ESSAYS ON MARRIED WOMEN LABOR SUPPLY

A Dissertation

by

XINRONG LI

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2011

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Approved by:

Co-Chairs of Committee,	Li Gan
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ABSTRACT

Essays on Married Women Labor Supply. (December 2011)

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Co-Chairs of Advisory Committee: Dr. Li Gan
Dr. Qi Li

One of the very interesting demographic features in the US over the last three decades of the 20th century is the increase of the married women labor force participation rate. Over the same period, estimated labor supply elasticity varies substantially. This dissertation is to investigate the reasons behind them.

I first study the determinants of the increase of the labor participation rate for married women with preschool-aged children over the last three decades of the 20th century. Using 5% samples of the Integrated Public Use Microdata Series (IPUMS) for 1980, 1990 and 2000, I find that the existing explanations proposed in the literature may only account for 9.6% increase in the 1980s and 70% decrease in the 1990s. In this paper, I find that the rising ratio of career type women can explain 30.33% of the growth in the labor force participation rate, and the change in the composition of career motivating career type women can at least explain 17.22% growth across cohorts. Women who have been working three years before their first childbearing are more likely to return to work after the childbearing period. The analyzing data is the National Longitudinal Survey of Young Women (NLSYW) from 1968 to 2003 and the National Longitudinal Survey of Youth 1979 (NLSY79) from 1979 to 2008.

This dissertation sheds some insight about a puzzle on estimated married women's labor supply elasticity variation. This important puzzle (sometimes referred to as the Hausman puzzle) is that the estimated labor supply elasticity varies substantially even when similar frameworks and similar datasets are used. I study the role of budget sets in producing this wide range of estimates. In particular, I study the effect of the typical convexification approximation of the non-convex budgets, and the well-known Heckman critique of the lack of bunching at the kink points of budget sets in the Hausman model. I introduce measurement error in nonlabor income to create an uncertain budget constraint that no longer implies bunching at kink points. Using the Panel Study of Income Dynamics (PSID) of 1984 and 2001, I find that neither the convexification approximation nor using a model with random budget sets affects the estimates. These results demonstrate that variations in budget constraints alone do not explain the different estimates of labor supply elasticity. Changing the level of budget sets, for example by ignoring the state individual income tax, could affect the variation in elasticities.

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Though only my name appears on the cover of this dissertation, a great many people have contributed to its production. I owe my gratitude to all those people who have made this dissertation possible and because of whom my graduate experience has been one that I will cherish forever.

My deepest gratitude is to my advisors: Dr. Li Gan and Dr. Qi Li. They encouraged and urged me along this unorthodox journey in creating this dissertation. They taught me how to question thoughts and express ideas. Their patience and support helped me overcome many crisis situations and finish this dissertation. I hope that one day I would become as good an advisor to my students as they have been to me.

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Most importantly, none of this would have been possible without the love and patience of my family. I would like to dedicate this dissertation to my parents, Jianye Zhang and Henwu Li, and brother, Xinchang Li.

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CHAPTER I

INTRODUCTION

One of the very interesting demographic features in the US over the last three decades of the 20th century is the increase of the married women labor force participation rate. Over the same period, the participation rate of married women with preschool-aged children increased more. In Chapter II, I explore which changes in the determinants of labor supply mostly account for the increase in participation rate. Previous literatures attempt several factors to explain this large observed change in female labor supply, such as public policy reforms to encourage working, a drop in spousal income, a decrease in wage-gender gap and child care cost, and an asymmetrical increase in average commuting time and "power couples" across urban areas. My contributions here are to quantify contributions of various factors in previous literatures. I find previous explanations may only account for 9.6% of the increasing in labor force participation rate of married women with preschool-aged children from 1980 to 1990.

Chapter II argues that career type decision is an important factor to investigate. I introduce a new measure on career work experience and labor force participation rate, which is the ratio of the number of weeks worked and the total number of weeks during the career period and during the labor force participation period, respectively. I suggest

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This dissertation follows the style of *The Journal of Human Resources*.

that there are two types of individuals. For one type, career women can grasp a professional set of skills and networking in order to return after the childbearing period, while for another type, non-career type women would like to be housewives. Changes in labor force participation rate across cohorts are driven by shifts in the composition of married women with preschool-aged children, while it is possible that changes are motivated by changes in average behavior. The women's attitude about the female's career role in the family is the key variable to influence the women's employment preference. My results show that the rising of the percentage of career women can explain 30.33% of the growth across cohorts. Among the unexplained changes, the change in the composition of career motivating career type women can at least explain 51.2%. That means it can at least explain 17.22% growth in the labor force participation rate across cohorts.

My research topic in Chapter III is how different ways of calculating budget constraints lead to different estimates of wage elasticities in structural models.

Wage elasticity is a very important parameter in public policy and there is a large literature to estimate this parameter. Economists differ in their ways. Even with the same framework, for example, Hausman structural model, people produce quite different values on wage elasticity. There are some attempts in the literature explaining and addressing the discrepancies in estimates, such as nonlinear or nonparametric function specification. But the role of budget sets in producing the wide range of estimates has not been studied yet. My contributions here are to study the effect of different ways of calculating budget constraints, typically such as convexification approximation of the non-convex budgets, and uncertain budget constraints.

Since my focus is on the former discrepancy revealed by previous literature, I have strictly followed their data selection. Using the PSID which is the Panel Study of Income Dynamics, of year 1984 and 2001 to analyze non-disable married women who got paid (non-disable means a tax payer could not receive any disable benefit), I find that both the convexification approximation and random budget sets have insignificantly affected the estimates. However, changing the level of budget sets, for example, by ignoring the state individual income tax, can largely affect the variation in elasticities.

Reasons to consider structural models to analyze labor supply elasticities is that federal and state individual income tax are progressive at accumulated amount of income level, and the phase-out brackets in social security payments and EITC program, individual budget constraints are hence piecewise-linear. For example, the marginal tax rate is 5% when you have worked less than 10 hours per week. The marginal tax rate will increase to 15% if your working hours are over 10. Therefore, we are having a convex kink point around 10 working hours. In the opposite case of concave kink point, the tax rate will decrease if the working hour increases. With the piecewise-linear budget constraints, the after-tax wage rate and working hours are decided simultaneously, which is an endogenous problem. Hausman introduces a labor supply model of utility maximization for individual with respect to choices about leisure and other consumption goods, where the price of consumption goods is normalized to be 1. Hausman structural model can catch the institutional features of the tax system and incorporates the fixed cost of holding a job. Unfortunately, the wage elasticity varies a lot. What is even more puzzling is studies using the same or similar data sources have reported significant different elasticities. Hausman uses PSID of 1975 and finds a wage effect close to zero.

MaCurdy uses the same data set, makes smooth the budget segments and reports a negative wage effect. And Trist uses PSID of 1984 and gets a positive wage effect. Previous literatures find the estimates of wage elasticities are sensitive to the function specification. The different measurement in the gross wage rate also affects the estimates. And there is very little work analyzing the role of budget sets.

In Chapter III, I consider two questions on budget sets. One is previous studies are based on the convexified budget sets. That means the relevant region around concave kink points is replaced by a single convex segment to construct convex budget sets. However, the effect of convexification approximation is unknown, both theoretically and empirically. Intuitively, if leisure and consumption are near perfect substitutes, a minor difference in the convexification approximation will cause a large change in hours of work. I have investigated the effect of convexification approximation on the labor supply elasticities under both convexified and non-convexified budget sets.

The second question I consider in this chapter is Heckman critique. The basic assumption of Hausman structural model is that there is bunching around the kink points. In reality, few of tax payers bunch at the kink points of the US income tax schedule. Heckman concludes budget segments aren’t able to be accurately measured in most cases because econometricians do not know the amount of tax payers’ itemized deduction. To address Heckman’s critique, I introduce measurement error in nonlabor income. Such measurement error naturally shifts the intercept on the vertical axis of the budget constraints and changes the location of the kink points of the budget constraints. The slope of the budget sets is uncertain, which is in line with Heckman’s comments.

I start with a linear specification of the demand function first, and then recover the indirect utility function using Roy's identity. When a person is at a kink point, the indifference curve is not tangent to the budget sets, the utility level can only be obtained from the direct utility function. If both the piecewise-linear budget constraints and the utility curve are convex, the unique tangent/joint point is global optimization point because of weak axiom of revealed preference. But the econometrician can't assign the worker to a particular segment or kink point because of the individual heterogeneity preference. The probability can be computed by integrating out the heterogeneity preference error term. Then I program maximum likelihood method to estimate. Given the piecewise-linear budget constraints are non-convex, and a utility curve is tangent to a particular segment, after shifting this utility curve, it can be tangent to another segment or joint to another kink points. Therefore, after comparing the utility value I can be pretty sure which point is the global optimization point. It is impossible to use previous optimization trick here due to unable to get a range of heterogeneity preference error term. The much more complicated simulated maximum likelihood method will be used to solve this issue, which has randomly drawn the error term 1000 times. In addition, for calculating the score vector and information matrix, I introduce a kernel function to let likelihood function be continuous and differentiable. I apply my method to estimate the labor supply for married women ages 25 to 55 using the PSID data of 1984 and 2001. The U.S. individual income tax systems in 1983 and 2000 are used to construct non-convexified budget constraints. The tax system includes federal income tax, state income tax, social security, Medicare payments, and the EITC. Previous studies average the state tax rates over the segments created by the federal tax. I construct more precisely budget constraints by adding additional segments to the federal budget constraints. And because of the itemized deduction, the marginal tax rate and the corresponding changes of the effective taxable incomes need to be re-calculated using a self-derived formula.

The relative difference of elasticity under random and nonconvexified budget sets is about 20% in 1983 and 10% in 2000. The relative difference of elasticity under convexified and nonconvexified budget sets is about 10% in 1983 and 2000, respectively. Consequently, the variation in budget sets does not explain the different estimates of labor supply elasticity. If the state individual tax is excluded to construct budget sets, there will be a large bias in the level of budget constraints which causes about 30 to 50% relative difference of wage elasticity.

CHAPTER II

CAREER WORK EXPERIENCE BEFORE THE FIRST BIRTH AND CHANGES IN LABOR SUPPLY OF MARRIED WOMEN WITH PRESCHOOL-AGED CHILDREN

2.1 Introduction

Women's labor force participation rate has increased dramatically over the last three decades of the 20th century, especially for married females with preschool-aged children. From 1970 to 1996, the percentage of women in the labor market rose from 43.3% to 59.3%. Over the same period, the participation rate of married women with preschool-aged children was more than doubled, from 30.3% to 62.7%. The goal of this chapter is to explore the potential economic explanations accounting for this observed increase trend of labor supply in married women.

The previous research suggests several factors to explain the large observed change in female labor supply. These factors include public policy reforms to encourage working, a drop in spousal income, a decrease in wage-gender gap and child care cost, and an asymmetrical increase in average commuting time and "power couples" across urban areas. Using 5% samples of the Integrated Public Use Microdata Series (IPUMS) for 1980, 1990 and 2000, I find previous explanations may only account for 9.6% of the increasing in labor force participation rate of married women with preschool-aged children from 1980 to 1990.

It has been documented that the largest increase in labor supply participation rate is in the group of married women with preschool-aged children. To understand the reasons for the change of the labor supply behavior for this group of women, I focus their behavior before the first child. In this chapter, I introduce a new measure of career work experience and define the career women to estimate the labor supply participation model. The increase ratio of career women is able to explain 30.33% of the growth in female labor supply participation across cohorts, cohorts that are born in 1943-53 and in 1957-64. And the change in the composition of career motivating career type women can at least explain 17.22% growth across cohorts.

Section 2.2 goes through the economic forces which might as well serve as potential explanations for the observed increase rate. Only 30.88% of the increasing rate in the 1980s is able to be explained by using 5% samples of IPUMS for 1980, 1990 and 2000. Section 2.3 contains the primary economic contribution of this chapter. A new variable is introduced to measure the heterogeneity of female's career work experience. I examine how the career work experience before the first child affects female's labor force participation and predict how much growth of participation rate is from the change of measured factors. I also have a discussion about the phenomenon that more women are becoming the career type in the latter cohort. Finally, the conclusion is in Section 2.4.

2.2 Previous Research

2.2.1 Possible Explanations

The previous empirical evidence presents an array of factors which are responsible for the increase in the female labor force participation rate.

The first explanation is the reform of the cash-transfer program. Eissa and Hoynes (2003) examine the labor force participation response of married couples to the Earned Income Tax Credit (EITC) expansions between 1984 and 1996. They find the labor force participation rate of married men increased by about 0.2% and that of married women decreased by just over a full percentage point. There is at most 2% of the change in participation rate of married women related to the expansions.

The second explanation is to compensate the drop of spousal income. Blau and Kahn (2007), Heim (2007, 2009) and Triest (1990) find significant negative effects of spousal income on the participation probability while Juhn (1992) and Juhn, Murphy and Pierce (1993) find real average weekly wages for the less-educated male decreased. It is possible that married women increase their labor supply to offset the decrease of their spouses, which is doubted by Juhn and Murphy (1997).

The third explanation is related to the decrease of the wage-gender gap. When the wage-gender gap decreases, the opportunity cost of being out of labor force rises and females increase their employment. Attanasio, Low and Marcos (2008), Buttet and Schoonbroodt (2005), and Jones, Manuelli and McGrattan (2003) construct life-cycle models of female participation and estimate the effect of the wage-gender gap.

The forth interpretation is the decrease of child care cost. Attanasio, Low and Marcos (2008), Ribar (1992), Powell (1997), Kimmel (1992) find significant negative effects of child care costs on the employment probability. Michalopoulos, Robins and Garfinkel (1992), Blau and Robins (1991) and Ribar (1995) find little effect of that on employment. The role of child care costs is mixed.

The fifth explanation is the change of commuting time. Kolesnikova (2007) uses Census Public Use Micro Sample date for 1980, 1990 and 2000 and documents married women's labor force participation decisions appear to be negative correlated with commuting time across urban areas. She shows that metropolitan areas which experienced relatively large increases in average commuting time between 1980 and 2000 also had slower growth of labor force participation of married women.

The sixth explanation is “power couple” urbanization. Costa and Kahn (2000) shows that college educated couples are more likely to be located in the big metropolitan areas, and the average participation rate in these areas would be higher than the non-big MSA. If “power couple” is disproportionately living in big MSA, the participation rate in big metropolitan areas increases more than in the non-big metropolitan areas. Compton and Pollak (2006) use PSID and find no support for Costa and Kahn (2000). The conclusions about the role of “power couple” asymmetrical urbanization are ambiguous.

2.2.2 Empirical Strategy

I make attempts here to discuss which factors account for the increase of female employment with the 5% samples of the Integrated Public Use Microdata Series (IPUMS) for 1980, 1990 and 2000. I estimate the following static employment model for a pooled sample:

$$LFP_i = \Phi(\alpha + \alpha_1 D_{1980i} + \alpha_2 D_{2000i} + Z_i\gamma + u_{1i} \geq 0) \tag{2.1}$$

$$\begin{aligned} LFP_i = \Phi(&\alpha + \alpha_1 D_{1980i} + \alpha_2 D_{2000i} + \\ &\beta_1 WageRatio_i + \beta_2 ChildCost_i + \beta_3 Nonlabor_i + \beta_4 Minutes_i + Z_i\gamma + u_{2i} \geq 0) \end{aligned} \tag{2.2}$$

where for each individual, LFP is married women labor force participation, D1980 is a 1980 year dummy variable, D2000 is a 2000 year dummy variable, Z is a vector of control variables (including age and age square, years of education, indicator for living in central city, and indicator for paying mortgage), *WageRatio* is the wage-gender gap, *ChildCost* is the child care cost, *Nonlabor* is one’s spousal wage income, *Minutes* is the average work males’ commuting time (in 10 minutes) across states, and u_1 and u_2 are disturbance terms.

Model (2.1) is a traditional static participation function in which coefficient α_1 indicates the unexplained increasing in participation rate of married women with preschool-aged children from 1980 to 1990 except contributions of control variables, while α_2 indicates the unexplained decreasing in participation rate in the 1990s. The participation rate of married women with preschool-aged children dramatically increased in the 1980s and slightly decreased in the 1990s. I expect coefficient α_1 and α_2 are negative and $\alpha_1 < \alpha_2$. Model (2.2) quantifies contributions of various factors in previous literatures, including wage-gender gap, child care cost, spousal income and Commuting time. I suppose previous factors can partly explain the participation change of married women with preschool-aged women. Coefficient α_1 and α_2 are increased. I also expect coefficient α_1 and α_2 are negative and $\alpha_1 < \alpha_2$ in Model (2.2).

Estimation of Model (2.1) and (2.2) shows an array of econometric difficulties. First, my question is on married women with preschool-aged children. Figure 1 in Appendix A tells us that the distribution of this group among married women didn't change a lot in the 1980s (from 23.5% to 23%). As the marriage rate falls, married women may become more marriage-prone relative to the total population of women, on average. I assume there is no relationship between marriage-proneness and the motivation to work in the market. Second, the wage rate of nonparticipating wives is not observed. I use Heckman's sample selection procedure to impute the latent wage rate as actual wage rate, which is shown in the appendix C. Naturally, given the selection process of women into the labor market, the imputed actual wives' wage rates are over-predicted in lower participation period because working women are disproportionately drawn from the high end of the talent pool. I am not able to obtain the direct evidence on the child care cost.

I focus on a sample of married women between 18 and 65, eliminating observations where the wife reported disabled and self-employment. My sample sizes are 2,088,458, 2,172,046 and 2,175,973 observations for 1980, 1990 and 2000, respectively. Figure 2 in appendix A reports the growth in the labor force participation across different categories of married females: no children, with preschool-aged children, and with school-aged children. The participation rate of women with preschool-aged children increased 15.4% from 38.8% to 54.2% in the 1980s. Over the same period, the employment of women without child increased 6.1% and rose 12.3% for women with school-aged children. Figure 1 in appendix A describes the distribution of women among different family structures. The percentage of females without child increased 1.1% in the 1980s, from 33.6% to 34.7%. For married females with school-aged children and with preschool-aged children, it separately decreased 0.6% and 0.5% in the 1980s. There was a slight change in the participation rate and the distribution of married females with different fertility choices in the 1990s.

