Labour Economics 17 (2010) 150–169

Contents lists available at ScienceDirect

Labour Economics

journal homepage: www.elsevier.com/locate/labeco

Joint estimation of sequential labor force participation and fertility decisions using Markov chain Monte Carlo techniques

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ARTICLE INFO

Article history:
Received 27 October 2007
Received in revised form 14 April 2009
Accepted 5 July 2009
Available online 16 July 2009

JEL classification:
C11
C15
J13
J22

Keywords:
Female labor supply
Endogenous fertility decisions
Heterogeneous children effects
Multinomial probit model
Gibbs sampler

ABSTRACT

We analyze the effect of children on the labor supply of married women in a framework that accounts for the endogeneity of labor market and fertility decisions, for the heterogeneity of the effects of children and their correlation with the fertility decisions, and for the correlation of sequential labor market decisions. Women with stronger propensity for market work have fewer children, work more before the first birth, and face larger negative effects of children. The total effect of a child remains considerable long after birth; prior birth-related reductions in labor supply account for a significant share of the total effect.

1. Introduction

Over the past several decades most developed economies have seen an increase in the labor force participation rate of women while simultaneously experiencing a decline in fertility rates. In addition, economic and social developments have lead to a rise in the private costs of children 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.[1] Moreover, some recent economic and developmental psychology literature have suggested that longer periods of maternal care improve child cognitive and behavioral outcomes.[2]

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 have lead policy makers to try and implement policies, such as parental leave benefits and subsidies for families that have children, that are aimed at reducing the opportunity cost of children. The efficient design of these policies depends on an accurate estimate of the effect of children on women's level of labor market involvement.

This has led to a large literature estimating the effect children on women's labor supply.[3] However, estimating this effect has proven challenging for several reasons. 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.[4] Second, the effects of children on labor supply are heterogeneous and are correlated with the fertility decisions. Heterogeneous preferences for market work and for 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. The correlation between the number of children and the effects of children on labor supply

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[1] Folbre (1994).

[2] Waldfogel et al. (2002), Brooks-Gunn et al. (2002), Ruhm (2004).

[3] Browning (1992) and Nakamura and Nakamura (1992) provide reviews of the history of this literature.

[4] Browning (1992), Rosenzweig and Wolpin (1980), Angrist and Evans (1998), Carrasco (2001).

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doi:10.1016/j.labeco.2009.07.003

means that evaluating policies designed to reduce the opportunity cost of children requires knowledge of the entire distribution of effects of children on women's labor supply. This is because the effect of policy-driven changes in the opportunity cost of children will depend on the magnitude of the effect of children on the labor supply of women at the decisional margin and on the degree of heterogeneity of the effect of children, since policy changes will primarily affect women at the decisional margin and have very little effect on infra-marginal women. Estimates of the average effect of children on women's labor supply will produce misleading predictions of policy effects because the average effect underestimates the effect of additional children on women who would chose not to have them in the absence of the policy and overestimates their impact on women who would choose to have them.[5]

Another difficulty in estimating the effect of children on women's labor supply is that sequential labor market decisions are correlated. In the period following birth, children will have both a direct and an indirect effect on women's supply of labor to the market. The direct effect represents the reduction in labor supply generated by the increased demand placed on their time by newborn children. The indirect effect captures the reduction in labor supply generated by the maternity-related work interruptions or reductions in the level of labor market involvement. Providing estimates of the direct and the indirect components is also important for the design of efficient policies. If the direct effect is dominant, that is if women take time out of the labor market to raise children, but these interruptions have little effect on subsequent labor market prospects, a policy aiming to reduce the implicit cost of children would primarily involve transfers to families with children. If, on the other hand, the indirect effect is significant, efficient policies would include measures facilitating women's return to work such as longer maternal leave, subsidized day care, flexible work schedule for periods following birth, tax credit for income earned by mothers.

The goal of this paper is to analyze the magnitude and the structure of the effect of children on the level of labor market involvement of married women. We do so in a framework that explicitly accounts for the 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 fertility decisions, and for the correlation of sequential labor market decisions. Sequential labor market decisions and fertility decisions 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. We estimate the model using Markov chain Monte Carlo (MCMC) methods and panel data from 1979 National Longitudinal Survey of Youth (NLSY79). We use the NLSY79 data because these data provide a fairly complete picture of both these women's labor market and fertility histories and contain a rich set of family background variables.

Our paper contributes to the literature on the effect of children on female labor supply in a number of ways. First, using simulations based on the estimation results we construct the entire distribution of the individual-level effects of children on women's level of labor market involvement, and we assess the correlation between these effects and fertility decisions. Second, following the suggestion in Browning (1992), we explicitly examine the relationship between fertility and women's labor supply in the period before the birth of the first child, which allows us to assess how differences in the demand for children affects labor supply decisions prior to the birth of any children. Third, for the period following birth, we decompose the total effect of children into the direct and indirect effect and examine both the size of these effects and how they change with the age of the child. Fourth, for multiple children, we estimate separate effects for each child. The previous literature has exploited exogenous variation in the probability of the second or the third birth to measure the causal effect of children on women's labor supply.[6] If the effect of a child declines with the rank of the child, these estimates will understate the effect of the first child. Finally, we model labor market participation using four states: full time, full time part year, part time, and nonparticipation. If one of the primary effects of children on women's labor supply is through the number of hours worked, this four state model will better capture the dynamics of labor market participation than models with two or three states previously used in the literature.[7]

We find that individual heterogeneity plays an important role in the relationship between labor market and fertility decisions. Propensity to work, likelihood to have more children, and the effects of children on the level of labor market involvement vary significantly across individuals. Individual differences in labor market and fertility behavior are correlated. Women with stronger propensity for market work are likely to have fewer children, work more before the birth of the first child, and face larger negative effects of children on labor supply. The total effect of a child declines with the age of the child, but remains considerable long after birth. The indirect effect of a child–the effect of birth related interruptions on subsequent level of labor market involvement–represents a large share of the total effect. The relative importance of the indirect effect suggests that the depreciation of human capital during birth-related interruptions and the cost of returning to the labor market are important components of the opportunity cost of children.

Our findings imply that policies aimed at increasing fertility through uniform reductions in the opportunity costs of children, such as cash grants or child care subsidies offered to all women, will either have a small impact on fertility or will entail large costs. Women who choose to have few or no children make significant pre-market and early-career investments in human capital, consistent with their preferences. These investments increase the opportunity costs of children. As a result, raising the fertility of these women will involve substantial costs. The importance of the indirect effect suggests that, if policy makers' goals include increasing female labor force participation, efficient policies include measures designed to lower the apparently large costs faced by women who chose to return the labor market.

The remainder of the paper is structured as follows. In the next section, we discuss the theoretical background of our empirical approach. In Section 3 we describe the construction of the panel data set used in the estimation and provide a preliminary, non-parametric analysis of the relationship between fertility and labor market decisions. In Section 4 we present the econometric model, the estimation procedure, the simulation design, and the construction of the direct and indirect effects. In Section 5 we present the results of the empirical analysis. In Section 6 we summarize the main results and discuss their implications.

2. Conceptual framework

The effect of children on women's labor supply is an important element of women's decisions regarding investments in human capital and subsequent labor market and fertility decisions. Our approach to studying the effect of children rests on three basic facts suggested by the previous literature.

First, children have a negative effect on women's labor supply, but this effect fades away as children grow older. Many different factors account

[5] These issues are the same issues raised in the recent literature on estimating treatment effects and the overall effectiveness of active labor market policies. See Heckman and Robb (1985), Björklund and Moffitt (1987), Imbens and Angrist (1994), Heckman and Vytlacil (1999, 2000, 2001), Carneiro, Heckman, and Vytlacil (2001), Moffitt (2005).

[6] Carrasco (2001), Angrist and Evans (1998), Rosenzweig and Wolpin (1980).

[7] See Blank (1989, 1994), Giannelli (1996), Angrist and Evans (1998), Hyslop (1999), Carrasco (2001), Chib and Jeliazkov (2003), Voicu and Buddelmeyer (2003).

for these findings. Women's physical capacity for performing market work is sharply diminished during the period surrounding birth; rearing children is time-intensive and initially involves a taxing personal and family adjustment process. As children grow, caring for them requires less time, which makes it less costly to work in the labor market. Families also learn new ways of performing tasks, which lowers the costs of children. This effect can be formalized and studied using various models. Neoclassical labor supply theory assumes that individuals make employment decisions by comparing the utility of working in the market with the utility of working in the home. The value of working relative to not working increases as the child ages (Mincer, 1962; Heckman, 1980; Leibowitz et al., 1992). In a job-search framework (Mortensen, 1986) the value of time in alternative (non-work) states can be assumed to vary with the number of children and their ages. The birth of a child will raise the value of time in alternative use and, through it, the reservation wage. As a result, the probability of employment will decline.

Second, sequential labor market decisions of women are correlated and, as a result, labor market interruptions or temporary reductions in the level of labor market involvement are associated with lower employment probability in subsequent periods. There are multiple sources of correlation. Human capital theory predicts that skills accumulated through experience raise the probability of working in the future. Fixed costs of entering the labor force make future participation more likely for individuals already working. Job matching models where employers and employees learn about the quality of the match induce state dependence even if there is little investment in firm-specific human capital. Periods of nonparticipation or low level of labor market involvement are associated with lower levels of investment in human capital, or even depreciation of the human capital stock, loss of information on the quality of the match, and costly search for a new job.

Third, preferences for market work and children differ across individuals.[8] Assuming that utility is derived both from market work (either directly or through consumption) and from the presence of children in the household and that the feasible combinations of market work and children are described by a production possibilities curve whose marginal rate of transformation is determined by pre-market and early-career investments in human capital, women decide to have an additional child as long as the opportunity cost of that child does not exceed the loss in utility from a reduction in the market activity that keeps the individual on the same indifference curve. Other things equal, women with stronger preferences for market work would find it optimal to choose relatively higher levels of pre-market and early-career investments in types of human capital that raise their market productivity. These investment choices translate into higher levels and longer periods of labor market involvement before the birth of the first child. They also produce different production possibilities curves for women with different preferences: the marginal rates of transformation and, therefore, the opportunity costs of children will be higher for women with stronger preferences for work. Together, heterogeneous preferences and heterogeneous opportunity cost of children determine the distribution of optimal combinations of children and levels of labor market involvement. Women with stronger preferences for market work will choose to have fewer children and higher levels of labor market involvement.

