification and -0.14 in the CRE-Probit-IV specification.[21]

The estimated wage elasticities from the three panel data specifications with IV in columns (2), (4), and (6) are not precise enough to be statistically distinguishable. Indeed, a Hausman-type specification test on a subset of coefficients on key variables- after-tax wage, virtual lagged assets and current asset - had a p-value of 0.49 and failed to reject the CRE

[20]One limitation with fixed effects models is that average partial effects and therefore, elasticities are, in general, not identified, as the unobserved effects are not estimated (Wooldridge (2010), Abrevaya and Hsu (2011) Chernozhukov et al. (2009)). For the fixed effect logit, first the predicted probability of participating in the labor force was calculated conditional on a positive outcome for each individual. The mean of this predicted probability was used to calculate the adjustment factor for calculating marginal effects. Having calculated marginal effects, elasticities were calculated by multiplying with the ratio of mean wage to mean labor force participation.

[21]Cumulative one period dynamic response has been calculated as suggested in Stock and Watson (2007).

Probit-IV model in column (6) vis-à-vis FE-Logit-IV model in column (4).[22] This is interpreted as evidence in favor of the CRE-Probit specification (Hausman (1978)).

The instrumental variables have significant explanatory power in the first stage regressions for all the three endogenous variables - after-tax wage, lagged asset and current asset - as the p-values on a joint test of instruments were well below 0.05. The p-values on the overidentification test, shown in the bottom panel, in columns (2) and (6) suggest that overidentification restrictions cannot be rejected, and therefore the instruments are valid. The p-value on the joint test of correlated random effect terms in column (6) indicates rejection of the hypothesis that, the terms controlling for correlation between the unobserved heterogeneity and the other model regressors are zero.

5.2 Intensive Margin Elasticities

The intensive margin results in Table 3 show a somewhat different pattern than those in Table 2 as they are more sensitive to unobserved effects specifications. The wage elasticity from the selection-corrected CRE-IV model in column (6) is about 44 percent smaller than the pooled-Heckman-IV results in column (2), although the confidence intervals around the estimates overlap. The estimated elasticity from instrumental variable semiparametric FE-IV model in column (4) is 0.35 and not statistically significant. The wealth elasticities on the intensive margin are similar to extensive margin estimates, with the one period cumulative wealth elasticity in column (6) of -0.10. Assets elasticities from the semiparametric FE-IV model are not significant. Given the large difference in estimated

[22]The Hausman test can fail if the difference between variance-covariance matrices of the efficient and consistent specification may not be positive semidefinite. A suggestion in (Jeffrey M. Wooldridge, 2010) page 331 is used to calculate the Hausman test statistic for only a subset of coefficients of primary interest, i.e. after-tax wage, virtual lagged asst and current asset.

elasticity between CRE-IV and FE-IV models, a Hausman-type specification test with a p-value of 0.013 rejects the CRE-IV model in column (6) vis-à-vis the FE-IV model in column (4).

5.3 Total Hours Elasticities from Tobit-type Models with Panel Data

The overall hours elasticities obtained from the Tobit-type censored labor supply models presented in Table 4 show that semiparametric FE-IV estimates in column (4) are just about half of the CRE-Tobit-IV estimates in column (6).[23] Wage elasticities from CRE-Tobit-IV are similar to pooled-Tobit-IV estimates in column (2). A Hausman-type specification test of CRE-Tobit-IV model in column (6) versus the fixed effects model in column (4), yielded a negative test statistic. The total wage elasticity from the CRE-Tobit-IV model in column (6) is 1 and the one period cumulative wealth elasticity is -0.16.

5.4 Sensitivity to economic assumptions regarding lifecycle behavior and taxes

By conditioning on lagged and current asset, labor supply models estimated in Tables 2, 3, and 4 appropriately accounted for the realities of joint nonlinear taxation of labor and capital income taxation. How do these estimated elasticities compare with models that apply only to linear tax settings or to static models? Columns (4), (5), and (6) of Table 5 present estimated elasticities from models that condition on virtual net savings and, therefore, are consistent with assumptions of either no taxes or a linear capital income tax. Columns (7), (8), and (9) present results from static models of female labor supply estimated

[23] Marginal effects in the semiparametric fixed effects models for nonlinear panel data are, in general not identified. However, the marginal and elasticities for such models in the paper are calculated by simply treating the estimated coefficients as marginal effects.

in much of the previous literature using cross-section data. For comparison, columns (1), (2), and (3) reproduce participation elasticities from Table 2 and hours elasticities from Table 3.

Estimated elasticities are somewhat sensitive to economic assumption of a static versus a lifecycle model. The CRE-Probit-IV estimate of the participation wage elasticity from the static model in column (9) is 0.46, smaller than 0.56 from the general lifecycle-consistent model in column (3). The static model, however, yields a larger estimate of participation wage elasticity of 0.7 from the FE-Logit-IV model than the lifecycle-consistent estimate of 0.43. Wealth elasticities in columns (1)-(3) are significantly larger than responses due to increases in net savings from lifecycle model valid under linear taxes in columns (4)-(6), but not much different from income elasticities from static model in columns (7)-(9)

The intensive margin wage elasticities, in the lower panel, show a much different pattern across the unobserved effects lifecycle-consistent and static models. Hours elasticities from fixed effects as well as CRE static models are less than half those from lifecycle consistent models and statistically insignificant.

Adding up the extensive and the intensive margins, lifecycle-consistent model with nonlinear taxes and nonseparable budget constraint yields an overall wage elasticity of 0.87 from the CRE specification and 0.77 from the fixed effects model, although, the intensive margin elasticities are not statistically different from zero. On the other hand, overall wage elasticities from a model consistent with linear taxes and hence time-separable budget set are 0.82 from the CRE and 0.59 from a fixed effects model. The static model produces an overall elasticity of 0.59 from the CRE and 0.86 from fixed effects. Figure 1 plots the estimated uncompensated and compensated wage elasticities from different IV models.

5.5 Robustness to Regressors and Alternative Instruments

Tables 6 and 7 present results on robustness of lifecycle-consistent participation and hours elasticities to inclusion of regressors and to use of alternative instruments. Results are robust to controlling for a quadratic time trend in columns (3) and (4), and to accounting for spouse's wage in columns (7) and (8). Controlling for the unemployment rate to account for business cycle effects in columns (5) and (6), however, yields markedly different results on participation elasticities in the upper panel compared with the baseline model in columns (1) and (2). Both participation elasticities and hours elasticties in the CRE model in column (6) are insignificant when unemployment rate is included. A possible explanation could be that the unemployment rate is mechanically correlated with participation and therefore an invalid control in the upper panel of column (6).

