The Effect of Children on the Level of Labor Market Involvement of Married Women: What is the Role of Education?

Kenneth R. Troske

University of Kentucky

IZA, The Institute for the Study of Labor,
Bonn, Germany

Alexandru Voicu

City University of New York,
College of Staten Island

and

IZA, The Institute for the Study of Labor,
Bonn, Germany

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Abstract

We analyze the way women's education influences the effect of children on their level of labor market involvement, using panel data that capture women's' labor market and fertility histories and an econometric model that accounts for the endogeneity of labor market and fertility decisions, the heterogeneity of the effects of children and their correlation with the fertility decisions, and the correlation of sequential labor market decisions. Our results show that women with higher education are likely to have fewer children, work more before the birth of the first child, but children have larger negative effects on their level of labor market involvement. Differences across education levels are significantly more pronounced with respect to full time employment than with respect to participation, because in response to the birth of a child women with higher education are relatively more likely to move from full time work to part time work, whereas women with lower education are relatively more likely to stop working. Other things equal, the higher wages of more educated women reduce the effect of children on labor supply. Controlling for wages, women with higher education face larger negative effects of children on labor supply which suggest they are characterized by a combination of stronger preferences for time-intensive child quality, higher marginal product of time spent in the production of child quality, and higher marginal product of time relative to the marginal product of other inputs into the production of child quality.

Keywords: Female Labor Supply, Education, Endogenous Fertility Decisions, Heterogeneous Children Effects, Multinomial Probit Model, Gibbs Sampler.

JEL codes: C11, C15, J13, J22

1 Introduction

Theoretical household models of time allocation (Mincer, 1962, Becker, 1965, Willis, 1973, Michael, 1973, Leibowitz, 1974, Gronau, 1977, Angrist and Evans, 1996, 1998) suggest that children may have a larger negative effect on the labor supply of women with higher education. In these models, families maximize inter-temporal utility functions defined over a set of commodities, which include the number and the quality of children (the utility-generating characteristic of a given child), produced at home with combinations of goods and services purchased on the market and time inputs of the household members. Utility is maximized subject to the wealth constraint, which equates lifetime income with the expenditure on utility-generating commodities evaluated at their respective opportunity costs.[1] The solution to the optimization problem entails, on the one hand, the demand functions for the utility-generating commodities, and, on the other hand, the optimal allocation of household members' time among leisure, market work, and home production.[2] The derived demand for children is the underpinning element of economic models of fertility. On the supply side, the optimal allocation of time allows predictions about the effect of changes in wage offers, non-labor income, productivity of time spent in home production, and the number of children on the supply of time to the market, leisure, and time spent in home production.

Women's education enters these models through several channels: through preferences, through the wage offers – women with higher education have higher wages – and through the home production functions if the schedules of the marginal product of time spent in the home production of utility-generating commodities are different for women with different levels of education. Higher wages have both an income and a substitution effect. The increase in income shifts the production possibility frontier outwards, increases consumption of all utility-generating commodities, and reduces time spent working in the market. An income-compensated increase in earnings would induce a shift in consumption away from utility generating commodities that are time-intensive towards commodities that are intensive in market goods and services and substitution of market goods and services for time in producing the utility-generating commodities. In this setting, the relative price of child quality, which is time-intensive, would be higher to higher-income families. The birth of a child could have a larger negative effect on the labor supply of more educated women under several circumstances: first, if more educated women have stronger preferences for child quality and if the production of child quality is intensive in women's time, with very little possibility of substituting market goods and services for women's time; second, if more educated women are more efficient at producing child quality relative to the number of children; and third, if the increase in education increases the marginal product of woman's time more than the marginal products of the other inputs into the production of child quality, women with higher education will tend to devote more time per child to the production of child quality and will produce children who are more quality intensive.

Previous studies of the way in which women's education shapes the effects of children on their labor supply have generated mixed results. Early empirical evidence suggests children have stronger effects on the labor supply of more educated women. Gronau (1973) finds that children have a positive effect on the shadow value of women's time and this effect increases with education; Hill and Stafford (1980) and Leibowitz, 1972, AER 1974 find that time inputs in child care increase

[1] The opportunity costs of the utility generating commodities include the prices of the inputs purchased on the market and the shadow value of the time spent in home-producing inputs and consuming the commodity.

[2] The distinction between leisure and time spent in home production (discussed by Mincer, 1962, and Gronau, 1977) as inputs into the production of utility-generating commodities is that leisure is an input with no market substitutes, whereas market substitutes are easily available for time spent in home production.

with mother's education and, as a result, labor supply of more educated women is more sensitive to the presence of children than the labor supply of less educated women; Mincer and Polacheck (1974, 1978) find that the rate of depreciation of human capital due to market work interruptions is larger for more educated women and, therefore, birth related interruptions would have a stronger adverse effect on the labor supply of more educated women. Two more recent studies, however, found otherwise. Angrist and Evans (1996, 1998), who used exogenous variation in the probability of the third birth to measure the causal effect of children on women's labor supply, found that the third child would reduces participation by 0.09-0.1 percentage points and that the effect of a child on labor force participation declines with mother's education. Hyslop (1999), who used panel data to estimate a two state dynamic model of labor force participation, found that the reduction in the participation probability is 0.11-0.17 percentage points when the child is 0-2 years old, the effect declines with the age of the child and is smaller for women with higher education.

This discrepancy could have been, in part, generated by methodological differences (Angrist and Evans account for the endogeneity of fertility decisions, Hyslop uses panel data). This possibility notwithstanding, whether the effect of children on women's labor supply increases or decreases with education and what is the source of the variation across levels of education is important from a policy perspective. Economic and social developments that have taken place over the past few decades led to a rise in the private costs of children incurred by parents, especially by mothers, while increasingly making children a public good. Better job opportunities and higher wages for women raised the opportunity cost of children; the growth of transfer payments like social security or public health systems and taxation of future generations through reliance on public debt have raised the public benefits of children.[3] Moreover, some recent economic and developmental psychology literature have suggested that longer periods of maternal care improve child cognitive and behavioral outcomes.[4] The existence of positive externalities from raising children and from longer periods of maternal care as well as from mothers' investments in their own education and training creates the scope for new or improved public policy aimed at reducing the implicit cost of children. The efficient design of these policies depends on the accurate description of the magnitude and the structure of the effect of children on women's level of labor market involvement.

The goal of this paper is to analyze the way in which the effect of children on the level of labor market involvement of married women varies with education. We use an econometric model that explicitly accounts for endogeneity of labor market and fertility decisions, for the heterogeneity of the effect of children on labor supply, for the correlation between the effect of children and subsequent fertility decisions, and for the correlation of sequential labor market decisions. Sequential labor market decisions, represented by a four-state multi-period multinomial probit, and fertility decisions, represented by a dynamic probit model, are jointly modeled in a mixed-effects simultaneous equation framework. Correlated individual-specific random coefficients included in labor market and fertility equations capture the variation in labor market and fertility behavior, the heterogeneity of the effects of children on the level of labor market involvement, as well as the correlation between the effects of children on labor supply and fertility behavior. In this framework, women's education affects their labor market and fertility decisions through two channels. First, expected wages included in the participation equations both by themselves and in interaction with the variables describing the number and age distribution of children are a function of education. Second, a set of education-specific random coefficients captures the variation of the labor supply, of the demand for children, and of the effects of children on labor supply across levels of education, controlling for

[3] Folbre, 1994.
[4] Waldfogel at al. (2002), Broogs-Gunn et al. (2002), Ruhm (2004)

own wage and other family-related relevant variables. The second channel compounds the effects of differences in preferences and productivity of household work across levels of education. We estimate the model using Markov chain Monte Carlo (MCMC) methods and panel data from 1979 National Longitudinal Survey of Youth (NLSY79). The 25-year (1979-2003) unbalanced panel we constructed[5] follows women from their entry into the labor force and captures almost complete fertility histories. We use simulations based on estimation results to compute the effects of children on women's level of labor market involvement, we compare these effects across levels of education, and we study the extent to which these differences are generated by differences in wage offers or by factors like preferences and productivity in household work which are captured by the random coefficients.

Our analysis shows that births reduce both participation and the level of labor market involvement of those who continue to participate; the effects of children on both participation and the level of labor market involvement of participants decline with the rank of the child, and the total effect of a child declines with the age of the child, but remains significant long after birth. Women with higher education are likely to have fewer children and work more before the birth of the first child, but children have larger negative effects on their level of labor market involvement. Differences across education levels are significantly more pronounced with respect to full time employment than with respect to participation, because in response to the birth of a child women with higher education are relatively more likely to move from full time work to part time work, whereas women with lower education are relatively more likely to stop working. The larger effect of children on the level of labor market involvement of women with higher education is generated by differences in preferences and marginal product of time spent in the production of child quality, differences captured by the random coefficients. Other things equal, the higher wage offers of women with higher education reduce the magnitude of the effect of children on the level of labor market involvement. These results suggest that women with higher education have a combination of stronger preferences for time-intensive child quality, higher marginal product of time spent in the production of child quality, and higher marginal product of time relative to the marginal product of other inputs into the production of child quality.

The policy significance of our results is twofold. On the one hand, the fact that higher wage offers reduce the effect of children on women's level of labor market involvement implies that public policies offering higher parental benefits will have the opposite effect, a larger reduction in the level of labor market involvement following the birth of a child. On the other hand, the fact that the larger effects of children on the labor supply of more educated women is most likely generated by stronger preferences for child quality and higher productivity of time spent in the production of child quality implies that there is very little public policy can accomplish in terms of reducing the effect of children on the level of labor market involvement, and thus the implicit cost of children, for women with higher education. If policy makers' goals include increasing fertility by reducing the opportunity costs of children, efficient policies include paid maternity leave with the temporary benefits correlated with individual opportunity costs.

The remainder of the paper is structured as follows. In the next section, we describe the construction of the panel data set used in the estimation and provide a preliminary, non-parametric analysis of the way in which the relationship between fertility and labor market decisions varies

[5] The panel is considerably longer than those previously used in the literature. For example Hyslop (1999) uses a 7-year panel of continuously married or women, with husbands continuously working, to estimate a two state model of labor force participation, Carrasco (2001) uses a 3-year panel of married or cohabitating women to estimate jointly two-state labor force participation decisions and fertility decisions.

across levels of education. In section 3 we present the econometric model and the estimation procedure. In section 4 we present the estimation and simulation results. In section 5 we summarize and discuss the main results.

2 Data

We study the effect of children on the level of labor market involvement of married women using panel data from the 1979 National Longitudinal Survey of Youth (NLSY79). The NLSY79 contains a representative sample of individuals with ages between 14 and 21 years in 1979, who are surveyed every year between 1979 and 1994, and every other year thereafter. For the purpose of our study, NLSY79 has two important features. First, it contains detailed information on respondents' labor supply history. Second, it contains information on the birth dates of respondents' children and on the beginning and end dates of respondents' marriages. Using this information, we constructed complete labor market, marital status, and fertility histories for each individual.

We use data from the nonmilitary sample of the 1979-2004 surveys and we exclude women who live on a farm larger than 100 acres at any point in the period. Since we focus on the labor supply of married women, we restrict the sample to women who are not married and are childless in 1979, get married after 1979, and remain married until 2004, only have children while married, and only have biological children in the household over the period of our data (this latter criteria eliminates women who adopt children or who marry men who have children who live with them). Imposing these strict selection criteria (specially the continuous marriage requirement) over a long period of time reduces the sample size, circumscribes the scope of our research to a narrower set of experiences and, potentially, leads to non-random selection of individuals with respect to unobserved traits that are relevant to their labor market and fertility behaviors. The focus on married women, however, is very common in the literature that studies the relationship between fertility and labor market decisions of women (Carrasco, 2001, Hyslop, 1999, Angrist and Evans, 1998, Heckman and Willis, 1977, etc). The motivation for this focus is twofold. On the one hand, married women, specially married women with children, have driven the dramatic change in the labor supply behavior among women that took place over the past few decades (Blau, 1998, Blau, Ferber, and Winkler, 1998, Leibowitz and Klerman, 1995). On the other hand, underlying theoretical models (Mincer, 1962, Becker, 1965, Leibowitz, 1972, Willis, 1973, Michael, 1973, Gronau, 1977, Angrist and Evans, 1996, 1998) are household production models. Our sample is in a way more informative than those used in previous studies using panel data (e.g. Hyslop, 1999 and Carrasco, 2001) which contain women who are continuously married or cohabitating for the entire duration of the sample. Our panel is significantly longer and, since we begin following these individuals when they enter the labor market, we observe their level of labor market involvement both before and during marriage.[6]

In order to abstract from the trade-off between schooling and working, we only consider a woman at risk to work or to have a child once she has been out of school for at least 18 months continuously (once a women leaves school we consider her still at risk even if she returns to school). Finally, we require at least five years of data for each woman. It is important to note that all women are childless and have no labor market history in their first period in the sample, which implies that initial conditions are identical across individuals in the sample.

[6] To test the robustness of our results to sample selection, however, we estimated our model with a sample that did not impose the marriage-related restrictions. While the average level of labor market involvement is lower in this larger sample, the qualitative results regarding the effect of children on the level of labor market involvement hold.

Table 1 provides an overview of the variables used in the analysis. Panel A presents summary statistics, by year, for the time-varying personal characteristics used in the analysis. Column 2, which presents the number of women considered at risk in a given year, shows the unbalanced nature of the data. In 1979 only 116 women are considered at risk, by 1997 all 645 women are considered at risk. Column 3 shows the proportion of women at risk that are married. Husband's income and income from other sources (columns 4 and 5 show averages per woman at risk) have been deflated using the CPI-U and are in 1979 dollars. Since after 1994 NLSY79 was conducted every other year, we imputed observations for the post-1994 missing years as well as several missing observations from the available years; our exact imputation procedure is described in the data appendix.

Column 6 shows the yearly birth rates and columns 7 to 9 show the average number of children by age category, for women at risk. No women had any children prior to 1981; in 2003, the average number of children was 1.8, and the average numbers of children for each age category were 0.05 for ages 0 to 1, 0.14 for ages 2 to 4, and 1.61 for 5 years older.

We represent the labor market decisions using a model with four states – full time, full time part year, part time, and nonwork – that provides a more accurate description of the level of labor market involvement than the two- or three-state models previously used in the literature. As we will show, a majority of women work full time before the birth of the first child. Longer or shorter birth-related interruptions are followed by a return to full-time work, a switch to part-time work, or a longer period of market inactivity. Many of birth-related interruptions, specially the shorter ones, are the result of women using accumulated vacation time, sick leave, formal maternity leave, and unpaid leave before returning to work, which helps women avoid the loss of job-search costs, firm specific human capital, and match-specific information.[7] In a two-state model (work, nonwork) in which labor market states are defined using hours worked in a given year, as is the case in this paper and in most of the previous literature, women who return to full time work after short birth-related interruptions will be classified as working during the year. Therefore, the two-state model does not capture the variation in the number of hours, which may represent a significant share of the effect of children. A three-state model (full-time, part-time and nonwork) inaccurately classifies many of the years in which birth-related interruptions occur as part time when, in fact, they are combinations of full-time work and inactivity (paid and unpaid leave), giving rise to a large number of birth-related, spurious transitions to and from part time and, thus, artificially reducing the persistence of the part-time state.

The empirical probability distribution of the labor market states of women at risk is showed in columns 10 to 13. To be considered working a woman must have both positive hours worked and positive income. Women who worked more than 1750 hours in a year are classified as full time. Women who work between zero and 1750 hours, but who work on average more than 35 hours a week, are considered full time part year. Women who work between zero and 1750 hours, but who work on average less than 35 hours a week, are considered part time (we imputed missing observations on the number of hours worked for several individuals; the imputation procedure is described in the data appendix). Women who work zero hours or who have zero income are considered not working. The percentage of women working full time and working full time part year declines over time while the percentage of women not working rises. The percentage of women working part time remains fairly constant.