The 5% sample of IPUMS provides information on employment status. The three categories are employed, unemployed and not in the labor force. My basic measure of labor force participation is a dummy variable to indicate whether married female is employed. All monetary variables are inflated or deflated to real dollars from the year 2000 with using consumer-price-index. I consider hourly wage observations as invalid if they are less than $1 or greater than $100 per hour in 2000 dollars. For those with invalid wage observations, wages are imputed with using Heckman's sample selection procedure. Buttet and Schoonbroodt (2005) use the wage of single women to approximate the return to experience of married women to avoid the wage penalty. I use male's wage model to impute female wage rate to avoid the wage penalty and the wage-gender gap. I measure the wage gap with wage ratio, which is the female's actual wage rate divided by the imputed wage rate. Attanasio, Low and Marcos (2008) present some evidence on the child care cost with the price of child care workers. I present the child care cost with the average hourly wage rate of child care workers over state. Nonlabor income is defined as spousal income. To examine the effect of commuting time on women's participation decision, it is necessary to introduce a new measure. Because of the selection process of women into the labor market, I use the male's commuting time as a proxy for the fixed time cost of going to work, which is done as Kolesnikova (2007). In addition to previous explanation measures, I include a set of control variables that are common to Model (2.1) and (2.2). These include her age and age square, how much schooling has been received, dummy variable indicating for living in central city, and for paying mortgage.

Since the participation rate of married women with preschool-aged children dramatically increased in the 1980s, I focus on to analyze the behavior change and composition change of married women with preschool-aged children. The summary statistics are shown in TABLE B1.1. The sample sizes are 490,552, 499,297 and 453,786 observations for 1980, 1990 and 2000, respectively. The wage ratio increased from 0.70 to 0.80 in the 1980s, a 0.10 upward change. The wage ratio rose 0.07 in the 1990s, to 0.87. The wage ratio indicates that wage-gender gap decreased largely in the 1980s and slightly in the 1990s, which is matching with the report (1998) by the council of economic advisors. TABLE B1.1 reports the wage rate of child care workers in 1990 is \$7.82 (in 1999 dollars), which is \$0.32 less than in 1980 (in 1999 dollars). The child cost changed in the opposite direction in the 1990s, which increased \$0.98 to \$8.8 in 2000 (in 1999 dollars). Attanasio, Low and Marcos (2008) report the same trend of initial fall followed by a partial recovery. Spousal income increased \$6400 in the 1980s (from \$37300 to \$43700) and \$7300 in the 1990s to \$51000. Commuting time slightly increased 3% in the 1980s, from 23 minutes to 23.7 minutes. It increased 16% in the 1990s, to 27.5 minutes.

TABLE B1.2 reports the change of commuting time and married women labor force participation across the size of MSA from 1980 to 2000. The commuting time increased 0.91 minutes in the non-big MSA in the 1980s. Compared to this, the commuting time increased less in the big MSA, a 0.31 minutes rise over the same period. Following Kolesnikova (2007) and Costa and Kahn (2000)'s conclusion, the increase of participation rate in big MSA would be more. In fact, the employment rate in non-big MSA increased 11.3% in the 1980s, which is higher than in big MSA. Even more, although there was a revealing difference in commuting time between big MSA and non-big MSA in 1980 or 1990, I can't find any participation difference in married women with preschool-aged children across the size of metropolitan areas in 1980 and 1990.

2.2.3 Findings

The estimated results are shown in the left two columns of TABLE B1.3. The right two columns of TABLE B1.3 describe the marginal effect of each independent variable. As expected, the coefficient α_1 and α_2 in Model (2.1) are significantly negative, and the absolute value of α_1 (0.341) is larger than that of α_2 (0.0467). Since including various factors in previous literatures, the absolute value of α_1 in Model (2.2) is decreased to it in Model (2.1), 0.303. Also the absolute value of α_2 in Model (2.2) is less than it in

Model (2.1), 0.0306. The coefficient α_1 and α_2 in Model (2.2) are also significantly negative, and the absolute value of α_1 is larger than that of α_2. The marginal effect of 1980 year dummy in Model (2.1) is negative (-0.1349) and less than that of 2000 year dummy (-0.0186). The marginal effect of 1980 year dummy in Model (2.2) is negative (-0.1201) and less than that of 2000 year dummy (-0.0122). The difference of marginal effect on 1980 year dummy between Models (2.1) and (2.2) is 0.0148, which is the contribution of various factors in previous literatures. The actual participation rate increase of married women with preschool-aged children is 0.1538 in the 1980s, from 38.82% to 54.2%. Those various factors can only explain 9.6% increasing in participation rate in the 1980s. The difference of marginal effect on 2000 year dummy between two models is 0.0064 and the actual participation rate decrease 0.0091 in the 1990s to 53.29%. Previous factors can explain 70% decreasing in the 1990s.

Let us examine results in more detail. TABLE B1.3 indicates that the participation decision of married women with preschool-aged children is positively and significantly related to their wage ratio in Model (2.2). The marginal effect of wage ratio is then largest among various factors in previous literatures, 0.244. Child care cost and spousal income significantly and negatively influence the participation decision of these focused married women. Marginal effects are -0.0148 and -0.0224, respectively. The coefficient of transportation time is insignificantly positive.

The second set of major results in TABLE B1.3 concerns the impact of control variables across both models. The coefficient on age is nonlinear and significant. As expected, the coefficient on years of education and indicator of paying mortgage is significant and positive. Interestingly, the coefficient on indicator of living in the central city is significantly positive in Model (2.1) and negatively in Model (2.2).

TABLE B1.4 reports the predicted changes in wives' participation rate. Changes in labor force participation rate from 1980 to 2000 are driven by shifts in the composition of married women with preschool-aged children, while it is possible that changes are motivated by changes in average behavior. But I assume the coefficient on measure factors are the same over the last two decades. Since the average behavior on each measure factor is the same, I consider separate contributions of composition changes in each measured factor.

Across the three years' equations shown in TABLE B1.3, measured factors explain 2.23% and 4.75% of the growth in female participation rate over the 1980s using Model (2.1) and (2.2), respectively. Overall, control variables predict 14.5% increasing in participation rate over the 1980s, which is the ratio between explanation rate and actual change rate. Those control variables and various factors in previous literatures are able to explain more, 30.9% change in participation rate over the 1980s. Using Model (2.1) and (2.2), measured factors predict 0.89% and 0.24% increase in employment rate over the 1990s, which is opposite to the actual drop.

In consideration of the contribution of each independent variable, the decrease of wage-gender gap can explain 2.44% growth over the 1980s, and 1.71% increase over the 1990s. The decrease of child care cost can account for 0.43% growth in the 1980s, and the increase of child care cost explains 1.47% decrease in the 1990s. Spousal income can predict 1.43% drop in the 1980s and 1.64% decrease in the 1990s. Transportation time can account for 0.02% increase in participation rate over the 1980s, and 0.13% increase in the 1990s. The next major results in TABLE B1.4 concern contributions of each control variable across both models. The increase age can account for 0.07% increase in the 1980s and 0.14% decrease in the 1990s using Model (2.1). Using Model (2.2), the independent variable, age, can explain more, 0.39% and 0.17% rise in the 1980s and 1990s, respectively. The increase of years of education can explain more than contribution of age in Model (2.1) and (2.2). The coefficient sign of indicator in living in the central city is opposite. The decrease percentage of married women in central city predicts 0.02% decrease and 0.04% increase in the 1980s in both models, respectively. Since this percentage kept sTABLE in the 1990s, the indicator in living in the central city predicts no change in the 1990s.

2.3 Career Work Experience Explanations

2.3.1 Empirical Strategy

Goldin (1997, 2004) defines the concept "Career" as working full-time during the preceding three years to analyze the college-educated women's family decision. Light and Ureta (1995) find it takes four years for married women to catch up to their continuously employed counterparts. I assume women can grasp a professional set of skills and networking in order to return in the future after three years working accumulation. There are three important fertility stages: first is the career period, second is the childbearing period and last is the labor force participation period after childbearing. I define the childbearing period as two months before the birth, plus four months after the birth. The career period is defined as three years preceding the first birth. The labor force participation period is pointed from the first birth to six years after the first birth or to six years after the second birth if this female has two children and spacing between first and second birth is less than 6 years or to six years after the third birth if this female has over two children and spacing between second and third birth is less than 6 years. There are only 1% sample (84 observations) with over three children in the National Longitudinal Survey of Young Women (NLSYW) and 5% sample (270 observations) in the National Longitudinal Survey of Youth 1979 (NLSY79). I introduce a new measure on career work experience and labor force participation rate, which is the ratio of the number of weeks worked and the total number of weeks during the career period and during the labor force participation period, respectively. I focus on the first birth because it is the first time for most women to make an unemployment decision. The more women work during the three years preceding their first birth, the more they are likely to return to work after the childbearing period. Shapiro and Mott (1994) find labor force participation post first birth is an important predictor of women's future working behavior. My new measure is used in Goldin (1989) and Light and Ureta (1995), but this is the first time for it to be used to analyze the change in female labor force participation.

I make attempts here to quantify contribution of career work experience for the increase of married women participation rate with the NLSYW from 1968 to 2003 and NLSY79 from 1979 to 2008. I estimate the following static participation model for a pool sample:

$$LFPR_i = \alpha + \alpha_1 D_{NLSY79i} + Z_i\gamma + u_{1i} \tag{2.3}$$

$$LFPR_i = \alpha + \alpha_1 D_{NLSY79i} + \beta_1 WageRatio_i + \beta_2 Nonlabor_i + Z_i\gamma + u_{2i} \tag{2.4}$$

$$LFPR_i = \alpha + \alpha_1 D_{NLSY79i} + \delta_1 Career + \beta_1 WageRatio_i + \beta_2 Nonlabor_i + Z_i\gamma + u_{3i} \tag{2.5}$$

where for each individual, LFPR is married women labor force participation rate during the labor force participation period, DNLSY79 is a NLSY79 cohort dummy variable, Z is a vector of control variables (including age at the first birth and age square, years of education, indicator for living in South, and indicator for Black and Hispanic race), *WageRatio* is the relative child care cost, *Nonlabor* is one's spousal wage income, *Career* is the career work experience, and u_1 , u_2 and u_3 are disturbance terms.

Model (2.3) is a traditional static participation function in which coefficient α_1 indicates the unexplained increasing in participation rate of married women with preschool-aged children across cohorts except contributions of control variables. Since the participation rate of married women with preschool-aged children dramatically increased across cohorts, I expect coefficient α_1 is positive. Model (2.4) quantifies contributions of various factors in previous literatures, including child care cost and spousal income. I also suppose previous factors can partly explain the participation change of married women with preschool-aged women. Coefficient α_1 is decreased and positive. Model (2.5) measures contribution of career rate. Coefficient α_1 in Model (2.5) is decreased further and positive. Estimation of Model (2.3), (2.4) and (2.5) faces the same econometric difficulties as Model (2.1) and (2.2). First, the wage rate of nonparticipating wives is not observed. I use Heckman's sample selection procedure to impute the latent wage rate as actual wage rate, which is shown in the appendix C. Second, I am not able to obtain the direct evidence on the child care cost. I merge the average real price of child care workers by year from March CPS between 1960 and 2010. I control the effect of child care cost and introduce the wage ratio between the actual wage rate before childbearing and the price of child care child care cost as an independent variable. Nonlabor income is used to represent the spousal income.

Married females' working behaviors vary a lot during the career period. This heterogeneity is shown in cumulative career experience in TABLE B1.5. This evidence suggests that the traditional measure of career experience (first birth age – education - 6) is not adequate for describing married females' working behaviors. One of my date sets is from the NLSYW. All respondents were 14-24 years old when first surveyed in 1968. The career experience is based on NLSYW "key" variables reporting the number of weeks worked since the last interview or in the last year. There are often gaps when I do not know how many weeks worked. When gaps arise, I subtract the missing time from both the numerator and denominator of my "weeks worked" measure. The other date set is from the NLSY79. All respondents were 14-22 years old when first surveyed in 1979. These individuals were interviewed annually through 1994 and then on a biennial basis. The career experience is based on NLSY79 variables reporting LABOR FORCE STATUS on a weekly basis. I restrict my sample to those women who are non-military, and have their first child after 18 years old.

TABLE B1.5 reports the cumulative distribution function of career experience. The first two rows of the TABLE B1.5 tells us that 66% of women born from 1943-53 work more than 10% of the time, 46% work more than 50% of the time and only 20% work more than 90% of the time during their career period. Generally, women born from 1957-64 work more during their career period in each group: 73% of women work more than 50% of the time, a 27% increase. The percentage of women who work more than 90% of the time doubled from 20% to 43%. If I further analyze the cumulative distribution function by education category, the general changes follow uniformly. The distribution shifts to the right for every education category, but the degree of shifting is different, respectively. High school dropouts shift the most to the right. Interestingly, the percentage of high school dropouts decreases across cohorts. TABLE B1.5 also describes that the relationship between the increase in work continuity and years of education is noticeable within cohort. The difference in time spent on working between women with different education background decreases in the latter cohort. I see that 21% of high school dropout women born from 1943-53 work more than 50% of the time. For women with 12 years of education, it is 60%, a 40% increase. The number is 83% for college graduates. In 1957-64 cohorts, 47% of women with 0-11 years of education work more than 50% of the career period. For high school graduates, it is 60%, a 13% increase. It is clear that traditional working experience or the timing of first birth is not enough control for career work experience. TABLE B1.6 reports the cumulative distribution function of labor force participation for women with preschool-aged children. I find that a considerable amount of heterogeneity in distribution remains even after controlling education category.

The summary statistics are shown in TABLE B1.9. The sample sizes are 2796 and 2876 observations for NLSYW and NLSY79, respectively. The wage ratio rose 0.46 across cohorts, from 2.0944 to 2.5499. The wage ratio indicates that the relative wage rate increased and real child care cost decreased across cohorts. Figure 3 in appendix A describes the trend of the child care expense from 1962 to 2010, which is measured by the average wage of child care workers from the March CPS. The child care price decreased in the 1980s from $7.31 to $3.64 and increased in the 1990s to $10.7. Spousal income increased $2,157 across cohorts, from $35,721 to $37,878.

To simplify my analysis, I define “career” women with career rate more than 50%. The “non-career” type is used to specify women who spend less than 50% working during the career period. I use the same criteria to define the labor force participation type. My hypothesis is that career women are more likely to return to the labor force after their childbearing period. TABLE B1.7 reveals the frequencies of career type and labor force employment type across cohorts. Looking across the left panel of TABLE B1.7, I see that 53.9% of women born in 1943-53 are non-career type, while only 27.4% of women born in 1957-64 choose to be non-career type. I can see that the percentage of career type women increases largely across cohorts, from 46.1% to 72.6%.

I also analyze that the change of the taste between non-career type and career type. To derive the preference of different career type women, it is straight forward to consider the joint distribution of career type and labor force participation type. It is shown as below:

$$\begin{aligned} &\Pr(\text{LFP After birth} >= 0.5) \\ &= \Pr(\text{LFP After birth} >= 0.5, \text{Career} >= 0.5) + \Pr(\text{LFP After birth} >= 0.5, \text{Career} < 0.5) \\ &= \Pr(\text{LFP After birth} >= 0.5 \mid \text{Career} >= 0.5)\Pr(\text{Career} >= 0.5) \\ &+ \Pr(\text{LFP After birth} >= 0.5 \mid \text{Career} < 0.5)\Pr(\text{Career} < 0.5) \end{aligned} \tag{2.6}$$

I use actual distribution in TABLE B1.7 across cohorts to calculate the labor force participation rate with equation (2.6):

$$\Pr(\text{LFP After birth} >= 0.5)_{\text{Cohort 1943-53}} = \frac{27.29}{46.1} \times 46.1 + \frac{18.35}{53.9} \times 53.9 = 0.59 \times 46.1 + 0.34 \times 53.9$$

$$\Pr(\text{LFP After birth} >= 0.5)_{\text{Cohort 1957-64}} = \frac{47.67}{72.6} \times 72.6 + \frac{9.94}{27.4} \times 27.4 = 0.66 \times 72.6 + 0.36 \times 27.4$$

The preference to work continuously after childbearing for career women is represented by the conditional distribution in the first item of second equation of equation (2.6). It increases from 59% to 66% across cohorts, a 7% upward change. For non-career women, the preference of working after childbearing is shown in the second item of second equation of equation (2.6). It increases 2%, from 34% to 36%. Possibly, a factor accounts for the change of the preference to work after the childbearing period regardless of different career type.

The above analyses are roughly but enough to lead to a point: the remarkable increase in the percentage of career women is a potential factor to explain the trend of the labor supply employment of married women with preschool-aged children.

2.3.2 Empirical Separating Composition Change and Preference Change

As discussed in section 2, changes in labor force participation rate across cohorts are driven by shifts in the composition of married women with preschool-aged children, while it is possible that changes are motivated by changes in average behavior. But I assume the coefficient on career type is the same across cohorts in Model (2.5). I estimate the following model:

$$LFPR_i = \alpha + \alpha_1 D_{NLSY79i} + \delta_1 Career_{NLSYWi} + \delta_2 Career_{NLSY79i} + \beta_1 WageRatio_i + \beta_2 Nonlabor_i + Z_i\gamma + u_{4i} \quad (2.7)$$

I assume the coefficient on career type is different across cohorts, which is the difference between Model (2.5) and (2.7). Coefficients δ_1 and δ_2 are able to capture the preference change across cohorts. I expect coefficients δ_1 and δ_2 are significantly positive and $\delta_1 < \delta_2$. Since coefficient α_1 indicates the unexplained preference increasing in participation rate of married women with preschool-aged children across cohorts except contributions of control variables in Model (2.7), I expect coefficient α_1 is insignificant.

From Model (2.7) I am not able to figure out whether the change in the labor force participation rate is driven by the change in the composition of career women or the working preference of career women. Why would more and more career married women prefer to work after the childbearing? It comes natural to us to analyze the relationship between fertility choice and marriage selection (Cancutt, Guner and Knowles (2002), Ge (2011) and Sheran (2007)). Cancutt, Guner and Knowles (2002) find that the marriage decision of young women explains the incentives for fertility delay. Ge (2011) considers the relationship between women's college decision and marriage choice. Sheran (2007) formulates and estimates a discrete dynamic labor supply model in which marriage, fertility, and education are choice variables. She finds that women choose different career and family life-cycle paths because of uncertainties and their different tastes.

TABLE B1.8 reveals the average age at first birth and first marriage over career types and labor force employment types across cohorts. Behaviors of career women's marriage and fertility choice are surprisingly sTABLE across cohorts. Non-career women usually give birth at 21 years old while career women have their first baby at 26 years old. The first marriage age is 20 for the non-career women and 23 for the career women. It becomes straight forward that a woman's fertility choice and marriage selection are not cause and effect, which is contrary to Sheran's assumption. Thus I have assumed that a woman's fertility choice and marriage selection are simultaneously determined by other factors, such as the women's work attitude in the family.

