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Abstract

The increase in female employment and participation rates is one of the most dramatic economic changes to have taken place during the last century. However, while the employment rate of married women more than doubled during the last fifty years, that of unmarried women remained almost constant. In order to empirically analyze these trends we divide the paper into two parts: In the first, we empirically estimate a traditional female dynamic labor supply model using an extended version of Eckstein and Wolpin (1989) in order to compare the various explanations in the literature for the observed trends. The main finding is that the rise in education levels accounts for about one-third of the increase in female employment while about 40 percent remains unexplained by observed household characteristics. We show that this unexplained portion can be empirically attributed to changes in preferences or the costs of childrearing and household maintenance. In the second part, we formulate and estimate a new framework for the couple intra-family game that is then used to analyze the household dynamic labor supply. We find that female labor supply may have increased significantly due to a change in the form of the household game**.**

Keywords: Dynamic Discrete Choice, Female Employment, Accounting, Household Game

JEL: E24, J2, J3

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1 Introduction

The increase in female employment and participation rates is one of the most dramatic changes to have taken place during the last century, with both social and economic implications. One way of measuring the importance of this change is to calculate the contribution of female employment to the growth in per capita GDP in the US, which increased by an annual rate of 2.12 percent from 1964 to 2007 (Figure 1.1). Using a simple Solow-style calculation, it can be shown that if the labor input of women had remained at its 1964 level, the level of per capita GDP in 2007 would have been 40 percent lower.[3] Using the same logic, if the relative quality of female work hours had remained unchanged, the increase in the quantity of female work hours would have contributed 17 percent to the level of per capita GDP in 2007. Moreover, Figure 1.1 indicates that until about 1980 the growth in per capita GDP is almost entirely due to the increase in the quantity of female labor input and only subsequently does its quality have an effect.[4]

Are all women working more? While the employment rate of *married* women more than doubled during the last fifty years, from 30 percent in 1962 to 62 percent in 2007 (Figure 1.2), the employment rate among unmarried women (single, divorced and widowed) remained almost constant at about 70 percent.[5] This result implies that changes in family behaviour must be taken into account in order to understand female employment trends. In this paper, we empirically implement the traditional female dynamic labor supply model (Becker, 1974, 1981; Heckman, 1974; Weiss and Gronau, 1981; and Eckstein and Wolpin, 1989). In addition, we formulate and then estimate a new framework for the couple intra-family game that is then used to analyze the household dynamic labor supply (Lifshitz, 2004).

The literature on employment of married women is voluminous and cannot be fully reviewed here.[6] Instead, we will categorize the literature according to the five main trends in observed female characteristics that are claimed to be important in explaining employment patterns: a) the increase in women's education (schooling); b) the increase in women's earnings as well as the narrowing of the gender wage gap; c) the decrease in women's fertility; d) the decrease in the marriage rate and the increase in the divorce rate; and e) "other" factors that are more difficult to measure and which include: technological progress in household production, the decrease in the cost of childrearing and changes in

[3] See Appendix A for the detailed calculations using the March CPS data from 1964 to 2007 (see Appendix B.1).

[4] It is commonly claimed that this is an overestimate of women's contribution since it ignores their home production before they entered the workforce. It should be noted that there has been significant technological change in home production (Greenwood et al., 2004) and as a result both men and women continue to work at home. It is not clear that the value added in home production that is not measured by GDP has been declining relative to GDP over the last half-century.

[5] This fact is well known and documented by Barton, Layard and Zabalza (1980), Coleman and Pencavel (1993) and Mincer (1993).

[6] Blundell and MaCurdy (2000) provide an excellent survey.

social norms. In section 2 we present the main facts to be explained and a survey of the relevant literature.

To what extent does each of these five trends explain the growth in female employment? To answer this question, we use a quantitative model for female employment that embeds all the potential explanations and provides a good fit to the cross-section and time series aggregate data.[7] Our starting point is the Eckstein and Wolpin (1989) (hereafter: EW) dynamic stochastic discrete choice labor supply model which is modified slightly for our needs.[8] In particular, although our model's (only) endogenous variable is employment,[9] as in EW, we set the first period of optimization at age 23 when almost all individuals have completed their education. We take the state of the individual at age 22, i.e. schooling, marital status, employment, wage, fertility, husband's employment and wages, as exogenously given. From age 23 to 65 the evolution of these state variables follows a simple state-dependent discrete stochastic dynamic process and the wages of women and men (husbands) follow standard Mincer/Ben-Porath functions. Given this environment, a woman solves a dynamic programming (DP) model whereby she maximizes the expected present value of utility by choosing whether or not to work, subject to the budget constraint.

We estimate the dynamic model using the Simulated Method of Moments (SMM) and repeated cross-section CPS data for women born during the period 1953-57, who we define as the "1955 cohort". The estimated parameters are qualitatively similar to the results in EW and the model provides a good fit to the female employment rates of this cohort (Figure 3.1).

How much of the change in female employment rates across cohorts can be accounted for by each of the explanations proposed in the literature? We attempt to answer this question using the estimated dynamic labor supply model for the 1955 cohort. This involves sequentially and additively changing the dynamic distributions of schooling, wages (of both women and men), fertility and marital status to fit this specific cohort and then using the estimated parameters of the 1955 cohort's household preferences and costs to simulate predicted female employment for all other cohorts (i.e. 1925 to 1975).

For example, the employment rate is 0.65 for women aged 28-32 in the 1955 cohort and 0.49 for the 1945 cohort. When we impose the schooling distribution and other initial state variables of the 1945 cohort, but leave unchanged the other processes and parameters of the 1955 cohort, we find that the

[7] The March CPS annual survey is the main data source generally used for this purpose and is the one used here.

[8] The first to implement a dynamic stochastic model of female decision making was Wolpin (1984). Extensions of the EW paper include: Van der Klaauw (1996), Francesconi (2002), Keane and Wolpin (2006) and Ge (2008). The gain from using a structural dynamic model as opposed to a reduced form model is well-explained in EW, Keane and Wolpin (2007) and in Section 3.

[9] Keane and Wolpin (2007) allowed for the individual to choose schooling, marriage and children in addition to employment. We focus our attention on the change in employment and therefore in order to keep the accounting analysis manageable, we allow only employment to be a choice variable with other outcomes being the result of state-dependent dynamic stochastic processes. It is straightforward to extend the model presented here by making the other main outcomes dependent on endogenous choices. The potential gains and costs of doing so are discussed in Section 3.

predicted employment rate for women aged 28-32 is reduced by 0.02 (from 0.65 to 0.63; Table 3.2). Thus, schooling can be said to explain 0.02 of the 0.16 difference (i.e. 13 percent). We then proceed in a similar manner by sequentially adding the wages of women and men, fertility rates and finally marital status for the 1945 cohort. What is not explained by these four observed variables, (i.e. schooling, wages, fertility and marital status), is associated with "other" explanations. We do the same for all cohorts from 1925 to 1975 at five-year intervals.[10]

The results of this accounting exercise can be summarised as follows: Of the observable factors, schooling makes the most important contribution and accounts for more than one-third of the overall increase in female employment. The contribution of wages (of both women and men) to explaining female employment is large (about 20 percent on average) and varies across cohorts. Thus, its contribution is particularly large, both in terms of the change in employment rate and the proportion of its contribution, for the cohorts of 1935, 1930 and 1925 and particularly small for the most recent cohorts. The contribution of fertility in explaining female employment is very small on average and far less important than schooling and wages. Nonetheless, it does have a significant effect on the 1935 to 1950 cohorts. Finally, the contribution of marital status is only about one percent on average and zero for later cohorts. This is a surprising result since the employment rates of unmarried women are much higher than those of married ones and the proportion of unmarried women has increased during the sample period. Notwithstanding this result, the main results are robust to the ordering of the observable factors.

The remaining unexplained portion of female employment amounts to about 38 percent on average and is of a large magnitude for almost all cohorts and age groups, except for the most recent ones. It is important to note that the unexplained portion is always positive or zero and therefore using only the observable factors will always under-predict the change in female employment.

We offer two empirical explanations for the large unexplained portion: First, we allow the model to estimate the utility/cost of home production and raising children aged 0-5 (for working mothers) for each cohort separately. The additional two free parameters enable us to produce a good fit to the female employment rate by age for all cohorts. For cohorts born before 1955, the utility/cost of home production is somewhere in the range of $4.50 to $5 per hour higher than for the 1955 cohort and the utility/cost of raising children aged 0-5 is $3 per hour higher. For the 1960 to 1975 cohorts, only the cost of raising young children is estimated to be lower (by about one dollar per hour) than for the 1955 cohort. These results are relevant in evaluating the effect of technological change in home production

[10] Note that the observations of women born during the entire five-year interval are included in the cohort in order to have enough observations for the analysis.

(Greenwood et al., 2004) and the reduction in the cost of childrearing (Attanasio, Low and Sanchez-Marcos, 2008 and Albanesi and Olivetti, 2006).

Second, we examine the hypothesis of changing social norms in Section 4, which is related to the couple's intra-family employment decision. In particular, the model describes two alternative rules for household interactions that are the result of different social norms and determine the household's labor supply. The decision of the first type of household, which we call "Classical" (C), are determined by an intra-family game in which the husband plays the role of a Stackelberg leader who takes the first move in each period while the wife relates to the husband's move as given. The husband and wife's decisions in the other type of household, which we call "Modern" (M), are simultaneous and symmetric. The main goal of the analysis is to show that these two definitions can lead to significantly different quantitative and qualitative results for female (and potentially male) labor supply. In the estimation, we relate to the type of household as unobserved heterogeneity and the results provide a way of quantifying the potential increase in female employment due to a change in the rules of the game, i.e. in social norms. This analysis also demonstrates the benefits in using dynamic stochastic games in quantitative studies of households (Flinn and Brown, 2006; Flinn and DelBoca, 2009; and Tartari, 2008).

The results of estimating the model using PSID data and SMM show that the labor supply of women in M households is predicted to exceed that of women in C households by 10 percent, though the labor supply of men in each type of household is about the same. Since men have higher job-offer rates and higher potential wages, they have greater choice in employment in both types of household. However, given the simultaneous choices in M households and the higher level of risk aversion among women, more M women choose to participate in the workforce and they work more than their counterparts in C households.

The model provides a framework for the analysis of married female labor supply and, more generally, for the economics of families (Chiappori, 1997).[11] In particular, the modeling of households using a game involving more than one person (i.e. a wife and husband), in which each maximizes his own lifetime utility but where the constraints are common, is a new and promising setting for analyzing the household economic outcomes of dynamic labor supply. Our analysis emphasizes the potential channels through which household games can produce new and novel insights into the labor supply of both women and men. The fact that married women have been the source of growth in female labor supply (Figure 1.2) indicates that interaction within the family should be able to shed light on the main trends in female labor supply.

[11] Household games have been analyzed by Brown and Manser (1980) and McElroy and Horney (1981).

The rest of the paper is organized as follows: The next section describes the main facts used in support of the various explanations of female employment trends and the literature that has proposed these explanations. Section 3 presents the standard dynamic female labor supply model and the estimation results using the CPS data. It also presents the accounting analysis that attempts to quantify the sources of growth in female employment across cohorts. Couple labor supply is analyzed and estimated in Section 4 based on alternative household games (social norms). Section 5 concludes.

2 Main Facts and the Literature

From 1962 to 2007, the employment rate for married women increased by more than 32 percent while the rate among unmarried women (single, divorced and widowed) remained almost constant at about 70 percent. This is one of the main trends in female labor supply that requires explanation (Figure 1.2). As mentioned above, the relevant literature can be divided according to five possible explanations (four observable and "others"): a) the increase in schooling; b) the increase in wages of women and men and the wage ratio between them; c) the decline in women's fertility; d) the decrease in the marriage rate and the increase in the divorce rate; and e) "other" explanations that are more difficult to measure, such as technological progress in household production, the decreased cost of childrearing and changes in social norms.

In what follows, we provide a more in-depth treatment, including a survey of the relevant literature, of the first four observable explanations for married women, while also mentioning their differing impact on married and unmarried women.

Schooling

We measure schooling according to five levels of education: high school dropouts (HSD), high school graduates (HSG), some college education (SC), college graduates (CG) and post-college studies (PC). The employment rate of married women increased from 1964 to 2007 for all these categories (Figure 2.1). The increase was largest for HSG (27 percent) and SC (32 percent) and relatively small for HSD and PC. Moreover, the level of schooling among married women has been increasing throughout the 43-year sample period (Figure 2.2): among the SC group it increased from 11 percent to 28 percent, among the CG group from 6 percent to 22 percent and among the PC group from 0.6 percent to 11 percent. At the same time, the employment rate for the lower education levels has decreased substantially. It should be noted that very similar trends have been observed for unmarried women while for men a similar pattern began earlier and reached a stable distribution by the turn of the century (see also www.tau.ac.il/~eckstein/FLS/FLS_index.html and Eckstein and Nagypl, 2005).

Almost every published paper on female labor supply since Becker (1974) has emphasized the importance of schooling in explaining the observed increase in employment and participation of women. Most papers have based this result on the cross-sectional differences in employment rates by schooling (Figure 2.1) while only a few have empirically analyzed the joint endogenous decisions for employment and schooling. Recent work using DP models of employment and schooling and lifecycle panel data (Keane and Wolpin, 1997, 2006; Eckstein and Wolpin 1999; and Ge, 2008) found that the initial characteristics of the individual (at age 16 or 18) are the main factors that determine the schooling choice.[12] This is also how schooling choice is explained in Heckman and Cameron (1998, 2001) and Cameron and Taber (2004). In this paper, we take as given the level of schooling at age 22 for both women and men. However, it is not clear why increased levels of schooling among women have increased the employment rate of married women while having no impact on unmarried women. Furthermore, why has the employment rate among men declined when the trends in their levels of schooling have followed the same pattern as those of women. These facts indicate that it is the dramatic increase in the couple's level of schooling that primarily affected married female labor supply and that is the subject of this paper.

Earnings

Unconditional mean wages for men and women have increased continuously from 1962 to 2007 (Figure 2.3). However, the wage ratio of women to men slightly decreased from 1962 to 1980 and subsequently increased sharply for almost three decades, as the gender wage gap narrowed significantly. Given the widely-recognized large and positive impact of schooling on earnings, it is clear that the increase in schooling has been an important factor in this trend. Furthermore, although economic growth affects average wages proportionally, the impact has not been uniform for all occupations and the growth in services has contributed to the narrowing of the gender wage gap (Lee and Wolpin, 2006).

The impact of increased earnings on female employment is certainly an important aspect of all female labor supply models (Heckman and McCurdy, 1980).[13] The narrowing of the gender gap as one of the main factors in increasing married female labor supply has been recognized in the literature (Goldin, 1990, 1991 and Jones, Manuelli and McGrattan, 2003). Other studies have emphasized the different occupational distributions of men and women and the importance of human capital in those occupations (Galor and Weil, 1996 and Lee and Wolpin, 2008). However, Blau and Kahn (2000) have pointed out that the wage gap remained almost constant during the period up until 1980, which was characterized by a substantial increase in female labor force participation (Figure 2.3). Hence, unless

[12] These studies used the NLSY79 panel survey which consists of the cohort born during the period 1960-5.
[13] See also Altug and Miller (1990, 1998), Hotz and Miller (1993) and Pencavel (1998).

labor supply elasticity for women is particularly high, the narrowing of the gender gap can only be a small part of the explanation. Recently, Gayle and Golan (2007) showed that a decrease in statistical discrimination and increases in productivity account for a large percentage of the decline in the gender earnings gap, which jointly provide some of the explanation of the increase in the female employment rate.

Wages have been growing proportionately with GNP for many decades; however, labor supply should have remained constant since the marginal utility of leisure relative to that of consumption remains constant on a balanced growth path. Hence, it is the change in the gender wage gap within the married household that may account for the decrease in male employment and the increase in the employment of married women. In Section 4, we estimate the impact of this factor.

Fertility

The mean number of children under 18 decreased from 1.6 to 1.0 per married female by 1985, but remained unchanged subsequently (Figure 2.4). Convergence occurred earlier for children under six and this is clearly reflected in the behaviour of cohorts born before the post-baby-boomers (who were born in 1955 and later). Gronau (1973) showed the effect of young children on their mother's labor supply and argued that it will vary by level of education; however, he could not find support for his hypothesis in the data. Heckman (1974) demonstrated the same effect and pointed out that it is much stronger for children under six. Rosensweig and Wolpin (1980) argued that the fertility decision is endogenous and therefore cannot explain the female participation rate. Heckman and Willis (1977) pointed out that the growth in female employment had primarily occurred among married women with children. They focused on the need for a dynamic labor supply model and the use of panel data to identify the unobserved heterogeneity component from the "true" time dependence in labor supply. They provided the starting point for Eckstein and Wolpin (1989) whose work is in turn the basis for the present study.[14]

The impacts of fertility and exogenous cohort change due to other factors can be separated even if one assumes that fertility is a dynamic process that depends on women's state variables (van der Klaauw, 1996). We follow this approach in differentiating between fertility changes and other potential explanations that are reflected in the trends of female lifecycle employment rates for different cohorts.

Marriage and divorce

Between 1962 and 1990, the marriage rate for women decreased from 80 percent to about 60 percent and the divorce rate increased from 3.5 percent to 13 percent and remained at these levels until 2007

[14] Additional research on the interaction of fertility and female labor supply includes: Hotz and Miller (1988), Schultz (1990), Browning (1992), Mira (2007) and Jones, Schoonbroodt and Tertilt (2008).

(Figure 2.5). Weiss and Willis (1985) claimed that the failure of divorced fathers to comply with court-mandated child support awards caused divorced mothers to work more in order to support their children. As a result, the increase in the probability of divorce increased married women's incentive to work and thus accumulate experience. Later on, Weiss and Willis (1997) showed that it is incorrect to treat marital status as being exogenous to the employment decision since an unexpected increase in the husband's earning capacity reduces the divorce hazard, while an unexpected increase in the wife's earning capacity raises the divorce hazard.

Cross-sectional variations make it possible to quantify the impact of the increase in *schooling,* a higher female-to-male *earnings* ratio, the decease in *fertility* and *marriage* and the increase in *divorce* on female employment rates. However, these changes affect the aggregate data through their impact on the behaviour (decisions) of new cohorts over their lifetime and the exogenous changes that influence the distributions of new cohorts according to these observed characteristics. The question to be answered is whether these changes can explain the entire increase in married female employment by cohort.