These three facts have the following implications. First, the effects of children will differ across individuals. Women with stronger preferences for market work choose higher levels and longer periods of labor market involvement before the birth of the first child and, therefore, face larger effects of children. Second, women with stronger preferences for market work and higher opportunity costs of children will choose to have fewer children and higher levels of labor market involvement over their life time. Third, children have a negative effect on women's labor supply. The total effect of children on women's level of labor involvement has two components: a direct effect that measures the reduction in labor supply generated by the increased demand placed on their time by newborn children and an indirect effect that captures the additional reduction in labor supply generated by the maternity-related work interruptions or reductions in the level of labor market involvement. For every individual, the direct effect should fade with a child's age, while the indirect effect should be stronger the longer the maternity-related interruption and the lower the level of labor market involvement during that spell.

In this paper we model labor market and fertility decisions in a mixed-effect simultaneous-equation framework that addresses the main theoretical concerns inherent in the estimation of the effect of children on labor market behavior: the endogeneity of labor market and fertility decisions, the heterogeneity of the effects of children on labor supply, the correlation between these effects and fertility decisions, and the dependence of sequential labor market and fertility decisions.

3. 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 who were between 14 and 21 years old in 1979. Individuals were 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.[9] 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, 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). 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 5 years of data for each woman.

Imposing these strict selection criteria (especially the continuous marriage requirement) 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. We impose these restrictions for two reasons. First, the focus on married women is very common in the literature studying the relationship between children and women's labor supply (e.g., see Carrasco, 2001; Hyslop, 1999; Angrist and Evans, 1998; Heckman and Willis, 1977) because married women, especially 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 et al., 1998; Klerman and Leibowitz, 1994). 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

8 Browning et al. (1999) review a large body of empirical evidence suggesting that marginal rates of substitution across goods are heterogeneous even within narrowly defined demographic groups.

9 We exclude women who live on a farm larger than 100 acres at any point in the period because it is difficult to identify hours worked for individuals living on a farm.

Table 1
Summary statistics of the variables in the data set.

A. Time-varying characteristics

Year (1)	Number at risk (2)	Married (3)	Avg. husband's income (4)	Avg. other income (5)	Birth rate (6)	Number of children per woman at risk, by age: Age 0–1 (7)	Age 2–4 (8)	Age 5+ (9)	Labor market status: 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 background variables

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

market, we observe their level of labor market involvement both before and during marriage.[10] Second, the dynamic specification of the econometric model we propose requires us to account for the distribution of the number of children in the initial period. The way in which we select our sample ensures that the number of children in the initial period is identical, zero, for all individuals in our sample.

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 for woman at risk) have been deflated using the CPI-U and are in 1979 dollars. Since after 1994 individuals in the NLSY79 were only interviewed every 2 years 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 7–9 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 0–1, 0.14 for ages 2–4, and 1.61 for 5 years older.

The distribution of the labor market states of women at risk is showed in columns 10–13. To be considered working a woman must have both positive hours worked and positive income. Women who worked more than 1750 h in a year are classified as full time. Women who work between zero and 1750 h, but who work on average more than 35 h a week, are considered full time part year. Women who work between zero and 1750 h, but who work on average less than 35 h 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 background variables that are used as observed sources of heterogeneity: education, race, labor market status of respondent's mother, and parents' education. Thirty-six percent of the

[10] We have carefully considered the possibility of using a sample that did not impose the marriage-related restrictions. We have decided not to pursue this avenue for several reasons. At the most basic level, a binary variable can capture the difference between single and married status, but it is inappropriate for describing marital histories of individuals who divorce or have multiple marriages — a nested categorical variable would be necessary. Second, marital status affects not only the level of labor market involvement, but also the effects of children on the level of labor market involvement. In the setting of our model this would mean adding interactions between the children variables and the variables describing marital status and, accordingly, expanding the layer of random effects that capture the role of time-invariant personal characteristics and individual level heterogeneity. Finally, removing marriage-related sample selection restrictions makes endogenous modeling of marital status more stringent. Technically, the Markov chain Monte Carlo techniques we employ in this paper provide an estimation framework flexible enough to model another binary variable, like marital status, endogenously. In practice, however, even if the binary variable provided an accurate representation of marital histories, we would be hard-pressed to find valid instruments. In addition, a significantly larger sample and a larger number of equations translate into significantly higher computational costs. 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.

women in the sample have 12 years of education or less, 27% have between 13 and 15 years of education, while 37% 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 worked full time and 1/3 did not work at all. For 75% of the sample neither parent has a college education, for 16% one parent has college education, and for 9% both parents have college education.

Figs. 1 and 2 show the effect of a birth on the level of labor market involvement and the way in which the relationship between fertility and the level of labor market involvement differs across individuals with different levels of fertility. Fig. 1 presents the dynamics of the labor force status in the years surrounding birth for women who have one child by 2003. Prior to birth, 80% of women work full time, with the rest either working part time or full time part year. Very few women do not work at all. In the year of the birth the percentage of women working full time drops considerably, while there is a jump up in the percentage working full time part year and modest increase in the percentage working part time or not working. After birth the percentage of women working full time part year returns to the pre-birth level while there is a continual increase in the percentage of women in all other labor market states. The spike in the probability of working full time part year in the year of the first birth suggests that a large percentage of women work full time before the birth and stop working for a relatively short period around birth; many women return to full-time work the year after the birth, others find part-time working arrangements, while still others do not return to work after birth.

Fig. 2 shows the relationship between fertility, measured by the number of children born by 2003 and the dynamics of the level of labor market involvement in the periods surrounding the births. The four panels of Fig. 2 present the probability of working full time, full time part year, part time, and not working, by the number of children. We focus exclusively on the periods before the birth of the first child and after the birth of the last child; the graphs omit the level of labor market involvement between the first and the last birth. The negative numbers on the *X*-axis represent years before the first birth, the positive numbers represent years after the last birth. The level of labor market involvement follows similar patterns for women with one, two, and three children. The comparison of the four panels, however, reveals three key differences. First, women who have more children work less before the birth of the first child: the top left-hand panel shows that women who have two or three children are 5 percentage points less likely to work full time prior to the birth of their first child than women who have only one child. Second, the reduction in the level of labor market involvement at the first birth is larger for women who have more children: both the decline in full time probability and the increase in the probability of not working are larger for women with two and three children. Third, at the last birth, the level of labor market involvement is lower for women with more children–the full-time probability is smaller, the probability of not working is higher–potentially reflecting the combined effect of additional children present in the household, more birth-related interruptions, and factors that also generated the differences before the first birth.

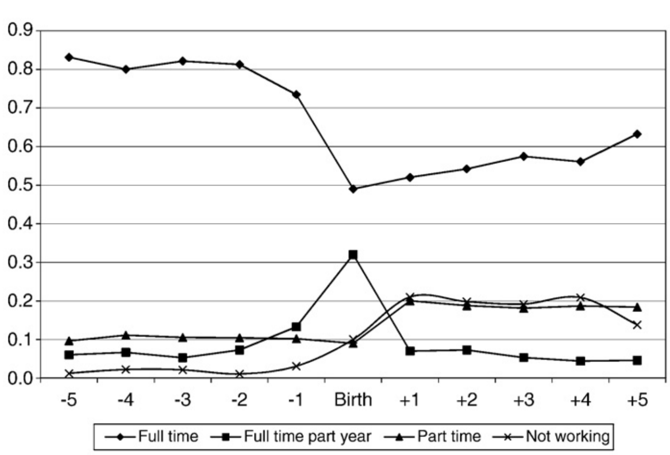

Fig. 1. Labor force participation rates for women with 1 child by 2003.

The patterns observed in the data may be generated in part by differences in observable personal characteristics and one goal of the subsequent analysis is to assess the extent to which that is the case. This caveat notwithstanding, the lower level of labor market involvement before the birth of the first child for women who have more children is consistent with the prediction that women with stronger preferences for children choose lower levels of early-career investments in human capital. The larger reductions in the level of labor market involvement at the first birth for women who have more children can be the result of a selection process in which women with strong preferences for market work have children only if they face relatively smaller effects of children on labor supply.

4. The econometric model

The goal of the econometric model we propose is to analyze the magnitude and the structure of the effect of children on the level of labor market involvement of married women in a framework that simultaneously addresses 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 the correlation of sequential labor market decisions.

We represent the labor market decisions using a model with four states — full time (FT), full time part year (FP), part time (PT), and nonwork (NW). This model 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 showed, a majority of women work full time before the birth of the first child. However, there is substantial variation in women's labor supply after birth with some women returning to full-time work, some switching to part-time and some choosing to remain out of the labor market for an extended period. In a two-state model (work, nonwork) in which labor market states are defined using hours worked in a given year, women who return to full-time work after short birth-related interruptions will be treated the same as women who switch to part-time work. 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 they are combinations of full-time work and inactivity (paid and unpaid leave). This will make it appear as if women are transiting to part-time work in the year of the birth of a child when, in fact, they are actually leaving the labor market. This in turn will make it appear as if part-time work is less persistent.