The women's attitude about the female's career role in the family is the key variable to influence the women's employment decision. In NLSYW and NLSY79, the respondents were asked a few questions related to the female's attitude towards women's status in the family and career. One of the questions is: "It is much better for everyone concerned if the man is the achiever outside the home and the women takes care of the home and family." And there are four categories of answers: 1 strongly disagrees, 2 disagree, 3 agree and 4 strongly agree. The variable --work attitude to the women's status is 1 if the answer is disagree or strongly disagree, otherwise it is 0. Around 50% and 63.8% of women's attitude about the roles of husband and wife are non-traditional in NLSYW and NLSY79, respectively (see TABLE B1.10).

I estimate the following model:

$$\begin{aligned}&LFPR_i = \alpha + \alpha_1 D_{NLSY79i} + \beta_1 WageRatio_i + \beta_2 Nonlabor_i + Z_i\gamma \\ &+ \delta_{11} Career_{NLSYWi} + \delta_{12} Career_{NLSYWi} \times WorkAttitude_{NLSYWi} \\ &+ \delta_{21} Career_{NLSY79i} + \delta_{22} Career_{NLSY79i} \times WorkAttitude_{NLSY79i} + u_{5i}\end{aligned} \tag{2.8}$$

I assume the coefficient of career type is δ_1 in NLSYW and δ_2 in NLSY79 and $\delta_1 < \delta_2$. I also assume the coefficient of family motivator's career type is δ_{11} and that of career motivator's career type is $\delta_{11}+\delta_{12}$ in NLSYW. They are δ_{21} and $\delta_{21}+\delta_{22}$ in NLSY79. My hypothesis is the composition of career motivators among career type has changed if $\delta_{11} = \delta_{21}$ and $\delta_{11}+\delta_{12} = \delta_{21}+\delta_{22}$.

Because I know:

$$\begin{aligned}&pr(\text{family motivator}^{\text{NLSYW}} \mid \text{career type}) + pr(\text{career motivator}^{\text{NLSYW}} \mid \text{career type}) \\ &= pr(\text{family motivator}^{\text{NLSY79}} \mid \text{career type}) + pr(\text{career motivator}^{\text{NLSY79}} \mid \text{career type})\end{aligned}$$

Then I can express $\delta_2 - \delta_1$ as below:

$$\begin{aligned}&\delta_2 - \delta_1 = Exp[\delta_{21} \times pr(\text{family motivator}^{\text{NLSY79}} \mid \text{career type}) \\ &+ (\delta_{21}+\delta_{22}) \times pr(\text{career motivator}^{\text{NLSY79}} \mid \text{career type}) \\ &- \delta_{11} \times pr(\text{family motivator}^{\text{NLSYW}} \mid \text{career type}) \\ &- (\delta_{11}+\delta_{12}) \times pr(\text{career motivator}^{\text{NLSYW}} \mid \text{career type})] \\ &= Exp[\delta_{21} \times (pr(\text{family motivator}^{\text{NLSY79}} \mid \text{career type}) - pr(\text{family motivator}^{\text{NLSYW}} \mid \text{career type})) \\ &+ (\delta_{21}+\delta_{22}) \times (pr(\text{career motivator}^{\text{NLSY79}} \mid \text{career type}) - pr(\text{career motivator}^{\text{NLSYW}} \mid \text{career type}))]\end{aligned}$$

TABLE B1.10 tells us that the ratio of career motivators among career type women increases 12.19% across cohorts, from 54.38% to 66.57%. In the opposite way, the ratio of family motivators among career type women decreases across cohorts. Then:

$$Exp[(\delta_{21}+\delta_{22})\times(pr(\text{career motivator}^{\text{NLSY79}}\mid\text{career type})-pr(\text{career motivator}^{\text{NLSYW}}\mid\text{career type}))]>0$$
$$Exp[\delta_{21}\times(pr(\text{family motivator}^{\text{NLSY79}}\mid\text{career type})-pr(\text{family motivator}^{\text{NLSYW}}\mid\text{career type}))]<0$$

Naturally, I am able to know the reason that δ_1 is less than δ_2 is from the change in the composition of career motivators among career type women, not from the shifts in average preference. Therefore I expect coefficient α_1 is insignificant in Model (2.8) and the coefficient on career motivator's career type is equal across cohorts.

2.3.3 Findings

TABLE B1.11 provides the results of Model (2.3)-(2.5) and (2.7)-(2.8) across cohorts. As expected, the coefficient α_1 in Model (2.3)-(2.5) is significantly positive. Since including various factors in previous literatures, the value of α_1 in Model (2.4), 0.0761, is decreased to it in Model (2.3), 0.0828. And the value of α_1 in Model (2.5) is the least among Model (2.3)-(2.5). The difference of marginal effect on NLSY79 cohort dummy between Models (2.3) and (2.4) is 0.0067, which is the contribution of various factors in previous literatures. The actual labor force participation rate increase of married women with preschool-aged children is 0.1088 across cohorts, from 45.87% to 56.75%. Those various factors can only explain 6.16% increasing in participation rate across cohorts. The difference of marginal effect on cohort dummy between Models (2.4) and (2.5) is 0.0397 and the composition change of career type can explain 30.33% growth across cohorts. In Model (2.7) I assume the coefficient on career type is different across cohorts, preference change in labor force participation rate of married women with preschool-aged children across cohorts is able to be explained by the change of coefficient on career type. As expected, the coefficient α_1 in Model (2.7)-(2.8) is insignificant. The difference of marginal effect on cohort dummy between Models (2.5) and (2.7) is 0.0364 and the preference change in career type can explain 33.46% growth across cohorts.

As analyzed in section 3.2, it is possible that the preference change in career type is from the change in the composition of career motivating career type women, not from the shifts in average preference. Let us examine results in more detail on career type in Model (2.5) and (2.7)-(2.8). TABLE B1.11 indicates that the labor force participation rate of married women with preschool-aged children is positively and significantly related to their career type. In Model (2.5), the average marginal effect of career type is 0.217 across cohorts. The marginal effect is 0.189 and 0.249 in NLSYW and NLSY79 in Model (2.7), respectively. The coefficient gap on career type is 0.06. In Model (2.8), it is more complicated. The marginal effect of career motivating career type is 0.252 and 0.271, and the difference is only 0.019. The predicted coefficient change in career type from the change in the composition of career motivating career type women is 0.0307 or 0.033 which is the product of the marginal effect (0.252 or 0.271) and the composition change (12.19% from TABLE B1.10) of this type women. The marginal effect of family motivating career type is 0.12 and 0.215 in NLSYW and NLSY79, and this difference is 0.095. The composition of family motivating career type women drops from 45.62% to 33.43%. I am not able to separate the preference change from the composition change for the career motivating career type women. The predicted coefficient change in career type from these group women is 0.0171 which is the difference of the product of the marginal effect and the composition (0.215*33.43%-0.12*45.62%). The change in the composition of career motivating career type women can at least explain 51.2% of the coefficient change on career type.

TABLE B1.11 indicates that the participation decision of married women with preschool-aged children is positively and significantly related to their wage ratio and negatively related to their spousal income in Model (2.4)-(2.5) and (2.7)-(2.8). The next results in TABLE B1.11 concern the impact of control variables across five models. The coefficient on age at first birth is nonlinear and significant. The coefficients on years of education, indicator of Black race, Hispanic race, and living in the South are significantly positive.

Women’s labor force participation after childbearing grows 10.88% across cohorts. To what extent can this change be explained by measured factors and by shifting in women’s labor supply preference? TABLE B1.12 describes a decomposition of the changes in women’s labor force participation by showing the effect of different levels on the explanatory variables across cohorts.

Across the results shown in TABLE B1.11, measured factors explain 2.6%, 3.27%, and 7.24% of the growth in female participation rate across cohorts using Model (2.3)-(2.5), respectively. Overall, control variables predict 23.9% increasing in participation rate across cohorts, which is the ratio between explanation rate and actual change rate. Those control variables and various factors in previous literatures are able to explain more, 30.06% change in participation rate across cohorts. Using Model (2.5) with career type factor, measured factors can explain 66.54% increase in employment rate across cohorts. Since Model (2.7) is able to capture the preference change in the career type women across cohorts, the unexplained changes (33.46%) in Model (2.5) suggest that the preference of career type women shifts to the right across cohorts. Measured factors in Model (2.7) and (2.8) can explain 101% growth in participation rate across cohorts. I claim there are two kinds of career women, one is family motivating type and the other one is career motivating type. Model (2.8) includes the motivation factor and finds the change in the composition of career motivating career type women can at least explain 17.22% growth in the labor force participation rate across cohorts.

Let us look at the contribution of each independent variable. The increase of wage ratio can explain 1.33%-1.79% growth across cohorts. Spousal income can predict 0.47% drop across cohorts. Model (2.3) predicts that the increase age at first birth can account for 1.37% increase; Model (2.4) predicts 0.94% increase. After including career type as an independent variable, the increase age at first birth predict 0.44%-0.47% drop. It is natural that career type women prefer to delay their first birth.

2.4 Conclusions

The labor supply participation of married women increased dramatically over the last three decades of the 20th century, especially married women with preschool-aged children. A lot of possible factors are used to explain this growth in employment, such as the reform of the cash-transfer program, the compensation for the drop of spousal income, the decrease of wage-gender gap, the decrease of child care price, the change of commuting time across urban areas, and the urbanization of power couples. Using 5% samples of the Integrated Public Use Microdata Series (IPUMS) for 1980, 1990 and 2000, I investigate previous explanations and can't find a sensible conclusion. Using the National Longitudinal Survey of Young Women (NLSYW) from 1968 to 2003 and the National Longitudinal Survey of Youth 1979 (NLSY79) from 1979 to 2008, I focus on the increase in labor supply of females with preschool-aged children. I introduce a new variable to measure the heterogeneity of females' career work experience and define career women and non-career women. The increase in the female labor supply employment is very responsive to a wife's career type before the first birth. My results show that the rising of the percentage of career women can explain 30.33% of the growth across cohorts. Among the unexplained changes, the change in the composition of career motivating career type women can at least explain 51.2%. That means it can at least explain 17.22% growth in the labor force participation rate across cohorts.

CHAPTER III

BUDGET CONSTRAINTS IN STRUCTURAL MODELS

3.1 Introduction

The parameters of interest in the estimation of labor supply are the uncompensated (Marshallian) and compensated (Hicksian) elasticity. These parameters show how labor supply reacts to changes in economic variables and are the key to evaluating the effect of a large array of public policies, including tax and social welfare programs. The most popular estimation method is referred to as the Hausman structural method, which is developed by Burtless and Hausman (1978), Hausman (1981), and Hausman (1985). The Hausman approach explicitly models individuals' desired hours of work as the outcome of utility maximization subject to the nonlinear budget constraints. The utility function parameters, which also are parameters in the corresponding labor supply function, are estimated by the maximum likelihood method. As discussed in Blundell and MaCurdy (1999), the Hausman method has several attractive features: it recognizes the institutional features of the tax systems, and it incorporates the fixed cost of holding a job.

Unfortunately, economists find different values for these key parameters. TABLE 2 in Blundell and MaCurdy (1999) summarizes eleven papers using non-linear budget constraints for married women. The uncompensated wage elasticity varies from .28 (Triest 1990) to .97 (Hausman 1981). Even more puzzling, studies using the same or similar data sources, econometric specification and estimation technique often report different elasticities. Hausman (1981) uses PSID of 1975 and finds a wage effect close to zero. MaCurdy, Green and Paarsch (1990) use the same data set and report a negative wage rate coefficient. Triest (1990) tries PSID of 1983 and gets a positive wage effect. These conflicting results are called as the “Hausman puzzle” in Blomquist (1996).

There are some attempts in the literature to explain and address the discrepancies in estimates within Hausman’s framework. MaCurdy, Green and Paarsch (1990) demonstrate that the econometric model produced by piecewise-linear formulation implicitly imposes parametric restrictions that constrain the sign of estimated substitution and income effects. MaCurdy, Green and Paarsch suggest smoothing the budget segments so make them differentiable everywhere, and hence insure only one solution for each individual. However, this approach negates the advantages of Hausman’s framework. Even when using the same model some have found the econometric specification itself causes different results. Triest (1990) tries a linear function specification. Blomquist and Hansson-Brusewitz (1990) choose nonlinear function specification. Blomquist and Newey (2002) investigate nonparametric specification. The estimates of Marshallian and Hicksian elasticities are sensitive to the function specification. Finally, some have advanced measurement error in the wage rate as an explanation. Eklof and Sacklen (2000) suggest that the wage measure adopted by MaCurdy, Green, and Paarsch (1990) might cause a severely downward-biased wage effect.

While plenty of explanations try to figure out the variation in elasticities, Blundell and MaCurdy (2007) point out that there is very little work analyzing the budget sets of the piecewise-linear procedure. This chapter discusses the role of budget sets in producing this wide range of estimates. In particular, Hausman (1981), Triest (1990), MaCurdy, Green, and Paarsch (1990) and Heim (2008) use convexified budget sets. If hours and consumption are not near perfect substitutes, a minor difference in the convexification approximation would not cause a large change in hours of work. I study if the convexification approximation has important consequences on labor-supply estimates.

Heckman (1983) also suggests some other major concerns of Hausman's approach, which are later extended by Burtless and Moffitt (1984), Friedberg (2000), Heim and Meyer (2004) and Saez (1999, 2009). Heckman's key concerns are that budget segments can't be accurately measured in most cases. The basic assumption of Hausman's approach is that there is bunching around the kink points. In reality, few of taxpayers bunch at the kink points of the U.S. income tax schedule. Burtless and Moffitt (1984) and Friedberg (2000) observe bunching at the convex kink induced by retirement. Heim and Meyer (2004) indicate that there tends to be a noticeable amount of bunching of the data around certain levels of hours, such as 2000 annual hours or 40 weekly hours. Saez (1999, 2009) points out that clear evidence of bunching is found only at the first kink point. I investigate if estimations are sensitive to the uncertain budget constraints.

In the comment on Hausman's method, Heckman (1983) wrote, "*Hausman's econometric procedures require that the budget set confronting the consumer be known to the econometrician*."[1] To address Heckman's criticism, I introduce measurement error in nonlabor income to solve the Heckman critique of Hausman's approach. I define nonlabor income as the family's income less the wife's labor income.[2] Such measurement error is conceptually well-founded. It naturally shifts the intercept on the vertical axis of

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1 Italics originally in Heckman (1983).
2 Triest (1990) defines nonlabor income as equal to the sum of their husbands' labor income and asset income. We try these two different variables in estimation. Different definitions do not influence results.

the budget constraints and changes the location of the kink points of the budget constraints. Then it changes the slope of the budget constraints. Hence, it generates the uncertain budget segments, which seem to be precisely in line with Heckman's comments.

This chapter will (1) propose a new model to estimate labor supply function to solve Heckman's critique and (2) estimate with nonconvexified piecewise-linear budget constraints. I apply my method to estimate the labor supply for married women using the Panel Study of Income Dynamics (PSID) data of 1984 and 2001. I find that neither the convexification approximation nor using a model with random budget sets affects the estimates. Variations in budget constraints are not the main explanations for the different estimates of elasticities. Changing the level of budget sets, for example ignoring the state individual income tax, could affect the variation in elasticities.

The main objective is to estimate and test various specifications of the model in the convexified, the nonconvexified and random constraints. The rest of the paper is organized as follows. In Section 3.2, I discuss in detail the various models. Used data sets, the U.S. individual tax system and convexification of the budget constraints are described in Section 3.3. Section 3.4 estimates the models and outlines results. I conclude in Section 3.5.

3.2 Different Specifications of Three Models

Hausman (1981) introduces a static equilibrium labor supply model, and assumes that the before-tax wage is constant without inter-temporal optimization of labor supply. Hausman's approach begins with a typical labor supply model of utility maximization for individual i with respect to choices about leisure and other consumption goods x_i, where the price of x is normalized to be 1. The hours of work are defined to be h_i, so $T\text{-}h_i$ is leisure. Without taxes, the person's nonlabor income is y_i, and the real wage rate is w_i. The indirect utility $v(w_i,y_i)$ is the maximum value of the direct utility $u(x_i,h_i)$ that can be obtained when facing the budget constraint:

$$\begin{aligned} &v(w_i, y_i) = \max{}_{x,h}\, u(x_i, h_i) \\ &s.t. \quad x_i - w_i h_i = y_i \end{aligned} \tag{3.1}$$

Hausman (1981) assumes a linear specification of the demand function first, and then recovers the indirect utility function for that demand function using Roy's identity,

$$\frac{\partial v(w,y)/\partial w}{\partial v(w,y)/\partial y} = h$$

The indirect utility function when $h_i > 0$ is

$$v(\tilde{y}_{ij}, w_{ij}) = e^{\beta w_{ij}}\left(\tilde{y}_{ij} + \frac{\alpha}{\beta}w_{ij} - \frac{\alpha}{\beta^2} + \frac{s}{\beta}\right)$$

If it is the dual additive errors model, then $s = Z_i\gamma + \varepsilon_i$ and $\beta = \beta_0$; if it is Hausman's random income coefficient model, then $s = Z_i\gamma$ add $\beta = \beta_0 + \varepsilon_i$. $\tilde{y}_{ij}$ is the virtual income, defined as the intercept of the line that extends this budget segment to the zero-hours axis (see TABLE B2.1).

When a person is at a kink point, the indifference curve is not tangent to the budget sets, so the utility level can only be obtained from the direct utility function. At kink point j, the direct utility function corresponding to the labor supply function is

$$u(y_{ij}^a, h_{ij}) = \exp\left(\frac{\beta y_{ij}^a + s - h_{ij}}{h_{ij} - \alpha/\beta}\right)\left(\frac{h_{ij} - \alpha/\beta}{\beta}\right)$$

where y_{ij}^a is the after-tax income.

3.2.1 Budget Segment and Tax Revenues

An individual *i* faces a piecewise-linear budget constraint. Let a tax bracket be characterized by {t_j; Y_{j-1}, Y_j}, where t_j is the marginal tax rate for a person whose before-tax income lies within the interval (Y_{j-1}, Y_j]. Information about {t_j; Y_{j-1}, Y_j} can be found from tax tables. Note the relevant budget set is based on after-tax income. Let the end points of the segment in a budget set that corresponds to bracket {Y_{j-1}, Y_j} be {y_{j-1}^a, y_j^a} where y^a refers to after-tax income. A complete characterization of budget segments requires information on working hours that corresponds to the set [y_{j-1}^a, y_j^a], and I denote these hours as [H_{j-1}, H_j]. To calculate the location of each budget segment, I start with the first budget segment and proceed through all budget segments. Besides the before-tax wage rate *w*, another critical piece of information is Y^n, the individual's nonlabor income. Let y^n be after-tax nonlabor income, where the tax is calculated as if the person had no labor income. Then any labor income pushes the person into even higher tax brackets. I summarize information on budget segments in TABLE B2.1.

