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DYNAMIC FEMALE LABOR SUPPLY

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The increase in female employment and participation rates is one of the most dramatic changes to have taken place in the economy during the last century. However, while the employment rate of married women more than doubled during the last 50 years, that of unmarried women remained almost constant. To empirically analyze these trends, we estimate a female dynamic labor supply model using an extended version of Eckstein and Wolpin (1989) to compare the various explanations in the literature for the observed trends. This dynamic model provides a much better fit to the life-cycle employment pattern than a static version of the model and a standard static reduced form model (Heckman (1979)). The main finding using the dynamic model is that the rise in education levels accounts for about 33 percent of the increase in female employment, and the rise in wages and narrowing of the gender wage gap account for another 20 percent, while about 40 percent remains unexplained by observed household characteristics. We show that this unexplained portion can be empirically attributed to cohort-specific changes in preferences or the costs of child-rearing and household maintenance. Finally, the decline in fertility and the increase in divorce rates account for only a small share of the increase in female employment rates.

KEYWORDS: Dynamic discrete choice, female employment, accounting, education, gender wage gap, fertility and marriage.

1. INTRODUCTION

THE INCREASE IN FEMALE EMPLOYMENT and participation rates is one of the most dramatic changes to have taken place during the last century, and it has both social and economic implications. One way to measure its importance is to calculate the contribution of female employment to the growth in per capita gross domestic product (GDP) in the United States, which increased by an annual rate of 2.12 percent from 1964 to 2007 (Figure 1). Using a simple Solow-style calculation, it can be shown that if the labor input of women had remained at its 1964 level, the level of per capita GDP in 2007 would have been 40 percent lower.[2] Using the same logic, if the relative quality of female work hours had remained unchanged, the increase in the quantity of female work hours would have contributed 17 percent to the level of per capita GDP in 2007. Moreover, Figure 1 indicates that until about 1980, the growth in per

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[2]See Appendix A for the detailed calculations using the March Current Population Survey (CPS) data for 1964–2007.

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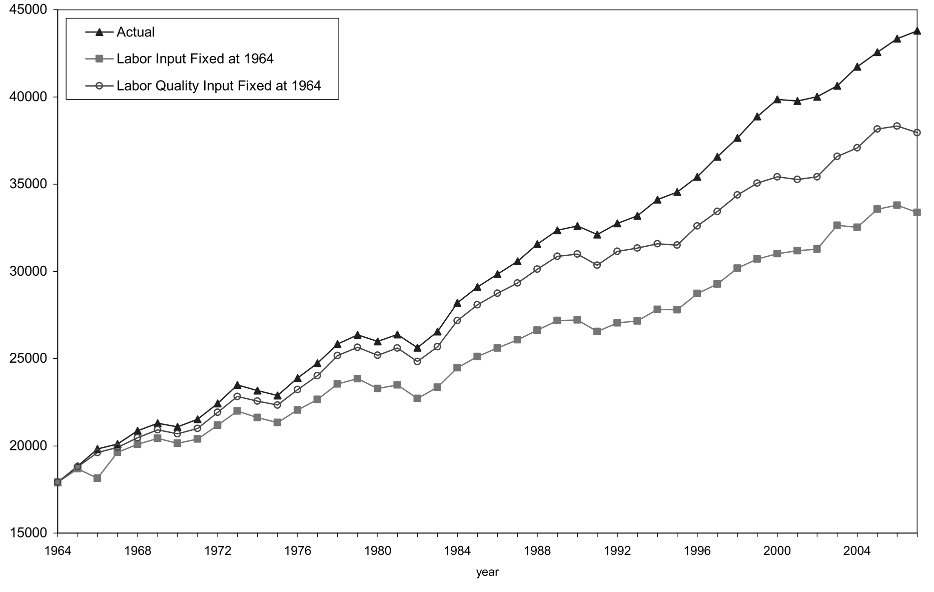

FIGURE 1.—United States per capita GDP (2006 prices).

capita GDP was almost entirely due to the increase in the quantity of female labor input and only subsequently does its quality have an effect.[3]

Are all women working more? While the employment rate of *married* women more than doubled during the last 50 years, from 30 percent in 1962 to 62 percent in 2007 (Figure 2), the employment rate of unmarried women (single, divorced, and widowed) remained almost constant at about 70 percent.[4] This result implies that changes in family behavior must be taken into account so as to understand female employment trends. In this paper, we empirically implement the traditional female dynamic labor supply model (Grunau and Weiss (1981) and Eckstein and Wolpin (1989)) and, in addition, its static specification (Becker (1974, 1981) and Heckman (1974 and 1979)) so as to investigate the empirical gain from the dynamic specification.

The literature on employment of married women is voluminous and cannot be fully reviewed here.[5] Instead, we categorize the literature according to the

[3]It is commonly claimed that this is an overestimation of women's contribution since it ignores their home production before they entered the work force. It should be noted that there has been significant technological change in home production (Greenwood and Seshadri (2005)) and as a result both men and women continue to work at home. It is not clear that the value added in home production that is not measured by GDP has been declining relative to GDP over the last half-century.

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

[5]Blundell and MaCurdy (1999) provided an excellent survey.

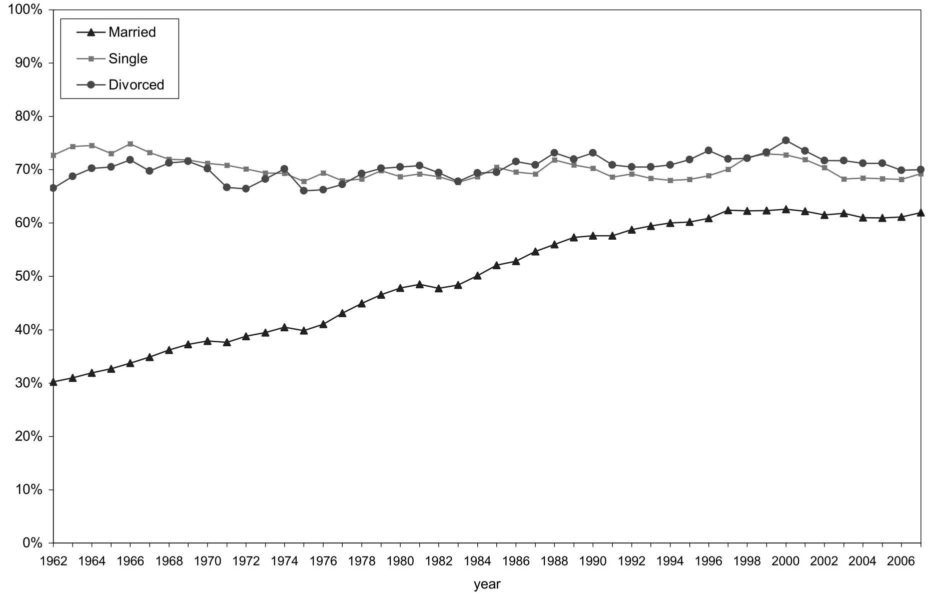

FIGURE 2.—Employment rates by marital status: Women (aged 22–65; proportion of women working 10+ weekly hours).

five main trends in observed female characteristics that are claimed to be important in explaining employment patterns: (a) the increase in women's education (schooling); (b) the increase in women's earnings as well as the narrowing of the gender wage gap; (c) the decrease in women's fertility; (d) the decrease in the marriage rate and the increase in the divorce rate; and (e) "other" factors that are more difficult to measure, which include technological progress in household production, the decrease in the cost of child-rearing, and changes in social norms. In Section 2, we present the main facts to be explained and a survey of the relevant literature.

To what extent do each of these five trends explain the growth in female employment? To answer this question, we use a quantitative model for female employment that embeds all the potential explanations and provides a good fit to the cross-section and time series aggregate data.[6] Our starting point is the Eckstein and Wolpin (1989) (hereafter EW) dynamic stochastic discrete-choice labor supply model, which is modified slightly for our purposes.[7] In par-

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

[7]The first to implement a dynamic stochastic model of female decision making was Wolpin (1984). Extensions of the EW paper include Van der Klaauw (1996), Francesconi (2002), Keane and Wolpin (2006), and Ge (2011). The gain from using a structural dynamic model as opposed to a reduced form model is well explained in EW, in Keane and Wolpin (2007), and in Section 3. Hys-

ticular, although our model's (only) endogenous variable is employment,[8] as in EW, we set the first period of optimization at age 23 when almost all individuals have completed their education. We take the state of the individual at age 22, that is, schooling, marital status, employment, wage, fertility, and husband's employment and wage, as exogenously given. From age 23 to 65, the evolution of these state variables follows a simple state-dependent discrete stochastic dynamic process, and the wages of women and men (husbands) follow standard Mincer/Ben-Porath functions. Given this environment, a woman solves a dynamic programming (DP) model whereby she maximizes the expected present value of utility by choosing whether to work, subject to the budget constraint.

The identification conditions for the dynamic model using cross-section data are the same as in Heckman (1979). We estimate the dynamic model and a static version of it using the simulated method of moments (SMM) and repeated cross-section CPS data for women born during the period 1953–1957, who we define as the 1955 cohort. For comparison purposes, we also estimate a reduced form model following the classic Heckman (1979) two-step method, which is widely used in standard programs (such as STATA). The estimated parameters of the dynamic and static versions are qualitatively similar to the results in EW.

The estimated dynamic model provides a good fit to the female employment rates of the 1955 cohort and a better fit than its static counterpart (Figures 9–11 and Table II). Moreover, an equivalent reduced form specification that follows Heckman's (1979) two-step standard estimation method does not provide a good fit to this cohort's employment rate. These results hold for all schooling levels and aggregate employment rates.

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

For example, the employment rate is 0.65 for women aged 28–32 in the 1955 cohort and 0.49 for those in the 1945 cohort. When we impose the schooling

lop (1999) used the dynamic labor force participation framework to motivate estimating probit and linear probability models to analyze the state dependence structure of female labor supply.

[8]Keane and Wolpin (2007) allowed for the individual to choose schooling, marriage, and children in addition to employment. They found that the initial characteristics of an individual are the main determinant of schooling. This is almost identical to assuming that schooling is given at age 22. We focus our attention on the change in employment: therefore, to keep the accounting analysis manageable, we assume employment to be a choice variable with other outcomes being the result of state-dependent dynamic stochastic processes. It is straightforward to extend the model presented here by making the other main outcomes dependent on endogenous choices. The potential gains and costs of doing so are discussed in Section 3.

distribution and other initial state variables of the 1945 cohort, but leave unchanged the other processes and parameters of the 1955 cohort, we find that in the dynamic model, the predicted employment rate for women aged 28–32 is reduced by 0.02 (from 0.65 to 0.63; Table IIIA). Thus, schooling can be said to explain 0.02 of the 0.16 difference (i.e., 13 percent). We then proceed in a similar manner by sequentially adding the wages of women and men, fertility rates, and finally marital status for the 1945 cohort. What is not explained by these four observed variables (i.e., schooling, wages, fertility, and marital status) is associated with other explanations. We do the same for all cohorts from 1925 to 1975 at 5-year intervals.[9]

The results of this accounting exercise can be summarized as follows: Of the observable factors, schooling makes the most important contribution and accounts for 33 percent of the overall increase in female employment using the dynamic model. In the static model, schooling accounts for a somewhat smaller share and in the reduced form model, the share of schooling ranges from 20 to 40 percent (see Table IV). The contribution of wages (of both women and men) to explaining female employment is large (about 20 percent on average) and varies across cohorts when using the dynamic model. Its contribution is particularly large, both in terms of the change in employment rate and the proportion of its contribution, for the 1925, 1930, and 1935 cohorts, and is particularly small for the most recent cohorts. In the static model, the contribution of wages is about 10 percent and it is practically zero in the reduced form model since only the husband's wage affects female labor supply in that model. The contribution of fertility in explaining female employment is very small, on average, and far less important than schooling and wages in all the models. Nonetheless, it does have a significant effect on the 1935–1950 cohorts. Finally, the contribution of marital status is only about 1 percent on average and zero for later cohorts for all models. This is a surprising result since the employment rates of unmarried women are much higher than those of married women and the proportion of unmarried women has increased during the sample period. Notwithstanding this result, the main results are robust to the ordering of the observable factors.

