THREE ESSAYS IN ESTIMATING INTERTEMPORAL SUBSTITUTION ELASTICITIES OF HOME PRODUCTION

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Abstract

Three Essays in Estimating Intertemporal Substitution Elasticities of Home Production

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This dissertation contains three essays that estimate the intertemporal substitution elasticities of a life cycle model that includes home production. The first essay studies the impact of including home work hours in the estimated intertemporal substitution elasticity of labor supply. We use the employment information of employed males obtained from Panel Study in Income Dynamics and Canadian Time Use datasets. We then estimate the elasticities using a two-stage estimation strategy. Our results suggest that the estimated inter-temporal substitution elasticity in the extended home production life cycle model is lower than the one in standard life cycle model without including home production. Our results are in contrast to the results obtained by Rupert et al. (2000), where they report the estimated inter-temporal substitution elasticity in the home production model to be higher than the one in standard life cycle model.

The second essay critically evaluates the estimated results obtained by Rupert et al. (2000). We investigate the estimated employed male labor supply elasticities of the home production function by using the Three Time Use datasets that are employed by Rupert et al. By utilizing the two-stage estimation strategy and the generalized least square estimating method, we find that there is no evidence indicating that the estimated

inter-temporal labor elasticities of employed male with home production are higher than the ones without home production.

The final essay measures the inter-temporal labor supply elasticities with home production using various employed female datasets as well as different estimation methods. Using the same methodology and datasets as the previous two essays, we find that the empirical results do not provide any conclusive evidence to support the hypothesis that the home production function has increased the estimated intertemporal substitution elasticity of employed female compared to the previous results estimated without home production. Overall, the estimated results of all three essays indicate that there seems to be some willingness to substitute total (market and home) hours over the life cycle for both the employed male group and the employed female group, but it is most likely smaller than the willingness to substitute market hours over the life cycle in response to wage changes.

Acknowledgements

First and foremost, I would like to express my appreciation to Professor Susumu Imai for his excellent guidance, constructive criticism, and continuous support. In addition, he has always been extremely generous with his time and knowledge. I thank Professor Zeng-Rung Liu for his friendship, encouragement, and helpful suggestions. I would also like to thank Eric Lee for his generous time in proof reading on this thesis for improving the clarity of my writing. Professor Carol Lau read my papers carefully and I am grateful to her for valuable comments and suggestions.

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ESSAY 1

ESTIMATING THE INTERTEMPORAL SUBSTITUTION ELASTICITY OF EMPLOYED MALE WITH HOME PRODUCTION UNDER UNCERTAINTY

1.1 Introduction

The modern real business cycle theory tries to explain the macroeconomic fluctuations over the business cycle by using a competitive general equilibrium model, where representative agents optimally choose consumption and labor supply in a dynamic model with future uncertainty. In order to explain the labor hour fluctuations over the business cycle, it assumes that the intertemporal elasticity of substitution, which is defined to be the change in labor hours due to a unit change in (anticipated) real wage, is high. As a result, the estimation on the labor supply's response to wage changes has received a lot of attention from researchers. Lucas and Rapping (1969) examined whether people were willing to substitute leisure and work hours intertemporally by using U.S. aggregate data. They found that the short run labor supply elasticity is between 1.35 and 1.58, while the long run labor supply elasticity is between zero and 1.12. In other words, the short run elasticity is higher than the long run elasticity. Many economists have also estimated the intertemporal elasticity of labor supply using micro panel data sets, such as the PSID (Panel Study of Income Dynamic) and the NLSY (National Longitude Survey of Youth).

Most of the studies that use panel data estimate the intertemporal elasticity of substitution to be around 0.4, which is too low for the real business cycle models to explain the fluctuation of the aggregate labor hours over the business cycle. One of the first papers in this area was MaCurdy (1981), which used a two-stage estimation strategy to estimate the intertemporal substitution elasticity of prime-age married white males. Altonji (1986), Ham (1986), Browning, Deston and Irish (1985) reached similar results.

Recently, Rupert et al. (2000) used the following three times use surveys: (1) The Americans' Time Use (1965-1966) (2) the Time Use Longitudinal Panel Study (1975-1976) and (3) the Time Use Longitudinal Panel Study (1981) to construct a synthetic cohort data set to estimate labor supply elasticity. Their paper concluded that the estimated elasticity of the home production life cycle model was higher than the estimated elasticity of a standard life cycle model. In this paper, we utilize the PSID data and Canadian Quality of Life data to re-examine the intertemporal elasticity of labor supply of the home production life cycle model. The result we obtain is that the estimated elasticity of the home production labor supply model is lower than the estimated elasticity of the standard labor supply model.

The reminder of this paper is as follows: section 1.2 presents the standard life cycle model which is briefly reviewed; section 1.3 includes an extended home production life cycle model which is discussed; section 1.4 describes the characteristics of the data; section 1.5 reports the life cycle profiles; section 1.6 is the estimation results and section 1.7 is the conclusion.

1.2 The life cycle model with uncertainty

We first briefly review the standard life cycle labor supply model estimated by MaCurdy (1981). The assumptions used include a known life length T. An individual is uncertain about his future taste, income, and interest; accordingly, the individual updates his decision on consumption and work hours based on the information available each period. Consider an individual who solves the following problem:

Maximizes $\quad E\sum_{t=1}^{T}\beta^{t}u(c_{mt}, L_{mt}, \varepsilon_{mt})$ (1)

Where $L_{mt} = H - h_{mt}$

Subject to

$c_{mt} + A_t \leq A_{t-1}(1+r) + w_t h_{mt}$ (2)

$H \geq h_{mt}$ (3)

A_t denotes exogenous variables observed by the researcher and ε_t is a component unobserved by the researcher. Furthermore, H is total hours, L_{mt} is total leisure hours and h_{mt} the total work hours. H is the per period time endowment. C_{mt} is the market consumption variable where h_{mt} denotes the number of market work hours; w_t equals real wages; r represents the real interest rate; β is the time preference; and A_t depicts the asset holdings. Utility function u is assumed to be concave. The objective function is additive over time.

We set up the Bellman's equations as follows:

$$V_t(A_t, w_t) = Max_{C_t, h_t}\{u(c_t, H - h_t) + \beta EV_{t+1}[A_{t+1}, w_{t+1}]\}$$

where $A_{t+1} = (1+r)[A_t + w_t h_t - c_t]$

Hence, substituting the budget constraint, we get

$$V_t(A_t, w_t) = Max_{C_t, h_t}\{u(c_t, H - h_t) + \beta EV_{t+1}[(1+r)[A_t + w_t h_t - c_t], w_{t+1}]\}$$

The first order conditions are:

$$u_c(c_t, H-h_t) - (1+r)\beta E V_{A,t+1}[A_{t+1}, w_{t+1}] = 0 \tag{4}$$

$$-u_L(c_t, H-h_t) + w_t(1+r)\beta E V_{A,t+1}[A_{t+1}, w_{t+1}] = 0 \tag{5}$$

Differencing the value function with respect to A_t, we get

$$V_{A,t}(A_t, w_t) = (1+r)\beta E V_{A,t+1}[A_{t+1}, w_{t+1}] \tag{6}$$

Denote $\lambda_t = V_{A,t}(A_t, w_t)$, then

$$\lambda_t = \beta(1+r)E_t[\lambda_{t+1}] \tag{7}$$

where λ_t is the marginal utility of wealth at time t.

The above equations imply that an individual revises his consumption and work hour planning based on the new information available each period. In other words, he adjusts all future values of λ if there are changes in wealth, expected future wages, expected future interest, or uncertainty about future resources. Let us define η_{t+1} as a one period forecast error from unexpected changes of variables at time t. That is, $\eta_{t+1} = \lambda_{t+1} - E[\lambda_{t+1}]$. Then,

$$\lambda_t = \beta(1+r)[\lambda_{t+1} - \eta_{t+1}] \tag{8}$$

Taking log and then using Taylor expansion around $\ln \lambda_{t+1}$, we get

$$\ln \lambda_{t+1} = \ln \frac{1}{\beta(1+r)} + \ln \lambda_t + \ln \eta_{t+1} \tag{9}$$

We assume that $E[\ln \eta_{t+1} \mid \Omega_t] = 1$, where Ω_t is the set that includes all information up to period t. Consider $U(c_{mt}, h_{mt}) = u(c_{mt}) - v(h_{mt})$ and $v(h_{mt}) = \phi h_{mt}^{\gamma}$; then the regression function becomes:

$$(\gamma - 1)\ln h_{mt} = \ln\frac{\lambda_t}{\gamma\phi} + \ln w_t \tag{10}$$

$$\ln h_{mt} = \delta \ln\frac{\lambda_t}{\gamma\phi} + \delta \ln w_t \tag{10'}$$

where $\delta = \dfrac{1}{\gamma - 1}$

At period t+1:

$$(\gamma - 1)\ln h_{mt+1} = \ln\frac{\lambda_{t+1}}{\gamma\phi} + \ln w_{t+1} \tag{11}$$

$$\ln h_{mt+1} = \delta \ln\frac{\lambda_{t+1}}{\gamma\phi} + \delta \ln w_{t+1} \tag{11'}$$

Subtracting equation (10') from equation (11') and using equation (9) yields:

$$D\ln h_{mi}(t) = B + \delta D \ln W_i + \varepsilon_i(t) \tag{12}$$

D is the first different operator $DX_i = X_i(t) - X_i(t-1)$.

The first differencing eliminates individual effects and provides a single system of simultaneous equations. However, there is a negative correlation between the regressor and the error term. For instance, when wages increase, the marginal value of wealth is falling. The OLS estimate is biased as $E[\varepsilon_i lX] \neq 0$. This comes from the error term of equation (9). The reason is that the unanticipated wage increase, due to wealth effect, is negatively correlated with η_{t+1}, which is the unanticipated component of the marginal value of wealth. The wage growth equations, *DlnWij*, j=2,…,n are treated as endogenous variables and two-stage least square procedure (2SLS) is used to estimate the intertemporal substitution elasticity, δ. The set of instruments are family background variables, such as education, age, etc. These instruments are correlated with the endogenous variable (*DlnW*) but are uncorrelated with the disturbance. We briefly discuss the method how to estimate the temporal elasticity in this section. The next section is to present the home production life cycle model with uncertainty which has similar features of the standard life cycle model.

1.3 The Home Production Life Cycle Model with Uncertainty

The home production life cycle model with uncertainty is an extended version of the standard life cycle model with uncertainty. This paper uses the model developed by Rupert, Rogerson, and Wright (2000). The worker solves the following maximization problem.

$$E\sum_{t=1}^{T}\beta^t u(c_{mt}, c_{nt}, h_{mt}, h_{nt}) + w_T(A_T)$$

subject to

$$A_{t+1} \le (1+r)[A_t + w_t h_{mt} - c_{mt} - i_{n,t}]$$

$$c_{nt} \le g_t(h_{nt}, k_{nt})$$

$$k_{nt+1} = (1-\delta)k_{nt} + i_{nt}$$

$$H \geq h_{mt} + h_{nt}$$

Cmt is the market consumption and *Wt* denotes the real hourly wage; *hmt* depicts the annual hours of market work at time t; A_t represents the asset at period t. β is the subjective discount factor; *r* is the interest rate, and *H* is the per period time endowment. The home production function is $g_t(h_{nt}, k_{nt})$. A non-tradable home consumption good (c_{nt}) is produced by h_{nt} annual hours of home work plus home capital (k_{nt}). The productivity in home production changes over the life cycle and it is time dependent. The variable i_n denotes the investment in home capital and δ the depreciation rate. Function *U* is assumed to be concave. Rupert et al. (2000) assume that $W_T(A_T)$ is the utility the individual receives at the terminal period, which is a function of assets at the final stage of one's life. State variables are $Z_t = (A_t, k_{nt})$ and control variables are $a_t = (h_{mt}, h_{nt}, c_{mt}, A_{t+1}, k_{n,t+1})$. We then can set up the Bellman equation as follows:

$$V_t(A_t, k_t) = Max\{u[c_{mt}, g(h_{nt}, k_{nt})] - v[h_{mt} + h_{nt}] + \beta EV_{t+1}(A_{t+1}, k_{t+1})\}$$

The first order conditions (for interior solution) are:

$$c_{mt} : u_m(t) - (1+r)\beta EV_{t+1}(A_{t+1}, k_{t+1}) = 0 \tag{13}$$

$$h_{nt} : u_n(t) g_h(t) - v'(t) = 0 \tag{14}$$

$$h_{mt} : -v'(t) + w_t(1+r)\beta EV_{A,t+1}(A_{t+1}, k_{t+1}) = 0 \tag{15}$$

$$i_t : (1+r)EV_{A,t+1} + EV_{k,t+1} = 0 \tag{16}$$

Differencing the value function, we derive:

$$A_t : V_{At}(A_t, k_t) = (1+r)\beta EV_{t+1}(A_{t+1}, k_{t+1}) \tag{17}$$

$$k_t : V_{kt}(A_t, k_t) = u_n(t)g_k(t) + (1-\delta)EV_{k,t+1} \quad (18)$$

Define $\lambda_t = V_{At}(A_t, k_t)$, then (17) implies

$$-v'(t) + w_t(1+r)\beta E\lambda_{t+1} = 0$$

Equation (17) and (18) imply the Euler equation to be

$$\lambda_t = \beta(1+r)E_t[\lambda_{t+1}] \quad (19)$$

If $v(h_{mt}) = \phi(h_{mt} + h_{nt})^{\gamma}$ then the following equation can be derived:

$$(\gamma - 1)\ln(h_{mt} + h_{nt}) = \ln\frac{\lambda_t}{\gamma\phi} + \ln w_t \quad (20)$$

$$\ln(h_{mt} + h_{nt}) = \delta\ln\frac{\lambda_t}{\gamma\phi} + \delta\ln w_t \quad (21)$$

Notice that the only difference between equation (21) and (10) is that hours spent at work at (10) become the sum of the hours spent at work and home production. The home production model has the same distribution features of the standard life cycle model except the dependent variable is $D\ln(h_{mt} + h_{nt})$ instead of $D\ln(h_{mt})$. The same method and procedure used by the standard life cycle model are used to examine the home production model. Using the first differencing method to eliminate the fixed effects, we can apply the 2SLS procedure to estimate the intertemporal substitution elasticity using the log differenced regression equation $D\ln(h_{mt} + h_{nt}) = B + \delta D\ln W_t + \varepsilon_t$.

The estimated parameter δ represents the percent changes in total hours as the wage varies by one percent in the life cycle model. The regression equation is $D\ln(h_{mt}) = B + \delta D\ln W_t + \varepsilon_t$ for a standard life cycle labor supply function. If the home production hours are positively correlated with wages over the life cycle, the estimated δ

will be higher than the one without home production hours. However, if they are negatively correlated, the estimated δ will be lower.

The synthetic cohort approach is also used in this paper. Synthetic cohorts are constructed from individual observations drawn from a single year. Individuals are grouped by their age and by the other observables. We first use the differencing procedure to remove the fixed effects; then we use the 2SLS to estimate δ for both the standard life cycle model and the home production model.

1.4 Data Structure

Our sample consists of individuals in the PSID between the years 1969 to 1997, who were married; white males between the ages of 25 and 60; and reported positive earnings and work hours for at least five consecutive years. The samples from the year 1968, 1975 and 1982 are excluded because they did not report home production hours. The data in years 1999 and 2001 are not annual survey reports; therefore, they were not included in the sample. The labor supply variables are the number of annual work hours and the annual hours of home production. We selected only males between the ages of 25 and 60 to avoid the complication associated with schooling and retirement. The wages are real average hourly earnings that are measured by dividing annual earnings by annual hours worked. The hourly earnings are then deflated by the Consumer Price Index to obtain the real earnings.

Additionally, we use the Quality of Life Survey that is a Canadian data set that has been panel surveyed for the following 3 years: 1977, 1979 and 1981. Each year contains approximately 650 variables and more than three thousand respondents. A panel of about two thousand respondents was interviewed throughout the three years. Since only 1979 dataset has information of home work hours, we only employed 1979 data set. From the data we selected employed males between ages of 20 and 65 to form the synthetic cohort. The wages are real average hourly earnings and the labor supply variable is the weekly work hours.

We constructed age profiles from the PSID. Using the information from the PSID we formed the age-wage profile, age-work hour profile, and age-home work hour profile. The survey reported the home production hours per week, weekly working hours and wages. We also constructed a three year (1969, 1976 and 1981) age-wage profile; age-work hour profile; and age-home work hour profile from the PSID in order to compare the profiles from Rupert et al. (2000), who only used those three years. Their paper states that the age-home work hour profiles show a positive correlation between home work hours and wages. What we are trying to do is to check whether the age-home work hours profiles show a similar trend. We constructed similar profiles from the Canadian Quality of Life Survey.