We model sequential labor market decisions using a multinomial probit model with auto-correlated error terms. Fertility decisions are modeled using 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 simultaneously makes a fertility decision. The level of labor market involvement is selected from the set of four alternatives, by comparing the utility associated with each state. The value functions associate with each state are denoted by U_{it}^{FT}, U_{it}^{FP}, U_{it}^{PT}, and U_{it}^{NW} where the subscript i indicates individuals, $i = 1,\ldots, N$; the subscript t indicates time periods, $t = 1,\ldots, T_i$ and the superscripts denote the labor market state. 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. The fertility decision is whether to conceive a child during the current period. Fertility choices are made

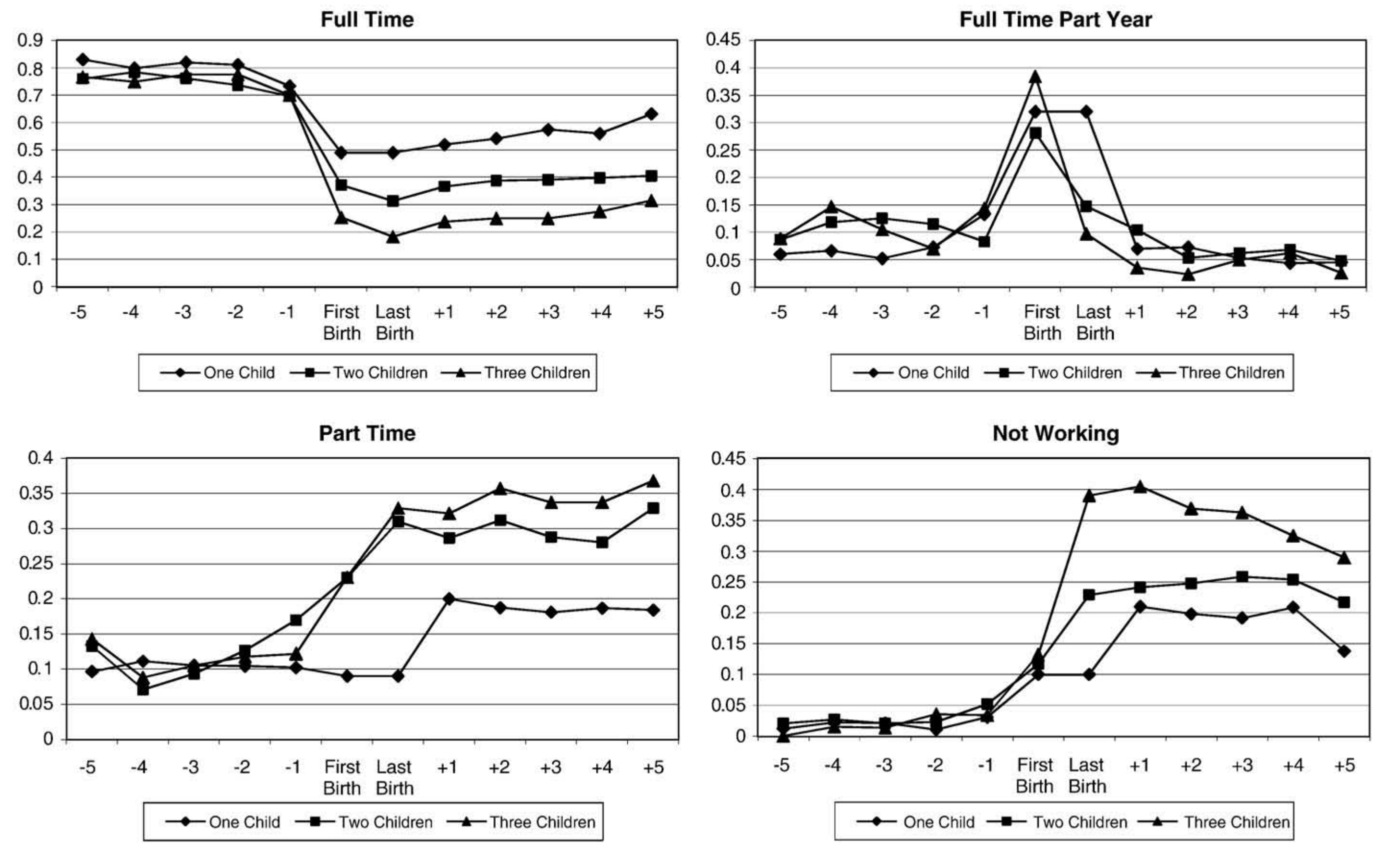

Fig. 2. Level of labor market involvement before the first birth and after the last birth.

by comparing the value functions corresponding to having and not having a child. We denote the difference between these value functions U^{F}_{it}. The transformed value functions that drive the labor market and fertility decisions have the following specifications:

$$U^1_{it} = U^{\mathrm{FT}}_{it} - U^{\mathrm{NW}}_{it} = K_{it}\alpha^1 + X^{\mathrm{LM}}_{it}\beta^1 + Z^1_{it}\gamma + \sum_m K_{it}\delta^1_{ml(i,m)} + u^1_{it}$$
$$U^2_{it} = U^{\mathrm{FP}}_{it} - U^{\mathrm{NW}}_{it} = K_{it}\alpha^2 + X^{\mathrm{LM}}_{it}\beta^2 + Z^2_{it}\gamma + \sum_m K_{it}\delta^2_{ml(i,m)} + u^2_{it}$$
$$U^3_{it} = U^{\mathrm{PT}}_{it} - U^{\mathrm{NW}}_{it} = K_{it}\alpha^3 + X^{\mathrm{LM}}_{it}\beta^3 + Z^3_{it}\gamma + \sum_m K_{it}\delta^3_{ml(i,m)} + u^3_{it}$$
$$U^{\mathrm{F}}_{it} = K_{it}\alpha^{\mathrm{F}} + X^{\mathrm{F}}_{it}\beta^{\mathrm{F}} + \sum_m K_{it}\delta^{\mathrm{F}}_{ml(i,m)} + u^{\mathrm{F}}_{it}.$$

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.[11] This specification is a departure from the previous literature which primarily 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 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 in order to 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 making current fertility decisions a function of past fertility decisions.

X^{LM}_{it} is a vector of personal characteristics that affect labor market decisions. X^{LM}_{it} 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^{F}_{it}, is a vector of personal characteristics that affect fertility decisions. X^{F}_{it} includes other income, the region of residence, whether the respondent resides in an urban or rural area, and the number of siblings with children.

Z^1_{it}, Z^2_{it}, Z^3_{it} are expected hourly wages in each of the alternative labor market states. Because multinomial probit models such as this are frequently difficult to identify due to flat spots in the likelihood function we follow the suggestion of Geweke et al. (1997) and include the Z_{it} variables in the model.[12] The variable Z_{it} varies over i, t, and labor market state, and the coefficient on Z_{it} is constrained to be the

[11] 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, as one anonymous referee suggested, the likelihood of termination could be correlated with labor supply decisions.

[12] While expected wages play a functional role in our model, 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.

same across states. 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 and is estimated using all women in the NLSY between 1979 and 2004.[13]

We do not include wages in the fertility equation. However, since wages affect the values of alternative levels of labor market involvement, and since we allow the value functions corresponding to labor market decisions to be correlated with the value function corresponding to the fertility decision, wages will affect fertility decisions in our framework.

We also do not include marital status or spouse's wage in the fertility equation because our data only includes 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 cannot be identified. However, it is unlikely our results will be affected by significant age effects since the age range in our sample is only 7 years.

The key feature of our model is the mixed-effect structure, which combines fixed and random coefficients and which has not been previously used in studies measuring the effect of children on women's labor supply. The α's, β's, and γ in our model are vectors of global (fixed effect) parameters which are common across individuals in the sample. We allow five ($m = 1,\ldots, 5$) independent sources of heterogeneity to affect 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 individual heterogeneity has l_m levels. We have three levels 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) and three for parents' education (none of the parents, one, or both parents have college education); the number of levels for individual-level heterogeneity is equal to the number of individuals in the sample. Each individual in the data is assigned a level for each source of heterogeneity $l(i, m)$.

To level l of heterogeneity source m corresponds the vector of random coefficients $\delta_{ml} = [\delta_{ml}^{1'}|\delta_{ml}^{2'}|\delta_{ml}^{3'}|\delta_{ml}^{F'}]$. The four components of δ_{ml}, $\delta_{ml}^{1'}$, $\delta_{ml}^{2'}$, $\delta_{ml}^{3'}$, $\delta_{ml}^{F'}$ correspond to the four equations of the model. Each component includes four elements, one random effect and three random coefficients, corresponding to the four variables in the vector K_{it}. We assume δ_{ml} are normally distributed, independent across the l_m levels of heterogeneity of source m, $\delta_{ml} \sim MVN(0, D_m)$, 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 allow us to model the effects of these time-invariant personal characteristics on labor market and fertility decisions. 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 preferences 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 captures the correlation between preferences for market work and children, effects of children on labor supply, and fertility behavior.[14]

We assume error terms are jointly normally distributed.

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

Over time, error terms follow an AR(1) stationary process, $u_{it} = Ru_{it-1} + \varepsilon_{it}$, where $\varepsilon_{it} = [\varepsilon_{it}^{1}|\varepsilon_{it}^{2}|\varepsilon_{it}^{3}|\varepsilon_{it}^{F}]'$ is distributed $IIDN(0, \Psi)$, $\Psi = I_4$, and it is uncorrelated with the random coefficients δ_{sk} and variables X_{it}^{LM}, X_{it}^{F}, Z_{it}, and R is a 4×4 diagonal matrix whose elements are the AR(1) coefficients corresponding to the four equations, ρ_1, ρ_2, ρ_3, and ρ_F.[15]

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.

We exploit several sources of identification. 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. This non-linearity is generated by the way in which we construct the number the children variables–number of children in certain age categories–as well as by measuring fertility as the date of conception (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).

Finally, we include the number of siblings with children in the fertility equation but not in the labor market equations.[16] Our use of this instrumental variable rests on significant evidence that siblings' fertility behavior affects an individual's fertility decisions through social interaction occurring in the context of interpersonal networks.[17] In a panel

[13] The regression 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] For each source of heterogeneity, random coefficients are assumed to be correlated within and between equations.

[15] The dynamic specification of both participation and fertility decisions requires assumptions regarding initial conditions. Specifically, we need to account for the distribution of the error terms and for the distributions of the children variables in the initial period. We assume that error terms follow stationary AR(1) processes, and we treat pre-sample error terms as parameters of the model. The selection of the sample ensures the number of children in the initial period is 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.