The remaining unexplained (other) portion of female employment varies from 37 to 42 percent for the dynamic model, and is of a large magnitude for almost all cohorts and age groups except for the most recent cohorts. The share of the unexplained portion is larger for the static model and the reduced form (Heckman) model (see Table IV). It is important to note that the unexplained portion is almost always positive or zero and, therefore, using only the observable factors always underpredicts the change in female employment. These results clearly indicate the importance of unobservable indicators in explaining the increase in employment rates by cohort.

[9]Note that the observations for women born during the entire 5-year interval are included in the cohort to provide sufficient observations for the analysis.

We offer an empirical explanation for the large unexplained portion by using the dynamic model to estimate the parameters of the utility/cost of home production and raising children aged 0–5 (for working mothers) for each cohort separately. The additional two free parameters enable us to produce a good fit for the female employment rate by age for all cohorts. For cohorts born before 1955, the utility/cost of home production is somewhere in the range of $4.50–5 per hour higher than for the 1955 cohort and the utility/cost of raising children aged 0–5 is $3 per hour higher. For the 1960–1975 cohorts, only the cost of raising young children is estimated to be lower (by about $1 per hour) than for the 1955 cohort. These results are relevant in evaluating the effect of technological change in home production (Greenwood and Seshadri (2005)) and the reduction in the cost of child-rearing (Attanasio, Low, and Sanchez-Marcos (2008) and Albanesi and Olivetti (2009b)). However, given that these parameters vary by cohort and do not imply the need for a time shift, they can be interpreted as indicators of cohort-specific changes in social norms (see, for example, Lifshitz (2004) and Fernandez (2008)).

How do we justify treating schooling, fertility, and marriage as exogenously determined? First, it facilitates and simplifies the comparison between the different models. Second, this is the assumption widely followed in the literature. Without this assumption, we would have to specify alternative exogenous variations for the model and, as a result, the potential explanation provided by the observables would be lower. Third, by starting at the age of 22, 95 percent of lifetime schooling attainment has been completed. Fourth, almost all recent studies with endogenous schooling, marriage, and fertility (such as Keane and Wolpin (1997, 2006), Cameron and Heckman (2001), and Ge (2011)) indicate that innate ability and family background are the main explanations for schooling level. However, by using cross-section CPS data, we are unable to empirically account for the unobserved heterogeneity as a given exogenous structural feature of the model.

The rest of the paper is organized as follows: The following section describes the main facts used in support of the various explanations of female employment trends and surveys the relevant literature. Section 3 presents the dynamic female labor supply model. Section 4 discusses the estimation of the dynamic model, the static model, and the reduced form (Heckman) model of labor supply. Section 5 presents the estimation results using the CPS data and Section 6 presents the accounting analysis that attempts to quantify the sources of growth in female employment across cohorts for all models. Section 7 presents the results for estimating the change in parameters by cohort in the dynamic model and the fit of the dynamic model to aggregate female employment rates. Section 8 concludes.

2. MAIN FACTS AND THE LITERATURE

From 1962 to 2007, the employment rate for married women increased by more than 32 percentage points while the rate among unmarried women (single, divorced, and widowed) remained almost constant at about 70 percent (Figure 2). In what follows, we analyze the main observable explanations for the increase in employment among married women, that is, the increase in schooling, the increase in wages of both women and men, and the narrowing of the gap between them, the decline in women's fertility, the decrease in the marriage rate, and the increase in the divorce rate. We also survey the relevant literature, including research that proposes explanations not directly related to variables reported in the CPS, which we include in the other category.

Schooling

We measure schooling according to five levels of education: high school dropouts (HSD), high school graduates (HSG), some college education (SC), college graduates (CG), and post-college studies (PC). The employment rate of married women increased from 1964 to 2007 for all these categories (Figure 3). The increase was largest for the HSG (27 percent) and SC (32 percent) groups, and relatively small for the HSD and PC groups. Moreover, the level of schooling among married women has been increasing throughout the 43-year sample period (Figure 4): from 11 percent to 28 percent for the SC group, from 6 percent to 22 percent for the CG group, and from 0.6 percent to 11 percent for the PC group. At the same time, the employment rate for the lower education levels has decreased substantially. It should be noted that similar

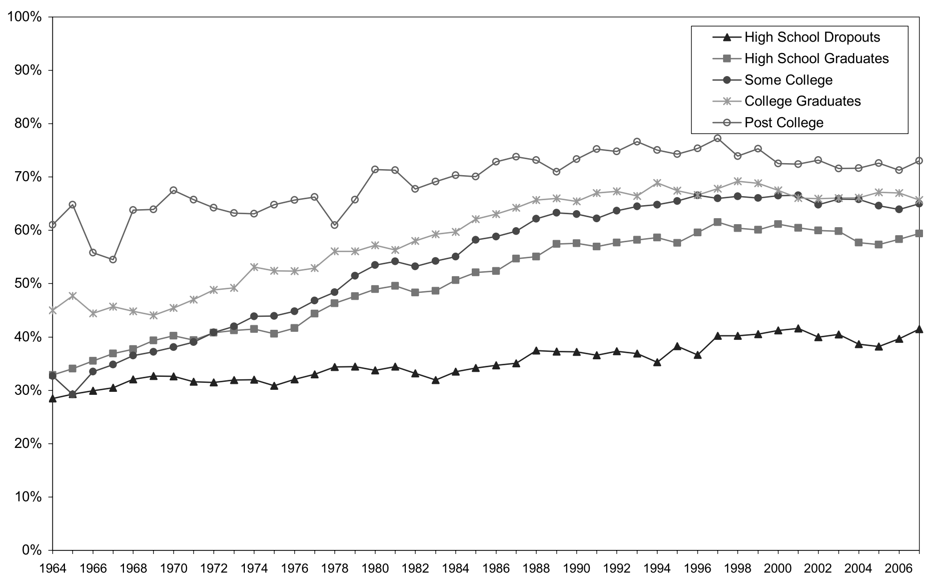

FIGURE 3.—Employment rates by level of education: married women (ages 22–65; proportion of women working 10+ weekly hours).

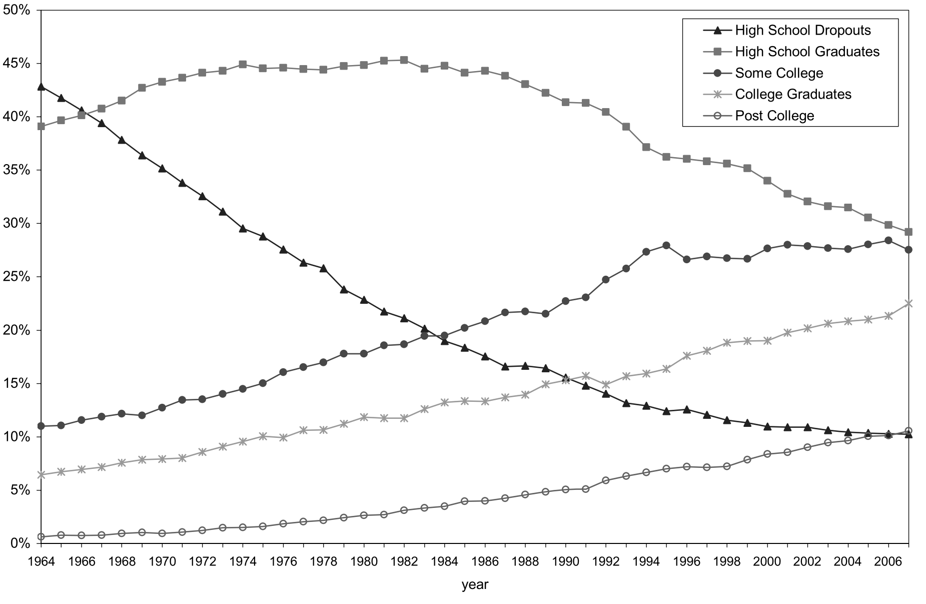

FIGURE 4.—Breakdown of married women by level of education (ages 22–65).

trends are observed for unmarried women, while for men a similar pattern began earlier and reached a stable distribution by the turn of the century (see also the Supplemental Material (Eckstein and Lifshitz (2011)) and Eckstein and Nagypal (2004)).

Almost every published paper on female labor supply since Becker (1974) has emphasized the importance of schooling in explaining the observed increase in employment and participation of women. Most papers have attributed this result to the cross-sectional differences in employment rates by schooling (Figure 3) while only a few have empirically analyzed the joint endogenous decisions regarding employment and schooling. Recent work using DP models of employment and schooling with life-cycle panel data (Keane and Wolpin (1997, 2006), Eckstein and Wolpin (1999), and Ge (2011)) found that the initial characteristics of the individual (at age 16 or 18) are the main factors that determine schooling choice. This is also how schooling choice is explained by Cameron and Heckman (2001) and Cameron and Taber (2004).[10]

In this paper, we take as given the level of schooling at age 22 for both men and women. This is consistent with the above results on the main factors that determine schooling. However, it is not clear why higher levels of schooling among women have increased the employment rate of married women while

[10]These studies used the National Longitudinal Survey of Youth (NLSY79) panel survey, which consists of the cohort born during the period 1960–1965.

having no impact on unmarried women. Furthermore, why has the employment rate among men declined when the trends in schooling for men have followed the same pattern as those of women. These facts indicate that the dramatic increase in the couple's level of schooling is primarily responsible for the increase in the labor supply of married women and that is the focus of this study.

Earnings

Unconditional mean wages for men and women have increased continuously from 1962 to 2007 (Figure 5). However, while the wage ratio of women to men in fact decreased slightly from 1962 to 1980, it subsequently rose sharply for almost three decades, as the gender wage gap narrowed significantly. Given the widely recognized large and positive impact of schooling on earnings, it is clear that the increase in schooling has been an important factor in this trend. Furthermore, although economic growth has affected average wages proportionately, the impact has not been uniform for all occupations and the growth in services has contributed to the narrowing of the gender wage gap (Lee and Wolpin (2006)).

The impact of increased earnings on female employment is certainly an important aspect of all female labor supply models (Heckman and McCurdy

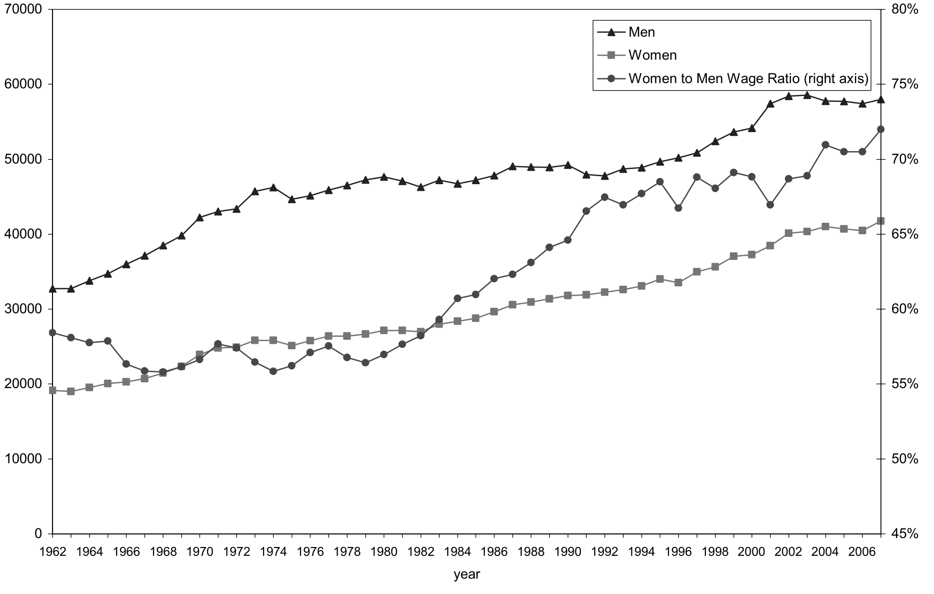

FIGURE 5.—Annual wages of full-time workers (ages 22–65; full-time full-year workers with nonzero wages; 2006 prices).