Panel B presents summary statistics for the time-invariant personal characteristics and family

[7] These women are technically employed not at work. Klerman and Leibowitz (1994) use CPS data to show that the sharp increase in the labor force participation of mothers with very young children (3 months old and younger) during the 70s and 80s is mostly due to increase in paid and unpaid leave rather than work.

background variables that are used as observed sources of heterogeneity: education, race, labor market status of respondent's mother, and parents' education. We construct three educational categories: 12 years of education or less, 13-15 years of education, and 16 years of education or more. Thirty-six percent of the women in the sample have 12 years of education or less, 27 percent have between 13 and 15 years of education, while 37 percent have 16 years of education or more. Seventy percent of our sample is white, with the remainder evenly split between Hispanic and black. About 1/3 of respondents' mothers work full time and 1/3 do not work at all. For a large majority of the sample, 75 percent, none of the parents has college education, for 16 percent one parent has college education, and for 9 percent both parents have college education.

Table 2 presents a summary of several important fertility and labor market outcomes by level of education. Panel A, which compares the average and the distribution of the number of children, shows that women with higher levels of education have fewer children. The average number of children is 1.966 for women with 12 years of education or less, compared with 1.703 for women who have between 13 and 15 years of education, and 1.731 for women with 16 years of education or more. The difference between the averages is generated by larger probability of not having children for women with higher education. The probability of not having any children is 0.145 for women with 12 years of education or less, 0.174 for women with 13-15 years of education, and 0.223 for women with 16 years of education or more. Panel B shows that the timing of marriage, measured as the average number of years from entry into the sample (that is, from finishing full-time education) is very similar across levels of education. Panel C and figure 1 show the timing of the first birth measured as the number of years from marriage. Panel C, which compares the average number of years between marriage and first birth, indicates that women with lower levels of education have their first birth sooner after marriage. Figure 1 describes the distribution of the timing of the first birth by education. For women with 12 years of education or less, 34.3 percent of the first births are concentrated in the year following marriage; for women with 13-15 years of education, roughly equal shares of the first births (22 percent) take place in the first two years after marriage; finally, for women with 16 years of education or more the largest share of the first births, 22.5 percent, take place in third year after marriage.

Panels D, E, and F present an analysis of the way in which the relationship between fertility and the level of labor market involvement differs across individuals with different levels of education. Panel D compares the level of labor market involvement before the birth of the first child by level of education, for women who have at least one child between 1979 and 2003, panel E compares across levels of education the level of labor market involvement after the birth of the first child, for women who have exactly one child between 1979 and 2003, and panel F compares across levels of education the level of labor market involvement after the birth of the second child, for women who have exactly two children between 1979 and 2003. Panel D shows that differences in participation before the first birth are small across levels of education (96.2 for women with 12 years of education or less, 97.2 for women with 13-15 years of education, and 98.1 percent for women with 16 years of education or more), but women with higher levels of education are more likely to work full time (the probability of working full time is 0.704 for women with 12 years of education or less, 0.751 for women with 13-15 years of education, and 0.805 for women with 16 years of education or more). The comparison of panels D and E, shows that the decline in participation and in the level of labor market involvement of those that continue to participate is smaller for women with higher education. Participation declines by 0.149 for women with 12 years of education or less, by 0.090 for women with 13-15 years of education, and by 0.037 for women with 16 years of education or more. The probability of working full time declines by 0.155 for women with 12 years of education or less, by 0.144 for women with 13-15 years of education, and by only 0.056 for women with 16 years of education or more. A comparison of results in panels E and F shows that the effects of the second child on both participation and the level of labor market involvement of the participants are larger for women with higher education. Participation increases by 0.016 for women with 12 years of education or less, and decreases by 0.129 for women with 13-15 years of education and by 0.124 for women with 16 years of education or more.

These results may be generated in part by differences in observable personal characteristics we do not control for. The patterns observed in the data – more educated women have fewer children, have the first birth later in life, have higher levels of labor market involvement before the birth of the first child, and face significantly stronger effects of the second child on the level of labor market involvement – suggest, however, a data-generating mechanism consistent with the predictions of the theoretical household models of time allocation.

3 The econometric model

Several problems arise in the estimation of the effects of children on women's labor supply.[8] First, labor market and fertility decisions are endogenous, as the number and timing of children are variables that are controlled, at least in part, by women.[9] Second, the effects of children on labor supply are heterogeneous and are correlated with the fertility decisions. Heterogeneous preferences for market work and children influence pre-market and early career investments in human capital, which, in turn, affect the opportunity cost of children. Together, heterogeneous preferences and correlated, heterogeneous opportunity costs of children jointly determine women's fertility and labor market decisions. Third, sequential labor market decisions are correlated and, therefore, maternity-related work interruptions or reductions in the level of labor market involvement affect labor supply in subsequent periods. The goal of the econometric model we propose is to capture the variation in labor market and fertility behavior as well as in the effects of children on the level of labor market involvement across levels of education in a framework that simultaneously addresses the three key issues in the estimation of the effects of children on labor supply: the endogeneity of labor market and fertility decisions, the heterogeneity of the effects of children on labor supply and their correlation with fertility decisions, and correlation of sequential labor market decisions.

Sequential labor market decisions are represented by a multinomial probit model with auto-correlated error terms while fertility decisions are represented by a probit model with state-dependence and auto-correlated error terms. Labor market decisions and fertility decisions are driven by a sequential optimization process. At the beginning of each period an individual chooses the level of labor market involvement for the current period and makes a fertility decision. The level of labor market involvement is selected from the set of four alternatives, full-time work (FT), full-time part-year work (FP), part-time work (PT), and non work (NW), by comparing their associated value functions denoted by U_{it}^{FT}, U_{it}^{FP},U_{it}^{PT}, and U_{it}^{NW}, where the subscript i indicates individuals, $i = 1, ..., N$ and subscript t indicates time periods, $t = 1, ..., T_i$. Fertility choices are driven by the comparison of the value functions corresponding to having and not having a child whose differences are denoted by U_{it}^{F}. Since the choice of a level of labor market involvement depends only on differences of value functions, we transform the model by considering only values relative to the nonwork state.

[8] Browning (1992) and Nakamura and Nakamura (1992) provide reviews of the history of this literature.
[9] Browning (1992), Rosenzweig and Wolpin (1980), Angrist and Evans (1998), Carrasco (2001).

$$U_{it}^1 = U_{it}^{FT} - U_{it}^{NW} = K_{it}\alpha^1 + X_{it}^{LM}\beta^1 + Z_{it}^1\gamma + \left(K_{it} * Z_{it}^1\right)\delta + \sum_m K_{it}\theta_{ml(i,m)}^1 + u_{it}^1$$
$$U_{it}^2 = U_{it}^{FP} - U_{it}^{NW} = K_{it}\alpha^2 + X_{it}^{LM}\beta^2 + Z_{it}^2\gamma + \left(K_{it} * Z_{it}^2\right)\delta + \sum_m K_{it}\theta_{ml(i,m)}^2 + u_{it}^2$$
$$U_{it}^3 = U_{it}^{PT} - U_{it}^{NW} = K_{it}\alpha^3 + X_{it}^{LM}\beta^3 + Z_{it}^3\gamma + \left(K_{it} * Z_{it}^3\right)\delta + \sum_m K_{it}\theta_{ml(i,m)}^3 + u_{it}^3$$
$$U_{it}^F = K_{it}\alpha^F + X_{it}^F\beta^F + \sum_m K_{it}^F\theta_{ml(i,m)}^F + u_{it}^F$$

The transformed latent variables define the discrete labor market and fertility decisions the following way:

$$\begin{aligned}
y_{it}^{FT} &= 1 \text{ if } U_{it}^1 > U_{it}^2 \text{ and } U_{it}^1 > U_{it}^3 \text{ and } U_{it}^1 > 0; 0 \text{ otherwise} \\
y_{it}^{FP} &= 1 \text{ if } U_{it}^2 > U_{it}^1 \text{ and } U_{it}^2 > U_{it}^3 \text{ and } U_{it}^2 > 0; 0 \text{ otherwise} \\
y_{it}^{PT} &= 1 \text{ if } U_{it}^3 > U_{it}^1 \text{ and } U_{it}^3 > U_{it}^2 \text{ and } U_{it}^3 > 0; 0 \text{ otherwise} \\
y_{it}^{NW} &= 1 \text{ if } U_{it}^1 \leq 0 \quad \text{and } U_{it}^2 \leq 0 \text{ and } U_{it}^3 \leq 0; 0 \text{ otherwise} \\
y_{it}^{F} &= 1 \text{ if } U_{it}^F > 0; 0 \text{ otherwise}
\end{aligned}$$

The fertility decision is represented by a binary variable which takes value 1 if a child is conceived in a given year. We construct the fertility variable from data on children's birth dates and we do not consider pregnancies that end in miscarriage, stillbirth, or abortion.[10] This specification is a departure from previous literature which mostly used the occurrence of a birth to describe fertility decisions. Our specification rests on the premise that time-varying personal characteristics and variables describing a woman's relevant socioeconomic environment affect the fertility process through the conception decision, rather than through the birth of the child.

The vector K_{it} contains a constant term and three variables describing the number of children in three age categories (0-1, 2-4, 5 and older), where age is measured at the last birthday. The variables describing the number of children and their age distribution are included in the participation equation where they capture the effect of children on the level of labor market involvement. These variables which describe the entire history of fertility decisions – how many children have been born and how far in the past – are also included in the fertility equation, thus rendering current fertility decisions dependent on the entire fertility history.

X_{it}^{LM} is a vector of personal characteristics relevant to labor market decisions that includes marital status, spouse's wage, other income, the region of residence (North East, North Central, South, and West), and whether the respondent resides in an urban or rural area. X_{it}^F, is a vector of personal characteristics relevant to fertility decisions that includes other income, the region of residence, whether the respondent resides in an urban or rural area, and the number of siblings with children.

The number of siblings with children provides a description of the fertility behavior of a person's siblings. Our use of this variable rests on significant evidence from demographic literature that siblings' fertility behavior affects fertility decisions through social interaction occurring in the context

[10] NLSY 79 contains information on the number of pregnancies ending in miscarriage, stillbirth, or abortion but not on the date those pregnancies begin. In addition, the likelihood of termination could be correlated with labor supply decisions.

of interpersonal networks.[11] The number of siblings with children is excluded from the equations of labor market decisions.[12] In a panel data setting, identification comes from changes in the number of siblings with children. The temporal structure of the decision process we assume in this paper makes it unlikely that changes in the number of siblings with children are correlated with the error terms in the participation equations. While respondent's fertility variable captures the conception of a child during the current year, the number of siblings with children refers to the situation at the beginning of the same calendar year (children born to siblings during the past calendar year) and, therefore, reflects past fertility decisions made by the siblings. Even if contemporaneous shocks to labor supply are correlated across siblings, the number of siblings with children is predetermined. In Appendix table 1, we analyze the relationship between fertility and the change in the number of siblings with children. The table presents the estimation results of three OLS regressions that have the number of children born between 1979 and 2003 as dependent variable and the change in the number of siblings with children during the same period and a set of controls (number of siblings, respondent's education and race, respondent's parents' education) as dependent variables. The coefficient for the change in the number of siblings with children is significant in all specifications. In the specification that includes all controls, the coefficient for the change in the number of siblings is 0.1.[13]

Marital status or spouse's wage are not included in the fertility equation because, as we focus on the effects of children on the labor supply of married women, the sample includes only women who have children while married. We do not include respondent's age in the specification of the labor market and fertility decisions. Since we account for the dependence of sequential labor market and fertility decisions by specifying AR(1) structures for the error terms of the four equations, the effect of age measured as the age of individual i at time t cannot be identified. It is also unlikely our results will be affected by significant cohort effects since the age range in our sample is only seven years.

Education affects labor market and fertility decisions through two channels. First, education enters the model through the expected wages which are a function of the number of years of education. Expected wages for each of the alternative labor market states, $Z_{it}^1, Z_{it}^2, Z_{it}^3$, are included in the

[11] Montgomery and Casterline (1996) provide a theoretical framework in which siblings' fertility affect fertility decisions through social interaction. Numerous papers provide empirical evidence that siblings' behavior influences a wide range of indices of fertility behavior. Hogan and Kitagawa (1985) found a significant effect of siblings' behavior and teenage motherhood. Powers and Hsueh (1997) found that older sister's out-of-wedlock childbearing affects younger sister's age at premarital birth. Rowe et al. (1989), Rodgers and Rowe (1988) and Haurin and Mott (1990) examined the influence of older siblings on the adolescent sexual behavior of younger siblings and fond that younger siblings tend to mimic sexual behavior of their older siblings. Axinn, Clarkberg, and Thornton (1994) find that siblings' fertility behavior exerts an important influence on family size preferences even when other factors common to all family factors are held constant.

[12] Finding an instrument for identifying the effect of children on labor supply is notoriously challenging. The instruments used so far in the literature are based on natural experiments - gender composition of the first two children (Carrasco, 2001; Angrist and Evans, 1998) and the birth of twins at the first birth (Rosenzweig and Wolpin 1980). These instruments capture exogenous variation in the probability of the second or third birth. If the cost of having children declines with the number of children this may lead to underestimating the effect of children on labor supply. In a dynamic setting the challenge of finding an appropriate instrument is even greater because the variable has to change with individual and time period.

[13] By comparison, Rosenzweig and Wolpin (1980), who use twins at the first birth as instrument for fertility, find that among women who have the first birth between 15 and 24, completed fertility, as measured 20 years later, was 0.15 greater for those women who had twins than for those women without twins; Angrist and Evans (1998) who use the gender of the first two children as instrument for the birth of the third child find that among parents with 2 or more children, the proportion that have the 3 child is 0.06 greater if the first two children were of the same sex than if they were of opposite sex.

participation equations by themselves to capture the way in which expected wages associated with the three labor market states affect the level of labor market involvement and in interaction with the variables describing the number and age distribution of children, $\left(K_{it} * Z_{it}^{1}\right), \left(K_{it} * Z_{it}^{2}\right), \left(K_{it} * Z_{it}^{3}\right)$, to describe the way in which the effect of children varies with the wage. We use the observed hourly wage for the current labor market state and impute the hourly wage for the alternative states. The imputation is based on a standard wage regression that includes second degree polynomials of years of education and experience, a full set of interactions between the terms of these polynomials and the labor market states, and the urban and region dummy variables.[14] It is important to note that expected wages and the interaction terms between expected wages and the children variables vary over i, t, and labor market state, and their coefficients are constrained to be the same across states. Geweke, et al. (1997) point out that the inclusion of variables whose values differ across alternative choices and whose coefficient is constrained to be the same across states.is important in the identification of multinomial probit models such as this, which would otherwise be difficult due to flat spots in the likelihood function.

Second, controlling for wages, education affects labor supply, demand for children, and the effects of children on labor supply through differences in preferences and in the productivity of time spent in home production of utility generating commodities. We capture these differences using a set of education-specific random coefficients. The mixed-effect structure, which combines fixed and random coefficients, allows us to study how the relationship between fertility and labor market behavior varies across education levels and other time-invariant personal characteristics like race, and family background characteristics, and, controlling for these variables, to assess the role of individual-level heterogeneity. $\alpha' s, \beta' s, \gamma$ and $\delta' s$ are vectors of global (fixed effect) parameters which are common across individuals in the sample. We use five, $m = 1, ..., 5$, independent sources of heterogeneity affecting individuals' decisions: individuals' time invariant personal characteristics (education and race), family background variables related to tastes for work and family (the labor market status of respondent's mother and the education levels of respondent's parents), and individual-level heterogeneity. Each source of heterogeneity has l_m levels. The number of levels is three for education (12 years or less, 13-15 years, 16 years or more), three for race (white, black, and Hispanic), two for respondent's mother's labor market status (full time and other) three for parents' education (none of the parents, one, or both parents have college education) and is equal to the number of individuals in the sample for individual-level heterogeneity. Each individual in the data is assigned a level for each source of heterogeneity $l(i, m)$ (individual i's level of education, race, mother's labor market status, parents' education, her individual-specific level of heterogeneity). To level l of heterogeneity source m corresponds the vector of random coefficients $\theta_{ml} = \left[\theta_{ml}^{1'} | \theta_{ml}^{2'} | \theta_{ml}^{3'} | \theta_{ml}^{F'}\right]$. The four components of θ_{ml}, $\theta_{ml}^{1'}, \theta_{ml}^{2'}, \theta_{ml}^{3'}$, and $\theta_{ml}^{F'}$, correspond to the four equations of the model. Each

[14] We acknowledge that including expected wages in the specification of the value functions raises the question of their endogeneity. The main potential source of endogeneity is the possibility that parameters of the wage offer distributions are correlated with time-invariant individual-specific components of the error terms in the participation equations. We account for this possibility by incorporating individual heterogeneity in the participation equations. Even after accounting for individual heterogeneity, there is still the possibility that shocks to the wage offer distribution may be correlated with shocks to the unobserved determinants of the level of labor market involvement. In a different setting (two-state model of labor force participation, which does not account for endogeneity of fertility and for individual heterogeneity) Geweke and Keane (2000) have showed how wages can be modeled endogenously. The extension of their model to our setting faces daunting challenges both technical (sharp increase in the number of dependent variables of the model) and substantive (the lack of appropriate instruments). Therefore, we do not pursue this avenue of research in this paper, choosing instead to focus on the endogeneity of fertility and the accurate definition of the level of labor market involvement.

component includes four elements, one random effect and three random coefficients, corresponding to the four variables in the vector K_{it}. We assume θ_{ml} are normally distributed, independent across the l_m levels of heterogeneity of source m, $\theta_{ml} \sim MVN\left(0, D_m\right)$, independent across sources of heterogeneity, and uncorrelated with the regressors $X_{it}^{LM}, X_{it}^{F}, Z_{it}$ and the error terms u_{it}.