It is well documented in the literature that in the presence of piecewise-linear budget constraints a person's optimal hours may be at a kink point instead of being on a segment.[3] Let N_i be the total number of segments of the budget set of individual *i*. Define

$$
\begin{aligned}
S_{ij} &= \begin{cases} 1 \text{ if on segment j,} \\ 0 \text{ otherwise;} \end{cases} \qquad j = 1,\ldots, N_i \\
K_{ij} &= \begin{cases} 1 \text{ if at kink point j,} \\ 0 \text{ otherwise;} \end{cases} \qquad j = 0,1,\ldots, N_i
\end{aligned}
\tag{3.2}
$$

---

3 We define "being on segment" as being in the interior of (H_{j-1}, H_j).

Following common practice, I assume the labor supply function is linear. Let h_{ij}^* be the optimal hours for person *i* if his budget constraint were on segment *j*, and let w_{ij} be the after tax wage rate for person *i* if his budget constraint were on segment *j*. Then,

$$h_{ij}^* = \begin{cases} \alpha w_{ij} + \beta \tilde{y}_{ij} + Z_i \gamma + \varepsilon_{i,} & \text{if positive} \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

where $\tilde{y}_{ij}$ is virtual income and Z_i represents other socio-demographic variables that affect the labor supply, such as the number of children in the household, the age of the worker, the worker's education, and the local unemployment rate. Since Z_i does not vary across different segments, the term $Z_i\gamma$ will not be included in my equations hereafter to simplify the notation, although the term is included when the model is estimated. One important term in (3.3) is ε_i, representing heterogeneity in preferences based on unobservable factors. Given the labor supply function in (3.3), the necessary condition for $S_{ij} = 1$ is

$$S_{ij} = 1 \quad \text{if} \quad H_{ij-1} < \alpha w_{ij} + \beta \tilde{y}_{ij} + \varepsilon_i < H_{ij},\ j = 1,\ldots, N_j \tag{3.4}$$

The necessary condition for $K_{ij} = 1$ is:

$$\begin{aligned} &K_{i0} = 1 \quad \text{if} \quad \alpha w_{i1} + \beta \tilde{y}_{i1} + \varepsilon_i \le 0 \\ &K_{iN_i} = 1 \quad \text{if} \quad \alpha w_{iN_i} + \beta \tilde{y}_{iN_i} + \varepsilon_i \ge H_{i\max} \\ &K_{ij} = 1 \quad \text{if} \quad \alpha w_{ij+1} + \beta \tilde{y}_{ij+1} + \varepsilon_i \le H_{ij} \le \alpha w_{ij} + \beta \tilde{y}_{ij} + \varepsilon_i,\ \ j = 1,\ldots, N_i - 1 \end{aligned} \tag{3.5}$$

If a budget set is globally convex, the highest indifference curve must either touch a single kink point or be tangent to a single segment because of the weak axiom of revealed preference (WA). Conditions (3.4) and (3.5) are necessary and sufficient and $\sum_{j=1}^{N_i} S_{ij} + \sum_{j=0}^{N_i} K_{ij} = 1$. However, if a budget set is non-convex due to the fixed cost of working or some income transfer program (such as EITC, AFDC or TANF),[4] then

$\sum_{j=1}^{N_i} S_{ij} + \sum_{j=0}^{N_i} K_{ij}$ may be greater than 1. A global utility comparison is required to determine the work hours desired. The optimal hours worked should offer the maximum utility among all the segments and kink points. I use simulated maximum likelihood estimation to catch non-convex budget constraints.

Various specifications of labor supply are suggested in the literature. They differ in their treatment of the error terms of Equation (3.3). Next, I introduce two influential specifications and then discuss my specification.

3.2.2 Hausman's Original Model

Hausman (1981) introduces the random income coefficient model. Let h_i^* be the true working hours for individual *i*, specified as:

$$h_i^* = \alpha w_{ij} + (\beta_0 + \varepsilon_i)\tilde{y}_{ij} \tag{3.6}$$

where the coefficient β in Equation (3.3) becomes a random variable, $\beta = \beta_0 + \varepsilon_i$. The random error ε_i is not observed by the econometrician. Blomquist and Hansson-Brusewitz (1990) and Triest (1990) introduce the dual additive errors model, which is shown in (3.3). I call these two models Hausman's original model. The necessary and sufficient decision rule under global convex budget sets is summarized in (3.7).

$$\begin{aligned} S_{ij} = 1 \quad & \text{iff} \quad H_{ij-1} \le \alpha w_{ij} + \beta \tilde{y}_{ij} + \varepsilon_i \tilde{x}_{ij} \le H_{ij} \\ K_{iN_i} = 1 \quad & \text{iff} \quad \alpha w_{iN_i} + \beta \tilde{y}_{iN_i} + \varepsilon_i \tilde{x}_{iN_i} \ge H_{i\max} \\ K_{ij} = 1 \quad & \text{iff} \quad \alpha w_{ij+1} + \beta \tilde{y}_{ij+1} + \varepsilon_i \tilde{x}_{ij+1} \le H_{ij} \le \alpha w_{ij} + \beta \tilde{y}_{ij} + \varepsilon_i \tilde{x}_{ij} \end{aligned} \tag{3.7}$$

4 The Earned Income Tax Credit (EITC) is a subsidy program with positive net wage rates; Aid to Families with Dependent Children (AFDC) was replaced in 1996 by Temporary Assistance for Needy Families (TANF).

When $\tilde{x}_{ij} = \tilde{y}_{ij}$, the decision rule in (3.7) is for Hausman's random income coefficient model. The stochastic term ε_i, as argued by Hausman (1981), arises due to the heterogeneity of preferences. This term is not observed by econometricians but is known to individual *i*. When $\tilde{x}_{ij} = 1$, the decision rule (3.7) is for the dual additive errors model, which is suggested in Triest (1990) and Blomquist and Hansson-Brusewitz (1990). The stochastic term ε_i is the heterogeneity in preferences.

When a budget set is non-convex due to some income transfer program (such as the EITC), the decision rule becomes more complicated.

$$\begin{aligned}
&S_{ij} = 1 \ \text{ iff } \ H_{ij-1} \le \alpha w_{ij} + \beta \tilde{y}_{ij} + \varepsilon_i \tilde{x}_{ij} \le H_{ij} \ \text{ and } \ v(S_{ij} = 1) = u_i^{\max} \\
&K_{ij} = 1 \ \text{ iff } \ \alpha w_{ij+1} + \beta \tilde{y}_{ij+1} + \varepsilon_i \tilde{x}_{ij+1} \le H_{ij} \le \alpha w_{ij} + \beta \tilde{y}_{ij} + \varepsilon_i \tilde{x}_{ij} \ \text{ and } \ u(K_{ij} = 1) = u_i^{\max} \qquad (3.8) \\
&\textit{where} \quad u_i^{\max} = \max\{\max\{u(H_{ij}, y_{ij}^a, \varepsilon_i),\ j = 0,..., N_i\}, \max\{v(w_{ij}, \tilde{y}_{ij}, \varepsilon_i),\ j = 1,..., N_i\}\}
\end{aligned}$$

In this framework, I assume the true budget set for each individual is known by both the econometrician and the worker. However, the econometrician cannot assign the worker to a particular segment or kink point because of the individual heterogeneity ε_i. The probabilities that the worker is at each segment or kink point can be computed by the econometrician from the decision rule in (3.7) or (3.8).

There is yet another error in this framework: the measurement error in working hours, denoted as u_i. The observed working hours h_i deviates from the true working hours by u_i:

$$h_i = h_{ij}^* + u_i \qquad (3.9)$$

The decision rules in (3.7) or (3.8) do not include those who do not work. Following Hausman (1981), the decision rule for people with zero hours of work can come from two sources: the optimal hours zero regardless the values of u_i, i.e., $h_i^* \le 0$, or

u_i is negative enough that $h_i \leq 0$ when $h_i^* > 0$. The decision rule for zero hours is summarized in (3.10):

$$K_{i0} = 1 \text{ if } \begin{cases} \alpha w_{i1} + \beta \tilde{y}_{i1} + \varepsilon_i \tilde{x}_{i1} \leq 0 \\ S_{ij} = 1 \text{ and } u_i \leq -(\alpha w_{ij} + \beta \tilde{y}_{ij} + \varepsilon_i \tilde{x}_{ij}) \\ K_{ij} = 1 \text{ and } u_i \leq -H_{ij} \end{cases} \tag{3.10}$$

Hausman (1981) assumes that observed hours is equal to zero whenever desired hours are zero. The density function of observed hours when $h_i > 0$, $f(h_i)$, based on the decision rule in (3.7) and the measurement error in (3.9) is given by

$$\begin{aligned} f(h_i > 0) = {} & \sum_{j=1}^{N_i} \int_{(H_{ij-1} - \alpha w_{ij} - \beta \tilde{y}_{ij}) / (\tilde{y}_{ij}\lambda + (1-\lambda))}^{(H_{ij} - \alpha w_{ij} - \beta \tilde{y}_{ij}) / (\tilde{y}_{ij}\lambda + (1-\lambda))} f_u(h_i - \alpha w_{ij} - \beta \tilde{y}_{ij} - \varepsilon_i(\tilde{y}_{ij}\lambda + (1-\lambda))) dF_\varepsilon(\varepsilon_i) \\ & + \sum_{j=1}^{N_i - 1} \left[F_\varepsilon\left(\frac{H_{ij} - \alpha w_{ij+1} - \beta \tilde{y}_{ij+1}}{(\tilde{y}_{ij+1}\lambda + (1-\lambda))} \right) - F_\varepsilon\left(\frac{H_{ij} - \alpha w_{ij} - \beta \tilde{y}_{ij}}{(\tilde{y}_{ij}\lambda + (1-\lambda))} \right) \right] f_u(h_i - H_{ij}) \\ & + \left(1 - F_\varepsilon\left(\frac{H_{i\max} - \alpha w_{iN_i} - \beta \tilde{y}_{iN_i}}{(\tilde{y}_{iN_i}\lambda + (1-\lambda))} \right) \right) f_u(h_i - H_{i\max}) \end{aligned} \tag{3.11}$$

The first term is the joint density of desired hours being in the interior of one of the segments of the budget constraints, the second term is the joint density of desired hours being at one of the kink points, and the last term is the joint density of desired hours being equal to the maximum possible value. The probability of observed hours when $h_i = 0$ based on the decision rule in (3.10) is given by:

$$\Pr(h_i = 0) = \sum_{j=1}^{N_i} \int_{(H_{ij-1}-\alpha w_{ij}-\beta\tilde{y}_{ij}) / (\tilde{y}_{ij}\lambda+(1-\lambda))}^{(H_{ij}-\alpha w_{ij}-\beta\tilde{y}_{ij}) / (\tilde{y}_{ij}\lambda+(1-\lambda))} F_u(-\alpha w_{ij} - \beta\tilde{y}_{ij} - \varepsilon_i(\tilde{y}_{ij}\lambda + (1-\lambda)))dF_\varepsilon(\varepsilon_i)$$
$$+ \sum_{j=1}^{N_i-1} \left[F_\varepsilon\left(\frac{H_{ij} - \alpha w_{ij+1} - \beta\tilde{y}_{ij+1}}{(\tilde{y}_{ij+1}\lambda + (1-\lambda))} \right) - F_\varepsilon\left(\frac{H_{ij} - \alpha w_{ij} - \beta\tilde{y}_{ij}}{(\tilde{y}_{ij}\lambda + (1-\lambda))} \right) \right] F_u(-H_{ij})$$
$$+ F_\varepsilon\left(\frac{-\alpha w_{i1} - \beta\tilde{y}_{i1}}{(\tilde{y}_{i1}\lambda + (1-\lambda))} \right) \tag{3.12}$$
$$+ \left(1 - F_\varepsilon\left(\frac{H_{i\max} - \alpha w_{iN_i} - \beta\tilde{y}_{iN_i}}{(\tilde{y}_{iN_i}\lambda + (1-\lambda))} \right) \right) F_u(-H_{i\max})$$

The third term is the probability that desired hours of work is zero, and the remaining three terms correspond to the three terms in (3.11). If the budget constraints are not globally convex, the density function of observed hours when $h_i>0$, $f(h_i)$, based on the decision rule in (3.8) and the measurement error in (3.9) is given by

$$f(h_i > 0) = f(h_i > 0, h_i^* > 0 \mid X_i) = f(h_i > 0 \mid X_i, h_i^* > 0)P(h_i^* > 0 \mid X_i)$$
$$= E[f_u(u_i \mid X_i, h_i^* > 0, \varepsilon_i)1(h_i^* > 0) \mid X_i]$$
$$= E\left[f_u(h_i - \alpha w_{ij} - \beta\tilde{y}_{ij} - \varepsilon_i(\tilde{y}_{ij}\lambda + (1-\lambda)))1(U = U_i^{\max})1(h_i^* > 0) \mid X_i \right] \tag{3.13}$$
$$\approx \frac{1}{R}\sum_{r=1}^{R} \sum_{U_j = U_{ij}^{\max}} f_u(h_i - \alpha w_{ij} - \beta\tilde{y}_{ij} - \varepsilon_{ir}(\tilde{y}_{ij}\lambda + (1-\lambda)))1(h_i^*(\varepsilon_{ir}) > 0)$$

where the indirect utility function is

$$v(\tilde{y}_{ij}, w_{ij}) = e^{(\beta+\lambda\varepsilon_{ir})w_{ij}} \left(\tilde{y}_{ij} + \frac{\alpha}{\beta + \lambda\varepsilon_{ir}} w_{ij} - \frac{\alpha}{(\beta + \lambda\varepsilon_{ir})^2} + \frac{Z_i\gamma + (1-\lambda)\varepsilon_{ir}}{\beta + \lambda\varepsilon_{ir}} \right). \tag{3.14}$$

The direct utility function is

$$u(y_{ij}^a, h_{ij}) = \exp\left(\frac{(\beta + \lambda\varepsilon_{ir})y_{ij}^a + Z_i\gamma + (1-\lambda)\varepsilon_{ir} - h_{ij}}{h_{ij} - \alpha/(\beta + \lambda\varepsilon_{ir})} \right)\left(\frac{h_{ij} - \alpha/(\beta + \lambda\varepsilon_{ir})}{\beta + \lambda\varepsilon_{ir}} \right). \tag{3.15}$$

The last term in (3.13) is an approximate value of the density of h by simulated maximum likelihood (SML) and randomly drawing the error term ε 1000 times. Because the indicator function $1(h_i^*(\varepsilon_{ir}) > 0)$ is neither continuous nor differentiable, I introduce a kernel function (3.16) to calculate the score vector and information matrix.

$$1(h_i^*(\varepsilon_{ir}) > 0 \mid X_i) = k(h_i^*((\varepsilon_{ir}))) = \begin{cases} 0 & if \quad h_i^*(\varepsilon_{ir}) <= 0 \\ \frac{1}{2}\left(1-\cos\left(\frac{\pi h_i^*(\varepsilon_{ir})}{\Delta}\right)\right) & if \quad 0 < h_i^*(\varepsilon_{ir}) < \Delta \\ 1 & if \quad h_i^*(\varepsilon_{ir}) >= \Delta \end{cases} \quad (3.16)$$

The probability of observed hours when h_i=0 is given by

$$\begin{aligned} &\Pr(h_i = 0 \mid X_i) = \Pr(h_i^* <= 0 \mid X_i) + \Pr(h_i^* > 0, h_i^* + u_i <= 0 \mid X_i) \\ &= E\left[1(U = U_i^{\max})1(h_i^* <= 0) + 1(U = U_i^{\max})1(h_i^* > 0, h_i^* + u_i <= 0) \mid X_i\right] \quad (3.17) \\ &\approx \frac{1}{R}\sum_{r=1}^{R}\sum_{U_j = U_{ij}^{\max}}(1 - 1(h_{ij}^*(\varepsilon_{ir}) > 0)) + \frac{1}{R}\sum_{r=1}^{R}\sum_{U_j = U_{ij}^{\max}} F_u(-\alpha w_{ij} - \beta\tilde{y}_{ij} - \varepsilon_{ir}(\tilde{y}_{ij}\lambda + (1-\lambda)))1(h_i^*(\varepsilon_{ir}) > 0) \end{aligned}$$

Utility function form follows (3.14) and (3.15). When λ = 0, this encompassing model becomes the dual additive errors model. When λ = 1, it becomes Hausman's random income coefficient model. By virtue of this nesting, likelihood ratio tests can be performed.

Although the likelihood function in (3.11) and (3.12) assumes perfect knowledge of the budget segments for each individual by the econometrician, assigning a person to a kink point or a budget segment is not perfect because of heterogeneity in preferences among individual. The model does not suffer from observations piling up at any point. But rather, each observed working hours may have positive probabilities at any segment or at any kink point.

As pointed out by Blundell and MaCurdy (2007), there are two problems in this model: (1) The model makes a rather suspicious assumption of perfect knowledge of the entire budget constraints by econometricians, the same as Heckman's critique, and (2) The measurement error in hours of work implies measurement error in wages, an issue which is not addressed in this setting. In the next part, I consider an alternative specification, namely, measurement error in nonlabor income. This alternative addresses both criticisms of Hausman's original models.