(1980, 1982)).[11] The narrowing of the gender gap as one of the main factors in increasing married female labor supply has been recognized in the literature (Goldin (1990, 1991) and Jones, Manuelli, and McGrattan (2003)). Other studies have emphasized the different occupational distributions between men and women and the importance of human capital in those occupations (Galor and Weil (1996) and Lee and Wolpin (2006)). However, Blau and Kahn (2000) pointed out that the wage gap remained almost constant during the period up until 1980, which was characterized by a substantial increase in female labor force participation (Figure 5). Hence, unless the labor supply elasticity for women is particularly high, the narrowing of the gender gap can only be a small part of the explanation. Recently, Gayle and Golan (2007) showed that a decrease in statistical discrimination and increases in productivity account for a large percentage of the decline in the gender earnings gap, which jointly are able to explain part of the increase in the female employment rate.

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

Fertility

The mean number of children under 18 had decreased from 1.6 to 1.0 per married female by 1985, but remained unchanged subsequently (Figure 6). Convergence occurred earlier for children under 6 and this is clearly reflected in the behavior of cohorts born after the post-baby-boomers (1955 and later). Gronau (1973) showed the effect of young children on their mother's labor supply and argued that it varies by level of education; however, he could not find support for his hypothesis in the data. Heckman (1974) demonstrated the same effect and pointed out that it is much stronger for children under 6. Rosenzweig and Wolpin (1980a, 1980b) argued that the fertility decision is endogenous and therefore cannot explain the female participation rate. Heckman and Willis (1977) pointed out that the growth in female employment had primarily occurred among married women with children. They focused on the need for a dynamic labor supply model and the use of panel data to differentiate the unobserved heterogeneity component from the "true" time dependence in labor supply. They provided the starting point for Eckstein and Wolpin (1989), whose work is in turn the basis for the present study.[12]

[11]See also Altug and Miller (1990, 1998), Hotz and Miller (1993), and Pencavel (1998).

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

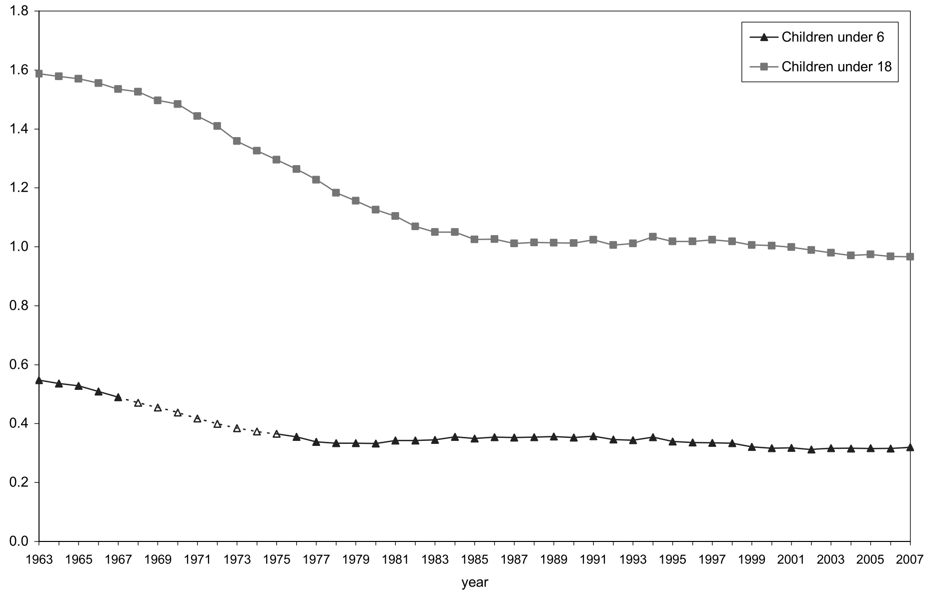

FIGURE 6.—Number of children per married woman (ages 22–65; extrapolated data for number of young children during 1968–1975).

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

Marriage and Divorce

Between 1962 and 1990, the marriage rate for women decreased from 80 percent to about 60 percent, and the divorce rate increased from 3.5 percent to 13 percent and remained at these levels until 2007 (Figure 7). Weiss and Willis (1984) claimed that the failure of divorced fathers to comply with court-mandated child support awards forced divorced mothers to work more to support their children. As a result, the increase in the probability of divorce increased married women's incentive to work and thus accumulate experience. Later on, Weiss and Willis (1993) showed that it is incorrect to treat marital status as being exogenous to the employment decision since an unexpected increase in the husband's earning capacity reduces the divorce hazard, while an unexpected increase in the wife's earning capacity raises the divorce hazard.

Cross-sectional variations make it possible to quantify the impact of the increase in *schooling*, the increase in the female-to-male *earnings* ratio, the de-

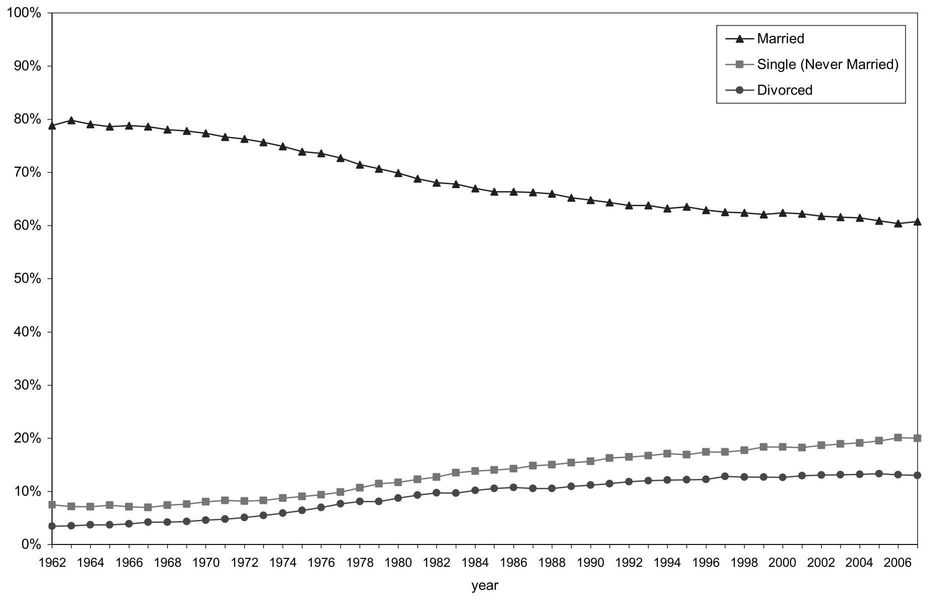

FIGURE 7.—Breakdown of women by marital status (ages 22–65).

crease in *fertility* and *marriage*, and the increase in *divorce* on female employment rates. However, these changes affect the aggregate data through their impact on the behavior (decisions) of new cohorts over their lifetimes and the exogenous changes that influence the distributions of new cohorts according to these observed characteristics. The question to be answered is whether these changes can explain the entire increase in married female employment by cohort.

Female Employment by Cohort: Other Explanations

The dramatic change in the employment rates of married women by age and cohort for the period 1962–2007 can be seen in Figure 8 for the 1925–1975 cohorts. For simplicity and to create a large enough sample for each cohort, we define the women born from 1953 to 1957, for example, as the 1955 cohort and similarly for the entire CPS data set. Figure 8 clearly shows that from the early cohorts until the baby boomers of 1945, married female employment increased for all ages. The 1965 and 1975 cohorts show almost the same female employment rates by age, although during the intervening years, female employment increased among younger women (Buttet and Schoonbroodt (2005)). The changes by cohort are attributed in the literature to the observables men-

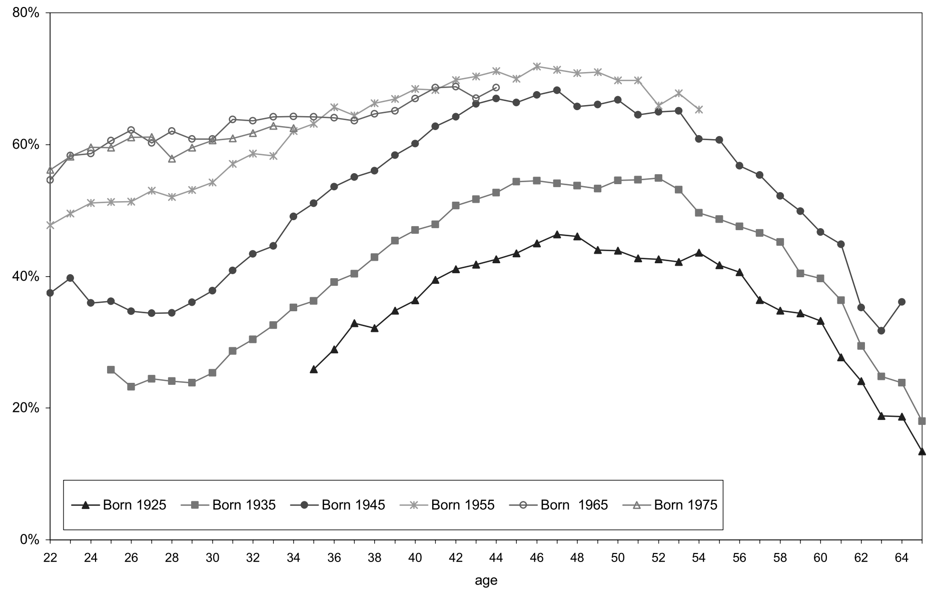

FIGURE 8.—Married female employment rates by cohort (years 1962–2007; proportion of women working 10+ weekly hours; see definitions of cohorts in Section 2).

tioned above as well as to changes in social norms, technological progress, and other factors.[13]

Goldin (1991) investigated the effects of WWII on women's labor force participation and found that almost half of the women who entered the labor market during the war years were still working in 1950. She argued that the attitudes toward working women may have changed considerably during this period. Fernandez, Fogli, and Olivetti (2004) found evidence suggesting that a man is more likely to have a working wife if his own mother worked. More recently, Fernandez (2007, 2008) investigated the role of culture as learning in explaining changes in female employment. In her model, individuals hold heterogeneous beliefs regarding the relative long-run payoffs for working women, which evolve rationally via an intergenerational learning process. These papers are part of a larger trend that emphasizes the long-run impact of changing social norms.

A few recent papers have argued that the cost of child-rearing has decreased during the last 50 years, thus making it easier for women with children (especially young ones) to enter the labor market. Albanesi and Olivetti (2009a) claimed that until the early 20th century, women spent more than 60 percent

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

of their prime years either pregnant or nursing. Since then, improved medical knowledge, advances in obstetric practices, and the introduction of infant formula have reduced the time-cost associated with raising children and have led to an increase in participation between 1920 and 1960 by married women with children. Attanasio, Low, and Sanchez-Marcos (2008) studied the life-cycle labor supply of three cohorts of American women born in the 1930s, 1940s, and 1950s. They found that the combination of a reduction in the cost of children alongside a narrowing of the wage gender gap is needed to explain the increase in the labor supply of mothers. These factors are clearly related to the enormous technological progress in household production, which is the prime reason cited by Greenwood, Seshadri, and Yorukolu (2005) and Greenwood and Seshadri (2005). Their main argument is that the introduction of labor-saving appliances associated with technological progress in the home sector may have enabled more women to enter the work force. They also argued that the time spent on housework fell from 58 hours per week in 1900 to just 18 hours in 1975, thus making it much easier for married women to enter the labor force.