1.5 Life Cycle Profiles

Figure 1.1: Age-Wage Profile (PSID 1969-2001)

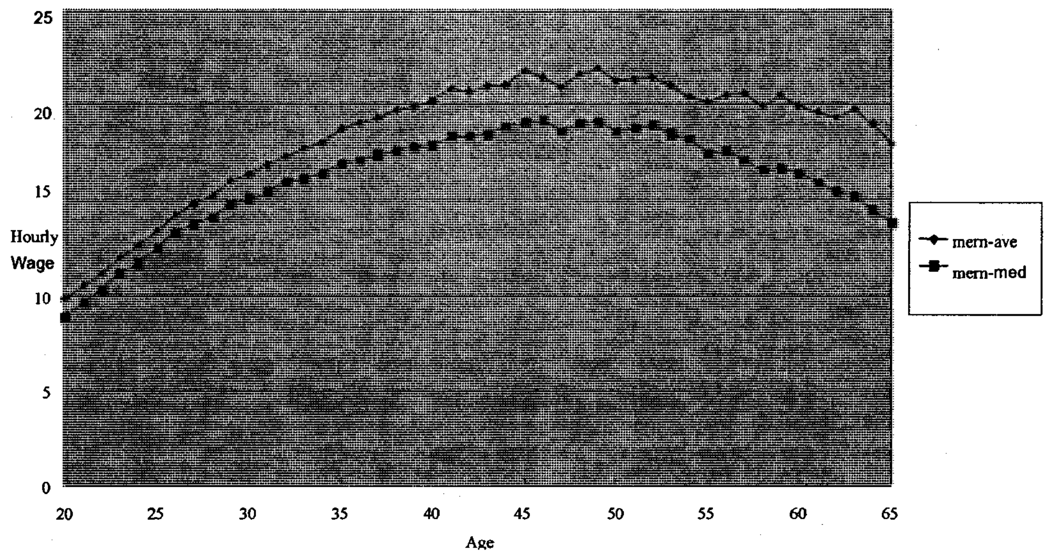


Figure 1.2: Age-Wage Profile (PSID 1968, 1976, 1981)

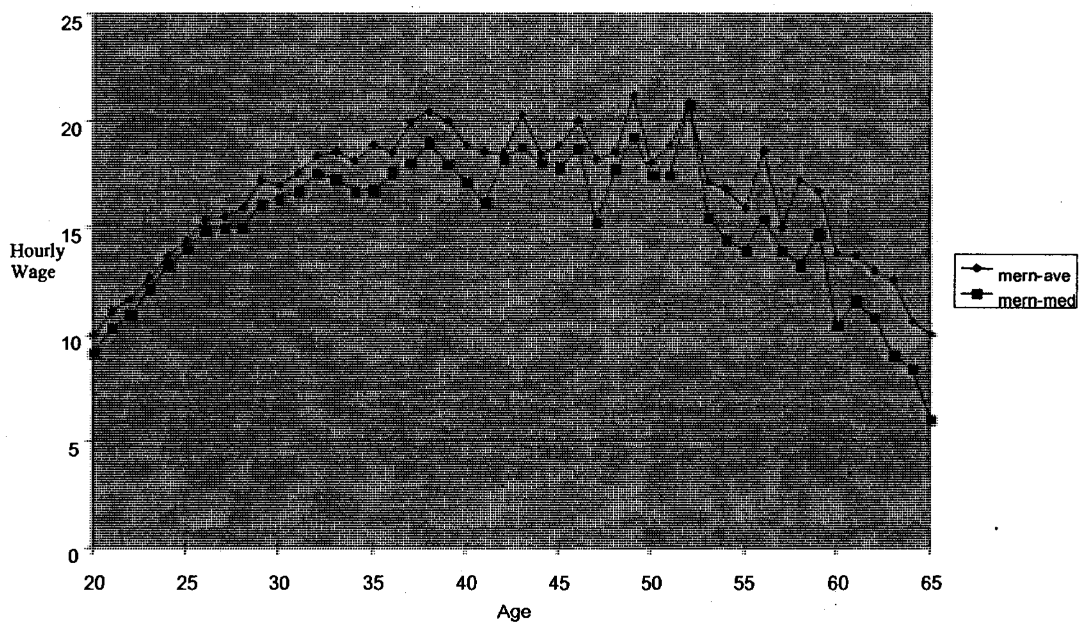


Figure 1.3:Age-Wage Profile (Canadian Survey, 1979)

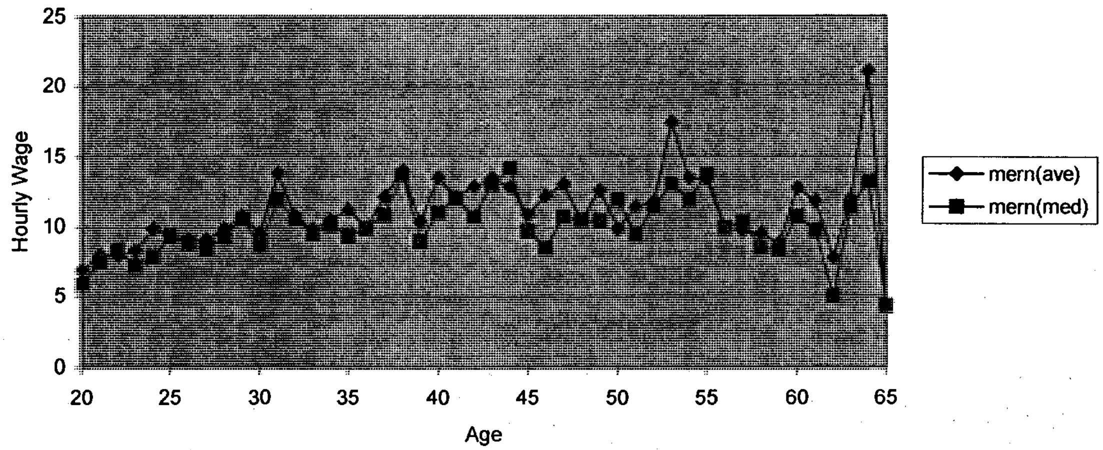


Figure 1.4: Age-Work Hour Profile (PSID 1969-2001)

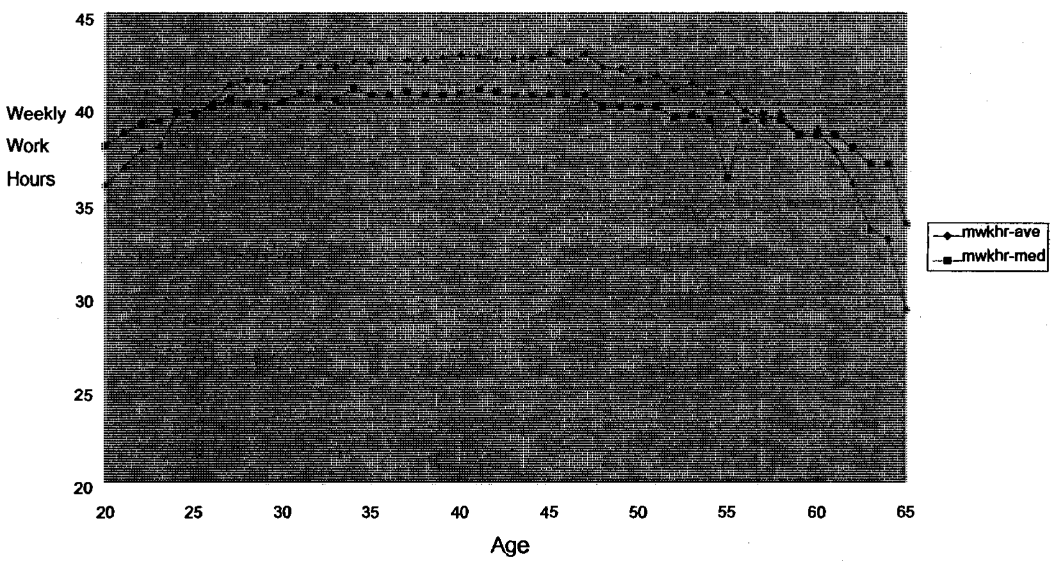


Figure 1.5: Age-Work Hour Profile (PSID 1968, 1976, 1981)

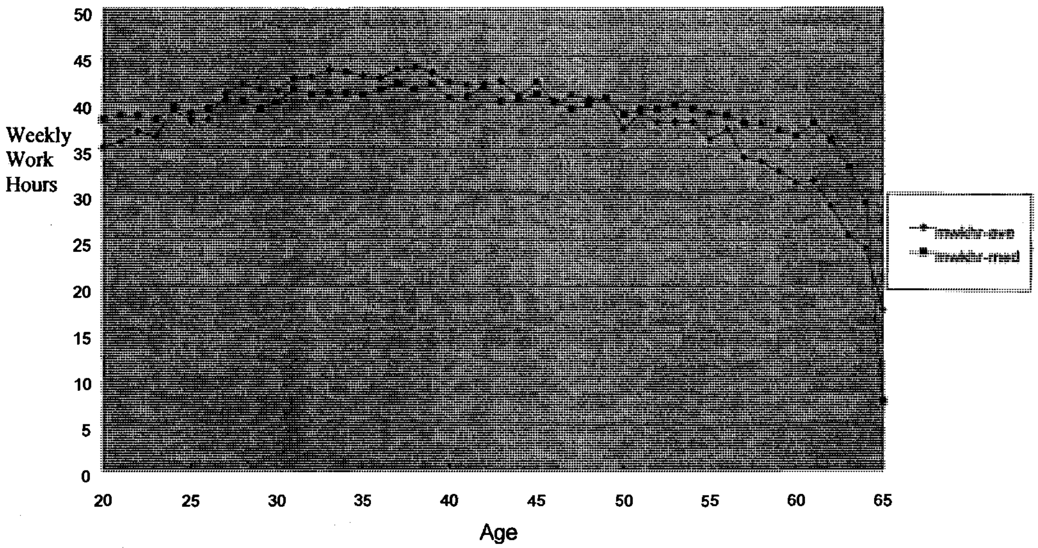


Figure 1.6: Age-Work Hours Profile (Canadian Survey, 1979)

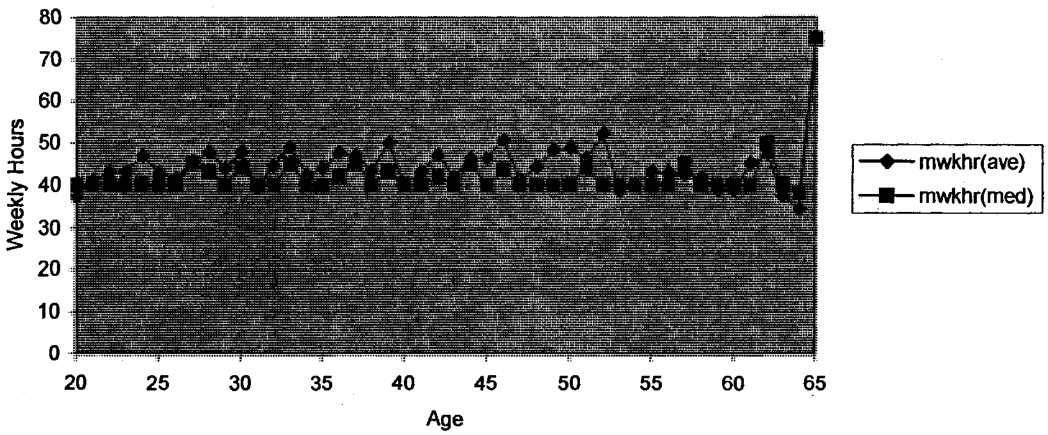


Figure 1.7: Age-Home Work Profile (PSID 1969-2001)

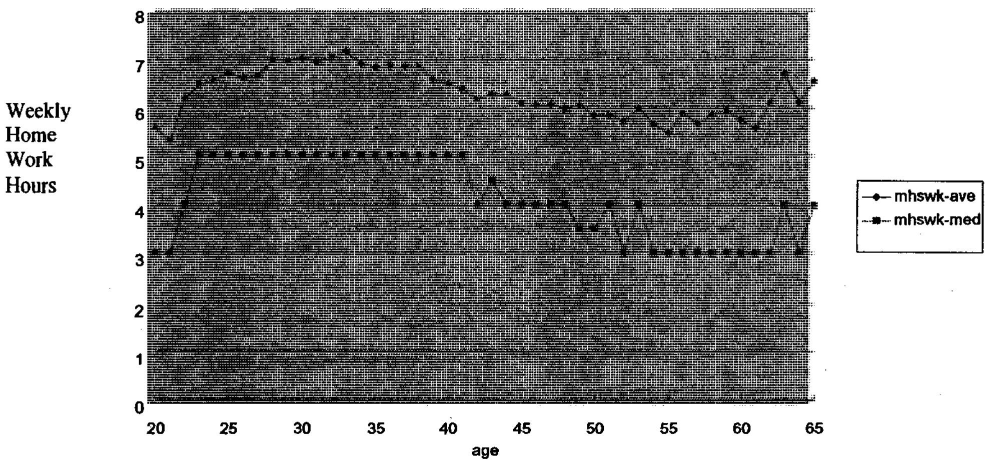


Figure 1.8: Age-Home Work Profile (PSID 1968, 1976, 1981)

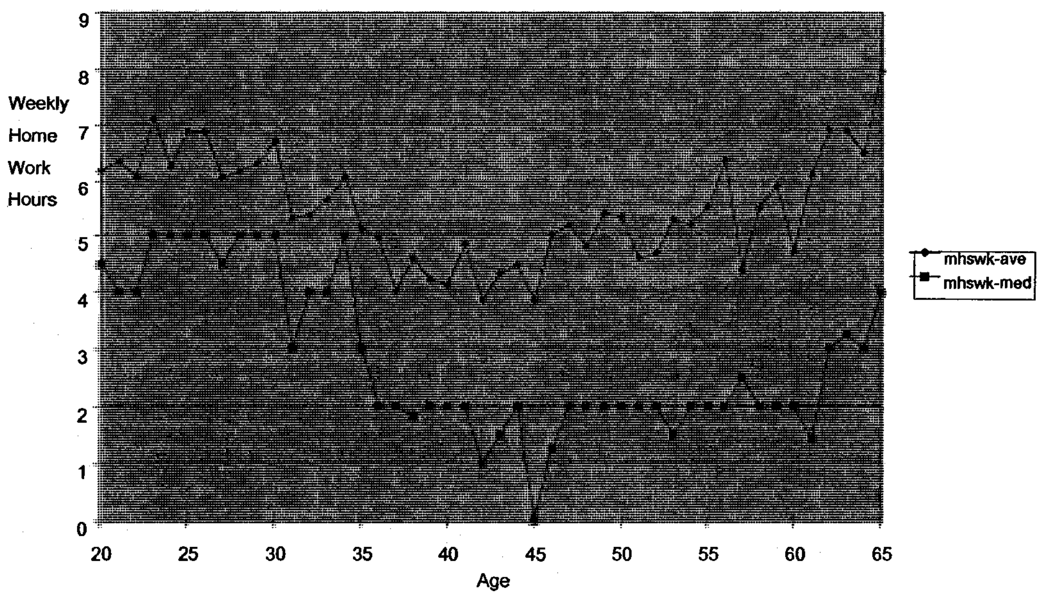
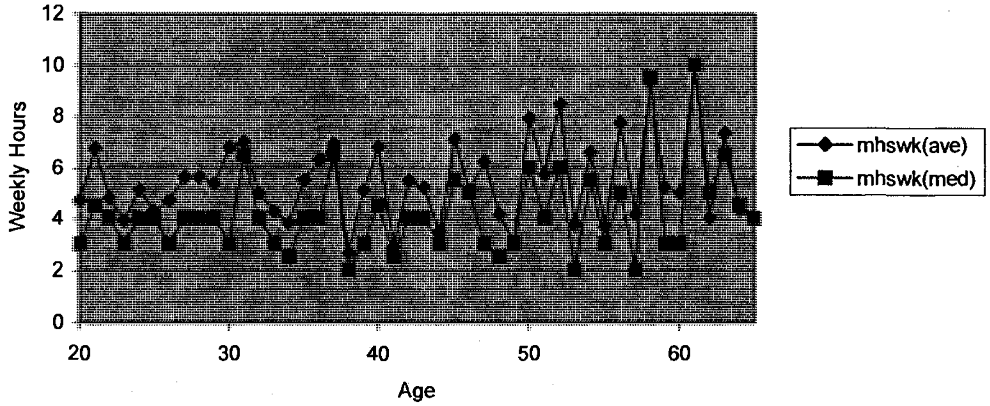


Figure 1.9: Age-Home Work Hours Profile (Canadian Survey, 1979)



mhswk-ave is the average weekly home work hours of the male workers.
mhswk-med is the median weekly home work hours of the male workers
mwkhr-ave is the average weekly work hours of the male workers.
mwkhr-med is the median weekly work hours of the male workers.
mern-ave is the average weekly hourly wage of the male workers.
mern-med is the median weekly hourly wage of the male workers.

Figure 1.1 plots the male age-wage profiles of the PSID (1969-2001) data and Figure 1.2 plots the same profile with PSID (1968, 1976 and 1981) for only 3 years. Figure 1.3 does the same for the Canadian Quality of Life Survey (1979). All three age-wage profiles exhibit a sharp rise from age 20 to age 40, then the trend starts to flatten and eventually falls at around 50. One potential reason for this could be that for men market productivity starts low in the early 20's, while they are still in training or searching for a career, then it rises rapidly with age at around mid 20's to mid 40's, and it eventually tails off and even falls in the later years. The sample size of Canadian Quality of Life Survey (1979) is 732 while there are only two samples at age 65 who happen to have a sharp rise of averaged wage at age 65. Figure 1.4 to 1.6 plots the age-work hour profiles for PSID, PSID with only 3 years of data and the Canadian Quality of Life

Survey. All age-work hour profiles display a pattern similar to age-wage profiles. But overall, the age-work hour profiles are much flatter than those of age-wage profiles. This is the reason why conventional instrumental variable (IV) estimates, which essentially identify the intertemporal elasticity of labor supply parameter through changes in those two age profiles, provide only small estimates of the labor supply elasticity. Figure 1.7 to 1.9 plots the age-home work hour profiles. The pattern of the age-home work hour profile differs significantly from the pattern for the age-wage and the age-work hour profiles. The pattern of age-home work hour profile demonstrates that individuals increase their home work hours during their early 20's to 30's; then they reduce them when they are between 30's to 50's; and they increase their home work hours when approaching retirement. The age-wage profiles and age-home work hour profiles show that wages and home work hours are negatively correlated. It seems that individuals tend to reduce their home work hours in order to increase their work hours when their wages are increasing and the other way round when wages are decreasing. Our findings are contrary to those of Rupert et al. (2000).

Rupert et al. (2000) concludes that the estimated intertemporal substitution elasticity is higher than the conventional estimates if the dependent variable is the sum of home work hours and work hours. The authors claim that males are demanding more home work hours at their prime age when they have high productivity (i.e. wages). Prime age male workers increase their home work hours when their wages raise. Therefore, they argue that the life cycle studies that do not consider home work hours in the model lead to biased parameter estimates. This is not consistent with our results where a person tends to increase his market work and reduce his home work hours when his wage is high. A person's wage mostly starts low in his youth, then rises rapidly with age and levels off or drops in his later years. With an expected pattern of his wages over his lifetime, a person can make a prediction on his lifetime wealth. He can then use his prediction to decide the costs of leisure and home work time he will face at various wages. By taking the expected lifetime wealth into account, he will react to wage increases by increasing his market hours. Consequently, the anticipated wage increase raises the cost of leisure and home work hours. This wage increase causes a substitution effect that leads to an increase in work hours during periods of high productivity, and a reduction in the consumption of leisure and home work hours at the same time. The above figures show that the latter explanation seems to explain the age profiles of PSID and the Canadian Quality of Life Survey better than the former.

In this paper, we use the PSID to test whether the life cycle model with home production will give us higher estimates of the intertemporal substitution elasticity than the ones estimated from the standard life cycle labor supply model. Furthermore, we also estimate the data with the outliers removed to check whether they affect the estimates. We only use data that satisfy the following conditions: (1) workers must report positive and less than 5,824 total hours (the sum of home production hours and work hours) per year; (2) the absolute value of the difference in his real average hourly earnings in adjacent years cannot exceed $45 or a change of 200 percent; (3) the absolute value of the difference in the total hours in adjacent years cannot exceed 3000 hours or a change of 190%. The rest are defined to be outliers. Finally, when we use the Canadian Quality of Life data set, we form a synthetic cohort approach to estimate the home production model. In the next section we present the estimation results.

1.6 Estimation Results

Table 1.1: Hours Regression (Married White Males)
PSID 1969-1997 (excluded 1975 and 1985)

	Log (hours) on log (wages) age 25-60 (No outliers)		(With outliers)	
	NHP(hmt)	HP(hmt+hnt)	NHP(hmt)	HP(hmt+hnt)
OLS				
Cons	7.9710	8.0945	8.0190	8.1226
S.E.	(0.0142)	(0.0124)	(0.0130)	(0.0110)
Log w	-0.0992	-0.0938	-0.1222	-0.1087
S.E.	(0.0047)	(0.0041)	(0.0042)	(0.0036)
First Differencing				
Cons	0.0046	0.0051	0.0070	0.0072
S.E.	(0.0016)	(0.0015)	(0.0019)	(0.0017)
Log w	-0.2853	-0.2457	-0.2747	-0.2183
S.E.	(0.0057)	(0.0054)	(0.0047)	(0.0042)
First Differencing with 2SLS				
Cons	-0.0120	-0.0103	-0.0052	-0.0041
S.E.	(0.0054)	(0.0049)	(0.0054)	(0.0047)
Log w	0.6158	0.5607	0.4773	0.4149
S.E.	(0.2184)	(0.1982)	(0.2163)	(0.1884)

Table 1.2: Hours Regression (Employed Male) Canadian Quality of Life Survey 1979

Log (hours) on log (wages) age 22-62		
	NHP(hmt)	HP(hmt+hnt)
OLS		
Cons	3.8669	3.9231
S.E.	(0.1184)	(0.1306)
Log w	-0.0498	-0.0212
S.E.	(0.0525)	(0.0579)
First Differencing		
Cons	-0.0007	0.0005
S.E.	(0.0147)	(0.0184)
Log w	-0.1254	-0.0564
S.E.	(0.0564)	(0.0706)
First Differencing with 2SLS		
Cons	0.0037	0.0022
S.E.	(0.0182)	(0.0200)
Log w	0.0975	0.0732
S.E.	(0.3922)	(0.4325)

In Table 1.1, we report results of regression for the PSID where the dependent variables are log hours and the independent variables are log wages. For the log hours, $\ln(h_t)$, we use $h_t = h_{mt} + h_{nt}$ in the home production model (HP), and $h_t = h_{mt}$ in the non-home production model (NHP) where we only use market hours in the elasticity estimation. The OLS estimates, the first differenced least square estimates, the first differenced 2SLS estimates are reported. Table 1.2 shows the results from the Canadian Quality of Life Survey data (1979) using the same methods mentioned above.