[16] 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.

[17] Montgomery and Casterline (1996) provide a theoretical framework in which siblings' fertility affects 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 found 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.

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. Evidence that changes in the number of siblings with children do impact a women's fertility decision is provided in Appendix Table 1. In this table we present the results from three OLS regressions where the number of children born between 1979 and 2003 is the dependent variable and the change in the number of siblings with children during the same period, along with the number of siblings, respondent's education and race, and respondent's parents' education are independent variables. The coefficient on 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 with children is 0.1.[18]

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 of multiple integrals at each step of the maximization process whose dimensions increase very quickly with the number of equations to be estimated. The estimation algorithm we use 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 the 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 A.

4.1. Simulation design

To measure the effects of children on the probability distribution of the four labor market states and to assess the way these effects vary with education, race, and across individuals, we use simulations based on the estimation results. 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 the first 8 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. In all three fertility histories marriage takes place in the second year. The conception of the first child takes place during the second period and the first birth takes place at the beginning of the third period. The conception of the second child takes place during the fourth period and the second birth takes place at the beginning of the fifth period. The timing of marriage, the timing of the first birth, and the spacing of the two births we use in the simulation scenario are those with the highest frequency in our data: 15% of all marriages take place 1 year after entry into the labor market, 23% of the first conceptions take place in the year of marriage, and 32% of the second conceptions take place 2 years after the first conception.

We construct five individual profiles: white woman with 12 years of education, white woman with 14 years of education, white woman with 16 years of education, black woman with 12 years of education, and Hispanic woman with 12 years of education. For all the profiles we assume that none of the respondent's parents has college education and that the respondent's mother did not work full time, characteristics that have highest frequencies in our sample. We set the spouse's wage and other family income at their respective median levels, the region of residence to North-East, and the type of residence to urban. 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 (education, urban location, and region).[19]

To incorporate individual heterogeneity, we draw a random subsample of 100 individuals and attach their respective individual random effects to each of the five individual profiles, generating a total of 500 observations. For each of the 500 observations we compute the joint probability distribution of all possible labor market and fertility histories.[20]

It is important to recall that labor market experience enters the probability distribution of the labor market states through two channels. 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 total labor market experience.

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, $t=1$, …, 8, 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 $f(s_1, s_2, \ldots, s_8, h_j)$ 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 five $f(h_2)$, along with the probability of all possible labor market histories conditional on the specific fertility history $f_j(s_1, s_2, \ldots, s_8)$. 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

[18] 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 two or more children, the proportion of those that have the third child is 0.06 greater if the first two children were of the same sex than if they were of opposite sex.

[19] With eight time periods and four labor market states, there are 65,536 possible labor market histories.

[20] 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).

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:

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

The effect of the second birth, which takes place at the beginning of year 5, is computed by comparing the probability distributions for the fertility histories with one and two births, in the years following the second birth:

$$TE_t^2 = f_2(s_t) - f_1(s_t), t \geq 5.$$

4.2. Direct and indirect effects

The reduction in the level of labor market involvement that we observe in the periods following the birth of the child is generated in part by the presence of the child in the household (direct effect) and in part by the impact that leaving the labor market has on subsequent levels of labor market involvement. One of our goals is to quantify the size and dynamics of these two effects.

Simply put, for both the first and second child, the decomposition of the total effect into the direct and indirect effects is based on constructing counterfactual scenarios in which a woman does not give birth to a child, but experiences a temporary reduction in the level of labor market involvement as if she did give birth. For example, we compute the total effect of the first child on the probability of working full time in the periods following birth, $t=4, \ldots, 8$, as the difference between the probability of working full time conditional on having one child born in year 3, and the probability of working full time conditional on having no children

$$TE_t^1 = f_1(s_t = ft) - f_0(s_t = ft), t = 4, \ldots, 8.$$

The indirect effect is obtained by comparing the probability of working full time conditional on not having a child but having experienced the reduction in the prior level of labor market involvement with the probability of working full time conditional on not having the child. Consider the case of the first child born in period 3. The probability of working full time in year 4 conditional on having a child born in period 3 can be written as

$$f_1(s_4 = ft) = \sum_{s_1 \in S} \sum_{s_2 \in S} f_1(s_1, s_2) \times \left[\sum_{s_3 \in S} f_1(s_3 | s_1, s_2) \times f_1(s_4 = ft | s_1, s_2, s_3) \right] \quad (1)$$

and the probability of working full time in year 4 conditional on having no children is

$$f_0(s_4 = ft) = \sum_{s_1 \in S} \sum_{s_2 \in S} f_0(s_1, s_2) \times \left[\sum_{s_3 \in S} f_0(s_3 | s_1, s_2) \times f_0(s_4 = ft | s_1, s_2, s_3) \right] \quad (2)$$

where $f_j(s_1, s_2)$ denotes the joint probability distribution of the labor market states in years 1 and 2, and $f_j(s_3|s_1, s_2)$ and $f_j(s_4|s_1, s_2, s_3)$ are conditional probability distributions of the labor market states in years 3 and 4. The probability of working full time in year 4 conditional on having no children but having experienced the same reduction in the level of labor market employment in year 3 as that produced by the birth of a child is

$$f_0'(s_4 = ft) = \sum_{s_1 \in S} \sum_{s_2 \in S} f_0(s_1, s_2) \times \left[\sum_{s_3 \in S} f_1(s_3 | s_1, s_2) \times f_0(s_4 = ft | s_1, s_2, s_3) \right]. \quad (3)$$

Eqs. (1) and (2) show that the birth affects the probability of working full time in period 4 through two channels. First, it reduces mother's level of labor market involvement in the year of the birth, which implies that the conditional probability distribution $f_1(s_3|s_1, s_2)$ attaches higher probabilities to labor market states with lower level of labor market involvement than $f_0(s_3|s_1, s_2)$. Second, the child born in period 3 becomes part of the household in period 4 changing the vector of personal characteristics (i.e. the number of children ages 0–1). As a result $f_1(s_4=ft|s_1, s_2, s_3)$ will also attach higher probabilities to labor market states with lower level of labor market involvement than $f_0(s_4=ft|s_1, s_2, s_3)$.

The indirect effect is the change in the probability of working full time in year 4 due to the reduction in the level of labor market involvement in the year of birth. Since the birth occurs in period 3, the probability distribution of the labor market states in the first 2 years does not depend on the number of births, $f_0(s_1, s_2)=f_1(s_1, s_2)=f(s_1, s_2)$.

$$IE_4^1 = f_0'(s_4 = ft) - f_0(s_4 = ft) =$$
$$\sum_{s_1 \in S} \sum_{s_2 \in S} f(s_1, s_2) \times \left[\sum_{s_3 \in S} (f_1(s_3 | s_1, s_2) - f_0(s_3 | s_1, s_2)) \times f_0(s_4 = ft | s_1, s_2, s_3) \right].$$

The direct effect measures the extent to which the presence of the child in the household reduces the probability of working full time.

$$DE_4^1 = f_1(s_4 = ft) - f_0'(s_4 = ft) =$$
$$\sum_{s_1 \in S} \sum_{s_2 \in S} f(s_1, s_2) \times \left[\sum_{s_3 \in S} f_1(s_3 | s_1, s_2) \times (f_1(s_4 = ft | s_1, s_2, s_3) - f_0(s_4 = ft | s_1, s_2, s_3)) \right].$$

The decomposition is performed in the same fashion for years 5, 6, 7 and 8.

For the second child, the decomposition of the total effect is based on comparing the probability of working full time conditional on having two children born in years 3 and 5, the probability of working full time conditional on having one child born in year 3, and the probability of working full time conditional on having one child born in year 3 but having experienced an additional reduction in the level of labor market employment commensurate to that produced by the birth of the second child. For both the first and the second child, we compute the total, direct and indirect effects for participation, and for the three working labor market states: full time, full time part year, and part time.

5. Results

The goal of the empirical analysis is to measure the effects of children on women's levels of labor market involvement, to assess the individual-level heterogeneity of the effects of children on women's labor supply and the correlation between these effects and fertility behavior, and to decompose the total effect into the direct and indirect components and examine their dynamics and their relative magnitude.

5.1. Estimation results

Although coefficient estimates are difficult to interpret because of the non-linearity of the model, the estimation results provide essential insight into the effect of children on women's labor supply.

Table 2 shows the posterior means and the posterior standard deviations (PSTD) for the global parameters of the model.[21] The coefficients on the three children variables are negative in all participation

[21] Since we examine the role of personal characteristics and that of the individual heterogeneity in detail in the next sections, for brevity considerations, we do not show the posterior means of the random coefficients corresponding to the personal and family background characteristics or the individual-specific random coefficients. These results are available upon request.

Table 2
Estimation results.

Equation	Full time–nonwork		Full time part year–nonwork		Part time–nonwork		Fertility	
	Mean	PSTD	Mean	PSTD	Mean	PSTD	Mean	PSTD
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.208	0.264	−0.748	0.202	−1.337	0.255	−1.401	0.072
Children age 0–1	−1.392	0.178	−0.947	0.138	−0.194	0.130	0.283	0.052
Children age 2–4	−1.145	0.179	−0.960	0.147	−0.210	0.131	−0.070	0.054
Children age 5+	−0.894	0.147	−0.760	0.101	−0.158	0.130	−0.784	0.066
Married	−1.100	0.148	−0.672	0.123	−0.754	0.167		
Spouse's wage	−0.024	0.012	−0.017	0.010	−0.009	0.011		
Other income	−0.017	0.013	−0.039	0.012	−0.017	0.012	0.029	0.006
Region								
North East	0.280	0.227	0.033	0.152	0.131	0.196	−0.046	0.063
North Central	0.470	0.210	0.301	0.138	0.322	0.184	0.077	0.063
South	0.283	0.202	−0.032	0.136	−0.026	0.176	−0.071	0.062
Urban	0.224	0.106	0.126	0.084	0.111	0.100	0.007	0.047
Wage	0.631	0.012	0.631	0.012	0.631	0.012		
Siblings with children							0.030	0.012
ρ	0.700	0.017	0.033	0.043	0.713	0.031	−0.281	0.026

Posterior means and standard deviations for the coefficients.