Lee and Wolpin (2006) argued that the growth in the service sector between 1950 and 2000 increased the demand for female workers. The proportion of total employment in this sector grew from 57 to 75 percent during this period. In a more recent paper, Lee and Wolpin (2010) provided an accounting analysis of wages and employment during the period 1968–2000 using an equilibrium model in which both schooling and wages are endogenous. The main exogenous changes are the value of leisure, fertility, and cohort size as supply indicators, and a number of technological advances as demand indicators. This accounting analysis is linked to assumed changes in preferences, demographics, and technology. We focus on the changes that are given for an individual who makes lifetime decisions at the age of 22.

3. A DYNAMIC FEMALE EMPLOYMENT MODEL

In this section, we formulate and estimate a simple dynamic model of female employment based on EW. A woman maximizes the present value of her utility over a finite horizon by choosing whether to work ($p_t = 1$). Each period is 1 year long and the period of working age begins at age 22 and ends at age 65. At age 22, the education level (S) is given and the supply of labor can potentially begin.[14] Marital status and number of children are discrete random states given exogenously that depend on the woman's choice of employment and other state variables, as described below.

[14]Given that we start at age 22, the assumption on schooling is consistent with the finding that the main explanatory variables for high school graduation and college attendance are the individual's exogenous characteristics at age 16 (see, for example, Keane and Wolpin (1997), Cameron and Heckman (1998), and Eckstein and Wolpin (1999)). Note that there are minor changes in schooling levels after age 22.

A married female is indicated by $M_t = 1$, a single or divorced woman is denoted by $M_t = 0$, and the number of children is denoted by N_t. The objective of each female is to choose p_t from period t (the year she completes her education) until retirement, to maximize

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

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

The female budget constraint is given by

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

where α is a fraction that denotes the share of a married woman in household income, y_t^h denotes the husband's earnings, y_t^w denotes the female's earnings, $c_j + c_{jm}(1-M_t)$ is the cost in goods per child of age j, and $b + b_m(1-M_t)$ is an additional cost for maintaining the household if the woman works. These costs are expected to be higher for a working woman if she is unmarried (c_{jm}, $b_m > 0$). Following the classical approach (Becker (1974) and Heckman (1974)), we assume that the husband's employment is taken as predetermined in the female employment decision. Equation (3.2) implies that neither saving nor borrowing is feasible.[15]

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

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

where t is a time trend that captures aggregate growth in labor productivity[16] and ε_t is the standard zero-mean, finite-variance, serially independent error that is uncorrelated with K and S. The number of children of age group j evolves according to

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

[15]This assumption is extreme though standard in the modeling of dynamic labor supply. When utility, as specified in (3.1), is linear and additive in consumption, the problem is reduced to that of wealth maximization modified by the psychic value of work and children, as is basically assumed here.

[16]The trend in the wage equation should be interpreted as an exogenous change in labor demand due to aggregate growth in productivity for all schooling levels.

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

Following EW, we adopt the per period specification of utility

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

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

The dynamic programming solution to the optimization problem is obtained by a process of backward recursion and has become standard in the dynamic discrete choice literature (see EW).[17] Let $V_t(K_{t-1}, \varepsilon_t, \Omega_t)$ be the maximum expected discounted lifetime utility given K_{t-1} periods of experience, a wage draw of ε_t, and all other relevant components of the state space, Ω_t. The state space $\Omega_t = [K_{t-1}, S_t, p_{t-1}, M_t, MT_t, \bar{y}_t^h, N_{tj}]$ includes work experience, schooling, past employment, a discrete approximation of the husband's income given by $\bar{y}_t^h$, and number of children by age.[18] Following the standard dynamic programming procedure, the value function is defined as

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

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

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

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

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

where current utility is derived from insertion of the budget constraint (3.2) into (3.5) such that[19]

$$
\begin{aligned}
(3.8)\qquad & U_t^1(K_{t-1}, \varepsilon_t, v_t, \Omega_t) \\
&= \alpha_1 + v_t - (b + b_m M_t) + \alpha_3 K_{t-1} + \sum_{j=1}^{J} \alpha_{4j} N_{tj} + \alpha_5 S + f(N_{tj}) \\
&\quad + (1+\alpha_2)\Bigg(((1-\alpha)(1-M_t) + \alpha) \\
&\quad \times (\exp\{\beta_0 + \beta_1 K_{t-1} + \beta_2 K_{t-1}^2 + \beta_3 S + \beta_4 t + \varepsilon_t\} + \bar{y}_t^h M_t) \\
&\quad - \sum_{j=1}^{J} (c_j + c_{jm} M_t) N_{tj} \Bigg)
\end{aligned}
$$

and

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

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

$$(3.9)\qquad \Pr_t = \frac{\exp(\rho_0 + \rho_1 \cdot S + \rho_2 \cdot K_{t-1} + \rho_3 \cdot K_{t-1}^2 + \rho_4 \cdot p_{t-1})}{1 + \exp(\rho_0 + \rho_1 \cdot S + \rho_2 \cdot K_{t-1} + \rho_3 \cdot K_{t-1}^2 + \rho_4 \cdot p_{t-1})}.$$

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

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

$$
\begin{aligned}
(3.10)\qquad \Pr(N_t = N_{t-1} + 1) &= \Phi(\lambda_0 + \lambda_1 \cdot \mathrm{AGE}_t + \lambda_2 \cdot (\mathrm{AGE}_t)^2 + \lambda_3 \cdot S \\
&\quad + \lambda_4 p_{t-1} + \lambda_5 \cdot N_{t-1} + \lambda_6 \cdot N_{t-1}^2 + \lambda_7 M_t),
\end{aligned}
$$

[19]Note that α_1 and b, as well as the α_4's and c_j's, are not separately identified due to the linearity of preferences.

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

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

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

$$(3.12)\qquad \Pr(M_t = 0|M_{t-1} = 1) \\ = \Phi(\xi_0 + \xi_1 \cdot \mathrm{MT} + \xi_2 \cdot \mathrm{MT}^2 + \xi_3 \cdot N_t + \xi_4 \cdot S + \xi_5 \cdot p_t + \xi_6 y_t^h).$$

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

A special case of the model is a static model where $\delta = 0$ and the female chooses to work if

$$(3.13)\qquad U_t^1(K_{t-1}, \varepsilon_t, v_t, \Omega_t) > U_t^0(K_{t-1}, \Omega_t).$$

The solution for this case is straightforward.

The estimation of the static model that is implied by (3.13) can be carried out by using the structural specification or by following Heckman's (1979) classic two-step method of the reduced form. We estimate the dynamic model (equation (3.6)) and the static model (equation (3.13)) using structural optimization and Heckman's reduced form specification, as described in the next section.

Discussion: The Choice of Models

There are three main issues in the choice of models and their estimation for our accounting exercise:

(i) Use of a structural optimization model rather than an ad hoc standard reduced form: Heckman's method of using a reduced form specification of the probit equation for the employment choice and a standard wage equation is standard in applied studies of labor supply.[20] We implement this specification as an alternative (referred to here as the Heckman model) to the above dynamic programming model and its static version (i.e., equation (3.13)).[21] This comparison demonstrates the gain from structural optimization using the

[20] For recent applications of the reduced form probit equation for dynamic female employment, see Hyslop (1999) and DelBoca and Sauer (2009).

[21] In the literature, Heckman's reduced form specification is primarily used to correct for selection in the wage equation rather than for female employment analysis. For a recent paper that focuses on female employment and wages using the Heckman model, see Mulligan and Rubinstein (2004).

cross-equation restrictions that reflect the simultaneous impact of the state variables (education, wages, marriage, divorce, and children; equations (3.10)–(3.12)) on the predicted employment decision. This is accomplished by comparing the fit of the models to actual employment and comparing the results to those of the accounting exercise.

(ii) The dynamic forward-looking structure of the model in contrast to the static structural model: The dynamics of the model are captured by the value of the future-value function in equation (3.7). The change in this value according to age and in the values of the state variables has a dominant influence in determining the effect of the state variables on the change in predicted employment and their impact on future employment and, as a result, on the future value of utility based on current decisions. Using a static version ($\delta = 0$) for estimation and the accounting exercise enables us to measure the gains from using the dynamic specification.

(iii) The use of employment as the only choice variable: Employment, as the focus of this paper, must be treated as endogenous. The Introduction presented four reasons for not treating other state variables, such as schooling, fertility, and marriage, as endogenous. The fourth reason states that treating these variables as endogenous would require extensive panel data, such as the NLSY, since we would need to control for unobserved heterogeneity as the main potential exogenous source of variation in these outcomes (Keane and Wolpin (1997, 2006) and Eckstein and Wolpin (1999)). To do this would require panel data for estimating the unobserved heterogeneity and controlling for the changes in these variables for each cohort. In recent applications, unobserved heterogeneity is specified as being correlated with family background variables. However, this is not a feasible solution in our case since there are no panel data that include family background variables for the cohorts born before 1950 and it is these cohorts that have shown the largest changes in female employment. To perform an accounting exercise in which all the variables are endogenous based on panel data for more recent cohorts is a task for a future project.

4. DATA AND ESTIMATION

We estimate the *dynamic model* using data from the March CPS for the period 1964–2007 and define the cohort of women born in the years 1953–1957 as the 1955 cohort. Similarly, we divide the entire sample into cohorts that include women born 2 years before and 2 years after the reference year. For the accounting exercise and the aggregation, we use data on women who were born during the period 1923–1977. For the 1955 cohort, there are complete data from the age at which schooling is completed until age 54 and therefore it will be used as the benchmark for the estimated model in the accounting exercise below.[22]

[22]The latest available data are for 2007 when women born in 1953 turned 54.

As indicated above, we divide the women into five groups according to level of education: HSD, HSG, SC, CG, and PC.[23] For each group, we calculate the following moments for ages 23–54: employment rate, average hourly wage, marriage rate, and the empirical distributions of the number of children (i.e., no children, one child, two children, and three or more children) according to age group (0–5 or 6–18). We denote this vector of moments as m^A.[24]

Dynamic discrete-choice models are usually estimated using panel data. In this case, repeated cross-section CPS data are used to better link the results to aggregate data and to increase sample size. The estimation's main objective is to demonstrate that there are consistently estimated parameters that provide a good fit to the observed female employment rates. When using cross-section data, the most straightforward method of estimation is simulated method of moments (SMM), as proposed by McFadden (1989) and Pakes and Pollard (1989).[25] We implement it here by minimizing the distance between the actual moments and the moments simulated by the model.

Conditional on a vector of parameters (θ) that fully describe the model, we numerically solve and randomly simulate outcomes. For each woman, we simulate her choices and wages from the model starting from the actual observed distribution at age 22. This distribution includes the observed years of schooling according to the five categories described above. For each initial level of schooling, we have an artificial representative sample based on the population's observed distribution.[26] For each female i in each period t, we perform the following simulations: a wage shock, a utility shock, the realization of a job offer, the birth of an additional child, and a change in the woman's marital status from single or divorced to married and vice versa. We also simulate the husband's wage using the estimators from a Mincerian wage regression for men.[27] With these realizations, the model produces an employment outcome. This probability outcome can be interpreted as a dynamic rational expectations probit function, which is an extension of Heckman's (1974) classic female employment model. We repeat this for 1000 women to obtain the predicted rate of employment for each level of schooling from the year after schooling is completed until retirement at age 65.

[23]See Appendix B for details on the definitions for each observation.

[24]See Appendix D and the Supplemental Material for further details on the moments and identification. For the accounting exercise in Section 6, we created the same moments for all cohorts born during the period 1923–1977.

[25]The computation of the likelihood function for each cross-section observation conditional on using the dynamic model is quite complicated. Furthermore, using employment rates for the SMM enables us to obtain good fit within sample and to use it for the out-of-sample accounting exercise.