The random coefficients corresponding to education, race, and family background variables capture the effects of these time-invariant personal characteristics on labor market and fertility decisions, while the individual-specific random coefficients describe the individual-level heterogeneity in labor market and fertility behavior. The random coefficients corresponding to the constant terms in the four equations capture the variation in propensities for market work and children. The random coefficients corresponding to the children variables in the participation equations describe the heterogeneity of the effects of children on the level of labor market involvement, while those corresponding to the children variables in the fertility equation capture individual variation in the timing and spacing of births (for example, a relatively small individual-specific coefficient for the variables describing the presence of young children and a relatively large individual-specific coefficient for the variable describing the presence of older children indicates the occurrence of births at larger intervals). Finally, the general correlation structure of the random coefficients – for each source of heterogeneity, random coefficients are assumed to be correlated both within and between equations – captures the correlation between preferences for market work and children, effects of children on labor supply, and fertility behavior (timing and spacing of births).

We assume error terms are jointly normally distributed.

$$u_{it} = \left[u_{it}^1 | u_{it}^2 | u_{it}^3 | u_{it}^F\right]' \sim N\left(0, \Sigma\right).$$

Over time, error terms follow a AR(1) stationary process, $u_{it} = Ru_{it-1} + \varepsilon_{it}$, where $\varepsilon_{it} = \left[\varepsilon_{it}^1 | \varepsilon_{it}^2 | \varepsilon_{it}^3 | \varepsilon_{it}^F\right]'$is distributed $IIDN\left(0, \Psi\right), \Psi = I_4$, and it is uncorrelated with the random coefficients θ_{sk} and variables X_{it}^{LM}, X_{it}^{F}, Z_{it},

$$R = \begin{bmatrix} \rho_1 & 0 & 0 & 0 \\ 0 & \rho_2 & 0 & 0 \\ 0 & 0 & \rho_3 & 0 \\ 0 & 0 & 0 & \rho_F \end{bmatrix}$$

Work experience, while not explicitly included in the specification of labor market decisions, enters our model in two ways. First, since we explicitly model dependence of sequential labor market decisions, the level of labor market involvement in the previous periods directly affects current decisions. Second, current labor market decisions depend on potential wages in each labor market state, which, in turn, depend on labor market experience – the realization of past labor market decisions.

In addition to exclusion restrictions mentioned earlier, two other sources contribute to identification in this model. First, we assume that the vectors of random coefficients corresponding to each source of heterogeneity have a joint normal distribution. Second, children variables entering the participation equations are non-linear transformations of the lagged dependent variables in the fertility equation. Non-linearity is generated by the construction of the children variables (number of children in certain age categories) as well as by the use of conception as the fertility variable (the decision to conceive a child in a given year could result in the birth of a child in the same calendar year or in the following calendar year, as well as in the birth of twins).

The dynamic nature of both participation and fertility decisions requires assumptions regarding initial conditions. Given our specification, we need to know the distributions of children variables in the initial period and the distribution of the error terms. The selection of the sample ensures that initial conditions are identical across individuals – we choose the first year out of school as the first period in the sample and we include only women who marry and have children only after entering our sample.

To estimate the model, we employ Markov chain Monte Carlo techniques (MCMC). MCMC methods avoid one of the major difficulties inherent in the alternative maximum likelihood or simulated maximum likelihood estimation methods – the evaluation at each step of the maximization process of multiple integrals, whose dimensions increase very quickly with the number of equations to be estimated. The estimation algorithm we propose in this paper builds on several sources in the literature: Geweke et al. (1997) who propose a Gibbs sampler algorithm for estimating a panel multinomial probit model where errors follow an AR(1) process, McCulloch and Rossi (1994) who estimate a multi-period multinomial probit model with random effects, and Gilks et al. (1993) who propose an algorithm for the estimation of a single-equation, panel-data model with random coefficients. We extend existing work by combining two discrete choice processes and jointly estimating the parameters of interest in both models and by combining the use of random coefficients and AR(1) error structure. For the parameters of interest we choose proper but noninformative prior distributions. The estimation algorithm and the exact form of our assumptions concerning the prior distributions are presented in Appendix 1.

4 Estimation Results

Although coefficient estimates are difficult to interpret because of the non-linearity of the model, the estimation results presented in tables 3, 4, and 5 provide essential insight into the effect of children on women's labor supply. Table 3 shows the posterior means and the posterior standard deviations (PSTD) for the global parameters of the model. The coefficients of the three children variables are negative in all participation equations, and their absolute values are largest for full-time work (column 1) and weakest for part-time work (column 5). The coefficient for children with ages between 0 and 1 year is -1.464 in the equation of full time relative to nonwork, -1.001 in the equation of full time part year relative to nonwork, and -0.178 in the equation of part time relative to nonwork. This suggests that children lower women's level of labor market involvement by reducing the attractiveness of work relative to nonwork and the attractiveness of full time and full time part year work relative to part time. The coefficients for older children are smaller in absolute value, indicating that the effect declines with the age of the child. For example, in the equation of full time relative to nonwork the coefficients are -1.464 for a child age 0-1, -0.977 for a child age 2-4, and -0.538 for a child with age 5 years or more.

The coefficients for marital status are negative, large in absolute value, and significant in all equations, which indicates that marriage has a strong negative effect on the level of labor market involvement. Higher spouse's wage and non-labor income are associated as well with lower levels of labor market involvement. Women leaving in urban areas are more likely to hold full-time jobs.

The coefficient for wage, 0.699, indicate that, for women without children, higher wage offers associated with a certain labor market state increase the likelihood of occupying that state. The coefficients for the interaction terms between wage offers and the children variables, -0.015 for the interaction between wage and the number of children with ages between 0 and 1, -0.059 for the interaction between wage and the number of children with ages between 2 and 4, and -0.095 for the interaction between wage and the number of children with ages age 5 years or more, suggest that while higher wages will increase the probability of returning to work after the birth of a child, their effect declines with the age of the child.

The estimates of the AR(1) coefficients, ρ, are 0.701 for the equation of full time relative to nonwork, 0.017 for full time part year relative to nonwork, and 0.729 for part time relative to nonwork. Given the definitions of the four labor market states in which full time part year describes relatively short work interruptions, whereas full time, part time, and nonwork describe longer spells with constant level of labor market involvement, the small coefficient for full time part year,0.017, suggests that short birth-related interruptions will have a small effect on subsequent labor supply. On the other hand, the large coefficients in both full time and part time equations suggest that full time, part time, and nonwork are persistent states and, therefore, longer periods of nonparticipation or reduced labor market involvement will have strong negative effects on future labor supply.

Table 4 shows the posterior means of the random coefficients corresponding to education, race, the labor market status of respondent's mother, and the levels of education of respondent's parents.[15] Education is the strongest determinant of women's labor supply and of the effects of children on labor supply. The effect of education is largest in the full-time equation. The coefficients corresponding to the constant term (column 1) are -0.337 for women with less than 12 years of education, 0.138 for women with 13-15 years of education, and 0.199 for women with 16 or more years of education, suggesting that women with higher education are relatively more likely to work full time. The coefficients corresponding to the children variables (columns 2-4) show that the negative effects of children on the probability of working full time are stronger for women with higher education. The coefficients corresponding to the number of children with ages between 0 and 1 (column 2) are 0.245 for women with 12 years of education or less, -0.042 for women with 13-15 years of education, and -0.203 for women with 16 or more years of education. These values imply that the presence of a child with age between 0 and 1 reduces the propensity to work full time (the latent variable corresponding the full time work by 1.219 for women with 12 years of education or less, compared with 1.506 for women with 13-15 years of education and 1.668 for women with 16 years of education or more. Similarly, the effects of older children on the propensity to work full time are stronger for more educated women. The coefficients corresponding to the constant term in the fertility equations, 0.046 for women with 12 years of education or less, -0.015 for women with 13-15 years of education, and -0.031 for women with 16 or more years of education, indicate that propensity to have children declines with the level of education.

White women are more likely to work full time compared to black and Hispanic women: the coefficients corresponding to the constant term are 0.124 for white women, 0 for black women, and -0.124 for Hispanic women. The negative effects of children on the probability of working full time are stronger for white women relative to black and Hispanic women. The coefficients corresponding to the constant term in the fertility equations indicate that Hispanic women have a higher propensity to have children than both white and black women. The effects of family background variables are also concentrated in the full time equation: respondents whose mothers worked full time are more likely to work full time, while those whose parents were both college educated are less likely to work

[15] The interpretation of these coefficients is analogous to that of the coefficients of a complete interaction between the children variables and each of the four variables in a classical regression setting. For example, to compute the effect of having one child with age between 2 and 4 on the propensity of working full time by education level, we add the coefficient for children with ages between 2 and 4 in the full time equation from table 2 with the coefficients for children with ages 2 to 4 in the full time equation from table 3. Thus, having one child between ages 2 and 4 reduces the propensity of working full time by -0.977+0.238=-0.739 for someone with less than 12 years of education, by -0.977-0.085 = -1.062 for someone with 13-15 years of education, and by -0.977-0.153 = -1.130, for someone with 16 or more years of education.

full time.

The individual-level variation in labor market and fertility behavior and the correlation of these differences are captured by a set of 16 correlated random coefficients. For each individual, we estimate the posterior means of these coefficients; then, using the posterior means for all the individuals in the sample, we calculate the full set of bivariate correlation coefficients, which we present in table 5. The correlations between the random coefficients corresponding to the constant terms in the participation equations and the random coefficient corresponding to the constant term in the fertility equation vary from very low, 0.041, for full time and fertility, to 0.394 for full time part year and fertility, to 0.254 for part time and fertility, which indicates that women with stronger propensities for lower levels of labor market involvement have a relatively higher propensity to have children. The random coefficients corresponding to the children variables in the full time and full time part year equations are positively correlated with the random coefficients corresponding to the constant term in the fertility equation. The correlations range between 0.363 and 0.492 for the children variables in the full time equation, between 0.375 and 0.565 for the children variables in the full time part year equation. The positive correlations indicate that larger random coefficients corresponding to the effects of children, i.e., smaller negative effects of children, are associated with larger random coefficients corresponding to the constant term in the fertility equation, which suggests that strong negative effects of children on the level of labor market involvement are associated with lower propensities to have children.

5 Simulation Results

We use simulations based on the estimation results to measure the effects of children on the probability distribution of the four labor market states, to measure the variation of these effects across levels of education, and to assess the extent to which these differences are generated by differences in wage offers or by factors like preferences and productivity in household work which are captured by the random coefficients. The large number of possible labor market and fertility histories forces us to simplify our analysis in two ways. First, we limit our analysis to twenty years following entry into the labor market. Second, while we recognize that both the number of births and their timing may affect women's labor market behavior, we focus exclusively on the number of births and confine our analysis to three fertility histories: no birth, one birth, and two births. Table 6 describes the timing of the relevant events. In all three fertility histories marriage takes place in the second year. The conceptions of the two children take place in years two and eight, and the births take place at the beginning of years three and nine. The timing of marriage and the timing of the first birth we use in the simulation scenario are those with the highest frequency in our data: 15.3 percent of all marriages take place one year after entry into the labor market, 23 percent of the first conceptions take place in the year of marriage. The largest share of the second conceptions (32 percent) take place two years after the first conception, but we chose this particular timing for the second birth to avoid spurious results generated by the discrete changes in the ages of children. A child born at the beginning of year 3 moves into age category 2-4 in period 5 and into age category 5 years and older in period 8. The discrete changes in the age of the first child, specially the move in age category 5 years and older, generate large changes in the level of labor market involvement and, because of the non-linearity of the multivariate normal cumulative distribution function, will have an impact on the effects of subsequent children.

To measure the total effect of education, we construct three basic individual profiles: white woman with 12 years of education, white woman with 14 years of education, and white woman with 16 years of education. For all three profiles we assume that none of the respondent's parents has college education and that the respondent's mother did not work full time, and we set other family income at zero, the region of residence to North-East, and the type of residence to urban, characteristics that have the highest frequencies in our sample. For each individual profile, we set the random coefficients corresponding to the individual heterogeneity to zero, the average value. For all profiles, we set the spouse's wage at 15530, the median level. For every period along each possible labor market history, we compute wages corresponding to the three labor market states, full time, full time part year, and part time, using the coefficient estimates from the wage equation, the characteristics associated with the relevant individual profile (number of years of education, urban location, region), and the labor market experience accumulated until that point in time.

To assess the extent to which the differences across levels of education are generated by differences in the random coefficients, which capture differences in preferences and productivity of household work, or by differences in the mean of wage offers, we take women with 12 years of education as baseline and, for each of the other two levels of education, we construct a counterfactual profile which assumes the level of education relevant for the setting of the mean wage offer is maintained at 12 years, while the level of education relevant for the determination of the random coefficients is 14 or 16 years.

Levels of education relevant for the determination of random coefficients and wages

	Basic profile 1	Counterfct. profile 1	Basic profile 2	Counterfct. profile 2	Basic profile 3
Rand. Coeff.	12 years	14 years	14 years	16 years	16 years
Wage	12 years	12 years	14 years	12 years	16 years

For each of the five individual profiles we compute the joint probability distribution of all possible labor market and fertility histories (the probability of a complete history is the cumulative distribution function of a multivariate normal distribution; to calculate the multivariate normal CDFs, we use the GHK smooth recursive simulator of Geweke, 1989, Hajivassiliou, 1990, and Keane, 1994). Let S denote the set of four possible labor market states in a period, full time (ft), full time part year (fp), part time (pt) and non work (nw), s_t denote the labor market state in period $t, t = 1, ..., 15$, and h_j denote the fertility history, where $j = 0, 1, 2$,represents the number of births taking place in the respective fertility history. Further, let $f(s_1, s_2, \ldots, s_{15}, h_j)$ denote the joint probability distribution of all possible labor market histories and fertility histories. This probability distribution is conditional on a vector of observed characteristics and a level of individual-specific unobserved heterogeneity, but we omit this conditioning to simplify notation. Given these joint probabilities, for each observation, we compute the probability of having no children $f(h_0)$, one child in year three $f(h_1)$ and two children in years three and nine $f(h_2)$, along with the probability of all possible labor market histories conditional on the specific fertility history $f(s_1, s_2, \ldots, s_{15}|h_j)$, which to simplify notation we denote by $f_j(s_1, s_2, \ldots, s_{15})$. Finally, we compute the probability distribution of the labor market states in every time period conditional on a given fertility history, which is denoted by $f_j(s_t)$.