3.2.3 Measurement Error in Nonlabor Income

In this section, I introduce measurement error in nonlabor income Y_i^n. Let

$$Y_i^n = Y_i^{n*} - \varepsilon_i \tag{3.18}$$

where Y_i^{n*} is the true nonlabor income, known by individual i, but unobserved by econometricians. The measurement error for an observed value Y_i^n is ε_i. Again, let H_{ij}^* and $\tilde{y}_{ij+1}^*$ be the true values observed by individual i but not to the econometrician. Obtained from TABLE B2.1, Equation (3.19) lists the relationships between observed values and the true values.

$$\begin{aligned} H_{ij} &= H_{ij}^* + \varepsilon_i / w_i \\ \tilde{y}_{ij} &= \tilde{y}_{ij}^* - \varepsilon_i (1 - t_{i0} + t_{i1} - t_{ij}) \equiv \tilde{y}_{ij}^* - \varepsilon_i m_{ij} \end{aligned} \tag{3.19}$$

Since individual i observes true values H_{ij}^* and $\tilde{y}_{ij+1}^*$, the optimal choice of segment j or kink point j is based on the true values. The true necessary decision process by individual i can be expressed as

$$\begin{aligned} S_{ij} &= 1 \quad \text{iff} \quad H_{ij-1}^* \le \alpha w_{ij} + \beta \tilde{y}_{ij}^* \le H_{ij}^* \\ K_{iN_i} &= 1 \quad \text{iff} \quad \alpha w_{iN_i} + \beta \tilde{y}_{iN_i}^* \ge H_{i\max} \\ K_{ij} &= 1 \quad \text{iff} \quad \alpha w_{ij+1} + \beta \tilde{y}_{ij+1}^* \le H_{ij}^* \le \alpha w_{ij} + \beta \tilde{y}_{ij}^* \end{aligned} \tag{3.20}$$

Since the decision process in (3.20) is not perfectly observed by the econometrician due to measurement error in Y_i^n, it is only possible to assign values of K_{ij} and S_{ij} based on observed values of Y_i^n. In (3.21), I rewrite (3.20) in terms of observables H_{ij} and $\tilde{y}_{ij}$. The necessary decision rules when $h_i > 0$ are

$$\begin{aligned}
&S_{ij} = 1 \quad \text{iff} \quad H_{ij-1} \le \alpha w_{ij} + \beta \tilde{y}_{ij} + \varepsilon_i (1/w_i + \beta m_{ij}) \le H_{ij} \\
&K_{iN_i} = 1 \quad \text{iff} \quad \varepsilon_i (1/w_i + \beta m_{iN_i}) \ge H_{i\max} - \alpha w_{iN_i} - \beta \tilde{y}_{iN_i} \\
&K_{ij} = 1 \quad \text{iff} \quad H_{ij} - \alpha w_{ij} - \beta \tilde{y}_{ij} \le \varepsilon_i (1/w_i + \beta m_{ij}), \text{and} \\
&\qquad\qquad\quad H_{ij} - \alpha w_{ij+1} - \beta \tilde{y}_{ij+1} \ge \varepsilon_i (1/w_i + \beta m_{ij+1})
\end{aligned} \tag{3.21}$$

Let u_i be the usual residual in the linear working hours equation based on true variables. The model in (3.3) becomes:

$$h_i = \begin{cases} \alpha w_{ij} + \beta \tilde{y}^*_{ij} + u_i & \text{if} \quad \mathrm{S}_{ij} = 1 \\ H^*_{ij} + u_i & \text{if} \quad \mathrm{K}_{ij} = 1 \end{cases} \tag{3.22}$$

Rewriting (3.22) into (3.23) with observed variables:

$$h_i = \begin{cases} \alpha w_{ij} + \beta \tilde{y}_{ij} + u_i + \beta \varepsilon_i m_j & \text{if} \quad \mathrm{S}_{ij} = 1 \\ H_{ij} + u_i - \varepsilon_i / w_i & \text{if} \quad \mathrm{K}_{ij} = 1 \end{cases} \tag{3.23}$$

Again, following Hausman (1981), the observations that $h_i = 0$ are obtained from two sources: those whose optimal hours are zero, and those when $u_i < -h_i^*$. The necessary decision rules that $h_i = 0$ are given in (3.24)

$$K_{i0} = 1 \text{ if } \begin{cases} \alpha w_{i1} + \beta \tilde{y}_{i1} + \beta \varepsilon_i m_{i1} \le 0 \\ S_{ij} = 1 \quad \text{and} \quad u_i \le -(\alpha w_{ij} + \beta \tilde{y}_{ij} + \beta \varepsilon_i m_{ij}) \\ K_{ij} = 1 \quad \text{and} \quad u_i \le -H_{ij} \end{cases} \tag{3.24}$$

Because measurement error in nonlabor income implies the random budget constraints, I do not know whether random budget sets are globally convex or not. The necessary decision rules (3.21) and (3.24) may not be sufficient. The density function of observed hours when $h_i > 0$, $f(h_i)$ is

$$
\begin{aligned}
& f(h_i > 0) = f(h_i > 0, h_i^* > 0 \mid X_i) = f(h_i > 0 \mid X_i, h_i^* > 0) P(h_i^* > 0 \mid X_i) \\
& = E[f_u(u_i \mid X_i, h_i^* > 0, \varepsilon_i) 1(h_i^* > 0) \mid X_i] \\
& = E\left[f_u(h_i - \alpha w_{ij} - \beta(\tilde{y}_{ij} + \varepsilon_i m_{ij})) 1(U = U_i^{\max}) 1(h_i^* > 0) \mid X_i\right] \\
& \approx \frac{1}{R} \sum_{r=1}^{R} \sum_{U_j = U_{ij}^{\max}} f_u(h_i - \alpha w_{ij} - \beta(\tilde{y}_{ij} + \varepsilon_{ir} m_{ij})) 1(h_i^*(\varepsilon_{ir}) > 0)
\end{aligned} \tag{3.25}
$$

The indirect utility function is

$$
v(\tilde{y}_{ij}, w_{ij}) = e^{(\beta) w_{ij}} \left((\tilde{y}_{ij} + \varepsilon_{ir} m_{ij}) + \frac{\alpha}{\beta} w_{ij} - \frac{\alpha}{(\beta)^2} + \frac{Z_i \gamma}{\beta} \right)
$$

The direct utility function is $u(y_{ij}^a, h_{ij}) = \exp\left(\frac{(\beta) y^{*a}_{ij} + Z_i \gamma - h_{ij}}{h_{ij} - \alpha/(\beta)} \right) \left(\frac{h_{ij} - \alpha/(\beta)}{\beta} \right)$

The probability of observed hours when $h_i = 0$ is

$$
\begin{aligned}
& \Pr(h_i = 0 \mid X_i) = \Pr(h_i^* <= 0 \mid X_i) + \Pr(h_i^* > 0, h_i^* + u_i <= 0 \mid X_i) \\
& = E\left[1(U = U_i^{\max}) 1(h_i^* <= 0) + 1(U = U_i^{\max}) 1(h_i^* > 0, h_i^* + u_i <= 0) \mid X_i\right] \\
& \approx \frac{1}{R} \sum_{r=1}^{R} \sum_{U_j = U_{ij}^{\max}} (1 - 1(h_{ij}^*(\varepsilon_{ir}) > 0)) + \frac{1}{R} \sum_{r=1}^{R} \sum_{U_j = U_{ij}^{\max}} F_u(-\alpha w_{ij} - \beta(\tilde{y}_{ij} + \varepsilon_{ir} m_{ij})) 1(h_i^*(\varepsilon_{ir}) > 0)
\end{aligned} \tag{3.26}
$$

The log likelihood function is $\sum_i 1_{h_i > 0} \log f(h_i) + 1_{h_i = 0} \log \Pr(h_i = 0)$. I henceforth refer to equations (3.25) and (3.26) as the MENLI model, for the “Measurement Error in Nonlabor Income” model. In this regard, it resolves the Hausman-Heckman concern. More importantly, the measurement error in nonlabor income leads to uncertainty for the econometrician about each individual's budget constraints. This is exactly in line with Heckman's concern.

3.3 Data

In this section, I apply the various models discussed in the previous section to two data sets: the Panel Study of Income Dynamics (PSID) data of 1984 and 2001. Typically, the errors ε_i and u_i in Hausman’s framework are assumed to be jointly normal.

3.3.1 The U.S. Individual Income Tax System in 1983 and 2000

Wave XVII of the Panel Study of Income Dynamics (PSID) is one of the sources of data for my empirical work. Data for this wave is collected in 1984 but pertains to the calendar year 1983. The 1983 U.S. Individual Income Tax System is described in Section 3 of Triest (1990). I consider federal income tax, state income tax, social security and Medicare payments, and the Earned Income Tax Credit (EITC). The PSID of 2001 is the second source of data for my empirical work. The U.S. federal individual income tax of 2000 consists of a progressive 6 bracket system. TABLE B2.2 presents the taxable income ranges and marginal tax rates.

The personal exemption is \$2,800 and a \$7,350 deduction is built into couples' budget constraints of 2000 if sample couples indicate they use the standard deduction and their filing status is married filing jointly. If couples claim to use itemized deductions, their deduction value is assigned by the average itemized deduction (excluding the state tax payments deduction) within their adjusted gross income class published in Individual Income Tax Returns 2000 (Internal Revenue Service 2003, p.38). Following Triest (1990), I assume that couples who itemize deductions on their federal returns also itemize on their state returns and claim the same amount of deductions.

State individual income tax rates of 2000 vary. Nine states do not impose a state individual income tax. Another nine states impose a flat tax. Among them, Colorado, Illinois, Indiana and Michigan impose a flat rate on federal adjusted gross income with modification; Rhode Island and Vermont impose a flat rate on federal income tax liability; Tennessee, Pennsylvania and New Hampshire impose a flat rate on dividends and interest. There are 33 states imposing a progressive tax similar to the federal income tax.

In the United States, state tax payments may be deducted from federal taxable income by those who itemize. The effective marginal tax rate decreases from $(t_f + t_s)$, where t_f is the federal marginal tax rate and t_s are the state marginal tax rate, to $(t_f + t_s - t_f t_s)$ for itemizers due to this deduction. In addition, sixteen states (in 1983) and nine states (in 2000) allow a deduction for federal tax payments. The marginal tax rate thus declines to $(t_f + t_s - 2\, t_f t_s) / (1 - t_f t_s)$. Following Hausman (1981), Triest average the state tax rates over the segments created by the federal tax. In this chapter, I construct the piecewise-linear budget constraints by adding additional segments to the federal budget constraints. This is one sources of difference between in my budget constraints and in Triest's budget sets. If a sample member is in a state that allows the taxpayer to fully deduct the federal income tax to reduce her effective marginal tax rate, there are mutual deductions of payments. The federal income tax schedule is changed to $D_f(1 - t_f t_s) /(1 - t_s)$, and the state income tax schedule is changed to $D_s (1 - t_f t_s) /(1 - t_f)$, where D_f denotes the distance from the current taxable income to the end point of this federal interval bracket if t_f does not change, and D_s denotes the distance from the current taxable income to the end point of this state interval bracket if t_s keeps constant. Therefore, the tax interval bracket is the minimum number between the federal income tax schedule and the state income tax schedule. If a sample member is in a state that does not allow deducting the federal income tax, this sample member's federal income tax schedule is changed and state income tax schedule is not. The federal income tax schedule is changed to $D_f /(1 - t_s)$.

The tax interval bracket is the minimum number between the federal income tax schedule and the state income tax schedule.

Although federal and state individual income tax rates are globally convex, phase-out brackets in social security payments and the EITC program create concave kink points in individual budget constraints. In addition to the income tax, workers contribute 6.2 percent of their earnings (up to $76,200) in social security payments of 2000 and 1.45 percent of their earnings (no upper limit) in Medicare payments of 2000; employers make the same matching contribution. I treat the employee contribution as a pure tax, and ignore the employer contribution.

The EITC is a refundable tax credit, which is designed to encourage low-income workers to work and reduce the burden of U.S. payroll taxes. TABLE B2.3 shows the Earned Income Tax Credit Parameters in 1983 and 2000. Compared to the EITC in 1983, the EITC in 2000 is expanded both intensively and extensively. In the tax year 2000, there is a much more modest credit for couples without children that reached a maximum credit of $353. A claimant with one qualifying child could receive a maximum credit of $2,353. A claimant with two qualifying children could receive a maximum credit of $3,888. In other words, for a person with two qualifying children, the credit is equal to 40% of the first $9,720 of earned income, reaching a plateau of $3,888 and staying there until earnings increase beyond $12,690, at which point the credit begins to phase out at 21.06%, reaching zero as earnings pass $31,152. Figure 4 in appendix A shows that the EITC creates a concave budget constraint of OABCD, making it theoretically much more likely that an individual's utility-maximizing bundle will include some hours of work. At kink point A, because the phase-out rate is larger than the IRS tax rate, A is a concave point.

One source of differences in my budget sets could be caused by how I treat the EITC in wives' budget sets. Triest (1990) and Heim (2008) assume that women take their husbands' earnings as given. Actually, few wives were eligible for the credit in EITC. Triest and Heim do not consider the EITC in wives' budget sets and eliminate any concave kink points. This modification will potentially preclude married women's optimal decisions.

In the end, about 50% of the married women face at least two nonconvex segments of their budget sets. There are 494 observations in PSID (1984) and 522 wives in PSID (2001) facing concave kink points.

Convexification of the budget constraint is done in MaCurdy, Green and Paarsch (1990).[5] Figure 5 in appendix A shows the process I use to approximate budget sets. The solid lines represent the general budget constraints, while the dotted line represents the convexification over the concave kink points. As shown, the relevant region around concave kink points is replaced by a single convex segment to construct convex budget sets. The absolute difference is given by (C1 – C2) dollars. The relative difference is calculated by $\left(\frac{C_1 - C_2}{C_2}\right) \times 100$. The largest absolute difference is \$5721 in 1984 and \$1266 in 2001. The mean of absolute difference is \$236 in 1984 and \$237 in 2001. The

5 TABLE 1 in MaCurdy, Green and Paarsch (1990) show that the difference between the convexified and the nonconvexified constraints is small, but MaCurdy, Green and Paarsch do not compare and imply that convexification has unimportant consequences on labor-supply estimates.

maximum relative difference is 21% in 1984 and 22% in 2001. The mean value is about 1%.

3.3.2 Data Sets

I analyze wave XVII of the PSID (1984) and the PSID of 2001. The extraction criterion is the same as Triest (1990). I focus on non-disabled married couples between ages 25 and 55. Because of the backward bending supply curve of labor and the assumed linear labor supply function, I consider salaried workers, with average hourly earnings between \$1 and \$50 in 1983 and between \$1 and \$80[6] in 2000. This selection procedure results in 1050 observations from 1984 and 1171 observations from 2001.

I assume that the difference between total household income and wives' labor income is nonlabor income. For characteristic variables to describe wives' observed heterogeneity, I add annual mortgage payments and a dummy for house ownership. Descriptive statistics for the variables used in the labor supply estimation are presented in TABLE B2.4. The female labor force participation rate is larger in 2000 (84.12%) than in 1983 (73.43%). I use Heckman's sample selection procedure to impute the latent wage rates of nonparticipating wives. It is shown in the appendix D.

3.4 Estimation

I use direct search methods, gradient methods and simulated annealing[7] to find the optimum value of the likelihood function. I also experiment with different starting points to obtain a global optimum result. [8]

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6 If we correct wives' wage rate using CPI-Urban Price Index, \$50 in 1983 is equal to \$86 in 2000.
7 In matlab, *fminsearch* is a direct search method that does not use numerical or analytic gradients. *fmincon* uses a sequential quadratic programming (SQP) method. In this method, the function solves a quadratic programming (QP) subproblem at each iteration. *fmincon* updates an estimate of the Hessian of the Lagrangian at each iteration using the BFGS formula. Simulated annealing (SA) is a generic probabilistic

TABLEs B2.5, B2.6 and B2.7 show results from the PSID of 1984. Results from the PSID of 2001 are shown in TABLE B2.8. TABLE B2.5 shows the estimates for all three models: Hausman's random income coefficient model, the dual additive errors model and the MENLI model under the federal individual tax, listed in TABLE B2.2. I assume all households take the standard deduction ($3,400 in 1983) and file jointly. Estimators from the above three models under the U.S. individual tax system without convexification are shown in TABLE B2.6. The U.S. individual tax system is introduced in section 3.3. I approximate the budget sets, shown in Figure 5 in appendix A, and estimations are shown in TABLE B2.7.

TABLE B2.5 lists the results for five different econometric specifications. The first column corresponds to the dual additive errors model in (3.11) and (3.12) with $\lambda = 0$. Hausman (1981) models heterogeneity in preferences as a random income coefficient, which is estimated and reported in the third column. The second column represents the statistical model that nests Hausman's random income coefficient model and the dual additive errors model. The value of λ shows which model performs better. The fourth column is the MENLI model, with density given by (3.25) and (3.26). I can model measurement error in nonlabor income with non-zero mean, which represents the mean tax liability or deduction. Results are reported in the fifth column.

In TABLE B2.6, although poor health and education are not significant according to Hausman's random income coefficient model, they are significant, respectively, at the

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metaheuristic for the global optimization problem of applied mathematics, namely locating a good approximation to the global optimum of a given function in a large search space. It is often used when the search space is discrete.

8 Blomquist and Hansson-Brusewitz (1990) use about 20 starting points to obtain a global optimum. We try at least 10 starting point for each model with each optimization method to find a global optimum.

10 percent and 1 percent level in the dual additive errors model. From the results of the MENLI model with non-zero mean, having an additional preschool-age child reduces working hours by 297 while a 6 to 18-year-old child reduces working hours by 108. On average, older women work less, reducing their labor supply 17 hours for every birthday. If the principal owed on all mortgages and land contracts increases $1000, married women prefer to work 26 hours more. However, due to the mortgage interest deduction, house ownership actually decreases wives' labor supply.

The wage rate parameter α in Hausman's random income coefficient model is 65.17(17.54), and β, the virtual income parameter, is -0.012(0.0028). In the dual additive errors model α is 62.35(12.67), which is slightly less in magnitude than Hausman's random income coefficient estimate, and β is -.0131 (.0019). In the MENLI model estimate α is 77.7(12.97), which is larger in magnitude than estimates from Hausman's original models. The estimate for β is -.0112(.0029). In the nesting model between Hausman's random income coefficient model and the dual additive errors model, the nesting parameter λ is .497, close to 0.5. The dual additive errors model and Hausman's random income coefficient model explain the data equally well. If I let the mean of the measurement error in nonlabor income ε vary, from Equation (3.18), Y_i^{n*} is the true value of the nonlabor income that the person *i* uses to obtain her budget set. If $E(\varepsilon) < 0$, then $E(Y_i^{n*}) < E(Y_i^{n})$. Because of the U.S. individual tax system without convexification, the approximate state tax liability and the social security tax liability must be included in the budget constraints. On average, each wife faces no extra tax liability. The mean of the measurement error is not significant. [9] Given the slight difference in the key parameters, it is not surprising to see the small difference in elasticity. The overall female uncompensated and compensated labor supply elasticities in Hausman's random income coefficient model are 0.21 and 0.26, respectively. Based on the dual additive errors model, the uncompensated elasticity is 0.20, and the compensated elasticity is 0.26.[10] The MENLI model says that the Marshallian elasticity is about 0.25 and the Hicksian elasticity is 0.30, which are 19.8% larger than the dual additive errors model and 16.1% larger than Hausman's random income coefficient model. The MENLI model with non-zero mean gives the same elasticities as the MENLI model.