Female employment by cohort: "other" explanations

The dramatic change in employment rates of married women by age for the period 1962 to 2007 can be seen in Figure 2.6 for the 1925 to 1975 cohorts. For simplicity and in order to have a large enough sample for each cohort, we define the women born from 1953 to 1957, for example, as the "1955 cohort" and similarly for the entire CPS data set. Figure 2.6 clearly shows that from the early cohorts to the baby boomers of 1945, married female employment increased for all ages. The 1965 and 1975 cohorts show almost the same female employment by age although during the intervening years female employment increased among younger women (Buttet and Schoonbroodt, 2005). The changes by cohort are attributed in the literature to the observables mentioned above, as well as to changes in social norms, technological progress and other factors.[15]

Goldin (1991) investigated the effects of WWII on women's labor force participation and found that almost half of the women who entered the labor market during the war years were still working in 1950. She argued that the attitudes toward working women may have changed considerably during this period. Fernandez, Fogli and Olivetti (2004) found evidence suggesting that a man is more likely to have a working wife if his own mother worked. And more recently, Fernandez (2007) investigated the role of culture as learning in explaining changes in female employment. In her model, individuals hold heterogeneous beliefs regarding the relative long-run payoffs for working women, which evolve

[15] Mulligan and Rubinstein (2004) show that the estimated Heckman selection coefficient for the labor supply of women changed from negative to positive between cohorts.

rationally via an intergenerational learning process. These papers are part of a larger trend that emphasizes the long-run impact of changing social norms.

A few recent papers have argued that the cost of childrearing has decreased during the last fifty years, thus making it easier for women with children (especially young ones) to enter the labor market. Albanesi and Olivetti (2007) claimed that until the early part of the 20th century, women spent more than 60 percent of their prime years either pregnant or nursing. Since then, improved medical knowledge, advances in obstetric practices and the introduction of infant formula reduced the time-cost associated with raising children and led to an increase in participation by married women with children between 1920 and 1960. Attanasio, Low and Sanchez-Marcos (2008) studied the lifecycle labor supply of three cohorts of American women born in the 1930s, 1940s and 1950s. They found that the combination of a reduction in the cost of children alongside a narrowing of the wage-gender gap is needed in order to explain the increase in the labor supply of mothers. These factors are clearly related to the enormous technological progress in household production, which is the prime reason cited by Greenwood et al. (2002) and Greenwood and Seshadri (2004). Their main argument is that the introduction of labor-saving appliances associated with technological progress in the home sector may have enabled more women to enter the workforce. They also argue that the time spent on housework fell from 58 hours per week in 1900 to just 18 hours in 1975, thus making it much easier for married women to enter the labor force.

Lee and Wolpin (2005, 2006) argue that the growth in the service sector between 1950 and 2000 increased the demand for female workers. The proportion of total employment in this sector grew from 57 to 75 percent during this period. In a more recent paper, Lee and Wolpin (2008) provided an accounting analysis for the growth in female employment. Their goal was to quantitatively assess the relative importance of demand and supply factors (such as, for example, changes in skill-biased technical progress, changes in fertility rates, etc.) in accounting for wage and employment changes during the 1968-2000 period.

This study focuses on quantifying the effects of schooling, wages, fertility and marital status in explaining the growth in female employment. To do so requires an estimable model that includes these four observed variables as potential explanations for female employment and closely fits the repeated cross-sectional CPS data. These four variables are easily measured using the CPS data and can be determined for each observation. The "other" explanations are more difficult to measure for each family or individual observation. Therefore, we modify the EW model for our purposes and then simulate it in order to quantify the effects of the variables within a unified and internally consistent framework. The most interesting task will be to determine the importance of each observed variable and the remainder that is left to “other" explanations.

3 A Dynamic Female Employment Model

In this section, we formulate and estimate a simple dynamic model of female employment based on EW.[16] A woman maximizes the present value of her utility over a finite horizon by choosing whether or not to work $(p_t = 1)$. Education is predetermined and the supply of labor starts when the female completes her schooling. Marital status and number of children are discrete random states given exogenously that depend on her choice of employment and other state variables that are described below.

A married female is indicated by $M_t = 1$ and a single or divorced woman by $M_t = 0$. Number of children is given by $N_t = N_{t-1} + n_t$, where the event of birth, $n_t = 1$, is also a given random event that depends on employment and other states. The objective of each female is to choose p_t from period *t* (the year she completes her education) until retirement, in order to maximize:

$$E_t\left[\sum_{k=0}^{T-t}\delta^j U\left(p_{t+k}, x_{t+k}, K_{t+k-1}, N_{t+k,j}\,(j=1..J), S, M_{t+k}\right)\right] \tag{3.1}$$

where x_t is consumption, K_{t-1} is the number of periods that the woman has worked such that $K_t = K_{t-1} + p_t$, N_{tj} is the number of children in year *t* of age group *j*, *S* is the predetermined level of schooling, δ is the subjective discount factor and T is the length of the decision horizon.

The female budget constraint is given by:

$$((1-\alpha)(1-M_t)+\alpha)(y_t^w p_t + y_t^h M_t) = x_t + \sum_{j=1}^{J}(c_j + c_{jm}(1-M_t))N_{tj} + (b + b_m(1-M_t))p_t, \tag{3.2}$$

where α is a fraction that denotes the share of the woman in household income when she is married, y_t^h denotes the husband's earnings and y_t^w denotes the female's earnings. $c_j + c_{jm}(1-M_t)$ is the cost in goods per child of age *j* and $b + b_m(1-M_t)$ is an additional cost for maintaining the household if the woman works. These costs are expected to be higher for a working woman if she is unmarried (c_{jm},, $b_m>0$). Following the classical approach (Becker, 1974 and Heckman, 1974), we assume that the husband's employment is taken as predetermined for the female employment decision. Equation (2) implies that neither saving nor borrowing is feasible.[17]

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[16] Hyslop (1999) and DelBoca and Sauer (2009) approximate the DP model by using reduced-form estimated equations. Their approach misses the main mechanism of the DP model implemented here, which is forward-looking and includes cross-equation restrictions. See also the discussion at the end of this subsection.

[17] This assumption is extreme though standard in the modeling of dynamic labor supply. When utility, as specified in (1), is linear and additive in consumption, the problem is reduced to that of wealth maximization modified by the psychic value of work and children, as is basically assumed here.

We also adopt the standard Mincer/Ben-Porath earning function,

$$\ln y_t^w = \beta_0 + \beta_1 K_{t-1} + \beta_2 K_{t-1}^2 + \beta_3 S + \beta_4 t + \varepsilon_t, \tag{3.3}$$

where *t* is a time trend that captures aggregate growth, ε_t is the standard zero-mean, finite-variance and serially independent error that is uncorrelated with *K* and *S*. The number of children of age group *j* evolves according to:

$$N_{tj} = N_{t-1,j} + n_{tj} - d_{tj,} \tag{3.4}$$

where $n_{tj} = 1$ if a child enters the age group *j* at *t* and zero otherwise and $d_{tj} = 1$ if a child leaves the age group *j* at *t* and zero otherwise.

Following EW, we adopt the following per period specification of utility,

$$U_t = \alpha_1 p_t + x_t + \alpha_2 p_t x_t + \alpha_3 p_t K_{t-1} + \sum_{j=1}^{J} \alpha_{4j} N_{tj} p_t + \alpha_5 p_t S + f(N_{tj}) \tag{3.5}$$

where $f(N_{tj}) = \gamma_0 N_{tj} - (\gamma_1 + \gamma_2 S_{tj}) N_{tj}^2$ is a specific functional form that is meant to capture the way in which children enter the utility function. Notice that the utility function is not assumed to be inter-temporally separable $(\alpha_3 \neq 0)$. $\alpha_3 < 0$ reflects diminishing marginal utility of accumulated working periods and is consistent with endogenous retirement. In contrast, $\alpha_3 > 0$ can be interpreted as habit persistence in accumulating working periods.

The dynamic programming solution to the optimization problem is obtained by a process of backwards recursion and has become standard in the dynamic discrete choice literature (see EW). Let $V_t(K_{t-1}, \varepsilon_t, \Omega_t)$ be the maximum expected discounted lifetime utility given K_{t-1} periods of experience, a wage draw of ε_t and all other relevant components of the state space, Ω_t. The state space $\Omega_t = [K_{t-1}, S_t, p_{t-1}, \bar{y}_t^h, N_{tj}]$ includes work experience, schooling, past employment, a discrete approximation of the husband's income given by $\bar{y}_t^h$ and number of children by age.[18] Following the standard dynamic programming procedure, the value function is defined as:

$$V_t(K_{t-1}, \varepsilon_t, \Omega_t) = \max\left[V^1{}_t(K_{t-1}, \varepsilon_t, \Omega_t), V^0{}_t(K_{t-1}, \Omega_t)\right], \tag{3.6}$$

where $V_t^1(\cdot)$ and $V_t^0(\cdot)$ represent maximum expected discounted utility when the female is working at time *t* $(p_t = 1)$ and when she isn't $(p_t = 0)$, respectively. That is,

$$\begin{aligned} V_t^1(\Omega_t, \varepsilon_t, t) &= U_t^1(K_{t-1}, \varepsilon_t, \Omega_t) + \beta \cdot E\left(V_{t+1}(K_t, \varepsilon_{t+1}, \Omega_{t+1}) \middle| \Omega_t, p_t = 1\right) \\ V_t^0(\Omega_t, t) &= U_t^0(K_{t-1}, \Omega_t) + \beta \cdot E\left(V_{t+1}(K_t, \varepsilon_{t+1}, \Omega_{t+1}) \middle| \Omega_t, p_t = 0\right) \end{aligned} \tag{3.7}$$

[18] The husband's income is not directly observed and we use an approximation based on a random draw from the data to determine the husband's experience, education and employment. This discrete prediction is fully explained in Appendix B.2

where current utility is derived from the insertion of the budget constraint (2) into (5) such that,[19]

(3.8)

$$U^1_t\left(K_{t-1},\varepsilon_t,\Omega_t\right) = \alpha_1 + \left(1+\alpha_2\right)\left(((1-\alpha)(1-M_t)+\alpha)\left(\exp\left\{\beta_0+\beta_1 K_{t-1}+\beta_2 K^2{}_{t-1}+\beta_3 S+\beta_4 t+\varepsilon_t\right\}+\bar{y}^h_t M_t\right)-\sum_{j=1}^{J}(c_j+c_{jm}M_t)N_{tj}\right)$$
$$-(b+b_m M_t)+\alpha_3 K_{t-1}+\sum_{j=1}^{J}\alpha_{4j}N_{tj}+\alpha_5 S+f\left(N_{tj}\right)$$

and,

$$U^0{}_t\left(K_{t-1},\Omega_t\right)=\alpha\bar{y}^h_t-\sum_{j=1}^{J}c_j N_{tj}+f\left(N_{tj}\right).$$

In each period, the woman can receive at most one job offer. The probability of receiving a job offer at time t depends on previous-period employment $\left(p_{t-1}\right)$, as well as the woman's schooling and accumulated work experience. We adopt the following logistic form for the job-offer probability,

$$\Pr ob_t = \frac{\exp\left(\rho_0+\rho_1\cdot S+\rho_2\cdot K_{t-1}+\rho_3\cdot K^2_{t-1}+\rho_4\cdot p_{t-1}\right)}{1+\exp\left(\rho_0+\rho_1\cdot S+\rho_2\cdot K_{t-1}+\rho_3\cdot K^2_{t-1}+\rho_4\cdot p_{t-1}\right)}. \qquad (3.9)$$

In addition, a woman may be fired in each period and become unemployed with a probability that is inversely related to her accumulated experience and education.

We supplement the model with several given dynamic probabilities for demographic characteristics, whose expectations are potentially important in determining female labor supply. The probability of having another child is a function of the female's employment state in the previous period, age, education,[20] martial status and the current number of children (see van der Klaauw, 1996) and is given by:

$$\Pr(N_t=N_{t-1}+1)=\Phi\left(\lambda_0+\lambda_1\cdot AGE_t+\lambda_2\cdot\left(AGE_t\right)^2+\lambda_3\cdot S+\lambda_4 p_{t-1}+\lambda_5\cdot N_{t-1}+\lambda_6\cdot N^2_{t-1}+\lambda_7 M_t\right) \qquad (3.10)$$

where $\Phi(\cdot)$ is the standard normal distribution function. The probability of getting married is a function of the woman's age, education and whether she was divorced in the previous period. Thus:

$$Pr(M_t=1\,|\,M_{t-1}=0)=\Phi\left(\varsigma_0+\varsigma_1 AGE+\varsigma_2 AGE^2+\varsigma_3 D_{t-1}+\varsigma_4 S\right) \qquad (3.11)$$

The probability of divorce is a function of the duration of marriage (*MT)*, number of children, the husband's wage, the female state in the labor force and education. Thus,

$$\Pr(M_t=0\,|\,M_{t-1}=1)=\Phi\left(\xi_0+\xi_1\cdot MT+\xi_2\cdot MT^2+\xi_3\cdot N_t+\xi_4\cdot S+\xi_5\cdot p_t+\xi_6 y^h_t\right) \qquad (3.12)$$

The model is solved backwards from the terminal period T (age 65) assuming that $V_T\left(\Omega_T,T+1\right)=0$.

[19] Note that α_1 and b, as well as the α_4 's and c_j 's, are not separately identified due to the linearity of preferences.
[20] s = 1 if the female is HSD, s = 2 if the female is HSG, s = 3 if the female is SC, s = 4 if the female is CG and s = 5 if the female is PC.

Discussion: Choosing the Model

Three issues arise in the choice of model and its estimation for our accounting exercise: the gain from using a structural optimization model rather than an ad-hoc standard reduced form; the gain from the dynamic forward--looking structure of the model; and the use of only employment as a choice variable.

First, in using a reduced form the simulated solution of the dynamic programming of equations (3.7) and (3.8) would be replaced by a probit equation of employment. The main problem with this approach is that it ignores the cross-equation restrictions that reflect the simultaneous impact of the state variables (education, wages, marriage, divorce and children; equations 3.10-3.12) on the predicted employment decision. These cross-equation restrictions provide the economic rationale for the predicted impact of changes in the distributions of these state variables on the female's employment. These changes are the basis for the accounting exercise we propose. Using a reduced form employment probit function (see, for example, Hyslop, 1999 and DelBoca and Sauer, 2009) would make it impossible to directly measure how much of the change in employment is due to changes in the explanatory variables proposed in the literature. This is particularly important since the analysis of the impact of changes in the state variables is done in steps, as described below.

Second, the dynamics of the model are captured by the value of the future-value function in equation (3.7). The change in this value according to age and in the values of the state variables has a dominant influence in determining the effect of the state variables on the change in predicted employment and their impact on future employment and, as a result, on the future value of utility based on current decisions. Reduced form equations are able to capture this by using age-dependent state variables. However, this would require a much larger number of parameters in order to properly capture the dynamics and their interactions with the distributions of the state variables.

Third, employment, as the focus of this paper, must be treated as endogenous. Taking other state variables, such as schooling, fertility and marriage, to be endogenous would greatly complicate the model though it would require fewer parameters. As long as we are not analysing the explanations for changes in these other variables, it is legitimate to take their outcomes as given stochastic dynamic processes that are affected by other state variables, including employment. Last, but not least, making only employment a choice variable keeps the model as close as possible to EW and keeps it simple to solve.

3.1 Data and Estimation

We estimate the model using data from the March CPS for the period 1964 to 2007 and define the cohort of women born in the years 1953-57 as the 1955 cohort. We divide the entire sample into cohorts that include women born two years before and two years after the reference cohort. For the accounting exercise and the aggregation, we use data on women who were born during the period 1923-1977. There is almost complete data for the 1955 cohort from the year schooling is completed until retirement and, therefore, it is the optimal benchmark for the estimated model in the accounting exercise below.

We divide the women into five groups according to level of education: high school dropouts (HSD); high school graduates (HSG); some college (SC); college graduates (CG) and post-college degree (PC).[21] For each education group, we calculate the following moments for ages 23 to 54: employment rate, average wage, marriage rate and the empirical distributions of the number of children (i.e. no children, one child, two children and three or more children) according to their age group (0 to 5 or 6 to 18). We denote this vector of moments as m^A.[22]

Note that dynamic discrete models are usually estimated using panel data. Here we use repeated cross-section CPS data in order to better link the results to aggregate data and to increase sample size. However, the use of cross-section data implies that certain parameters are weakly identified and unobserved heterogeneity, a-la Heckman and Singer (1984), cannot be estimated.

The estimation's main objective is to demonstrate that there are consistently estimated parameters that provide a good fit to the observed female employment rates. When using cross-section data, which does not facilitate the specification of the likelihood of observations for each individual, the best available method of estimation is Simulated Method of Moments (SMM), as proposed by McFadden (1989) and Pakes and Pollard (1989). We implement it here by minimizing the distance between the actual moments and the moments simulated by the model.

Conditional on a vector of parameters (θ) that fully describe the model, we numerically solve and randomly simulate outcomes on the computer. For each woman, we simulate her choices and wages from the model starting from the actual observed state at age 22 (to be defined below).[23] This state includes the observed years of schooling according to the five categories described above. For each initial level of schooling, we have an artificial representative sample based on the population's observed distribution.[24] For each female i in each period t, we perform the following simulations: a wage shock, the realization of a job offer, the birth of an additional child and a change in the woman's marital status from single or divorced to married. We also simulate the husband's wage using the estimators from a Mincerian wage regression for men.[25] Using these realizations, the model produces an employment outcome. This probability outcome can be interpreted as a dynamic rational expectation probit function,

[21] See Appendix B.1 for details.

[22] See Appendix B.3 and www.tau.ac.il/~eckstein/FLS/FLS_index.html for further details on the moments and identification. For the accounting exercise in Section 3.3, we created the same moments for all cohorts born during the period 1923-1977.

[23] For CG and PC, we use the initial condition at 23 and a dynamic process.

[24] For example, in the HSG group, 64 percent are married at the age of 23, 50 percent do not have young children, 32 percent have one young child, etc. The artificial representative sample will be constructed according to these percentages.

[25] Information about the husbands can be found in Appendix B.2.

which is an extension of Heckman (1974)'s classic female employment model. We repeat this for 1000 women in order to obtain the predicted rate of employment for each level of schooling from the year after schooling is completed until retirement at age 65.

The simulations also generate wage observations conditional on schooling for each age group. Given the simple probability functions for marriage, divorce and number of children by age (see equations 3.10-3.12), we generate the proportions of marriage, divorce and number of children for each woman by schooling and age. In parallel to the data construction, we calculate the following moments for women aged 23 to 54 for each level of education: employment rate, average wage, marriage rate and the empirical distribution of the number of children (no children, one child, two children and three or more children) according to their age group (0 to 5 or 6 to 18). We denote this vector of simulated moments as m^S.

Let m_j^A be moment *j* in the data and let $m_j^S(\theta)$ be moment *j* from the model simulation given the parameter vector θ, where $j = 1,\dots,J$ and J is the total number of moments. The difference between these two vectors is given by the following vector:

$$g'(\theta) = \left[m_1^A - m_1^S(\theta),\dots,m_j^A - m_j^S(\theta),\dots,m_J^A - m_J^S(\theta)\right]$$

We minimize the objective function $J(\theta) = g(\theta)' W\, g(\theta)$ with respect to θ, where the weighting matrix W is set to be a diagonal matrix consisting of the inverse of the estimated variance of each moment. We obtain the standard errors using the inverse of the Jacobian matrix.