We measure the effects of the two children on the level of labor market involvement by comparing the probability distributions of the labor market states $f_j(s_t)$, for all time periods, across the three fertility histories. The effect of the first birth, which takes place at the beginning of year 3, is computed by comparing the probability distributions for the fertility histories with zero and one birth, in the years following the birth:

$$TE_t^1 = f_1(s_t) - f_0(s_t), t = 3, ..., 15$$

The effect of the second birth, which takes place at the beginning of year 9, is computed by comparing the probability distributions for the fertility histories with one and two births, in the years following the second birth:

$$TE_t^2 = f_2(s_t) - f_1(s_t), t = 9, ..., 15$$

We assess the way education influences the effect of children on women's labor supply by comparing the total effects of the two children for women with 14 and 16 years of education with the total effect for the baseline case, women with 12 years of education. For each level of education (14 or 16 years) the component corresponding to the random coefficients is constructed by comparing the corresponding counterfactual profiles with the baseline profile, while the component corresponding to the differences in the mean wage offer is computed comparing the basic profiles 2 and 3 with their respective counterfactual profiles.

Table 7a shows the levels of labor market involvement before the first birth, by level of education. Women with higher education work more before the birth of the first child. The difference is not as much in the participation rates as in the level of labor market involvement of those who participate. Participation rates are 0.914 for women with 12 years of education, 0.966 for women with 14 years of education, and 0.978 for women with 16 years of education. The probability of working full time is 0.565 for women with 12 years of education (61.8 percent of those who participate), 0.708 for women with 14 years of education (73.3 percent of participants), and 0.744 for women with 16 years of education (76.1 of participants). The probabilities of working full time part year and part time are higher for women with lower levels of education: probability of working full time part year is 0.205 for women with 12 years of education compared with 0.165 for women with 14 years of education and 0.156 for women with 16 years of education, while the probability of working part time is 0.144 for women with 12 years of education compared with 0.093 for women with 14 years of education and 0.078 for women with 16 years of education.

Table 7b shows the decomposition of the differences between the levels of labor market involvement before birth of women with 14 years of education relative to women with 12 years of education (columns 1 and 2), and of women with 16 years of education relative to women with 12 years of education (columns 3 and 4). The differences across education levels are in great part captured by the random coefficients. Other things equal, higher wages increase participation and the probability of working full time, but their effect is much smaller than that captured by the random coefficients. For example, the participation probability of women 16 years of education is 6.4 percentage points larger than that of women with 12 years of education; the component corresponding to the random coefficients is 3.7 percentage points, while the component corresponding to wages is 2.8 percentage points. The probability of working full time of women with 16 years of education is 17.9 percentage points larger than that of women with 12 years of education; the component corresponding to the random coefficients is 15.5 percentage points, while the component corresponding to wages is 2.4 percentage points.

The total effect of the first child and the results of the decomposition are presented in figures 2, 3, and 4. Figure 2 compares the total effect of the first child on the level of labor market involvement across levels of education; figure 3 shows the decomposition of the difference between the effect of the first child on the level of labor market involvement of women with 14 years of education relative to women with 12 years of education, and figure 4 shows the decomposition for women with 16 years of education relative to women with 12 years of education. Each figure contains four panels depicting the effect of the child and the results of the decomposition separately for participation and for the probabilities of the three working labor market states, full time, full time part year, and part time.

Figure 2 shows that the birth of the first child reduces participation and the probabilities of working full time and full time part year and increases the probability of working part time, for all levels of education. The effect of the child is largest immediately after birth and declines with the age of the child.[16] The participation profile for women with 12 years of education is the lowest, while the profile for women with 16 years of education is the highest, which indicates that the effect of the first child on participation decreases with education. The opposite is true for the probability of working full time. The profile for women with 12 years of education are the highest, while the profile for women with 16 years of education are the lowest, indicating that the effect of the first child on the probability of working full time increases with education. The birth of the first child reduces the probability of working full time part year and increases the probability of working part time. For both full time part year and part time the effects of the first child are stronger for more educated women. The discrepancy between the effects of education on participation and on the probability of working part time is explained by the fact that more educated women are more likely to start working part time following the birth of the first child, rather than to stop working.

Figures 3 and 4, which show the results of the decomposition, display similar patterns. In both figures, for both participation and full time, the component corresponding to wage differences is positive, which means that the higher wage offers of the more educated women reduce the effects of children on participation and on the probability of working full time. The components corresponding to the random coefficients, which capture differences in preferences and productivity of home production, are negative for both participation and full time. This suggests that more educated women are characterized by a combination of stronger preferences for child quality and higher productivity of time spent in production of child quality relative to women with lower education, and higher productivity of time spent in production of child quality relative to other inputs. For full time part year and part time, the components corresponding to both wages and the random coefficients are positive.

Figures 5, 6, and 7 show the total education effects and the results of the decomposition for the second child. The most notable difference between the results for the first child and those for the second child is the fact that the negative effect of the second child on participation is stronger for more educated women. Otherwise, the results for the second child are similar to a large extent to those for the first child. Following the birth of the second child, participation and the probabilities of working full time and full time part year decline, while the probability of working part time increases, and the effects decline with the age of the child. The negative effect of the first child on the probability of working full time and the positive effect on the probability of working part time are stronger for more educated women, while the reduction in the probability of working full time part year is stronger for women with lower education. For both participation and full time, the component corresponding to wage differences is positive, suggesting that higher wages reduce the effect of the second child on participation and full time, and the component corresponding to the random coefficients is negative. For full time part year and part time, the components corresponding

[16] The discrete changes in the direct effect of children are generated by the definition of the variables that describe the age of the children. In reality, the age of the child and the direct effect change continuously. An interpolation of our results would probably capture more accurately the dynamics of the direct and indirect effects and would mitigate the patterns that occur at discontinuity points.

to both wages and the random coefficients are positive.

6 Summary and Discussion

We analyze the way in which the effect of children on the level of labor market involvement of married women varies with education. The econometric framework we propose explicitly accounts for endogeneity of labor market and fertility decisions, for the heterogeneity of the effect of children on labor supply, for the correlation between the effect of children and subsequent fertility decisions, and for the correlation of sequential labor market decisions. We use a model with four labor market states which provides an accurate description of the level of labor market involvement and estimate our model using a 25-year panel, considerably longer than those previously used in the literature,[17] which follows women from their entry into the labor force and captures almost complete fertility histories. We model the effect of women's education on their labor market and fertility decisions through two channels: first, we include expected wages and interaction terms between expected wages and the variables describing the number and age distribution of children in the participation equations; second, education-specific random coefficients capture the variation of the labor supply, of the demand for children, and of the effects of children on labor supply across levels of education, controlling for own wage and other family-related relevant variables.

We find that women with higher education have fewer children. Before the birth of the first child, women with higher education have higher rates of participation and among participants they have higher levels of labor market involvement. Differences in participation and in the level of labor market involvement of participants are generated by both wage differences and differences in preferences and productivity in home production which are captured by the education-specific random coefficients.The birth of the first child reduces participation and the level of labor market involvement of those who continue to participate. The reduction in participation is larger for women with lower levels of education, but the reduction in the probability of working part time is larger for women with higher education, who are relatively more likely to respond to the birth of the first child by lowering their level of labor market involvement rather than by dropping out of the market. The effect of the second child on both participation and probability of working full time is larger for women with higher education

We decompose the differences across levels of education in two components: a component generated by differences in wage offers across levels of education, captured by wage offers and interaction terms between wage offers and the variables describing the number and the age distribution of children, and a component generated by differences in preferences and differences in the productivity of time spent in home production of child care/quality, captured by a set of education-specific random coefficients. For both participation and full time, the wage component is positive, which indicates that, other things equal, higher wage offers reduce the effect of children on the level of labor market involvement. For both participation and full time, the component captured by the random coefficients is negative, which suggests two things: differences in preferences and productivity of time spent in home production of child care are responsible for the larger effect of children on the labor supply of more educated women; women with higher education have stronger preferences for child quality and higher productivity of time spent in the production of child quality.

[17] For example Hyslop (1999) uses a 7-year panel of continuously married or women, with husbands continuously working, to estimate a two state model of labor force participation, Carrasco (2001) uses a 3-year panel of married or cohabitating women to estimate jointly two-state labor force participation decisions and fertility decisions.

These results are similar to those in Gronau (1973), Hill and Stafford (1980), Mincer and Polacheck (1974, 1978). Our results suggest that one of the primary effects of children on women's labor supply is through the number of hours worked and that women with higher education are relatively more likely to respond to the birth of a child by reducing the number of hours. Studies of labor market participation will underestimate the effect of children on women's labor supply and the differences in the effect of children across levels of education.

With Gronau's (1977) the time-allocation model as reference, our results have the following theoretical implications. Before the birth of the first child, women derive utility from the consumption of commodities unrelated to children, produced with a combination of goods and services purchased on the market and time and allocate their time between leisure (time inputs without market substitutes), market work, and home production (time inputs with market substitutes). Higher wages induce women to shift time from home production to market work (they substitute market goods and services for own time in the production of utility generating commodities) until the marginal productivity at home is equal to the wage, to substitute goods-intensive commodities for time intensive commodities, thus reducing leisure (the substitution effect), and to consume more of each commodity, thus increasing leisure at the expense of market work (the income effect). Our results indicate that other things equal, the higher wages of more educated women increase the level of labor market involvement which implies that either the substitution effect dominates the income effect or, if the income effect is dominant, the transfer of time from home production to market work exceeds the time reallocated from market work to leisure. Much of the difference in level of labor market involvement is captured, however, by the random coefficients. This suggests that more educated women have either stronger preferences for utility generating commodities that are goods intensive, lower productivity in the home production of utility generating commodities - which, holding the wage constant, induces them to spend less time in home production - or lower productivity of time relative to other inputs into the production of utility generating commodities.

When the first child is born, women who have been working start reallocating leisure and market time to the production of child-related, utility-generating commodities (number, quality). The transfer continues until the marginal product of time spent in home production of child care is equal to the wage or (if the market time is not sufficient) with the marginal product of time spent in the home production of utility-generating commodities unrelated to children. Women who have not been working in the market will reallocate leisure and time spent in the home production of utility-generating commodities unrelated to children to child care activities. Other things equal (productivity of home production of child care) higher wages imply that, following the birth of the child, the transfer of time from market work to home production of child care will be smaller (the transfer takes place until marginal product equals wage; decreasing marginal product and higher wage means that less time will have to be transferred to equate the two). Hence, other things equal, higher wages should be associated with smaller effect - and this is what we find. There is no theoretical guidance as to how preferences and productivity at home are related to education. Our results - the fact that the component captured by the random coefficients is negative - suggest more educated women have higher productivity of time in the production of child quality. Controlling for wage, higher marginal product schedule means that more time has to be transferred to child care before the marginal product equals wage. Hence, controlling for wages, women with higher education will spend more time per child in home production of child quality.

The policy significance of our results is twofold. On the one hand, the fact that higher wage offers reduce the effect of children on women's level of labor market involvement implies that public policies offering higher parental benefits will have the opposite effect, a larger reduction in the level of labor market involvement following the birth of a child. On the other hand, the fact that the larger effects of children on the labor supply of more educated women is most likely generated by stronger preferences for child quality and higher productivity of time spent in the production of child quality implies that there is very little public policy can accomplish in terms of reducing the effect of children on the level of labor market involvement, and thus the opportunity costs of children, for women with higher education. If policy makers' goals include increasing fertility by reducing the opportunity costs of children, efficient policies include temporary benefits correlated with individual opportunity costs.

7 Appendix.

7.1 Estimation algorithm

To estimate the model, we employ Markov chain Monte Carlo techniques. Our approach combines elements from several sources in the literature. Geweke et al. (1997) propose a Gibbs sampler algorithm for estimating a panel MNP model where errors follow an AR(1) process. McCulloch and Rossi (1994) also use a Gibbs sampler to estimate a multiperiod multinomial probit model with random effects. The general random effects framework has been used for a long time in Bayesian hierarchical modeling of longitudinal data. In this paper we use the same approach as in Gilks et al. (1993). Also related, albeit in a continuous setting, is the paper by Chib and Greenberg (1995) on hierarchical SUR models with correlated errors. Finally, MCMC techniques for estimating multivariate probit models have been introduced by Chib and Greenberg (1998). We extend existing work by combining two discrete choice processes and jointly estimating the parameters of interest in both models.

The data set is an unbalanced panel, with N individuals $i = 1,..,N$, each individual i is observed for T_i periods. The total number of observations is $df = \sum_{i=1}^{N} T_i$. Let $W_{it}^{LM} = \left[K_{it}|X_{it}^{LM}\right], W_{it}^{F} = \left[K_{it}|X_{it}^{F}\right]$, and define the block diagonal matrices

$$\tilde{W}_{it} = \begin{bmatrix} W_{it}^{LM} & 0 & 0 & 0 \\ 0 & W_{it}^{LM} & 0 & 0 \\ 0 & 0 & W_{it}^{LM} & 0 \\ 0 & 0 & 0 & W_{it}^{F} \end{bmatrix}, \tilde{K}_{it} = \begin{bmatrix} K_{it} & 0 & 0 & 0 \\ 0 & K_{it} & 0 & 0 \\ 0 & 0 & K_{it} & 0 \\ 0 & 0 & 0 & K_{it} \end{bmatrix}$$

The conforming matrix of parameters is $\tilde{\beta} = \left[\alpha^{1\prime}|\beta^{1\prime}|\alpha^{2\prime}|\beta^{2\prime}|\alpha^{3\prime}|\beta^{3\prime}|\alpha^{F\prime}|\beta^{F\prime}\right]'$. Define $U_{it} = \left[U_{it}^1|U_{it}^2|U_{it}^3|U_{it}^F\right]'$, $\tilde{Z}_{it} = \left[\left(Z_{it}^1|\left(K_{it} * Z_{it}^1\right)\right)'|\left(Z_{it}^2|\left(K_{it} * Z_{it}^2\right)\right)'|\left(Z_{it}^3|\left(K_{it} * Z_{it}^3\right)\right)'|0\right]'$. Let $\tilde{\gamma} = \left[\gamma|\delta'\right]'$Using this notation the model becomes

$$U_{it} = \tilde{W}_{it}\tilde{\beta} + \tilde{Z}_{it}\tilde{\gamma} + \sum_m \tilde{K}_{it}\theta_{ml(i,m)} + u_{it}$$

Define $U_{i0} = u_{i0}, \tilde{K}_{i0} = [0], \tilde{W}_{i0} = [0], \tilde{Z}_{i0} = [0]$. Finally, let $\dot{U}_{it} = U_{it} - RU_{it-1}$; $\dot{\tilde{W}}_{it} = \tilde{W}_{it} - R\tilde{W}_{it-1}$; $\dot{\tilde{K}}_{it} = \tilde{K}_{it} - R\tilde{K}_{it-1}$; $\dot{\tilde{Z}}_{it} = \tilde{Z}_{it} - R\tilde{Z}_{it-1}$.

To describe the sequence of labor market and fertility decisions, define $d_{it}^{LM} = \left[d_{it}^1, d_{it}^2, d_{it}^3, d_{it}^0\right] = \left[y_{it}^{FT}, y_{it}^{FP}, y_{it}^{PT}, y_{it}^{NW}\right], d_{it}^F = y_{it}^F, d_{it} = \left[d_{it}^{LM}, d_{it}^F\right], d_i = \left[d_{i1}, ..., d_{iT}\right]$.

The posterior kernel is given by the product of a multivariate normal kernel, the kernel of the unconditional distribution of the pre-sample error terms, the prior distributions of the parameters, and an indicator function controlling the ordering and the signs of the latent variables.