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 −1.392 in the equation of full time relative to nonwork, −0.947 in the equation of full time part year relative to nonwork, and −0.194 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 −1.392 for a child age 0–1, −1.145 for a child age 2–4, and −0.894 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 also associated with lower levels of labor market involvement. Women leaving in urban areas are more likely to hold full-time jobs. Finally, higher wage offers associated with a certain labor market state increase the likelihood of occupying that state.

The estimates of the AR(1) coefficients, ρ, are 0.700 for the equation of full time relative to nonwork, 0.033 for full time part year relative to nonwork, and 0.713 for part time relative to nonwork. The small coefficient for full time part year suggests that short birth-related interruptions 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 a strong negative effect on future labor supply.

5.2. The effect of children on the level of labor market involvement

5.2.1. White women with 12 years of education

We measure the effects of the first and second 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. Fig. 3 displays these probability distributions for white women with 12 years of education, the case we chose as a benchmark.[22] We begin with panel A that shows the trajectory of the level of labor market involvement when there are no births. In the first year of the simulation scenario, the year before marriage, both the labor force participation and the level of labor market involvement of participants are very high. The participation probability–the sum of full time, full time part year, and part time probabilities–is 0.95. The probability of working full time is 0.73, which implies that 77% of those who participate work full time. The probability of working full time part year is 0.09 (10% of those who participate) and the probability of working full time part year is 0.12 (13% of those who participate). Marriage reduces both participation and the level of labor market involvement of those who participate. In the year of marriage, participation probability drops by 13 percentage points. The probability of working full time declines by 20 percentage points, while the probabilities of working full time part year and part time increase both by 4 percentage points.

Comparing panels A and B shows the effect of one child born at the beginning of year 3. The birth of the first child reduces both participation and the level of labor market involvement of those who continue to work. In panel B, the probability of participation in year 3, the year of the first birth, is 0.61, 22 percentage points lower than the corresponding participation probability in panel A. The probability of working full time falls by 19.1 percentage points, the probability of working full time part year falls by 6.1%, while the probability of working part time increases by 3.2 percentage points. Among participants, the share working full time declines by 8.7 percentage points, the share working full time part year declines by 4 percentage points, and the share working part time increases by 12.7 percentage points.

Comparing these figures also shows that the effect of the first child diminishes as the child grows older, but remains significant 5 years after birth. In panel B, the probability of participation in year 8 is 12.1 percentage points lower than the corresponding participation probability in panel A; the probability of working full time is 10.2 percentage points lower, the probability of working full time part year is 6.2 percentage points lower, while the probability of working part time is 4.3 percentage points higher.

The effect of the second child, born at the beginning of year 5, can be measured by comparing panels B and C. The birth of the second child reduces both participation and the level of labor market involvement of those who continue to participate, but the effects are smaller than those of the first child. Participation probability falls by 16.1 percentage points, the probability of working full time falls by 11.1 percentage points, the probability of working full time part year falls by 3.6 percentage points, and the probability of working part time falls by 1.4 percentage points. The larger reductions in the probability

[22] We have averaged out the individual-specific effects when computing these probabilities.

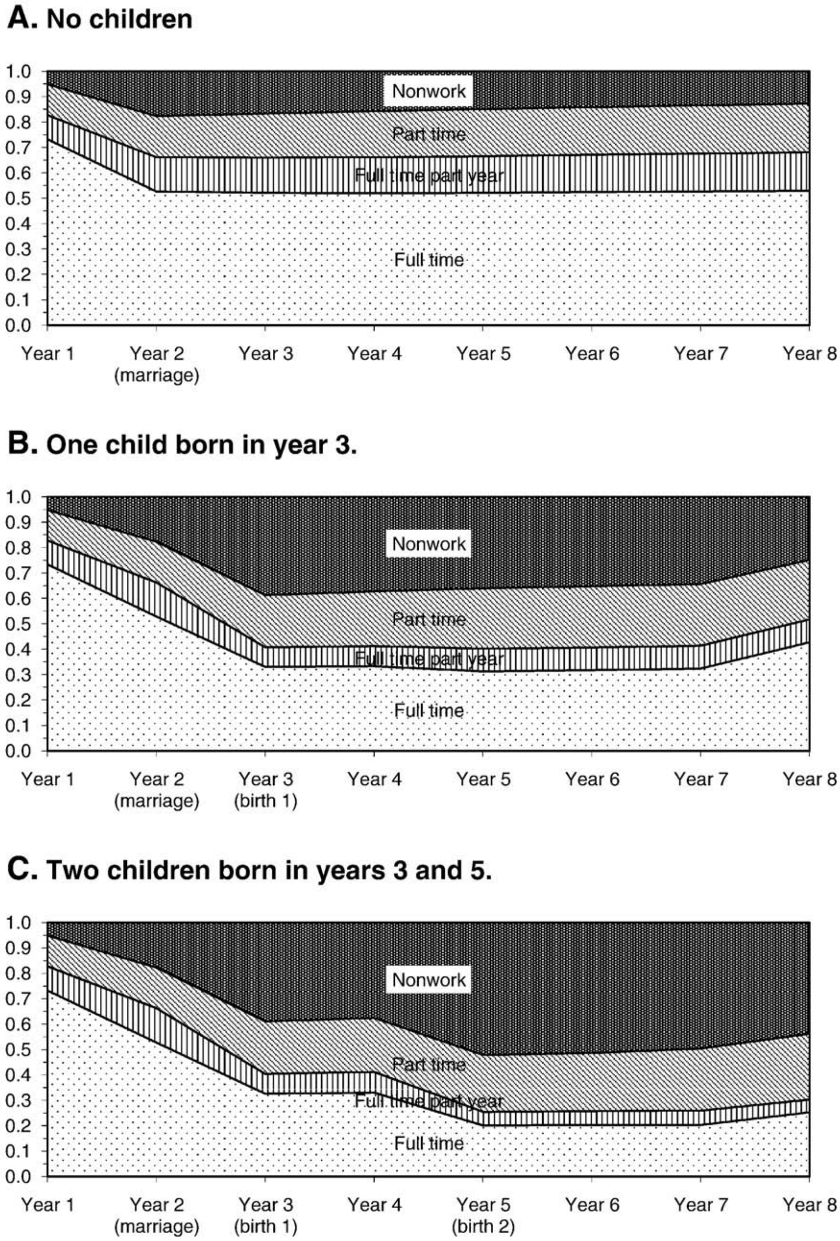

Fig. 3. The probability distributions of the labor market states for three fertility histories. White women with 12 years of education.

of working full time relative to the other working states imply that the share of participants working full time drops by 6.8 percentage points while the share working part time increases by 9.6 percentage points.

5.2.2. Education and race

To assess the way the effects of children vary with education and race, we focus on three key measures of the dynamics of the level of labor market involvement: the probability distribution of the four labor market states in the year before the birth of the first child, $f_0(s_2)$, which provides an indication of a woman's early career investments in market-relevant human capital, the change in the distribution of the labor market states in the year of the first birth, and the change in the distribution of the labor market states in the year of the second birth. The effect of the first birth is computed by comparing the probability distributions in the period of the first birth (period 3) for the fertility histories with zero and one birth:

$$TE_3^1 = f_1(s_3) - f_0(s_3).$$

The effect of the second birth is computed by comparing the probability distributions in the period of the second birth (period 5) for the fertility histories with one and two births:

$$TE_5^2 = f_2(s_5) - f_1(s_5).$$

Table 3 compares the values of $f_0(s_2 = ft)$, TE_3^1, and TE_5^2 across education and race after averaging out the individual-specific effects. The entries in the table show, for each one of the three measures, the participation probability and the probabilities for full time, full time part year, and part time (columns 1,3, and 5), as well as the share of participants corresponding to each of the three working labor market states (columns 2, 4, and 6). Panel A compares the dynamics of labor market involvement for white women, across levels of education, and panel B compares the dynamics of labor market involvement of women with 12 years of education, by race.

The results in panel A tell two stories. First, women with higher education work more before the birth of the first child, but children

Table 3
The dynamics of the level of labor market involvement by education and race.

A. White women by education	Before first birth		Change at first birth		Change at second birth	
	Prob.	% of part.	Prob.	% of part.	Prob.	% of part.
	(1)	(2)	(3)	(4)	(5)	(6)
Educ. 12 years						
Participation	0.823		−0.221		−0.161	
Full time	0.527	0.640	−0.191	−0.087	−0.111	−0.068
Full time part year	0.135	0.163	−0.061	−0.040	−0.036	−0.028
Part time	0.162	0.197	0.032	0.127	−0.014	0.096
Educ. 14 years						
Participation	0.880		−0.230		−0.178	
Full time	0.648	0.736	−0.238	−0.111	−0.159	−0.121
Full time part year	0.113	0.129	−0.050	−0.030	−0.033	−0.029
Part time	0.119	0.135	0.059	0.142	0.014	0.150
Educ. 16 years						
Participation	0.893		−0.235		−0.187	
Full time	0.676	0.757	−0.262	−0.133	−0.178	−0.142
Full time part year	0.111	0.124	−0.050	−0.030	−0.033	−0.028
Part time	0.106	0.119	0.077	0.163	0.024	0.170

B. Women with 12 years of education, by race	Before first birth		Change at first birth		Change at second birth	
	Prob.	% of part.	Prob.	% of part.	Prob.	% of part.
	(1)	(2)	(3)	(4)	(5)	(6)
White						
Participation	0.823		−0.221		−0.161	
Full time	0.527	0.640	−0.191	−0.087	−0.111	−0.068
Full time part year	0.135	0.163	−0.061	−0.040	−0.036	−0.028
Part time	0.162	0.197	0.032	0.127	−0.014	0.096
Black						
Participation	0.818		−0.176		−0.154	
Full time	0.479	0.586	−0.131	−0.046	−0.085	0.003
Full time part year	0.174	0.212	−0.047	−0.015	−0.039	−0.025
Part time	0.165	0.202	0.002	0.061	−0.030	0.022
Hispanic						
Participation	0.813		−0.174		−0.149	
Full time	0.453	0.556	−0.124	−0.044	−0.080	−0.003
Full time part year	0.189	0.232	−0.043	−0.005	−0.033	−0.011
Part time	0.172	0.211	−0.007	0.049	−0.037	0.014

have stronger negative effects on their labor supply. In the year before the first birth, women with higher education have both higher participation and higher levels of labor market involvements of those who participate. The probability of participation of women with 16 years of education is 0.893, 1 percentage point higher than that of women with 14 years of education and 7 percentage points higher than that of women with 12 years of education. At the first birth, the reduction of both participation and level of labor market involvement of those who continue to participate are larger for more educated women. The birth of the first child reduces participation probability by 23.5 percentage points for women with 16 years of education and by 22.1 percentage points for those with 12 years of education. The probability of working full time falls by 26.2 percentage points for those with 16 years of education compared and 19.1 percentage points for those with 12 years of education. The effects of the second child are smaller than those of the first child for all levels of education, but women with higher education face stronger effects than those with lower education.