3.2 Results: 1955 Cohort

The estimated parameters of the utility and wage equations for the 1955 cohort of women have the expected signs, which are also the same as those obtained by EW using panel data (see Table 3.1). According to the parameters, leisure is more valuable than employment, consumption and employment are substitutes ($\alpha_2 < 0$) and accumulated years of experience increase the value of leisure ($\alpha_3 < 0$) for married women. In addition, younger children cost more than older children and, unlike EW, utility from education is positive.[26] The parameter indicating the cost of home activity for employed unmarried women is positive and high ($b_m > 0$). In other words, single women are more likely to work, as expected.[27]

The parameters of the Mincer/Ben-Porath wage function have the standard estimated values with a lower than usual value for experience (due to the addition of the time trend (t)). Schooling is estimated

[26] Here schooling is categorized into five levels while in EW it was measured by actual years and one parameter. The result that utility increases with schooling appears to be more reasonable.
[27] We assume that the cost of children by age is independent of marital status, i.e. $c_{jm} = 0$.

according to five discrete levels and, assuming that each level has a duration of about two years, we obtain an average estimated annual rate of return of 8 percent from high school through college graduation which jumps to 17 percent for the completion of a post-college (PC) degree. The estimated parameters for the probabilities of job offers, marriage, birth of an additional child and divorce are consistent with what one would expect (see Table 3.1 and Table B.5). In particular, a high school education, additional experience and being employed at *t-1* achieve a higher job-offer arrival rate.

The quality of the model's fit to the data is measured here by the difference between the predicted aggregate employment rates and actual employment rates by level of schooling (see Figure 3.1a,b). Given the estimated parameters of the model, we simulate employment for each education group and then calculate the aggregate employment rate using the actual education distribution for this cohort. The aggregate lifecycle employment rate patterns differ significantly across education levels. A good fit is obtained to the aggregate 1955 cohort employment rates, as well as to the employment rates and their main patterns for each schooling level. The strong hump-shaped profile for HSD and HSG and the flat profile for PC are accurately captured by the model and it is the wage and utility parameters for schooling that have the most impact. The difference in employment rate patterns between younger age groups (i.e. when the employment rate is decreasing) and older age groups (i.e. when the employment rate is increasing) for HSG, SC and CG are also captured by the model. The decrease in employment rates for SC and CG after the age of 45 is not, however, captured accurately since the effect of age (i.e. health) on utility and wages is not taken into account. As a result, the actual and predicted aggregate employment rates produce an excellent fit until age 50; however, the model over-predicts employment after that age. Since job-offer rates are estimated, the model can also provide predictions for non-employment rates that fit the data well.[28]

3.3 Accounting for the Increase in Female Employment

The goal of this section is to measure the contribution of each of the four trends discussed in Section 2 to the increase in female employment rates for each cohort using the estimated model for the 1955 cohort. To this end, we need to perform separate counterfactual simulations of female employment rates for each cohort for changes in the dynamic distribution of the main explanatory variables. The benchmark is given by the employment rates predicted for the estimated model of the post-baby-boomers (i.e. the 1955 cohort). We implement the counterfactual simulations using the parameters for utility and job-offer rates as estimated though we allow for changes in the main state variables that the model treats as given dynamic processes. In other words, we estimate the initial distributions and

[28] See www.tau.ac.il/~eckstein/FLS/FLS_index.html.

dynamic process for schooling (S), wages of women (y^w) and of men (y^h), fertility (N) and marriage and divorce (M) for each cohort separately and then use them sequentially to predict the employment rates for each cohort.

The first column of Table 3.2 reports the benchmark employment rates aggregated by age group for the 1955 cohort (as in Figure 3.1). The row labeled *Actual* reports the actual employment rate for each cohort for the same age group. Thus, for example, the actual employment rate is 0.47 for the 1945 cohort aged 23 to 27 while the predicted employment rate for the 1955 cohort is 0.62. The question is how much of this increase in the employment rate (i.e. 0.15) is due to changes in the *schooling distribution* and *initial conditions* of the 1945 cohort. To answer this question, we change the initial conditions of the state variables at age 22 for each schooling level, as well as the schooling distribution, using the data of the 1945 cohort. We then use the estimated model to predict employment rates for the 1945 cohort. The row *schooling+initial* reports these predicted rates for the 1945 cohort and similarly for all other cohorts.[29] Thus, for example, the employment rate for the 1945 cohort aged 23-27 would have decreased from 0.62 to 0.59 as a result of the change in schooling and initial conditions. In other words, 20 percent (0.03 out of 0.15) of the gap in employment rates between the 1955 and 1945 cohorts at ages 23 to 27 is accounted for by schooling and other initial state variables at age 23. Similarly, for the 1930 cohort aged 38-42, schooling and initial conditions account for 31 percent (0.08 out of 0.26) of the gap in employment rates. Thus, by using the parameters estimated for the 1955 cohort, we can determine the contribution of the change in schooling by cohort to the increase in employment rates.

Our goal is to determine the contribution of each of the state variable (S, y^w, y^h, N, M) in reducing the difference between actual employment rate by cohort and the predicted employment rate for the 1955 cohort for each age group appearing in Table 3.2. The presence of empty columns is due to the low number or total lack of observations for the relevant age groups in some cohorts.

We now turn to the contributions of the wages of women and their husbands, fertility and marriage and divorce rates to the change in employment rates by cohort. Although we take these processes as given, their estimated parameters are subject to dynamic selection (see EW). Therefore, we re-estimate each of these processes jointly using the given estimated parameters for utility and job-offer rates.[30]

In order to measure the contribution of the change in wages, we use the cohort-specific estimated wage functions for husbands as simple regressions and the wage function for their wives as explained above. We predict employment rates using the changes in the distributions of schooling and the initial state variables and the "new" wage functions. The predicted employment rates are reported in the line

[29] The impact of initial conditions alone is very small and therefore we combined it with that of schooling. Appendix B.7 examines the robustness of the results to changes in this analysis.

[30] See Appendix B.6 for the details on how the estimation was done and the above-mentioned web site for more detailed results.

labeled *Wages* in Table 3.2. Thus, for example, for the 38-42 age group in the 1925 cohort, the actual employment rate is 0.45 which is 0.39 less than the predicted employment rate (0.74) for the 1955 cohort. Adding to this the effect of the change in wages, we obtain a predicted employment rate of 0.56. The change in the wages of women and their husbands accounts for an additional 0.08, which constitutes 20 percent of the gap. Note that the change in schooling distribution accounts for 26 percent of the explained change in employment rates for this age group in the 1925 cohort.

Similarly, we measure the contributions of the fertility, marriage and divorce processes once we have estimated the parameters for each of the cohorts, as explained above. The results are reported in Table 3.2 and clearly show that these changes are less important than those in schooling, wages and *"other"*. The row labeled *other* represents that portion of the change in employment rates that is not accounted for by the model's observable variables (i.e. the "unexplained" portion). The contribution of each factor in explaining the change in female employment rates differs across cohorts and age groups (Table 3.2).

It is worthwhile to now summarize the results of the accounting exercise:[31]

1. **Schooling**: The change in the schooling distribution determines 35 percent on average of the deviation from the female employment rate for the 1955 cohort and is the most important explanation. The contribution is less significant for the 33-42 age group in the 1950 and earlier cohorts and is particularly small (less than 13 percent) for the 23-27 age group in the 1960 and later cohorts. Nonetheless, the overall impact is large and robust.[32]

2. **Wages:** The change in wages of women and men determines about 20 percent of the deviation on average. This figure is larger (reaching about 23 percent) for the 1950 and earlier cohorts but is only 16 percent for the cohorts born after 1960. The contribution ranges from 30 to 58 percent for the earlier cohorts of 1935, 1930 and 1925, but is particularly small for most recent cohorts.

3. **Fertility**: The contribution of fertility to female employment is only 5 percent on average though it is significantly larger (between 10 and 20 percent) for the cohorts born during the period 1935 to 1950.[33]

4. **Marital Status**: The contribution of marital status is about one percent on average and zero for later cohorts. This is a surprising result since employment rates are higher among unmarried women than among married women and the proportion of the former has been increasing over time. Nonetheless, this result appears to be correct since schooling and fertility are already controlled for.[34]

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[31] See the web site for the calculations of the contributions appearing in Table 3.2.

[32] The order in which the state variables are added does not significantly affect the results. To check robustness, we tried alternative orders and obtained the same result for schooling and wages and a small change in the results for fertility and marital status (see Appendix B.7).

[33] These two results are consistent with the change in trends seen in Figures 2.3 and 2.4.

[34] In the test of robustness, marital status reached an average level of 2 percent (see Appendix B.7).

5. **Other:** The part that remains unexplained by the changes in the observed variables ("*other*" or "unexplained") amounts to about 38 percent on average - 45 percent for women under the age of 39, 26 percent for older age groups and much higher for cohorts born before 1940. A glance at Figure 2.6 reveals why it is in fact not surprising that 37 percent of the predicted change in the female employment rate relative to the predicted rate for the 1955 cohort is unexplained for the 1925-1935 cohorts. On the other hand, the unexplained portion is almost zero for the same age groups in the recent cohorts. Overall, the unexplained portion accounts for the largest proportion of the gap between the 1955 cohort and the others.

It is important to note that the unexplained portion is always positive or zero. In other words, the predictions using *all* the observed processes that affect female employment choice in the model always over-predict actual observed employment rates for the 1950 and earlier cohorts and under-predict them for the 1960 and later cohorts. This result is robust since it is not imposed in any way on the procedure and the *unexplained* portion is the "last" change to be introduced. Therefore, we are able to claim that our estimate of "other" explanations is a "lower bound" for the potential contribution of the other sources discussed in Section 2.[35]

The question arises as to whether the classical female dynamic labor supply model outlined above can provide a simple fit for the large "*unexplained*" portion produced by the accounting analysis. To provide an answer, we need to consider modifications to the model that can explain why the unexplained portion is higher on average for women aged 23-27 (55 percent) and lower for women aged 48-52 (31 percent). We change only two parameters: household technology and social norms, which can be included in order to capture the utility/cost parameter of not working, i.e. α_1, and which affect the labor supply of women of all ages, and changes in the cost of raising young children, which can be captured through a change in α_{41} and affects the labor supply of younger women. In order to evaluate these possible explanations for the increase in female employment, we now allow only these two parameters to deviate from the estimated 1955 cohort values while making use of the adjusted process used for the accounting analysis presented in Table 3.2. The results are presented in Table 3.3.

We are indeed able to produce a close fit to the unexplained portion for all cohorts by adjusting only the values of these two parameters (i.e. α_1 and α_{41}) away from their estimated values for the 1955 cohort (which appear in bold in Table 3.3). As a result, the value of leisure for the 1940 and later cohorts becomes equal to that of the 1955 cohort while the utility/cost of household time is raised by about 60 percent for the 1925, 1930 and 1935 cohorts. Since the model is linear, we are able to calculate this change in terms of dollar per hour of work (in 2000 prices), such that working at home is about \$5 (\$4.5) an hour "more costly" than working outside the home for the 1925 (1935) cohorts.

[35] This statement is conditional on leaving the utility and job-offer rates unchanged for all cohorts.

The cost of raising children while at work varies monotonically for all cohorts.[36] Thus, it is more than three times higher for the 1945 and earlier cohorts than for the 1955 cohort and four times lower than for recent cohorts (Table 3.3). In terms of dollars per hour, these estimates imply that the cost of rearing children below six years of age while working is higher by $2.10 for the 1950 cohort and about $3.20 higher for cohorts born before that. For cohorts born later than 1955, it is about one dollar less.

The estimated parameters needed to adjust the cost/utility of housework and raising young children when working outside the home in order to produce a good fit to the female employment of these cohorts are consistent with the explanations provided in the literature (see Section 2). Furthermore, these explanations are quantitatively important and in line with those presented in recent papers. We now turn to the question of whether the adjusted estimated model provides a good fit to the aggregate female employment trends.

3.4 Aggregate Fit

It is important to now determine whether the estimated model for the 1955 cohort is able to predict the increase in the employment rate for married women and the stability in the rate for unmarried women. In the previous section, we used the estimated model for the 1955 cohort which was modified using the relevant state variables and the exogenous processes driving education, wages, fertility and marriage status for all other cohorts. In addition, two parameters - α_1 and α_{41} - were modified for several cohorts (see Table 3.3) and as a result a good fit was produced for the trend in the employment rate for each cohort. We now wish to determine if aggregation by cohorts provides a good fit to the aggregate employment rates of married and unmarried women. To do so, we use the predictions from the accounting analysis to forecast the aggregate employment rate for married and unmarried women from 1980-2007.[37] Figure 3.2 shows the aggregate fit which is remarkably good. The only significant deviation is a small over-prediction of married female employment rates from 2003 to 2007 and a small under-prediction of unmarried female employment rates from 1995 to 2004.

3.5 Discussion

The majority of the increase in married female employment is explained by the increase in years of schooling. The rise in female wages also contributes a large part of the explanation while changes in fertility and marital status do not have much of an impact, which is a somewhat surprising result. Furthermore, the unexplained portion is quite large and positive; in other words, for cohorts born before 1955 the simulations over-predict female employment and for more recent cohorts under-predict it.

[36] For the cohorts of 1925 and 1930, this parameter cannot be estimated since there were not enough observations for young women in these cohorts. Therefore, we imposed the parameter estimated for the 1935 cohort.

[37] The reason for starting in 1980 is the lack of data for the early cohorts.

Therefore, there must be other changes occurring among married women by cohort. We showed above that it is consistent with the model to claim that technological progress in household activities brought down their cost for working women. Moreover, the claim that the cost of raising young children (aged 0 to 5) has also declined significantly for all cohorts born after 1935 is also consistent with the estimated model.

Note that we are not able to separate utility and costs and therefore it may well be a change in social norms that provides the explanation rather than a change in costs. Therefore, it may be worthwhile to examine the changes in social norms that affect household labor supply. The changes in social norms have to do with society's changing preferences or behaviour. It is possible that the value of home production by women is determined by social norms which change over time. This occurs because different individuals possess different values, thus creating unobserved heterogeneity that can change over time. Another possibility not captured by the model is that households internally allocate resources by some form of intra-family game (Chiappori, 1997) and it is this line of thought that is the subject of the next section, which develops an estimable dynamic model of household labor supply. This derives from the need to consider models of household behavior that can potentially endogenize and quantify the complicated decisions involving labor supply, fertility, children, education and divorce (Flinn and Brown, 2006; Flinn and DelBoca, 2009; and Tartari, 2008). The next section takes a step in this direction using the model described above as a benchmark.

4 Household Labor Supply

The goal of this chapter is to measure the potential impact of social norms on female labor supply where the female's decisions and those of her partner (husband) are determined jointly within a household. By using this setting, we achieve two main objectives: First, the model provides a framework for the analysis of married female labor supply and of family economics in general (Koorman and Kapteyn, 1990 and Chiappori, 1997). In particular, a household game involving the wife and husband, in which each maximizes his own lifetime utility subject to a common constraint, is an innovative and promising setting for the analysis of dynamic household labor supply outcomes. We emphasize the potential channels through which household games can produce novel insights into the dynamics of both female and male labor supply. The fact that the increase in female labor supply has occurred only among married women (see Figure 1.2) would appear to indicate that interaction within the family is an important factor in explaining the data.

Second, the setting used here allows us to treat social norms as the rules of a game played within the household. The estimation of the model will make it possible to determine how much of the increase in female employment is due to the change in the rules of the game, i.e. the change in social norms, which determine a household's joint labor supply. In particular, the model describes two alternative rules that govern household interactions and affect its labor supply and assumes that these two rules are related to two alternative cultural norms. We will define them as “Classical” (C) and “Modern” (M). Our main goal is to show that each of these definitions can lead to significantly different results, both quantitative and qualitative, for female and, potentially, male labor supply from one household. We conclude that modeling household outcomes using internally-played games is a useful empirical venue that should be further explored in the literature.

In particular, we assume that from the point in time at which a couple marries, their household is determined to be either "Classical" (C) or "Modern" (M). In the Classical household game, the husband is characterized as a Stackelberg leader. In other words, the husband first decides on his labor supply and subsequently the wife responds with her best choice. The Modern household game is characterized by a simultaneous and symmetric Nash equilibrium. In other words, the husband and wife make their labor supply decisions at the same time and based on the same information, such that each takes their spouse's actions as given. We view the two types of households as two unobserved types that can be estimated using panel data (Heckman and Singer, 1984).

There are alternative games that could have been used. For example, in Chiappori (1997)'s bargaining game, the female's bargaining power should be higher in an M household than in a C household. As a result, the labor supply of women in M households would be lower than that in a C household since in the former women will choose more leisure. However, this does not provide the desired outcome of higher female employment in an M family. Perhaps, then, the bargaining game should have been used only for a C family. In fact, the Stackelberg game is a special case of the bargaining game in which the husband has full bargaining power, which provides the justification for choosing our model.

Finally, the justification for using a Nash game to model an M household is that the woman in an M household chooses a higher level of employment than a woman in the C household. The other interesting result is that in this framework the M-type household may choose a non-optimal excess level of employment (Tartari, 2009).[38]

4.1 The Model

The model extends the standard dynamic female labor supply model described above in three ways: First, it deals with the labor supply of both members of the household, i.e. husband and wife. Second,

[38] There is an objection to calling a household Modern if the outcome may not be optimal. The formulation of the household game is an exciting and important research issue, which we hope will gain greater attention in the future.

the state of "out of the labor force" has been added in order to differentiate between unemployment and non-employment. To this end, we assume that each period is divided into two sub-periods: During the first sub-period, an individual who is out of the labor force (OLF) or unemployed (UE) decides whether or not to search for a job. If s/he chooses to search, s/he receives at most one job offer and then decides whether or not to accept it. If s/he is initially employed (E), s/he can choose between OLF and E or is fired and becomes unemployed. Thus, during the second sub-period there are three possible states: E, UE and OLF. Third, we add the internal household game discussed above.

In order to focus on the impact of the internal family game on household labor supply, we assume that utility functions, wage functions and job-offer rate parameters differ between husband and wife but are the same across the two types of household. Our interest is empirical and thus must take into account that household type is unknown to the researcher, but known to the households themselves. Therefore, during estimation the model is solved for each household twice - once for M and once for C - and then the value of the objective function is calculated separately for the Classical and Modern households. Thus, unobserved heterogeneity enters the model in a manner proposed by Heckman and Singer (1984).

In each period *t* from the wedding day (*t = 0*) until retirement (*t = T*), each spouse chooses an element a from her (his) choice set *A*, which contains at most three alternatives: employment (*a = 1*), unemployment (*a = 2*) and being out of the labor force (*a = 3*). The choice variable d_{tj}^{a} equals 1 if individual $j = H,W$ chooses alternative a at time t and zero otherwise, such that the three alternatives are mutually exclusive, i.e. $\sum_{a=1}^{3} d_{tj}^{a} = 1$ for all *t*.