- The kernel of the joint normal distribution is:

$$|\Psi|^{-\frac{df}{2}} \exp\left\{-\frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(u_{it} - Ru_{i,t-1}\right)'\Psi^{-1}\left(u_{it} - Ru_{i,t-1}\right)\right\}$$

where $u_{it} = U_{it} - \tilde{W}_{it}\tilde{\beta} - \tilde{Z}_{it}\tilde{\gamma} - \sum_m \tilde{K}_{it}\theta_{mi}$

- The kernel of the unconditional distribution of the pre-sample error:

$$|V_0(R,\Psi)|^{-\frac{N}{2}} \exp\left\{-\frac{1}{2}\sum_{i=1}^{N} u_{i0}' [V_0(R,\Psi)]^{-1} u_{i0}\right\}$$

where $[V_0(R,\Psi)]_{jk} = \dfrac{\psi_{jk}}{\rho_j \rho_k}$

- The indicator function for consistency and signs of U's:

$$\prod_{i=1}^{N}\prod_{t=1}^{T_i} H(U_{it}, d_{it})$$

- Prior distributions

  a. $\beta_j \sim N(\beta_{j0}, B_{j0}), j \in (1,2,3,F)$
  b. $\gamma \sim N(\gamma^0, \Gamma_0)$
  c. $\rho_j \sim TN\left(\rho_j^0, \sigma_{\rho_j^0}\right), j \in (1,2,3,F)$
  d. $D_m^{-1} \sim W(b_m, B_m)$

The prior distribution for $\tilde{\beta}$ is multivariate normal with mean 0 and a variance matrix of 100 times the identity matrix, the prior distribution for $\tilde{\gamma}$ is univariate normal with mean 0 and variance 100, the prior distribution for ρ is truncated normal with mean 0.5 and variance 0.25, the prior distribution for the precision matrix D_m^{-1} is Wishart with parameters $b_m = 3, B_m = 0.01 * I$, where I is an identity matrix with appropriate dimension.

A seven-step Gibbs sampling algorithm is employed to construct draws from the posterior distribution.

- Step 1. Draw U_{it} $(i = 1, ..., N, t = 1, ..., T_i)$

$\left[U_{it}|\tilde{\beta}, \tilde{\gamma}, \theta_{sk(i,s)}, D_s, R, u_{i0}\right]$ is a truncated multivariate normal distribution with mean $\begin{bmatrix} \mu_{i1} + Ru_{i0} \\ ... \\ \mu_{iT} + R^T u_{i0} \end{bmatrix}$ and variance $G(I_T \otimes \Psi) G'$ where $\mu_{it} = \tilde{W}_{it}\tilde{\beta} + \tilde{Z}_{it}\tilde{\gamma} + \sum_s \tilde{K}_{it}\theta_{sk(i,s)}$ and

$$G = \begin{bmatrix} I_4 & 0 & 0 & ... & 0 & 0 \\ R & I_4 & 0 & ... & 0 & 0 \\ ... & ... & ... & ... & ... & ... \\ R^{T-1} & R^{T-2} & R^{T-3} & & R & I_4 \end{bmatrix}$$

To draw from a truncated normal distribution, we used the method proposed by Geweke (1991).

- Step 2. Draw u_{i0} $(i = 1, ..., N)$.

The conditional distribution $\left[u_{i0}|U_{it}, \tilde{\beta}, \tilde{\gamma}, \theta_{sk(i,s)}, D_s, R\right]$ is only a function of u_{i1}, R, and Ψ.

$$u_{i0} \sim N[Cu_{i1}, V_0(R,\Psi) - CV_0(R,\Psi)C']$$

where $C = [V_0(R,\Psi)]R[V_0(R,\Psi)]^{-1}$

- Step 3. Draw ρ. The conditional distribution distribution $\left[\rho|U_{it}, \tilde{\beta}, \tilde{\gamma}, \theta_{sk(i,s)}, D_s, u_{i0}\right]$ is

$$N\left[H_\rho\left(\nu_\rho + V_\rho^{-1}\rho^0\right), \left(H_\rho + V_\rho^{-1}\right)^{-1}\right]$$

truncated to the hypercube dictated by stationarity, where

$$H_\rho = \begin{bmatrix} \psi^{11}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(u_{it-1}^1\right)^2 & ... & \psi^{13}\sum_{i=1}^{N}\sum_{t=1}^{T_i}u_{it-1}^1 u_{it-1}^3 & \psi^{1F}\sum_{i=1}^{N}\sum_{t=1}^{T_i}u_{it-1}^1 u_{it-1}^F \\ ... & ... & ... & ... \\ \psi^{13}\sum_{i=1}^{N}\sum_{t=1}^{T_i}u_{it-1}^1 u_{it-1}^3 & ... & \psi^{33}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(u_{it-1}^3\right)^2 & \psi^{3F}\sum_{i=1}^{N}\sum_{t=1}^{T_i}u_{it-1}^3 u_{it-1}^F \\ \psi^{F1}\sum_{i=1}^{N}\sum_{t=1}^{T_i}u_{it-1}^F u_{it-1}^1 & & \psi^{F3}\sum_{i=1}^{N}\sum_{t=1}^{T_i}u_{it-1}^F u_{it-1}^3 & \psi^{FF}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(u_{it-1}^F\right)^2 \end{bmatrix}$$

$$\nu_\rho = \begin{bmatrix} \sum_j \psi^{1j}\sum_{i=1}^{N}\sum_{t=1}^{T_i}u_{it-1}^1 u_{it}^j \\ ... \\ \sum_j \psi^{3j}\sum_{i=1}^{N}\sum_{t=1}^{T_i}u_{it-1}^1 u_{it}^j \\ \sum_j \psi^{Fj}\sum_{i=1}^{N}\sum_{t=1}^{T_i}u_{it-1}^F u_{it}^j \end{bmatrix}, V_\rho = diag\left(\sigma_{\rho_1^0}, \sigma_{\rho_1^0}, \sigma_{\rho_3^0}, \sigma_{\rho_F^0}\right)$$

Due to the truncation, an acceptance step is necessary. Draws are rejected if $\left|\rho_j\right| \geq 1$ for any j, then accepted with probability

$$\left|V_0\left(R, \Psi\right)\right|^{-\frac{N}{2}} \exp\left\{-\frac{1}{2}trS_{u_0}V_0\left(R, \Psi\right)^{-1}\right\} \div \left|\frac{1}{N}S_{u_0}\right|^{-\frac{N}{2}} \exp\left(-\frac{NL}{2}\right)$$

where $S_{u_0} = \sum_{i=1}^{N} u_{i0}u_{i0}^{'}$

- Step 4. Draw $\tilde{\beta}_j, j = 1, 2, 3, F$. Conditional distribution $\left[\tilde{\beta}_j|U_{it}, \tilde{\gamma}, \theta_{sk(i,s)}, D_s, R, u_{i0}\right]$ is a multivariate normal $\tilde{\beta}_j \sim N\left[b_j, B_j\right]$

$$B_j = \left[B_{j0}^{-1} + \psi^{jj}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\widetilde{\dot{W^j}}_{it}\widetilde{\dot{W^j}}'_{it}\right]^{-1}$$

and mean

$$b_j = B_j\left(B_{j0}^{-1}\beta_{j0} + \sum_l \psi^{jl}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\widetilde{\dot{W^j}}_{it}w_{it}^{l(j)'}\right)$$

where $w_{it}^{l(j)} = \dot{U}_{it}^{l} - \dot{\widetilde{W}^{l}}_{it}\tilde{\beta}_l - \dot{\widetilde{Z}^{l}}_{it}\tilde{\gamma} - \sum_m \tilde{K}_{it}\delta_{ml(i,m)}$, for $l \neq j$ and $w_{it}^{j(j)} = \dot{U}_{it}^{j} - \tilde{Z}_{it}^{j}\tilde{\gamma} - \sum_m \tilde{K}_{it}\theta_{ml(i,m)}$

- Step 5. Draw $\tilde{\gamma}$.Conditional distribution $\left[\tilde{\gamma}|U_{it}, \tilde{\beta}, \theta_{sk(i,s)}, D_s, R, u_{i0}\right]$ is normal $\gamma \sim N\left[g, \Gamma\right]$

where the variance is

$$\Gamma = \left[\Gamma_0^{-1} + \sum_{i=1}^{N}\sum_{t=1}^{T_i}\sum_{l}\sum_{j}\psi^{jl}\dot{\tilde{Z}}_{it}^{j}\dot{\tilde{Z}}_{it}^{l\prime}\right]^{-1}$$

and the mean is

$$g = \Gamma\left(\Gamma_0^{-1}\tilde{\gamma}_0 + \sum_{i=1}^{N}\sum_{t=1}^{T_i}\sum_{l}\sum_{j}\psi^{jl}\dot{Z}_{it}^{j}\left(\dot{U}_{it}^{l} - \dot{\tilde{W}}_{it}^{l}\tilde{\beta}_l - \sum_m K_{it}\theta_{ml(i,m)}^{l}\right)\right)$$

where $j, l = 1, 2, 3, F$.

- Step 6. Draw θ_{ml} for each source of heterogeneity. Conditional distributions $\left[\theta_{ml}|U_{it}, \tilde{\beta}, \tilde{\gamma}, D_s, R, u_{i0}\right]$ are multivariate normal

$$[\theta_{ml} \mid .] = N\left(D_m \sum_{i:l(i,m)=k}\sum_{t=1}^{T}\tilde{K}_{it}\Psi^{-1}e_{mit}, D_m\right)$$

where

$$D_m = \left[\Omega_m^{-1} + \sum_{i:l(i,m)=k}\sum_{t=1}^{T}\tilde{K}_{it}\Psi^{-1}\tilde{K}_{it}'\right]^{-1}$$

and

$e_{mit} = U_{it} - \tilde{W}_{it}\tilde{\beta} - \tilde{Z}_{it}\tilde{\gamma} - \sum_{g:g\neq m}\tilde{K}_{it}\theta_{gl(i,g)}$. Here, $\sum_{i:l(i,m)=k}$ means sum for all individuals observations i for whom factor m is at level k and $\sum_{g:g\neq m}$ means sum for all factors except m.

- Step 7. Draw D_m^{-1} for each source of heterogeneity. Conditional distributions $\left[D_m^{-1}|U_{it}, \tilde{\beta}, \tilde{\gamma}, \theta_{ml}, R, u_{i0}\right]$ are Wishart.

$$D_m^{-1} \sim W\left(b_m + k_m, B_m + \sum_{l=1}^{l_m}\theta_{ml}\theta_{ml}'\right)$$

Convergence is assessed using the method proposed by Gelman and Rubin (1992) with the modified correction factor proposed by Brooks and Gelman (1998). One preliminary run of 14000 iterations, with OLS coefficients as starting values, was used to construct starting values for four independent chains. The starting values were extreme values chosen from the posterior distribution of the coefficients. The four independent chains, each with 15000 iterations were used to compute the scale reduction factor. Appendix Table 2 shows the scale reduction factors for the slope coefficients, and for the AR(1) coefficients.

7.2 Data Appendix

Due to problems with the data we needed to impute some of the data values. The three main problems we faced were, top-coding of income, missing values for wages and income, and missing values for hours worked. Here we will briefly outline how we addresses each problem

7.2.1 Top-Coding of Spouse's Wage, Income from Business and Other Income

The top-coding of income data in the NLSY varies by year. From 1979 to 1984 all income values above $75,000 were truncated to $75,001. From 1985 to 1900 all income values greater than $100,000 were truncated to $100,001. Since this method produced a downward bias in the mean value of income, starting in 1989 all values above the cutoff value were replaced with the average of the true values of income above this level. For our analysis the method used in the later period is acceptable, where as the method used in the earlier period two periods should not result in a bias in our parameter estimates. To adjust the top-coded values in the early years so that they match the values in the latter years we first compute the mean income for the top ten percent of non-top coded values in all years of the data. We then compute the average of the ratio of the top coded values with the mean of the top ten percent of the non-top coded values, across all of the latter years of the data (1989-2004). We multiplied this ratio by the mean of the top ten percent of the non-top coded values in the early years of the data (1979-1984). Finally we replaced the top coded values in the early years with this new value.

7.2.2 Imputing Missing Wages and Income

Once we fixed the top coding problem we then imputed missing wages and income for all individuals in our sample. For individuals who had more than three observations we regressed either log wages or log income on a constant and a time trend and used the results from this regression to impute the missing data. If only one or two values were available, we imputed the missing values with the mean deflated value of the wage or income. After 1994, NLSY74 was conducted every other year. We impute the values for the missing post-1994 years by interpolating the deflated values of the wage or income of adjacent years.

7.2.3 Imputing Missing Hours Worked

The NLSY collects information on hours worked each week for every week in the survey. We aggregate these weekly hours worked into hours worked in each year for individuals in our sample. If someone has a missing or invalid value for hours worked in a week we impute the value for that week by taking a weighted mean over all valid values of weekly hours worked in the survey. The weight we use is $0.5/m$ where m is the difference between the current week and the week of the valid observation.

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Figure 1. Timing of the first birth from marriage, by education.

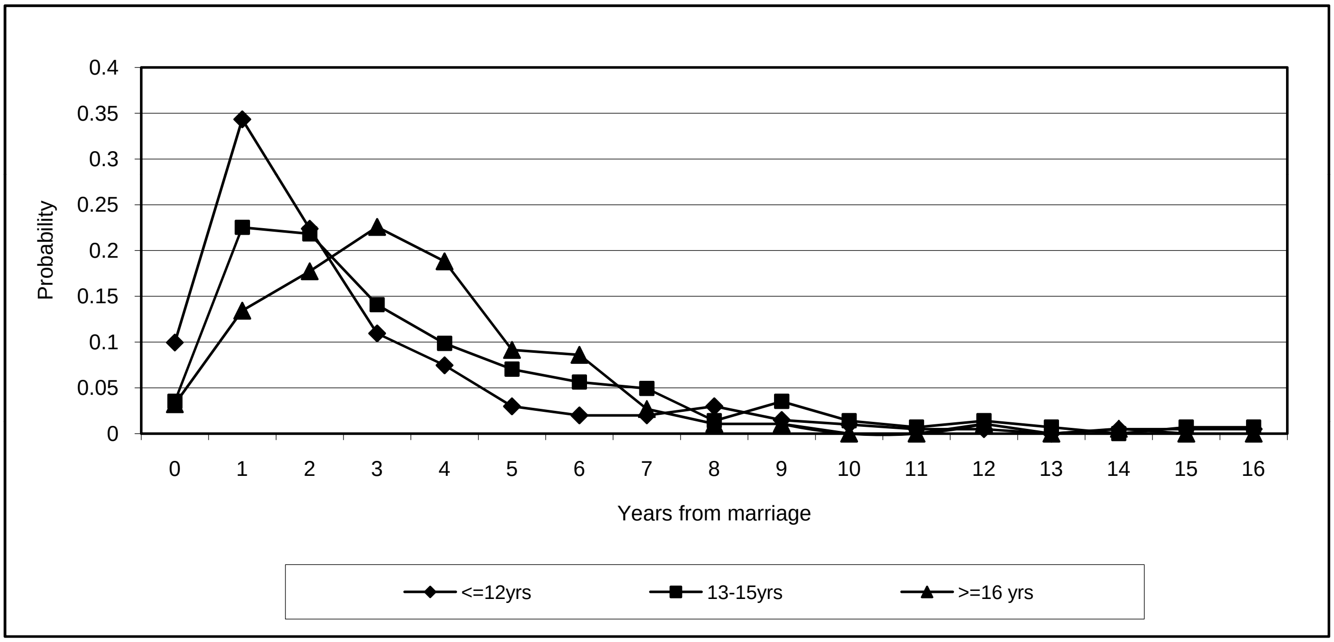
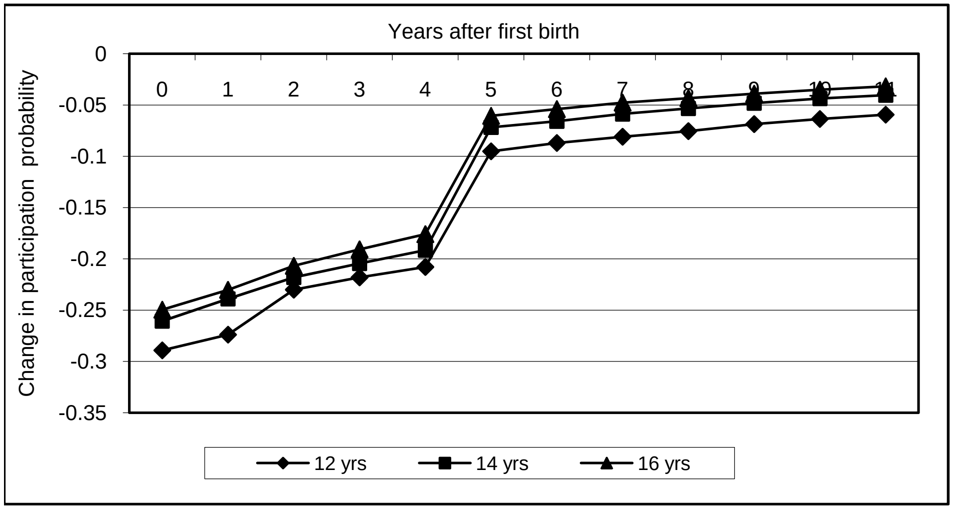
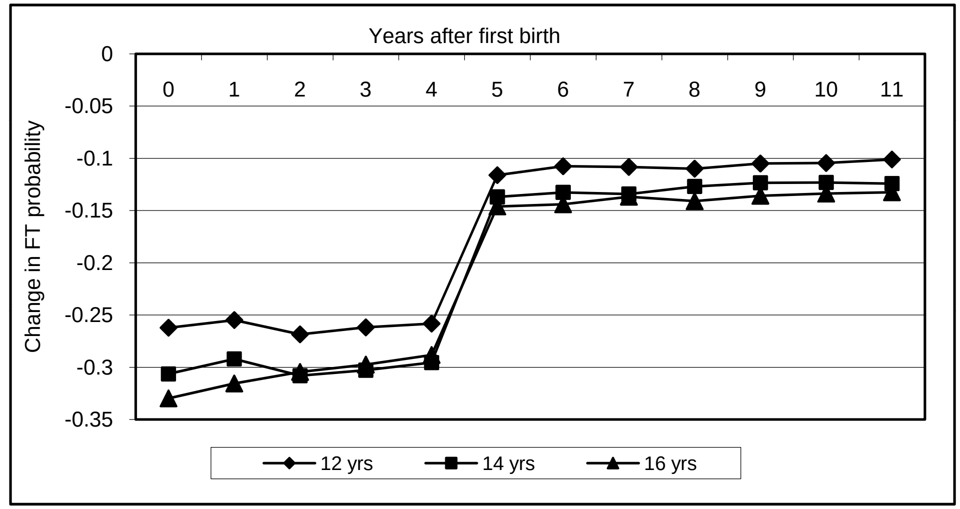


Figure 2. The effect of the first birth on the level of labor market involvement. By education.