In Table 1.1, we present two groups of estimates from PSID. In the first group we use the outlier removed data while in the second group we use the entire data. The instruments for the log wage are the age of the individual, the age squared, the number of family members in a family unit, the number of children, the number of children less than age 6, parent's wealth when the individual reaches adulthood, and the individual's mother's education level.

We start to analyze the first group of estimates that use outliers removed data. The OLS estimates and first differencing estimates of the $D\ln(W_t)$ coefficient *(δ)* are all negative in both the standard model and the home production model, whereas the IV estimates are both positive. This is due to the endogeneity of the wage, i.e. the differenced log wages are correlated with the error term. There are two reasons for it. First, this is due to the measurement errors in wages. For instance, the hourly wage rate is measured by dividing the worker's annual earnings by the annual work hours. As a result, the error created in measuring the hours creates a spurious negative correlation between hours and wages, and this negative correlation will still exist even after taking the first differences in the wages and working hours. Secondly, this is due to an income effect. That is, an unanticipated increase in wages reduces the marginal utility of wealth due to the income effect, which then decreases the error term. Next, we discuss the IV strategies to deal with the endogeneity issue in detail.

In the first stage regression of the 2SLS, we fit the change in log wages using the instruments such as age, parental background. The fitted wages essentially are predicted wages, which are orthogonal to the unanticipated change in wages and the measurement error. The IV estimates of the intertemporal substitution elasticities are all positive. The estimated δ (0.5607 or 0.4149) of the home production model is smaller than the estimated δ (0.6158 or 0.4773) without home production. This is contrary to the results reported by Rupert et al. (2000). Similar results are obtained when we remove the outliers. Furthermore, for the standard lifecycle model the estimated intertemporal substitution elasticity with outliers included is lower than those without them. For the standard life cycle model and life cycle model with home production with outliers, the OLS estimates and the first differenced estimates of intertemporal substitution elasticity are all negative.

In addition, we used the Canadian Quality of Life data set and formed a synthetic cohort to examine the home production life cycle model. Synthetic cohorts are constructed from individual observations drawn from a single year. Individuals are grouped by their age and by the averaged observations of individuals in the same age group. The same formulas and function forms are being used from the above. Since the data set for 1977 and 1981 have no information on home production hours, we only use 1979 data. The estimated results from the 1979 data set are in Table 1.2. Similarly, the OLS estimates, the first differenced least square estimates, the first differencing with the 2SLS estimates are reported.

All estimated results from the OLS and first differenced regression are small and negative. In the 2SLS results using the synthetic cohort the estimated elasticity (0.0732) from the home production model is lower than the estimated elasticity (0.0975) from the standard life cycle model; however, both estimates are small and not significant.

1.7 Conclusions

Two data sets (PSID and Canadian Quality of Life) have been employed to examine the intertemporal labor supply elasticity of the home production model. The estimates of the intertemporal labor supply elasticity are smaller than those of the standard life cycle labor supply model without home production. This is in contrast to the conclusion drawn by Rupert et al. (2000). The age-home work hour profiles indicate that people decrease their home work hours when their wages are increasing. As a result, home production hours are negatively correlated with the wage rate. Therefore, introducing the home production labor supply into standard intertemporal labor supply model will not increase the estimates of the intertemporal labor supply elasticity. Further investigation should be performed, especially for the female labor supply model with home production.

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EASSY 2

ESTIMATING THE INTERTEMPORAL SUBSTITUTION ELASTICITY OF EMPLOYED MALES WITH HOME PRODUCTION USING THREE TIME USE SURVEYS

2.1 Introduction

The home production life cycle model that we analyzed in the first paper utilizes panel data and cross sectional data. Rupert et al. (2000) estimated the intertemporal elasticity of substitution in labor supply using three time use survey dataset: Americans' Use of Time (1965-1966), The Time Use Longitudinal Panel Study (1975-1976) and the Time Use Longitudinal Panel Study (1981)), from which they constructed a synthetic cohort data. They conclude that there is a downward bias in the estimated employed male labor supply elasticity in the standard life cycle model. Their reasoning is that the standard life cycle model ignores changes in the hours of homework over the life cycle. Our paper employs the same data used by Rupert et al. (2000). In particular, in addition to the time use surveys, we follow Rupert et al. and use two datasets, namely, Current Population Survey (CPS) and Panel Study of Income Dynamics (PSID) to construct synthetic wage data. The objective of this paper is to examine whether there is an evidence of downward bias of the intertemporal elasticity of substitution in labor supply in the standard life cycle model, as argued by Rupert et al. (2000).

The remainder of this paper is organized as follows: Section 2.2 illustrates the home production life cycle models. Section 2.3 describes the data sources and section 2.4 analyses life cycle profiles. A statistical summary and regression results are presented in section 2.5, while the conclusions and suggestions for further research are discussed in Section 2.6.

2.2 The Model and the Estimation Strategy

The home production life cycle labor supply model in this section is identical to the framework discussed in the first paper of the thesis. The utility function of the home production life cycle model is

$$U(c_{mt}, c_{nt}, h_{mt}, h_{nt}) = u(c_{mt}, c_{nt}) - v(h_{mt}, h_{nt})$$

where C_{mt} is the consumption of market goods and C_{ht} the consumption of home goods, such as home cooked meals. The variable h_{mt} is the hours spent in the labor market while employed, and h_{nt} is the hours spent on non-paid home production. Per period utility function is assumed to be separable in consumption and labor hours. We assume the disutility of the labor function to have the following functional form:

$$v(h_{mt}, h_{nt}) = \phi(h_{mt} + h_{nt})^{\gamma}$$

Then, the first order condition for optimal labor supply can be derived as follows:

$$\phi\gamma(h_{mt} + h_{nt})^{\gamma-1} = w_t\lambda_t$$

where λ_t is the marginal value of asset at period t. The above equation can be rewritten as:

$$\ln(h_{mt} + h_{nt}) = -\frac{\ln(\phi\gamma)}{\gamma - 1} + \frac{\ln(\lambda_t)}{\gamma - 1} + \frac{1}{\gamma - 1}\ln w_t$$

Assuming that λ_t is a function of time period and a random term that represents unanticipated disturbances of the model, based on the above equation, we estimate the following regression equation:

$$\ln(h_{mt} + h_{nt}) = \alpha_0 + \alpha_1 t + \alpha_2 \ln w_t + \varepsilon_t \qquad (1)$$

Similarly, the regression equation of the standard life cycle model under uncertainty is given by:

$$\ln h_{mt} = \alpha_0 + \alpha_1 t + \alpha_2 \ln w_t + \varepsilon \qquad (2)$$

To construct the data set, we selected a group of individuals from the three time use surveys. These surveys include (1) the Americans' Use of Time (1965-1966); (2) the Time Use Longitudinal Panel Study (1975-1976) and (3) the Time Use Longitudinal Panel Study (1981); these time use surveys provide detailed information about how individuals allocate their time between several activities, such as market work, home work, leisure and child care. We then divided the groups based on age and calculated the average of their labor supply, their homework hours, and other related variables. This is how we derived the labor supply, and home work hour profiles for a representative individual.

The coefficient α_2 in equation (1) and (2) can be interpreted as the intertemporal elasticity of labor supply. MaCurdy (1982), Altonji (1985) and others have pointed out that by simply running regressions on equations similar to equation (1) would result in a bias in α_2. This is because the error term, which includes the marginal value of wealth shock, taste shock, and measurement errors, would likely be correlated with the log wage. To deal with this endogeneity issue, MaCurdy (1982), Altonji (1985) and others used instrumental invariables (IV). The instruments are correlated with the wage rate but uncorrelated with the error term. In the Two Stage Least Squares (2SLS) procedure, the researcher obtains the "predicted wage" in the first stage, which is used as the regressor in the second stage. The resulting α_2 would be a consistent estimator of the intertemporal elasticity of labor supply because the "predicted wage" is orthogonal to the unanticipated wealth and taste shocks of labor, as well as the measurement error. An alternative to IV estimations is to use a synthetic cohort. The synthetic cohort removes the bias for similar reasons because the age-wage profile can be interpreted as the "predicted" wage. If individuals use the population average as the predictor, then any unanticipated wage shocks and measurement errors are averaged out. However, the population variance is likely to be heteroskedastic. The solution, as discussed in Rupert et al. (2000), is to use GLS estimators. They use two different versions of the GLS. The first estimator weighs the observations by their cohort size and the second estimator weighs the observations by the inverse of the variance within cohort groups.

In order to avoid the problem that comes from the aggregation bias when using the synthetic cohort approach, Rupert et al. (2000) made several assumptions about the wage process and individual preferences. The first assumption is that the mean of log ϕ is constant across time and equals to $\bar{\phi}$. The second assumption is essentially assuming a balanced growth, i.e., the life-cycle wage profiles shift upward at rate x across cohorts for a given type i, and the home production function and initial assets also grow at the rate x each period. Given the functional form assumptions of individuals' utility of consumption and disutility of labor, their consumption will increase by $1+x$ for all cohorts such that the marginal value of asset for an individual of type i in cohort "a" is

$\lambda_{ai} = \lambda_i (1+x)^{-a}$, where λ_i does not depend on the cohort. In other words, the average of $\log(\lambda_{ai})$ of a given cohort "a" is approximately equal to $\overline{\log(\lambda)} - xa$. Given these assumptions, the labor supply equation of an individual of age "a" and type "i" becomes:

$$(\gamma - 1)\log(h_{mai} + h_{nai}) = \log(\lambda_{ai}) - \log\gamma - \log\phi_{ai} - a\log\beta(1+r) + \log w_{ai} \quad (3)$$

By adding up different individuals of the same age, we generate a synthetic cohort. By summing up all individuals of the same cohort and then dividing by the number of individuals we derive the following sample analog of the synthetic cohort equation:

$$(\gamma - 1)\hat{h}_a = \hat{\lambda}_a - \log\gamma - \hat{\phi}_a - a\log\beta(1+r) + \hat{w}_a \quad (4)$$

where $\hat{h}_a$ is the sample average of $\log(h_{mai} + h_{nai})$, $\hat{w}_a$ is the sample average of $\log(w_{ai})$. The variable $\hat{\phi}_a$ is the sample average of $\log\phi_{ai}$; and $\hat{\lambda}_a$ is the sample average of $\log\lambda_{ai}$ Hence, for a large sample, the estimation equation becomes:

$$h_a = \alpha_0 + \alpha_1 a + \alpha_2 \hat{w}_a + \varepsilon_a \quad (5)$$

where

$$\varepsilon_a = \varepsilon_{\phi a} + \varepsilon_{\lambda a} + \varepsilon_{wa}$$

$$\varepsilon_{\phi a} = \phi_a - \hat{\phi}$$

$$\varepsilon_{\lambda a} = \hat{\lambda}_a - (\bar{\lambda} - x_a)$$

$$\varepsilon_{wa} = \hat{w}_a - \overline{w}_a$$

and α_0 is a constant, $\alpha_1 = [\log\beta(1+r) - x]/(\gamma - 1)$ and $\alpha_2 = 1/(\gamma - 1)$.

The error term ε_a represents the sum of the variation in preferences ($\varepsilon_{\phi a}$), the variation in wage (ε_{wa}) and the Lagrange multiplier ($\varepsilon_{\lambda a}$). Notice that the sample size of each age group in the synthetic cohort fluctuates for each cohort. Furthermore, the variance of ε_a is likely to be different across ages, even if the sample size for each age is the same. Consequently, the error term is likely to have heteroskedasticity and the OLS estimator is likely to be inefficient. Also note that the above empirical specifications and assumptions of the life cycle models by Rupert et al.(2000) may not be appropriate for a life cycle model under uncertainty. We will discuss the reasons why this may be the case later.

Individuals, in a life cycle model of consumption and labor supply with uncertainty, confront various sources of uncertainties in their future periods. These uncertainties include changes in real interest rates, wages and preferences, as well as the relative future price of work and leisure. Under the synthetic cohort approach, individuals maximize their expected utility subject to asset accumulation constraints by choosing consumption, work hours and savings. The natural log of work hours of an individual of type i at age t is a simple linear function of the individual's age t, the wages w_{it} plus the disturbance term ε_{it} where the intercept term α_i is referring to specific type i. The disturbance term represents an unobserved component that includes omitted variables and forecast errors. As pointed out by MaCurdy (1986), since α_1 is assumed to be the same for all age groups, this model is implicitly assuming away any cohort effects. If cohort effect is present, then in the above specification it would be included in an error term. However, this means that the age variable would be correlated with the error term, resulting in bias. Similarly, any cohort specific anticipated wage variation would also be correlated with the error term, resulting in bias of the elasticity estimate. Hence, it is important to note that a least square estimation of the linear equation (5) will yield consistent estimates when using the synthetic cohort data only when there are no cohort effects. In that case, OLS with synthetic cohort data is similar to using the group mean as an instrument.

Becker (1975) and Smith (1977) dealt with the vintage effect by assuming α_1 to be a linear function of age, average property income, and average family size. Vintage effects are age specific components that are different for each cohort, or each vintage. For example, some individuals who are 50 years old in the Time Use Survey 1966-67 come from 1916 "vintage", while some individuals who are 20 years old in the same survey come from 1946 "vintage". Each vintage may have different age components. Their approach requires all vintage effects to be uncorrelated with wages. Without such a strong assumption, the synthetic cohort method may provide biased estimates for the intertemporal substitution effect because wage shocks could be correlated with the cohort effect and thereby yielding an incorrect α_2. Because of these concerns, we not only follow the estimation procedures adopted in Rupert et al. (2000) but also follow the procedures that are somewhat similar to MaCurdy (1981). We use first differencing to eliminate individual effects and then we apply instrumental variable techniques to estimate the intertemporal substitution elasticity. The instruments are family background variables such as age, the number of family members and the number of children. Because they are either given or fully anticipated before the shocks are realized, they are uncorrelated with the error term. The regression equations that we estimate are given as follows:

$$D\overline{\ln h_{mt}} = \beta + \delta D\overline{\ln w_t} + \overline{\varepsilon_t} \tag{6}$$

$$D\overline{\ln(h_{mt}+h_{nt})}=\beta+\delta D\overline{\ln w_t}+\overline{\varepsilon_t} \tag{7}$$

where $\overline{X_t}$ means cohort average of variable X at age t. Equation (6) describes the labor supply equation of the dynamic labor supply model without home production and (7) describes that with home production. The instruments influence current changes in the wage rates and the factors that affect preference of work hours. With our specification of the functional form of labor supply, we treat the individual effects α_1 as cohort specific fixed effects and eliminate them by first differencing. We then apply the instruments on the differenced wage variable. In contrast to MaCurdy (1981), we use aggregated data for estimation. This is due to the limitation that we do not have panel data.

Notice that if we had not used first differencing and the 2SLS method, we would be making strong assumptions that the across cohort growth rate of λ_0 is the same as the across cohort wage growth. However, if younger cohorts have higher lifetime wealth while they are facing lower wage rates than older workers, then the estimate of δ will be contaminated by vintage effects, resulting in bias. This cohort bias can only be removed if λ_t is allowed to have different values for each cohort, which then requires first differencing of the data.

However, as indicated by MaCurdy (1981), first differenced wages may be correlated with the fixed effects. Hence, MaCurdy used differencing with the 2SLS method, which is adopted here as well.

2.3 Data sources

For hours of work and home production, we use the following three time use surveys: (1) The Americans' Use of Time (1965-1966); (2) the Time Use Longitudinal Panel Study (1975-1976) and (3) the Time Use Longitudinal Panel Study (1981). The total sample size from these three time use surveys is 1154 for men between the ages of 22 and 62. The sample size of the Americans' Use of Time survey has a sample size of 633. The Time Use Longitudinal Panel Study has a sample size of 442 and the Time Use Longitudinal Panel Study has a sample size of 79.

The Americans' Time Use (1965-1966) data were obtained by having respondents keep a complete diary of their activities between Nov. 15 and Dec. 15, 1965, or between March 7 and April 29, 1966. It surveyed individuals over either a weekday or a weekend for a twenty-four hour period. The survey is based on a diary that was left behind for the respondents to fill in, and then the interviewer collected those forms on the following day. The two latter surveys asked individuals to record their time use for four days that consisted of two weekdays, a Saturday and a Sunday, over a twelve-month period. The respondents were asked to specify the details of activities during the preceding day. Both studies also obtained multiple diaries from respondents in separate interviews spaced approximately three months apart. The market work category represents the sum of direct work hours, trip to work hours, and other work related time spent.

For the purpose of this paper we only select the male workers who have a positive number of hours of market work. This is to avoid corner solutions. For prime age males, it is well known that only very few of them work zero hours. Hence, ignoring corner solution is likely to be of minor consequence. However, this may lead to a sample selection problem for older workers. To deal with this issue, we examine two groups: men between the ages of 22 and 45 and men between the ages of 22 and 62. Since the wage data in the above three time use surveys have a high non-responsive rate, we extracted the wage data of years 1968, 1976 and 1981 in PSID. The average hourly earnings for male workers between the ages of 22 and 62 from these three years are used to construct a synthetic wage for the synthetic cohort. We also used the male wage data from the CPS from 1976-1981 in order to form another synthetic wage variable.

2.4 Life Cycle Profiles

As mentioned, the data were pooled from the following three time use surveys: The Americans' Use of Time (1965-1966), the Time Use Longitudinal Panel Study (1976-1977) and the Time Use Longitudinal Panel Study (1981). Adults allocated their 24 hours of daily time among ten major categories; and each of these categories was subdivided into smaller subcategories. The ten major time use activity categories are: paid market work, house/yard work, childcare, services/shopping, personal care, education, organization, social entertainment, active leisure, and passive leisure. (see Juster and Stafford, 1988, p.135). We constructed two homework hour variables. The first homework hour variable includes three main categories, namely, house/yardwork, services/shopping hours, and childcare. House/yardwork hours consist of cooking, laundry, and house cleaning, services/shopping hours consist of shopping, repairs, care to pets or plants, and childcare hours consist of hours spent on baby care, child care, child health, helping with study, talking to the child, indoor play, outdoor play, and baby-sitting.

In the first paper, we estimated the employed male labor elasticities by employing PSID and we concluded that the estimated elasticity has not increased with the inclusion of home work hours in the estimation. Note that the PSID defines housework as follows:

"About how much time do you spend on housework in an average week? (I mean time spent cooking, cleaning, and doing other work around the house.)"

Also notice that housework in PSID does not include childcare. In order to examine whether the exclusion of childcare hours would affect the estimated elasticities, we calculated the second homework variable that only includes house/yardwork and services/shopping hours and excludes childcare.