We deviate from the standard model in an important way by making consumption (*x*) a joint outcome and as a result the household budget constraint in each period *t, t=1,…,T*, is given by:

$$y_{tW} \cdot d_{tW}^{1} + y_{tH} \cdot d_{tH}^{1} = x_t + c_t \cdot N_t. \tag{4.1}$$

As above, y_{tW} and y_{tH} are the wife's and husband's wages, respectively, but x_t is now the couple's joint consumption during period *t*. To maintain simplicity, we define the cost in goods per child (per-child consumption), denoted as c_t, as $c_t = \theta \cdot (\frac{y_{tW} \cdot d_{tW}^{1} + y_{tH} \cdot d_{tH}^{1}}{N_t})$, where θ is a given fraction of family income per child and N_t is the number of children in the household.

As in the standard model, we adopt the Mincerian/Ben-Porath wage function for each *j* where experience is endogenously determined, such that:

$$\ln y_{tj} = \beta_1^{j} + \beta_2^{j} K_{t-1j} + \beta_3^{j} K_{t-1j}^{2} + \beta_4^{j} S_j + \varepsilon_{jt}^{1}. \tag{4.2}$$

where K_{t-1j} is actual work experience accumulated by the individual according to $K_{tj} = K_{t-1j} + d_{tj}^1$, for which the initial value is the level of experience on the day of the wedding and S_j denotes the individual's years of schooling.

We deviate from the linearity of the utility function assumed in the standard model by introducing constant relative risk aversion for utility from consumption.[39] The periodic utility of the husband or the wife is given by:

$$U_{tj} = u_j(x_t) + \alpha_j \cdot l_{tj} + f(N_t), \tag{4.3}$$

where $u_j(x_t) = \frac{(x_t)^{\gamma_j}}{\gamma_j}$ is utility from total household consumption, l_{tj} is the individual's leisure and $f(N_t)$ is a specific function for utility from children:

$$f(N_t) = \gamma_0 \cdot N_t + \gamma_2 c_t + \frac{\gamma_1}{age_t}\left[\frac{l_{tW}+l_{tH}}{N_t}\right] \tag{4.4}$$

Each parent's utility from their children increases with the number of children, with the given consumption per child, c_t,, and with the parents' total leisure per child, which decreases with the average age of children (age_t). By inserting the budget constraints (equation (4.1)) into current utility (equation (4.3)) we obtain the wife's utility for each employment state:

$$\begin{aligned} U_{tW}^1 &= u_W\left((1-\theta)\left(y_{tW} + y_{tH} \cdot d_{tH}^1\right)\right) + f(N_t) \\ U_{tW}^2 &= u_W\left((1-\theta)\left(y_{tH} \cdot d_{tH}^1\right)\right) + f(N_t) + \alpha_W \cdot (l_{tW} - SC) + \varepsilon_{tW}^2 \\ U_{tW}^3 &= u_W\left((1-\theta)\left(y_{tH} \cdot d_{tH}^1\right)\right) + f(N_t) + \alpha_W \cdot l_{tW} + \varepsilon_{tW}^3 \end{aligned} \tag{4.5}$$

When the wife is unemployed (*a = 2*) the utility from leisure, $\alpha_W \cdot l_{tW}$, is adjusted for the cost of search SC and $\varepsilon_{tW}^2, \varepsilon_{tW}^3$ are utility shocks for the states of unemployment and being out of the labor force, respectively. The random shocks to preferences and wages are determined by the vector $\varepsilon_{tj} = \left[\varepsilon_{tj}^1, \varepsilon_{tj}^2, \varepsilon_{tj}^3\right]$ which is assumed to be joint normal and serially uncorrelated, where $\varepsilon_{tj} \sim N(0, \Sigma)$, *i.i.d.* and Σ is unrestricted.

Equivalently, the husband's utility for each employment state is given by:

$$\begin{aligned} U_{tH}^1 &= u_H\left((1-\theta)\left(y_{tH} + y_{tW} \cdot d_{tW}^1\right)\right) + f(N_t) \\ U_{tH}^2 &= u_H\left((1-\theta)\left(y_{tW} \cdot d_{tW}^1\right)\right) + f(N_t) + \alpha_H \cdot (l_{tH} - SC) + \varepsilon_{tH}^2 \\ U_{tH}^3 &= u_H\left((1-\theta)\left(y_{tW} \cdot d_{tW}^1\right)\right) + f(N_t) + \alpha_H \cdot l_{tH} + \varepsilon_{tH}^3. \end{aligned} \tag{4.6}$$

The individual can always choose to be at home, i.e. out of the labor force (*a =3*), though there are other choice states available to the individual in each period *t*. Thus, the individual receives at most

[39] We continue using the assumption that all earnings are consumed (no saving).

one job offer per period with its probability depending on the labor market state variables. As in the standard model, we use the following specification for this probability:

$$\text{Pr}ob_{tj} = \frac{\exp\left(\rho_{01j} \cdot d_{tj}^1 + \rho_{02j} \cdot d_{tj}^2 + \rho_{03j} \cdot d_{tj}^3 + \rho_{1j} \cdot S_j + \rho_{2j} \cdot K_{t-1j} + \rho_{3j} \cdot year\right)}{1 + \exp\left(\rho_{01j} \cdot d_{tj}^1 + \rho_{02j} \cdot d_{tj}^2 + \rho_{03j} \cdot d_{tj}^3 + \rho_{1j} \cdot S_j + \rho_{2j} \cdot K_{t-1j} + \rho_{3j} \cdot year\right)}. \tag{4.7}$$

Note that it depends on the aggregate state of the economy as approximated by the variable *year,* which is a time trend. In addition, we assume that in each period the individual may lose his job with a probability that is negatively correlated with his accumulated experience and education and depends on the time trend. This probability function for being laid off is identical to (4.7) except that it has different parameter values.

As in the standard model, we assume that there are given probabilities for divorce and an additional child (see Appendix C.1). The probability of an additional child is given by equation (3.10), with the addition of the following variables: husband's age, husband's schooling and the age of the youngest child. The probability of divorce is given by equation (3.12) except that the husband's wage is replaced by his employment state.

The dynamic programming solution to the optimization problem is obtained by a process of backward recursion. The solution for the first sub-period within each period depends on the household type. Therefore, in what follows, we describe the solution of the game for each type of household.

Solution for the Classical Household (C)

The solution for the classical household is reached in three stages: First, the husband chooses whether or not to search. Let $V_{tH}(\Omega_{tH})$ be the maximum expected discounted lifetime utility given the relevant state space Ω_{H}, such that $\Omega_{tH} = \left[k_{tH}, k_{tW}, S_H, S_W, d_{tH}, d_{tW}, N_t, \overline{age_t}\right]$. In the first stage, the husband solves the following value function,

$$V_{tH}(\Omega_{tH}) = \max\left[\left\{prob_{tH} \cdot \max\left[V_{tH}^1(\Omega_{tH}), V_{tH}^2(\Omega_{tH})\right] + (1 - prob_{tH}) \cdot V_{tH}^2(\Omega_{tH})\right\},\ \left\{V_{tH}^3(\Omega_{tH})\right\}\right], \tag{4.8}$$

where $V_{tH}^1(\cdot)$, $V_{tH}^2(\cdot)$, $V_{tH}^3(\cdot)$ are the maximum expected discounted utilities for each potential choice. Once the husband chooses whether or not to search, he knows the realization of ε_{tH}^3 ; however, since he does not actually search at this point, he does not know the realizations of ε_{tH}^1, ε_{tH}^2. Neither does he know his wife's choices and therefore he calculates her expected choices and wages.

If he chooses not to search, i.e. $a = 3$, then his utility is $V_{tH}^3(\Omega_{tH})$. If he does choose to search, he will receive a job offer with the probability given by (4.7). In the second stage, if he receives an offer he chooses whether or not to accept it.[40] In other words, he solves: $\max\left[V_{tH}^{1}(\Omega_{tH}),\ V_{tH}^{2}(\Omega_{tH})\right]$ and if he does not receive a job offer, then he is unemployed, i.e. a = 2, and his utility is $V_{tH}^{2}(\Omega_{tH})$.

In the third stage, the wife chooses whether or not to search. Her state space, Ω_{tW}, includes the husband's actual choice and actual wage, if he is working. In other words, she reacts to his actual labor supply. Since the utility from joint consumption (joint earnings) is decreasing, her value of search (participation) is negatively correlated with her husband's wage. The wife's optimization problem is therefore:[41]

$$V_{tW}(\Omega_{tW})=\max\left[\left\{prob_{tW}\cdot\max\left[V_{tW}^{1}(\Omega_{tW}),V_{tW}^{2}(\Omega_{tW})\right]+(1-prob_{tW})\cdot V_{tW}^{2}(\Omega_{tW})\right\}\ ,\ \left\{V_{tW}^{3}(\Omega_{tW})\right\}\right]. \quad (4.9)$$

She only knows the realization of ε_{tW}^{3} when she chooses whether or not to search and only if she chooses to search does she learn the realization of ε_{tW}^{1}, ε_{tW}^{2}. For both husband and wife, the value function $V_{tj}^{a}(\cdot)$ is given by Bellman (1957) as:

$$\begin{aligned} V_{tj}^{a}(\Omega_{tj}) &= U_{tj}^{a}+\beta\cdot E\left(V_{t+1j}(\Omega_{t+1j})\middle|\Omega_{tj},d_{tj}^{a}=1\right) \\ V_{Tj}^{a}(\Omega_{Tj}) &= U_{Tj}^{a} \end{aligned} \quad (4.10)$$

where β is the discount factor.

The solution is recursive: first we find the state of participation (to search or not to search) that maximizes the utility of the wife for each possible state of the husband (*a = 1, 2, 3*). Subsequently, the husband maximizes his utility by making his labor supply choice, while taking into account his prediction regarding his wife's choices, which is the same as the wife's prediction. Once the outcome of the husband's decision is known, we find the state that maximizes her utility. The optimization of the wife in this game is similar to that of the standard female dynamic labor supply model described in Section 3 since she takes the husband's employment and wage as given.

Solution for a Modern Household (M)

In the Modern household, the husband and wife make their decisions simultaneously. Each of them maximizes his expected utility for each of his partner's potential choices using the true probabilities. This game has only two stages: first the husband and wife choose whether or not to search and since they act simultaneously they have the same state space, Ω_{tj}. Therefore, in the first stage both solve the following value function:

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[40] If he chooses to search, he obtains the realization of ε_{tj}^{1}, ε_{tj}^{2}

[41] $\Omega_{tW}=\left[d_{tH},k_{tH},k_{tW},S_{H},S_{W},d_{t-1H},d_{t-1W},N_{t},\overline{age}_{t}\right]$

$$V_{tj}(\Omega_{tj}) = \max\left[\left\{prob_{tj} \cdot \max\left[V_{tj}^1(\Omega_{tj}), V_{tj}^2(\Omega_{tj})\right] + (1 - prob_{tj}) \cdot V_{tj}^2(\Omega_{tj})\right\},\ \left\{V_{tj}^3(\Omega_{tj})\right\}\right]. \tag{4.11}$$

As before, when they choose whether or not to search they know only the realization of ε_{tj}^3, but not that of ε_{tj}^1, ε_{tj}^2. Neither do they know their partner's choice, but can calculate his/her expected choices and wages. If one of them chooses not to search, then $a = 3$; if he chooses to search, s/he receives a job offer with the probability described by (4.7). In the second stage, if one of them receives an offer, s/he chooses whether or not to accept. In other words, $\max\left[V_{tj}^1(\Omega_{tj}),\ V_{tj}^2(\Omega_{tj})\right]$ and if s/he does not receive a job offer then s/he is unemployed, i.e. $a = 2$.

The husband's optimization problem and his information set are exactly the same as in the case of the Classical household and therefore the husband's choices are similar. In contrast, the wife's information set is different. Thus, in the Classical household the wife knows her husband's employment choice and wage and chooses to enter the labor force only if his wage is "too low". Since the Modern wife does not know her husband's choice and wage, her decision is not a reaction to her husband's and therefore there should be less negative correlation between their labor supplies. We assume that the equilibrium for the Modern household game is that of Nash equilibrium. In other words, we calculate the value of the two choices for each of the family members in order to form a 2X2 matrix which is used to formulate a standard Nash solution.[42]

Do Modern Women Work More?

The main implication of the analysis is that women in M households work more than those in C households even though the model imposes no differences in any parameter related to the employment or participation choices of women based on type of household. We were not able to prove this result as a general analytical outcome and therefore we used simulations of a two-period model to arrive at some conclusions regarding employment. Based on the simulations, we find that for a female in an M household to work as much or more than a female in a C household, **one** of the following two sufficient conditions must be fulfilled:[43]

1. Women's wages are lower than men's, but all other parameters are equal.[44]
2. The risk aversion parameter for women is lower than that for men, but all other parameters are equal.[45]

[42] Since, in theory, a solution may not exist, we checked this possibility using the estimated parameters and found that a solution does always exists.

[43] The sufficient conditions hold for certain values of the model's parameters, which we consider to be reasonable. A full description of the results can be found at the website www.tau.ac.il/~eckstein/FLS/FLS_index.html,

[44] For a low job-offer probability (0.7 or less), a wage gap of only 3 percent induces the C female to search only if her husband is unemployed while the M female always searches. For a higher probability, we need a larger wage gap.

[45] The combination of a lower wage, a lower job-offer probability and higher risk aversion produces similar results.

Thus, the main result depends on the difference in opportunities (wages) and preferences between women and men. The first condition is explained by the fact that decisions in the M household are simultaneous. Therefore, the M female reacts to the man's actual, rather than expected, employment and income outcome. Men are expected to attain better outcomes than women. However, in C households, the female faces her husband's actual income and will react only if the male ends up earning less than expected. Hence, women in M households more frequently choose to work. The second condition implies that the more risk-averse female in a simultaneous decision game (i.e. in an M household) will work more than if she was reacting after having observed her husband's outcomes (as in a C household).

4.2 Data and Estimation Method

The data is taken from the PSID (Panel Study of Income Dynamics) survey for the period 1983-93. Here we use quarterly data which is available only from 1983 onward and restrict the model to the first ten years of marriage.[46] In order to create similar initial conditions for all individuals, we restrict the data - as in the model - to start from the date of the wedding and consider all married couples during the period 1983-4. The data contains information on 863 couples and tracks them until 1993 or until they separate. During the sample period, 36.3 percent of the couples divorced or separated and 14.5 percent left the sample for other reasons, such that after 10 years 49.2 percent of the couples remained in the sample.

The data includes demographic and employment information on individuals and households, such as wages, working hours, unemployment (job search) and non-participation.[47] The employment rate of women in the sample was 68 percent in 1984, which increases to 75.9 percent after 10 years of marriage while the unemployment rate falls from 5.1 percent to 2.6 percent during that period. The employment rate for men was 82.1 percent in 1984, which climbs to 89.9 percent. The unemployment rate decreases from 10 percent in 1984 to 3.5 percent in 1993.

In the estimation stage, the model is solved for each household twice, once for M households and once for C households, and the value of the objective function is calculated for each member of each type of household separately.[48] We treat the probabilities of the two types of household according to the standard non-parametric probability of constant proportions, $\pi_M + \pi_C = 1$ (Heckman and Singer, 1984).

[46] The value function in the 11th year is assumed to be a parameterized function of the state space in the 40th quarter, i.e. the levels of education and accumulated experience. In particular, we assume the following terminal value function:

$$V_T(\Omega_{T+1}, T+1) = \delta_1 + \delta_2 \cdot k_{iT} + \delta_3 \cdot school_{iT} \quad .$$

[47] More detailed information on the data and the assumptions regarding the variables is available on request.

[48] In the model, we assume that the household type probability is a given parameter. In analyzing the results, we use the estimated model to correlate the posterior probability of each family with observables (Eckstein and Wolpin, 1999).

The model is estimated using SMM (Simulated Method of Moments) following Pakes and Pollard (1989). Let T_i be the length of time we observe household *i* and θ be the vector of parameters, including *Σ*. We denote the data on actual choices made by the husband and wife in household *i* as $(d_{itj}^o; t=1,...,T_i; j=W,H)$ and the predicted equivalent for a family type *h* = M, C as $(d_{itj}^p(h,\theta); t=1,...,T_i; j=W,H)$. We define:

$$D_{itj}^h(\theta)=0 \quad if \;\; d_{itj}^o = d_{itj}^p(h,\theta)$$
$$D_{itj}^h(\theta)=1 \qquad otherwise$$

$D_{itj}^h(\theta)$ equals zero if the model correctly predicts the choice of individual *j* in household *i* in period *t* under the specification of family type *h* and one otherwise. The sum of these elements is the first moment to be minimized and is given by:

$$g_1^h(\theta)=\sum_{i=1}^{863}\sum_{t=1}^{T_i}\sum_{j=H,W} D_{itj}^h(\theta).$$

We define the weighted vector of the two household types according to the assumed proportions, π_C and $1-\pi_C$, as:

$$g_1(\theta,\pi_C)' = \pi_C g_1^C(\theta)' + (1-\pi_C) g_1^M(\theta)'$$

We denote the actual wage of the individual as $(w_{itj}^o; t=1,...,T_i; j=W,H)$ and the predicted equivalent for a household of type *h* as $(w_{itj}^p(h,\theta); t=1,...,T_i; j=W,H)$. The second set of moments is based on the difference between observed and predicted wages. Specifically, we calculate the squared difference between the average over households of the observed and predicted weighted wage per household in every quarter *t* for H and W separately. The average weighted wage of the two household types is $\overline{w}_{tj}^p(\theta,\pi_C)=\pi_C \overline{w}_{tj}^p(C,\theta)+(1-\pi_C)\overline{w}_{tj}^p(M,\theta)$.

Let $g_2(\theta,\pi_C)'$ be the vector of these 80 moments as follows:

$$g_2(\theta,\pi_C)' = \left[\left(\overline{w}_{1H}^o - \overline{w}_{1H}^p(\theta,\pi_C)\right)^2,...,\left(\overline{w}_{40H}^o - \overline{w}_{40H}^p(\theta,\pi_C)\right)^2,\left(\overline{w}_{1W}^o - \overline{w}_{1W}^p(\theta,\pi_C)\right)^2,...,\left(\overline{w}_{40W}^o - \overline{w}_{40W}^p(\theta,\pi_C)\right)^2\right].$$

We define the vector of moments as $g(\theta,\pi_C)' = [g_1(\theta,\pi_C), g_2(\theta,\pi_C)']$.

The SMM is defined by the minimum of the objective function:

$$J(\theta,\pi_C)=g(\theta,\pi_C)'W\,g(\theta,\pi_C)$$

with respect to θ and π_C, where the weighting matrix *W* is a diagonal matrix. The weight assigned to each moment is the inverse of the estimated standard deviation of the specific moment in the data. We find the estimated standard errors using the inverse of the Jacobian matrix.