In TABLE B2.7, elasticities from estimation of the dual additive errors model (Column 1) and Hausman's random income coefficient models (Column 3) are virtually identical. Compared with results in TABLE B2.6, the uncompensated elasticities decrease 11% and 6.8%, respectively. The nesting parameter in the nest model (Column 2) is 0.5, which is the same as before. Consequently, the difference in the convexified and the nonconvexified constraints does not imply large variation in labor supply estimates.

Estimates from considering only the federal individual income tax are shown in TABLE B2.5. Given the large difference in the key parameters, it is not surprising to see the large difference in elasticity. The overall female uncompensated and compensated labor supply elasticities in Hausman's random income coefficient model are 0.29 and

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9 ε_1 is the measurement error in husband labor income, ε_2 is the measurement error in family nonlabor income. The reason we separate them is the social security tax base is labor income and federal and state individual tax base is AGI.

10 We change the unit of dependent variable from 1000 hours to 1 hour to compare our results with those of Triest (1990). But it is difficult to determine why the results here differ so markedly from those of Triest(1990). We extract data from the PSID following the procedure in Triest (1990). Some difference appears between our data and the Triest data. Our data set has 1,050 observations while the Triest data set has only 978 observations. As Triest claimed, computational problems may also play a role.

0.42. From the dual additive errors model, the uncompensated elasticity is 0.34, and the compensated elasticity is 0.46.[11] The MENLI model indicates that the Marshallian elasticity is 0.22 and the Hicksian elasticity is 0.32, which are smaller than both the dual additive errors model and Hausman's random income coefficient model. Estimates from the MENLI model with non-zero mean are smaller than the MENLI model with zero mean. On average, each couple needs to pay an extra $3673 for the state tax and the social security tax. In the nesting model between Hausman's random income coefficient model and the dual additive errors model, the nesting parameter λ is .0025. The dual additive errors model matches the data set better than Hausman's random income coefficient model. Thus, if I miss the state individual tax to construct budget constraints, there is a bias in the level of budget constraints and this bias causes a large variation of estimates.

In TABLE B2.8, the first three columns show results under the nonconvexified budget constraints. The right two columns represent estimates under the convexified budget sets. As expected, the difference in the convexified and the nonconvexified constraints does not imply variation in labor supply estimates in the PSID of 2001. Due to the convexified approximation, the uncompensated elasticities in the dual additive errors model and Hausman's random income coefficient model change 1.7% and 19.7%, respectively. The compensated elasticities in the dual additive errors model and Hausman's random income coefficient model change 11.5% and 7.8%, respectively. The relative difference of uncompensated elasticity between the MENLI model and Hausman's random income coefficient model is 8.1% under the nonconvexified budget

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11 See footnote 10.

sets. The difference in elasticities between 1983 and 2001 are striking. The uncompensated elasticity in the MENLI model under the nonconvexified budget constraints drops from 0.25 to 0.07, a decrease of 73.5%. Hausman's random coefficient model and the dual additive errors model follow the same trends under the convexified and the nonconvexified budget constraints. [12]

3.5 Conclusions

Hausman's framework to estimate labor supply on piecewise-linear budget constraints has many advantages over the reduced-form approach. The estimated labor supply elasticity varies substantially even though the similar frameworks and data sets are used. The role of budget sets in producing this wide variation is not known. This chapter investigates the implications of convexification and uncertain budget constraints on labor supply estimates. I consider a new version within Hausman's framework to handle the uncertain budget sets. I introduce measurement error in nonlabor income. Particularly, I assume that individuals know their incomes well. But econometricians do not have perfect knowledge about individual's nonlabor income. Uncertainty in nonlabor income leads to a random budget set for each individual, which seems to be precisely in line with comments in Heckman (1983). My empirical estimates demonstrate that variation in budget sets does not explain the different estimates of labor supply elasticity. But the budget constraints shift substantially if state individual income tax or social security tax is omitted. The bias in the level of budget constraints can cause the large variation of estimates.

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12 Using different methodologies, three recent papers (Heim 2007, 2008 and Blau and Kahn 2007) also find smaller female wage elasticities in recent data.

CHAPTER IV

CONCLUSION

This dissertation makes three main contributions to the explaining changes in female labor supply literature. First, it contributes to the econometric solution to explain changes in the participation rate of married women with preschool-aged children by proposing a new model to quantify contributions of various factors in previous literatures. A lot of possible factors are used to explain this growth in employment, but I focus on wage-gender gap, child care cost, spousal income, and commuting time with using 5% samples of the Integrated Public Use Microdata Series (IPUMS) for 1980, 1990 and 2000. After investigation, the change in the composition of married women with preschool-aged children drives the increase in labor force participation rate in the 1980s. But I can't find a sensible conclusion, only 9.6% increase in the 1980s.

Second, this dissertation introduces the concept of "career" to investigate. This new variable can measure the heterogeneity of females' career work experience with using the National Longitudinal Survey of Young Women (NLSYW) from 1968 to 2003 and the National Longitudinal Survey of Youth 1979 (NLSY79) from 1979 to 2008. I further define career women and non-career women to analyze this observed interesting growth of the participation rate.

Third, I figure out the changes in labor force participation rate are driven by shifts in the composition of married women or by changes in their preference. The increase in the female labor supply employment is very responsive to a wife's career type before the first birth. My results show that the rising of the percentage of career women can explain 30.33% of the growth across cohorts. Among the unexplained changes, the change in the composition of career motivating career type women can at least explain 51.2%. That means it can at least explain 17.22% growth in the labor force participation rate across cohorts.

To explain and address the discrepancies in estimates under structural models, I focus on the role of budget sets in producing the wide range of estimates. My contributions here are to study the effect of different ways of calculating budget constraints, typically such as convexification approximation of the non-convex budgets, and uncertain budget constraints. Intuitively, if leisure and consumption are near perfect substitutes, a minor difference in the convexification approximation will cause a large change in hours of work. First, I have investigated the effect of convexification approximation on the labor supply elasticities under both convexified and non-convexified budget sets.

The second question I consider the uncertain budget constraint, which can’t be accurately measured in most cases because econometricians do not know the amount of tax payers’ itemized deduction. I introduce measurement error in nonlabor income. Such measurement error naturally shifts the intercept on the vertical axis of the budget constraints and changes the location of the kink points of the budget constraints. The slope of the budget sets is uncertain. Using the Panel Study of Income Dynamics (PSID) of 1984 and 2001, I find that neither the convexification approximation nor using a model with random budget sets affects the estimates. These results demonstrate that variations in budget constraints alone do not explain the different estimates of labor supply elasticity.

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APPENDIX A

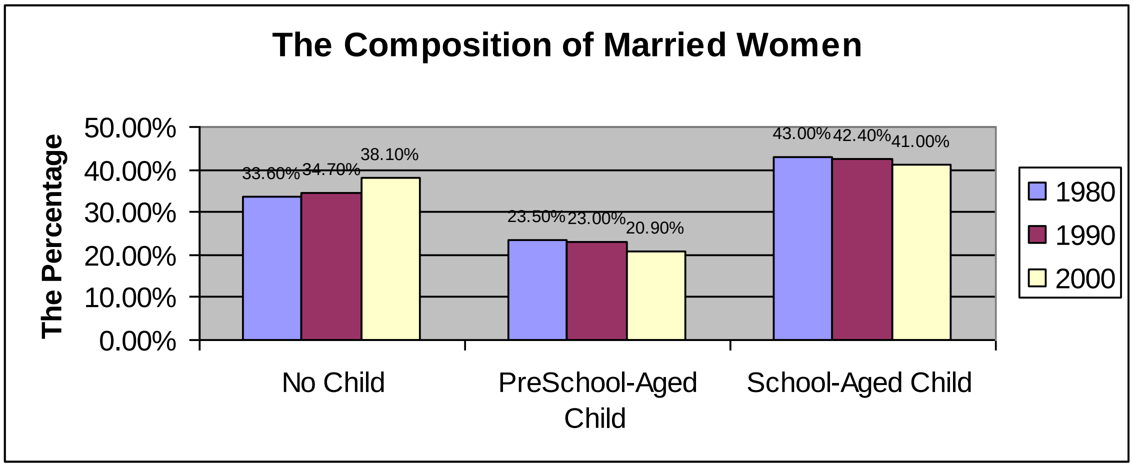

Figure 1. The trend of Married Women Distribution

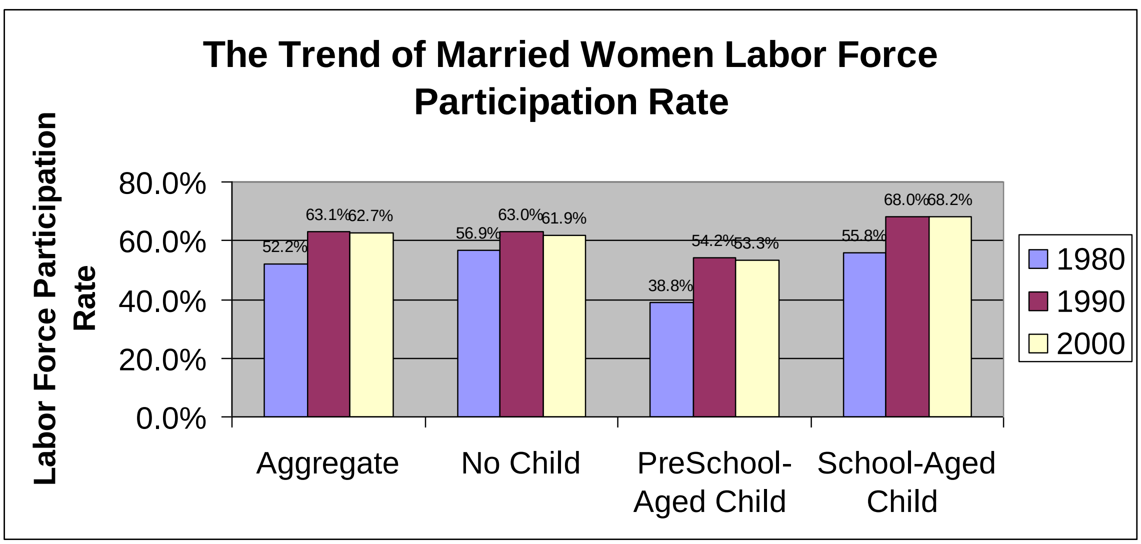

Figure 2. The trend of Married Women Labor Force Participation Rate

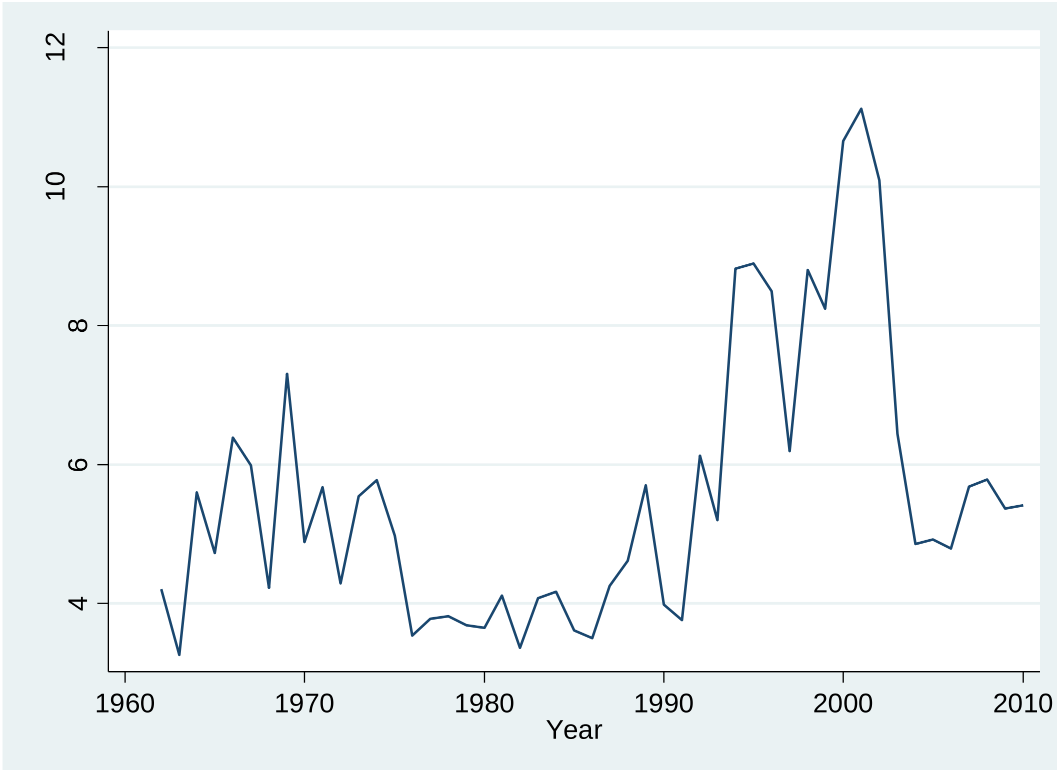

Figure 3. The Trend of Child Care Workers' Wage Rate from 1962 to 2010

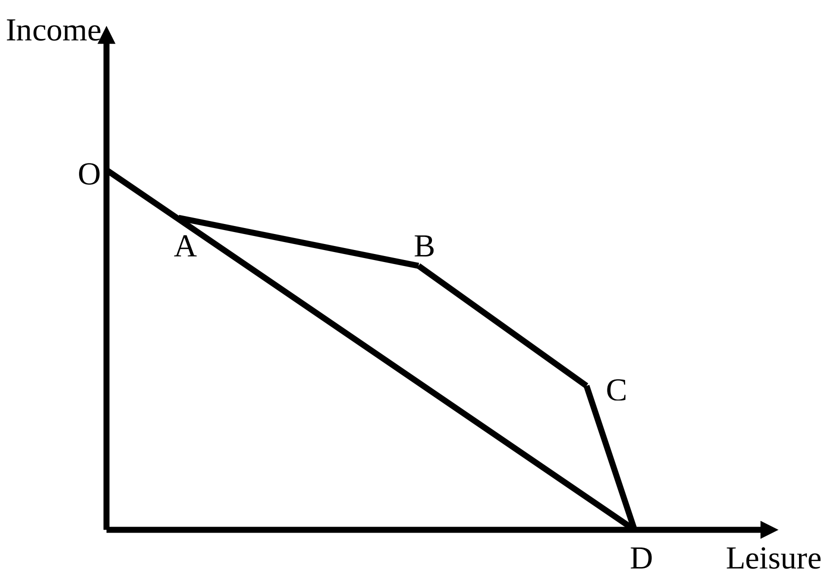

Figure 4. The Earned Income Tax Credit (EITC)

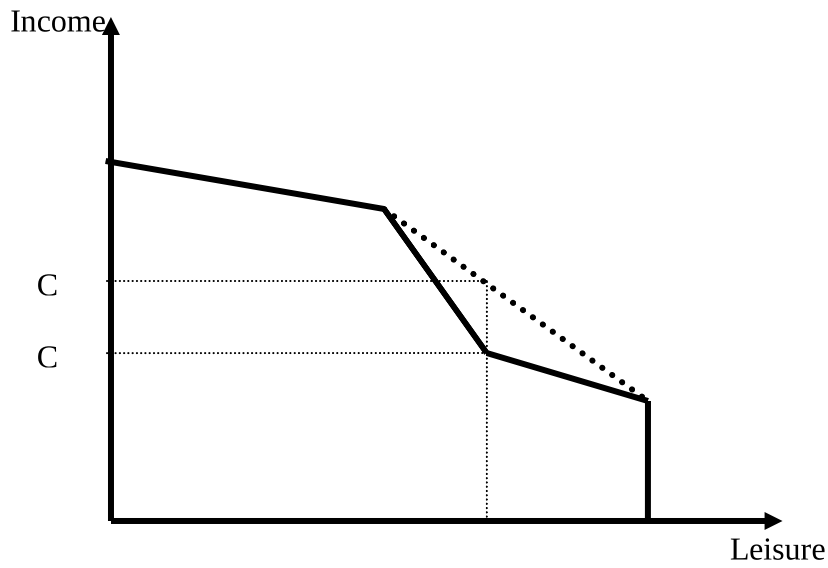

Figure 5. Convexification of a Budget Constraint

APPENDIX B

TABLE B1.1. Summary Statistics of IPUMS (1980-2000)

	5% samples of IPUMS for 1980		5% samples of IPUMS for 1990		5% samples of IPUMS for 2000	
Variable	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Labor Force Participation	0.3882	0.4873	0.5420	0.4982	0.5329	0.4989
Wage Ratio	0.7048	0.3575	0.7983	0.4017	0.8663	0.5046
Child Cost ($)	8.1246	1.0148	7.8265	0.9635	8.8239	0.7970
Nonlabor Income($10000)	3.7325	2.4230	4.3698	3.8356	5.1019	5.5233
Commuting Time(10 Minutes)	2.2995	0.2583	2.3658	0.2288	2.7453	0.1874
Age	28.3607	5.4757	30.2110	5.5800	31.4086	6.0257
Age×Age/100	8.3431	3.3477	9.4384	3.5450	10.2281	3.9029
Years of Education	12.3909	2.7368	12.9542	2.6577	13.2192	2.9063
Central City Dummy	0.1739	0.3790	0.1268	0.3328	0.1297	0.3360
Mortgage Dummy	0.4883	0.4999	0.5814	0.4933	0.6223	0.4848
Actual Wage Rate	9.8399	5.5579	11.6472	7.1732	13.4196	9.2292
# Observations	490552		499297		453786	

TABLE B1. 2. The Change of Commuting Time and LF participation Rate across MSA (1980-2000)

	# observations	Percentage	Commuting Time Male	LFP Rate	LFP Rate No Child	LFP Rate School-aged children	LFP Rate Preschool-aged children	Δ Time	Δ LFPR
5% samples of IPUMS for 1980									
Total	2088458			52.2%					
Non Big MSA	1170000	56.0%	20.79	51.2%	54.6%	55.7%	38.8%		
Big MSA	918458	44.0%	26.02	53.4%	59.7%	55.9%	38.8%		
5% samples of IPUMS for 1990									
Total	2172046			63.1%					10.9%
Non Big MSA	1276682	58.8%	21.70	62.5%	60.5%	68.5%	54.4%	0.91	11.3%
Big MSA	895364	41.2%	26.33	64.0%	66.7%	67.4%	53.9%	0.31	10.6%
5% samples of IPUMS for 2000									
Total	2175973			62.7%					-0.4%
Non Big MSA	1240121	57.0%	25.71	63.2%	60.4%	70.0%	54.9%	4.01	0.7%
Big MSA	935852	43.0%	29.47	62.0%	64.2%	65.9%	51.4%	3.14	-2.0%