We next plot the wage profiles and the other life cycle profiles of the synthetic cohorts obtained from the three time use surveys. Figure 2.1 is the wage profile of the PSID and Figure 2.2 is that of the CPS. The "hump" shapes of those age-wage profiles imply that earnings and hours rise over the early years and peak at middle age, then they gradually decline. Figure 2.3 illustrates the life cycle profiles of homework hours, house/yardwork hours, services/shopping hours and childcare hours. The profiles of the homework hours, house/yardwork hours, and services/shopping hours exhibit a slight downward trend at an early age until the subjects are in their late 30's and early 40's, then increased thereafter. Only the childcare hours of the subjects show a downward trend over age.

Figure 2.1: Age-Wage Profile (PSID 1968, 1976, 1981) for ATW and BTW

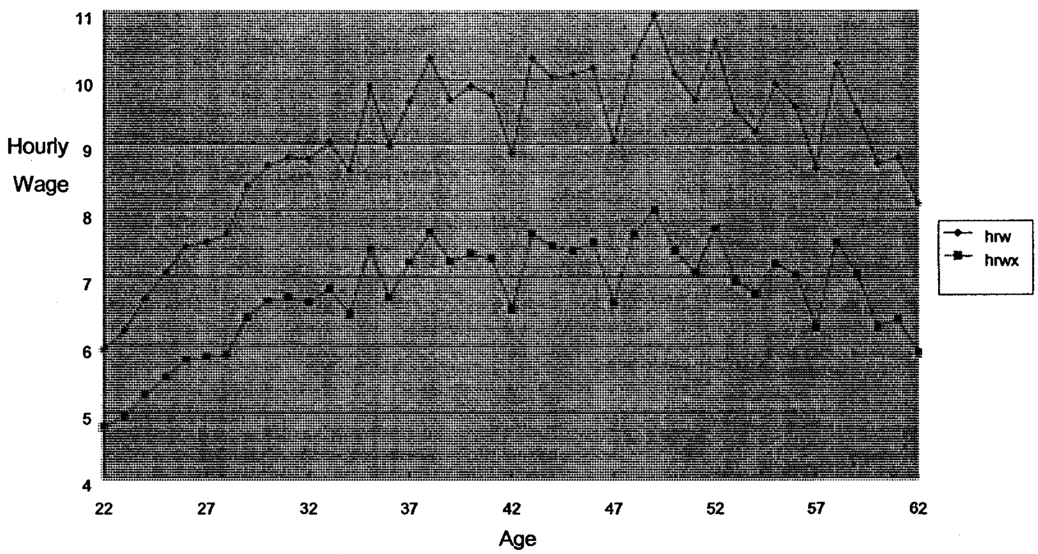
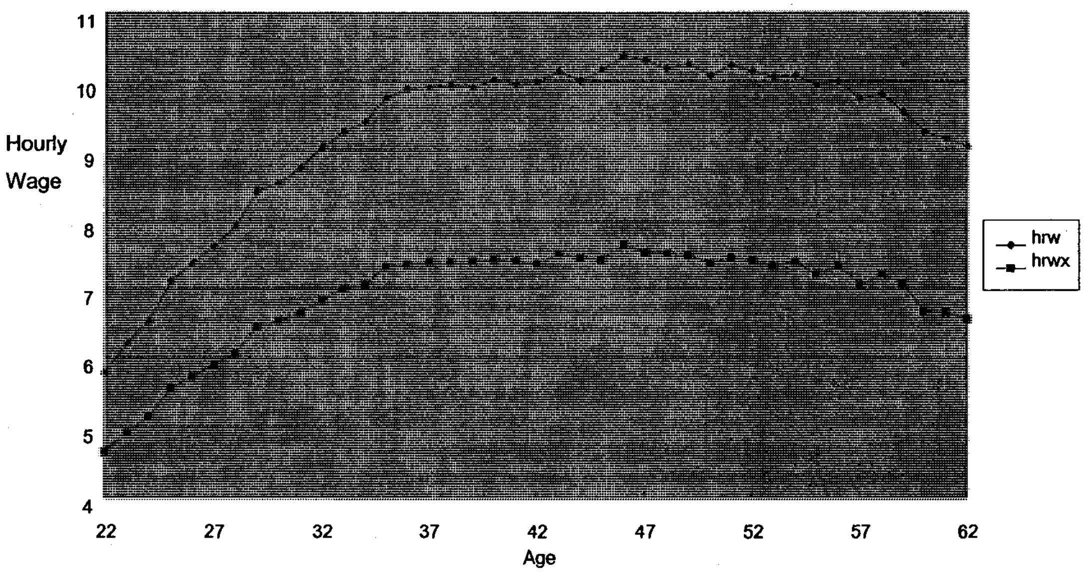


Figure 2.2: Age-Wage Profile (CPS 1976-81) for ATW and BTW



hrw - before tax hourly wage
hrwx - after tax hourly wage

Figure 2.3: Age-Home Work Hours Profile (Three time use surveys)

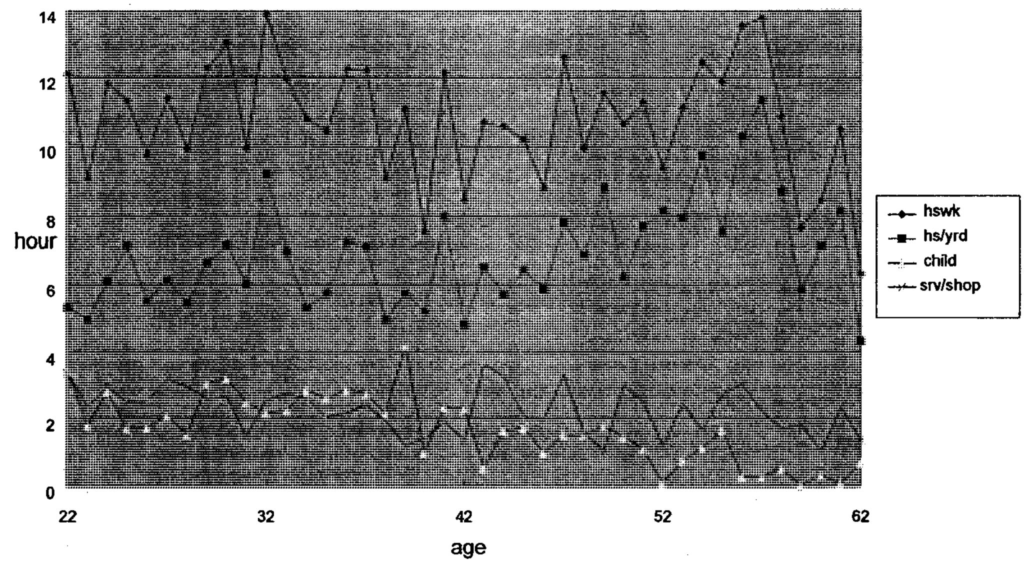
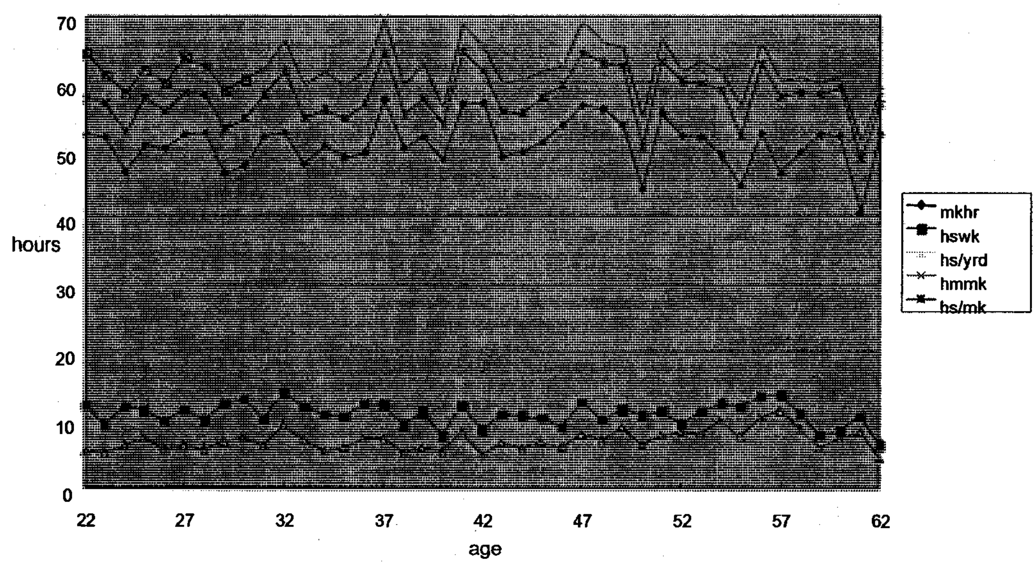


Figure 2.4: Age-Hours Profile (Three time use surveys)



hswk: average homework hours per week.
hs/yrd: average house/yardwork hours per week.
child: average childcare hours per week
srv/shop: average services/shopping hours per week
mkhr: the average market work hours per week.
hmmk: sum of average weekly home work hours and weekly market work hours.
hs/mk: the sum of average weekly house/yardwork hours and weekly market work hours.

We define total hours to be the sum of time spent working in the market and at home. Figure 2.4 plots the life cycle profile of total hours (hmmk) and market hours (mkhr) for males between the ages of 22 and 62. Total hours profile shows a slight hump shaped pattern. It peaks around age 40, which is similar to that of the real wages. In order to compare with the results from the first paper, we construct the sum of average weekly house/yardwork hours and weekly market work hours. The sum of house/yardwork hours and market hours are similar to the ones defined by the first paper using PSID (sum of home and market hours). Rupert et al. (2002) claim that the elasticity of labor supply is downwardly biased if only market hours are used as hours of work. In order for the estimated labor supply elasticity to have a downward bias, homework hours have to be positively correlated with real wages over the life cycle. To examine if this is indeed the case, we calculated the correlation matrix of log hours and log wages using the synthetic cohort data. We present the results in Table 2.1.

Table 2.1: The Correlation Matrix[1] of the Synthetic Cohort Variables

	log h_m	log w_{cps}	log w_{psid}	log h_n	log(h_m+h_n)
log h_m	1.0000				
log w_{cps}	0.0379	1.0000			
log w_{psid}	0.0944	0.8893	1.0000		
log h_n	-0.0233	-0.0113	-0.027	1.0000	
log(h_m+h_n)	0.8892	0.1025	0.1278	0.3173	1.0000

[1] log h_m is the log market hours, log h_n is the log home work hours, log (h_n+h_m) is the sum of the time spent in the market hours and home work hours, log w_{cps} is the log CPS (1976-81) synthetic wage and log w_{psid} is the log PSID (68, 76, 81) synthetic wage.

The correlation matrix in Table 2.1 shows that homework hours are negatively correlated with the two synthetic real wages over the life cycle while the market hours are positive correlated with both of them.

2.5 Statistical Summary and Econometric Results

To reduce the number of outliers, we restrict the sum of the homework hours and market work hours to be less than 112 hours each week so that a person has at least eight hours of sleep, leisure and resting time per day. We present the summary statistics of the hours of different activities in Table 2.2 for two age groups: from age 22 to 45 and from age 22 to 62.

Table 2.2: Summary of Three Time Use Surveys

	Employed Males in the age group 22-45	Employed Males in the age group 22-62
	Mean hours/week (N=792)	Mean hours/week (N=1154)
Market hours	50.83	50.81
S.E.	(16.90)	(17.03)
Home hours	10.84	10.78
S.E.	(9.87)	(9.85)
House/Yardwork hours	6.16	6.63
S.E.	(7.61)	(7.91)
Childcare hours	2.28	1.86
S.E.	(4.21)	(3.98)
Service/shopping hours	2.40	2.29
S.E.	(3.93)	(3.81)

Table 2.2[2] shows that both age groups display similar mean market work hours and mean homework hours. Only the means of childcare hours and means of house/yardwork hours show some differences. The reason may be that employed males started to have young children when they were at age 22 to 45. Then their children were mostly grown up and independent when the employed males were around the age 46 to 62. As a result, they spent less time on childcare from the age 46 to 62. On the other hand, they spent less time on yard work from age 22 to 45 as they had to spend most of their time on market work. As they were aging and reaching retirement, they increased their time on yard work.

As mentioned before, Americans' Use of Time Survey (1966-1967) has one interview for each individual. Consequently, some age groups did not have weekend hours reported. Table 2.3 reports the number of observations within weekdays (Monday to Friday) and weekends (Saturday and Sunday) for 22-62 age groups in Americans' Use of Time Survey.

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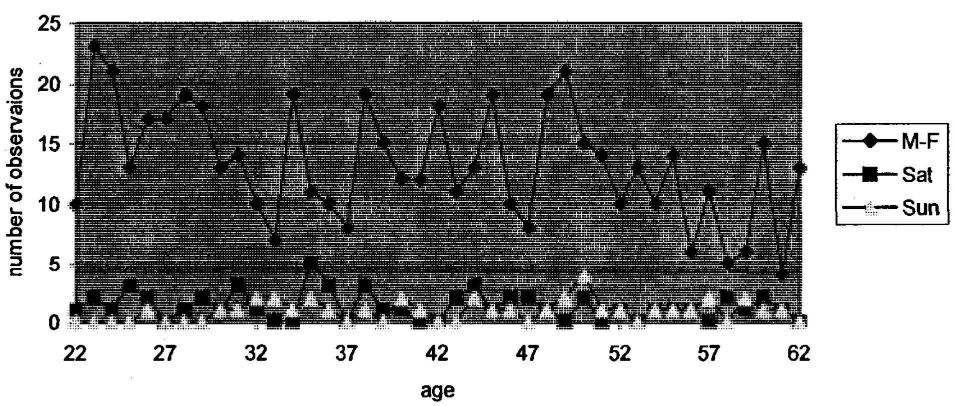
[2] Source: Three Time Use Surveys: (1) The Americans' Use of Time (1965-1966); (2) the Time Use Longitudinal Panel Study (1975-1976) and (3) the Time Use Longitudinal Panel Study (1981). For the Americans' Use of Time Survey data, there are daily activity aggregates for all individuals while the weekly activity aggregates are not available. We multiply the daily activity aggregates of each observation by seven and we treat these estimates as weekly aggregates for all observations in Americans' Use of Time Survey. For the latter two Time Use Surveys, individuals have either two weekdays, a Saturday, and a Sunday (pattern 1), or one weekday, a Saturday, and a Sunday (pattern 2). Weekly aggregates were created by multiplying the time spent in the weekday diaries by 2.5; then adding up the aggregate weekday diaries to the Saturday diary and the Sunday diary for the respondents having pattern 1. Similarly, weekly aggregates for respondents in pattern 2 were created by multiplying the time spent in the weekday diaries by 5; then adding up the aggregate weekday diaries to the Saturday diary and the Sunday diary. Within each age group, we added up all individual weekly activity aggregates and divided them by the number of observations to obtain various mean hours in the Summary of Three Time Use Surveys.

Table 2.3: Number of Observations on Weekdays and Weekends for each Age Group: Americans' Use of Time Survey (1965-1966)

Age	M-F	Sat	Sun	Age	M-F	Sat	Sun
22	10	1	0	43	11	2	0
23	23	2	0	44	13	3	2
24	21	1	0	45	19	1	1
25	13	3	0	46	10	2	1
26	17	2	1	47	8	2	0
27	17	0	0	48	19	1	1
28	19	1	0	49	21	0	2
29	18	2	0	50	15	2	4
30	13	1	1	51	14	0	1
31	14	3	1	52	10	1	1
32	10	1	2	53	13	0	0
33	7	0	2	54	10	1	1
34	19	0	1	55	14	1	1
35	11	5	2	56	6	1	1
36	10	3	1	57	11	0	2
37	8	0	0	58	5	2	0
38	19	3	1	59	6	1	2
39	15	1	0	60	15	2	1
40	12	1	2	61	4	1	1
41	12	0	1	62	13	0	0
42	18	0	0				
				Sum	543	53	37

Figure 2.5: Number of Observaitons per age group
(American's Use of Time Survey, 1965-1966)



As shown in Table 2.3 and Figure 2.5, there are missing weekend (either Saturday, Sunday or both) reports in some age groups. For instance, people at age 27, 37, 42, 53 and 62 did not report their hours on weekends. Therefore, it is not possible to accurately estimate the weekly activity aggregates. The Americans' Use of Time Survey has one interview for each individual while the latter two surveys have four for each individual to form weekly activity aggregates. To obtain the weekly activity aggregates for each age group for the Americans' Use of Time Survey, we considered two methods in computing the weekly activity aggregates. First, we multiply the daily activity aggregates of each observation by seven and treat them as a weekly activity aggregate[3]. Second, we impute the weekly activity aggregates using the average hours during weekdays and weekends in the Americans' Use of Time Survey.

Table 2.4a: The Means of Employed Male Hours, Age 22 to 62, American's Use of Time (1965-66), Simple Averaging Method[4].

	M-F	Sat	Sun	Total (weekly)
N*	543	53	37	633
Market hours	7.997	6.002	2.77	52.67
Home hours	1.31	2.013	1.816	9.79

Table 2.4b: The Means of Employed Male Hours, Age 22 to 62, Americans' Use of Time (1965-66), Imputation Method[5].

	M-F	Sat	Sun	M-Sun (weekly)
N*	543	53	37	633
Market hours	7.997	6.002	2.77	48.757
Home hours	1.31	2.013	1.816	10.379

[3] Note that Table 2.2 is using the simple averaging method for Americans' Use of Time Survey to calculate the summary of Three Time Use Surveys.

[4] The weekly market hours are calculated as follows: (7.997x543+6.002x53+2.77x37) x 7/633=52.67. The weekly home hours are calculated as follows: (1.31x543+2.013x53+1.816x37) x 7/633=9.79.

[5] The weekly market hours are calculated by 7.997x5+6.002+2.77=48.757 while the weekly home hours are calculated by 1.31x5+2.013+1.816=10.378.

There are 543 weekdays (Monday to Friday) time use reports and 90 weekends (Sunday and Saturday) time use reports in the Americans' Use of Time (1965-1966) Survey in Table 2.4a and Table 2.4b. We divided the total number of hours (either market hours or home hours) by the total number of days to calculate the simple averaged hours (either market hours or home hours) in Table 2.4a. The simple averaging of those reports may lead to an upward bias of average market hours as the weekdays are 543/633=85.8% of the sample and weekends (Sunday and Saturday) are only 90/633=14.2% of them. The correct percentage of weekdays in a week should be 5/7=71.4% and the percentage of weekends 2/7=28.6%. To examine the accuracy of mean hours in Table 2.4a, we re-calculated the weekly activity aggregates by adjusting estimates from the Americans' Use of Time Survey. The imputation method allows the weekly market hours and weekly homework hours to be corrected by adjusting the number of weekdays and weekends within a week. Generally speaking, we multiply mean weekday hours (either market hours or homework hours) by five and add mean hours of weekends (Saturday and Sunday) to measure the weekly hours. Dividing the simple averaged market hour 48.757 by the imputed market hour 52.67, we obtained 0.926 (that are reported in Table 2.3a and Table 2.3b) which we multiplied to the market hours of all ages to correct the bias caused by oversampling of the weekdays. Similarly, dividing the simple averaged home hour 10.38 by the imputed home hour 9.79 and we obtain 1.06 (that are reported in Table 2.4a and Table 2.4b), which we multiplied to the homework hours of all ages.