4.3 Results

This section presents the SMM estimation results for the model. We first examine its fit to the observed average employment states, the transitions between states and average wages by gender. Given the good fit of the model to the data, we then interpret the estimated parameters and their implications. This leads to the analysis of the estimated model's counterfactual predictions (both within-sample and out-of-sample) for the labor supply of Classical and Modern households.

Goodness of Fit

Following the simulations used for estimation, we make use of the estimated parameters and the assumed random errors in order to calculate the predicted proportions of the three labor market states for the sample of 863 households. The calculation was done for all the observed households which were each classified as M or C and averaged using the estimated proportion of household type.

Figure 4.1 presents the actual and the predicted proportions of women and men in E and UE states. The estimated model fits the aggregate proportions well and the simple goodness-of-fit test for each choice over the entire sample gives a value which is under the critical 5 percent level for all cases, except UE for men.[49] We also perform goodness-of-fit tests for actual to predicted choices for each of the 40 quarters of data. In 36 (29) of the 40 quarters, the model passes the simple χ^2 goodness-of-fit test for women (men).[50] The model correctly predicts 45,925 of the 51,050 observed choices in the sample, which implies that the estimated model predicts almost 90 percent (pseudo R^2) of the choices made within the sample period. The model accurately predicts the trend and level of wages, except for the large increase in the last year of the sample (see Figure 4.2). The good fit of the estimated model to the data is not a complete surprise since these moments were used for the SMM estimation criterion.

Parameters

The estimated constants and experience parameters in the wage equation are higher for a husband than for his wife while the estimated rate of return on a year of schooling is slightly lower for the husband than for the wife (0.81 vs. 0.87). In the sample, husbands have slightly less schooling than wives (12.7 vs. 12.8). As a result, the expected wage offer for a newlywed male is higher than that for his newlywed wife unless she has significantly more years of schooling than he does, which is unexpected. Moreover,

[49] The values are presented at the bottom of Figure 4.1. The values of the χ^2 tests for OLF for women and men are 25.97 and 19.41, respectively.

[50] See the above-mentioned web site for the full results.

the job-offer probability parameters are higher for men than for women, which is as expected (see Table 4.1).[51] Hence, the job market opportunities of husbands are superior to those of their wives.

With regard to the utility from employment, women have a higher value of leisure and a higher level of risk aversion than men and we estimated an almost linear preference ($\gamma = 0.95$). The parameters of the utility from children (γ_1 and γ_2) have the expected sign and values.

Thus, we obtain the expected result that the husband's labor market opportunities and incentives are such that his search intensity is greater than that of his wife and, as a result, the husbands' employment rate is higher (80 percent). Since the C female reacts to the result of her husband's search, she usually searches if her husband is unemployed (20 percent) or if his income is low (due to a negative shock to his earnings). The M female searches simultaneously with her husband and, due to her level of risk aversion, searches more intensively and has a higher rate of employment than the C female, as explained above. The estimated proportion of C households in the sample is 0.61 with a small standard deviation and therefore a change in social norms can add significantly to employment, as will be described below.

Employment according to Type of Household

The predicted rates of employment and unemployment among women differ significantly between M and C households (see Figure 4.3). The employment of C women is on average 9.7 percent less than that of M women and this gap remains almost constant over the duration of a marriage. The unemployment rate for C women is 3.5 percent and is lower than that for M women by 0.6 percentage points. The main reason is that the C female searches less intensively and therefore has a lower probability of not finding a job and becoming unemployed. Simple chi-square tests (Figure 4.3) indicate that for all 40 quarters the employment state distributions of C and M households are significantly different.

By construction, the model imposes that all parameters are identical for the two types of households. Hence, the gaps in employment are only due to the different game that each household plays. As explained above, the main reason for the difference is that an M-type household makes simultaneous decisions while the C-type makes sequential decisions. This difference has implications for the choices of women due to their relatively high risk aversion ($\gamma_W = 0.85$) in consumption preferences.

Male employment rates are similar for Modern and Classical households (88.7 percent versus 89.1 percent, on average) and consequently, so are UE and OLF rates, such that the simple chi-square tests

[51] The other parameters are presented in Table C.2.

indicate that in all 40 quarters there are no significant differences in employment state distributions between C and M households for men. This similarity is due to two aspects of the model and its results: First, the estimated relative risk aversion for men is close to one (γ_H=0.95) and this affects the relation between the couple's employment decisions. Thus, given the low rate of risk aversion for men, a predicted change in the labor supply of women does not influence the husband's decisions in either type of household. Therefore, the type of game does not affect the husband's labor supply. Second, in both games, the male's decisions are made with the same information on female employment opportunities. Thus, even with a higher degree of risk aversion one would expect a smaller difference between men's employment outcomes by type of household.

One way to analyze the empirical content of the estimated unobserved types of household is through the correlation of the estimated type probability of each household conditional on the observed employment outcomes (i.e. the posterior probability; see, for example, Eckstein and Wolpin, 1999) with household demographic indicators, such as a husband with less than 12 years of schooling; an Afro-American husband; a Protestant husband; residence in a rural area, etc. (see Table 4.2). Using standard Bayesian conditional probability, we calculate the probability for each household that the game it plays is of type C or M. Table 4.2 shows that in an M household the couple is more likely to be younger, to have fewer children and to have a higher level of education and the head of the household is more likely to be white and Catholic. The probability that the M couple stays married for 10 years is lower than for the C household. These results are consistent with our prior probabilities on the demographic characteristics of modern and classical attitudes within a household and, therefore, our confidence in the model's interpretation of the data is reinforced.

4.4 Counterfactuals

In this section we use the estimated model to measure the potential increase in female employment that is due to the change in the rules of the game, i.e. in social norms, which determine the household's joint labor supply. This is done through two simulations: In the first, we assume that all households are of type M and leave the employment opportunities of men and women as estimated. This simulation measures the potential marginal impact on employment. In the second, we assume, in addition, identical employment opportunities for men and women in terms of wages and job-offer rates.

Simulation 1: All households are Modern

We assume that all of the households in the population are Modern instead of only 38.6 percent as estimated. As a result, the predicted female employment rate becomes 0.77 instead of the estimated 0.71 while the predicted male employment rate remains almost the same at 0.887 instead of the estimated 0.890. According to the predicted outcome of the simulation, even when the entire population consists of M households the male employment rate exceeds that of women by 11.3 percentage points. This is due to the differences in wages, job-offer probabilities and preferences as explained above (see Figure 4.4).

This result can be interpreted as follows: Changes in social norms over time, which can be expressed as a change in the proportion of M and C households for different cohorts, may have had a large impact on the employment rate of married women though they did not affect the rate for married men. This is consistent with the observation reported in Sections 2 and 3.

Simulation 2: All households are Modern and employment opportunities for both genders are identical

In addition to the assumptions of Simulation 1, we now calibrate the female wage function and job-offer probability parameters to the values of the estimated parameters for men. As a result, the female employment rate increases to 0.84 and that of men decreases to 0.88 (see Figure 4.5). Thus, male and female employment rates will differ by 3.2 percentage points which is due only to the difference in the utility function parameters. For example, the value of leisure is higher for women ($10 dollars per hour for women as compared to only $8.9 per hour for men). In addition the relative risk aversion of women is much higher (i.e. a lower γ) than that of men, as discussed above. In other words, the marginal utility from consumption is lower for women and therefore they require larger incentives to work outside the home.

Wages and job-offer rates are taken as exogenous here and we compare employment outcomes when social norms based on an M-type game maximize employment rates of married women. Obviously, in equilibrium the change in labor supply would affect the wages and job-offer rates of men and women. However, since we expect that preferences for leisure, consumption and other home amenities differ between men and women, we would also expect differences in the distributions of employment outcomes. This is the case in a fully symmetric game like that in M households.

5 Concluding Remarks

This paper demonstrates the usefulness of dynamic discrete choice models in the measurement and explanation of dynamic female labor supply and in household economics in general. The endogenous choice of employment provides an internally consistent framework for predicting labor supply in a dynamic stochastic environment in which past and future changes in schooling, wages, fertility and marital status are uncertain. This framework yields an empirical dynamic model with rational expectations and cross-equation restriction (Sargent, 1978) that controls for dynamic selection bias (Heckman, 1974). The framework is a rich one that can be used to consistently measure the contributions of competing hypotheses to explaining the dramatic rise in married female employment rates.

Can this framework predict the future increase in per capita US GDP due to the employment of married women? There are good reasons to believe that female levels of schooling will continue to rise and that female wages will approach those of men and will also increase as a result of economic growth. Furthermore, it is likely that technological change will continue to affect household activities, including the reduction in the cost of raising young children, and that social norms will continue to change in the direction of greater equality between men and women in household decisions. Nonetheless, Figure 1.2 indicates that female employment has been stable during the past decade. This is due to the surprising reduction in employment of PC women and an increase in the employment of HSD women, which together have resulted in a constant employment rate. The data on schooling (Figure 2.1) shows some signs of convergence and according to the household labor supply model discussed in Section 4 women choose to work less than their husbands due to differences in both preferences and labor market opportunities. It would be a challenge to use the model for predicting future changes in female employment. However, in the most likely scenario for coming years the contribution of women to the growth in per capita GDP will be significantly less than that seen in Figure 1.1.

6 References

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Appendix A

The following assumptions were made in calculating per capita GDP for the various specifications of female employment (quantity and quality): First, we assume a standard Cobb-Douglas function of the form $Y_t = (A_t K_t)^{\alpha} \cdot (L_t^{F*} + L_t^{M*})^{1-\alpha}$ where: $\alpha = 0.33$, A_t is the level of productivity, K_t is the capital stock, ${L^{F*}}_t$ is female aggregate labor supply for ages 22-65, ${L^{M*}}_t$ is male aggregate labor supply for ages 22-65. Since we wish to simulate changes in male and female employment, we define 90 sub-groups (types) of employees according to schooling, marital status and experience as follows: education (5 groups - HSD, HSG, SC, CG, PC); marital status (3 groups - married, single, others); experience (6 groups - by years of experience: 0-5, 6-10, 11-20, 21-30, 31-40, 40+).[52] The aggregate labor supply for either gender is then defined by: $L_t^* = \sum_{j=1}^{90} L_{tj} \cdot H_{tj} \cdot W_{tj}$, where L_{tj} is the number of employees of type j in period t, H_{tj} is the mean number of weekly hours for an employee of type *j* in period *t*; and W_{tj} is the mean hourly real wage of employees of type *j* in period *t* (proxy for productivity or quality). We use the CPS data to calculate the values of L_t^* for men and women and plug them into the production function. We then estimated the productivity and capital contribution as a residual when using actual per capita GDP and labor input, as defined.[53] We then simulated two different scenarios for female labor input as follows:

Simulation 1: *Female employment fixed at its 1964 level*

We assume that female employment remains constant, i.e. ${L^{F*}}_t = {L^{F*}}_{1964}$, and then calculate per capita GDP using the estimated productivity and capital contributions. In this scenario, per capita GDP reaches \$33,375 in 2007, which is 40 percent less than actual per capita GDP in that year.

Simulation 2: Quality of female labor fixed at its 1964 level

We assume that women's wages relative to those of men remain constant at their 1964 levels for each sub-group defined above. In other words, female employment with fixed quality is given as:

$$L_t^{F*} = \sum_{j=1}^{90} L_{tj} \cdot H_{tj} \cdot W_{1964j} \ .$$

[52] We define years of potential experience as the difference between age and years of schooling, where years of schooling is defined to be 18 years for the HSD group, 19 for the HSG group, 22 for the SC group and 23 for the CG and PC groups (including the 6 years before school).

[53] Real per capita GDP in 2006 dollars for the period 1964-2007.

In this scenario, per capita GDP increases to $37,954 in 2007, which is 23 percent less than the actual per capita GDP in that year.

Appendix B.1: The CPS Data for the Standard Model

Data was taken from the Annual Demographic Survey (March CPS supplement) conducted by the Bureau of Labor Statistics and the Bureau of the Census. This survey is the primary source for detailed information on income and work experience in the United States. A detailed description of the survey can be found at www.bls.census.gov/cps/ads/adsmain.htm. Our data, for the years 1962-2007, was extracted using the Unicon CPS utilities.

The sample is restricted to civilian adults, ignoring the armed forces and children. We divided the sample into five education groups: high school dropouts (HSD), high school graduates (HSG), individuals with some college (SC), college graduates (CG) and post-college degree holders (PC). In order to construct the education variable, until 1991 we used the years of schooling completed and added 0.5 years if the individual did not complete the highest grade attended and from 1992 we used years of schooling as is.

Weekly wages are constructed by taking the previous year's wage and salary income and dividing it by the number of weeks worked in the previous year. Hourly wages are defined as the weekly wage divided by the number of hours worked in the previous week in all jobs, while annual (annualized) wages are defined as the weekly wage multiplied by 52. Wages are multiplied by 1.75 for top-coded observations until 1995. Nominal wages are deflated using the Personal Consumption Expenditure (PCE) index from NIPA Table 2.3.4 (http://www.bea.gov/national/nipaweb/index.asp). Since wages refer to the previous year, we use the PCE for year X-1 for observations in year X and therefore all wages are expressed in constant 2006 dollars.

Information on number of children under six for the period 1968-1975, which is missing from the survey data, is completed where possible using the distributions of this variable in 1967 and 1976 for each gender, marital status and cohort separately. The completed information can be used to construct an aggregate trend, but not to identify the number of children for a specific individual.

Appendix B.2: Husband's Wage and Human Capital

This appendix explains how the data on husbands' wages, schooling and experience have been generated for the estimation and simulation of the model in Section 3. If a woman is married, we simulate her husband's human capital (i.e. education and accumulated experience) according to the actual distribution. Thus, we use the actual distribution of level of education (HSD, HSG, SC, CG, PC) and accumulated experience (0-10,10-20,20-30,30+)[54] for the husbands of a particular group of women[55] (done separately for each education group and cohort) and then make a random draw for the husband's characteristics. We also simulate whether or not the husband is employed using the employment rate of husbands for this specific group of women. We then simulate the husband's wage using the coefficient estimated from a standard Mincer/Ben-Porath wage equation for men. Here again, we use a separate wage equation for each cohort and education group of women. The characteristics of the husband and the wage regression estimators can be found at the above-mentioned web site.

Appendix B.3: Moments and Identification

We divide the sample into cohorts for 1925 to 1975, where each cohort consists of women born over a five-year interval (thus, the 1925 cohort consists of women born in the period 1923-27, the 1930 cohort consists of women born in 1928-32 and so on, up until the 1975 cohort).

For each education group within each cohort, we use the CPS data for 1964-2007 to calculate the following moments at each age from 23 to 54 (for CG and PC women we start at age 24):

- *Employment rate* (T*5 moments) - for the entire population, including absences and with no restrictions on weekly work hours.
- *Average hourly wages* (T*5 moments) - real hourly wage for employed women with non-zero wage.
- *Marriage rate* (T*5 moments) - including women with an absent spouse.
- *Divorce rate* (T*5 moments).
- *Distribution of number of children under 6: no children, one child, two children and three or more children* (T*5*4 moments).
- *Distribution of the number of children aged 6-18: no children, one child, two children and three or more children* (T*5*4 moments) - defined as the difference between the number of children under 18 and the number under 6.

We used the T*5*12 (T=32) moments above to identify the model parameters. We then compared these moment to the simulated moments of the model. Since we have 45 parameters, the model is identified. Each group of parameters is identified from a different set of moments:

[54] Years of potential experience as described in Appendix A.

[55] In order to construct couples, we kept only heads of households and spouses (i.e. no secondary families were used) and dropped households with more than one male or more than one female. We then merged women and men based on year and household id and dropped problematic couples (with two heads or two spouses, with more than one family or with inconsistent marital status or number of children).

- The utility parameters (9) and job-offer probability parameters (8) are identified using the employment rate moments.
- The wage parameters (8) are identified using the average hourly wage moments.
- The probability of another child parameters (8) are identified using the distribution of the number of children in the two age group moments.
- The marriage and divorce probability parameters (12) are identified using the marriage rate moments.

Appendix B.6: Description of the Accounting Exercise

For each cohort, we use the relevant initial condition to construct the representative sample: the marriage rate and distribution of children at the age of 23 and the distribution of husbands' characteristics for the specific cohort.

Schooling

In order to estimate the impact of the change in education on female employment, we use the estimated employment of each education group in the 1955 cohort and calculate aggregate employment using the education groups in the 1945 cohort. We repeat the same calculation for all the other cohorts using the relevant weights.

Wages

In order to estimate the influence of the change in wages on female employment we modify both the wages of the women and those of their husbands. For the husbands, we estimate reduced form wage regressions for every cohort and for each education group and use the repressors to simulate the husband's wages. For the wives, we re-estimate the parameters $\beta_1, \beta_2, \beta_3$ from equation (3) for every cohort. We use the new parameters to simulate female employment for every cohort.

Fertility

In order to estimate the influence of the number of children, their ages and the age of the women at childbirth on female employment we re-estimate the parameters $\lambda_1, \lambda_2, \lambda_3$ separately for every cohort from the probability function for having another child. We use the new parameters to simulate female employment.

Marital Status

For each cohort, we re-estimate the parameters $\varsigma_0, \varsigma_{1,}, \varsigma_2$ from the probability function for marriage and the parameters ξ_0, ξ_1, ξ_2 from the probability function for divorce. We use the new parameters to simulate female employment.

Appendix B.7: Robustness Analysis for the Order of the Simulations

The following order of simulation was used in the accounting exercise: schooling + initial conditions, wages, fertility and martial status.

The following orders were also looked at:

- Schooling, wages, martial status and fertility: no change in initial conditions.
- Wages + initial conditions, schooling, fertility, martial status.
- Wages + initial conditions, fertility, schooling, martial status.
- Wages + initial conditions, fertility, martial status, schooling.
- Schooling + initial conditions, wages, martial status, fertility.

The influence of the change in *schooling* was about 35 percent originally and remained above 30 percent in the robustness analysis. In all cases, it was larger than the effect of the change in *other*. The influence of wages remained almost unchanged (never below the original 20 percent and for some orders rose to levels of up to 24 percent). The influence of children decreased for some of the orders (from 5 percent to 3.5 percent on average) and in other cases remained the same, even when we changed the marital status distribution before the distribution of children. The influence of the marriage/divorce rate increased when we changed the marital status distribution before the distribution of children and the increase was larger for younger age groups. When the marriage/divorce rate was changed last it contributed less than 1 percent to female employment on average, though if we reverse the order, the effect increases to almost 2 percent. Overall, the changes in female employment were robust to the order of the simulation.