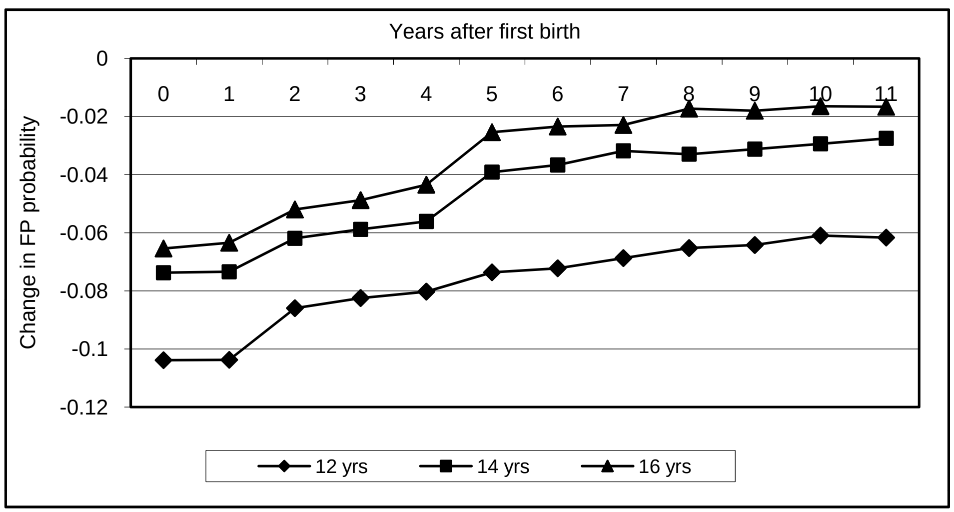
A. Participation



B. Full time



C. Full time part year



D. Part time

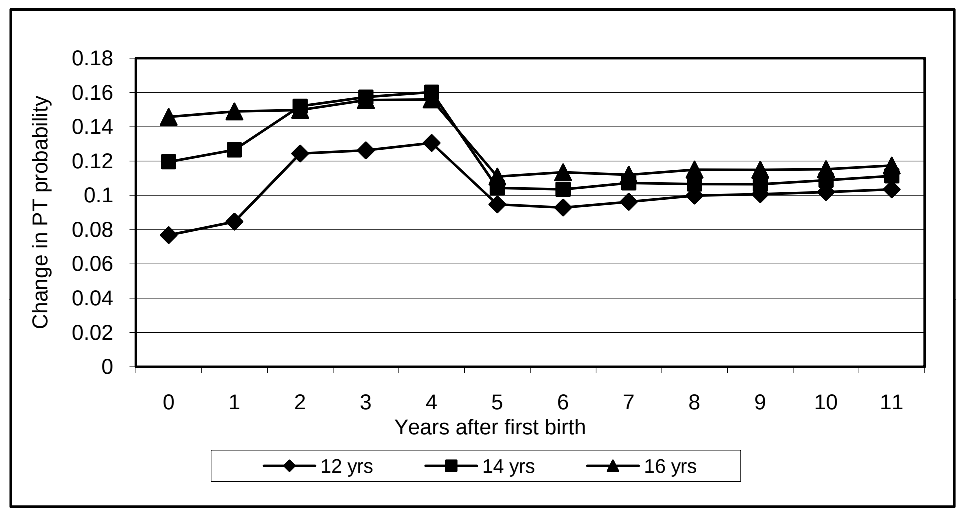


Figure 3. The components of the total effect of education correponding to the random coefficients and own wage. First birth. Women with 14 years of education compared with women with 12 years of education

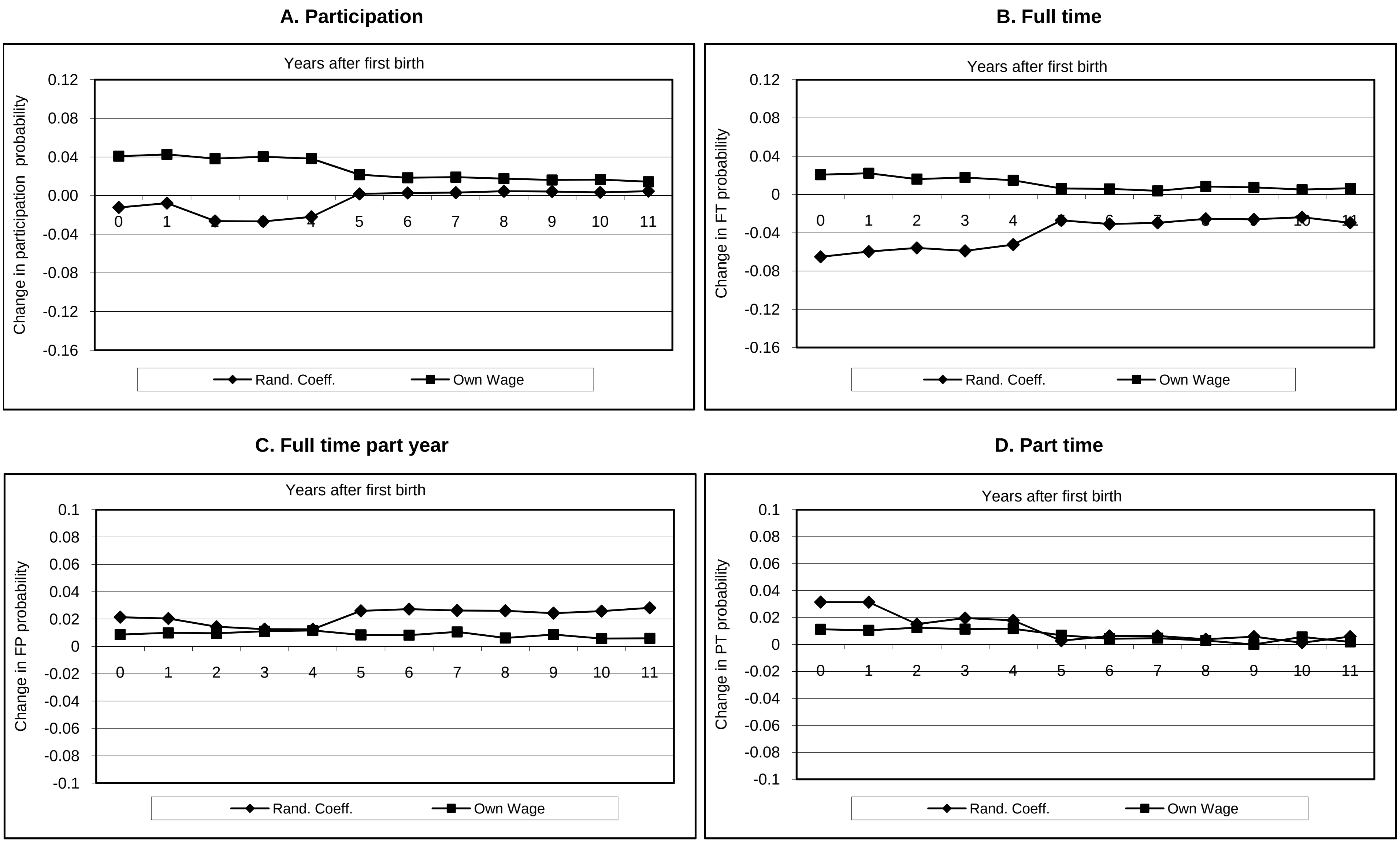
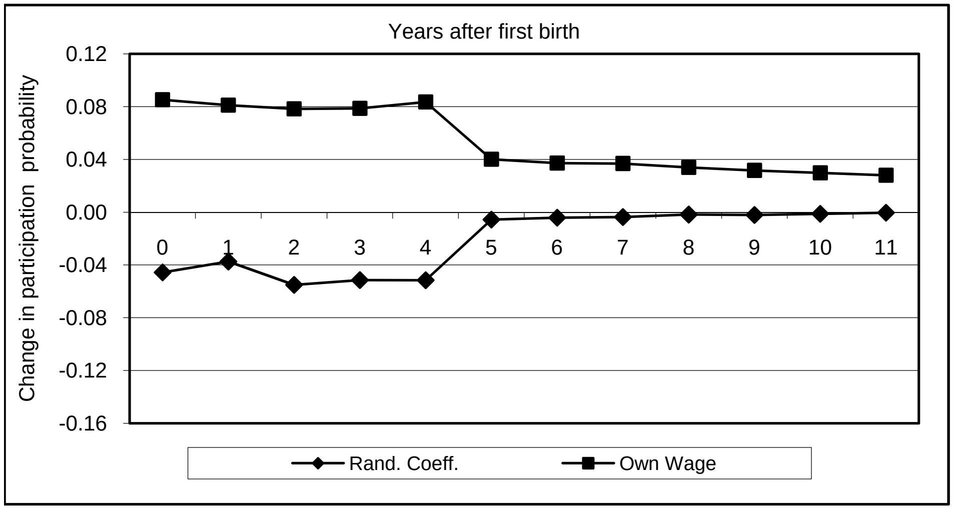
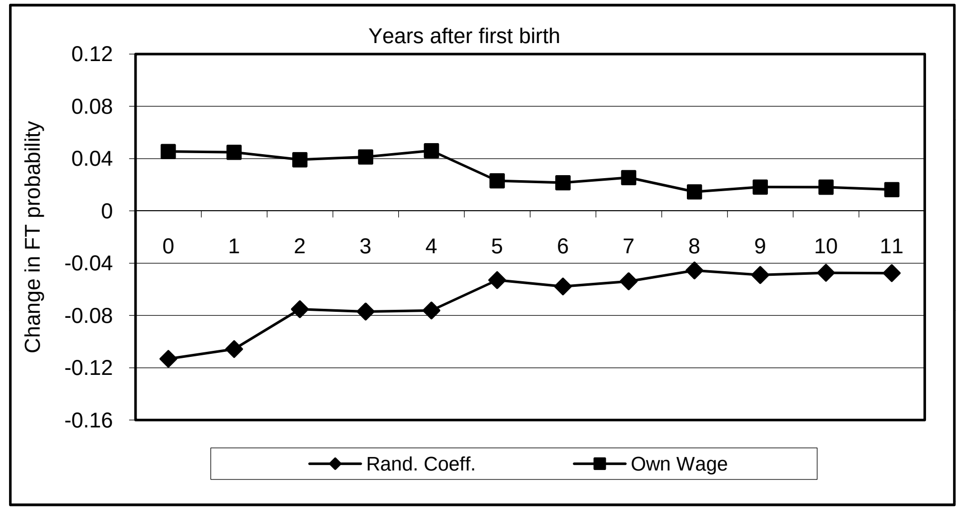


Figure 4. The components of the total effect of education correponding to the random coefficients and own wage. First birth. Women with 16 years of education compared with women with 12 years of education