[26]For example, in the HSG group, 64 percent of the women were married at the age of 23, 50 percent do not have young children, and 32 percent have one young child. For each individual, conditional on schooling, we randomly assign initial conditions according to the observed distribution, including marital status, number of children, and the husband's education and age.

[27]Information about the husbands can be found in Appendix C.

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

Let m_j^A be moment j in the data and let $m_j^S(\theta)$ be moment j from the model simulation given the parameter vector θ, where $j = 1, \dots, J$ and J is the total number of moments.

The difference between these two vectors is given by the vector

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

We minimize the objective function $J(\theta) = g(\theta)'Wg(\theta)$ with respect to θ, where the weighting matrix W is a diagonal matrix consisting of the inverse of the estimated variance of each moment. We obtain the standard errors using the inverse of the Jacobian matrix. δ is set to 0.952, σ_v is set to 1, c_{jm} is not identified due to linearity and therefore is set to zero, α is weakly identified and set to 1, and θ includes all the other parameters of the model.[28,29]

As mentioned above, we estimate two static versions of the model: a *static model* in which $\delta = 0$, although the parameters, specification, and estimation method are the same as for the *dynamic model* described above, and a *Heckman model* in which $\delta = 0$, although the estimation follows Heckman's (1979) two-step method. In this case, the wage equation is a standard one in which experience is measured by age and, therefore, we could not include the time trend as a separate variable. The participation probit equation is equivalent to (3.5), although we use the husband's wage as an instrument for the female's consumption, as is usually done (see, for example, Hyslop (1999)). The values for fertility (children), marriage, and divorce are given exogenously with certainty at each age and, therefore, equations (3.9)–(3.12) can be ignored. This specification is a reduced form of the static model.

Identification

A simple way to address the issue of identification using cross-sectional data is to consider the static version of the model in which $\delta = 0$. Since this param-

[28]We set $\alpha = 1$ as in EW since it becomes nonrobust when estimated. This is because we obtain α_2 to be close to zero, even though α is identified, and practically we could not separate α from b_m, which is easier to estimate.

[29]θ is given by: $\theta' = \{c_j, b, b_m, \alpha_1, \alpha_2, \alpha_3, \alpha_{4,0-6}, \alpha_{4,6-18}, \alpha_5, \beta_0, \beta_1, \beta_2, \beta_{3HSD}, \beta_{3SC}, \beta_{3CG}, \beta_{3PC}, \beta_4, \rho_0, \rho_1, \rho_2, \rho_3, \rho_4, \lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6, \lambda_7, \varsigma_0, \varsigma_1, \varsigma_2, \varsigma_3, \varsigma_4, \xi_0, \xi_1, \xi_2, \xi_3, \xi_4, \xi_5, \xi_6, \sigma_\varepsilon, \rho_{\varepsilon u}\}$.

eter is not estimated, the restriction implies that the above model collapses to the classic Heckman (1974, 1979) labor supply model. Hence, the identification conditions for the static model using cross-sectional data and a reduced form specification for the static model are those that appear in Heckman's classic paper. That is, the wage equation should include instruments that are not included in the participation equation.[30]

In the above model, experience squared and the time trend are omitted from the participation equation. The participation decision in the static version of the model (equation (3.13)) includes state variables that are not included in the wage equation (3.3). These identifying instruments include the wage of the husband if the woman is married (y^h), marital status (M), and the number of children by age group (N_j). Hence, the static model satisfies the classic Heckman conditions for identification. The dynamic model does not have any additional parameters when δ is set a priori, as is done here. Therefore, the dynamic model is identified from the cross-sectional data as is the standard static version.

Wages are observed only for working individuals and this selection process requires the identification conditions mentioned above. As mentioned, the experience parameters, β_1 and β_2, are not identified separately from the time trend, β_4, in the reduced form Heckman model since there are no direct data on experience as in standard panel data.[31] The identification of β_1 and β_2 separately from β_4 in the dynamic model is due to the nonlinear structural restrictions that are imposed by the theory. It should be noted that in panel data there are direct observations on experience and the identification is not a result of the structural nonlinear restrictions imposed from the theory (see EW).

The identification of the parameters of the offer probability equation (3.9) in the dynamic and static models is entirely due to the nonlinear restrictions imposed by the structural model. In other words, this equation is not identified separately from the participation equation for the dynamic and static models using cross-section data. Using panel data, this equation would have been identified from observations on transitions from nonemployment to employment and vice versa. In the dynamic and static models, the variables included in the dynamic exogenous discrete process for fertility (children), marriage, and divorce (equations (3.10)–(3.12)) are observed for all individuals. Hence, the parameters of these processes are identified and estimated consistently from the observed data as standard discrete processes using cross-section observations and identification.

[30]See also Keane and Wolpin's (2009, p. 4) discussion of the identification of the static female labor force participation model.

[31]In the Heckman model, we have to use age as a proxy for experience and, therefore, σ_v is not identified and is set to 1. In the static and dynamic models, σ_v is identified since the wage equation includes instruments that are not included in the participation equation. However, in the estimation we found that σ_v is only weakly identified and, therefore, we set it to 1. In this way it is also consistent with the specification in the Heckman model.

5. ESTIMATION RESULTS FOR THE 1955 COHORT

In this section we discuss the parameters and fit of the estimation results for the *dynamic* model, the *static* model, and the *Heckman* two-step reduced form model using the data for the 1955 cohort.

Parameters

There are three key differences between the structural models (dynamic and static) and the Heckman model. The first involves the utility parameters (equations (3.5) and (3.8)), where the term "utility" in Table I for the Heckman model relates to the corresponding parameters for the simple probit equation. This equation differs from the specification of the structural models (dynamic and static) since it does not include the woman's wage as a direct variable that affects the employment decision. Hence, the Heckman model neglects the cross-equation restrictions between the wage function and the participation decision (equation (3.7) for the dynamic model and equation (3.13) for the static model). These restrictions and the linearity of the structural models enable us to translate the parameters into monetary units that are equivalent to the hourly wage units used here.

The second difference involves the endogeneity of experience (K) in the structural models, which enables us to distinguish between the time trend in wages and the experience coefficients in the wage equation. As stated above, it is the structural model, which is based on the individual's optimization, that provides the restrictions that enable us to identify these parameters. The third difference lies in the fact that the structural models require the joint estimation of the dynamic processes for job offers (3.9), fertility (3.10), marriage (3.11), and divorce (3.12), while the reduced form model completely ignores these processes and takes the outcomes as given. These processes introduce an additional source of uncertainty into the employment decision, which is more important in the case of the dynamic model due to the future potential implications that enter through current decisions (see equation (3.7)).

The estimated parameters of the utility and wage equations for the 1955 cohort of women have the expected signs in all three specifications, which are also the same as those obtained by EW using panel data (see Table I). The parameters for utility in the dynamic and static models have the same meaning, the same signs, and, in general, similar values. They imply that leisure is more valuable than employment, that consumption and employment are substitutes ($\alpha_2 < 0$), and that accumulated years of experience increase the value of leisure ($\alpha_3 < 0$) for married women. In addition, younger children cost more than older children and, unlike in EW, the marginal utility of leisure increases with schooling.[32] The parameter that indicates the cost of home activity for

[32]Here schooling is categorized into five levels while in EW it was measured by number of years using one parameter. The result that utility increases with schooling appears to be more reasonable.

TABLE I

ESTIMATED PARAMETERS (1955 COHORT)[a]

	Utility[b]				Wage[c]				Job Offer Probability[d]	
	Dynamic	Static	Heckman		Dynamic	Static	Heckman		Dynamic	Static
$\alpha_1 + \alpha_{52}$	−15,658.08	−14,215.12	0.70	β_1	0.02	0.04	0.02	ρ_{11}	−0.02	−0.02
	(2705.71)	(2000.77)	(0.00)		(0.00)	(0.01)	(0.00)		(0.01)	(0.02)
α_2[e]	−0.04	−0.04	−0.001	β_2	−0.00002	−0.00036	−0.0001	ρ_{12}	−0.06	−0.03
	(0.02)	(0.02)	(0.00)		(0.00)	(0.00)	(0.00)		(0.00)	(0.01)
α_3	−29.33	−47.52	−0.003	β_{31}	2.15	2.15	1.79	ρ_{13}	0.19	0.19
	(24.46)	(30.75)	(0.00)		(0.04)	(0.09)	(0.00)		(0.00)	(0.01)
α_{41}	−2733.36	−2666.00	−0.51	β_{32}	2.41	2.39	2.08	ρ_{14}	0.50	0.50
	(730.62)	(360.79)	(0.00)		(0.03)	(0.03)	(0.00)		(0.01)	(0.01)
α_{42}	−487.28	−514.89	−0.09	β_{33}	2.63	2.64	2.30	ρ_{15}	0.81	0.81
	(94.22)	(211.72)	(0.00)		(0.05)	(0.06)	(0.00)		(0.01)	(0.01)
α_{51}	−1877.03	−1072.86	−0.61	β_{34}	2.88	2.92	2.56	ρ_2	0.05	0.07
	(169.37)	(170.97)	(0.00)		(0.05)	(0.07)	(0.00)		(0.00)	(0.00)
α_{53}	1731.62	1188.58	0.18	β_{35}	3.23	3.13	2.83	ρ_3	−0.001	−0.001
	(295.91)	(159.22)	(0.00)		(0.18)	(0.11)	(0.00)		(0.00)	(0.00)
α_{54}	2785.93	1642.37	0.36	β_4[f]	0.004	0.01		ρ_4	0.65	0.90
	(114.21)	(279.36)	(0.00)		(0.00)	(0.00)			(0.08)	(0.01)
α_{55}	3447.32	2603.68	0.60	σ_ε	0.50	0.19	0.72			
	(94.06)	(200.33)	(0.00)		(0.30)	(0.37)	(0.00)			
b_m	17,226.30	16,850.00	0.07	$\rho_{\varepsilon v}$	0.052	0.021	−0.054			
	(1273.61)	(2003.97)	(0.00)		(0.00)	(0.00)	(0.00)			

[a]Standard errors appear in parentheses.

[b]See equation (3.7). We assume $c_m = 0$ and $\sigma_v = 1$. Note that we set $\alpha = 1$ as in EW since it becomes nonrobust when estimated. Thus, although α is identified, we obtained a value close to zero for α_2. In practice, we could not separate α from b_m and, moreover, b_m is easier to estimate.

[c]See equation (3.3). We use five parameters for the five education groups, that is, β_{31}–β_{35} , rather than four education groups plus a constant β_0.

[d]See equation (3.8).

[e]In the Heckman model, the coefficient is for the husband's wage.

[f]In the Heckman model, there is no trend due to multicolinearity with exp.

employed unmarried women is positive and of a high magnitude ($b_m > 0$). In other words, single women are more likely to work, as expected.[33]

The estimated parameters of the Mincer/Ben-Porath wage function have values similar to those presented in the literature for both panel and cross-section data. It is interesting that the parameter values are similar even though the methods of estimation and the correction for potential selection bias differ between the models. In this equation, the return to schooling is estimated according to five levels of education and the constant is included. If we consider each level of education to involve 2 years of additional schooling, then the resulting annual return to schooling equals 0.14, 0.12, and 0.13 for the dynamic, static, and Heckman models, respectively, and is higher than that found in standard regressions. The rate of increase in wages due to experience differs across the models, although the coefficient is similar (0.02 for the dynamic and Heckman models and 0.04 for the static model).

The estimated parameters for the probability of job offers, marriage, birth of an additional child, and divorce are consistent with what one would expect (see Table I and Table F.I in Appendix F). For example, a higher level of education, additional experience, and being employed at $t-1$ increase the job-offer arrival rate.