We also examined the impact of a change in the initial conditions, which affected only the 23-27 age group. On average, the employment rate for this age group was no more than three percent higher if the initial conditions for the 1925-1940 cohorts were left unchanged and no more then two percent higher (lower) for the 1945-1950 (1960-1975) cohorts. The full results of the robustness analysis can be found at www.tau.ac.il/~eckstein/FLS/FLS_index.html.

Appendix C.1: Household Model: Logit Probability Functions for Fertility and Divorce and Terminal Value Functions

The probability of having another child

The probability of having another child is a function of the woman's employment state in the previous period, the woman's age and education and those of her husband, martial status, current number of children and the age of the youngest child (the woman's age and the number of children have a non-linear influence on the probability). The probability of having an additional child is given by Van der Klaauw (1996) as:

$$\Pr(N_t = N_{t-1} + 1) = \Phi\left(\lambda_1 \cdot AGE_t^W + \lambda_2 \cdot \left(AGE_t^W\right)^2 + \lambda_3 \cdot AGE_t^H + \lambda_4 \cdot S^W + \lambda_5 \cdot S^H + \lambda_6 d_{tW}^1 + \lambda_7 d_{tH}^1 + \lambda_8 \cdot N_t + \lambda_9 \cdot age_t\right) \qquad \text{(C.1)}$$

where $\Phi(\cdot)$ is the standard normal distribution function.

The probability of divorce

The probability of divorce is estimated as a function of how long the couple has been married (*t*), current number of children, the female's education and the employment states of the woman and her husband:

$$\Pr(M_t = 0 / M_{t-1} = 1) = \Phi\left(\xi_1 \cdot t + \xi_2 \cdot t^2 + \xi_3 \cdot N_t + \xi_4 \cdot S_t^W + \xi_5 \cdot d_{tW}^1 + \xi_6 d_{tH}^1\right) \qquad \text{(C.2)}$$

Terminal Value

The model is solved backwards from the terminal period *T* using a linear approximation for the value function in the final period, as follows

$$V_T(\Omega_T, T) = \delta_1^j + \delta_2^j \cdot K_T + \delta_3^j \cdot S \qquad \text{(C.3)}$$

Table 3.1: Estimated Parameters (1955 cohort)

Utility*	
$\alpha_1 + \alpha_{52}$ - employment for HSG	-15658.077 (2705.714)
α_2 - consumption	-0.039 (0.015)
α_3 - experience	-29.331 (24.46)
α_{41} - utility minus cost of children 0-6	-2733.357 (730.618)
α_{42} - utility minus cost of children 6-18	-487.284 (94.222)
α_{51} - HSD	-1877.034 (169.372)
α_{53} - SC	1731.615 (295.909)
α_{54} - CG	2785.931 (114.208)
α_{55} - PC	3447.321 (94.064)
b_m - leisure for unmarried	17226.303 (1273.606)

Wage**	
β_1 - experience	0.017 (0)
β_2 - experience^2	-0.00002 (0)
β_{31} - HSD	2.15 (0.036)
β_{32} - HSG	2.406 (0.027)
β_{33} - SC	2.627 (0.051)
β_{34} - CG	2.877 (0.053)
β_{35} - PC	3.229 (0.178)
β_4 - trend	0.004 (0)
σ_ε - error's std	0.05 (0.03)

Job Offer Probability***	
ρ_{11} - HSD	-0.022 (0.012)
ρ_{12} - HSG	-0.057 (0.0004)
ρ_{13} - SC	0.186 (0.003)
ρ_{14} - CG	0.496 (0.006)
ρ_{15} - PC	0.81 (0.013)
ρ_2 - experience	0.052 (0.002)
ρ_3 - experience^2	-0.001 (0.0001)
ρ_4 - employed previous period	0.651 (0.083)

Standard errors appear in parentheses

* See equation 3.7; we assume cm=0.

** See equation 3.3.

*** See equation 3.8.

Note: We set α=1 as in EW since it becomes non-robust when estimated. Thus, although α is identified we obtained a value close to zero for α_2. In practice, we could not separate α from b_m and moreover b_m is easier to estimate.

Table 3.2: Women's Employment Rates by Cohort, Age and Characteristics According to the Estimated Model

		Cohort									
		1925	1930	1935	1940	1945	1950	1960	1965	1970	1975
Age Group:	**Actual**				**0.40**	**0.47**	**0.55**	**0.65**	**0.68**	**0.70**	**0.71**
23-27	Schooling+initial				0.57	0.59	0.62	0.63	0.63	0.65	0.65
	Wage				0.52	0.55	0.59	0.63	0.64	0.66	0.65
1955 cohort	Children				0.50	0.54	0.58	0.63	0.64	0.66	0.65
Prediction	Marital Status				0.50	0.54	0.58	0.63	0.64	0.66	0.65
0.62	Other				**0.10**	**0.08**	**0.03**	**-0.03**	**-0.05**	**-0.04**	**-0.06**
Age Group:	**Actual**			**0.36**	**0.42**	**0.49**	**0.60**	**0.68**	**0.70**	**0.73**	**0.70**
28-32	Schooling+initial			0.58	0.60	0.63	0.65	0.66	0.67	0.68	0.68
	Wage			0.52	0.60	0.63	0.64	0.67	0.67	0.68	0.69
1955 cohort	Children			0.50	0.57	0.61	0.63	0.67	0.67	0.68	0.69
Prediction	Marital Status			0.50	0.57	0.61	0.63	0.67	0.67	0.68	0.69
0.65	Other			**0.14**	**0.15**	**0.12**	**0.03**	**-0.01**	**-0.03**	**-0.05**	**-0.01**
Age Group:	**Actual**		**0.40**	**0.45**	**0.51**	**0.59**	**0.67**	**0.71**	**0.72**	**0.71**	
33-37	Schooling+initial		0.62	0.63	0.65	0.67	0.69	0.70	0.70	0.71	
	Wage		0.53	0.57	0.64	0.67	0.69	0.70	0.71	0.71	
1955 cohort	Children		0.52	0.56	0.62	0.67	0.68	0.70	0.71	0.71	
Prediction	Marital Status		0.52	0.56	0.62	0.67	0.68	0.70	0.71	0.71	
0.69	Other		**0.12**	**0.11**	**0.12**	**0.07**	**0.01**	**-0.01**	**-0.02**	**0.00**	
Age Group:	**Actual**	**0.45**	**0.48**	**0.54**	**0.62**	**0.68**	**0.73**	**0.75**	**0.73**		
38-42	Schooling+initial	0.64	0.66	0.67	0.69	0.71	0.73	0.74	0.74		
	Wage	0.56	0.59	0.62	0.66	0.69	0.73	0.74	0.73		
1955 cohort	Children	0.56	0.58	0.61	0.64	0.69	0.73	0.74	0.73		
Prediction	Marital Status	0.56	0.58	0.61	0.64	0.69	0.73	0.74	0.73		
0.74	Other	**0.11**	**0.09**	**0.07**	**0.01**	**0.01**	**0.00**	**-0.01**	**0.00**		
Age Group:	**Actual**	**0.51**	**0.54**	**0.61**	**0.67**	**0.73**	**0.76**	**0.75**			
43-47	Schooling+initial	0.66	0.68	0.69	0.71	0.73	0.74	0.75			
	Wage	0.60	0.61	0.65	0.69	0.73	0.76	0.75			
1955 cohort	Children	0.60	0.60	0.65	0.68	0.73	0.76	0.75			
Prediction	Marital Status	0.60	0.60	0.65	0.67	0.73	0.76	0.75			
0.75	Other	**0.08**	**0.06**	**0.04**	**0.01**	**0.00**	**0.00**	**0.00**			
Age Group:	**Actual**	**0.52**	**0.56**	**0.61**	**0.67**	**0.72**	**0.75**				
48-52	Schooling+initial	0.65	0.66	0.68	0.70	0.73	0.74				
	Wage	0.62	0.64	0.67	0.70	0.73	0.75				
1955 cohort	Children	0.62	0.62	0.66	0.69	0.73	0.75				
Prediction	Marital Status	0.61	0.62	0.66	0.68	0.73	0.75				
0.75	Other	**0.09**	**0.06**	**0.05**	**0.01**	**0.01**	**0.00**				

Table 3.3: Change in Estimated Utility/Cost of Leisure and Young Children by Cohort

	parameters		interpeted parameters - change in dollar value per hour	
Cohort	α_1 - Constant	α_{41} - young children (0-6)	α_1 - Constant	α_{41} - young children (0-6)
1925	-25481.9	-8818.78	4.912	3.167
1930	-25360.5	-8818.78	4.851	3.167
1935	-24570.3	-8818.78	4.456	3.167
1940	-15658.1	-8980.07		3.251
1945	-15658.1	-8641.53		3.075
1950	-15658.1	-6804.98		2.119
1955	**-15658.1**	**-2733.36**		
1960	-15658.1	-1006.18		-0.899
1965	-15658.1	-606.78		-1.107
1970	-15658.1	-600.26		-1.110
1975	-15658.1	-620.11		-1.100

* In order to interpet α_1, we divided the difference between the value of the parameter in the specific cohort and the value of the parameter in 1955 by 2000 (# of hours worked per year).

* In order to interpet α_4, we divided the difference between the value of the parameter in the specific cohort and the value of the parameter in 1955 by the value of (1+α_2) and then by 2000 (# of hours worked per year).

Table 4.1: Estimated Parameters - Household Labor Supply

Utility*	Men	Women
γ_j - risk aversion	0.948 (0.886)	0.849 (0.151)
α_j - value of leisure	8.215 (1.32)	9.188 (2.874)
SC - search cost	4.802 (1.293)	
γ_1 - leisure per child	7.386 (1.903)	
γ_2 - consumption per child	0.606 (0.278)	

Wage**	Men	Women
β_1 - constant	1.135 (4.912)	0.89 (0.212)
β_2 - experience	0.066 (0.011)	0.057 (0.21)
β_3 - experience^2	-0.00001 (0)	-0.00001 (0)
β_4 - schooling	0.081 (0.043)	0.087 (1.626)

Job Offer Probability***	Men	Women
ρ_{01} - employed previous period	2.852 (0.511)	2.973 (0.688)
ρ_{02} - unemployed previous period	-0.439 (0.067)	-0.966 (0.288)
ρ_{03} - OLF previous period	-2.466 (0.397)	-2.801 (0.563)
ρ_1 - schooling	0.018 (0.002)	0.016 (0.005)
ρ_2 - experience	0.005 (0.003)	0.006 (0.001)
ρ_3 - trend	0.03 (0.006)	0.018 (0.003)

Type Proportion****	
Classical household	0.455 (0.114)

Standard errors appear in parentheses.

* See equations 4.4, 4.5 and 4.6 (note that γ_0 is unidentified).

** See equation 4.2.

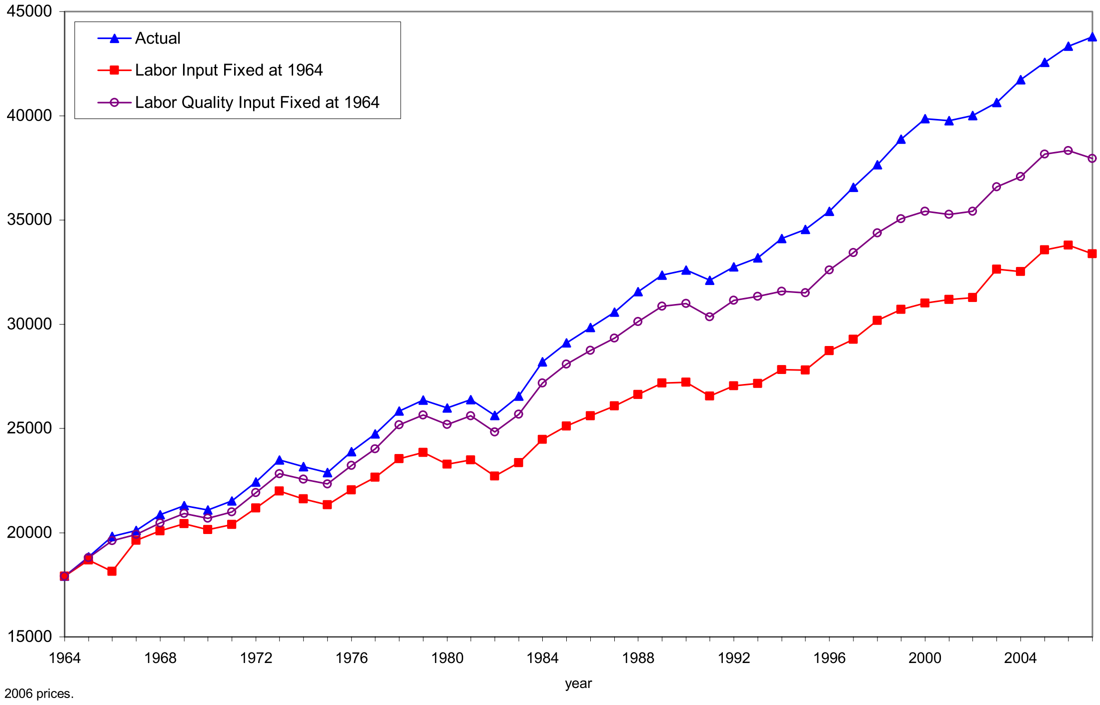
*** See equation 4.7.

**** The probability is given by exp(0.455)/(1+exp(0.455)).

Table 4.2: Correlation between Posterior Type Probability and Household Characteristics

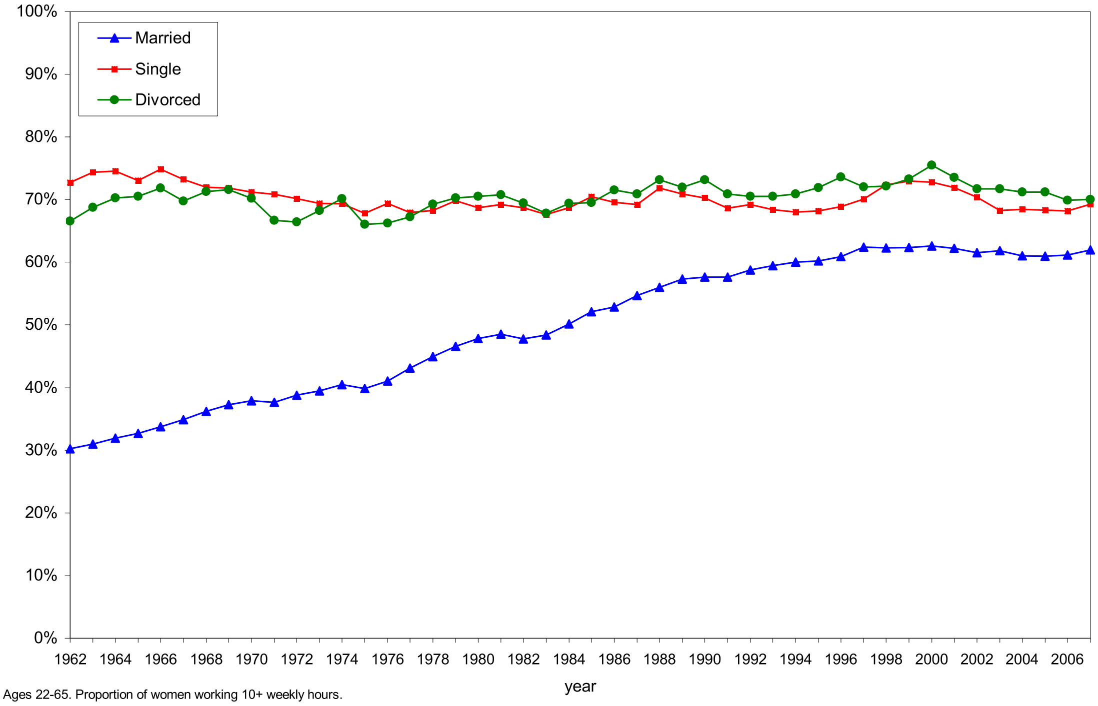
Variable	Estimated Probability of	
	C Household	M Household
Wife's age	0.107	-0.188
Husband's Age	0.089	-0.177
Wife's Education	-0.030	0.108
Husband's Education	-0.023	0.071
# of Children in Household	0.369	-0.371
White Husband	-0.048	0.080
Afro-American Husband	0.090	-0.077
Catholic Husband	-0.051	0.066
Protestant Husband	0.045	-0.031
Divorced during Sample Period	-0.106	0.129
Cities	0.014	0.006
Small Towns	-0.019	-0.010
Rural Area	0.063	-0.055

Figure 1.1: US Per Capita GDP



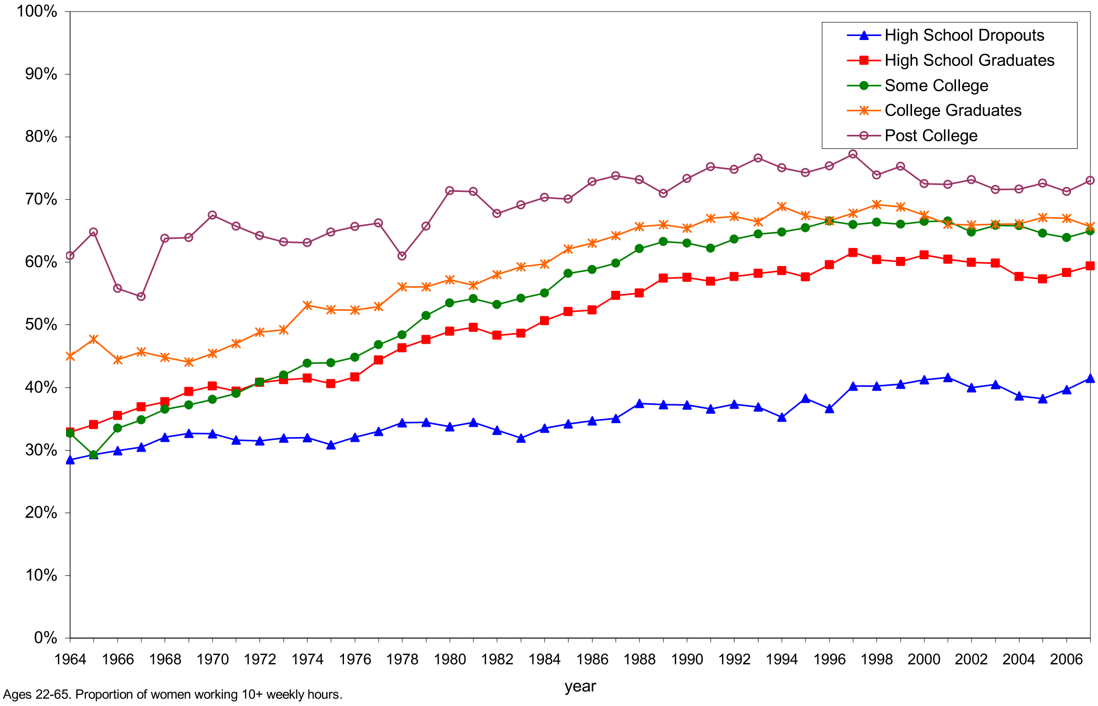
2006 prices.