To obtain the accurate weekly estimates for each age group, each age group must have at least one Sunday response, one Saturday response and one weekday response. As we have shown in Table 2.3 and Figure 2.5, there are missing weekend responses on some age groups. Hence it is not feasible to calculate the average properly for each age. As both methods do not provide a prefect weekly time use estimates, we argue that the estimates from a simple averaging method will provide more reasonable results than the estimates from using an imputation method. The reason is that the imputation method adjusts the weekly time use aggregates by some constants while the simple averaging method preserves the original weekly time use aggregates from the Americans' Use of Time dataset. However, these two methods do not result in significant differences in the time use aggregates[6].

Table 2.5 shows the estimates from using the imputation and simple averaging methods, respectively. Juster and Stafford (1985) calculated the average hours of the Americans' Use of Time (1965-1966), which we reported in Column 4 of table 2.5. Our sample statistics from the American Time Use (1966-1967) are similar to the original statistics from Juster and Stafford (1985).

Table 2.5: A Comparison of Estimates from the American's Time Use (1965-1966)[7]
Employed Men

	With imputation method	Simple Averaging method	Juster and Stafford (1985)'s estimates[8]
Age	22-62	22-62	25-64
Sample size	N=633	N=633	N=469
Total Market hours	49.76	52.67	51.55
Direct work hours	41.64	44.2	42.83
Trip to work	5.14	5.26	4.75
Other work-related	3.11	3.21	3.97
Home hours	10.38	9.79	11.53

[6] We added the imputed market hours and home hours in American's Use of Time to the other Two Time Use survey data and then computed the estimated elasticities of both home hour and market hour. The results were nearly identical to our final results and did not affect the conclusion of this paper. Consequently, we did not include those estimates in this paper.
[7] Note that home works are the sum of direct work hours, trip to work hours and other work-related hours.
[8] Sources: Juster, F.T., Stafford, F.P., 1985. Time Goods and Well-Being (1985) Chapter 12 A Note on Recent Changes in Time Use by T. Juster pp. 313-332.

Table 2.6 shows the sample statistics of the three time use surveys[9] obtained from using an imputation method and the simple averaging method on American's Time Use (1965-1966) data. For the purpose of the comparison, we first added the homework hours and the market hours from the simple averaging method to the averages of other two time use surveys. Secondly we added the homework hour and the market hour from the imputation method to the averages of other two time use surveys. Again, for the purpose of comparison, Juster and Stafford's statistics and those of Rupert et al. (2000) are also presented in Table 2.6.

Table 2.6 Comparison of the Average Hours of Employed Men

	Simple averaged hours	Imputed hours	Juster and Stafford (1985)	Rupert et al. (2000)	PSID
Age	22-62	22-62	25-64	22-62	20-65
Sample size	N=1154	N=1154	N=935	N=1165	N=115436
Total Market hours	50.81	49.06	47.58	43.3	40.96[10]
Direct market hours	42.72	41.26	40.09	-	-
Trip to work	4.63	4.45	4.14	-	-
Other work-related	3.46	3.35	3.35	-	-
Home hours	10.78	11.11	12.2	20.8	6.3[11]

Overall, the sample statistics of Juster and Stafford (1985) are similar to our results. In addition, we measure the average weekly market work hours and homework hours by using the PSID from 1969-2001 with a sample size of 115,436 for employed men between the ages of 20-65. The average weekly work hours are 40.96 hours and the average homework hours are 6.3 hours. Average weekly hours of Rupert et al. (2000) are 43.30 for work and 20.80 hours for homework. Those reported by Juster and Stafford

[9] As noted above, the two latter time use surveys (Longitudinal Panel studies) provided an aggregated weekly market work hours and home hours. Hence, no imputation is needed.

[10] PSID market work hours do not include hours spent commuting to work and other work related activities.

[11] PSID homework hours are defined as how many housework hours an individual does per week. The Three Time Use Surveys homework hours include yard work hours, shopping hours, and childcare.

(1985) are 47.58 hours for work and 12.20 hours for homework. Even though Rupert et al. (2000) were using the same data as Juster and Stafford (1985) and us, their mean results are very different from those of Juster and Stafford (1985) and ours, whereas our estimated mean of market hours (age groups 22 and 62, N=1154) at 50.81 and estimated mean of the homework hours at 10.78 are similar to results by Juster and Stafford (1985).

One of the reasons for the different estimates may be due to the fact that Rupert et al. (2000) are using a special procedure to impute values for missing days, which was based on age specific sample averages in the Americans' Use of Time (1965-1966) data. However, they did not provide detailed discussion on their imputation procedure. The estimated weekly market hours of PSID being around 40.96 hours seem to be low compared to our hours and that of Juster and Stafford (1985). We suspect that this is because hours data in PSID does not include hours spent on commuting to work and other work related activities. Next, we estimate the intertemporal substitution elasticity using our synthetic cohort data to see whether we can reach the same conclusion as Rupert et al. (2000) that the estimates of intertemporal substitution elasticities obtained from standard life cycle models are downward biased when home work is not included.

Table 2.7: Hours Regression, Part 1
Time Use 1966, 1976, 1981, CPS Wage 1976-1981

Log (hours) on log (wages) age 22-62	NHP(hmt)		HP(hmt+hnt)		HP(hmt+hyt)	
	BTW	ATW	BTW	ATW	BTW	ATW
OLS						
T	-0.0025	-0.0024	-0.0026	-0.0024	-0.0010	-0.0008
	(0.0021)	(0.0019)	(0.0014)	(0.0013)	(0.0017)	(0.0015)
log w	0.1669	-	0.1652	-	0.1537	-
	(0.1711)	-	(0.1193)	-	(0.1375)	-
log w(1-τ)	-	0.1965	-	0.1914	-	0.1776
	-	(0.1864)	-	(0.1298)	-	(0.1499)
First differencing						
Cons	-0.0037	-0.0049	-0.0057	-0.0069	-0.0043	-0.0045
	(0.3092)	(0.0299)	(0.02114)	(0.0204)	(0.0243)	(0.0235)
log w	0.3211	-	0.2149	-	0.3142	-
	(1.0612)	-	(0.7258)	-	(0.8331)	-
log w(1-τ)	-	0.5750	-	0.4335	-	0.4451
	-	(1.0493)	-	(0.7170)	-	(0.8244)
First differencing with 2SLS						
Cons	-0.0044	-0.0100	-0.0036	-0.0066	-0.0004	-0.0036
	(0.0292)	(0.0278)	(0.0218)	(0.0207)	(0.0244)	(0.0232)
log w	0.3246	-	0.1389	-	0.1252	-
	(1.1371)	-	(0.8483)	-	(0.9504)	-
log w(1-τ)	-	1.0419	-	0.5184	-	0.5127
	-	(1.1534)	-	(0.8588)	-	(0.9633)
GLS (cohort weighted)						
T	-0.0039	-0.0036	-0.0037	-0.0034	-0.0021	-0.0018
	(0.0021)	(0.0019)	(0.0014)	(0.0013)	(0.0016)	(0.0015)
log w	0.2831	-	0.2485	-	0.2544	-
	(0.1876)	-	(0.1255)	-	(0.1439)	-
log w(1-τ)	-	0.3340	-	0.2876	-	0.2944
	-	(0.2037)	-	(0.1361)	-	(0.1563)
GLS (variance weighted)						
T	-0.0033	-0.0032	-0.0025	-0.0024	-0.0009	-0.0008
	(0.0021)	(0.0019)	(0.0014)	(0.0013)	(0.0016)	(0.0015)
log w	0.1374	-	0.1126	-	0.1179	-
	(0.1709)	-	(0.1179)	-	(0.1377)	-
log w(1-τ)	-	0.1640	-	0.1340	-	0.1397
	-	(0.1857)	-	(0.1282)	-	(0.1499)

Table 2.8: Hours Regression, Part 2
Time Use 1966, 1976, 1981, CPS Wage 1976-1981

Log (hours) on log (wages) age 22-45	NHP(hmt)		HP(hmt+hnt)		HP(hmt+hyt)	
	BTW	ATW	BTW	ATW	BTW	ATW
OLS						
T	0.0043	0.0044	-0.0005	-0.0005	0.0026	0.0027
	(0.0067)	(0.0064)	(0.0053)	(0.0050)	(0.0060)	(0.0057)
log w	-0.1674	-	-0.0320	-	-0.0485	-
	(0.2792)	-	(0.2187)	-	(0.2496)	-
log w(1-τ)	-	-0.2036	-	-0.0350	-	-0.0633
	-	(0.3104)	-	(0.2435)	-	(0.2778)
First differencing						
Cons	0.0221	0.0240	0.01373	0.0095	0.0114	0.0117
	(0.0411)	(0.0390)	(0.0327)	(0.0313)	(0.0367)	(0.0350)
log w	-0.9373	-	-0.7227	-	-0.5007	-
	(1.1651)	-	(0.9243)	-	(1.0390)	-
log w(1-τ)	-	-1.2209	-	-0.6580	-	-0.6182
	-	(1.2559)	-	(1.0075)	-	(1.1258)
First differencing with 2SLS						
Cons	0.0184	0.0149	0.0086	0.0064	0.0080	0.0063
	(0.0439)	(0.0420)	(0.0349)	(0.0336)	(0.0391)	(0.0376)
log w	-0.7878	-	-0.5107	-	-0.3630	-
	(1.3219)	-	(1.0496)	-	(1.1788)	-
log w(1-τ)	-	-0.7748	-	-0.5053	-	-0.3512
	-	(1.4640)	-	(1.1716)	-	(1.3102)
GLS (cohort weighted)						
T	0.0047	0.0048	-0.0016	-0.0014	0.0035	0.0036
	(0.0069)	(0.0066)	(0.0054)	(0.0052)	(0.0061)	(0.0058)
log w	-0.1741	-	-0.0721	-	-0.0716	-
	(0.2798)	-	(0.2207)	-	(0.2470)	-
log w(1-τ)	-	-0.2097	-	-0.0773	-	-0.0861
	-	(0.3123)	-	(0.2467)	-	(0.2760)
GLS (variance weighted)						
T	0.0025	0.0025	0.0002	-0.0001	0.0022	0.0022
	(0.0064)	(0.0061)	(0.0051)	(0.0049)	(0.0057)	(0.0055)
log w	-0.1737	-	-0.0699	-	-0.0866	-
	(0.2648)	-	(0.2128)	-	(0.2359)	-
log w(1-τ)	-	-0.2044	-	-0.0749	-	-0.1009
	-	(0.2962)	-	(0.2371)	-	(0.2630)

Table 2.9: Hours Regression, Part 3
Time Use 1966, 1976, 1981, PSID Wage 1968, 1976, 1981

Log (hours) on log (wages) age 22-62						
	NHP(hmt)		HP(hmt+hnt)		HP(hmt+hyt)	
	BTW	ATW	BTW	ATW	BTW	ATW
OLS						
T	-0.0018	-0.0015	-0.0018	-0.0016	-0.0002	-0.0000
	(0.0017)	(0.0016)	(0.0012)	(0.0011)	(0.0013)	(0.0013)
log w	0.1532	-	0.1343	-	0.1338	-
	(0.1669)	-	(0.1170)	-	(0.1344)	-
log w(1-τ)	-	0.1734	-	0.1489	-	0.1482
	-	(0.1784)	-	(0.1252)	-	(0.1438)
First differencing						
Cons	0.0014	0.0004	-0.0019	-0.0028	0.0005	-0.0004
	(0.0286)	(0.0286)	(0.0194)	(0.0195)	(0.0225)	(0.0225)
log w	-0.3346	-	-0.3009	-	-0.2732	-
	(0.3997)	-	(0.2715)	-	(0.3138)	-
log w(1-τ)	-	-0.2673	-	-0.2419	-	-0.2282
	-	(0.3805)	-	(0.2590)	-	(0.2986)
First differencing with 2SLS						
Cons	-0.0067	-0.0037	-0.0050	-0.0035	-0.0020	-0.0006
	(0.0305)	(0.0309)	(0.0215)	(0.0216)	(0.0235)	(0.0236)
log w	1.1145	-	0.5582	-	0.5563	-
	(0.7978)	-	(0.5635)	-	(0.6145)	-
log w(1-τ)	-	1.2081	-	0.6116	-	0.6125
	-	(0.7692)	-	(0.5378)	-	(0.5863)
GLS (cohort weighted)						
T	-0.0027	-0.0022	-0.0026	-0.0022	-0.0010	-0.0006
	(0.0018)	(0.0017)	(0.0012)	(0.0012)	(0.0014)	(0.0013)
log w	0.2701	-	0.2113	-	0.2317	-
	(0.1840)	-	(0.1245)	-	(0.1417)	-
log w(1-τ)	-	0.3039	-	0.2325	-	0.2554
	-	(0.1955)	-	(0.1324)	-	(0.1507)
GLS (variance weighted)						
T	-0.0027	-0.0025	-0.0020	-0.0018	-0.0004	-0.0002
	(0.0017)	(0.0016)	(0.0012)	(0.0011)	(0.0013)	(0.0013)
log w	0.1433	-	0.1102	-	0.1196	-
	(0.1651)	-	(0.1149)	-	(0.1337)	-
log w(1-τ)	-	0.1643	-	0.1266	-	0.1366
	-	(0.1760)	-	(0.1228)	-	(0.1428)

Table 2.10: Hours Regression, Part 4
Time Use 1966, 1976, 1981, PSID Wage 1968, 1976, 1981

Log (hours) on log (wages) age 22-45	NHP(hmt)		HP(hmt+hnt)		HP(hmt+hyt)	
	BTW	ATW	BTW	ATW	BTW	ATW
OLS						
T	0.0060	0.0058	0.0022	0.0020	0.0044	0.0043
	(0.0055)	(0.0050)	(0.0044)	(0.0040)	(0.0050)	(0.0045)
log w	-0.3165	-	-0.1382	-	-0.1666	-
	(0.2790)	-	(0.2213)	-	(0.2524)	-
log w(1-τ)	-	-0.3732	-	-0.1602	-	-0.2018
	-	(0.3031)	-	(0.2414)	-	(0.2749)
First differencing						
Cons	0.0218	0.0174	0.0112	0.0076	0.0150	0.0118
	(0.0273)	(0.0267)	(0.0227)	(0.0225)	(0.0256)	(0.0251)
log w	-1.1441	-	-0.7625	-	-0.8042	-
	(0.4216)	-	(0.3509)	-	(0.3955)	-
log w(1-τ)	-	-1.1617	-	-0.7347	-	-0.8087
	-	(0.4194)	-	(0.3539)	-	(0.3952)
First differencing with 2SLS						
Cons	0.0237	0.0201	0.0135	0.0110	0.0126	0.0106
	(0.0299)	(0.0288)	(0.0250)	(0.0244)	(0.0281)	(0.0271)
log w	-1.2428	-	-0.8809	-	-0.6779	-
	(0.7493)	-	(0.6246)	-	(0.7038)	-
log w(1-τ)	-	-1.3363	-	-0.9530	-	-0.7332
	-	(0.7970)	-	(0.6757)	-	(0.7486)
GLS (cohort weighted)						
T	0.0071	0.0069	0.0034	0.0031	0.0056	0.0055
	(0.0056)	(0.0051)	(0.0045)	(0.0041)	(0.0051)	(0.0046)
log w	-0.3651	-	-0.1962	-	-0.2133	-
	(0.2820)	-	(0.2256)	-	(0.2527)	-
log w(1-τ)	-	-0.4320	-	-0.2233	-	-0.2536
	-	(0.3077)	-	(0.2474)	-	(0.2766)
GLS (variance weighted)						
T	0.0038	0.0035	0.0006	0.0004	0.0026	0.0024
	(0.0055)	(0.0051)	(0.0045)	(0.0041)	(0.0050)	(0.0046)
log w	-0.2955	-	-0.1239	-	-0.1305	-
	(0.2788)	-	(0.2250)	-	(0.2501)	-
log w(1-τ)	-	-0.3434	-	-0.1357	-	-0.1500
	-	(0.3060)	-	(0.2463)	-	(0.2742)

In tables 2.7, 2.8, 2.9 and 2.10, we used the synthetic cohort data where we simply averaged the hours for each age group to derive the cohort averages. We reported the results from the regressions where the dependent variables are log hours and the independent variables are time (T), and log wages. The hourly data are synthetic cohort data aggregated from the three time use surveys (1966, 1976, and 1981). The wage data in tables 2.7 and 2.8 are also synthetic cohort data aggregated from CPS (1976-1981), while the wage date in tables 2.9 and 2.10 are from PSID (1968, 1976 and 1981). The estimated utility function is v(h)=ϕh^{γ}, the dependent variable is the total hours $\ln(h_t)$, where $h_t = h_{mt} + h_{nt}$ in the home production model (HP) that includes market work hours, house/yardwork hours, service/shopping hours and childcare hours. We also estimate the yard work home production model where the total hours is the sum of market hours, house/yardwork hours and service/shopping hours. We then report the estimates of the non-home production model (NHP) where we only use market hours as hours worked in the elasticity estimation. In all four tables (2.7, 2.8, 2.9 and 2.10) we reported the OLS estimates, the first differenced least square estimates, first differencing with the 2SLS estimates, and estimates using the two GLS methods. In addition, we report both the results with before tax wages (BTW) and after tax wages (ATW). We followed Rupert et al. (2000) in using two GLS type estimators. The first estimator weighed observations by their cohort size and the second GLS estimator weighed observations by the inverse of the variance of the cohort observations by hours[12]. In addition to those we also used first differencing and the 2SLS to obtain consistent estimates. We also present the results for two age groups: 22-45, 22-62 in all four tables (2.7, 2.8, 2.9 and 2.10).

[12] Notice that hours refer to the market hours employing the NHP model while the sum of homework and market hours using the HP model.

In Tables 2.7 and 2.8 we report the results where we used the CPS synthetic wage. The age group is from age 22 to 62, and before tax wages are used. The OLS estimated wage coefficients (δ) are 0.1669 for the non-home production elasticity estimate, 0.1652 for the home production elasticity estimate and 0.1537 for home production where we used house/yardwork, service/shopping hours as home production hours. All these elasticity estimates are small and statistically insignificant. Similarly, the estimates for after-tax wages are small as well (0.1776, 0.1914 and 0.1965). In both cases, the HP models generated smaller elasticity estimates than the NHP models. For the age group 22-45, the OLS coefficients are often negative for both before tax wages and after tax wages. This may be due to the endogeneity of the wages as well, which affects the estimation of δ. First differencing is used to eliminate the fixed effects, but the subsequent estimates are all not significant: 0.2149, 0.3142 and 0.3211 for before tax wages and 0.4335, 0.4451 and 0.5750 for after tax wages in the age group 22-62. To deal with the endogenity of wages, we used 2SLS with the following instruments: first difference of log of number of family members and the first difference of log of number of children. The estimates of the intertemporal elasticity of substitution using before tax wages are 0.1252, 0.1389 and 0.3246 for two HP models and NHP models, subsequently. The estimated intertemporal elasticity of substitution parameters based on the home production models is actually smaller than that of the NHP model. Similar conclusions can be made in the estimates from after tax wages (0.5127, 0.5184 and 1.0419) where the NHP estimate (1.0419) is the highest. For the age group 22-45, the estimates (before tax wages and after tax wages) using first differencing with the 2SLS method, are always negative. This may be due to the fact that both wage rates and market hours are increasing from age 22 to 45.