Table 7 examines robustness to alternative instruments. Columns (1) and (2) drop the time dummies from the baseline instrument set and use just the lags of the endogenous variables evaluated at the first dollar tax rate and. Columns (3) and (4) reproduce the pooled-IV and CRE-IV results with the baseline set of instrumental variables from Tables 2 and 3 that include time dummies as in Ziliak and Kniesner (1999). The p-values on overidentifying restrictions in columns (3) and (4) confirm that time dummies are indeed valid instruments.

Columns (5) and (6) present results using groups formed by interaction of whether or not the individual had a high school diploma, year of birth category, and year as instruments similar in spirit to Blundell et al. (1998).[24] Columns (7) and (8) contain estimated

[24]Instruments were formed by interaction of 2 education groups, 4 year of birth groups, and 19 years.

elasticities using wage deciles by year groups as instruments, similar to Blau and Kahn (2007). The estimated participation elasticities are largely robust to use of alternative instruments. The point estimates of the intensive margin elasticity are substantially smaller from the CRE-IV specification in column (8) compared with those in columns (4) and (6). However, none of the elasticities in columns (4), (6), and (8) are statistically different from each other. P-vlaues in the bottom panel indicate that overidentifying restrictions on education by cohort by year groups in columns (5) and (6) and on wage deciles by year groups in columns (7) and (8) are rejected.

5.6 Implied Deadweight Loss and Frisch Labor Supply Elasticity

Estimates of uncompensated wage and wealth elasticities from the lifecycle-consistent specification can be used to calculate the deadweight loss from taxes and simulate the efficiency costs of tax policy. Adding up the wage elasticities on the participation and intensive margins, the overall wage elasticity from the CRE-IV specification is 0.87, while summing wealth elasticity on the two margins yields an estimate of -0.23. The implied compensated elasticity (e_W^{comp}) is 0.9.[25]

The well-known Harberger-Browning formula can then be used to simulate the increase in deadweight loss from changes in tax policy (Harberger (1964), Browning (1987)).[26] Allowing the Bush tax to expire for married women filing jointly with total

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[25]The compensated elasticity on labor supply can be recovered using the formula $e_W^{comp} = e_W^{uncomp} - \left(\frac{WH}{A_t}\right) e_{A_t}$ where $e_W^{comp}, e_W^{uncomp}, e_{A_t}$ are the uncompensated wage, compensated wage, and wealth elasticity, respectively. As the married womens' earnings relative to assets $\left(\frac{WH}{A_t}\right) = 0.19$, the compensated elasticity is 0.64.

[26] Deadweight loss equals $\frac{\left(\frac{1}{2}\right)\tau^2 e_W^{comp} WH}{1-\tau}$, where τ, is the marginal tax rate. This expression equals $0.028WH$ if $\tau = 0.25$ and $0.034WH$ if $\tau = 0.27$.

household earnings of \$100,000 a year, for example, will lead to an increase in federal income tax rate from 25% to 27%. The implied deadweight loss would go up from 3.8% of earned income before the tax change to 4.6% after.[27]

The estimated elasticities can also be used to recover the λ-constant elasticity- by using the formula $e_{\lambda} = e_W^{comp} - e^{IS} e_{A_t}^2 \left(\frac{WH}{A_t}\right)$, where e^{IS} is the intertemporal substitution elasticity (Browning (2005)). An estimate of the intertemporal substitution elasticity is needed to recover e_{λ}. With $e_{A_t}^2 \left(\frac{WH}{A_t}\right) = 0.008$, e_{λ} is not much different from e_W^{comp} for most plausible estimates of e^{IS}. Using an estimated e^{IS} of -0.69 from Blundell et al. (1993), the implied e_{λ} for the lifecycle-consistent CRE specificationis 0.92, about the same as the compensated elasticity.

5.7 Comparison with Elasticities of U.S. Married Women in the Previous Literature

The uncompensated overall wage elasticity of 0.87 and 0.76 from the CRE-IV and fixed effects-IV models, respectively, although well within the range of estimates is similar to the median estimate of 0.7-0.8 reported in two major survey papers by Killingsworth and Heckman (1986) and Blundell and Macurdy (1999). Estimated total labor supply elasticities are close to other papers using the PSID e.g. Hausman (1981), Hausman and Ruud (1984), and Triest (1990) who reported wage elasticities of 0.9, 0.76, and 1 respectively. The intensive margin elasticity of 0.30 from the CRE-IV model is very similar to Triest (1990).

[27]The calculation attempted here is at best a crude measure of deadweight loss from tax changes. Eissa et al. (2008) showed that the relevant tax rates for welfare cost calculations on the participation margins may be different. While the effective marginal tax is valid for the intensive margin, average rate is appropriate for the participation margin. Further, the calculation using labor supply elsticity ignores other margins of behavioral response i.e. effort, avoidance etc. A more comprehensive measure can be calculated using response on taxable income (Feldstein (1999), Saez et al. (2009)).

Elasticities in this paper are, however, substantially larger than from Mroz (1987) whose estimated married women's elasticities using the 1975 PSID were not much different from prime age men's.

Using non-PSID datasets, papers such as Cogan (1981), Rosen (1976)), Heckman and Macurdy (1980), and Kimmel and Kniesner (1998) estimated total hours elasticities larger than 2. Estimated elasticities are closer to those in Eissa (1995) who, using the CPS, estimated a total hours elasticity of 0.8 for high income women with roughly half of it on the extensive margin. The estimated participation elasticity of 0.56 from the CRE-IV model is more than twice that of 0.27 found in Eissa and Hoynes (2004) while the intensive margin elasticity is larger than 0.2 reported in Devereux (2004). Both participation and intensive margin elasticities from the CRE specifications are within the range of those in Blau and Kahn (2007) who found that participation elasticities declined from 0.58 to 0.28 from 1980 to 2000 while the hours elasticities dropped from 0.3 to 0.12. Heim (2009) also found a similar decline with participation elasticities declining from 0.2 to 0.1 and participation elasticities shrinking from 0.5 to 0.

6. Conclusion

Much of the previous literature on taxes and female labor supply in the U.S primarily estimated static models assuming myopic behavior and perfectly constrained capital markets. Estimates of within-period elasticities from purely static models are not lifecycle-consistent and can be inaccurate if households can transfer assets across periods. Estimating lifecycle-consistent specification of female labor supply in a two-stage budgeting framework can also help recover intertemporal preferences in the presence of nonlinear taxes, when λ-constant labor supply specifications are generally not valid. Despite their apparent usefulness, lifecycle-consistent two-stage budgeting specifications incorporating nonlinear taxes have not been estimated for female labor supply in the U.S.

This paper uses the PSID from 1979-2007 to estimate lifecycle-consistent labor supply elasticities of U.S. females with nonlinear taxes, in a two-stage budgeting framework. The paper is the first to estimate U.S. female labor supply models using semiparametric unobserved effects panel data methods with censoring, selection and endogeneity. The paper finds that female labor supply elasticities are sensitive to both the method used to account for unobserved effects and to economic assumptions regarding lifecycle behavior and taxes. Participation and hours wage elasticities are substantially smaller for unobserved effects panel data models compared with pooled panel models.