Figure 1.2: Employment Rates by Marital Status - Women



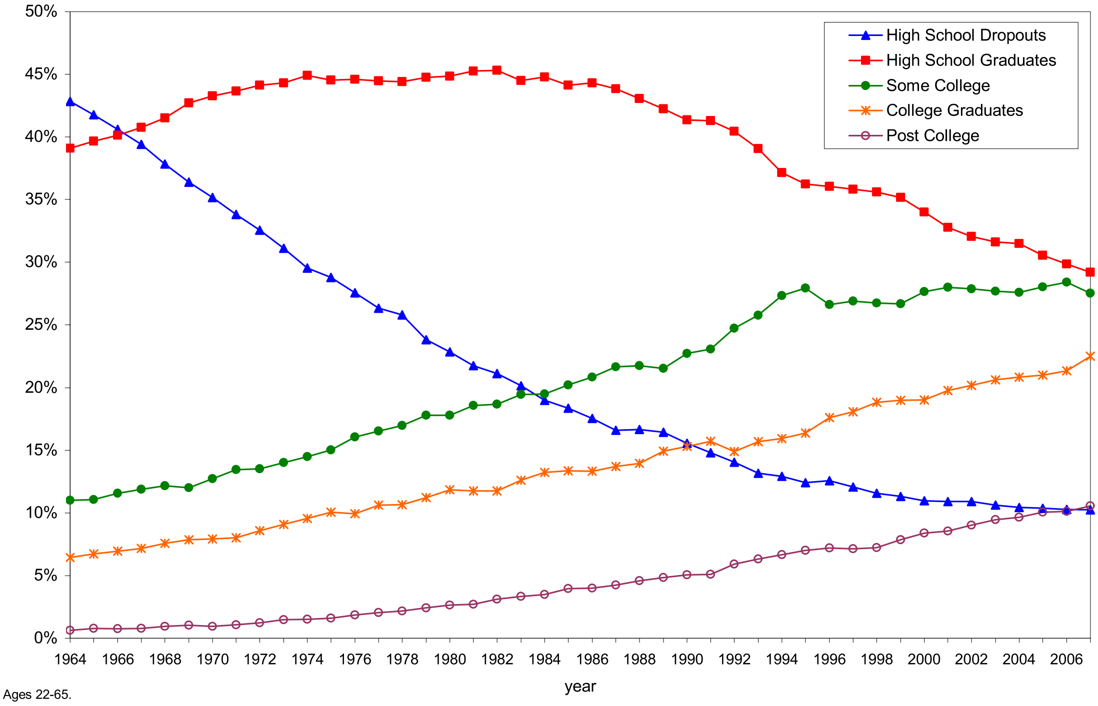
Ages 22-65. Proportion of women working 10+ weekly hours.

Figure 2.1: Employment Rates by Level of Education - Married Women



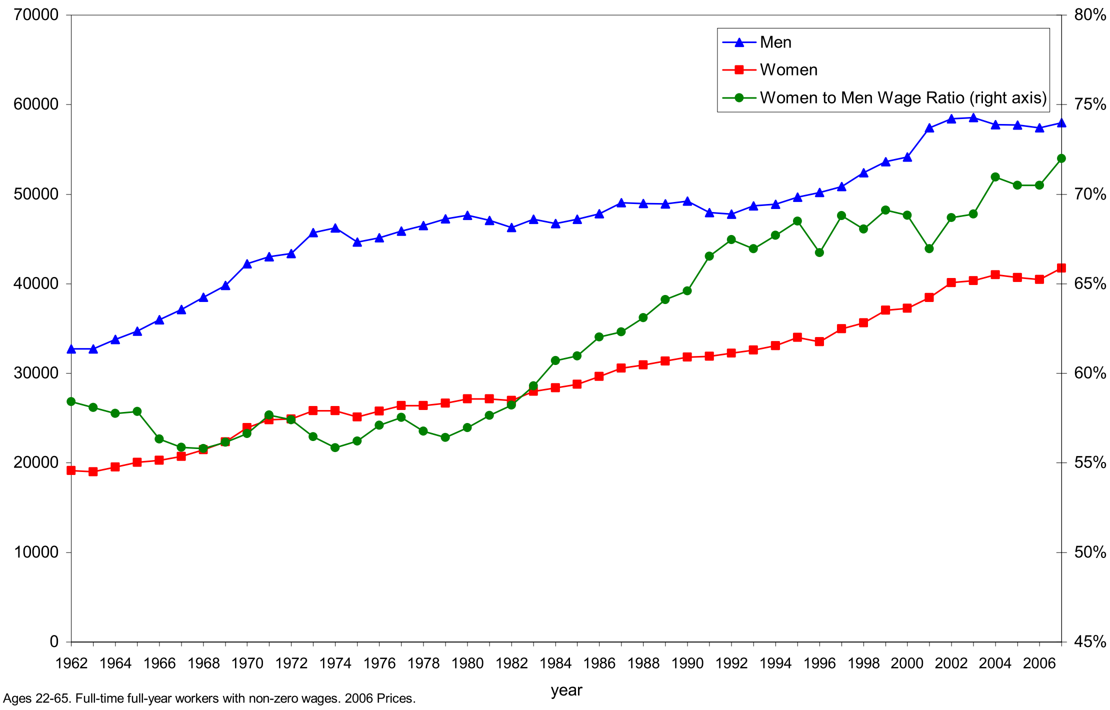
Ages 22-65. Proportion of women working 10+ weekly hours.

Figure 2.2: Breakdown of Married Women by Level of Education



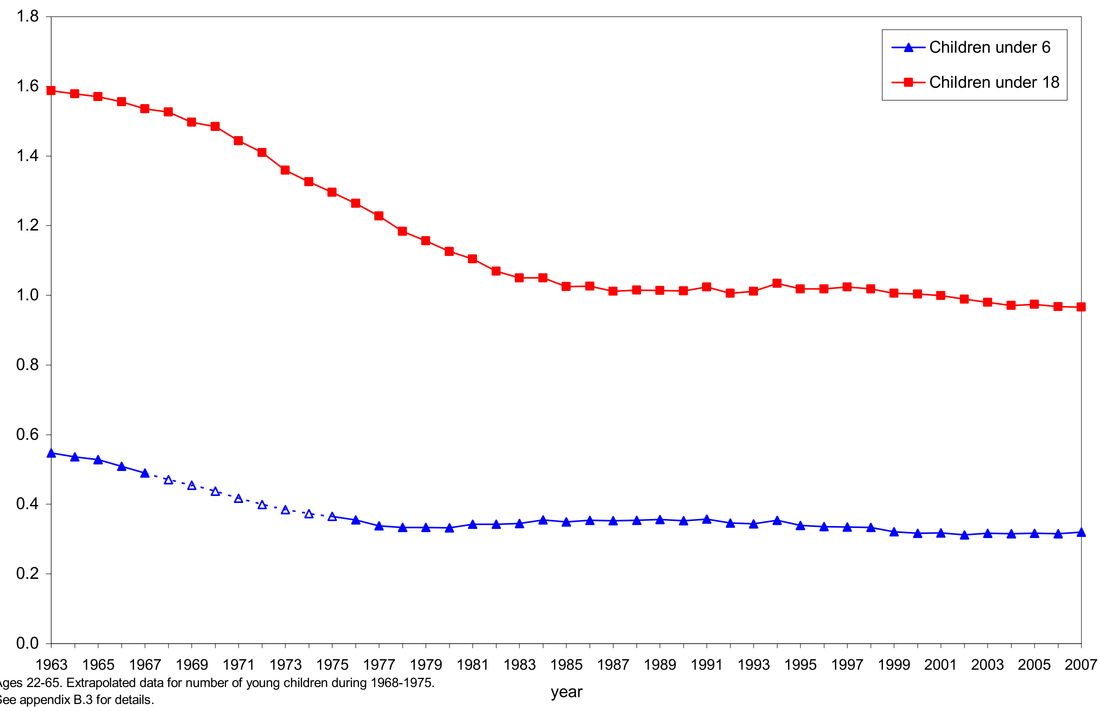
Ages 22-65.

Figure 2.3: Annual Wages of Full-Time Workers



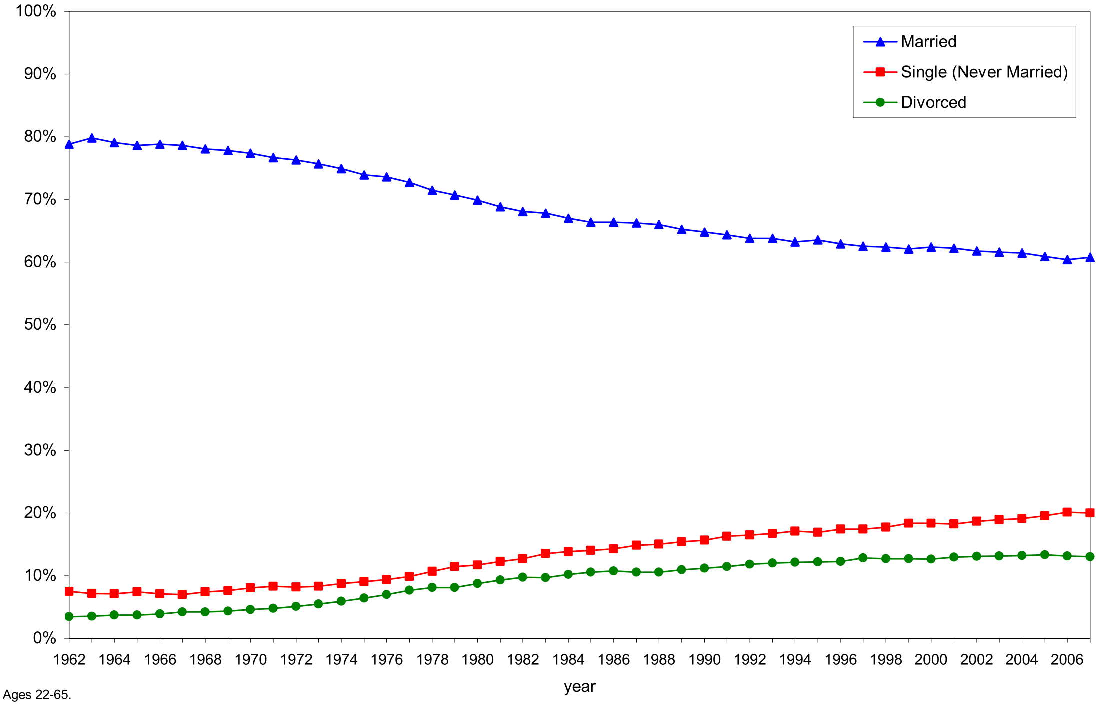
Ages 22-65. Full-time full-year workers with non-zero wages. 2006 Prices.

Figure 2.4: Number of Children per Married Woman



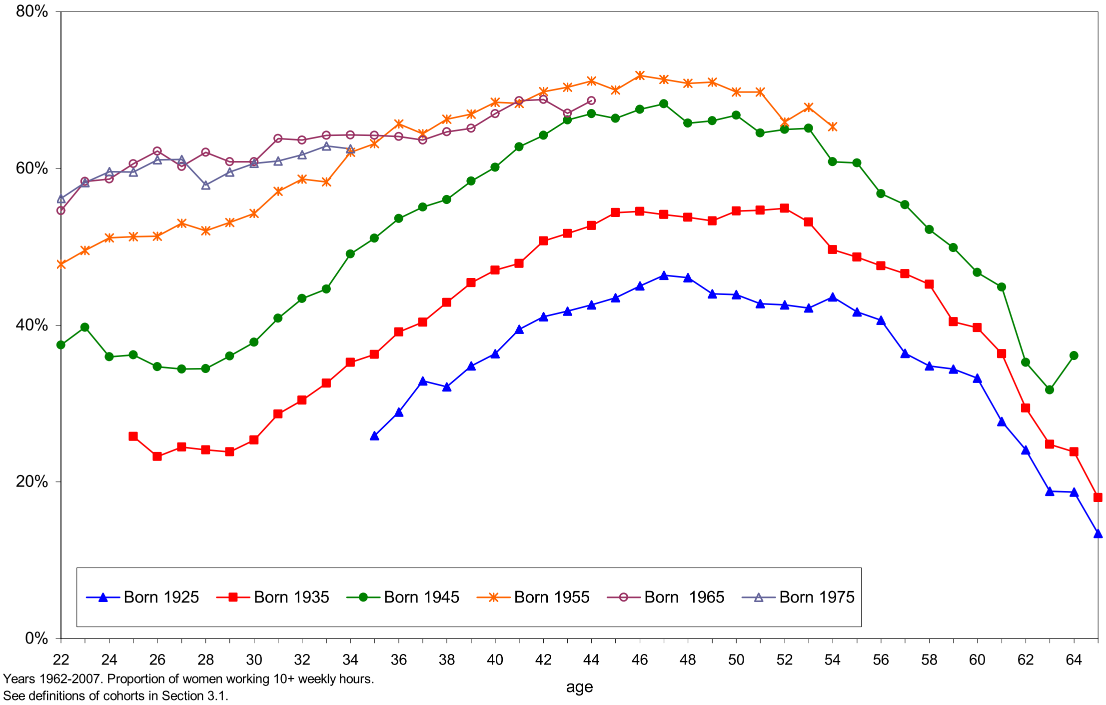
Ages 22-65. Extrapolated data for number of young children during 1968-1975.
See appendix B.3 for details.

Figure 2.5: Breakdown of Women by Marital Status



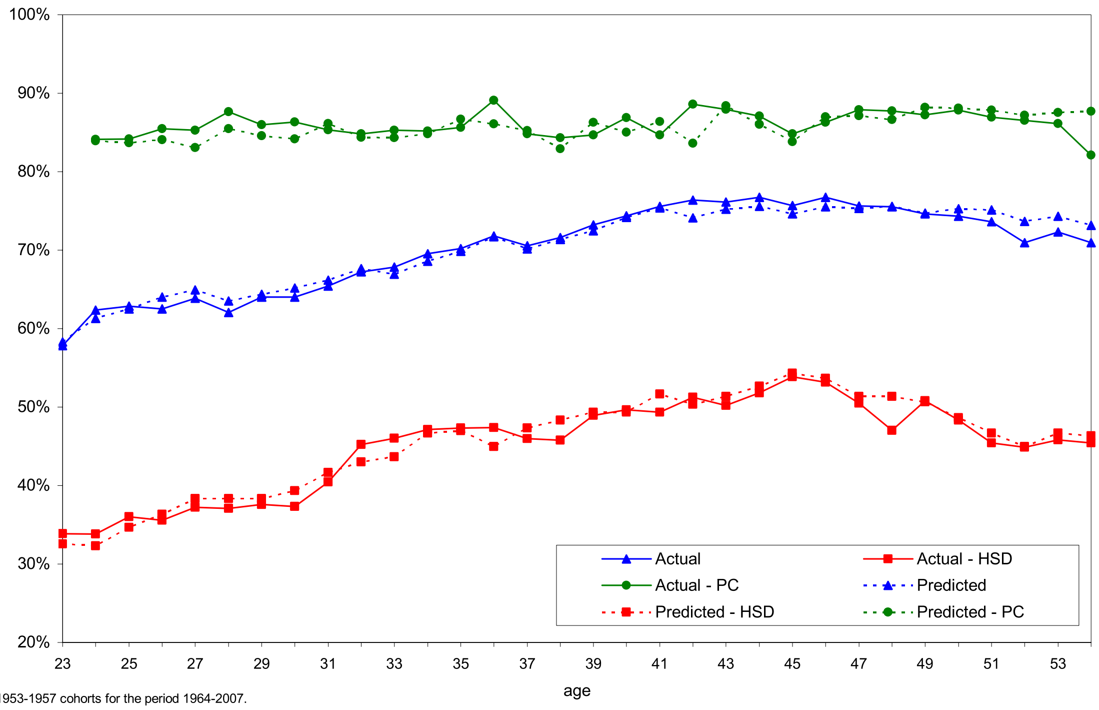
Ages 22-65.

Figure 2.6: Married Female Employment Rates by Cohort



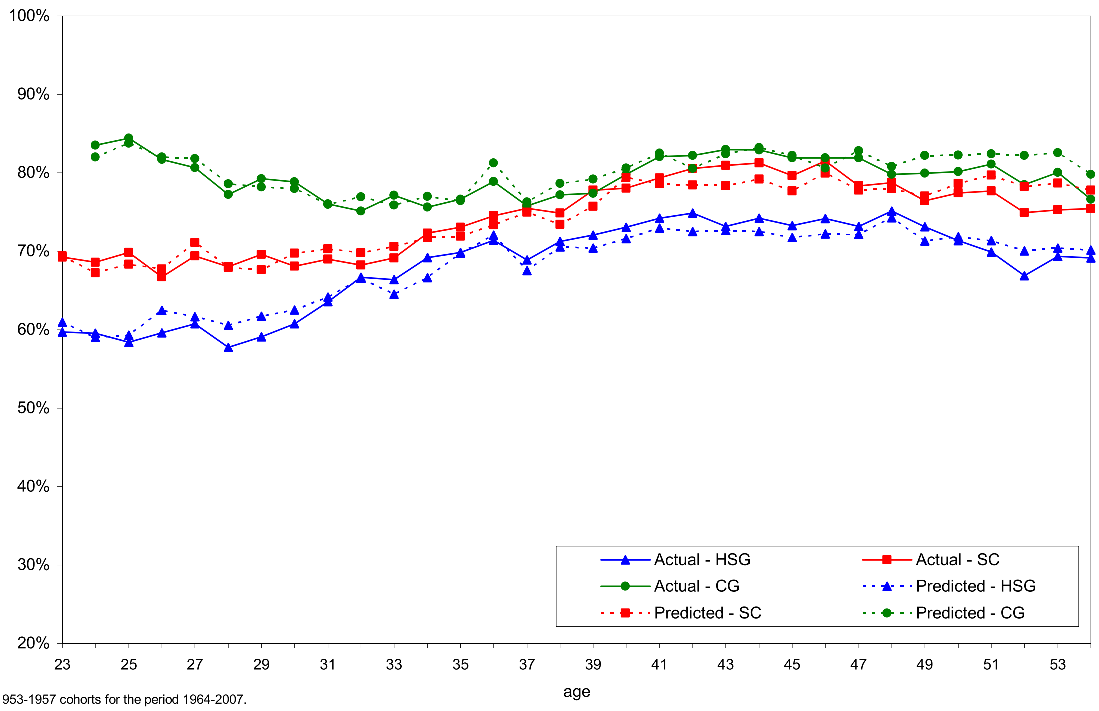
Years 1962-2007. Proportion of women working 10+ weekly hours.
See definitions of cohorts in Section 3.1.

Figure 3.1a: Actual and Predicted Employment Rates - 1955 Cohort



1953-1957 cohorts for the period 1964-2007.