Second, for all three measures–labor supply before the birth of the first child and the effects of the first and second children–differences across education are more pronounced with respect to the probability of working full time than with respect to participation. This implies that a large share of these differences lie in the differential dynamics in the number of hours worked by participants rather than in the differential dynamics of participation.

The patterns in panel B are to a large extent similar to those in panel A. Differences in participation among white, black, and Hispanic women are small. The level of labor market involvement of the participants, however, is higher among white women: the probability of working full time is 0.527 for white women compared with 0.479 for black women and 0.453 for Hispanic women. The first birth reduces both participation and the level of labor market involvement of those who continue to work, and on both counts the effects are stronger for white women than for black and Hispanic women. After the birth of the first child, the participation probabilities of black and Hispanic women are roughly 4 percentage points larger than those of white women, while the probability of working full time is similar for white and Hispanic women and 3 percentage points larger for black women. The effect of the second child is smaller than the effect of the first child for all races. At the same time, while white women still face larger effects for the second child, differences across races are substantially smaller. After the birth of the second child the participation probability of black and Hispanic women is 5–6 percentage points higher than that of white women, while the probability of working full time is 10 percentage points higher for black women and roughly 8 percentage points higher for Hispanic women than for white women.

5.2.3. Individual-level heterogeneity

To analyze individual-level heterogeneity in the level of labor market involvement before the first birth and in the effects of the first two children, we constructed the distributions of individual-specific levels of $f_0(s_2 = ft)$, TE_3^1, and TE_5^2. In Table 4, we present the 5th, 25th, 50th, 75th, and 95th percentiles of these distributions and the means with their 95% confidence intervals, for white women with 12 years of education, our benchmark category. After controlling for observed characteristics, there remains a large degree of individual-level heterogeneity with respect to both the pre-birth labor supply and the effects of children. The interquartile range for the probability of participating in the year before the first birth is 27 percentage points, between 0.717 and 0.982, while the 5th–95th percentile range is 60 percentage points, between 0.390 and 0.999 (panel A). The individual-level variation in the probability of working full time the year before birth is even stronger: the interquartile range is 50 percentage points, between 0.253 and 0.753, and the 5th to 95th percentile range is 81 percentage points, between 0.0.070 and 0.880. Probabilities of working full time part year and part time also vary widely across individuals.

The change in participation at the first birth varies between −0.629 and 0.021 (the 5th and 95th percentiles), while at the second birth the change in participation varies between −0.442, and 0.010 (panels B and C). The change in the probability of working full time varies between −0.467 and 0.060 at the first birth and between −0.338 and 0.064 at the second birth. The positive 95 percentiles for the changes in both participation and full time probability indicate that, for a nontrivial share of women, the birth of a child increases the level of labor market involvement. The variation with respect to the probability of working full time part year or part time, while substantial, is relatively weaker.

The large degree of heterogeneity in the effects of children on the level of labor market involvement means that for a substantial share of the sample, individual-level effects are very different from the average effects. The 25th percentiles for the changes in participation and in the probability of working full time at the first birth are almost twice as large as the respective average effects, while the effects at the 75th percentiles are 10% of the average effect for participation and 27% of the average effect for the probability of working full time. This implies that for 25% of the sample the effect of the first child is more than double the average effect, and for another 25% of the sample the effect is less than a quarter of the average effect.

Table 4
The dynamics of the level of labor market involvement by individual heterogeneity.

White women with 12 years of education								
A. Level of LM involvement before the birth of the first child								
	Percentile					Mean		
	5th	25th	50th	75th	95th	Value	95% conf. int.	
Participation	0.390	0.717	0.943	0.986	0.999	0.823	0.777	0.869
Full time	0.070	0.253	0.582	0.753	0.880	0.527	0.472	0.581
Full time part year	0.049	0.087	0.137	0.169	0.229	0.135	0.123	0.146
Part time	0.024	0.045	0.103	0.202	0.502	0.162	0.129	0.195
B. The change in the level of LM involvement in the year of the first birth (year 3)								
	Percentile					Mean		
	5th	25th	50th	75th	95th	Value	95% conf. int.	
Participation	−0.620	−0.396	−0.189	−0.024	0.021	−0.221	−0.265	−0.176
Full time	−0.467	−0.326	−0.180	−0.053	0.060	−0.191	−0.226	−0.157
Full time part year	−0.180	−0.094	−0.041	−0.011	0.020	−0.061	−0.074	−0.048
Part time	−0.107	−0.007	0.041	0.086	0.120	0.032	0.016	0.047
C. The change in the level of LM involvement in the year of the second birth (year 5)								
	Percentile					Mean		
	5th	25th	50th	75th	95th	Value	95% conf. int.	
Participation	−0.442	−0.255	−0.144	−0.024	0.010	−0.161	−0.191	−0.130
Full time	−0.338	−0.197	−0.078	−0.014	0.064	−0.111	−0.136	−0.086
Full time part year	−0.109	−0.058	−0.029	−0.008	0.010	−0.036	−0.043	−0.028
Part time	−0.164	−0.072	0.003	0.051	0.115	−0.014	−0.033	0.006

To assess the extent to which these individual-level differences in the level of labor market involvement before the birth of the first child and in the effects of the first and second children are correlated with the fertility decisions, we construct an indicator of the propensity to have children and compare the $f_0(s_2)$, TE_3^1, and TE_5^2 across the values of the indicator. The indicator of the propensity for children is constructed using principal component analysis of the probabilities of having zero, one, and two children, $f(h_0)$, $f(h_1)$, and $f(h_2)$.[23] We use the first component to capture the variation in the propensity for children. The first component had an eigenvalue of 2.53, was the only component with an eigenvalue larger than 1, and explained 86% of the variance in the fertility probabilities. The component weights were −0.94 for the probability of having zero children, 0.86 for the probability of having one child, and 0.96 for the probability of having two children, which indicates that high values of the index are associated with stronger propensities for children. Using this index, we divide the 100 levels of individual heterogeneity into three equal size groups: those with low propensity for children (more likely to have zero children), those with medium propensity for children (more likely to have one child), and those with high propensity for children (more likely to have two children).

Table 5 compares the values of $f_0(s_2 = ft)$, TE_3^1, and TE_5^2 for white women with 12 years of education across propensities for children. The results in the table indicate that the propensity for children is strongly correlated both with the level of labor market involvement before the birth of the first child and with the effects of children on labor supply. Women with low propensity for children work more before the first birth and face stronger effects of children on their labor supply. Before the birth of the first child women with low propensity for children have slightly lower participation probabilities than women with medium or high propensities for children. The level of labor market involvement among participants, however, is substantially higher for women with low propensity for children. The probability of working full time is 0.606 for women with low propensity for children (76.4% of participants work full time), compared with 0.416 for women with high propensity for children (50.6% of participants). At the same time, women with higher propensity for children are more likely to work part time or full time part year before the birth of the first child.

The effects of the first birth on both participation and the level of labor market involvement of those who continue to work are much stronger for women with lower propensity for children. In the year of the first birth, participation probability falls by 0.263 for women with low propensity for children compared with 0.078 for women with high propensity for children. The probability of working full time drops by 0.264 for women with low propensity for children (12.5 percentage point reduction in the share of participants) compared with 0.055 for women with high propensity for children (2.1 percentage points reduction in the share of participants). Differences between women with low and medium propensity for children with respect to the effect of the first birth are very small.

The first and the second birth have similar effects for women with high propensity for children: participation drops by roughly 8 percentage points and the share of participants working full time drops by 2 percentage points. For women with medium and low propensity for children, the effects of the second birth are smaller than those of the first birth. In addition, whereas the first birth had similar effects on women with medium and low propensity for children, the second birth takes a much large toll on women with low propensity for children. In the year of the second birth, the reduction in participation is 0.214 for women with low propensity for children and 0.188 for women with medium propensity for children. More importantly, the reduction in the probability of working full time is 0.175 for women with low propensity for children and only 0.109 for women with medium propensity for children.

5.3. Direct and indirect effects

Fig. 3 showed that the effect of a child on the level of labor market involvement is largest immediately after birth and, while it declines with the age of the child, remains significant for a long period. The large AR(1) coefficients in Table 2 suggest that labor market decisions are persistent and, therefore, temporary reductions in the level of

[23] Principal component analysis is a method designed to identify a small number of factors that explain most of the variance observed in a larger number of manifest variables.

Table 5
The dynamics of the level of labor market involvement by propensity for children.