The uncompensated wage elasticity from a lifecycle-consistent model with nonlinear taxes and nonseparable budget constraint, using CRE model with instrumental variables, is 0.56 on the extensive margin and 0.31 on the intensive margin, implying an overall wage elasticity of 0.87; fixed effects model yields an overall wage elasticity of 0.76 compared with close to one from the pooled panel model. Overall wage elasticity from a model consistent with linear taxes and hence time-separable budget set are not much different. The static model, however, produces an overall elasticity of 0.58 from the CRE model and 0.85 from fixed effects.

Some important caveats apply to the results in the paper. First, like most previous studies on taxes and labor supply, this paper estimates a secondary earners model of female labor supply in a unitary rather than collective framework. Second, by linearizing the budget set and adopting an instrumental variables approach, the paper has sidestepped complications from modeling the entire budget set and ignored any biases due to nonconvexities and fixed costs. Third, the estimated elasticities may be downward-biased as the paper does not account for human capital accumulation (Keane (2011), Imai and Keane (2004)). The model also does not account for optimization frictions which could cause observed elasticities to be different from their structural estimates (Chetty (2009)). And finally, marriage and fertility have been assumed to be exogenous. Addressing these features in the context of a lifecycle-consistent female labor supply model with nonlinear taxes using panel data is left to future research.

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Table 1: Summary Statistics

	1983-85	1986-89	1990-94	1995-99	2001-05	Overall
Annual Hours	1015.0	1114.8	1188.1	1311.0	1385.5	1187.3
	(882.1)	(875.8)	(873.8)	(891.5)	(895.3)	(889.4)
	[1062]	[1314]	[1460]	[1613.4]	[1716]	[1444]
Labor Force Participat'n	0.698	0.730	0.760	0.797	0.809	0.755
	(0.459)	(0.444)	(0.427)	(0.402)	(0.393)	(0.430)
	[1]	[1]	[1]	[1]	[1]	[1]
Real Gross Wage	11.59	12.27	12.33	12.95	14.30	12.56
	(4.494)	(5.293)	(6.328)	(6.976)	(6.782)	(6.047)
	[10.67]	[11.06]	[10.80]	[11.02]	[12.88]	[11.11]
Real Net Wage	7.531	8.349	8.482	8.741	9.695	8.494
	(2.647)	(3.396)	(4.078)	(4.470)	(4.303)	(3.862)
	[7.011]	[7.638]	[7.627]	[7.597]	[8.852]	[7.633]
First Dollar Predicted	11.59	12.79	13.27	15.43	17.57	13.80
Net Wage	(2.840)	(3.504)	(4.267)	(5.357)	(5.488)	(4.682)
	[11.11]	[12.05]	[12.27]	[14.23]	[16.38]	[12.71]
Marginal Tax Rate	0.341	0.311	0.303	0.316	0.312	0.315
	(0.0761)	(0.0687)	(0.0664)	(0.0686)	(0.0814)	(0.0724)
	[0.347]	[0.313]	[0.305]	[0.320]	[0.317]	[0.319]
First Dollar Tax Rate	-0.0325	-0.0580	-0.122	-0.311	-0.337	-0.151
	(0.007)	(0.013)	(0.056)	(0.027)	(0.033)	(0.122)
	[-0.033]	[-0.064]	[-0.108]	[-0.324]	[-0.324]	[-0.093]
Real AGI	66.86	72.18	70.65	78.302.3	83.66	73.33
	(36.07)	(40.43)	(39.12)	(44.27)	(47.26)	(41.31)
	[62.94]	[66.09]	[63.89]	[70.97]	[77.23]	[66.73]
Real Nonlabor	47.44	48.89	47.44	52.20	53.33	49.33
Income	(32.56)	(34.66)	(33.54)	(36.69)	(39.55)	(35.09)
	[44.94]	[45.15]	[43.04]	[45.76]	[45.62]	[44.71]
Virtual Real Nonlabor	52.73	52.68	49.78	54.98	56.07	52.64
Income	(37.62)	(38.89)	(35.79)	(39.12)	(41.67)	(38.27)
	[49.02]	[47.24]	[44.65]	[47.80]	[46.70]	[46.74]
Real Asset	76.92	82.20	72.58	73.71	88.68	78.00
	(78.27)	(97.46)	(85.22)	(78.11)	(129.9)	(93.74)
	[64.23]	[58.08]	[48.65]	[52.82]	[62.15]	[55.57]
Virtual Real Lagged	138.3	137.2	127.6	125.0	165.9	136.7
Asset	(134.1)	(159.8)	(146.5)	(123.3)	(336.9)	(184.4)

	[105.7]	[96.01]	[92.61]	[102.4]	[116.5]	[100.7]
Age	43.53	43.49	42.82	43.23	44.83	43.45
	(10.03)	(9.943)	(9.312)	(8.805)	(8.060)	(9.372)
	[43]	[43]	[42]	[43]	[44]	[43]
White	0.905	0.904	0.918	0.933	0.925	0.916
	(0.293)	(0.294)	(0.275)	(0.251)	(0.264)	(0.278)
	[1]	[1]	[1]	[1]	[1]	[1]
Years of Education	12.32	12.64	12.87	13.14	13.41	12.84
	(2.133)	(2.235)	(2.199)	(2.163)	(2.233)	(2.221)
	[12]	[12]	[12]	[12]	[13]	[12]
Less Than High School	0.199	0.164	0.140	0.109	0.0806	0.143
	(0.400)	(0.370)	(0.347)	(0.312)	(0.272)	(0.350)
	[0]	[0]	[0]	[0]	[0]	[0]
Highschool	0.528	0.494	0.451	0.429	0.382	0.461
	(0.499)	(0.500)	(0.498)	(0.495)	(0.486)	(0.499)
	[1]	[0]	[0]	[0]	[0]	[0]
Some College	0.144	0.184	0.231	0.254	0.282	0.216
	(0.351)	(0.388)	(0.421)	(0.436)	(0.450)	(0.411)
	[0]	[0]	[0]	[0]	[0]	[0]
College	0.129	0.158	0.178	0.207	0.255	0.180
	(0.335)	(0.365)	(0.382)	(0.406)	(0.436)	(0.384)
	[0]	[0]	[0]	[0]	[0]	[0]
Number of Children	1.173	1.075	1.114	1.059	1.185	1.117
	(1.227)	(1.174)	(1.127)	(1.130)	(1.158)	(1.162)
	[1]	[1]	[1]	[1]	[1]	[1]
Poor Health	0.146	0.155	0.152	0.143	0.117	0.145
	(0.353)	(0.362)	(0.359)	(0.351)	(0.321)	(0.352)
	[0]	[0]	[0]	[0]	[0]	[0]
Owns Home	0.883	0.859	0.853	0.929	0.926	0.882
	(0.322)	(0.348)	(0.354)	(0.257)	(0.261)	(0.323)
	[1]	[1]	[1]	[1]	[1]	[1]

Note: Summary statistics are based on the estimation sample of 14303 observations. The sample starts on 1983 as up to four lags of endogenous variables were used as instruments. For all variables standard deviation is in parenthesis, median is prsented in brackets. All the dollar variables are in real 2000 $. Gross Wage and After Tax Wage for non-workers is based on the predicted wage.