Next we consider the two GLS results. For the age group 22-62, both estimates from before tax wages (0.2485, 0.2544 and 0.2831) and after tax wages (0.2876, 0.2944 and 0.3340) indicate that estimates based on the NHP using the cohort weighted are larger than the ones based on others. In addition, this is the same case for the GLS estimates with a weighted variance. For the age group 22-62, the NHP estimates are the highest in both cases where we used before tax wages or after tax wages. For the age group 22-45 using the cohort weighted GLS, the estimated elasticity coefficients are either negative or small and statistically insignificant. Using the variance weighted GLS for the age group 22-45; all estimates are negative in value as well. Indeed, all of these estimates have the wrong negative sign. This implies that employed males were not particularly willing to substitute hours intertemporally especially when they were between ages 22 to 45.

To check whether a different synthetic wage affects the estimates, we employed the PSID (1968, 1976, and 1981) synthetic wage for the estimations in Tables 2.9 and 2.10. The OLS results from before tax wages for the age group 22-62 indicate that the NHP estimate is the largest among the three elasticity estimates (0.1338, 0.1343 for HP models and 0.1532 for the NHP model). Similar results are obtained if we use after-tax wages for the same age group (0.1482, 0.1489 and 0.1734). For the age group 22-45, all estimates for both before-tax wages and after-tax wages have the wrong signs. Similar results are obtained for the estimates based on first differencing for the two age groups as well as for before-tax wages and after-tax wages. The estimates based on differencing and 2SLS for the age group 22-62 with before-tax wages are 0.5563, 0.5582 for the two HP models and 1.1145 for the NHP model. The estimate (1.1145) of the NHP model is again the largest. Similarly, the NHP estimate (1.2081) is the largest (0.6116, 0.6125 and 1.2081) for the age group 22-62 with after-tax wages. All elasticity estimates from the age group 22-45 are negative when using first differencing with 2SLS method for both before-tax wages and after-tax wages.

We now turn to the estimates obtained from using GLS in Table 2.9. For the age group 22-62 with before-tax wages and after-tax wages, the NHP cohort weighted GLS estimates are higher than those of the HP models. The same conclusions apply to the estimates for before-tax wages and after-tax wages obtained by using the variance weighted GLS method. The NHP estimates indeed have the highest values ranging from for before-tax wages as well as after-tax wages. As we discussed earlier all estimates obtained from the cohort weighted GLS method are negative for the age group 22-45. Similarly to the estimates obtained from the variance weighted GLS method for the age group 22-45: all estimates are negative for before tax wages and after tax wages.

In general, the first differenced 2SLS yielded the highest estimates of intertemporal substitution elasticity, followed by the cohort weighted GLS and the variance weighted GLS. The results generally suggest that NHP estimates are higher than those based on the home production model. Our results clearly show that there is no significant increase in the estimate of the intertemporal substitution elasticity by incorporating homework hours into a standard labor supply model.

2.6 Conclusion

Rupert et al. (2000) argued that estimates of the intertemporal labor supply elasticities obtained from standard life cycle models are subject to a downward bias because they ignored changes in home work over the life cycle.

We have used the same dataset as Rupert et al. (2000) and have not found any evidence in support for their claim. We find that our estimates of the home production model are smaller than the estimates from the non-home production models, regardless of the econometric methods we used. We conclude that there is no evidence of a downward bias in the estimates of the employed male labor supply elasticity even if home production is not included.

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EASSY 3

ESTIMATING THE INTERTEMPORAL SUBSTITUTION ELASTICITY OF EMPLOYED FEMALES WITH HOME PRODUCTION USING VARIOUS TIME USE DATASETS

3.1 Introduction

This paper is the continuation of the first and second papers and it applies the same models to analyze the female home production function. Felices G. and Tinsley D. (2005) who employed the estimation strategy of Rupert el at. (2000) to examine British data concluded that the estimates of the female labor supply elasticity increase when the home production hours are added to the labor supply hours. In chapters 1 and 2, we estimated the intertemporal labor supply elasticity of prime age male workers using the home production model, and found that it is not estimated to be higher than those of the standard labor supply models. This paper examines whether this argument is valid when applied to the female home production model. First, this paper employs synthetic wages constructed from the following three time use surveys: (1) The Americans' Use of Time (1965-1966); (2) the Time Use Longitudinal Panel Study (1975-1976) and (3) the Time Use Longitudinal Panel Study (1981); and two additional datasets: CPS and PSID. Secondly, using the PSID data, we investigate the female home production life cycle model and compare it to the standard model. Finally, we use the Canadian Quality of Life data and form a synthetic cohort to examine the female home production life cycle model. The result is that there is no convincing evidence to indicate that the estimated elasticities of the female home production labor supply model are significantly higher than the estimated elasticities of the standard female labor supply model.

The remainder of this paper is organized as follows: section 3.2 reviews the issues of the female labor supply and home production; section 3.3 addresses the model of the female life cycle model that includes home production; section 3.4 explores the characteristics of the various data sets used; section 3.4 analyzes several life cycle profiles and section 3.5 concludes with several recommendations.

3.2 Issues of the female labor supply and home production model

A consensus among labor economists is that, compared to men, women have a low labor force participation rate. One of the explanations is that women prefer to allocate more home work hours than men. In other words, there may be a difference in productivity at home between males and females. Preferences and attitudes also may play a role regarding the female allocation of time between paid employment, childcare and home work.

Most literature and empirical research (see Killingsworth and Heckman 1986 for a survey) show that women are less committed to work than men. There are several possible explanations for it: women, especially married women, are more productive in home work than men. Women are more likely to have an interruption in their careers because of childbirth and childrearing which affect their expected return of human capital. Consequently, women's wage growth is likely to be less than that of men. Furthermore, women are usually the prime caretakers of the children within the family. A related reason for the low labor participation rate is due to the high costs of childcare facilities and the relatively low salary of women compared to men. Even though the overall wage gap is narrowing gradually, the wage-gap between sexes is still substantial. Although educational gap between sexes is declining, the relatively lower education level of women compared men is another contributing factor to the low employment participation rate. We will elaborate the above mentioned issues to women in the following section.

Many studies that are based on time-use surveys indicate that men spend more time at work compared to women while women spend more time at home. Differences in productivity for home work and market work between the sexes could be one of the reasons behind it. Preferences and social attitudes toward childcare, market work and leisure among sexes also help determine the female labor force participation rate. According to the neo-classical model of labor supply, individuals allocate their time to market work and leisure. By choosing the highest possible indifference curve, given their budget constraints, with a combination of goods and leisure, their utilities are maximized. The main factor to determine the labor force participation rate is the reservation wage that is the minimum cost of leisure or homework. Individuals who are not employed have to give up their leisure in order to obtain extra units of consumption by providing extra units of market work. In the general case, the reservation wage is measured as the slope of the indifference curve at zero market work hour. In other words, individuals with higher reservation wages will be less likely to work than those with lower reservation wages. Consequently, single women are most likely to have lower reservation wages and a higher employment participation rate than married women with children. The reason is that married women must pay for some of their home work like childcare if they decide to join the labor force.

3.3 The Model

We include home work into the labor supply model. Some non-market hours are devoted to produce services at home using both time and goods. Time is now divided into market work hours, home work hours and leisure hours. If we assume home work hours and market hours are perfect substitutes, the utility function depends on the sum of market hours and home work hours, and leisure. This is the case we are employing for this paper.

That is $U(c_{mt}, h_t) = u(c_{mt}) - v(h_t)$ where c_{mt} is the market consumption goods, $h_t = h_{mt} + h_{nt}$ where h_t, the total work hours, is the sum of market work hours h_{mt} and home work hours h_{nt}. The disutility of labor function is specified as follows: $v(h_t) = \phi h_t^{\gamma}$. Then the first order condition for the optimal labor supply is:

$$(\gamma - 1)\ln(h_{mt} + h_{nt}) = \ln\frac{\lambda_t}{\gamma\phi} + \ln w_t \tag{1}$$

Where λ_t is the marginal value of asset at period t. On the other hand, the standard labor supply function is specified as $v(h_{mt}) = \phi h_{mt}{}^{\gamma}$; then the first order condition becomes:

$$(\gamma - 1)\ln h_{mt} = \ln\frac{\lambda_t}{\gamma\phi} + \ln w_t . \tag{2}$$

If the wage rate is higher than the marginal productivity at home, individuals will choose to work in the labor market. However, if the wage rate is below the marginal benefit to work at home, they will choose to work at home. Models of female intertemporal labor supply (Heckman & MaCurdy, 1986) use econometric methods to deal with the corner solution's problem as female labor force participations often have non-employment spells. Empirical research on female labor supply shows that there is a wide range of estimates, from -0.3 to 14, for intertemporal labor elasticities (Killingworth & Heckman, 1986). The difference in estimates can be attributed to sample characteristics of the data, years of samples, definitions on wages and non-wage incomes and estimation procedures. Overall, Theeuwes & Woittiez (1992) suggest that four main causes of the variation are: the functional forms of the labor supply equation, data sources, econometric methods to deal with selection, and attrition bias and variation in the measurement of elasticities.

Most literature indicates that women have more uses for their time than men, which suggests that female labor supply has higher wage elasticity than that of men. While men would substitute leisure for market work when their wages increase, women would substitute leisure, home work and childcare for market work given the same situation. Moreover, men are more likely to have full-time work while women are more likely to have part-time work. We can compute both a conventional labor supply model and a home production model in order to have a comparison of labor supply elasticities between two models.

Juster & Stafford (1991) survey a cross-country comparison of time allocation between sexes. On average, women spend between 24 and 35 market work hours per week, about 70 hours on personal care and between 25 and 42 hours for leisure. Unsurprisingly, employed women spend less time on home work than unemployed women. Female market hours have increased while their home work hours declined over recent decades. On the other hand, male home work hours are roughly the same in all countries. Most industrialized countries have experienced a rapid increase in the female labor force participation rate, especially in the participation of married women over the last few decades. The previous U-shaped pattern of the female age-labor force participation rate profile that is due to high withdrawal from labor force because of marriage, childbearing and home work, has been flattened out recently. Explanations suggested by literature for a higher female participation rate are increases in wage rates and educational attainment by women, a decline in fertility and an increase in divorce rates. As educational attainment of women increases, women are faced with higher opportunity costs of home work and not working. Women also return to the labor force sooner after childbearing because they have less children and the society is providing better childcare than previously. Social attitudes are changing as parents and peers are expecting women to have continuous attachment to the labor force. Furthermore, the average age of marriage is rising, resulting in women working for longer periods of time uninterrupted. It has been pointed out earlier that the single women labor force participation rate is highest among females.

As mentioned earlier, over time, the wage gap between sexes is decreasing. More part time jobs and jobs requiring less working hours are factors contributing to a higher female labor force participation rate. In particular, married women who spend a lot of time on home production, the availability of flexible work hours has had a positive effect on their employment participation rate. Moreover, individuals have been retiring earlier over the last twenty years while female labor supply has increased over the last forty years. In 1947, female labor force participation rate was around 30% while that of male was around 85%. In 1999, the former increased to around 60%, while the latter declined to around 75%. (Blau, Ferber and Winkler, 2002). From the early 1980's to late 1990's, increases in women's relative wages have raised the female/male full time annual earnings ratio from 60% to slightly above 70%.

As the gender roles change, more women are in the labor force and some of them earn more than their husbands. The percentage of single women among them is increasing and at the same time the divorce rates among married women have increased substantially. Overall, female weekly market work hours declined while their labor force participation rate increased.

There are several difficulties in estimating the home production labor supply model on female data. First, we are not able to observe the household production processes. That is, we do not have any information on specific household production inputs and outputs. Furthermore, women sometimes choose not to participate in the labor market so that they have zero work hours. This creates a problem as we cannot observe the non-participants' wages which may create a sample selection bias, especially given the fact that the participation rate of married women remains lower than that of other women.

One way to deal with this sample selection bias problem could be to assign the potential wage to the non-employed workers, where the potential wage is the average wage of an employed person with the same observed market characteristics. However, this method has the censoring problem that the employed may be a self-selected group that possesses different characteristics from the unemployed workers. Even if the wage offers are observed, they can hardly be used as an estimate of home productivity.

In this paper we use PSID data and separately deal with single, non-single, and all women. Most studies focus on married females but we found less than 20 married women satisfying the requirements of five consecutive positive annual work hours in PSID from 1969 to 1997. Since the equation we estimate assumes an interior solution, we did not include observations for which market hours are zero. This may cause a sample selection bias in the resulting estimates; however, previous studies have not found this selection bias to be significant (Heckman and MaCurdy 1980). Using this method, we compare two age groups; ages 22-45 and ages 22-62. One way to avoid the sample selection bias is to incorporate the potential boundary solution and use the method of maximum likelihood to obtain parameter estimates using all available samples; we leave this for future work.

3.4 Data sources

We used the Canadian Quality of Life data set to form a synthetic cohort approach to estimate the female home production model and the estimation results are illustrated in table 3.5. Afterwards, we used PSID, where we first used the data with and without outlier removal. The criteria in the removal of the outliers are as follows: (1) the workers must report less than 5,824 total hours per year (the number of total hours is defined as the sum of home production hours and work hours); (2) the absolute value of the difference in the real average hourly earnings in adjacent years cannot exceed $45 or a change of 200 percent; (3) the absolute value of the difference in the total hours in adjacent years cannot exceed 3000 hours or a change of 190%.

We also used data from the following three time use surveys: (1) The American's Use of Time (1965-1966); (2) the Time Use Longitudinal Panel Study (1975-1976) and (3) the Time Use Longitudinal Panel Study (1981). The total sample size of Three Time Use Surveys is 762 for employed females between the ages of 22 and 62. The sample size of the Americans' Use of Time survey is 353 observations. The Time Use Longitudinal Panel Study has 362 samples and the Time Use Longitudinal Panel Study has 47 samples.

In order to avoid dealing with corner solutions, only female workers who have a positive number of hours of market work were selected. It turns out that relatively few prime age female workers worked zero hours. Hence, ignoring corner solutions is likely to be of small consequence. However, this may lead to a sample selection problem for older female workers. To deal with this issue, we examined two groups: females between the ages of 22 and 45 and between 22 and 62. Since the wage data in the Three Time Use surveys have a high non-response rate, we constructed the synthetic cohort wages using the wage data from years 1968, 1976 and 1981 from the PSID data set. Likewise, the female wage data from the Current Population Survey (CPS) from 1976-1981 was extracted to form another synthetic wages.

The other sample consists of females in the PSID between the years 1969 to 1997, who were white and between ages of 20 and 65, and reported positive earnings and hours for at least five consecutive years. The samples from the year 1968, 1975 and 1982, were excluded because they did not report home production hours. Data from years 1999 and

2001 are not included either because they are not annual survey reports. We used annual work hours and the annual hours of home production as labor supply variables.

We also divided the samples into single and non-single groups to verify if participation rates between singe and non-single females would affect the estimates. The real average hourly earnings were obtained by first dividing annual earnings by annual hours worked. Afterwards, hourly earnings were deflated by the Consumer Price Index.

Additionally, we used the Quality of Life Survey, which is a Canadian data set that has been panel surveyed for the following 3 years: 1977, 1979 and 1981. Each year contains approximately 650 variables and more than three thousand respondents. Since the sample size in each survey year is about 700 individuals, we followed the same procedure as the three time use surveys and selected employed females between the ages of 22 and 62 to form the synthetic cohort approach. Since only 1979 dataset has information of home work hours, we only employed 1979 data set. The wages used are real average hourly earnings and the labor supply variable is the weekly work hours.

Using the PSID, three time use surveys and Canadian Quality of Life Survey data sets, we constructed the following age profiles: an age-wage profile, age-work hour profile, and age-home hour profile. The surveys used reported the home production hours per week, weekly working hours and wages. We constructed profiles from the years (1968, 1976 and 1981) using PSID as well.

3.5 Life Cycle Profiles

Figure 3.1: Female Age-Wage Profile (PSID 1968, 1976, 1981)

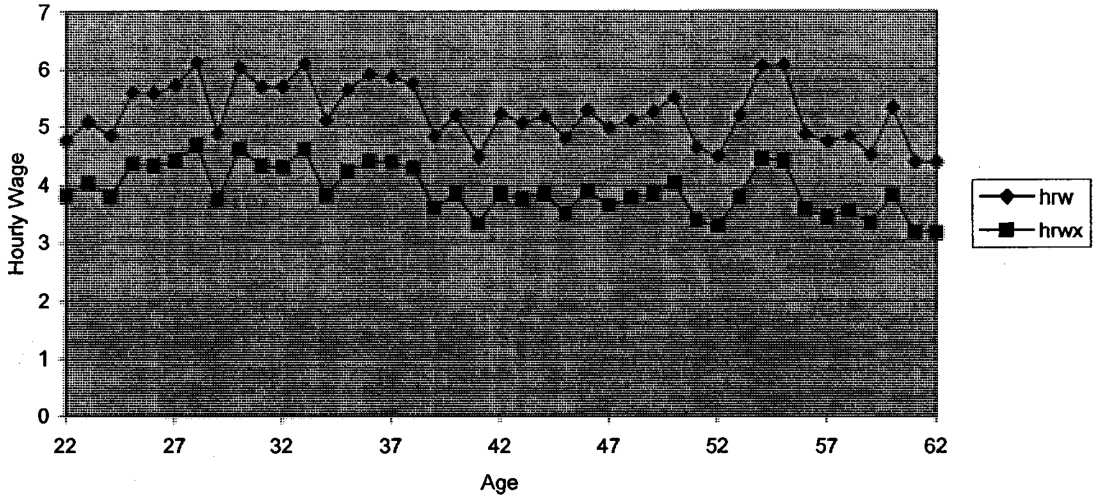
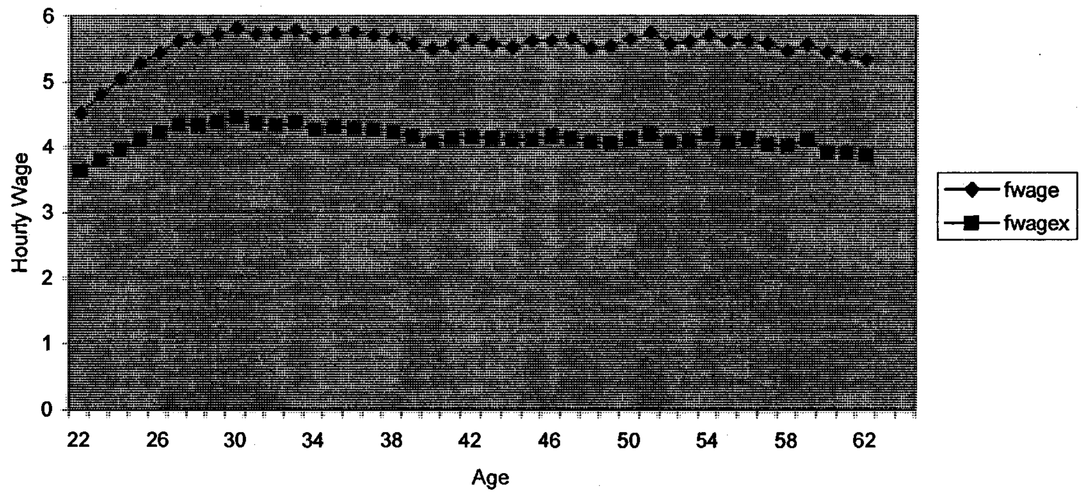


Figure 3.2: Female Age-Wage Profile (CPS 1976-1981)



hrw- the female before-tax hourly wages from PSID 1968, 1976 and 1981.
hrwx- the female after-tax hourly wages from PSID 1968, 1976 and 1981.
fwage- the female before-tax hourly female wages from CPS 1976 to 1981.
fwagex- the female average after-tax hourly female wages from CPS 1976 to 1981.