Figure 3.1b: Actual and Predicted Employment Rates - 1955 Cohort



1953-1957 cohorts for the period 1964-2007.

Figure 3.2: Aggregate Female Employment Rates, Ages 23-54

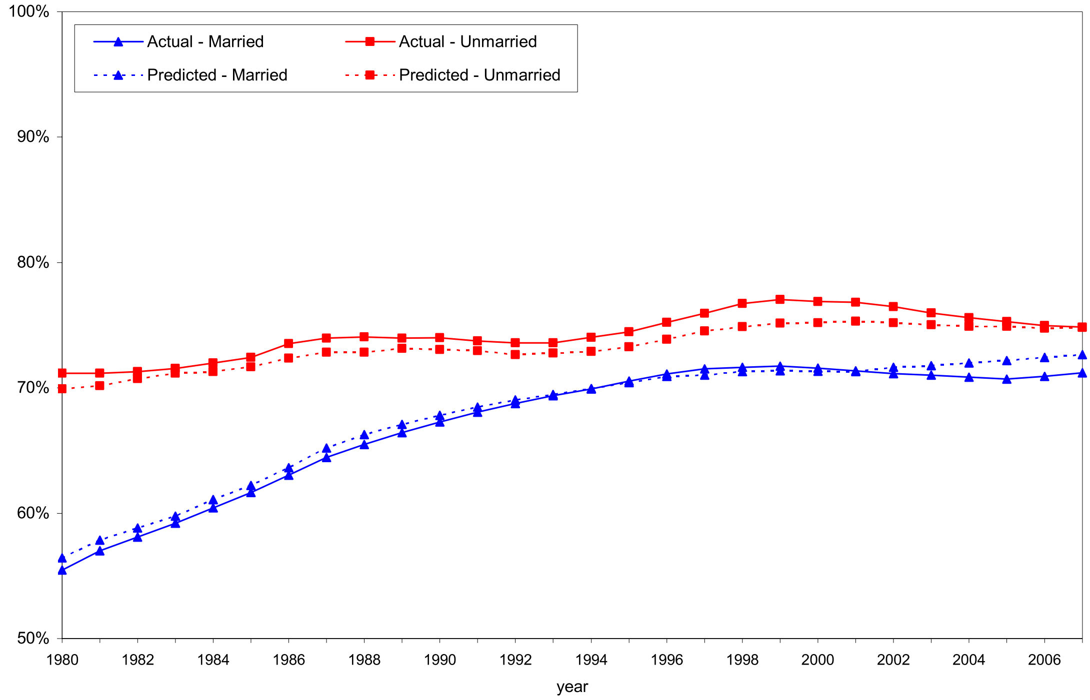
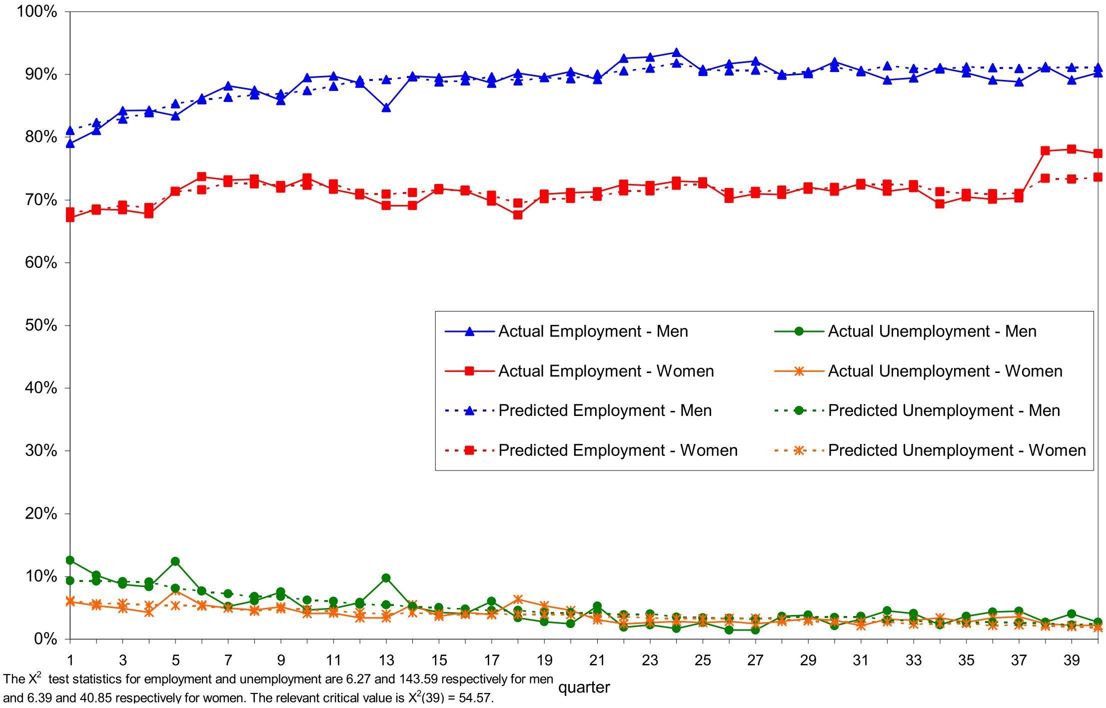
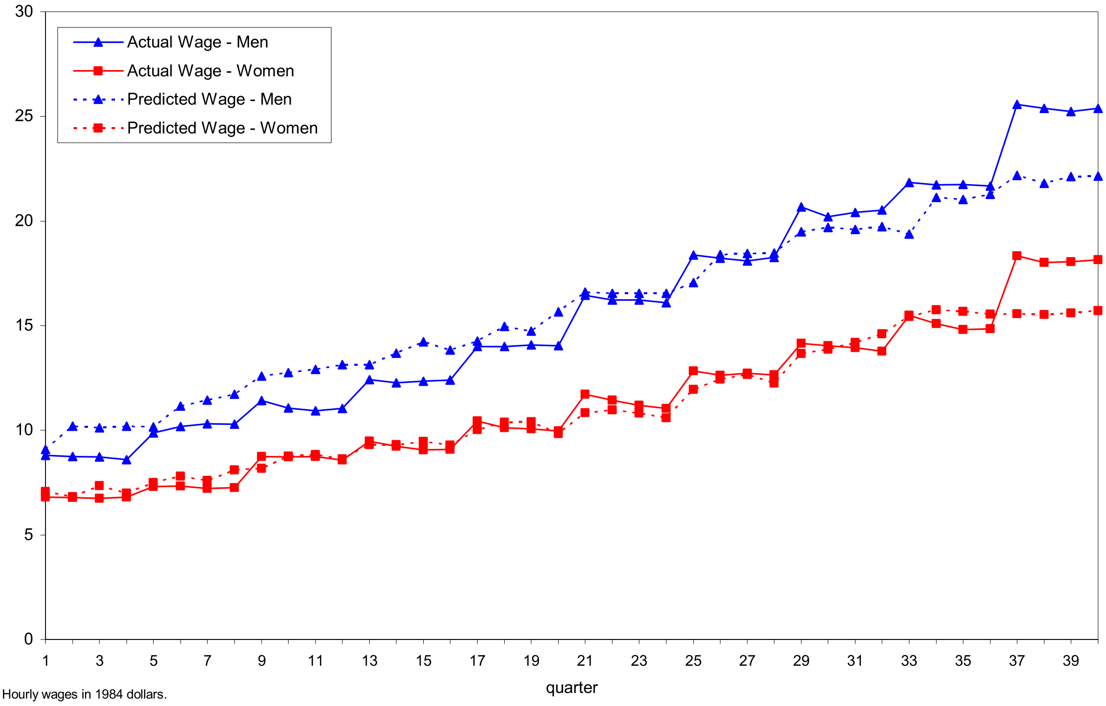


Figure 4.1: Actual and Predicted Choice Distribution



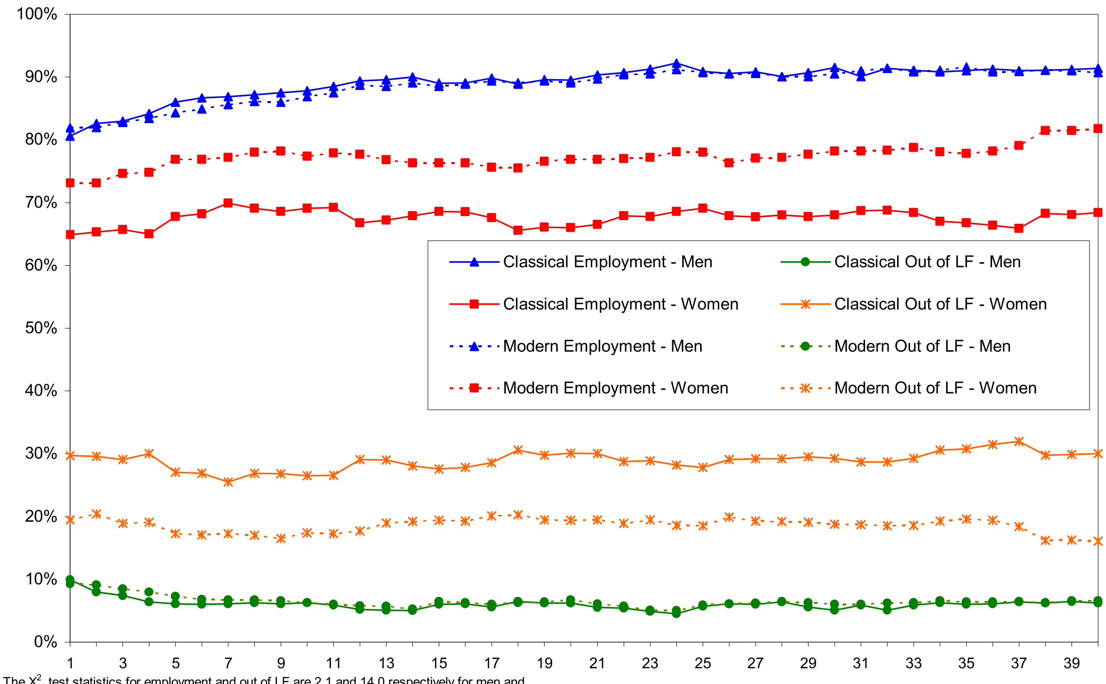
The X^2 test statistics for employment and unemployment are 6.27 and 143.59 respectively for men and 6.39 and 40.85 respectively for women. The relevant critical value is $X^2(39) = 54.57$.

Figure 4.2: Actual and Predicted Mean Wages



Hourly wages in 1984 dollars.

Figure 4.3: Predicted Choice Distribution in Classical and Modern Households



The X^2 test statistics for employment and out of LF are 2.1 and 14.0 respectively for men and 298.8 and 1418.1 respectively for women. The relevant critical value is $X^2(39) = 54.57$.

Figure 4.4: Simulation I - Predicted Employment Rates with 100% Modern Households

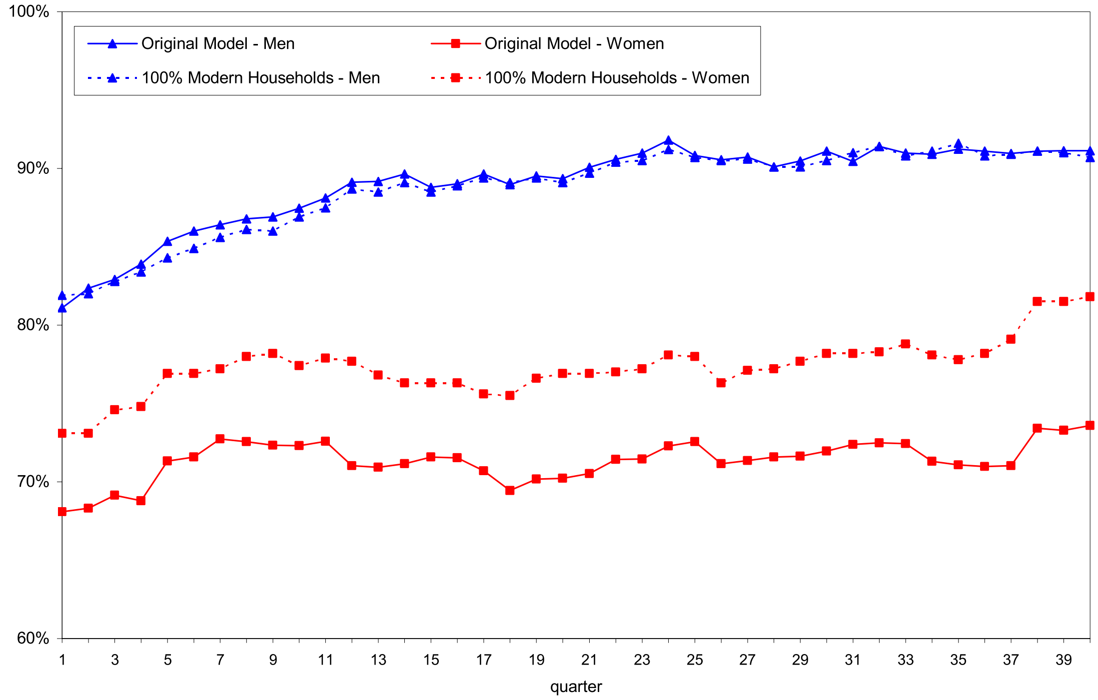


Figure 4.5: Simulation II - Predicted Employment Rates with 100% Modern Households and Identical Wages and Job Offer Probabilities

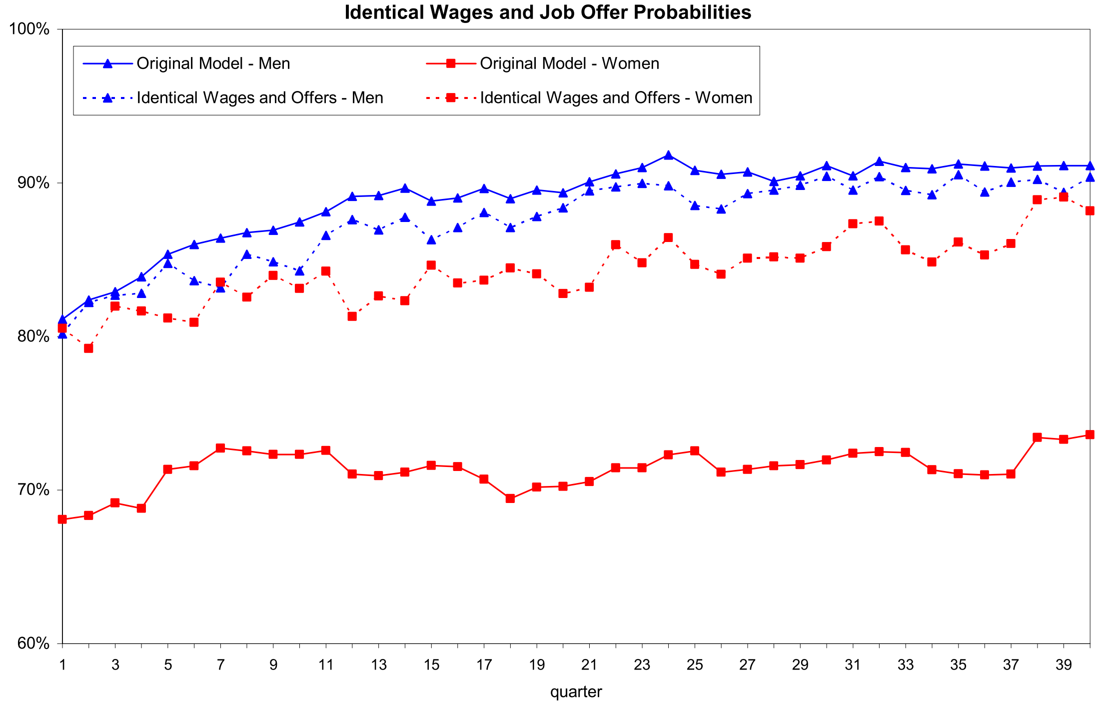


Table B.5: Logit Probability Functions for Fertility, Divorce and Marriage

Probaility of Another Child*	
λ_0 - constant	-2.333 (0.026)
λ_1 - age	0.212 (0.001)
λ_2 - age^2	-0.007 (0)
λ_3 - schooling	0.00002 (0.00002)
λ_4 - employed previous period	-0.341 (0.119)
λ_5 - # of children	0.083 (0.009)
λ_6 - # of children^2	-0.519 (0.043)
λ_7 - married	0.232 (0.116)

Probability of Divorce**	
ξ_0 - constant	-3.867 (0.033)
ξ_1 - years of marriage	0.016 (0.001)
ξ_2 - years of marriage^2	0.003 (0)
ξ_3 - # of children	-1.54 (0.027)
ξ_4 - schooling	0.00003 (0.00004)
ξ_5 - employed previous period	0.035 (0.02)
ξ_6 - husband's wage	-2.428 (2.642)

Probability of Marriage***	
ς_0 - constant	-4.158 (0.024)
ς_1 - age	0.001 (0.001)
ς_2 - age^2	-0.00003 (0.00002)
ς_3 - divorced previous period	-3.879 (1.478)
ς_4 - schooling	-0.0002 (0.0001)

Standard errors appear in parentheses.

* See equation 3.9.

** See equation 3.11.

*** See equation 3.10.

Table C.2: Additional Estimated Parameters - Household Labor Supply

Probaility of Another Child*	
λ_1 - wife's age	0.044 (0.014)
λ_2 - wife's age^2	-0.003 (0.002)
λ_3 - husband's age	0.058 (0.034)
λ_4 - wife's schooling	-0.061 (0.038)
λ_5 - husband's schooling	-0.048 (0.217)
λ_6 - wife employed previous period	-0.119 (0.033)
λ_7 - husband employed previous period	0.004 (0.001)
λ_8 - # of children	-0.258 (0.108)
λ_9 - youngest child's age	0.026 (0.009)

Probability of Divorce**	
ξ_1 - years of marriage	0.017 (0.01)
ξ_2 - years of marriage^2	-0.0004 (0)
ξ_3 - # of children	-1.476 (0.478)
ξ_4 - wife's schooling	0.021 (0.013)
ξ_5 - wife employed previous period	0.039 (0.024)
ξ_6 - husband employed previous period	-0.011 (0.008)

Terminal Value***	Men	Women
δ_1 - constant	126.555 (65.601)	117.641 (68.031)
δ_2 - experience	3.455 (2.798)	3.004 (0.646)
δ_3 - schooling	8.325 (2.192)	9.064 (1.857)

Cholesky Decomposition	
L(1,1)	0.113 (0.027)
L(2,1)	0.011 (0.003)
L(2,2)	1.357 (0.331)
L(3,1)	-0.107 (0.018)
L(3,2)	0.103 (0.019)
L(3,3)	-1.923 (0.474)

Standard errors appear in parentheses.

* See equation C.1.

** See equation C.2.

*** See equation C.3.