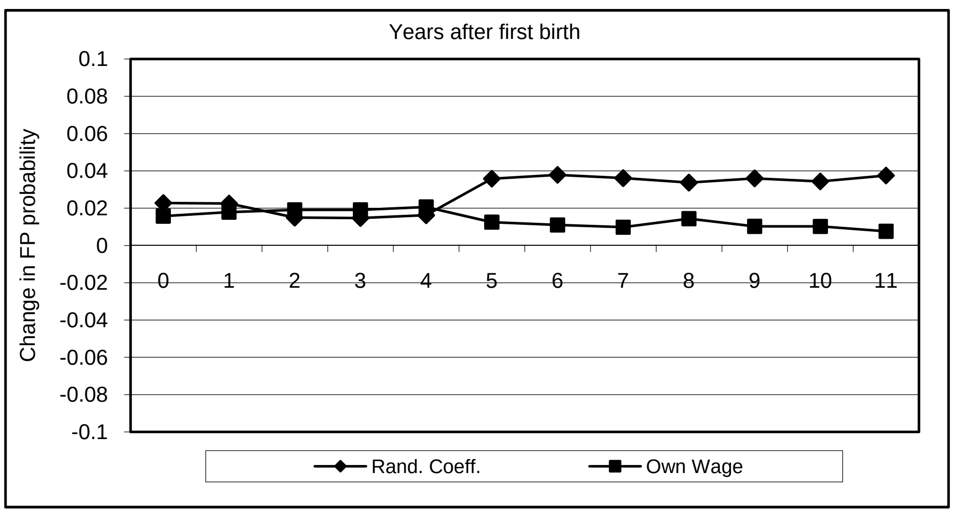
A. Participation



B. Full time



C. Full time part year



D. Part time

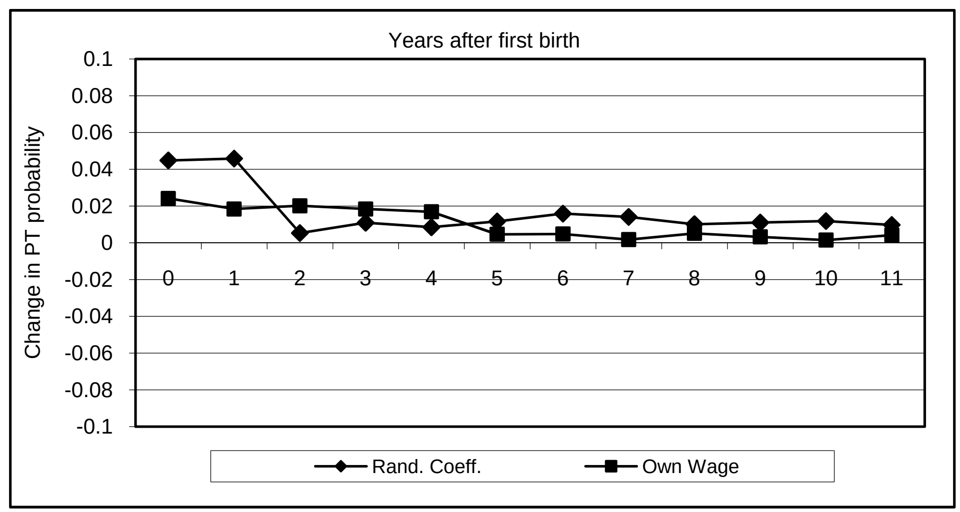
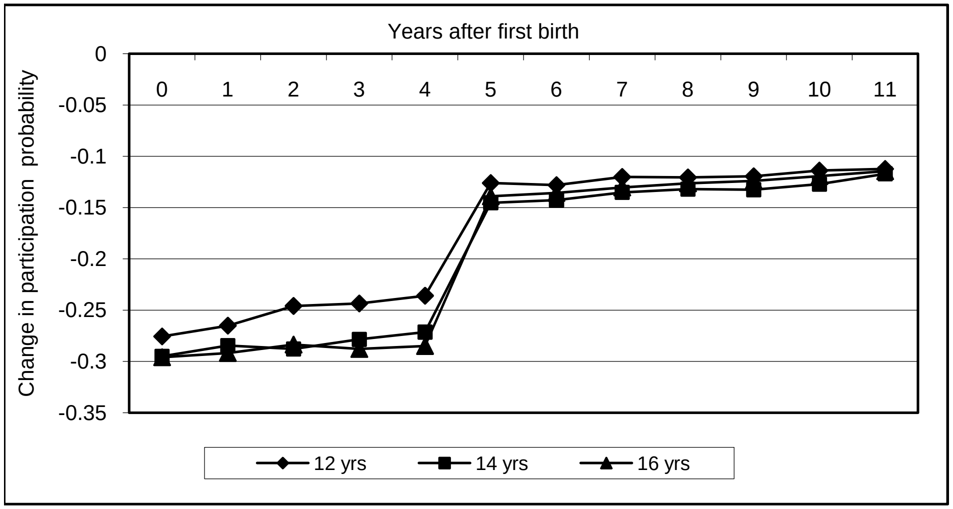
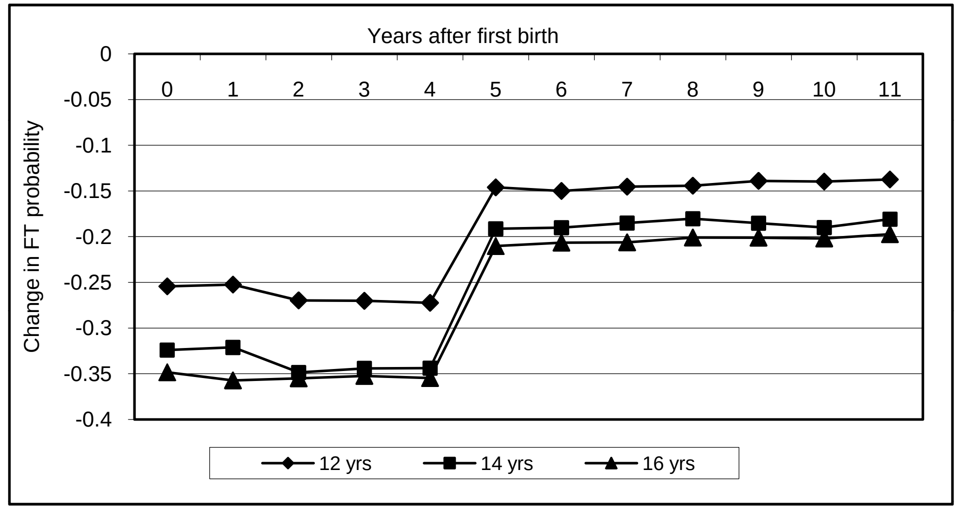


Figure 5. The effect of the second birth on the level of labor market involvement. By education.

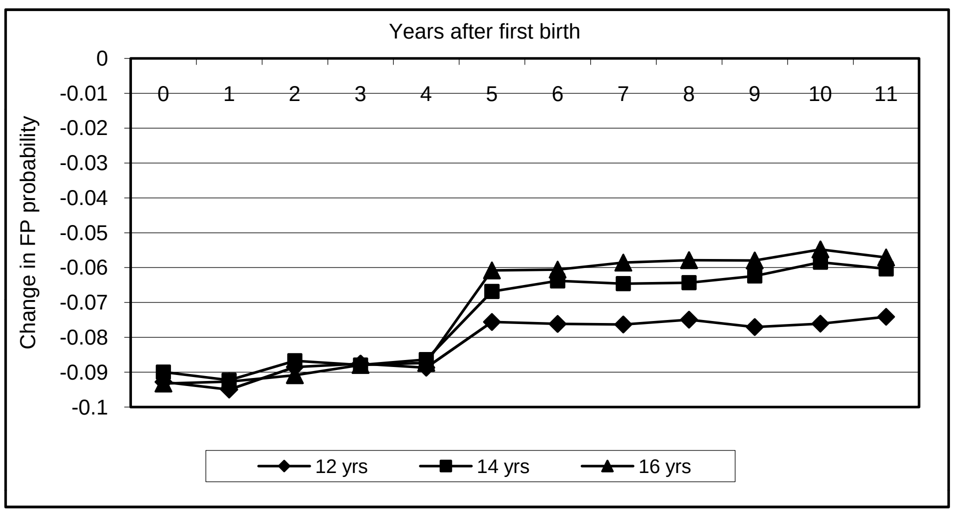
A. Participation



B. Full time



C. Full time part year



D. Part time

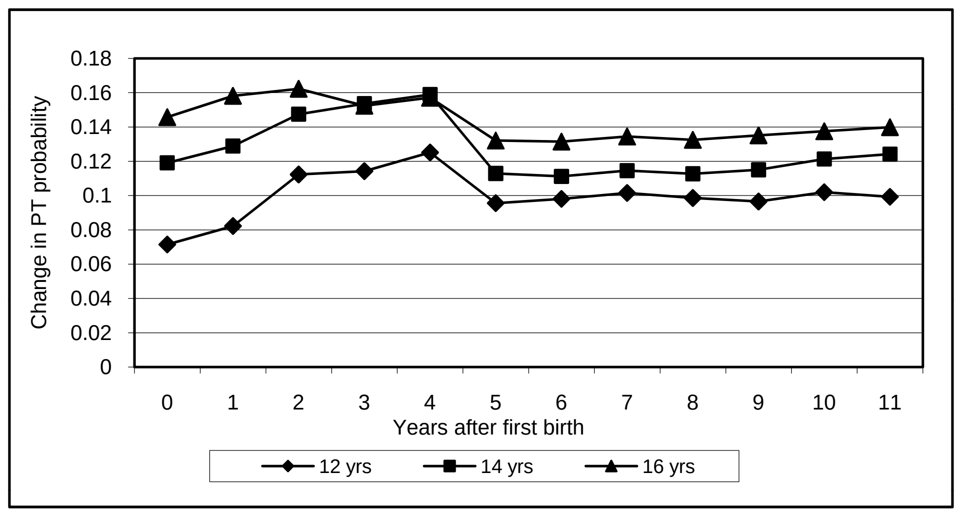


Figure 6. The components of the total effect of education correponding to the random coefficients and own wage. Second birth. Women with 14 years of education compared with women with 12 years of education

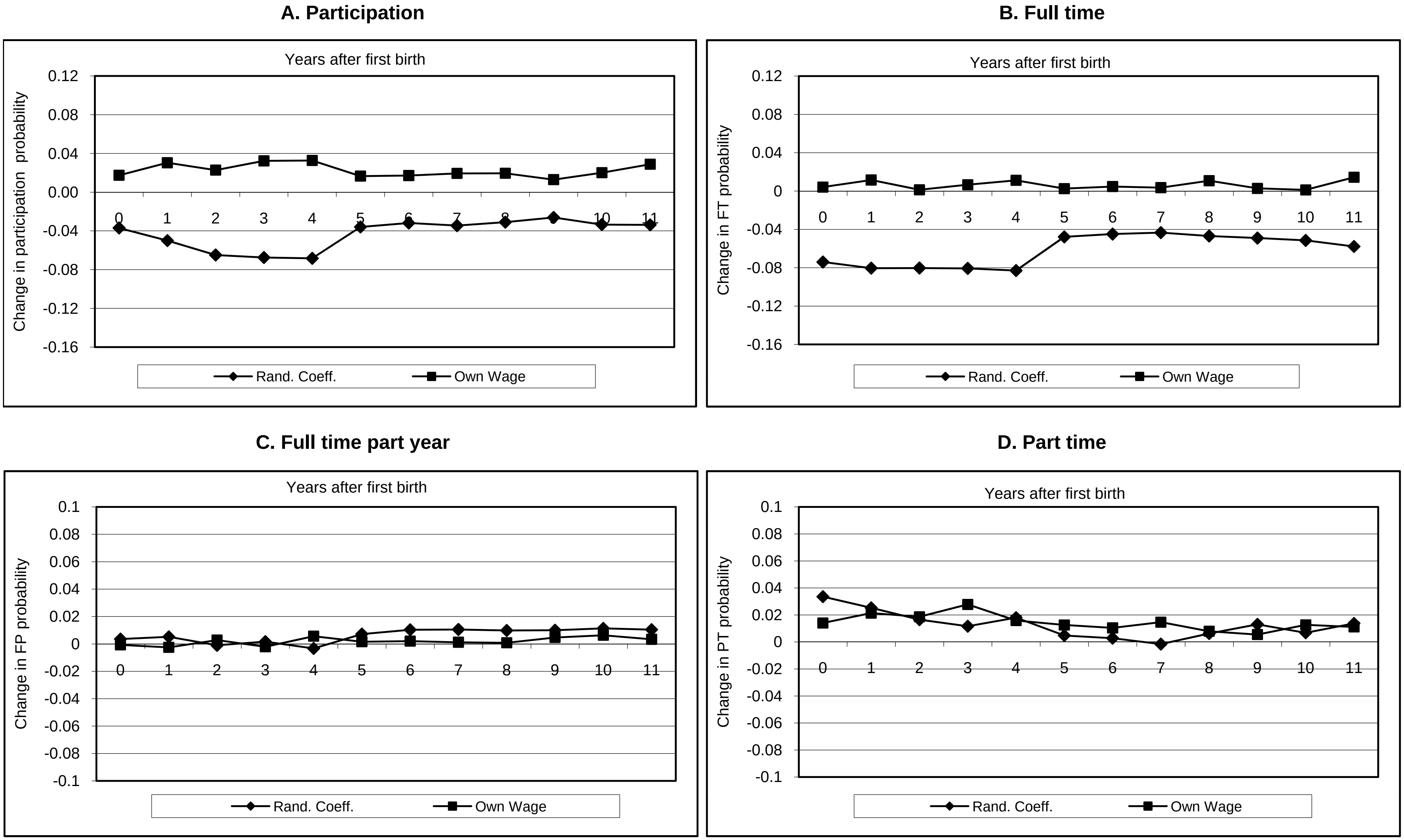
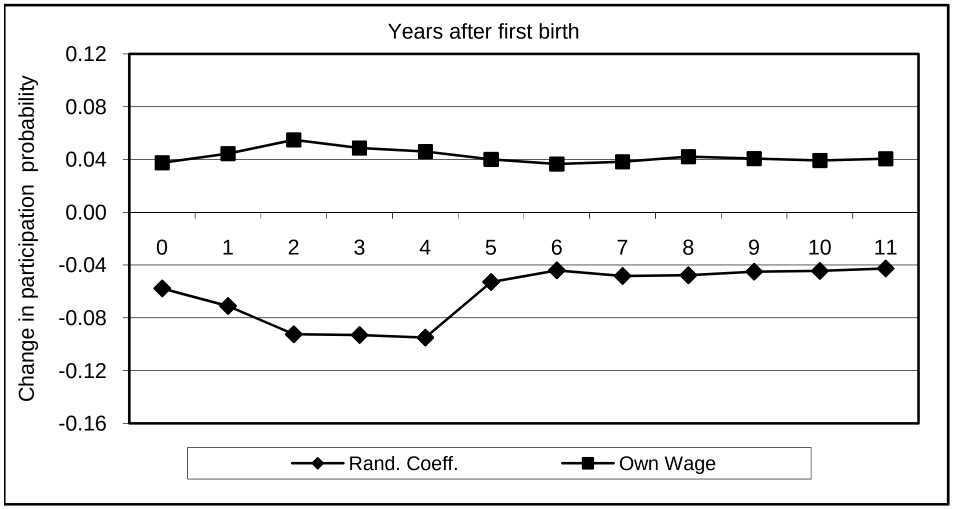
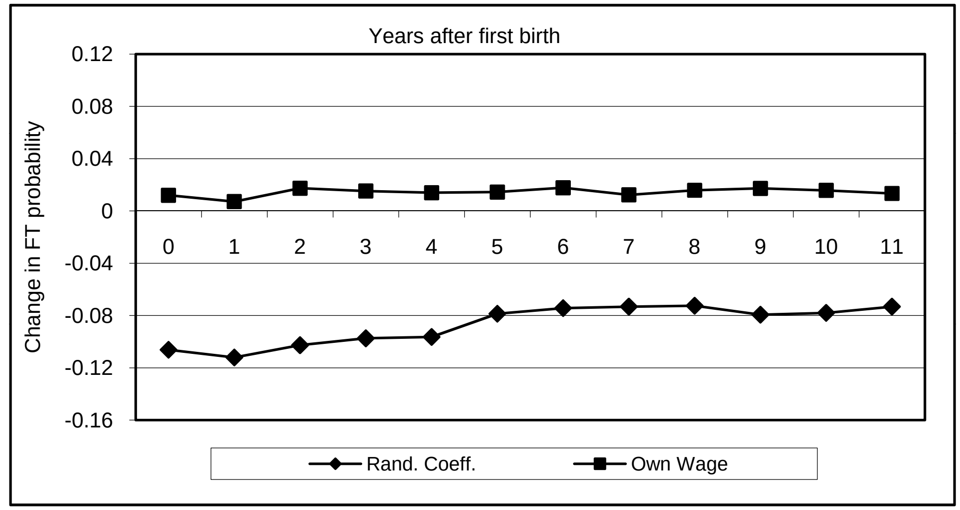


Figure 7. The components of the total effect of education correponding to the random coefficients and own wage. Second birth. Women with 16 years of education compared with women with 12 years of education