Figure 3.3: Female Age-Hour Profile (Three Time Use Surveys)

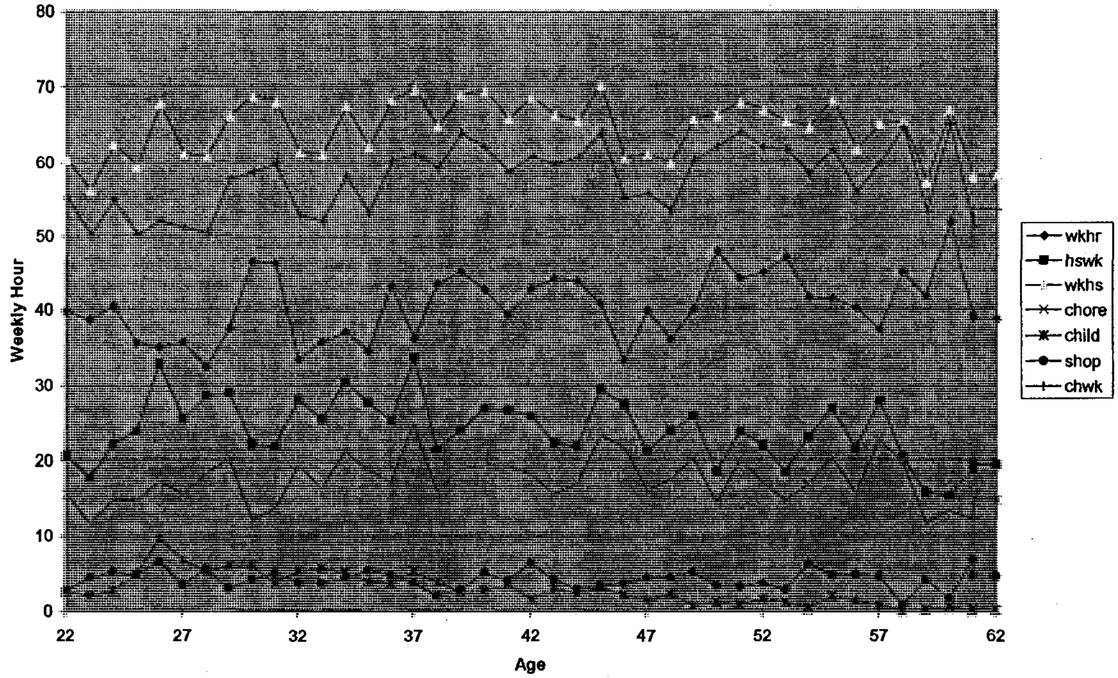
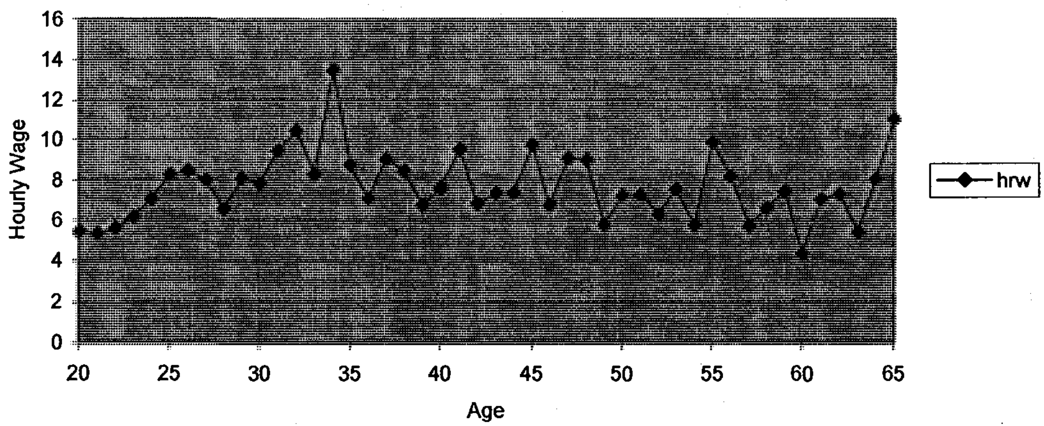


Figure 3.4: Female-Age Wage Profile (Canadian Survey, 1979)



wkhr- female weekly market work hours from three time use surveys.
hswk- female weekly homework hours from three time use surveys.
wkhs- the sum of female weekly market work hours and weekly homework hours from three times use surveys.
chore- female weekly chore work hours from three times use surveys.
child- female weekly childcare hours from three time use surveys.
shop- female weekly shopping hours from three time use surveys.
chwk-the sum of female weekly market work hours and weekly chore work hours from the Three Time Use dataset.
hrw- female hourly wages from Canadian Survey 1979.

Figure 3.5: Female Age-Hour Profile (Canadian Survey, 1979)

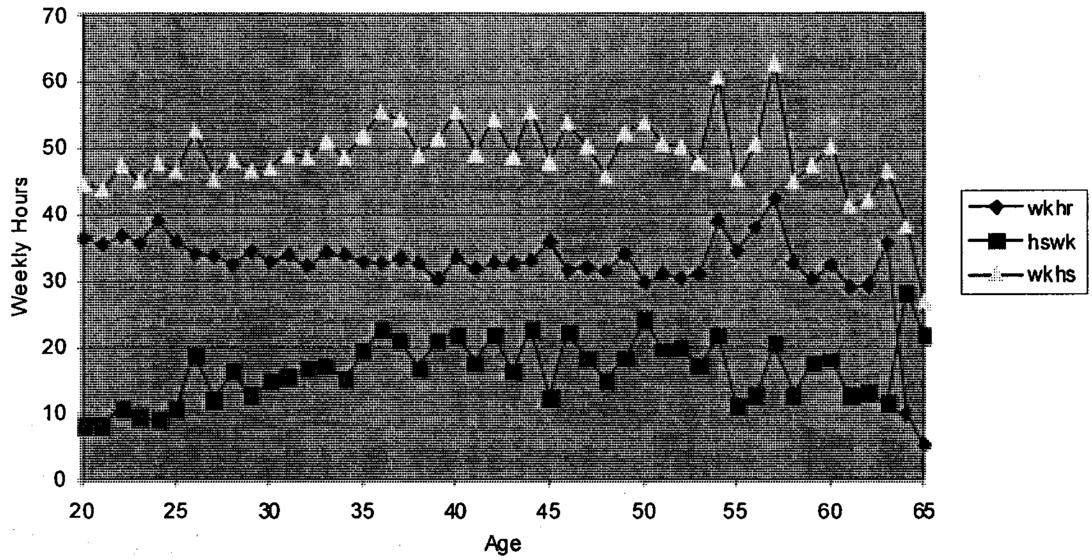
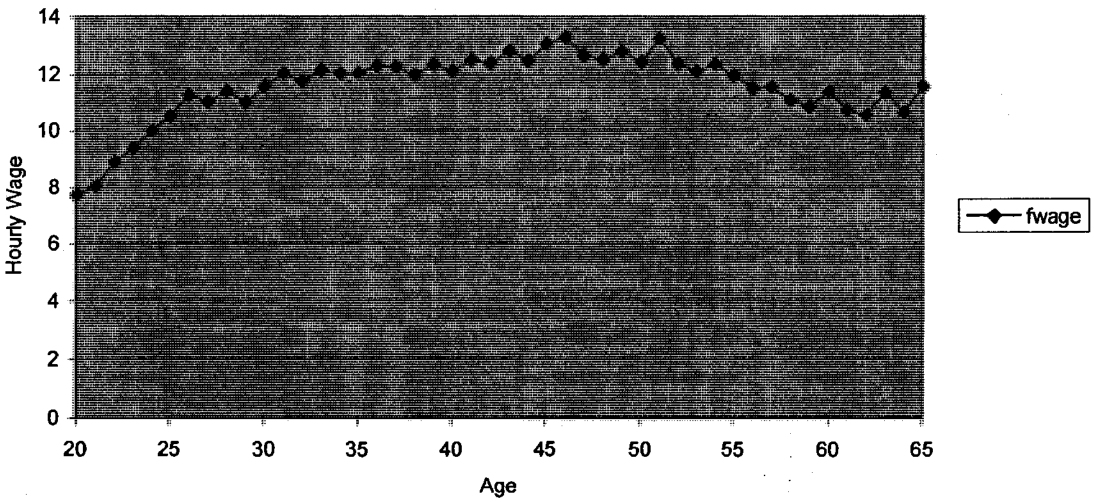
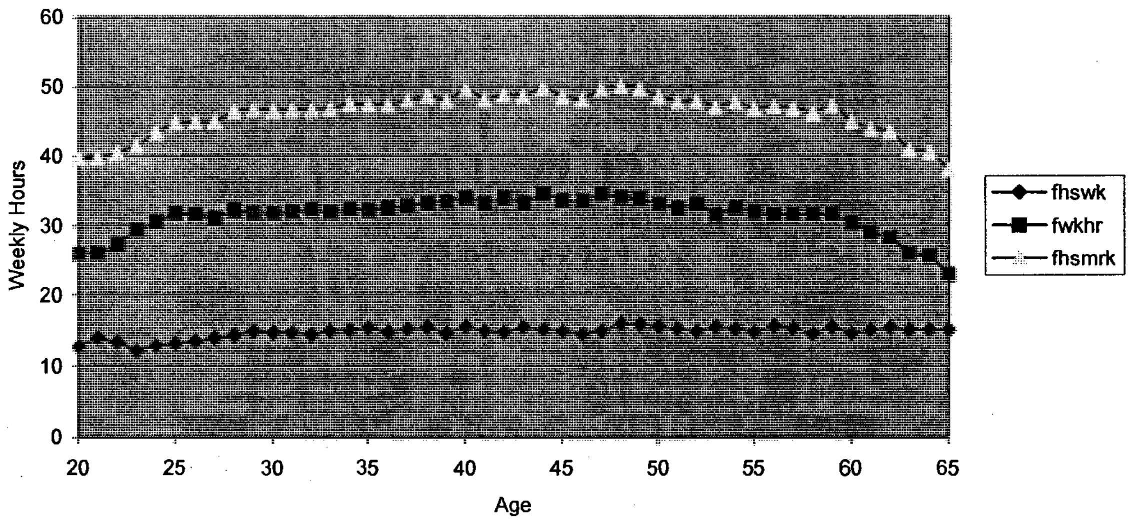


Figure 3.6: Female Age-Wage Profile (PSID 1969-2001)



wkhr- the female weekly market hours from the Canadian Quality of Life 1979.
hswk- the female weekly homework hours from the Canadian Quality of Life 1979.
wkhs- the sum of female weekly market work hours and weekly homework hours from the Canadian Quality of Life 1979.
fwage- the female before-tax hourly female wages from PSID 1969-2001.

Figure 3.7: Female Age-Hour Profile (PSID 1969-2001)



fwkhr- the female weekly market hours from PSID 1969-2001.
fhswk- the female weekly homework hours from PSID 1969-2001.
fhsmrk- the sum of female weekly market work hours and weekly homework hours from the PSID 1969-2001.

Figure 3.1 plots the female age-wage profiles of the PSID data for using 3 years (1968, 1976, 1981) data and figure 3.2 plots the same profile of CPS from 1976-1981. Figure 3.4 plots the same profile for the Canadian Quality of Life Survey (1979) and figure 3.6 does the same for the profile for the PSID data from 1968-2001. All four age-wage profiles exhibit a sharp rise in wages from age 20 to the mid 40's. Then the wages start to flatten out and eventually fall in the mid 50's. One explanation for this is that the market productivity of females is low in the early 20's, while they are still in training or searching for a career, then it rises rapidly around the mid 20's to mid 40's, and eventually flattens out and even falls in the later years. The two short time span age-wage profiles (PSID data for 3 years and Canadian Quality of Life Survey) displayed more volatile trends and both profiles indicate that wages increase in the mid 50's. This contrasts with the long time span age-wage profiles (PSID 1969-2001 and CPS 1976-1981) which displayed a smoother and flatter wage movements from the mid 40's to mid 60's. This result is as expected as the age-wage profile for a short time span does not follow the same individual over her life cycle.

Figure 3.3, figure 3.5 and figure 3.7 also illustrate the respective age-hours profiles for the three time use surveys, Canadian Quality of Life survey (1979), and PSID 1969-2001. They include market hours, homework hours and total work hours. We present hours of different homework chores as well. In Figure 3.3 work hours show a slight increase from early 20's, then displays a volatile hour movement until the age of 62. When smoothed, it shows a flattened trend. Home work hours that include hours spent on cooking, shopping and childcare increased from early 20's to mid 20's then decreased till the early 30's. After that, it continued to show a slightly downward trend till the early 40's and thereafter remains flat until the mid 50's. After the mid 50's home work hours decrease until the age of 62. We also plotted the age profiles of chore hours, which we define to include hours spent on cooking, laundry, and house cleaning, shopping hours but exclude childcare hours and the age profile of childcare hours. They all are roughly constant over the lifecycle. In addition, work hours plus home work hours and work hours plus chore hours illustrate a similar trend pattern as the work hours. Since labor supply elasticity is estimated as the response of lifecycle average hours change due to the life cycle change in average wages, we can infer that the labor supply elasticity is not substantially affected with the addition of home production.

In figure 3.5, the work hours displayed an upward trend from the early 20's to mid 30's, then flattened, and demonstrated an upward trend in the mid 50's till it tailed off after the late 50's. Home work hours showed an upward trend from the early 20's to the mid 30's, then flattened out till the mid 50's and then decreased till the early 60's. At the ages of 64 and 65, home work hours increased rapidly which caused us to suspect that this was due to the fact that the sample size was small. In figure 3.7, the work hours displayed an upward trend from the 20's to mid 30's, flattened out till the late 40's, and then gradually decreased. The age-home work hours profile was essentially flat over the whole lifecycle.

In sum, all age-work hour profiles displayed a similar pattern; an increase in the early 20's, then flattening out afterwards. Overall, the work hour profiles are more volatile than those of age-wage profiles. In the first paper, where we analyzed the male profile, all male age-work hours profiles displayed a similar pattern to the male age-wage profiles, while the male work hour profiles were much flatter than that of the male age-wage profiles. In contrast, the female age-work hour profiles displayed a more volatile pattern compared with the female age-wage profiles. Furthermore, all age-home work profiles demonstrate that individuals increase their home work hours during their early 20's to 30's, then they remain relatively flat afterward. By cursory looking at both the age-wage profiles and age-home work profiles, we can infer that wages and home work hours are not strongly correlated. Indeed, in later sections we show that our estimation results differ from those of Rupert et al.'s (2000), who suggested that wages and home hours are positively correlated.

3.6 Estimation Results

Table 3.1: Hours Regression (Female)
Time Use 1966, 1976, 1981, CPS Wage 1976-1981

Log (hours) on log (wages) age 22-62	NHP(hmt)		HP(hmt+hnt)		HP(hmt+hyt)	
	BTW	ATW	BTW	ATW	BTW	ATW
OLS						
T	0.0032	0.0034	-0.0010	0.0007	0.0020	0.0029
	(0.0024)	(0.0026)	(0.0010)	(0.0011)	(0.0012)	(0.0013)
log w	0.0878	-	0.8201	-	0.5277	-
	(0.6479)	-	(0.2586)	-	(0.3296)	-
log w(1-τ)[13]	-	0.1223	-	0.8241	-	0.4507
	-	(0.7823)	-	(0.3247)	-	(0.4046)
First differencing						
Cons	-0.0001	0.0015	-0.0007	0.0002	0.0015	0.0011
	(0.0383)	(0.0379)	(0.0163)	(0.0158)	(0.0196)	(0.0187)
log w	0.5024	-	0.0540	-	-0.4547	-
	(1.7540)	-	(0.7487)	-	(0.8977)	-
log w(1-τ)	-	0.0360	-	-0.9383	-	-1.4659
	-	(1.7737)	-	(0.7409)	-	(0.8783)
First differencing with 2SLS						
Cons	-0.0078	-0.0015	-0.0049	-0.0018	-0.0049	-0.0015
	(0.0399)	(0.0403)	(0.0173)	(0.0182)	(0.0211)	(0.0221)
log w	2.7737	-	1.2982	-	1.4358	-
	(2.9953)	-	(1.2787)	-	(1.5642)	-
log w(1-τ)	-	4.0024	-	1.6554	-	1.8725
	-	(3.7288)	-	(1.6838)	-	(2.0391)
GLS (cohort weighted)						
T	0.0002	0.0025	-0.0024	-0.0002	-0.0000	0.0019
	(0.0026)	(0.0031)	0.0011	(0.0013)	0.0014	(0.0017)
log w	0.9922	-	1.2374	-	1.0925	-
	(0.8225)	-	(0.3383)	-	(0.4399)	-
log w(1-τ)	-	1.3155	-	1.2443	-	1.0729
	-	(0.9620)	-	(0.4161)	-	(0.5298)
GLS (variance weighted)						
T	0.0051	0.0052	0.0014	0.0011	0.0031	0.0038
	(0.0022)	(0.0023)	(0.0010)	(0.0009)	(0.0011)	(0.0012)
log w	-0.0159	-	0.6736	-	0.4182	-
	(0.5874)	-	(0.3032)	-	(0.2992)	-
log w(1-τ)	-	0.0569	-	0.6559	-	0.2782
	-	(0.6985)	-	(0.2724)	-	(0.3613)

[13] log w(1-τ) of the table 3.1 to 3.4 is the after-tax wages (ATW) and log w is the before-tax wages (BTW). h=hm is the non-home production model, h=hm+hn and h=hm+hy are the home-production models. Standard errors are in parenthesis.

Table 3.2: Hours Regression (Female)
Time Use 1966, 1976, 1981, CPS Wage 1976-1981

Log (hours) on log (wages) age 22-45	NHP(hmt)		HP(hmt+hnt)		HP(hmt+hyt)	
	BTW	ATW	BTW	ATW	BTW	ATW
OLS[14]						
T	0.0105	0.0085	0.0048	0.0059	0.0098	0.0094
	(0.0048)	(0.0043)	(0.0017)	(0.0015)	(0.0020)	(0.0018)
log w	-0.6113	-	0.3690	-	-0.1179	-
	(0.6199)	-	(0.2205)	-	(0.2579)	-
log w(1-τ)	-	-0.5932	-	0.4314	-	-0.1414
	-	(0.7327)	-	(0.2589)	-	(0.3026)
First differencing						
Cons	0.0081	0.0036	0.0062	0.0077	0.0120	0.0109
	(0.0401)	(0.0382)	(0.0173)	(0.0165)	(0.0177)	(0.0170)
log w	-0.5123	-	0.2129	-	-0.4513	-
	(1.7376)	-	(0.7502)	-	(0.7752)	-
log w(1-τ)	-	-0.0082	-	0.0604	-	-0.6205
	-	(1.9685)	-	(0.8497)	-	(0.8730)
First differencing with 2SLS						
Cons	0.0007	0.0017	0.0119	0.0114	0.0136	0.0124
	(0.0430)	(0.0394)	(0.0188)	(0.0173)	(0.0191)	(0.0175)
log w	0.3322	-	-0.4399	-	-0.6390	-
	(2.4556)	-	(1.0731)	-	(1.0909)	-
log w(1-τ)	-	0.4120	-	-0.7312	-	-0.9471
	-	(2.7381)	-	(1.2047)	-	(1.2170)
GLS (cohort weighted)						
T	0.0091	0.0079	0.0046	0.0061	0.0094	0.0095
	(0.0048)	(0.0044)	(0.0016)	(0.0015)	(0.0020)	(0.0018)
log w	-0.3720	-	0.4600	-	0.0100	-
	(0.6952)	-	(0.2355)	-	(0.2815)	-
log w(1-τ)	-	-0.2721	-	0.5357	-	0.0086
	-	(0.8157)	-	(0.2753)	-	(0.3289)
GLS (variance weighted)						
T	0.0081	0.0069	0.0050	0.0063	0.0102	0.0099
	(0.0048)	(0.0044)	(0.0016)	(0.0014)	(0.0019)	(0.0017)
log w	-0.3722	-	0.3814	-	-0.0960	-
	(0.6059)	-	(0.2278)	-	(0.2645)	-
log w(1-τ)	-	-0.3019	-	0.4521	-	-0.1119
	-	(0.7100)	-	(0.2652)	-	(0.3077)

[14] In Table 3.1 to 3.5, the estimation equation for OLS, and two GLS is $\log h = \alpha_0 + \alpha_1 t + \alpha_2 \log w$, α_0 is the intercept and α_1 is the coefficient on age *"t"*. The estimation equation for first difference method and first differencing 2SLS method is $D(\log h) = cons + \delta D\log w$, cons is the intercept(constant).