Table 2: Lifecycle-Consistent Participation Elasticities For Married Women From The PSID (1983-2007)
(Dependent Variable: Labor Force Participation Dummy)

	(1) Pooled Probit NO IV	(2) Pooled Probit IV	(3) Fixed Effects Logit NO IV	(4) Fixed Effects Logit IV	(5) Corr. Random Effects Probit NO IV	(6) Corr. Random Effects Probit IV
Marginal Effects						
After-Tax Wage	0.011**	0.050**	-0.002	0.038**	0.010**	0.050**
	(0.002)	(0.012)	(0.004)	(0.015)	(0.002)	(0.015)
Virtual Lagged Asset	0.000**	-0.000*	0.000	-0.000**	0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Current Asset	-0.000**	-0.001**	0.000	-0.001*	-0.000**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Elasticities						
After-Tax Wage	0.123**	0.556**	-0.023	0.426**	0.114**	0.563**
	(0.019)	(0.137)	(0.048)	(0.163)	(0.019)	(0.171)
Virtual Lagged Asset	0.010**	-0.028*	0.003	-0.043**	0.010*	-0.037*
	(0.005)	(0.016)	(0.008)	(0.021)	(0.005)	(0.021)
Current Asset	-0.035**	-0.066**	0.000	-0.052*	-0.039**	-0.096**
	(0.008)	(0.018)	(0.002)	(0.029)	(0.008)	(0.040)
P-value on Overid Test		0.784				0.859
P-val on Corr Random Eff					0.000	0.000
Pseudo R-Sq	0.081	0.083	0.102	0.106	0.091	0.094
Observations	14303	14303	5652	5652	14303	14303

Note: The dependent variable is Labor Force Participation (LFP) dummy. CRE estimates in columns (5) and (6) were obtained using method in Papke and Wooldridge (2008). All marginal Effects and elasticities computed at the mean LFP of 0.79, mean net wage of 8.82/hour, mean asset of 73.32 (in '000), and mean lagged virtual asset of 140.88 (in '000). Bootstrapped standard errors using 100 replications and clustered at the individual level are reported in parenthesis. In addition to the variables listed in the table, other explanatory variables included in all specifications are quartic in age, number of children, dummy for children less than 7 years, and dummy for self-reported health status. The endogenous variables are after tax real wage, virtual lagged real asset and current year real asset. The instruments are the second lag of after tax predicted real wage, the second lag of virtual lagged real asset, the fourth lag of current real asset and a set of time dummies. Unobserved after-tax real wage for non-labor-force-participating females was replaced by wage imputed using a year-specific selection corrected wage regression on a quartic in age and education, race dummies,and state dummies. To estimate the wage equation, the first-step selection equation controlled for everything in the wage equation plus real nonlabor income, number of children and a dummy for children. less than 7 years. * $p<0.10$, ** $p<0.05$.

Table 3: Selection-Corrected Lifecycle-Consistent Hours Elasticities for Married Women from the PSID (1983-2007)
(Dependent Variable: Annual Hours Of Work)

	(1) Pooled Heckman NO IV	(2) Pooled Heckman IV	(3) Semiparametric Fixed Effects NO IV	(4) Semiparametric Fixed Effects IV	(5) Corr. Random Effects with Selection NO IV	(6) Corr. Random Effects with Selection IV
Marginal Effects						
After-Tax Wage	11.776**	99.107**	-8.978	61.031	23.931**	55.202*
	(3.878)	(46.741)	(46.978)	(53.969)	(4.279)	(32.300)
Virtual Lagged Asset	0.063	0.156	0.188	0.509	0.179**	0.151
	(0.063)	(0.169)	(0.454)	(0.731)	(0.064)	(0.352)
Current Asset	-0.658**	-2.248**	0.303	0.008	-0.688**	-2.612**
	(0.193)	(0.694)	(0.694)	(2.402)	(0.136)	(0.983)
Elasticities						
After-Tax Wage	0.065**	0.549**	-0.050	0.338	0.133**	0.306*
	(0.021)	(0.259)	(0.260)	(0.299)	(0.024)	(0.179)
Virtual Lagged Asset	0.005	0.013	0.001	0.003	0.015**	0.013
	(0.005)	(0.014)	(0.003)	(0.004)	(0.005)	(0.029)
Current Asset	-0.028**	-0.097**	0.002	0.000	-0.030**	-0.112**
	(0.008)	(0.030)	(0.004)	(0.013)	(0.006)	(0.042)
P-value on Overid Test		0.013		0.990		0.008
P-val on Corr Random Eff					0.000	0.000
R-Sq	0.08	0.07	0.01	0.03	0.10	0.06
Observations	10998	10998	6515	7156	10998	10998

Note: The dependent variable is annual hours of work. Semiparametric Fixed Effects estimates in columns (3) and (4) used method in Kyriazidou (1997). CRE estimates in columns (5) and (6) were obtained using method in Semykina and Wooldridge (2010). All marginal Effects and elasticities computed at the mean hours for labor force participants of 1589, mean net wage of 9.05/hour, mean asset of 70.81 (in '000), and mean lagged virtual asset of 141.40 (in '000). Bootstrapped standard errors using 100 replications and clustered at the individual level are reported in parenthesis. The endogenous variables are after tax real wage, virtual lagged real asset and current year real asset. The instruments are the second lag of after tax predicted real wage, the second lag of virtual lagged real asset, the fourth lag of current real asset and a set of time dummies. To obtain the inverse mills ratio, the first step reduced form LFP equation was estimated on the instruments, quartic in age, number of children, dummy for children less than 7 years , and dummy for self-reported health status. The exclusion restriction for the second step selection-corrected hours equation was dummy for children less than 7 years. * p<0.10, ** p<0.05

Table 4: Lifecycle-Consistent Total Labor Supply Elasticities for Married Women from the PSID (1983-2007)
(Dependent Variable: Annual Hours of Work)