Quality of Fit

The quality of the model's fit to the data is measured here by the difference between predicted and actual aggregate employment rates by level of schooling for all three models (see Figures 9–11). Given the estimated parameters of the model, we simulate employment for each education group and then calculate the aggregate employment rate using the actual education distribution for the 1955 cohort. It should be noted that these moments were used for estimation of the dynamic and static models, while the reduced form Heckman model was estimated using the standard method.

The humped shape of the employment rate by age for the 1955 cohort is best captured by the dynamic model, although the static model also provides a good fit, while the reduced form model provides a poor fit (see Figure 9). Nonetheless, an inspection of the fit for the employment age profile by schooling level shows that the impact of education on female labor supply has been captured.

The flat lifetime profile of employment for the PC group at about 85 percent is accurately predicted by the dynamic and static models (Figure 10). However, the static model overpredicts employment for ages 42–53 by about 3–5 percent. The Heckman model predicts a mild U-shaped employment profile that overpredicts for ages 24–28, underpredicts for ages 31–39, and provides a good fit for older women. Overall, the dynamic model provides a much better fit with a

[33]We assume that the cost of children by age is independent of marital status, that is, $c_{jm} = 0$.

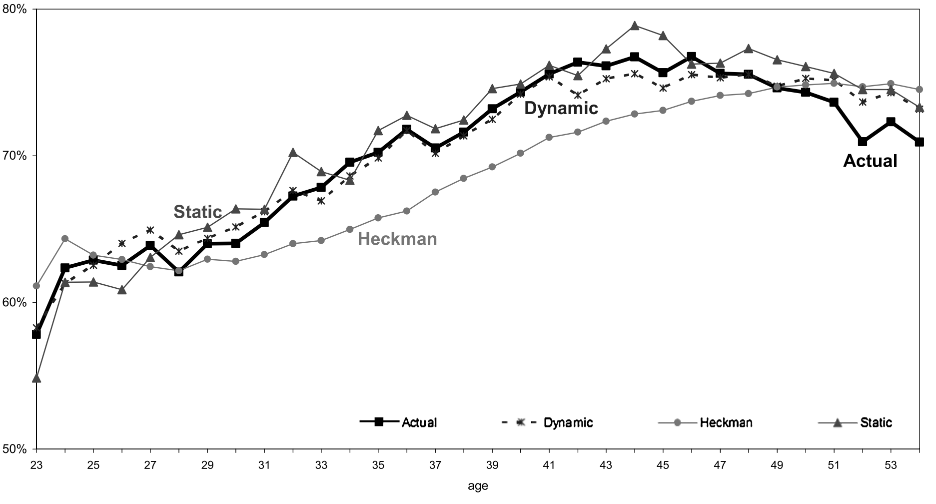

FIGURE 9.—Actual and predicted employment rates: 1955 cohort (1953–1957 cohorts for the period 1964–2007).

much lower sum of squared differences (SSD) (Table II) and the simple Pearson test for goodness of fit is not rejected. The same test for the HSD group in the static and dynamic models is rejected. The SC group's employment profile is flat at about 69 percent from age 23 to 33, then increases to about 78 percent at age 46, and subsequently returns to lower levels. The dynamic model

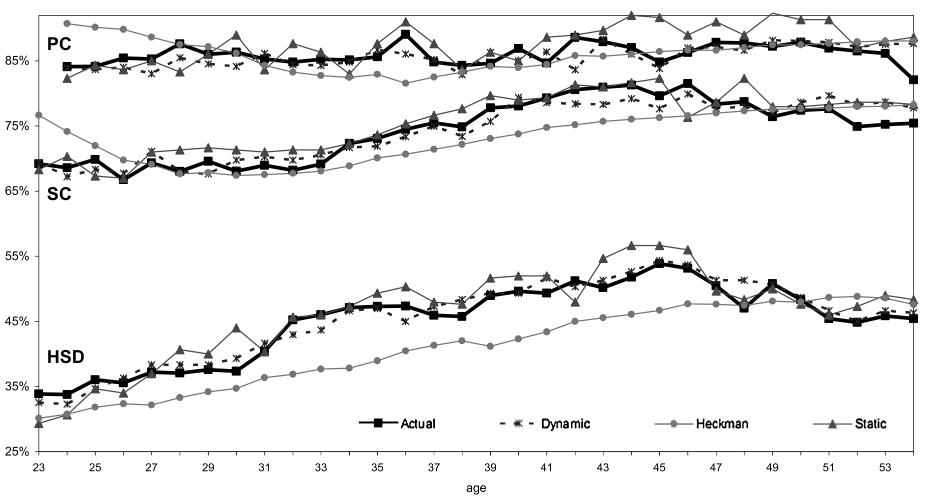

FIGURE 10.—Actual and predicted employment rates: 1955 cohort; HSD, PC, and SC (1953–1957 cohorts for the period 1964–2007).

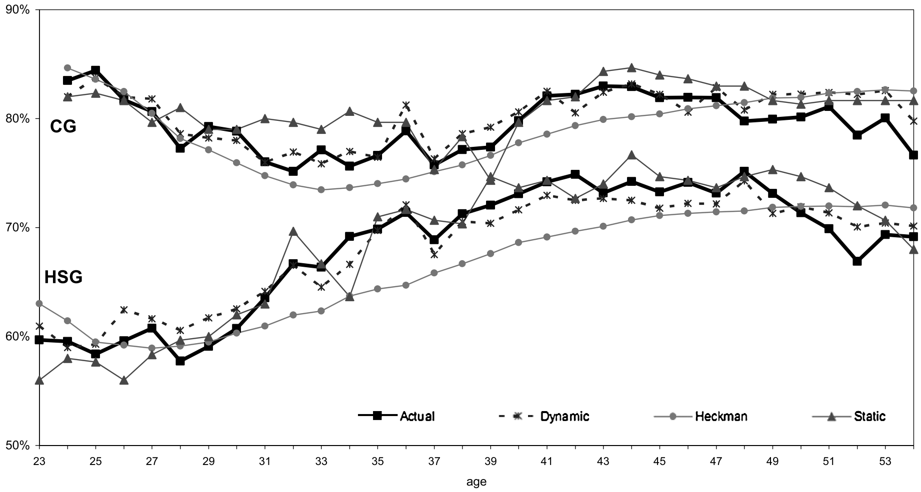

FIGURE 11.—Actual and predicted employment rates: 1955 cohort; HSG and CG (1953–1957 cohorts for the period 1964–2007).

has a superior fit over the static model and both of them have a better fit than the Heckman model. The Heckman model again tries to fit a mild U-shaped employment profile to the actual employment rate. The results from Figure 10 are confirmed by the goodness of fit tests in Table II. The hump-shaped profile for the HSD group starts from 35 percent at age 23, reaches about 50 percent at age 45, and then declines to 45 percent at age 54 and is captured well by the structural models. The reduced form model attains the correct shape but underpredicts employment for all ages below 48. The goodness of fit tests for the dynamic and static models are not rejected and their SSDs are much lower.

The quality of fit is similar for the CG and HSG groups, although the profile differs considerably (Figure 11). The U shape for the CG group and the hump shape for the HSG group are captured best by the dynamic model, fairly well by the static model, and poorly by the reduced form model. The formal goodness of fit tests provide the same result. The hump-shaped profile for the aggregate employment rate starts from 60 percent at age 23, reaches 77 percent at age 46, and then declines somewhat (Figure 9). The dynamic and static models perform better according to the goodness of fit tests and SSD than does the reduced form model.

The consistently good fit for all schooling levels translates well to the aggregate employment rate. Thus, the dynamic model provides the best fit and the static structural model also provides a good fit, although both structural models overpredict employment at ages above 50. In contrast, the reduced form model does not provide a good fit to the employment profile; it overpredicts employment for younger women, underpredicts for ages 30–46, and overpredicts for older women. Finally, the simple Pearson goodness of fit tests reject

TABLE II

GOODNESS OF FIT TESTS FOR THE THREE MODELS

	Dynamic		Static		Heckman	
	Pearson[a]	SSD[b]	Pearson[a]	SSD[b]	Pearson[a]	SSD[b]
HSD	7.96	71.93	26.65	238.42	112.53	897.94
HSG	6.24	83.44	12.58	167.33	29.60	394.77
SC	5.95	90.04	10.46	157.99	25.32	376.86
CG	4.69	75.73	10.89	175.86	11.49	180.97
PC	6.23	106.56	16.06	286.98	15.50	268.18
ALL	31.06	427.71	76.64	1026.59	194.43	2118.71

[a]Pearson's test statistic is given by

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i},$$

where χ^2 is the Pearson cumulative test statistic, O_i is an observed frequency, E_i is an expected (theoretical) frequency, and n is the number of cells in the table. The critical values are: $\chi^2_{(31,0.05)} = 18.5$, $\chi^2_{(31,0.01)} = 14.9$ (all groups, 77.9, 70.1).

[b]Sum of squared differences.

the Heckman model for almost all education levels and its SSDs are much higher (Table II).

Since job-offer rates are estimated, the structural models also provide predictions for nonemployment rates that fit the data well.[34] In summary, the dynamic structural model provides a superior fit to the data on schooling and aggregate employment for the 1955 cohort. The question remains whether it provides a good fit to aggregate data for all cohorts, which will be dealt with using the accounting analysis in the next section.

6. ACCOUNTING FOR THE INCREASE IN FEMALE EMPLOYMENT

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

[34]See the Supplemental Material.

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

The first column of Table IIIA reports the benchmark employment rates aggregated by age group for the 1955 cohort using the dynamic model.[35] The row labeled Actual reports the actual employment rate for each cohort for the same age group. Thus, for example, the actual employment rate is 0.47 for the 1945 cohort aged 23–27, while the predicted employment rate for the 1955 cohort is 0.62. The question is how much of this increase in the employment rate (i.e., 15 percentage points) is due to changes in the *schooling distribution* and *initial conditions* of the 1945 cohort. To answer this question, we change the initial conditions of the state variables at age 22 for each schooling level, as well as the schooling distribution, using the data for the 1945 cohort. We then use the estimated model to predict employment rates for the 1945 cohort. The row labeled Schooling + initial reports these predicted rates for the 1945 cohort and similarly for all other cohorts.[36] Thus, for example, the employment rate for the 1945 cohort aged 23–27 would have decreased from 0.62 to 0.59 as a result of the change in schooling and initial conditions. In other words, 20 percent (0.03 out of 0.15) of the gap in employment rates between the 1955 and 1945 cohorts at ages 23–27 is accounted for by schooling and other initial state variables at age 23. Similarly, for the 1930 cohort aged 38–42, schooling and initial conditions account for 31 percent (0.08 out of 0.26) of the gap in employment rates. Thus, by using the parameters estimated for the 1955 cohort, we can determine the contribution of the change in schooling and initial conditions by cohort to the increase in employment rates.

We therefore determine the contribution of each of the state variables (S, y^w, y^h, N, M) in reducing the difference between the actual employment rate by cohort and the predicted employment rate for the 1955 cohort for each age group for all three models (Tables IIIA, IIIB, and IIIC). The presence of empty columns is due to the low number or total lack of observations for the relevant age groups in some cohorts.

We now turn to the contributions of wages of women and their husbands, fertility, and marriage and divorce rates to the change in employment rates by cohort. Although we take these processes as given, their estimated parameters are subject to dynamic selection (see EW). Therefore, we reestimate each of

[35]We do the same calculations for the other two models and the corresponding results are presented in Tables IIIB and IIIC. In Table IV and the discussion in the Summary, we provide the main accounting results for all the models.

[36]The impact of initial conditions alone is quite small and, therefore, we combined it with schooling. The discussion at the end of this section examines the robustness of the results to changes in this analysis.