White women with 12 years of education, by propensity to have children						
	Before first birth		Change at first birth		Change at second birth	
	Prob.	% of part.	Prob.	% of part.	Prob.	% of part.
	(1)	(2)	(3)	(4)	(5)	(6)
Low propensity						
Participation	0.794		−0.263		−0.214	
Full time	0.606	0.764	−0.264	−0.125	−0.175	−0.174
Full time part year	0.095	0.119	−0.049	−0.032	−0.030	−0.033
Part time	0.093	0.117	0.050	0.157	−0.009	0.207
Medium propensity						
Participation	0.854		−0.317		−0.188	
Full time	0.557	0.653	−0.253	−0.093	−0.109	−0.050
Full time part year	0.146	0.171	−0.087	−0.058	−0.041	−0.043
Part time	0.150	0.176	0.022	0.151	−0.038	0.093
High propensity						
Participation	0.822		−0.078		−0.079	
Full time	0.416	0.506	−0.055	−0.021	−0.050	−0.019
Full time part year	0.162	0.198	−0.047	−0.041	−0.036	−0.030
Part time	0.243	0.296	0.023	0.062	0.007	0.049

labor market involvement will have a negative effect on labor supply in subsequent periods.

Table 6 shows the direct and indirect effects of children on participation and on the probabilities of the three working labor market states for white women with 12 years of education. Column 1 indicates the period for which the direct and indirect effects are calculated. The entries corresponding to year 3 for the first birth and year 5 for the second birth indicate the total effect of the birth on the relevant probability. All entries represent averages of individual-level effects. The results for year 3 in columns 6–9 indicate that the birth of the first child reduces participation by 22.1 percentage points, the probability of working full time by 19.1 percentage points, the probability of working full time part year by 6.1 percentage points, and increases the probability of working part time by 3.2 percentage points. The indirect effects in year 4 (columns 2–5) indicate that, for a woman that does not have a child, a reduction in the level of labor market involvement identical to that produced by a birth lowers the probability of participating and the probability of working full time in the following year by 0.047 and 0.096, respectively, while increasing the probability of working full time part year by 0.035 and the probability of working part time by 0.013. The values of the direct effect in year 4 (columns 6–9) indicate that the presence of the one-year-old child in the household further reduces participation probability by 0.168, the probability of working full time by 0.092, the probability of working full time part year by 0.097, and increases the probability of working part time by 0.021. In year 5, when the child born in year 3 moves into the age category 2–4 years, its presence in the household reduces the participation probability by 0.156, the probability of working full time by 0.100, and the probability of working full time part year by 0.094, while increasing the probability of working part time by 0.038 (year 4, columns 6–9).

Table 6
Direct and indirect effects of children on the level of labor market involvement.

White women with 12 years of education								
	Indirect effect				Direct effect			
Year	Particip.	Full time	Full time part year	Part time	Particip.	Full time	Full time part year	Part time
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
First birth								
3					−0.221	−0.191	−0.061	0.032
4	−0.047	−0.096	0.035	0.013	−0.168	−0.092	−0.097	0.021
5	−0.055	−0.108	0.040	0.014	−0.156	−0.100	−0.094	0.038
6	−0.057	−0.122	0.043	0.022	−0.154	−0.085	−0.101	0.032
7	−0.060	−0.127	0.042	0.025	−0.149	−0.076	−0.101	0.028
8	−0.064	−0.127	0.040	0.023	−0.057	0.026	−0.102	0.020
Second birth								
5					−0.161	−0.111	−0.036	−0.014
6	−0.056	−0.055	0.008	−0.008	−0.106	−0.059	−0.043	−0.004
7	−0.064	−0.065	0.010	−0.009	−0.088	−0.056	−0.043	0.011
8	−0.052	−0.069	0.016	0.001	−0.137	−0.105	−0.056	0.024

The indirect effects for participation and full time work (columns 2 and 3) increase with the length of the period of lower level of labor market involvement; the value for participation changes from −0.047 in year 4 to −0.064 in year 8, while the value for full time changes from −0.096 in year 4 to −0.127 in year 8. The indirect effects for both full time part year and part time remain positive and increase only modestly with the length of the interruption.

In contrast, the direct effects for both participation and full time work decline with the age of the child. In year 8, when the child born in year 3 moves into the age category 5 years and older, the direct effect on the participation probability drops by 9 percentage points to −0.057 (column 6), while the direct effect on the probability of working full time becomes 0.026, which indicates that the presence of the child in the household raises the probability of working full time.[24] The direct effect of the first child on the probability of working part time (column 9) is the largest when the child is in the age category 2–4 years old, which suggests that the presence of young preschoolers in the household increases the probability of working part time.

The second birth has a smaller effect on the level of labor market involvement than the first birth. The reduction in the participation probability is 0.161, and the probabilities for full time, full time part year, and part time decline by 0.111, 0.036, and 0.014, respectively (second birth, year 5, columns 6 to 9). The direct and the indirect effects on the probabilities of the three working states in the years following the second birth are smaller than those of the first child, but otherwise display similar dynamics and similar relative magnitudes. Compared with the first child, the second child has a relatively stronger effect on participation and a relatively weaker effect on the level of labor market involvement among women that continue to participate.

The results in Table 6 demonstrate the impact that reductions in the level of labor market involvement have on women's subsequent labor supply. In the year following the first birth, the indirect effect accounts for 22% of the total effect of the child on participation and for 51% of the total effect of the child on the probability of working full time. In addition, the relative size of the indirect effect increases with the length of the interruption. This is because for both the probability of participation and the probability of working full time the direct effect declines while the indirect effect remains fairly stable. By year 8, 5 years after birth, the indirect effect accounts for 53% of the total effect on participation and for the entire effect on full time. At least based on our estimates, reductions in the level of labor market involvement have a large long-run impact on women's subsequent level of labor market involvement.

The dynamics of the direct and indirect effects and their relative magnitudes are similar for the different education levels, races, and propensities for children. In addition, the differences in the magnitudes of the direct and indirect effects across education levels, races, and different propensities for children are consistent with the differences in the total effects discussed in the previous section.[25] The

[24] 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.

[25] We do not present here the comparison of the direct and indirect effects across levels of education, races, and different propensities for children. These results are available upon request.

direct and indirect effects of children on the participation probability vary little with education. On the other hand, the effects on the probability of working full time of both children increase with education, the differences being larger for the second child. The direct and indirect effects of children on participation, full time, full time part year, and part time are stronger for white women than for black or Hispanic women, while differences between black and Hispanic women are very small. Finally women with lower propensity for children face significantly stronger effects of children on their labor supply. For both the first and the second child, women with high propensity for children face much lower direct and indirect effects on both participation and the probability of working full time than women with either medium or low propensity for children.

6. Summary and discussion

In this paper we jointly model labor market and fertility decisions using a mixed-effect simultaneous-equation framework. This empirical approach addresses 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 the correlation of sequential labor market decisions. We estimate our model using a 25-year panel, considerably longer than those previously used in the literature,[26] which follows women from their entry into the labor force and captures almost complete fertility histories. Our empirical approach allows us to study in a unified framework a series of issues frequently addressed in women's labor supply literature and to offer some new, policy-relevant, insight about the magnitude and the structure of the effects of children on women's level of labor market involvement.

We find women have high levels of labor market involvement before marriage: average labor force participation is close to 95% and most of the participants work full time. Like Loughran and Zissimopoulus (2009) we find that marriage reduces the probability of participation and sharply reduces the level of labor market involvement of the participants — the probability of working full time declines on average by 20 percentage points. The estimated coefficients show that husband's wage and other non-labor income have a negative effect on the level of labor market involvement of women. Our estimates indicate that full time, part time, and nonwork are persistent states, a result similar to Blank (1989).[27] The full time part year state captures temporary interruptions around births, following which women either return to full time work, find more permanent part time arrangements, or stop working altogether.

We use our estimation results to simulate the effects of two births on a mother's level of labor market involvement. Our analysis shows that births reduce both participation and the level of labor market involvement of those who participate. The effects of children decline with the number of children, while the total effect of a child declines with the age of the child, but remains significant 5 years after birth. For white women with 12 years of education or less, we estimate the first birth reduces participation by 22 percentage points and the probability of working full time by 19 percentage points, while the second birth reduces participation by 16 percentage points and the probability of working full time by 11 percentage points. A child 5 years or older reduces participation by 12 percentage points and the probability of working full time by 10 percentage points.

The change in the level of labor market involvement of those who continue to participate is both an important component of the overall effect of a child and the main conduit through which socioeconomic personal characteristics and idiosyncratic traits influence the effect of children on women's labor supply. This finding, which is consistent with results of Nakamura and Nakamura (1994), suggests that models with two labor market states underestimate the effect of children on women's labor supply and the variation of this effect across socioeconomic characteristics. The magnitudes of the effects and the way they change between the first and second child are broadly consistent with comparable estimates in previous studies. The effect of the second child on participation is similar to Hyslop's (1999) estimate that a child 0–2 years old reduces participation by 11–17 percentage points. The pattern with respect to the rank of the child is consistent with the estimate of Angrist and Evans (1998) that the third child reduces participation by 9–10 percentage points. Our estimates, however, are considerably smaller than those of Rosenzweig and Wolpin (1980) who found that the second child reduces the participation probability by 37 percentage points. This difference is partly explained by the fact that Rosenzweig and Wolpin use data collected in 1965 and 1973, while data used by Hyslop and Angrist and Evans is roughly contemporaneous with ours, and likely reflects the shift that has occurred over the past few decades in the way women reconcile work and motherhood.

The mixed-effect framework allows us to study how the relationship between fertility and labor market behavior varies across levels of education and races. Our results show that women with higher education 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. These findings are consistent with a large body of empirical evidence which showed that the positive effect of children on women's shadow value of time increases with education (Gronau, 1973), that time inputs in child care increase with mother's education and, as a result, labor supply of more educated women is more sensitive to the presence of children (Hill and Stafford, 1980), and finally, that the rate of depreciation of human capital due to market work interruptions is larger for more educated women (Mincer and Polachek, 1974, 1978). The way in which the effects of children vary with education, suggests that the opportunity cost of children increase with pre-market investment in human capital. Before the birth of the child, women with higher education work more, while women with lower education are more involved in household production. More educated women will "finance" an increase in child care time through reductions in market work, while less educated women through reductions in the time devoted to household production unrelated to child care.