	(1) Pooled Tobit NO IV	(2) Pooled Tobit IV	(3) Semiparametric Fixed Effects NO IV	(4) Semiparametric Fixed Effects IV	(5) Corr. Random Effects Tobit NO IV	(6) Corr. Random Effects Tobit IV
Marginal Effects						
After-Tax Wage	34.722**	169.506**	-10.302**	69.476**	32.935**	141.465**
	(3.667)	(43.680)	(4.462)	(22.181)	(3.824)	(45.184)
Virtual Lagged Asset	0.211**	-0.277	0.214**	-0.403*	0.201**	-0.182
	(0.085)	(0.206)	(0.078)	(0.236)	(0.083)	(0.241)
Current Asset	-1.437**	-3.077**	-0.167	-1.663**	-1.518**	-2.480**
	(0.203)	(0.668)	(0.154)	(0.843)	(0.205)	(1.038)
Elasticities						
After-Tax Wage	0.245**	1.195**	-0.073**	0.490**	0.232**	0.997**
	(0.026)	(0.308)	(0.031)	(0.156)	(0.027)	(0.319)
Virtual Lagged Asset	0.023**	-0.030	0.023**	-0.043*	0.022**	-0.020
	(0.009)	(0.022)	(0.008)	(0.025)	(0.009)	(0.026)
Current Asset	-0.083**	-0.178**	-0.010	-0.096**	-0.088**	-0.144**
	(0.012)	(0.039)	(0.009)	(0.049)	(0.012)	(0.060)
P-value on Overid Test		0.756				0.675
P-val on Corr Random Eff					0.000	0.000
Pseudo R-Sq	0.010	0.011			0.012	0.012
Observations	14303	14303	14303	14303	14303	14303

Note: The dependent variable is annual hours of work. Semiparametric Fixed Effects estimates in columns (3) and (4) used method in Honoré (1992). CRE estimates in columns (5) and (6) were obtained using method in Papke and Wooldridge (2008) All marginal Effects and elasticities computed at the mean hours of 1156, mean net wage of 8.82/hour, mean asset of 73.32 (in '000), and mean lagged virtual asset of 140.88 (in '000). Bootstrapped standard errors using 100 replications and clustered at the individual level are reported in parenthesis. In addition to the variables listed in the table, other explanatory variables included in all specifications are quartic in age, number of children, dummy for children less than 7 years, and dummy for self-reported health status. The endogenous variables are after tax real wage, virtual lagged real asset and current year real asset. The instruments are the second lag of after tax predicted real wage, the second lag of virtual lagged real asset, the fourth lag of current real asset and a set of time dummies. Unobserved after-tax real wage for non-labor-force-participating females was replaced by wage imputed using a year-specific selection corrected wage regression on a quartic in age and education, race dummies,and state dummies. To estimate the wage equation, the first-step selection equation controlled for everything in the wage equation plus real nonlabor income, number of children and a dummy for children less than 7 years. * $p<0.10$, ** $p<0.05$

Table 5: Sensitivity of Estimated Labor Supply Elasticities to Taxes and Lifecycle-specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Lifecycle Model With Nonlinear Taxes			Lifecycle Model With Linear Taxes			Static Model With Taxes		
	Pooled IV	Fixed Effects IV	Corr. Random Effects IV	Pooled IV	Fixed Effects IV	Corr. Random Effects IV	Pooled IV	Fixed Effects IV	Corr. Random Effects IV
Participation Elasticity									
After-Tax Wage	0.556**	0.426**	0.563**	0.590**	0.444**	0.531**	0.534**	0.697**	0.457**
	(0.137)	(0.163)	(0.171)	(0.188)	(0.089)	(0.160)	(0.123)	(0.118)	(0.146)
Lagged Virtual Assets	-0.028*	-0.043**	-0.037*						
	(0.016)	(0.021)	(0.021)						
Current Assets	-0.066**	-0.052*	-0.096**						
	(0.018)	(0.029)	(0.040)						
Virtual Net Saving				-0.004	-0.002**	-0.005**			
				(0.003)	(0.001)	(0.002)			
Virtual Income							-0.187**	-0.119**	-0.056
							(0.030)	(0.038)	(0.068)
Hours Elasticity									
After-Tax Wage	0.549**	0.338	0.306*	0.523*	0.147	0.290**	0.579**	0.157	0.127
	(0.259)	(0.299)	(0.179)	(0.289)	(0.239)	(0.147)	(0.235)	(0.256)	(0.196)
Lagged Virtual Assets	0.013	0.003	0.013						
	(0.014)	(0.004)	(0.029)						
Current Assets	-0.097**	0.000	-0.112**						
	(0.030)	(0.013)	(0.042)						
Virtual Net Saving				0.002	0.004	-0.002			
				(0.004)	(0.007)	(0.005)			
Virtual Income							-0.153**	-0.008	-0.135*
							(0.054)	(0.035)	(0.072)
P-value Overid Test	0.784		0.859	0.705		0.729	0.186		0.213
Pseudo R-Sq	0.083	0.106	0.094	0.079	0.102	0.088	0.095	0.102	0.111

Observations	14303	14303	14303	14199	5597	14199	14303	14303	14303

Note: The dependent variable is Labor Force Participation (LFP) dummy for participation elasticity in the upper panel and annual hours of work for hours elasticity conditional on participation in the lower panel. Bootstrapped standard errors using 100 replications and clustered at the individual level are reported in parenthesis. See note to Table 2 for details of variables for the participation elasticity in columns (1) and (2) of the upper panel. See notes to Table 3 for details of variables for the selection corrected hours equation to estimate the hours elasticity in columns (1) and (2) of the lower panel. All the non-endogenous explanatory variables are the same as in Tables 2, 3, 4. For the estimates in columns (4)-(6) and (7)-(9), after-tax wage variable is the same but lagged virtual assets and real assets are replaced by virtual net savings or virtual nonlabor income and corresponding instruments replaced by the second lags of virtual net savings or virtual nonlabor income calculated at the first dollar tax rate. For calculating the elasticities, means of virtual net saving is 6.48 in the upper panel and 6.67 in the lower panel and virtual income used is 55.21 in upper panel and 53.9 in the lower panel, all in '000. See note to Tables 2 and 3 for means of other relevant variables. Unobserved after-tax real wage for non-labor-force-participating females for estimation of participation elasticities was replaced by wage imputed using a year-specific selection corrected wage regression on a quartic in age and education, race dummies,and state dummies. Real nonlabor income, number of children and a dummy for children. less than 7 years used as exclusion restriction to identify wage equation. The exclusion restriction for the second step selection-corrected hours equation to calculate hours elasticity in the lower panel was dummy for children less than 7 years. * $p<0.10$, ** $p<0.05$.