TABLE B1.3. Estimating the Participation Equation of Married Women with Preschool-aged Children

(Dependent Variable = Wife's Employment Dummy, 1980-2000)

	Estimation		Marginal Effect	
	Model (2.1)	Model (2.2)	Model (2.1)	Model (2.2)
Year=1980	-0.341***	-0.303***	-0.1349	-0.1201
	(-131.57)	(-112.42)		
Year=2000	-0.0467***	-0.0306***	-0.0186	-0.0122
	(-17.84)	(-9.10)		
Wage Ratio		0.612***		0.244
		(190.96)		
Child Cost ($)		-0.0371***		-0.0148
		(-30.70)		
Nonlabor Income($10000)		-0.0562***		-0.0224
		(-179.56)		
Commuting Time(10 Minutes)		0.00843		0.0034
		(1.64)		
Constant	-1.378***	-1.352***		
	(-64.55)	(-54.45)		

TABLE B1.3. Continued

	Estimation		Marginal Effect	
	Model (2.1)	Model (2.2)	Model (2.1)	Model (2.2)
Age	0.0304***	0.0185***	0.0121	0.0074
	(21.86)	(13.19)		
Age×Age/100	-0.0498***	-0.0226***	-0.0199	-0.009
	(-22.84)	(-10.27)		
Years of Education	0.0731***	0.0808***	0.0291	0.0322
	(173.50)	(183.81)		
Central City Dummy	0.00952**	-0.0211***	0.0038	-0.0084
	(3.12)	(-6.42)		
Mortgage Dummy	0.153***	0.188***	0.0608	0.075
	(66.72)	(79.65)		

* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE B1. 4. Predicted Changes in the Participation Rate

of Married Women with Preschool-aged Children

	Model (2.1)		Model (2.2)	
	1990-1980	2000-1990	1990-1980	2000-1990
Wage Ratio			2.44%	1.71%
Child Cost ($)			0.43%	-1.47%
Nonlabor Income($10000)			-1.43%	-1.64%
Commuting Time(10 Minutes)			0.02%	0.13%
Age	0.07%	-0.14%	0.39%	0.17%
Years of Education	1.63%	0.79%	1.80%	0.87%
Central City Dummy	-0.02%	0.00%	0.04%	0.00%
Mortgage Dummy	0.55%	0.24%	0.68%	0.30%
Total Explained	2.23%	0.89%	4.75%	0.24%
Total Actual Change	0.1538	-0.0090	0.1538	-0.0090

TABLE B1. 5. % of Married women with school aged child

who Work more than X% during three years before the first birth

Education Group and Birth Years	X 10	30	50	70	90	# Observations
0-16+ years						
1943-53	66.38%	55.47%	46.10%	33.87%	20.42%	2796
1957-64	89.01%	81.22%	72.60%	60.85%	43.32%	2876
Grade 11 or Less						
1943-53	40.64%	28.00%	21.12%	12.56%	6.72%	1250
1957-64	70.99%	57.53%	46.54%	31.73%	17.78%	810
Grade 12						
1943-53	83.76%	72.82%	60.27%	43.30%	27.18%	813
1957-64	94.46%	86.34%	75.98%	63.86%	44.87%	974
Some College						
1943-53	86.71%	76.81%	65.22%	52.42%	31.64%	414
1957-64	97.09%	92.73%	85.61%	74.56%	54.65%	688
College						
1943-53	96.55%	91.22%	83.07%	69.28%	42.32%	319
1957-64	98.27%	96.78%	94.55%	88.61%	71.53%	404

TABLE B1. 6. % of Married women with school aged child

who Work more than X% during three years after the first birth

Education Group and Birth Years	X: 10	30	50	70	90	# Observations
0-16+ years						
1943-53	76.36%	58.76%	45.64%	31.87%	17.17%	2796
1957-64	84.42%	71.77%	57.61%	44.23%	26.81%	2876
Grade 11 or Less						
1943-53	70.24%	50.64%	37.28%	23.60%	10.88%	1250
1957-64	79.51%	60.37%	42.10%	28.52%	12.96%	810
Grade 12						
1943-53	80.69%	63.84%	46.99%	32.72%	17.84%	813
1957-64	86.55%	74.64%	61.19%	46.41%	26.18%	974
Some College						
1943-53	80.19%	65.46%	56.28%	40.82%	23.43%	414
1957-64	86.92%	78.34%	66.28%	52.91%	35.90%	688
College						
1943-53	84.33%	68.97%	61.13%	50.47%	31.97%	319
1957-64	84.90%	76.49%	65.35%	55.69%	40.59%	404

TABLE B1.7. The Frequencies of Career Type

and LF Employment Type across cohorts

Career Before Birth \ LFP After Birth		Cohort 1943-53 <0.5	Cohort 1943-53 >=0.5	Cohort 1943-53 Total	Cohort 1957-64 <0.5	Cohort 1957-64 >=0.5	Cohort 1957-64 Total
Non Career	# Observations	994	513	1,507	502	286	788
Type	percentage	35.55	18.35	53.9	17.45	9.94	27.4
	# Observations	526	763	1,289	717	1,371	2,088
Career Type	percentage	18.81	27.29	46.1	24.93	47.67	72.6
	# Observations	1,520	1,276	2,796	1219	1,657	2,876
Total	percentage	54.36	45.64	100	42.39	57.61	100

TABLE B1.8. The First Birth

and Marriage age across Career Type across cohorts

Career Before Birth \ LFP After Birth		Cohort 1943-53 <0.5	Cohort 1943-53 >=0.5	Cohort 1943-53 Total	Cohort 1957-64 <0.5	Cohort 1957-64 >=0.5	Cohort 1957-64 Total
Age at First	Non Career Type	21	20.9	21.2	22	20.9	21.4
Birth	Career Type	25	26.6	26	26	26.2	26.1
Age at First	Non Career Type	20	20.5	20.3	21	21.2	21.2
Marriage	Career Type	23	23.5	23.2	23	23.4	23.2

TABLE B1.9. Summary Statistics of NLSYW and NLSY79

Variable	NLSYW Mean	NLSYW Std. Dev.	NLSY79 Mean	NLSY79 Std. Dev.
Labor Force Participation Rate	0.4587	0.3537	0.5675	0.3529
Career Type	0.4610	0.4986	0.7260	0.4461
Career Type × Work Attitude	0.2507	0.4335	0.4833	0.4998
Wage Ratio	2.0944	1.4757	2.5499	1.4632
Nonlabor Income ($10000)	3.5721	1.8085	3.7878	3.0144
Years of Education	13.5107	2.3413	13.7726	2.4893
Age at First Birth	23.4070	4.5932	24.8032	4.9918
Age at First Birth × Age at First Birth /100	5.6898	2.3996	6.4011	2.6843
Black	0.2085	0.4063	0.1638	0.3701
Hispanic	0.0111	0.1047	0.1777	0.3823
South	0.2901	0.4539	0.3355	0.4723
# Observations	2796		2876	

TABLE B1.10. The Frequencies of Work Attitude Type and Career Type across cohorts

Work Attitude\Career Type		Cohort 1943-53			Cohort 1943-53		
		0	1	Total	0	1	Total
0	# Observations	810	588	1,398	343	698	1,041
	percentage	28.97	21.03	50	11.93	24.27	36.2
1	# Observations	697	701	1,398	445	1,390	1,835
	percentage	24.93	25.07	50	15.47	48.33	63.8
Total	# Observations	1,507	1,289	2,796	788	2,088	2,876
	percentage	53.9	46.1	100	27.4	72.6	100

TABLE B1.11. Estimates of the Wife's Participation Equation

with Career Rate across cohorts (Dependent Variable = Wife's Employment Rate)

	Model (2.3)	Model (2.4)	Model (2.5)	Model (2.7)	Model (2.8)
Cohort=NLSY79	0.0828***	0.0761***	0.0364***	-0.000503	-0.000916
	(8.74)	(8.15)	(3.93)	(-0.03)	(-0.06)
Wage Ratio		0.0393***	0.0297***	0.0307***	0.0292***
		(10.77)	(8.33)	(8.60)	(8.22)
Nonlabor Income($10000)		-0.0221***	-0.0214***	-0.0218***	-0.0219***
		(-11.27)	(-11.31)	(-11.52)	(-11.60)
Career Type			0.217***		
			(20.01)		
Career Type×(Cohort=NLSYW)				0.189***	0.120***
				(13.74)	(7.18)
Career Type×(Cohort=NLSY79)				0.249***	0.215***
				(17.09)	(12.39)
Career Type × (Cohort=NLSYW) ×					0.132***
Work Attitude					(7.35)
Career Type × (Cohort=NLSY79) ×					0.0561***
Work Attitude					(3.77)
Constant	-0.338**	-0.0930	0.590***	0.596***	0.609***
	(-3.23)	(-0.88)	(5.49)	(5.55)	(5.70)

TABLE B1.11. Continued

	Model (2.3)	Model (2.4)	Model (2.5)	Model (2.7)	Model (2.8)
Years of Education	0.0247***	0.0248***	0.0252***	0.0250***	0.0232***
	(12.02)	(11.64)	(12.25)	(12.15)	(11.25)
Age at First Birth	0.0252**	0.00815	-0.0457***	-0.0451***	-0.0441***
	(3.06)	(0.99)	(-5.42)	(-5.35)	(-5.27)
Age at First Birth × Age at First	-0.0302*	-0.00278	0.0831***	0.0819***	0.0804***
Birth/100	(-1.96)	(-0.18)	(5.40)	(5.33)	(5.26)
Black	0.131***	0.118***	0.132***	0.132***	0.130***
	(10.76)	(9.78)	(11.26)	(11.30)	(11.23)
Hispanic	0.0549***	0.0413**	0.0498**	0.0518***	0.0534***
	(3.40)	(2.60)	(3.24)	(3.38)	(3.49)
South	0.0559***	0.0457***	0.0381***	0.0393***	0.0426***
	(5.61)	(4.66)	(4.02)	(4.14)	(4.51)

* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE B1.12. Predicted Changes in Wife's Participation Rate

with Career Rate across cohorts

Variable	Model (2.3)	Model (2.4)	Model (2.5)	Model (2.7)	Model (2.8)
Career Type×(Cohort=NLSYW)			-0.1000	-0.0871	-0.0553
Career Type×(Cohort=NLSY79)			0.1575	0.1808	0.1561
Career Type × (Cohort=NLSYW) × Work Attitude					-0.0331
Career Type × (Cohort=NLSY79) × Work Attitude					0.0271
Wage Ratio		0.0179	0.0135	0.0140	0.0133
Nonlabor Income ($10000)		-0.0048	-0.0046	-0.0047	-0.0047
Years of Education	0.0065	0.0065	0.0066	0.0065	0.0061
Age at First Birth	0.0137	0.0094	-0.0047	-0.0047	-0.0044
Black	-0.0059	-0.0053	-0.0059	-0.0059	-0.0058
Hispanic	0.0091	0.0069	0.0083	0.0086	0.0089
South	0.0025	0.0021	0.0017	0.0018	0.0019
Total Explained Change	0.0260	0.0327	0.0724	0.1093	0.1101
Total Actual Change			0.1088		

TABLE B2.1. Summary of budget segments

	Budget Segment 1	Budget Segment j > 1
function for after-tax income y^a	$y^a = y^n + w(1 - t_1)h$	$y^a = y^a_{j-1} + w(1 - t_j)(h - H_{j-1})$
kink points for after-tax income y^a	$y_0^a = y^n$	$y^a_j = y^a_{j-1} + w(1 - t_j)(H_j - H_{j-1})$
kink points for working hours h	$H_0 = 0$ $H_1 = (Y_1 - Y^n)/w$	$H_j = (Y_j - Y^n)/w$
virtual income $\tilde{y}$	$\tilde{y}_1 = y^n$	$\tilde{y}_j = \tilde{y}_{j-1} + w(t_j - t_{j-1})H_{j-1}$

This TABLE B2.1. is reproduced from Fullerton and Gan (2001).

I define t_1 as the first bracket applied to labor income of this person (after taxation of nonlabor income). Using the person's nonlabor income, t_j and Y_j are also individual-specific, but can be found from the tax table

TABLE B2.2. Federal Individual Income Tax Rates

1983		2000	
Tax Brackets	Rates	Tax Brackets	Rates
$0-$3,400	0	$0-$7,350	0
$3,400-$5,500	0.11	$7,350-$51,200	0.15
$5,500-$7,600	0.13	$51,200-$113,300	0.28
$7,600-$11,900	0.15	$113,300-$168,800	0.31
$11,900-$16,000	0.17	$168,800-$295,700	0.36
$16,000-$20,200	0.19	$295,700+	0.396
$20,200-$24,600	0.23		
$24,600-$29,900	0.26		
$29,900-$35,200	0.3		
$35,200-$45,800	0.35		
$45,800-$60,000	0.4		
$60,000-$85,600	0.44		
$85,600-$109,400	0.48		
$109,400+	0.5		

TABLE B2.3. Earned Income Credit Parameters

Calendar Year	Credit Rate (Percent)	Minimum income for maximum credit	Maximum Credit	Phase-out Rate (Percent)	Phase-out Range	
					Beginning Income	Ending Income
1983	10	5,000	500	12.5	6,000	10,000
2000						
No Children	7.65	4,610	353	7.65	5,770	10,380
One Child	34	6,920	2,353	15.98	12,690	27,413
Two Children	40	9,720	3,888	21.06	12,690	31,152

TABLE B2.4. Sample Descriptive Statistics

	PSID 1984				PSID 2001			
	Full Sample		Working Women		Full Sample		Working Women	
Variable Name	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Unearned Income($)	29374.56	16898.80	27465.77	14407.24	62392.00	53478.30	61074.50	54744.20
Hours of Work	1065.50	880.14	1451.07	703.65	1439.98	861.04	1711.90	644.65
Hourly earnings	7.33	3.96	7.62	4.50	15.76	9.48	16.25	10.14
Yearly Income	8139.82	8426.19	11085.35	8002.02	23820.82	21738.20	28319.00	20841.30
Children(0-5)	0.55	0.75	0.49	0.71	0.31	0.46	0.27	0.45
Children(6-18)	0.98	1.05	0.92	1.04	1.24	1.12	1.17	1.10
Age	35.28	7.60	34.95	7.51	39.76	7.95	39.97	8.03
Education(years)	12.89	2.06	13.02	2.10	13.74	2.05	13.82	2.00
Health	0.06	0.23	0.05	0.22	0.07	0.25	0.05	0.23
Housing	0.80	0.40	0.78	0.41	0.85	0.36	0.86	0.34
Mortgage($)	5.05	3.45	5.04	3.45	9211.70	9677.17	9318.43	8857.07
Sample Size	1050		771		1171		985	
Participation Rate	73.43%				84.12%			

TABLE B2.5. Estimation Results under Federal Tax System, PSID 1984

(Dependent Variable: Wife's annual hours of work in 1000 hours)

	Column 1	Column 2	Column 3	Column 4	Column 5
	Dual Additive Errors Model (1)	Nest Model (1) & (2)	Random Income Coefficient Model (2)	MENLI (3)	MENLI MU (4)
constant	1.53***	1.52***	1.44***	2.22***	2.28***
	(0.27)	(0.27)	(0.24)	(0.21)	(0.18)
wage (in $)	0.077***	0.076***	0.065***	0.045***	0.027***
	(0.015)	(0.014)	(0.013)	(0.012)	(0.0088)
nonlabor income (in $1000)	-0.025***	-0.025***	-0.026***	-0.018***	-0.018***
	(0.0035)	(0.0029)	(0.0031)	(0.0023)	(0.0021)
	(0.014)	(0.013)	(0.013)	(0.011)	(0.0097)
$\sigma_{\varepsilon 1}$	0.78***	0.74***	0.018***	8.03***	7.098***
	(0.059)	(0.065)	(0.0021)	(0.47)	(0.40)
σ_u	0.61***	0.61***	0.89***	0.76***	0.70***
	(0.07)	(0.065)	(0.029)	(0.03)	(0.020)
μ_1					-3.67***
					(0.40)
λ		0.0025***			
		(0.00016)			
log-likelihood	-1446.65	-1446.39	-1458.67	-1444.51	-1414.07
uncompensated elasticity	0.34		0.29	0.22	0.13
compensated elasticity	0.46		0.41	0.31	0.22

TABLE B2.5. Continued

	Column 1	Column 2	Column 3	Column 4	Column 5
	Dual Additive Errors Model (1)	Nest Model (1) & (2)	Random Income Coefficient Model (2)	MENLI (3)	MENLI MU (4)
# kids in age 0-5	-0.52***	-0.52***	-0.49***	-0.46***	-0.41***
	(0.046)	(0.041)	(0.035)	(0.034)	(0.031)
# kids in age 6-18	-0.17***	-0.17***	-0.17***	-0.15***	-0.13***
	(0.033)	(0.029)	(0.026)	(0.024)	(0.022)
age	-0.015***	-0.015***	-0.015***	-0.014***	-0.01***
	(0.0051)	(0.0047)	(0.0043)	(0.0036)	(0.0032)
education (in years)	0.043***	0.044***	0.051***	0.0039	-0.0006
	(0.017)	(0.017)	(0.015)	(0.013)	(0.011)
bad health	-0.20	-0.19	-0.17	-0.12	-0.11
	(0.12)	(0.12)	(0.10)	(0.11)	(0.087)
house (dummy)	-0.21*	-0.21***	-0.20*	-0.15*	-0.11
	(0.11)	(0.099)	(0.11)	(0.087)	(0.079)
mortgage(in $ 1000)	0.045***	0.046***	0.048***	0.032***	0.027***
	(0.014)	(0.013)	(0.013)	(0.011)	(0.0097)

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE B2.6. Estimation Results under the U.S. Individual Income Tax System,

PSID 1984

(Dependent Variable: Wife's annual hours of work in hour)

	Column 1	Column 2	Column 3	Column 4	Column 5
	Dual Additive Errors Model (1)	Nest Model (1) & (2)	Random Income Coefficient Model (2)	MENLI (3)	MENLI MU (4)
$\sigma_{\varepsilon 1}$	361.90***	0.0070***	0.0027***	844.08***	848.87***
	(18.93)	(0.0004)	(0.0005)	(141)	(174.09)
$\sigma_{\varepsilon 2}$				87.91***	35.96
				(31.7)	(17167.24)
σ_u	836.39***	1020.03***	1029.91***	1035.03***	1031.27***
	(29.76)	(37.09)	(37.61)	(38.11)	(39.21)
μ_1					0.0035
					(2.83)
μ_2					0.0021
					(1.33)
λ		0.497***			
		(0.00085)			
log-likelihood	-6726.9	-6696.83	-6697.86	-6692.65	-6692.26
uncompensated elasticity	0.20	0.21	0.21	0.25	0.25
compensated elasticity	0.26	0.26	0.26	0.30	0.30