White women have higher levels of labor market involvement before the birth of the first child, but the negative effect of children on their labor supply is substantially stronger. As a result, black and Hispanic women with children have higher levels of labor market involvement. Many previous studies have found larger effects of children for white women than for black women (Bell, 1974; Lehrer, 1992; Shapiro and Mott, 1994). These differences could be due to minority women having better access to informal child care. The similarity between the ways in which education and race affect the relationship between fertility and labor supply suggests, however, that differences across race and ethnicity could be in part generated by human capital differences: minorities are more likely to live in central city and racial and economic segregation in the housing market may affect quality of schooling leading to less human capital even for the same level of schooling (Aaronson, 1998; and Altonji and Blank, 1999).

In the period following birth, the indirect effect accounts for a large share of the reduction in the level of labor market involvement. Twenty two percent of the reduction in participation and half of the

[26] 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.

[27] The AR(1) coefficients for full time and part time are very similar in magnitude with those estimated by Hyslop (1999) for participation in a two state model, 0.69.

reduction in the probability of working full time are due to prior birth-related reductions in labor supply. The direct effect, the effect of the presence of the child in the household, declines with the age of the child for both participation and the probability of working full time, while the indirect effect increases with the length of the interruption. The relative importance and the dynamics of the indirect effect is similar to that described by Mincer and Polachek (1974, 1978), who found that birth-related work interruptions lead to human capital atrophy, longer interruptions have stronger effects, and, in turn, human capital depreciation reduces the probability of working in subsequent periods. Similar to Gronau (1973), our results imply that children have a major effect on women's value of time; this effect diminishes with the age of the child and is especially pronounced for women with higher education. Similar to Mincer and Polachek (1974), our results imply that the value of time has two components — the forgone wage and the reduction of wage from reduced participation over the life time.

After controlling for observed characteristics, we find a large degree of individual heterogeneity in labor market and fertility decisions. Propensity to work, likelihood to have more children, and the effects of children on the level of labor market involvement are different across individuals, and individual differences in labor market and fertility behavior are correlated. Women with higher propensity for children work less before the birth of the first child and face substantially smaller effects of children on the level of labor market involvement. These results are consistent with a model in which preferences for market work and children are heterogeneous; women with stronger preferences for children invest less in human capital that enhances market productivity, which translates into lower levels of labor market involvement before the birth of the first child and lead to lower opportunity costs of children; lower opportunity costs of children and relatively stronger preferences for children raise the probability of having more children.

From a policy perspective, our results have two main implications. First, the relative importance of the indirect effect and the fact that it increases with the length of the interruption imply that the cost of re-entering the market after birth and the depreciation of human capital during birth-related interruptions are important components of the opportunity cost of children. Social policies that aim to increase fertility or post-birth participation of women by reducing the opportunity cost of children are more effective if they mitigate the re-entry cost and human capital depreciation. Thus, it is not surprising that Ondrich et al. (1996) find that, in Germany, the length of the protected leave is the most important determinant of the timing of women's return to work after the birth of a child, while in a comparative study of Norway and Sweden, Rönsen and Sundström (1996) find that women who have the right to paid leave are much more likely to resume employment and return to work two to three times faster than those that do not.

Second, our results suggest that the effects of social policies that involve uniform reductions in the opportunity costs of children, such as cash grants or child care subsidies offered to all women, will either have a small impact on fertility or will entail large costs. This is because in order to have an impact on fertility the policies have to change the behavior of women who do not plan on having children or who plan on having very few children. That is, the policies will have to impact the behavior of infra-marginal women. To be effective in raising the fertility of women with stronger preferences for market work, benefits would have to be correlated with individual opportunity costs. An example of policy that satisfies this requirement is paid maternity leave with the payments being an increasing function of wage and previous work experience, which mitigates re-entry costs and offers benefits that are commensurate with individual opportunity costs of children. This policy will would lead to higher fertility by lowering the cost of children among women who have strong labor market attachments. This policy could also lead, over time, to higher levels of pre-market and early career investments in human capital among women with higher propensities for having children, thereby increasing the subsequent labor market attachment of these women.

Acknowledgement

We would like to thank Saku Aura, Emek Basker, Barton Hamilton and Peter Mueser for helpful comments, and Hielke Buddelmeyer for his help in creating the data set. This research was begun when Troske was a visiting fellow at IZA and he would like to thank them for generous financial support. The estimation has been carried out on the Athena computer cluster of the CUNY High Performance Computing Facility at the College of Staten Island and we would like to thank Michael Kress and the staff of HPC for their support. All remaining errors are our own.

Appendix A

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 $i=1,\ldots,N$, each individual i is observed for T_i periods. The total number of observations is $df=\sum_{i=1}^{N}T_i$. Let $W_{it}^{\mathrm{LM}}=[K_{it}|X_{it}^{\mathrm{LM}}]$, $W_{it}^{\mathrm{F}}=[K_{it}|X_{it}^{\mathrm{F}}]$, 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 $\tilde{\beta}=\left[\alpha^{1'}|\beta^{1'}|\alpha^{2'}|\beta^{2'}|\alpha^{3'}|\beta^{3'}|\alpha^{F'}|\beta^{F'}\right]'$. Define $U_{it}=[U_{it}^1|U_{it}^2|U_{it}^3|U_{it}^F]'$, $Z_{it}=[Z_{it}^1|Z_{it}^2|Z_{it}^3|0]'$. Using this notation the model becomes

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

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

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

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 $u_{it}=U_{it}-\tilde{W}_{it}\tilde{\beta}-Z_{it}\gamma-\sum_m\tilde{K}_{it}\delta_{mi}$.

- 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 $[V_0(R,\Psi)]_{jk}=\frac{\psi_{jk}}{\rho_j\rho_k}$.

- 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. $\rho_j\sim TN(\rho_j^0, \sigma_{\rho_j^0})$, $j\in(1,2,3,F)$
d. $D_m^{-1}\sim W(b_m, B_m)$.

The prior distribution for β is multivariate normal with mean 0 and a variance matrix of 100 times the identity matrix, the prior distribution for γ 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} $(i=1, \ldots, N, t=1, \ldots, T_i)\left[U_{it}|\tilde{\beta}, \gamma, \delta_{sk(i,s)}, D_s, R, u_{i0}\right]$ is a truncated multivariate normal distribution with mean $\begin{bmatrix}\mu_{i1}+Ru_{i0}\\ \ldots\\ \mu_{iT}+R^Tu_{i0}\end{bmatrix}$ and variance $G(I_T\otimes\Psi)G'$ where $\mu_{it}=\tilde{W}_{it}\tilde{\beta}+Z_{it}\gamma+\sum_s\tilde{K}_{it}\delta_{sk(i,s)}$ and

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

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

- Step 2. Draw u_{i0} $(i=1, \ldots, N)$.
The conditional distribution $\left[u_{i0}|U_{it}, \tilde{\beta}, \gamma, \delta_{sk(i,s)}, D_s, R\right]$ 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 $\left[\rho|U_{it}, \tilde{\beta}, \gamma, \delta_{sk(i,s)}, D_s, u_{i0}\right]$ is

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

truncated to the hypercube dictated by stationarity, where

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

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

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

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

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 $[\tilde{\beta}_j | U_{it}, \gamma, \delta_{sk(i,s)}, D_s, R, u_{i0}]$ is a multivariate normal $\tilde{\beta}_j \sim N[b_j, B_j]$

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

and mean

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

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

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

$$\Gamma = \left[\Gamma_0^{-1} + \sum_{i=1}^{N}\sum_{t=1}^{T_i}\sum_l\sum_j \psi^{jl}\dot{Z}_{it}^j\dot{Z}_{it}^{l'}\right]^{-1}$$

and the mean is

$$g = \Gamma\left(\Gamma_0^{-1}\gamma_0 + \sum_{i=1}^{N}\sum_{t=1}^{T_i}\sum_l\sum_j \psi^{jl}\dot{Z}_{it}^j\left(\dot{U}_{it}^l - \dot{W}_{it}^l\tilde{\beta}_l - \sum_m K_{it}\delta_{ml(i,m)}^l\right)\right)$$

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

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

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

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 $e_{mit} = U_{it} - \tilde{W}_{it}\tilde{\beta} - Z_{it}\gamma - \sum_{g:g \neq m}\tilde{K}_{it}\delta_{gl(i,g)}$. Here, $\sum_{i:l(i,m)=k}$ means sum for all individual 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 $[D_m^{-1}|U_{it}, \tilde{\beta}, \gamma, \delta_{ml}, R, u_{i0}]$ are Wishart.

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

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 14,000 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 15,000 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.

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.

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 10% 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 10% 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 10% 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.

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.

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.

Appendix Table 1
The relationship between fertility and the number of siblings with children.

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						
<12 years (omitted)						
13–15 years					−0.146	0.128
>15 years					−0.168	0.130
Race						
White (omitted)						
Black					−0.321**	0.151
Hispanic					0.194	0.141
Parents' education						
None college (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	

OLS estimation results. Dependent variable: number of children born between 1979 and 2003.
Note: **significant at 95% level of confidence; *significant at 90% level of confidence.

Appendix Table 2
Convergence study.

Variable	FT–NW	FP–NW	PT–NW	Fertility
Constant	1.0204	1.0130	1.1336	1.0001
Kid age 0–1	1.0959	1.0947	1.2859	1.0433
Kid age 2–4	1.0400	1.1111	1.2214	1.0428
Kid age 5+	1.0888	1.1585	1.5191	1.1857
Married	1.0005	1.0006	1.0199	
Spouse's wage	1.0033	1.0017	1.0005	
Other income	1.0052	1.0116	1.0191	1.0014
Region				
North East	1.0090	1.0056	1.0020	1.0020
North Central	1.0073	1.0048	1.0136	1.0012
South	1.0043	1.0059	1.0008	1.0024
Urban	1.0045	1.0034	1.0204	1.0024
Wage	1.0216	1.0216	1.0216	
Sibling with kids				1.0042
ρ	1.0024	1.0338	1.6686	1.0058

Scale reduction factors.
Note: FT = full time; FP = full time part year; PT = part time; NW = non work.

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