Table 6: Sensitivity of Estimated Lifecycle-Consistent Elasticities To Regressors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation	Pooled IV	Corr. Random Effects IV	Pooled IV	Corr. Random Effects IV	Pooled IV	Corr. Random Effects IV	Pooled IV	Corr. Random Effects IV
Participation Elasticity								
After-Tax Wage	0.556**	0.563**	0.470**	0.574**	0.187	0.123	0.566**	0.489**
	(0.137)	(0.171)	(0.141)	(0.166)	(0.117)	(0.150)	(0.146)	(0.171)
Lagged Virtual Assets	-0.028*	-0.037*	-0.026*	-0.040*	0.005	-0.021	-0.019	-0.034
	(0.016)	(0.021)	(0.016)	(0.021)	(0.017)	(0.021)	(0.016)	(0.022)
Current Assets	-0.066**	-0.096**	-0.057**	-0.106**	-0.046**	-0.086**	-0.051**	-0.083**
	(0.018)	(0.040)	(0.018)	(0.041)	(0.017)	(0.039)	(0.016)	(0.039)
Hours Elasticity								
After-Tax Wage	0.549**	0.306*	0.497**	0.328*	0.358*	0.243	0.632**	0.211
	(0.259)	(0.179)	(0.244)	(0.181)	(0.203)	(0.150)	(0.233)	(0.208)
Lagged Virtual Assets	0.013	0.013	0.013	0.007	0.027*	0.032	0.038**	0.022
	(0.014)	(0.029)	(0.014)	(0.031)	(0.016)	(0.027)	(0.014)	(0.026)
Current Assets	-0.097**	-0.112**	-0.091**	-0.115**	-0.088**	-0.105**	-0.042**	-0.062
	(0.030)	(0.042)	(0.028)	(0.040)	(0.022)	(0.039)	(0.020)	(0.038)
Quadratic Time Trend	No	No	Yes	Yes	Yes	Yes	No	No
Unemployment Rate	No	No	No	No	Yes	Yes	No	No
Spouse's Wage	No	No	No	No	No	No	Yes	Yes
P-value on Overid Test	0.784	0.859	0.855	0.795	0.468	0.748	0.491	0.468
Pseudo R-Sq	0.083	0.094	0.084	0.095	0.088	0.102	0.091	0.123
Observations	14303	14303	14303	14303	14303	14303	14303	14303

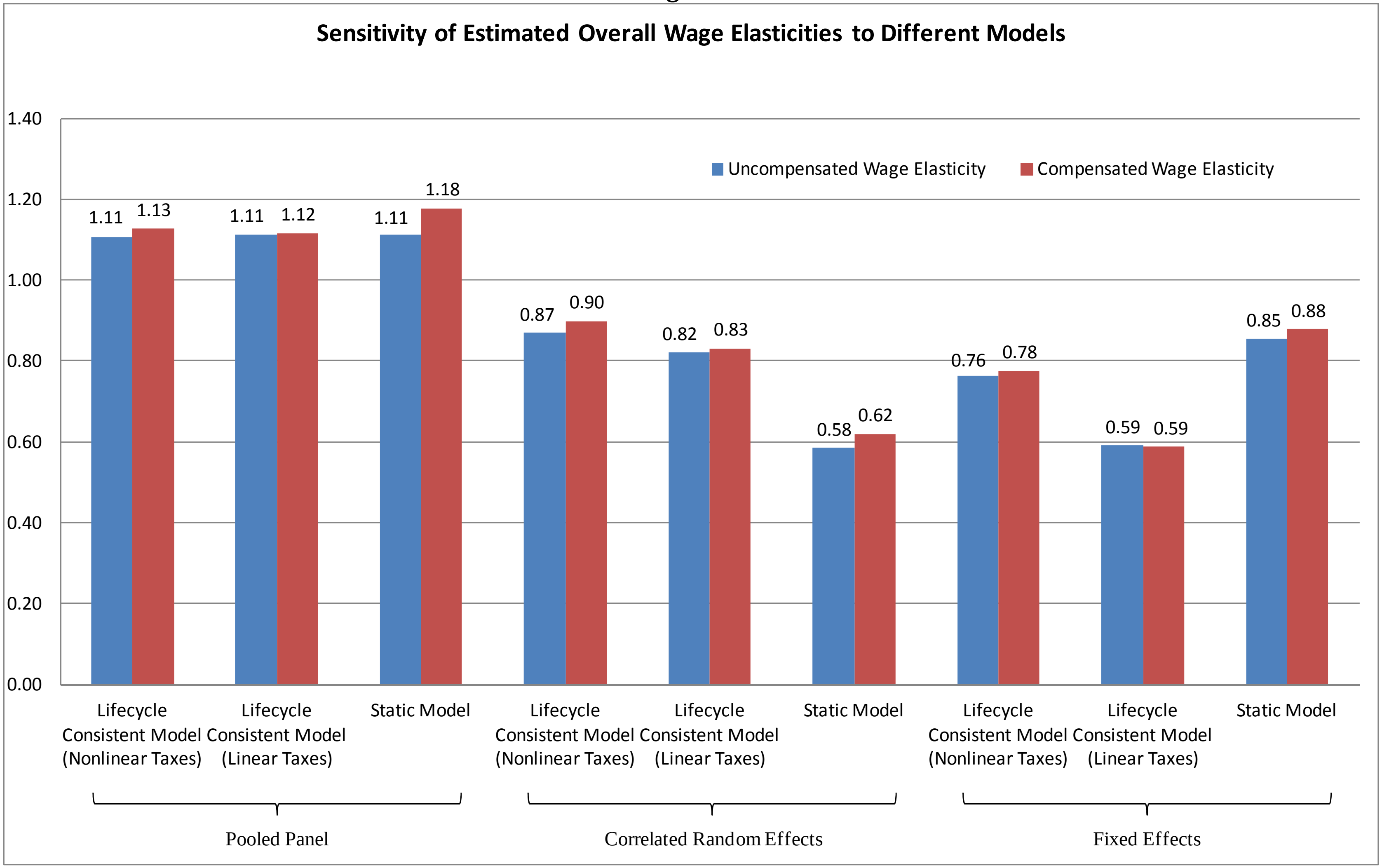
Note: The dependent variable is Labor Force Participation (LFP) dummy for participation elasticity in the upper panel and annual hours of work for hours elasticity conditional on participation in the lower panel. Bootstrapped standard errors using 100 replications and clustered at the individual level are reported in parenthesis. Columns (1) and (2) contain results from the baseline model. See note to Table 2 for details of variables for the participation elasticity in the upper panel. See notes to Table 3 for details of variables for the selection corrected hours equation to estimate the hours elasticity in the lower panel. All the non-endogenous explanatory variables are the same as in Tables 2 and 3. See note to Tables 2 and 3 for means of relevant variables for calculation of elasticities. Unobserved after-tax real wage for non-labor-force-participating females for estimation of participation elasticities was replaced by wage imputed using a year-specific selection corrected wage regression on a quartic in age and education, race dummies,and state dummies. Real nonlabor income, number of children and a dummy for children. less than 7 years used as exclusion restriction to identify wage equation. The exclusion restriction for the second step selection-corrected hours equation to calculate hours elasticity in the lower panel was dummy for children less than 7 years. * $p<0.10$, ** $p<0.05$.