TABLE B2.6. Continued

	Column 1	Column 2	Column 3	Column 4	Column 5
	Dual Additive Errors Model (1)	Nest Model (1) & (2)	Random Income Coefficient Model (2)	MENLI (3)	MENLI MU (4)
constant	1449.19***	1459.02***	1154.45***	1419.72***	1400.42***
	(8.24)	(19.51)	(21.84)	(26.19)	(142.64)
wage (in $)	62.35***	65.00***	65.17***	77.70***	78.46***
	(12.67)	(1.11)	(17.54)	(12.97)	(17.36)
nonlabor income (in $)	-0.013***	-0.011***	-0.012***	-0.011***	-0.011***
	(0.0019)	(0.0023)	(0.0028)	(0.0029)	(0.0029)
# kids in age 0-5	-336.89***	-349.04***	-321.19***	-291.33***	-296.62***
	(33.94)	(43.76)	(46.39)	(29.18)	(39.33)
# kids in age 6-18	-127.03***	-125.27***	-144.26***	-119.24***	-108.06***
	(23.03)	(22.41)	(3.80)	(24.77)	(16.46)
age	-10.97***	-15.44***	-2.56***	-17.38***	-17.29***
	(2.24)	(2.90)	(1.07)	(2.79)	(4.38)
education (in years)	26.14***	26.41***	17.17	27.60***	28.04***
	(7.04)	(7.97)	(10.42)	(6.57)	(12.05)
bad health	-209.46*	-292.93***	-187.80	-232.87***	-242.22*
	(107.55)	(128.29)	(128.94)	(6.1)	(138.75)
house (dummy)	-211.18***	-89.20***	-259.46***	-92.21***	-113.70***
	(36.97)	(11.56)	(86.38)	(34.57)	(56.58)
mortgage(in $ 1000)	30.48***	22.43***	45.91***	23.37***	26.36***
	(5.91)	(6.74)	(1.35)	(7.13)	(11.11)

TABLE B2.6. Continued

	Column 1	Column 2	Column 3	Column 4	Column 5
	Dual Additive Errors Model (1)	Nest Model (1) & (2)	Random Income Coefficient Model (2)	MENLI (3)	MENLI MU (4)

Notes:

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

In MENLI model or MENLI MU model:

(1) $\sigma_{\varepsilon 1}$ is the standard deviation of error term ε_1, which is the measurement error in husband labor income
(2) $\sigma_{\varepsilon 2}$ is the standard deviation of error term ε_2, which is the measurement error in asset income
(3) σ_u is the standard deviation of error term u, which is the measurement error in working hours
(4) μ_1 is the mean of error term μ_1
(5) μ_2 is the mean of error term μ_2

In dual additive errors model or Hausman random coefficient model:

(1) $\sigma_{\varepsilon 1}$ is the standard deviation of error term ε, which is the heterogeneity error in labor supply function
(2) σ_u is the standard deviation of error term u, which is the measurement error in working hours

ABLE B2.7. Estimation Results with the Convexified U.S. Individual Income Tax System, PSID 1984

(Dependent Variable: Wife's annual hours of work in hour)

	Column 1	Column 2	Column 3
	Dual Additive Errors Model (1)	Nest Model (1) & (2)	Random Income Coefficient Model (2)
constant	1100.95***	1274.12***	1282.37***
	(105.39)	(235.96)	(19.40)
wage (in $)	54.75***	55.55***	60.55***
	(12.51)	(17.45)	(16.57)
nonlabor income (in $)	-0.011***	-0.011***	-0.011***
	(0.0017)	(0.003)	(0.0029)
# kids in age 0-5	-341.35***	-345.26***	-351.01***
	(33.21)	(48.16)	(49.64)
# kids in age 6-18	-110.24***	-103.25***	-110.23***
	(27.95)	(29.22)	(30.57)
age	-11.05***	-14.04***	-13.92***
	(2.69)	(5.06)	(4.16)
education (in years)	47.32***	37.04***	36.81***
	(9.55)	(16.70)	(12.37)
bad health	-149.18	-206.79***	-216.78
	(105.97)	(59.64)	(135.38)
house (dummy)	-277.84***	-140.51	-163.92
	(124.65)	(122.24)	(120.68)
mortgage(in $ 1000)	34.97***	26.04*	27.63*
	(13.93)	(14.39)	(14.38)
$\sigma_{\varepsilon 1}$	57.35***	0.0038	0.002
	(14.31)	(0.0024)	(0.008)
$\sigma_{\varepsilon 2}$			
σ_u	1028.63***	1015.32***	1017.7***
	(38.67)	(39.71)	(38.66)
λ		0.497	
		(0.71)	
log-likelihood	-6689.55	-6691.12	-6691.22
uncompensated elasticity	0.17	0.18	0.19
compensated elasticity	0.22	0.23	0.24

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE B2.8. Estimation Results with the U.S. Individual Income Tax System, PSID 2001

(Dependent Variable: Wife's annual hours of work in hour)

	Nonconvexification of a Budget constraint			Convexification	
	Column 1	Column 2	Column 3	Column 4	Column 5
	Dual Additive Errors Model	Random Income Coefficient Model	MENLI	Dual Additive Errors Model	Random Income Coefficient Model
constant	1260.81***	1267.69***	1477.96***	1176.21**	1202.56
	(0.13)	(20.86)	(6.52)	(541.31)	(22685.2)
wage (in $)	21.48***	18.52***	17.013***	21.46***	21.77***
	(6.66)	(6.62)	(6.31)	(5.66)	(5.58)
nonlabor income	-0.0045***	-0.0065***	-0.0021**	-0.0023**	-0.0061***
	(0.00076)	(0.00097)	(0.00089)	(0.001)	(0.0011)
kids in age 0-5	-416.86***	-440.14***	-440.39***	-411.80***	-410.83***
	(1.36)	(49.80)	(71.91)	(66.45)	(72.10)
# children	-134.32***	-127.43***	-142.14***	-126.12***	-122.90***
	(23.39)	(24.74)	(27.22)	(26.65)	(26.37)
age	-4.11***	-1.90***	-6.63*	-0.60	0.13
	(1.40)	(0.65)	(3.50)	(2.29)	(4.44)
education (in	23.96***	28.62***	15.96	16.11	23.14
	(5.60)	(7.42)	(11.87)	(14.25)	(15.15)
bad health	-246.3**	-498.96***	-450.16***	-466.01***	-525.83***
	(96.96)	(56.46)	(100.86)	(99.21)	(95.40)
house (dummy)	349.74***	244.45***	221.67***	240.10***	234.61***
	(72.53)	(73.26)	(80.05)	(77.83)	(75.94)
mortgage(in $	0.0013	0.0041**	0.0035	0.00047	0.0053
	(0.0030)	(0.0017)	(0.0031)	(0.003)	(0.0032)
σ_{ε}	0.000065	0.0030***	42818.82***	0.055	0.0035
	(3058.12)	(0.00017)	(159.69)	(39028.05)	(1518840)
σ_{u}	928.05***	907.38***	921.47***	920.32***	890.16***
	(19.42)	(19.44)	(22.58)	(22.39)	(20.98)
log-likelihood	8347.13	8342.00	8345.78	8337.86	8329.84
uncompensated	0.13	0.11	0.10	0.13	0.13
compensated	0.17	0.18	0.12	0.15	0.19

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

APPENDIX C

This appendix provides the procedure used to impute wages for wives. TABLEs C1, C2, and C3 show results from the 5% samples IPUMS for 1980, 1990, and 2000, respectively. Results of imputing wives' wage rate in the NLSYW and NLSY79 are presented in TABLE C4 and C5, respectively.

I follow Triest's (1990) procedure to apply Heckman's (1979) technique to correct the sample selection bias. The second column shows results from male's wage regression model. I restrict male sample to those males who are married, healthy, non-self-employment and 18-65 years old. The fourth column in TABLE C1, C2, and C3 presents the results of the first step, which estimates a reduced form probit equation for wives' labor market participation. I use age and age square, years of education, spousal income, the wage rate of child care workers, indicator for paying mortgage, living in the big MSA and central city. Results of wives' wage imputation regression are shown in the sixth column of TABLEs C1, C2, and C3. Following the same empirical strategy, the second column in TABLE C4 and C5 presents the results of the first step, which estimates a reduced form probit equation for wives' labor market participation. I use age at the first birth and age square, years of education, spousal income, and indicator for marriage and race. Results of wives' wage imputation regression are shown in the fourth column of TABLEs C4 and C5.

TABLE C1. Imputation of Wives' Wage Rate (IPUMS 1980)

Wives' Wage Imputation with Male Model		Probit: Wives' Labor Force Participation		Wives' Wage Imputation Regression	
College Dummy	0.0772***	Age	0.0601***	College Dummy	0.0843***
	(38.87)		(116.91)		(32.19)
Age	0.00206***	Big MSA Dummy	0.0199***	Age	0.00993***
	(19.13)		(10.29)		(55.79)
Years of Education × Years of Education /10	0.00477***	Central City Dummy	0.0755***	Years of Education × Years of Education/10	0.0223***
	(22.96)		(30.66)		(74.89)
Age × Years of Education/10	0.00818***	Age × Age/100	-0.0811***	Age × Years of Education/10	-0.00255***
	(95.86)		(-130.83)		(-18.84)
Big MSA Dummy	0.135***	Years of Education	0.0620***	Big MSA Dummy	0.108***
	(149.31)		(191.85)		(98.01)
Central City Dummy	-0.0792***	Nonlabor Income ($10000)	-0.000204***	Central City Dummy	0.0142***
	(-67.69)		(-14.93)		(9.92)
		Child Care Cost	-0.0208***	Inverse Mills' Ratio	-0.370***
			(-22.82)		(-59.37)
		Mortgage Dummy	0.0790***		
			(42.66)		
Constant	2.131***	Constant	-1.640***	Constant	1.871***
	(611.36)		(-130.46)		(267.16)
R^2	0.1513	Log Likelihood	-1402418.7	R^2	0.137
# Observations	1703227	# Observations	2088458	# Observations	1025315

* significant at 5%; ** significant at 1%; *** significant at 0.1%

TABLE C2. Imputation of Wives' Wage Rate (IPUMS 1990)

Wives' Wage Imputation with Male Model		Probit: Wives' Labor Force Participation		Wives' Wage Imputation Regression	
College Dummy	0.00132 (0.67)	Age	0.107*** (195.44)	College Dummy	-0.00297 (-1.26)
Age	0.00985*** (79.02)	Big MSA Dummy	-0.00204 (-1.05)	Age	0.0193*** (102.35)
Years of Education × Years of Education/10	0.0273*** (113.86)	Central City Dummy	0.0237*** (8.09)	Years of Education × Years of Education/10	0.0442*** (141.43)
Age × Years of Education/10	0.00211*** (21.94)	Age × Age/100	-0.140*** (-217.74)	Age × Years of Education/10	-0.00915*** (-64.88)
Big MSA Dummy	0.169*** (193.57)	Years of Education	0.0784*** (225.52)	Big MSA Dummy	0.173*** (178.45)
Central City Dummy	-0.0842*** (-63.72)	Nonlabor Income ($10000)	-0.000675e*** (-34.73)	Central City Dummy	0.0341*** (22.82)
		Child Care Cost	-0.0162*** (-17.02)	Inverse Mills' Ratio	-0.422*** (-119.81)
		Mortgage Dummy	0.196*** (104.33)		
Constant	1.720*** (423.91)	Constant	-2.546*** (-191.00)	Constant	1.488*** (260.89)
R^2	0.2139	Log Likelihood	-1361228.2	R^2	0.2148
# Observations	1783183	# Observations	2172046	# Observations	1315153

* significant at 5%; ** significant at 1%; *** significant at 0.1%

TABLE C3. Imputation of Wives' Wage Rate (IPUMS 2000)

Wives' Wage Imputation with Male Model		Probit: Wives' Labor Force Participation		Wives' Wage Imputation Regression	
College Dummy	-0.00644**	Age	0.0843***	College Dummy	0.0313***
	(-3.14)		(145.20)		(14.08)
Age	0.0112***	Big MSA Dummy	-0.0974***	Age	0.0240***
	(79.38)		(-49.33)		(128.52)
Years of Education × Years of Education/10	0.0319***	Central City Dummy	-0.0549***	Years of Education × Years of Education/10	0.0398***
	(125.15)		(-18.60)		(135.26)
Age × Years of Education/10	-0.0000694	Age × Age/100	-0.117***	Age × Years of Education/10	-0.00918***
	(-0.66)		(-174.10)		(-68.76)
Big MSA Dummy	0.134***	Years of Education	0.0813***	Big MSA Dummy	0.189***
	(153.08)		(241.55)		(201.46)
Central City Dummy	-0.0699***	Nonlabor Income ($10000)	0.000141***	Central City Dummy	0.0460***
	(-51.48)		(14.56)		(31.33)
		Child Care Cost	-0.0260***	Inverse Mills' Ratio	-0.677***
			(-21.28)		(-163.42)
		Mortgage Dummy	0.238***		
			(120.82)		
Constant	1.696***	Constant	-1.676***	Constant	1.472***
	(386.25)		(-106.32)		(276.05)
R^2	0.2047	Log Likelihood	-1220083.6	R^2	0.2262
# Observations	1691056	# Observations	2175973	# Observations	1539688

* significant at 5%; ** significant at 1%; *** significant at 0.1%

TABLE C4. Imputation of Wives' Actual Wage Rate (NLSYW)

Probit: Wives' Labor Force Participation		Wives' Wage Imputation Regression	
Age at First Birth	0.558***	College Educated Dummy	-0.0907*
	(11.76)		(-1.99)
Age at First Birth × Age at First Birth/100	-0.888***	Age at First Birth	-0.00470
	(-9.93)		(-0.26)
Years of Education	0.0293*	Years of Education × Years of Education/10	-0.0102
	(2.42)		(-0.91)
Nonlabor Income($10000)	-0.0315*	Age at First Birth × Years of Education/10	0.0378**
	(-2.11)		(3.15)
Black Dummy	0.154*	Black Dummy	-0.0131
	(2.42)		(-0.47)
Hispanic Dummy	-0.297	Hispanic Dummy	-0.0465
	(-1.26)		(-0.43)
Marriage Dummy	-0.500***	Inverse Mills' Ratio	0.000849
	(-6.93)		(0.01)
Constant	-7.849***	Constant	0.343
	(-13.33)		(0.57)
Log Likelihood	-1813.5363	R^2	0.3075
# Observations	2949	# Observations	1515
		Including Year Dummy 1960-1993	

* significant at 5%; ** significant at 1%; *** significant at 0.1%

TABLE C5. Imputation of Wives' Actual Wage Rate (NLSY79)

Probit: Wives' Labor Force Participation		Wives' Wage Imputation Regression	
Age at First Birth	0.225*** (4.84)	College Educated Dummy	-0.132** (-2.64)
Age at First Birth × Age at First Birth/100	-0.311*** (-3.61)	Age at First Birth	0.0195 (1.14)
Years of Education	0.0664*** (5.49)	Years of Education × Years of Education/10	-0.00148 (-0.15)
Nonlabor Income($10000)	-0.0325*** (-3.54)	Age at First Birth × Years of Education/10	0.0404*** (4.07)
Black Dummy	0.0508 (0.68)	Black Dummy	-0.0608* (-2.01)
Hispanic Dummy	-0.0387 (-0.58)	Hispanic Dummy	0.00575 (0.19)
Marriage Dummy	0.00822 (0.11)	Inverse Mills' Ratio	1.080*** (5.57)
Constant	-3.920*** (-6.50)	Constant	-0.739 (-1.05)
Log Likelihood	-1594.2002	R^2	0.4141
# Observations	2704	# Observations	1830
		Including Year Dummy 1975-2005	

* significant at 5%; ** significant at 1%; *** significant at 0.1%

APPENDIX D

This appendix provides the procedure used to impute wages for wives. TABLE D1 shows results from the PSID of 1984. Results of imputing wives' wage rate in the PSID of 2001 are presented in TABLE D2. I follow Triest's (1990) procedure to apply Heckman's (1979) technique to correct the sample selection bias. The second column in TABLE D1 and D2 presents the results of the first step, which estimates a reduced form probit equation for wives' labor market participation. Different from Triest (1990), I use the number of education years, instead of a dummy variable. And a variable is equal to individuals' age minus 35 for women less than 35 and equal to age minus 25 for those over 35. Results of wives' wage imputation regression are shown in the fourth column of TABLEs D1 and D2.

TABLE D1. Imputation of Wives' Wage Rates (PSID 1984)

Reduced Form Probit: Wives' Labor Force Participation		Wives' Wage Imputation Regression	
Constant	-0.43	Constant	0.67
	(0.45)		(0.43)
# kids in age 0-5	-0.33***	College education	-0.11
	(0.071)		(0.098)
Family Size	-0.11***	Age - 35	0.0024
	(0.042)		(0.0073)
Age-35	0.031***	Age - 45	-0.010
	(0.016)		(0.018)
Age-45	-0.060***	Education ^{2}/10	0.024
	(0.025)		(0.015)
Education (in years)	0.12***	(Education * Age)/10	0.014
	(0.02)		(0.011)
Nonlabor income (in $1)	-.000018***	Bad Health	0.0022
	(2.82e-06)		(0.089)
Bad Health	-0.21	Inverse Mills' ratio	0.11
	(0.18)		(0.11)
Log likelihood	-552.16	R^2	0.15
# Observations	1050	# Observations	771

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE D2. Imputation of Wives' Wage Rates (PSID 2001)

Reduced Form Probit: Wives' Labor Force Participation		Wives' Wage Imputation Regression	
Constant	0.31	Constant	2.35***
	(0.47)		(0.40)
kids in age 0-5 (dummy)	-.60***	College education	-0.054
	(0.13)		(0.061)
Family Size	-0.075*	Age - 35	-0.005
	(0.044)		(0.007)
Age-35	0.002	Age - 45	0.034*
	(0.018)		(0 .018)
Age-45	-0.008	Education ^{2}/10	0.063***
	(0.027)		(0.015)
Education (in years)	0.097***	(Education * Age)/10	-0.012
	(0.024)		(0.010)
Nonlabor income (in $1)	-2.37e-06***	Bad Health	-0.014
	(7.31e-07)		(0.083)
Bad Health	-0.58	Inverse Mills' ratio	-0.098
	(0.16)		(0.15)
Log likelihood	-476.66	R^2	0.15
# Observations	1171	# Observations	985

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

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