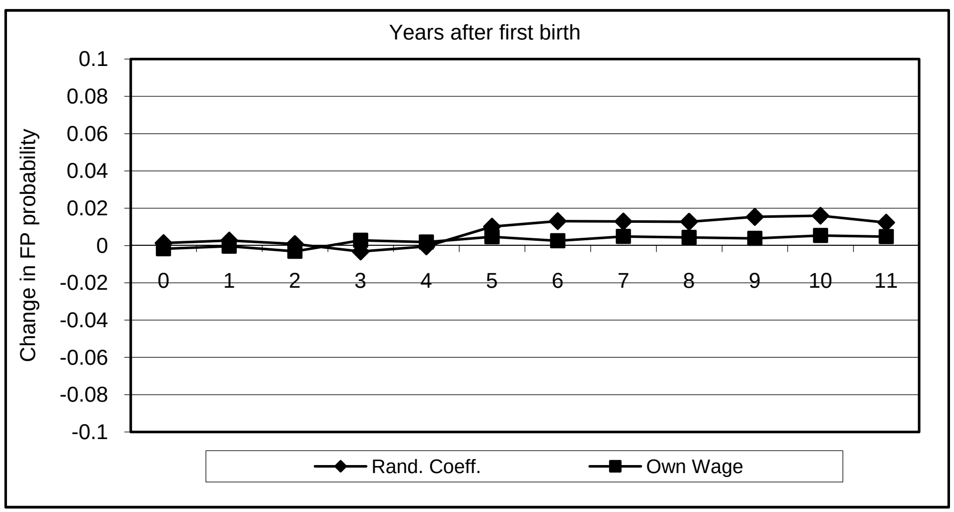
A. Participation



B. Full time



C. Full time part year



D. Part time

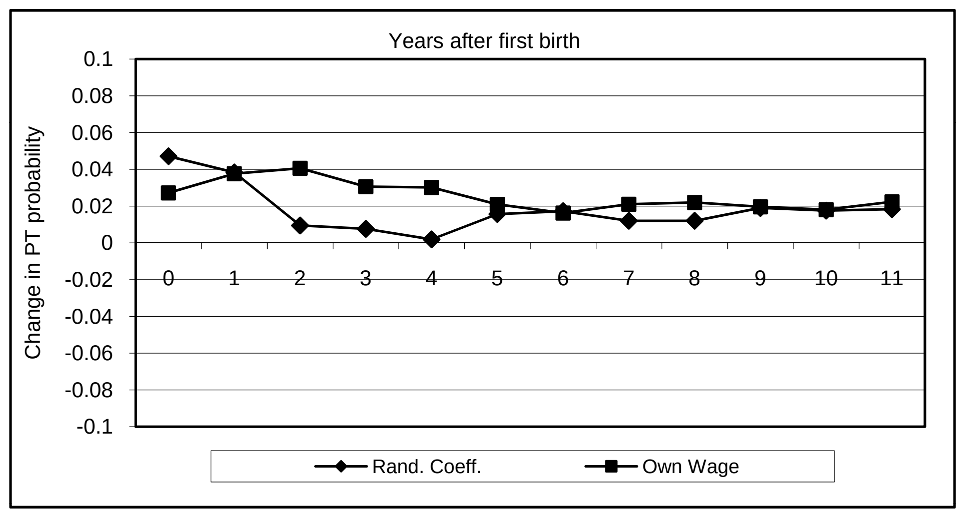


Table 1. Summary Statistics of the Variables in the Data Set

A. Time-Varying Characteristics

						Number of Children per Woman at Risk, by Age			Labor Market Status			
Year (1)	Number at Risk (2)	Married (3)	Avg. Husband's Income (4)	Avg. Other Income (5)	Birth Rate (6)	Age 0 to 1 (7)	Age 2 to 4 (8)	Age 5+ (9)	Full Time (10)	Full Time Part Year (11)	Part Time (12)	Not Working (13)
1979	116	0.00	0.0	72.4	0.00	0.00	0.00	0.00	0.67	0.18	0.11	0.03
1980	185	0.22	1507.9	123.7	0.00	0.00	0.00	0.00	0.62	0.18	0.14	0.06
1981	263	0.28	2488.6	119.8	0.02	0.02	0.00	0.00	0.57	0.15	0.19	0.08
1982	340	0.34	2725.6	94.5	0.04	0.06	0.00	0.00	0.58	0.15	0.18	0.09
1983	402	0.42	3924.8	221.7	0.05	0.08	0.01	0.00	0.58	0.16	0.15	0.10
1984	455	0.49	5266.3	313.1	0.07	0.11	0.05	0.00	0.58	0.18	0.15	0.09
1985	511	0.55	6157.3	526.6	0.09	0.15	0.08	0.00	0.59	0.15	0.18	0.08
1986	561	0.57	8106.4	646.7	0.09	0.17	0.12	0.01	0.62	0.12	0.17	0.10
1987	606	0.62	8749.0	704.5	0.09	0.17	0.16	0.03	0.61	0.14	0.17	0.08
1988	624	0.67	10373.9	907.7	0.11	0.20	0.21	0.06	0.60	0.11	0.19	0.09
1989	631	0.73	11684.7	963.5	0.12	0.23	0.24	0.12	0.59	0.12	0.17	0.12
1990	636	0.77	13015.5	711.6	0.13	0.25	0.27	0.19	0.59	0.10	0.18	0.12
1991	638	0.80	14435.0	668.0	0.13	0.26	0.32	0.26	0.55	0.11	0.20	0.14
1992	639	0.84	15547.3	698.6	0.13	0.27	0.35	0.35	0.55	0.09	0.23	0.14
1993	642	0.86	15981.3	1123.9	0.13	0.27	0.38	0.45	0.52	0.09	0.22	0.16
1994	643	0.89	18432.9	2213.6	0.13	0.26	0.39	0.57	0.52	0.08	0.22	0.19
1995	644	0.91	18083.1	2066.9	0.12	0.25	0.40	0.70	0.53	0.07	0.21	0.19
1996	644	0.93	20263.3	2104.9	0.10	0.22	0.39	0.83	0.49	0.09	0.23	0.19
1997	645	0.94	19878.5	1481.3	0.09	0.19	0.38	0.96	0.50	0.07	0.23	0.20
1998	645	0.95	21807.5	2149.2	0.09	0.18	0.34	1.09	0.52	0.05	0.23	0.20
1999	645	0.96	19960.9	2291.8	0.06	0.15	0.31	1.22	0.52	0.05	0.23	0.21
2000	645	0.97	23862.0	2768.1	0.06	0.12	0.27	1.34	0.51	0.04	0.24	0.20
2001	645	0.98	22397.7	1829.4	0.03	0.08	0.24	1.44	0.53	0.04	0.24	0.19
2002	645	0.99	24945.3	2838.3	0.03	0.06	0.20	1.53	0.52	0.06	0.24	0.18
2003	645	1.00	23925.9	2315.4	0.02	0.05	0.14	1.61	0.51	0.06	0.22	0.21

B. Time-Invariant Personal Characteristics and Family Backgound Variables

Education	%	Race	%	Mother's LM status	%	Parents' education	%
<=12yrs	36.4	White	69.9	Full-time	31.2	None college	74.6
13-15yrs	26.7	Black	13.8	Other	68.8	One college	16.0
>=16 yrs	36.9	Hispanic	16.3			Both college	9.5

Table 2. Fertility and Labor Market Outcomes, by Education

	Education		
	<=12yrs	13-15yrs	>=16 yrs
A. Number of children			
Average	1.966	1.703	1.731
Probability Distribution			
0	0.145	0.174	0.223
1	0.136	0.221	0.126
2	0.481	0.413	0.450
3	0.149	0.140	0.134
4	0.060	0.029	0.050
5	0.021	0.017	0.008
>5	0.009	0.006	0.008
B. Timing of marriage			
Average number of years from entry	4.643	4.640	4.588
C. Timing of the first birth			
Average number of years from marriage	2.637	3.641	3.468
D. The level of labor market involvement before the first birth			
Participation	0.962	0.973	0.981
Full Time	0.704	0.751	0.805
Full time part year	0.125	0.100	0.090
Part time	0.133	0.122	0.086
E. The level of labor market involvement after the first birth, women with one child			
Participation	0.813	0.883	0.943
Full Time	0.548	0.607	0.749
Full time part year	0.083	0.089	0.035
Part time	0.182	0.188	0.159
F. The level of labor market involvement after the second birth, women with two children			
Participation	0.830	0.754	0.820
Full Time	0.475	0.401	0.450
Full time part year	0.094	0.064	0.055
Part time	0.261	0.289	0.314
G. The level of labor market involvement after the third birth, women with three children			
Participation	0.628	0.703	0.470
Full Time	0.251	0.333	0.124
Full time part year	0.059	0.067	0.028
Part time	0.318	0.303	0.319

Table 3. Estimation Results. Posterior Means and Standard Deviations for the Coefficients.

	FT-NW		FP-NW		PT-NW		Fertility	
	Mean	PSTD	Mean	PSTD	Mean	PSTD	Mean	PSTD
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.144	0.234	-0.791	0.161	-1.404	0.231	-1.398	0.071
Children age 0-1	-1.464	0.171	-1.001	0.161	-0.178	0.128	0.292	0.048
Children age 2-4	-0.977	0.170	-0.854	0.133	-0.049	0.126	-0.069	0.047
Children age 5+	-0.538	0.134	-0.460	0.085	0.181	0.078	-0.798	0.052
Married	-1.152	0.148	-0.726	0.125	-0.812	0.157		
Spouse's wage	-0.025	0.011	-0.018	0.010	-0.009	0.011		
Other income	-0.015	0.013	-0.038	0.012	-0.017	0.012	0.030	0.007
Region								
North East	0.267	0.203	0.021	0.140	0.131	0.190	-0.048	0.064
North Central	0.463	0.196	0.324	0.138	0.356	0.186	0.088	0.063
South	0.277	0.192	-0.041	0.133	-0.041	0.181	-0.071	0.061
Urban	0.197	0.112	0.104	0.086	0.076	0.101	0.000	0.048
Wage	0.699	0.017	0.699	0.017	0.699	0.017		
Wage*Children age 0-1	-0.015	0.027	-0.015	0.027	-0.015	0.027		
Wage*Children age 2-4	-0.059	0.014	-0.059	0.014	-0.059	0.014		
Wage*Children age 5+	-0.095	0.010	-0.095	0.010	-0.095	0.010		
Sibling with kids							0.029	0.012
ρ	0.701	0.016	0.017	0.043	0.729	0.018	-0.282	0.025

NOTE: FT=Full time; FP=Full time part year; PT=Part time; NW=Non work

Table 4. Posterior Means of Random Coefficients. Observed Heterogeneity.

	FT-NW				FP-NW				PT-NW				Fertility			
		Children				Children				Children				Children		
	CT	0-1	2-4	5+	CT	0-1	2-4	5+	CT	0-1	2-4	5+	CT	0-1	2-4	5+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Education																
<=12yrs	-0.337	0.245	0.238	0.176	0.000	0.134	0.168	0.061	0.085	-0.037	0.043	0.021	0.046	-0.033	0.032	-0.004
13-15yrs	0.138	-0.042	-0.085	-0.050	0.028	-0.031	-0.061	-0.034	-0.013	-0.002	0.002	-0.024	-0.015	0.008	-0.015	0.000
>=16 yrs	0.199	-0.203	-0.153	-0.126	-0.028	-0.102	-0.106	-0.027	-0.072	0.039	-0.044	0.003	-0.031	0.024	-0.017	0.004
Race																
White	0.124	-0.241	-0.390	-0.297	-0.126	-0.175	-0.110	-0.075	-0.005	0.026	0.048	0.061	-0.046	-0.009	0.022	-0.010
Black	0.000	0.085	0.205	0.224	0.052	0.044	0.045	0.036	-0.002	0.006	-0.012	-0.014	-0.034	0.001	-0.004	0.003
Hispanic	-0.124	0.155	0.185	0.073	0.074	0.131	0.065	0.040	0.007	-0.031	-0.037	-0.047	0.080	0.009	-0.018	0.006
Respondent's Mother's labor market status																
Full-time	0.130	0.001	0.082	-0.002	0.030	-0.057	0.014	-0.011	-0.003	0.003	-0.007	0.024	0.002	-0.007	0.007	-0.002
Other	-0.130	-0.001	-0.082	0.002	-0.030	0.057	-0.014	0.011	0.003	-0.003	0.007	-0.024	-0.002	0.007	-0.007	0.002
Parents' education																
None college	0.161	0.177	0.030	0.255	0.164	-0.009	0.042	0.038	0.018	-0.039	-0.006	0.022	-0.015	-0.011	-0.016	-0.014
One college	0.018	0.036	-0.052	0.011	0.019	-0.033	-0.012	-0.031	-0.002	0.041	0.016	-0.024	0.003	-0.003	0.016	-0.020
Both college	-0.179	-0.213	0.022	-0.266	-0.183	0.041	-0.030	-0.007	-0.017	-0.002	-0.010	0.002	0.011	0.015	0.000	0.034

NOTE: CT=Constant term; Children 0-1=Number of children 0 to 1years old; Children 2-4=Number of children 2 to 4 years old; Children 5+=Number of children five years old and older. Age is age at last birthday.

Table 5. Posterior Correlation Matrix for the Effects of Unobserved Individual Heterogeneity

		FT-NW				FP-NW				PT-NW				Fertility			
			Children				Children				Children				Children		
		CT	0-1	2-4	5+	CT	0-1	2-4	5+	CT	0-1	2-4	5+	CT	0-1	2-4	5+
FT-NW	CT	1	-0.122	-0.129	-0.336	0.924	0.120	0.011	-0.314	0.574	-0.259	-0.222	-0.510	0.041	-0.204	-0.064	-0.234
	Children 0-1		1	0.992	0.939	0.019	0.951	0.977	0.935	-0.126	0.779	0.895	0.365	0.461	-0.492	-0.962	0.134
	Children 2-4			1	0.955	0.036	0.937	0.967	0.943	-0.054	0.713	0.849	0.294	0.492	-0.519	-0.942	0.137
	Children 5+				1	-0.185	0.799	0.858	0.987	-0.182	0.708	0.828	0.402	0.363	-0.356	-0.858	0.075
FP-NW	CT					1	0.258	0.172	-0.171	0.696	-0.309	-0.189	-0.625	0.394	-0.535	-0.127	0.057
	Children 0-1						1	0.990	0.793	0.038	0.698	0.819	0.201	0.536	-0.603	-0.955	0.160
	Children 2-4							1	0.853	-0.018	0.718	0.846	0.252	0.565	-0.613	-0.952	0.213
	Children 5+								1	-0.272	0.757	0.872	0.487	0.375	-0.368	-0.858	0.128
PT-NW	CT									1	-0.654	-0.522	-0.959	0.254	-0.340	0.088	-0.148
	Children 0-1										1	0.968	0.824	0.043	-0.053	-0.799	0.010
	Children 2-4											1	0.720	0.245	-0.258	-0.885	0.123
	Children 5+												1	-0.211	0.268	-0.346	0.063
Fertility	CT													1	-0.981	-0.315	0.826
	Children 0-1														1	0.384	-0.742
	Children 2-4															1	0.053
	Children 5+																1

NOTE: CT=Constant term; Children 0-1=Number of children 0 to 1years old; Children 2-4=Number of children 2 to 4 years old; Children 5+=Number of children five years old and older. Age is age at last birthday.

Table 6. Simulation Scenarios

	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10	year 11	year 12	year 13	year 14	year 15
Marital Status	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
								Fertility histories							
								1. No births							
Fertility	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Children 0-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Children 2-4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Children 5+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
								2. One child born in year 3							
Fertility	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Children 0-1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
Children 2-4	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0
Children 5+	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
								3. Two children born in years 3 and 9							
Fertility	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
Children 0-1	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0
Children 2-4	0	0	0	0	1	1	1	0	0	0	1	1	1	0	0
Children 5+	0	0	0	0	0	0	0	1	1	1	1	1	1	2	2

NOTE: Children 0-1=Number of children 0 to 1years old; Children 2-4=Number of children 2 to 4 years old; Children 5+=Number of children five years old and older

Table 7a. The Level of Labor Market Involvement Before the Birth of the First Child, by Education

	Educ. 12 yrs		Educ. 14 yrs		Educ. 16 yrs	
	Prob.	% of Part.	Prob.	% of Part.	Prob.	% of Part.
	(1)	(2)	(3)	(4)	(5)	(6)
Participation	0.914		0.966		0.978	
Full time	0.565	0.618	0.708	0.733	0.744	0.761
Full time part year	0.205	0.224	0.165	0.171	0.156	0.160
Part time	0.144	0.158	0.093	0.097	0.078	0.080

Table 7b. The components of the total effect of education correponding to the random coefficients and own wage.

	Educ. 12 yrs/Educ. 14 yrs		Educ. 12 yrs/Educ. 16 yrs	
	Rand. Coeff.	Wage	Rand. Coeff.	Wage
	(1)	(2)	(3)	(4)
Participation	0.036	0.016	0.037	0.028
Full time	0.130	0.013	0.155	0.024
Full time part year	-0.046	0.006	-0.061	0.012
Part time	-0.048	-0.003	-0.057	-0.009

Appendix Table 1. The relationship between fertility and the number of siblings with children. OLS regression results. Dependent variable: Number of children born between 1979 and 2003

Independent Variable	Model 1		Model 2		Model 3	
	Coeff	Std. Err	Coeff	Std. Err	Coeff	Std. Err
Constant	1.672 **	0.064	1.611 **	0.086	1.702 **	0.122
Change in the number of siblings with children	0.155 **	0.046	0.130 **	0.052	0.101 *	0.052
Number of siblings			0.025	0.023	0.031	0.025
Education						
<=12yrs (omitted)						
13-15yrs					-0.146	0.128
>=16 yrs					-0.168	0.130
Race						
White (omitted)						
Black					-0.321 **	0.151
Hispanic					0.194	0.141
Parents' education						
None Collge (omitted)						
One College					0.025	0.144
Both College					0.258	0.185
Observations	645		645		645	
Adjusted R-square	0.016		0.016		0.026	

NOTE: ** significant at 95% level of confidence; * significant at 90% level of confidence