Table 7: Sensitivity of Estimated Lifecycle-Consistent Elasticities to Alternative Instruments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled IV	Corr. Random Effects IV	Pooled IV	Corr. Random Effects IV	Pooled IV	Corr. Random Effects IV	Pooled IV	Corr. Random Effects IV
Participation Elasticity								
After-Tax Wage	-3.535	1.888	0.556**	0.563**	0.349**	0.343**	-0.173*	-0.353**
	(45.217)	(14.392)	(0.137)	(0.171)	(0.063)	(0.102)	(0.092)	(0.107)
Lagged Virtual Assets	-1.207	-0.781	-0.028*	-0.037*	-0.054**	-0.071**	0.850**	1.170**
	(13.005)	(11.139)	(0.016)	(0.021)	(0.023)	(0.030)	(0.216)	(0.231)
Current Assets	1.328	0.336	-0.066**	-0.096**	-0.021	-0.080*	-0.674**	-0.493**
	(8.869)	(6.834)	(0.018)	(0.040)	(0.018)	(0.043)	(0.159)	(0.213)
Hours Elasticity								
After-Tax Wage	0.979	-0.124	0.549**	0.306*	-0.053	0.241	0.209**	0.098**
	(3.021)	(1.846)	(0.259)	(0.179)	(0.052)	(0.190)	(0.050)	(0.029)
Lagged Virtual Assets	0.358	-0.070	0.013	0.013	0.050**	-0.011	-0.169	-0.042
	(0.555)	(0.795)	(0.014)	(0.029)	(0.017)	(0.047)	(0.128)	(0.094)
Current Assets	-0.410	-0.020	-0.097**	-0.112**	-0.063**	-0.035	0.064	-0.077
	(0.400)	(0.522)	(0.030)	(0.042)	(0.016)	(0.043)	(0.096)	(0.058)
Instrument Used								
2nd Lag of Net Wage Based on first dollar tax rate, virtual income/asset	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	No	No	Yes	Yes	No	No	No	No
Education X Year Groups	No	No	No	No	Yes	Yes	No	No
Wage Decile X Year	No	No	No	No	No	No	Yes	Yes
P-value on Overid Test			0.784	0.859	0.002	0.014	0.000	0.000
Pseudo R-Sq	0.081	0.093	0.083	0.094	0.083	0.094	0.093	0.112
Observations	14303	14303	14303	14303	14303	14303	14303	14303

Note: The dependent variable is Labor Force Participation (LFP) dummy for participation elasticity in the upper panel and annual hours of work for hours elasticity conditional on participation in the lower panel. Bootstrapped standard errors using 100 replications and clustered at the individual level are reported in parenthesis. See note to Table 2 for details of variables for the participation elasticity in columns (1) and (2) of the upper panel. See notes to Table 3 for details of variables for the selection corrected hours equation to estimate the hours elasticity in columns (1) and (2) of the lower panel. All the non-endogenous explanatory variables are the same as in Tables 2 and 3. See note to Tables 2 and 3 for means of relevant variables for calculation of elasticities. Unobserved after-tax real wage for non-labor-force-participating females for estimation of participation elasticities was replaced by wage imputed using a year-specific selection corrected wage regression on a quartic in age and education, race dummies,and state dummies. Real nonlabor income, number of children and a dummy for children. less than 7 years used as exclusion restriction to identify wage equation. The exclusion restriction for the second step selection-corrected hours equation to calculate hours elasticity in the lower panel was dummy for children less than 7 years. * $p<0.10$, ** $p<0.05$.

Figure 1



Note: Overall uncompensated wage elasticity is the sum of elasticity on the extensive and intensive margin from Table 5. Compensated elasticities calculated at overall mean real after-tax wage of $8.69, mean hours of 1188, mean current assets of 80760, mean virtual real net saving of $6480, and mean real virtual nonlabor income of $54570.

Appendix 1: Estimation Details

Pooled Panel Data Models

As a benchmark for comparison with models with unobserved effects, the paper first estimates simple pooled panel data models assuming that the dual error term $\alpha_i + \epsilon_{it}$ is a normally distributed random error that is uncorrelated with other regressors. The selection-corrected version of (7) on pooled data is estimated using a Heckman-type framework with inverse mills ratio from a first step labor force participation equation (Heckman (1979)). Endogeneity of ω_{it}, A^{v}_{it-1}, and A_{it} is addressed using conventional two-stage procedure. Estimates from pooled models will be biased if any of the right hand side variables are correlated with α_i. An option is to use a first-differencing or fixed effects specification.

Fixed Effect Models

Tobit-type Labor Supply Models with Fixed Effects

Nonlinear panel data models with censoring do not lend themselves to conventional fixed effects or first-differenced methods. To account for both censoring and fixed effects, the paper employs a semiparametric fixed effect estimator from Honoré (1992) who proposed a trimming mechanism to restore the symmetry of the error distribution affected by censoring or truncation, followed by least squares or least absolute deviation estimation.[28] Assuming that the errors in a pair of years, say t and $t-1$ are identically and independently distributed, the trimmed data can then be used to difference away the individual specific effects (Honoré (2002), Arellano and Honore (2001), Chay and Powell (2001). [29]

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[28] This is analogous to the method proposed in Powell (1986).

[29] Another alternative is to estimate bias-corrected estimates of Tobit with fixed effects suggested by Hahn and Newey (2004).

Although, this method accounts for correlation between right hand side variables and unobserved effect, parameter estimates will still be biased if endogenous variables, ω_{it}, A^{v}_{it-1}, and A_{it} are correlated with the time varying error term ϵ_{it} calling for an instrumental variables approach.[30] The control function method proposed in Blundell and Powell (2007) is combined with the semiparametric fixed effects method in (Bo E. Honoré, 1992) to deal with endogeneity.[31]

Labor Force Participation Models with Fixed Effects

Parameters of labor force participation equation are consistently estimated using fixed effects Logit models (Andersen (1970), Chamberlain (1982)). Endogeneity is corrected by extending the control function approach proposed in Blundell and Powell (2007), similar to the semiparametric censored model above.

Panel Selection-Corrected Hours Equations with Fixed Effects

This paper follows the selection-correction set-up in Heim (2009), except that the model incorporates individual specific fixed effects in both the selection equation and the hours equation. The selection equation is a fixed effects version of (8):

$$D_{it}^{LFP} = X^{S}\pi_1 + \eta_i + e_{it}, \tag{10}$$

where η_i are individual specific unobserved effects. The second step selection-corrected hours equation conditional on labor force participation can be written as:

$$H_{it} = \beta_0 + \beta_1\omega_{it} + \beta_2 A_{it} + \beta_2 A^{v}_{it-1} + X_{it}\gamma + \varphi(X^{S}_{it}\hat{\pi}_1 + \eta_i) + \alpha_i + \epsilon_{it} \tag{11}$$

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[30] The paper uses the code available from Honore's website to estimate semiparametric fixed effects models with censoring.