Table 3.3: Hours Regression (Female)
Time Use 1966, 1976, 1981, PSID Wage 1968, 76, 81

Log (hours) on log (wages) age 22-62	NHP(hmt)		HP(hmt+hnt)		HP(hmt+hyt)	
	BTW	ATW	BTW	ATW	BTW	ATW
OLS						
T	0.0026	0.0022	0.0001	-0.0001	0.0022	0.0017
	(0.0028)	(0.0032)	(0.0012)	(0.0014)	(0.0015)	(0.0017)
log w	-0.1634	-	-0.1224	-	-0.034	-
	(0.3426)	-	(0.1529)	-	(0.1805)	-
log w(1-τ)	-	-0.1749	-	0.0539	-	-0.1013
	-	(0.3532)	-	(0.1587)	-	(0.1854)
First differencing						
Cons	0.0015	0.0012	-0.0007	-0.0012	-0.0003	-0.0010
	(0.0378)	(0.0378)	(0.0161)	(0.0160)	(0.0192)	(0.0191)
log w	-0.0679	-	-0.1024	-	-0.1680	-
	(0.3934)	-	(0.1670)	-	(0.2000)	-
log w(1-τ)	-	-0.0916	-	-0.1517	-	-0.2179
	-	(0.3938)	-	(0.1662)	-	(0.1990)
First differencing with 2SLS						
Cons	0.0082	0.0206	0.0024	0.0074	0.0029	0.0080
	(0.0762)	(0.0844)	(0.0341)	(0.0366)	(0.0370)	(0.0397)
log w	4.1387	-	1.8133	-	1.8411	-
	(4.8283)	-	(2.1626)	-	(2.3441)	-
log w(1-τ)	-	4.5250	-	1.8679	-	1.97065
	-	(5.4358)	-	(2.3601)	-	(2.5567)
GLS (cohort weighted)						
T	0.0009	0.0012	-0.0014	-0.0013	0.0006	0.0005
	(0.0031)	(0.0035)	(0.0014)	(0.0016)	(0.0017)	(0.0020)
log w	0.1700	-	0.2511	-	0.1508	-
	(0.3634)	-	(0.1662)	-	(0.2048)	-
log w(1-τ)	-	0.1669	-	0.1933	-	0.0941
	-	(0.3688)	-	(0.1708)	-	(0.2087)
GLS (variance weighted)						
T	0.0051	0.0052	0.0008	0.0006	0.0033	0.0029
	(0.0023)	(0.0026)	(0.0010)	(0.0012)	(0.0012)	(0.0013)
log w	-0.0024	-	0.0620	-	-0.0524	-
	(0.2809)	-	(0.1207)	-	(0.1373)	-
log w(1-τ)	-	0.0115	-	0.0104	-	-0.0970
	-	(0.2845)	-	(0.1220)	-	(0.1374)

Table 3.4: Hours Regression (Female)
Time Use 1966, 1976, 1981, PSID Wage 1976-1981

Log (hours) on log (wages) age 22-45	NHP(hmt)		HP(hmt+hnt)		HP(hmt+hyt)	
	BTW	ATW	BTW	ATW	BTW	ATW
OLS						
T	0.0065	0.0053	0.0060	0.0058	0.0083	0.0073
	(0.0045)	(0.0051)	(0.0017)	(0.0019)	(0.0018)	(0.0020)
log w	-0.4017	-	-0.0214	-	-0.2453	-
	(0.3538)	-	(0.1349)	-	(0.1391)	-
log w(1-τ)	-	-0.3835	-	-0.0447	-	-0.2693
	-	(0.3768)	-	(0.1426)	-	(0.1464)
First differencing						
Cons	0.0036	0.0027	0.0080	0.0069	0.0080	0.0063
	(0.0368)	(0.0369)	(0.0150)	(0.0149)	(0.0141)	(0.0140)
log w	-0.2264	-	-0.2562	-	-0.3952	-
	(0.3565)	-	(0.1450)	-	(0.1366)	-
log w(1-τ)	-	-0.2093	-	-0.2691	-	-0.4053
	-	(0.3610)	-	(0.1457)	-	(0.1373)
First differencing with 2SLS						
Cons	0.0036	0.0079	0.0080	0.0086	0.0080	0.0068
	(0.0460)	(0.0468)	(0.0179)	(0.0176)	(0.0146)	(0.0145)
log w	1.0008	-	0.1813	-	-0.2274	-
	(1.8978)	-	(0.7388)	-	(0.6019)	-
log w(1-τ)	-	1.0376	-	0.1291	-	-0.2844
	-	(1.9388)	-	(0.7275)	-	(0.5995)
GLS (cohort weighted)						
T	0.0067	0.0062	0.0061	0.0060	0.0085	0.0079
	(0.0048)	(0.0055)	(0.0018)	(0.0020)	(0.0019)	(0.0022)
log w	-0.2365	-	0.0224	-	-0.1633	-
	(0.3655)	-	(0.1349)	-	(0.1441)	-
log w(1-τ)	-	-0.2081	-	0.0039	-	-0.1815
	-	(0.3853)	-	(0.1419)	-	(0.1509)
GLS (variance weighted)						
T	0.0055	0.0045	0.0062	0.0060	0.0089	0.0081
	(0.0045)	(0.0050)	(0.0016)	(0.0019)	(0.0018)	(0.0021)
log w	-0.3594	-	-0.0076	-	-0.1981	-
	(0.3547)	-	(0.1348)	-	(0.1430)	-
log w(1-τ)	-	-0.3402	-	-0.0257	-	-0.2174
	-	(0.3756)	-	(0.1429)	-	(0.1510)

Table 3.5: Hours Regression (Female) Canadian Quality of Life Survey 1979

Log (hours) on log (wages) age 22-62		
	NHP(hmt)	HP(hmt+hnt)
OLS		
T	-0.0036	0.0000
S.E.	(0.0016)	(0.0011)
log w	-0.2181	-0.0734
S.E.	(0.0937)	(0.0648)
First Differencing		
Cons	-0.0045	-0.0003
S.E.	(0.0225)	(0.0151)
log w	-0.1993	-0.2143
S.E.	(0.0839)	(0.0562)
First Differencing with 2SLS[15]		
Cons	-0.0031	-0.0003
S.E.	(0.0240)	(0.0151)
log w	-0.3915	-0.2141
S.E.	(0.2135)	(0.1341)
GLS (cohort weighted)		
T	-0.0031	-0.0024
S.E.	(0.0020)	(0.0013)
log w	-0.2385	-0.1513
S.E.	(0.0990)	(0.0649)
GLS (variance weighted)		
T	0.0028	-0.0020
S.E.	(0.0013)	(0.0009)
log w	-0.1570	-0.5561
S.E.	(0.0812)	(0.0772)

[15] The instruments for log wage in tables 3.1 to 3.4 are age, the number of family members in a family unit, the number of children in a family unit, and the education level of the subject.

Table 3.6: Hours Regression (Females)
PSID 1969-1997 (excluded 1975 and 1985)

Log (hours) on log (wages) age 20-65	(No outliers)		(With outliers)	
	NHP(hmt)	HP(hmt+hnt)	NHP(hmt)	HP(hmt+hnt)
OLS				
Cons	7.2763	7.8003	7.4182	7.8173
S.E.	(0.0396)	(0.0279)	(0.0318)	(0.0216)
log w	0.0846	-0.0152	-0.0119	-0.0471
S.E.	(0.0148)	(0.0104)	(0.0118)	(0.0081)
First Differencing				
Cons	0.0164	-0.0084	0.0214	-0.0076
S.E.	(0.0053)	(0.0039)	(0.0061)	(0.0045)
log w	-0.1941	-0.1528	-0.2993	-0.2003
S.E.	(0.0173)	(0.0129)	(0.0124)	(0.0090)
First Differencing with 2SLS				
Cons	-0.0010	-0.0258	-0.0163	-0.0375
S.E.	(0.0100)	(0.0084)	(0.0153)	(0.0116)
log w	0.7308	0.7591	1.0979	0.9372
S.E.	(0.3451)	(0.2909)	(0.4089)	(0.3127)

Table 3.7: Hours Regression (Non-Single Females)
PSID 1969-1997 (excluded 1975 and 1985)

	Log (hours) on log (wages) age 20-65			
	(No outliers)		(With outliers)	
	NHP(hmt)	HP(hmt+hnt)	NHP(hmt)	HP(hmt+hnt)
OLS				
Cons	7.1876	7.7806	7.3856	7.8304
S.E.	(0.0503)	(0.0337)	(0.0405)	(0.0257)
log w	0.1090	-0.0002	-0.0163	-0.0451
S.E.	(0.0188)	(0.0127)	(0.0152)	(0.0096)
First Differencing				
Cons	0.0166	-0.0138	0.0174	-0.0178
S.E.	(0.0069)	(0.0050)	(0.0083)	(0.0057)
log w	-0.1599	-0.1158	-0.3117	-0.1977
S.E.	(0.0214)	(0.0153)	(0.0154)	(0.0107)
First Differencing with 2SLS				
Cons	0.0067	-0.0215	-0.0126	-0.0389
S.E.	(0.0108)	(0.0076)	(0.0206)	(0.0143)
log w	0.6911	0.5048	1.2487	0.9345
S.E.	(0.3993)	(0.2836)	(0.7153)	(0.4982)

Table 3.8: Hours Regression (Single Females)
PSID 1969-1997 (excluded 1975 and 1985)

Log (hours) on log (wages) age 20-65	(No outliers)		(With outliers)	
	NHP(hmt)	HP(hmt+hnt)	NHP(hmt)	HP(hmt+hnt)
OLS				
Cons	7.5148	7.8484	7.5139	7.7855
S.E.	(0.0590)	(0.0497)	(0.0480)	(0.0404)
log w	0.0132	-0.0481	-0.0161	-0.0481
S.E.	(0.0219)	(0.0184)	(0.0178)	(0.0149)
First Differencing				
Cons	0.0182	0.0042	0.0277	0.0115
S.E.	(0.0079)	(0.0064)	(0.0085)	(0.0070)
log w	-0.2876	-0.2575	-0.2610	-0.2107
S.E.	(0.0294)	(0.0241)	(0.0208)	(0.0170)
First Differencing with 2SLS[16]				
Cons	-0.0127	-0.0151	-0.0201	-0.0213
S.E.	(0.0173)	(0.0126)	(0.0208)	(0.0153)
log w	0.7205	0.3599	0.9186	0.6046
S.E.	(0.4302)	(0.3136)	(0.3933)	(0.2912)

In tables 3.1 and 3.2, we report estimation results for the three time use surveys where the dependent variables are log hours and the independent variables are age and the log wage. The hour variable is a synthetic cohort variable constructed from three time use surveys (1966, 1976, and 1981). The wage variable is also a synthetic cohort data aggregated from CPS (1976-1981). The estimates using the PSID (1968, 1976, and 1981) synthetic wage data are displayed in tables 3.3 and 3.4.

The estimated utility function is v(h)=$\phi\, h^{\gamma}$; the dependent variable is $\ln(h_t)$, where $h_t = h_{mt} + h_{nt}$ in the home production model (HP); $h_t = h_{mt} + h_{yt}$ is the yard work home production model (HP yard), where home hours only include house/yardwork

[16] The instruments for the log wage in table 3.6 to 3.8 are the head's age, age squared, the number of family members in a family unit, the number of children in a family unit and the parent's wealth when the head reaches adulthood, an individual's father's education level and an individual's mother's education level.

hours, and $h_t = h_{mt}$ is the non-home production model (NHP) where we only used market hours. We report the OLS estimates, the first differenced least square estimates, the first differenced 2SLS estimates, and estimates using the two GLS methods which are similar to the ones used by Rupert et al. (2000). Rupert et al. (2000) utilized the following two GLS type estimators: the first estimator weighted the observations by their cohort size; the second GLS estimator weighted the observations by the inverse of the variance of the within cohort individual hours[17]. In this paper we use first differencing with the 2SLS to obtain elasticity estimates. We report results using before-tax wages (BTW) as well as after-tax-wages (ATW). We then report the results for the two age groups: 22-45, 22-62 in tables 3.1 to 3.4. Table 3.5 shows the results using the Canadian Quality of Life data (1979) using the aforementioned methods.

Tables 3.6 to 3.8 exhibit the estimated results for the PSID panel data from 1969 to 1997. Table 3.6 reports the results using the whole female sample while Table 3.7 has results where only non-single females are used. Furthermore, Table 3.8 reports the results for single females. All three tables (3.6 to 3.8) reported NHP estimates and HP estimates for data with and without outliers. The methods we used are: the OLS, the first differenced OLS and the first differenced 2SLS.

The results from three time use surveys are presented in tables 3.1 to 3.4. It is interesting to note that for the age group 22-62 whose results are displayed in table 3.1, when we use synthetic before-tax wages from the CPS (1976-1982), the NHP estimate (2.7737) is largest among the three specifications: 1.2982 for the home production (HP) model, 1.4358 for the yard production (YP) model and 2.7737 for the non-home

[17] Notice that hours refer to the market hours employing the NHP model while the sum of homework and market hours using the HP model.

production (NHP) model. The parameters were estimated by first differenced 2SLS. Similar conclusion can be reached when we use after-tax wages. There, the NHP estimate (4.0024) is the largest among three specifications: 1.6554 for the HP model, 1.8725 for the YP model, and 4.0024 for the NHP model. When the variance weighted GLS method is used, the NHP estimate (-0.0159) is the smallest among three specifications: 0.6736 for the HP model, 0.4182 for the YP model and -0.0159 for the NHP model, where before-tax wages were used. The same can be said for the results when we use after-tax wages. For the estimates in the cohort weighted GLS method, the NHP estimate (0.9922) is still the smallest among the three specifications: 1.2375 for the HP model, 1.0925 for the YP model and 0.9922 for the NHP model when before-tax wages were used. However, when after-tax wages are used, then among the three specifications: 1.2443 for the HP model, 1.0729 for the YP model and 1.3155 for the NHP model, the NHP estimate is the largest.

In Table 3.2, the results for the age group 22-45, using the CPS synthetic wage, are presented. Using the first differencing 2SLS method, only the NHP estimate (0.3322) for the before-tax wages and NHP estimate (0.4120) for the after-tax wages are positive. The other four HP estimates are negative. In contrast, if we use GLS, only HP model estimates (0.4600, 0.5357, 0.3814, and 0.4521) are positive and more significant. The other eight estimates are either negative or small and insignificant.

Tables 3.3 and 3.4 exhibit the results where the three time use surveys and the PSID synthetic wage are used. In Table 3.3, for the 22-62 age group, the estimated results using the first differenced 2SLS indicate that NHP estimates (4.1387 for BTW and 4.5250 for ATW) are largest among three estimates for both ATW and BTW; indeed, they are more than twice as much as the others. All estimates using both GLS methods are either negative or small. In Table 3.4, for the age group 22-45, the NHP estimates (1.0008 for BTW and 1.0376 for ATW) from the first differenced 2SLS are the largest ones among three models. On the other hand, the estimates for two GLS methods are either extreme small or negative. In sum, based on the estimation results using data from the three time use surveys, there is no conclusive evidence that HP estimates are significantly larger than NHP estimates.

In Table 3.5, we report estimation results where we use data from the Quality of Life survey (1979). We can observe that all estimates reported from the first differenced 2SLS and two GLS are negative. One explanation may be that one-year data set was used, thus it is impossible to eliminate the individual unobserved heterogeneities.

Tables 3.6 to 3.8 report the estimates using the PSID (1969-1997) for the ages 20-65. All OLS estimates and the first differenced OLS estimates from three tables are either very small or negative. In Table 3.6, the results using the first differenced 2SLS are shown. The estimates for all female samples indicate that the NHP estimate (0.7308) is slightly smaller than HP estimate (0.7591) with an outlier free sample. On the other hand, the NHP estimate (1.0979) is slightly larger than HP estimate (0.9372) when outliers are not removed. Table 3.7 shows that OLS estimates and first differenced OLS estimates are either small or negative for non-single females. If we use first differenced 2SLS, for samples with and without outliers, the NHP estimates (0.6911 and 1.2487) are slightly larger than HP estimates (0.5048 and 0.9345). Table 3.8 demonstrates similar results as the ones shown in Table 3.7. In the first differenced 2SLS, the NHP estimates (0.7205 and 0.9186) are larger than HP estimates (0.3599 and 0.6046) for samples with and without outliers. In Table 3.8, where we show the estimation results for the single women, the estimates based on OLS and first differenced OLS are all either small or negative. However, in case of first differenced 2SLS results, NHP estimates are much larger than HP estimates for both samples with and without outliers. Overall, in all the results using the PSID data set (1969-1997) the estimates with outlier samples are larger than the ones without outliers. These results are expected because removal of the outliers implicitly restricts the intertemporal variation in labor hours.

3.7 Conclusion

In this paper, we used three data sets (three time use surveys, PSID and Quality of Life) to empirically examine the female home production model. There is no conclusive evidence to indicate that the estimates of intertemporal labor supply elasticity of the home production labor supply model are larger than the ones of the standard labor supply models where home production hours are not included in labor supply. The age-home hour profiles indicate that women do not rapidly adjust their home work hours due to wage changes. Consequently, home production hours are not strongly correlated with the wage rate. Most of the results indicate that NHP elasticity estimates are larger than those of HP model, but the differences are small. HP and NHP elasticity estimates using the PSID panel data set (1969-1997) are nearly the same. Therefore, we can conclude that the home production labor supply will not significantly increase the estimates of the intertemporal labor supply.

Based on those results, we tentatively conclude that we do not find any supporting evidence for Rupert et al. (2000)'s claim that the willingness to substitute total hours (home work hours plus market work hours) over the life cycle is substantially larger than the willingness to substitute market hours in response to wage changes. Therefore, there is no evidence of a large downward bias in the estimates of the employed female labor supply elasticity if home production is not included. The important shortcoming of our analysis is that we did not include women who had zero labor supply hours in a given year. Estimating the intertemporal elasticity with corner solution in work hours is a topic that is left for future research.

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