TABLE IIIA

FEMALE EMPLOYMENT RATES BY COHORTS, AGES, AND CHARACTERISTICS USING THE DYNAMIC MODEL

		Cohort									
		1925	1930	1935	1940	1945	1950	1960	1965	1970	1975
Age group:	*Actual*				**0.40**	**0.47**	**0.55**	**0.65**	**0.68**	**0.70**	**0.71**
23–27	Schooling + initial				0.57	0.59	0.62	0.63	0.63	0.65	0.65
1955 cohort	Wage				0.52	0.55	0.59	0.63	0.64	0.66	0.65
prediction	Children				0.50	0.54	0.58	0.63	0.64	0.66	0.65
rate—0.62	Marital status				0.50	0.54	0.58	0.63	0.64	0.66	0.65
	Other				**0.10**	**0.08**	**0.03**	**−0.03**	**−0.05**	**−0.04**	**−0.06**
Age group:	*Actual*			**0.36**	**0.42**	**0.49**	**0.60**	**0.68**	**0.70**	**0.73**	**0.70**
28–32	Schooling + initial			0.58	0.60	0.63	0.65	0.66	0.67	0.68	0.68
1955 cohort	Wage			0.52	0.60	0.63	0.64	0.67	0.67	0.68	0.69
prediction	Children			0.50	0.57	0.61	0.63	0.67	0.67	0.68	0.69
rate—0.65	Marital status			0.50	0.57	0.61	0.63	0.67	0.67	0.68	0.69
	Other			**0.14**	**0.15**	**0.12**	**0.03**	**−0.01**	**−0.03**	**−0.05**	**−0.01**
Age group:	*Actual*		**0.40**	**0.45**	**0.51**	**0.59**	**0.67**	**0.71**	**0.72**	**0.71**	
33–37	Schooling + initial		0.62	0.63	0.65	0.67	0.69	0.70	0.70	0.71	
1955 cohort	Wage		0.53	0.57	0.64	0.67	0.69	0.70	0.71	0.71	
prediction	Children		0.52	0.56	0.62	0.67	0.68	0.70	0.71	0.71	
rate—0.69	Marital status		0.52	0.56	0.62	0.67	0.68	0.70	0.71	0.71	
	Other		**0.12**	**0.11**	**0.12**	**0.07**	**0.01**	**−0.01**	**−0.02**	**0.00**	

(*Continues*)

TABLE IIIA—*Continued*

		Cohort									
		1925	1930	1935	1940	1945	1950	1960	1965	1970	1975
Age group:	*Actual*	**0.45**	**0.48**	**0.54**	**0.62**	**0.68**	**0.73**	**0.75**	**0.73**		
38–42	Schooling + initial	0.64	0.66	0.67	0.69	0.71	0.73	0.74	0.74		
1955 cohort	Wage	0.56	0.59	0.62	0.66	0.69	0.73	0.74	0.73		
prediction	Children	0.56	0.58	0.61	0.64	0.69	0.73	0.74	0.73		
rate—0.74	Marital status	0.56	0.58	0.61	0.64	0.69	0.73	0.74	0.73		
	Other	**0.11**	**0.09**	**0.07**	**0.01**	**0.01**	**0.00**	**−0.01**	**0.00**		
Age group:	*Actual*	**0.51**	**0.54**	**0.61**	**0.67**	**0.73**	**0.76**	**0.75**			
43–47	Schooling + initial	0.66	0.68	0.69	0.71	0.73	0.74	0.75			
1955 cohort	Wage	0.60	0.61	0.65	0.69	0.73	0.76	0.75			
prediction	Children	0.60	0.60	0.65	0.68	0.73	0.76	0.75			
rate—0.75	Marital status	0.60	0.60	0.65	0.67	0.73	0.76	0.75			
	Other	**0.08**	**0.06**	**0.04**	**0.01**	**0.00**	**0.00**	**0.00**			
Age group:	*Actual*	**0.52**	**0.56**	**0.61**	**0.67**	**0.72**	**0.75**				
48–52	Schooling + initial	0.65	0.66	0.68	0.70	0.73	0.74				
1955 cohort	Wage	0.62	0.64	0.67	0.70	0.73	0.75				
prediction	Children	0.62	0.62	0.66	0.69	0.73	0.75				
rate—0.75	Marital status	0.61	0.62	0.66	0.68	0.73	0.75				
	Other	**0.09**	**0.06**	**0.05**	**0.01**	**0.01**	**0.00**				

TABLE IIIB

FEMALE EMPLOYMENT RATES BY COHORTS, AGES, AND CHARACTERISTICS USING THE ESTIMATED STATIC MODEL

		Cohort									
		1925	1930	1935	1940	1945	1950	1960	1965	1970	1975
Age group:	*Actual*				**0.40**	**0.47**	**0.55**	**0.65**	**0.68**	**0.70**	**0.71**
23–27	Schooling + initial				0.54	0.57	0.59	0.61	0.61	0.63	0.64
1955 cohort	Wage				0.53	0.55	0.59	0.61	0.63	0.64	0.66
prediction	Children				0.48	0.54	0.59	0.62	0.64	0.65	0.67
rate—0.60	Marital status				0.48	0.54	0.59	0.62	0.64	0.65	0.67
	Other				**0.08**	**0.07**	**0.05**	**−0.04**	**−0.04**	**−0.04**	**−0.04**
Age group:	*Actual*			**0.36**	**0.42**	**0.49**	**0.60**	**0.68**	**0.70**	**0.73**	**0.70**
28–32	Schooling + initial			0.59	0.61	0.63	0.66	0.67	0.67	0.69	0.69
1955 cohort	Wage			0.57	0.59	0.62	0.66	0.67	0.68	0.70	0.70
prediction	Children			0.55	0.54	0.60	0.66	0.67	0.69	0.71	0.71
rate—0.67	Marital status			0.55	0.54	0.60	0.66	0.67	0.69	0.71	0.71
	Other			**0.19**	**0.12**	**0.11**	**0.06**	**−0.01**	**−0.01**	**−0.02**	**0.01**
Age group:	*Actual*		**0.40**	**0.45**	**0.51**	**0.59**	**0.67**	**0.71**	**0.72**	**0.71**	
33–37	Schooling + initial		0.63	0.64	0.66	0.68	0.70	0.71	0.71	0.72	
1955 cohort	Wage		0.61	0.62	0.64	0.67	0.70	0.71	0.71	0.72	
prediction	Children		0.60	0.60	0.61	0.67	0.70	0.71	0.71	0.72	
rate—0.71	Marital status		0.59	0.60	0.60	0.67	0.70	0.71	0.71	0.72	
	Other		**0.20**	**0.15**	**0.10**	**0.07**	**0.03**	**0.00**	**−0.01**	**0.01**	

(*Continues*)

TABLE IIIB—*Continued*

		Cohort									
		1925	1930	1935	1940	1945	1950	1960	1965	1970	1975
Age group:	*Actual*	**0.45**	**0.48**	**0.54**	**0.62**	**0.68**	**0.73**	**0.75**	**0.73**		
38–42	Schooling + initial	0.65	0.67	0.68	0.70	0.72	0.74	0.75	0.75		
1955 cohort	Wage	0.62	0.64	0.66	0.68	0.71	0.74	0.75	0.75		
prediction	Children	0.61	0.63	0.66	0.67	0.71	0.74	0.75	0.75		
rate—0.75	Marital status	0.60	0.63	0.66	0.67	0.71	0.74	0.75	0.75		
	Other	**0.15**	**0.15**	**0.11**	**0.05**	**0.03**	**0.01**	**0.00**	**0.02**		
Age group:	*Actual*	**0.51**	**0.54**	**0.61**	**0.67**	**0.73**	**0.76**	**0.75**			
43–47	Schooling + initial	0.69	0.70	0.71	0.73	0.75	0.77	0.77			
1955 cohort	Wage	0.66	0.68	0.70	0.72	0.74	0.77	0.77			
prediction	Children	0.64	0.67	0.69	0.71	0.74	0.77	0.77			
rate—0.77	Marital status	0.64	0.67	0.69	0.71	0.74	0.77	0.77			
	Other	**0.12**	**0.13**	**0.08**	**0.04**	**0.01**	**0.01**	**0.02**			
Age group:	*Actual*	**0.52**	**0.56**	**0.61**	**0.67**	**0.72**	**0.75**				
48–52	Schooling + initial	0.66	0.68	0.70	0.71	0.74	0.76				
1955 cohort	Wage	0.63	0.65	0.68	0.70	0.73	0.76				
prediction	Children	0.62	0.65	0.67	0.70	0.73	0.76				
rate—0.76	Marital status	0.61	0.64	0.67	0.69	0.73	0.76				
	Other	**0.10**	**0.08**	**0.06**	**0.02**	**0.00**	**0.00**				

TABLE IIIC

FEMALE EMPLOYMENT RATES BY COHORTS, AGES, AND CHARACTERISTICS USING THE HECKMAN MODEL

		Cohort									
		1925	1930	1935	1940	1945	1950	1960	1965	1970	1975
Age group:	*Actual*				**0.40**	**0.47**	**0.55**	**0.65**	**0.68**	**0.70**	**0.71**
23–27	Schooling + initial				0.56	0.59	0.62	0.63	0.64	0.66	0.67
1955 cohort	Wage				0.57	0.59	0.62	0.63	0.64	0.66	0.67
prediction	Children				0.49	0.57	0.62	0.64	0.65	0.67	0.67
rate—0.63	Marital status				0.49	0.57	0.62	0.64	0.65	0.67	0.67
	Other				**0.09**	**0.10**	**0.07**	**−0.01**	**−0.04**	**−0.03**	**−0.05**
Age group:	*Actual*			**0.36**	**0.42**	**0.49**	**0.60**	**0.68**	**0.70**	**0.73**	**0.70**
28–32	Schooling + initial			0.55	0.57	0.60	0.62	0.63	0.64	0.65	0.66
1955 cohort	Wage			0.55	0.57	0.60	0.62	0.63	0.63	0.65	0.65
prediction	Children			0.46	0.50	0.58	0.61	0.63	0.64	0.65	0.65
rate—0.63	Marital status			0.46	0.50	0.58	0.61	0.63	0.64	0.65	0.65
	Other			**0.10**	**0.09**	**0.09**	**0.02**	**−0.05**	**−0.06**	**−0.07**	**−0.05**
Age group:	*Actual*		**0.40**	**0.45**	**0.51**	**0.59**	**0.67**	**0.71**	**0.72**	**0.71**	
33–37	Schooling + initial		0.57	0.58	0.60	0.63	0.65	0.66	0.66	0.67	
1955 cohort	Wage		0.57	0.58	0.60	0.63	0.65	0.65	0.66	0.67	
prediction	Children		0.50	0.52	0.57	0.63	0.65	0.66	0.65	0.66	
rate—0.66	Marital status		0.50	0.52	0.57	0.63	0.65	0.66	0.65	0.66	
	Other		**0.10**	**0.07**	**0.07**	**0.03**	**−0.01**	**−0.06**	**−0.07**	**−0.05**	

(*Continues*)

TABLE IIIC—*Continued*

		Cohort									
		1925	1930	1935	1940	1945	1950	1960	1965	1970	1975
Age group:	*Actual*	**0.45**	**0.48**	**0.54**	**0.62**	**0.68**	**0.73**	**0.75**	**0.73**		
38–42	Schooling + initial	0.60	0.61	0.63	0.65	0.68	0.69	0.70	0.71		
1955 cohort	Wage	0.60	0.61	0.63	0.65	0.67	0.69	0.70	0.70		
prediction	Children	0.56	0.57	0.60	0.65	0.68	0.70	0.70	0.69		
rate—0.70	Marital status	0.56	0.57	0.60	0.65	0.68	0.70	0.70	0.69		
	Other	**0.11**	**0.08**	**0.06**	**0.02**	**0.00**	**−0.03**	**−0.05**	**−0.04**		
Age group:	*Actual*	**0.51**	**0.54**	**0.61**	**0.67**	**0.73**	**0.76**	**0.75**			
43–47	Schooling + initial	0.63	0.65	0.67	0.69	0.71	0.73	0.73			
1955 cohort	Wage	0.64	0.65	0.67	0.69	0.71	0.73	0.73			
prediction	Children	0.61	0.63	0.66	0.69	0.72	0.73	0.73			
rate—0.73	Marital status	0.61	0.63	0.66	0.69	0.72	0.73	0.73			
	Other	**0.09**	**0.09**	**0.05**	**0.02**	**−0.02**	**−0.03**	**−0.02**			
Age group:	*Actual*	**0.52**	**0.56**	**0.61**	**0.67**	**0.72**	**0.75**				
48–52	Schooling + initial	0.65	0.67	0.68	0.70	0.73	0.74				
1955 cohort	Wage	0.65	0.67	0.69	0.71	0.73	0.74				
prediction	Children	0.65	0.67	0.69	0.71	0.73	0.75				
rate—0.75	Marital status	0.65	0.67	0.69	0.71	0.73	0.75				
	Other	**0.13**	**0.10**	**0.07**	**0.03**	**0.01**	**0.00**				

the processes separately using the given estimated parameters for utility and job-offer rates.[37]

To measure the contribution of the change in wages, we use the cohort-specific estimated wage functions for husbands as simple regressions and use the wage function for their wives as explained in Appendix E. We predict employment rates using the changes in the distributions of schooling and the initial state variables, and the "new" wage functions.