[31] A vector of residuals, $V_{it} = (v_{it}^{\omega_{it}}, v_{it}^{A_{it}}, v_{it}^{A^{v}_{it-1}})$, from the first stage linear fixed effects regressions of each of the endogenous variables ω_{it}, A^{v}_{it-1}, and A_{it} on instruments $\widehat{\omega}^{z}_{it-2}, A^{vz}_{t-3}, and\ A_{it-4}$ and other exogenous variables X_{it} is included in the model.

where $\varphi(X^S\hat{\pi}_1 + \eta_i)$ is the inverse mills ratio obtained from the first step. Although, individual specific effects α_i can be eliminated by differencing, η_i enters the equation nonlinearly through the inverse mills ratio and cannot be eliminated by differencing.

The paper applies a semiparametric selection correction method proposed in Kyriazidou (1997). First, parameters $\hat{\pi}_1$ of the selection equation (10) are estimated using a consistent estimator e.g. fixed effect Logit. Then for any two time periods, $t-1$ and t in which the female participates in the labor force, if $\Delta X_{it}^S\hat{\pi}_1 = X_{it-1}^S\hat{\pi}_1$ then first differencing (11) would difference away not only α_i but also η_i and $\varphi(X_{it}^S\hat{\pi}_1)$. Because X_{it}^S has both continuous and discrete elements, $\Delta X_{it}^S\hat{\pi}_1$ is unlikely to equal zero. However, estimation can be restricted to observations for which, $\Delta X_{it}^S\hat{\pi}_1$ is small. Better still, using all observations and estimating the following weighted least squares equation for labor force participants with weights going to zero if $|\Delta X_{it}^S|$ increases, yields consistent estimates:

$$\hat{\xi}\Delta H_{it} = \beta_1\hat{\xi}\Delta\omega_{it} + \beta_2\hat{\xi}\Delta A_{it} + \beta_2\hat{\xi}\Delta A_{it-1}^v + \hat{\xi}\Delta X_{it}\gamma + \hat{\xi}\Delta\epsilon_{it}, \tag{12}$$

where $\hat{\xi} = (\frac{1}{\mathrm{h_n}})\mathrm{K}(\frac{\hat{\pi}_1\Delta X_{it}^S}{\mathrm{h_n}})$ is a kernel weight function with $\mathrm{h_n}$, the bandwidth.

Endogeneity in (12) is dealt with following a straightforward application of the two-stage procedure adopted in Charlier et al. (2001) with $\Delta\widehat{\omega}_{it-2}^z, \Delta A_{t-3}^{vz}, and\ \Delta A_{it-4}$ used as instruments.

Semiparametric fixed effects methods solve the problem of correlated unobserved heterogeneity, heteroscedasticity, and nonnormality of the error distributions. However, an important limitation is that average partial effects and therefore, elasticities are, in general, not identified, as the unobserved effects are not estimated Wooldridge (2010). Papke and

Wooldridge (2008) and Wooldridge (2009) showed that estimating average partial effects is feasible in a correlated random effects framework.

Correlated Random Effects (CRE) Tobit and Probit Models

Letting α_i be a linear function of time means of $\omega_{it}, A_{it}, A^{v}_{it-1}, and\ X_{it}$, so that $\alpha_i = \zeta_0 + \zeta_1\overline{\omega_\iota} + \zeta_2\overline{A}_\iota + \zeta_3\overline{A^v}_{t-1} + \varsigma\overline{X}_\iota + a_i$ and substituting in (7) yields the CRE specification,

$$H^*_{it} = \kappa_0 + \beta_1\omega_{it} + \beta_2 A_{it} + \beta_2 A^{v}_{it-1} + \gamma X_{it} + \zeta_1\overline{\omega_\iota} + \zeta_2\overline{A}_\iota + \zeta_3\overline{A^v}_{t-1} + \varsigma\overline{X}_\iota + u_{it}, \qquad (13)$$

Assuming strict exogeneity and normality of the composite error term $u_{it} = a_i + \epsilon_{it}$ (13) is estimated using a Probit or a Tobit.[32]

Control function approach proposed in Papke and Wooldridge (2008) and Wooldridge (2009) is used to account for endogeneity. Letting X_{it}, represent the exogenous variables in the model and Z_{1it}, the instruments ($\widehat{\omega}^{z}_{it-2}, A^{vz}_{t-3}, and\ A_{it-4}$), so that $Z_{it} = (X_{it}, Z_{1it})$ represents the vector of all exogenous variables and instruments. Also let $\bar{Z}_i, \bar{X}_i, \bar{Z}_{1it}$ be the time means of all exogenous variables, included exogenous variables, and excluded instruments, respectively. The first stage in (13) consists of regressing each endogenous variable, ω_{it}, A_{it}, A^{v}_{it-1}, on Z_{it} and $\bar{Z}_i$ and getting the vector of residuals

[32]Typically such CRE specifications are applicable only for balanced panels. However, following Wooldridge (2009), CRE can be adapted for unbalanced panels by assuming that in addition to strict exogeneity of covariates selection into the panel is also strictly exogenous i.e. dropping out of the panel is not systematically correlated with ϵ_{it}.

$(v_{it}^{\omega_{it}}, v_{it}^{A_{it}}, v_{it}^{A_{it-1}^{v}})$. In the second stage, hours or labor force participation is regressed on $\omega_{it},\ A_{it},\ A_{it-1}^{v}, X_{it}, \bar{Z}_i, v_{it}^{\omega_{it}}, v_{it}^{A_{it}}, v_{it}^{A_{it-1}^{v}}$.[33]

Correlated Random Effect Models with Selection Correction

Semykina and Wooldridge (2010) proposed a parametric method to account for correlated individual effects in the selection equation (10) as well as the main equation (11), which combines the typical Heckman-type selectivity correction with correlated random effects models similar in spirit to (13). In the specification without endogeneity, in the first step, year-specific inverse mills ratio, $\hat{\lambda}_{it}$ are obtained by running a Probit of D_{it}^{LFP} on X_{it}^{S} and $\bar{X}_i^{S}$ for each t. In the second step, the specification in (13) is augmented with $\theta\hat{\lambda}_{it} + \sum_{t=1}^{T}\theta_t dt \times \hat{\lambda}_{it}$.

To account for endogeneity, Semykina and Wooldridge (2010) proposed 2SLS estimation similar in spirit to Papke and Wooldridge (2008) and Wooldridge (2009). In the first step a Heckman-type selection equation is estimated by running a reduced form Probit of labor force participation on Z_{it} and an exclusion restriction $dkidsu7$ for each year separately and the year-specific inverse mills ratio for each labor force participant, λ_{it}, saved. In the second step hours is regressed on $\omega_{it},\ A_{it},\ A_{it-1}^{v}, X_{it}, \bar{Z}_i, \hat{\lambda}_{it},\ dt \times \hat{\lambda}_{it}$ in a 2sls framework treating $\omega_{it},\ A_{it},\ A_{it-1}^{v}$ as endogenous.

[33] Note that time means of endogenous variables are not included in the second stage CRE specification. Instead the time means of exogenous variables X_{it} and instruments Z_{it} are included.