Similarly, we are able to measure the contributions of the fertility, marriage, and divorce processes once we have estimated the parameters for each of the cohorts (Appendix E). In this way, we fully account for the contribution of each of the observed variables. These variables may over- or underpredict the change in employment rate by age for cohorts other than 1955. The row labeled Other represents that portion of the change in employment rates that is not accounted for by the model's observable variables (i.e., the "unexplained" portion). The results consistently show an unexplained portion that is positive for cohorts prior to 1955 and negative or zero for subsequent cohorts. Furthermore, these results are based on sequential simulations using a particular order of the variables; the robustness of the results in this regard is examined below.

The contribution of each factor to explaining the change in female employment rates differs across cohorts and age groups (Tables IIIA–IIIC). It is worthwhile as this point to summarize the results of the accounting exercise as they appear in Table IV:[38]

• *Schooling*: Schooling accounts for the largest contribution from among the observed variables in all the models (Table IV) as follows: 33–36 percent in the dynamic model; 32–33 percent for earlier cohorts and 26 percent for later cohorts in the static model; and 39–42 percent for earlier cohorts and only 20 percent for later cohorts in the Heckman model. The contribution in the dynamic model is significantly smaller for the 23–37 age group for the 1950 and earlier cohorts.

• *Wages*: In the dynamic model, the change in wages of women and men accounts for 20–23 percent of the change in female employment rates. This figure tends to be larger (reaching about 23 percent) for the 1950 and earlier cohorts, but is only 20 percent for the cohorts born after 1960. The contribution ranges from 23 to 31 percent for the 1935, 1930, and 1925 cohorts. However, the contribution is particularly small for the recent cohorts born in 1970 and 1975 and for older females aged 48–52, for whom it declines to only 11 percent.

In the static model, the change in wages of women and men accounts for 9–11 percent of the changes in employment on average. However, the Heckman model implies that wages account for less than 1 percent of the change.

[37]See Appendix E for further details on the method of estimation and see the Supplemental Material for more detailed results for each model.

[38]See the Supplemental Material for calculations of the contributions appearing in Tables IIIA–IIIC.

TABLE IV

AVERAGE SHARE OF CHANGE IN FEMALE EMPLOYMENT RATES FOR THE COHORTS OF 1925–1975 BY EACH MODEL

	Dynamic	Static	Heckman
1925–1935			
Schooling + initial	36%	33%	42%
Wage	23%	10%	0%
Children	4%	5%	14%
Marital status	0%	1%	0%
Other	37%	51%	43%
Other, less than 38		No data	
Other, over 38	34%	48%	45%
1940–1950			
Schooling + initial	33%	32%	39%
Wage	22%	9%	1%
Children	8%	7%	5%
Marital status	1%	0%	0%
Other	36%	51%	55%
Other, less than 38	55%	63%	55%
Other, over 38	18%	40%	55%
1960–1975			
Schooling + initial	35%	26%	20%
Wage	20%	11%	1%
Children	2%	6%	4%
Marital status	1%	0%	0%
Other	42%	57%	75%
Other, less than 38	42%	50%	71%
Other, over 38		No data	

This result is almost certainly related to the fact that in the reduced form specification of Heckman's model, women's wages do not enter directly into the participation equation, as explained above.

- *Fertility*: The contribution of fertility to female employment in the dynamic model ranges from 2 to 8 percent only and is larger for the cohorts born during the period 1940–1950. The static and Heckman models provide similar results with the exception of older cohorts in the latter model, where children account for 14 percent of the decrease in employment rate in comparison to the 1955 cohort.
- *Marital Status*: The contribution of marital status varies from 0 to 1 percent on average in all the models. This is a surprising result, since employment rates are higher among unmarried women than among married ones and the proportion of unmarried women has been increasing over time. Nonetheless, this result appears to be correct, since schooling and fertility are already controlled for.

• *Other*: The portion that remains unexplained by the changes in the observed variables (Other or unexplained) is large in all the models and for all cohorts, but is larger for the static and Heckman models. In the dynamic model, it ranges from 36 to 42 percent on average and is much larger for younger women in the 1940–1950 cohorts (when there were sufficient data). The unexplained portion is 51–57 percent in the static model and 43–75 percent in the Heckman model. Both models left more for the Other category than the dynamic model, with inferior goodness of fit to the data of the 1955 cohort relative to that of the dynamic model.

It is important to note that the unexplained portion is always one-sided. In other words, the predictions using *all* the observed processes that affect female employment choice in the model always overpredict actual observed employment rates for the 1950 and earlier cohorts, and underpredict them for the 1960 and later cohorts. This result is robust, since it is not imposed in any way on the procedure and the *unexplained* portion is the "last" change to be introduced. Therefore, we are able to claim that our estimate of other explanations is a "lower bound" for the potential contribution of the other sources discussed in Section 2.[39]

Schooling is the most important observed variable in accounting for the increase in female employment. Overall it explains about one-third of the change relative to the 1955 cohort. It is interesting that the impact of the change in wages is large for the dynamic forward-looking model, declines by about half in the equivalent static model, and is almost zero for the Heckman model. Finally, the importance of children and marital status, when schooling is held constant, is relatively small.

It is also of interest that the unexplained portion (Other) is large for cohorts born both before and after 1955, even though the changes in unconditional employment differ significantly in size between the two periods (Figure 8). This result in addressed in the next section.

Robustness

The superior quality of fit and the accounting results convince us that the dynamic model provides the best platform for explaining the increase in married female labor supply. Therefore, the robustness of the accounting exercise is examined using the dynamic model and by changing the sequence of the simulations as follows: (i) schooling, wages, marital status, fertility (no change in initial conditions); (ii) wages + initial conditions, schooling, fertility, marital status; (iii) wages + initial conditions, fertility, schooling, marital status; (iv) wages + initial conditions, fertility, marital status, schooling; (v) schooling + initial conditions, wages, marital status, fertility.

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

The average influence of Schooling is about 34 percent when it is first in the sequence (Table IIIA) and ranges from 26–34 percent for the other sequences. It is worth noting that for sequence (iv), in which it is last, schooling accounts for 28 percent of the change in employment on average and that when the contribution of schooling decreases to only 26–28 percent, the proportion explained by Wage increases to 26 percent.

The proportion explained by wages (22–26 percent on average) remained almost unchanged when the sequence was changed. The change in number of children accounts for 3–5 percent; however, for the sequence in which marital status precedes number of children, its effect declines by about 1 percent. The effect of marital status increased to 5 percent when it precedes the change in number of children (cases (i) and (v)) and in all other sequences it remains about 1 percent on average. The effect of the change in Other remained almost unchanged, explaining 37–42 percent of the change in employment rates.

We also examined the impact of a change in the initial conditions, which affected only the 23–27 age group. On average, the employment rate for this age group was no more than 3 percent higher if the initial conditions for the 1925–1940 cohorts were left unchanged and no more than 2 percent higher (lower) for the 1945–1950 (1960–1975) cohorts.[40] We conclude that overall the changes in female employment were robust to the order of the simulation.

7. CHANGES BY COHORT AND AGGREGATE FIT

The question arises as to whether the female dynamic labor supply model outlined above can provide a simple explanation for the large unexplained (Other) portion produced by the accounting analysis.[41] To provide an answer, we considered modifications to the model that can explain why the unexplained portion is higher on average for women aged 23–27 (55 percent) and lower for women aged 48–52 (18 percent) for the 1940–1950 cohorts (see Table IV). Thus, we chose two parameters to modify for the various cohorts: the first and most obvious choice was to vary the utility/cost parameter of not working α_1, which affects the labor supply of women at all ages and can be interpreted as the change in household technology and/or social norms.[42] The second modification was to allow the cost of raising young children (0–6 years old) to vary between cohorts through α_{41}, which affects the labor supply of younger women.[43]

[40]Further details of the robustness analysis can be found in the Supplemental Material.

[41]We do not consider this case for the static and reduced form models, since the fit of these models to the data is far inferior and their unexplained portions are much larger.

[42]Since the change in the value of home production that we impose is by cohort and not over time, it may be more consistent with the interpretation of a change in social norms than a change in technology.

[43]See Albaseni and Olivetti (2009b) for evidence on the cost of pregnancy and raising young children for different cohorts. In their case, it is even harder to distinguish between changes in technology and changes in social norms.

TABLE V

CHANGE IN ESTIMATED UTILITY/COST OF LEISURE AND YOUNG CHILDREN BY COHORT: DYNAMIC MODEL[a]

	Parameters		Parameters Interpreted—Change in Dollar Value per Hour	
Cohort	α_1 – Constant	α_{41} Young Children (0–6)	α_1 – Constant	α_{41} Young Children (0–6)
1925	−25481.9	−8818.78	4.912	3.167
1930	−25360.5	−8818.78	4.851	3.167
1935	−24570.3	−8818.78	4.456	3.167
1940	−15658.1	−8980.07		3.251
1945	−15658.1	−8641.53		3.075
1950	−15658.1	−6804.98		2.119
1955	**−15658.1**	**−2733.36**		
1960	−15658.1	−1006.18		−0.899
1965	−15658.1	−606.78		−1.107
1970	−15658.1	−600.26		−1.110
1975	−15658.1	−620.11		−1.100

[a]To interpret α_1 we divided the difference between the value of the parameter in the specific cohort and the value of the parameter in 1955 by 2000 (number of hours worked per year). To interpret α_{41} we divided the difference between the value of the parameter in the specific cohort and the value of the parameter in 1955 by the value of $(1+\alpha_2)$ and then by 2000 (number of hours worked per year).

To evaluate these possible explanations for the increase in female employment, we allowed these two parameters to deviate from their estimated 1955 cohort values for all cohorts. In this case, we used the dynamic model where the exogenous dynamic processes were those estimated for the accounting analysis presented in Table IIIA, in which all observed explanations are used. The results are presented in Table V.

We are indeed able to produce a close fit for the unexplained portion in all cohorts by adjusting only the values of these two parameters (i.e., α_1 and α_{41}) away from their estimated values for the 1955 cohort (which appear in bold in Table V). As can be seen from Figures 12A and 12B, the modification of the two parameters, which are changed once for each cohort, eliminates the unexplained accounting gap for the 1940 and 1930 cohorts. For the 1940 cohort (Figure 12A), only α_{41} was changed relative to the 1955 cohort, since the unexplained gap exists only for women under 40. In the 1930 cohort, both parameters were changed, since the unexplained gap persists throughout the women's lifetimes. Equivalent results were obtained for all other cohorts, as indicated by Table V.[44]

The main results imply that the value of leisure for the 1940 and later cohorts became equal to that of the 1955 cohort when it was increased by 57–60 percent

[44]See the Supplemental Material.

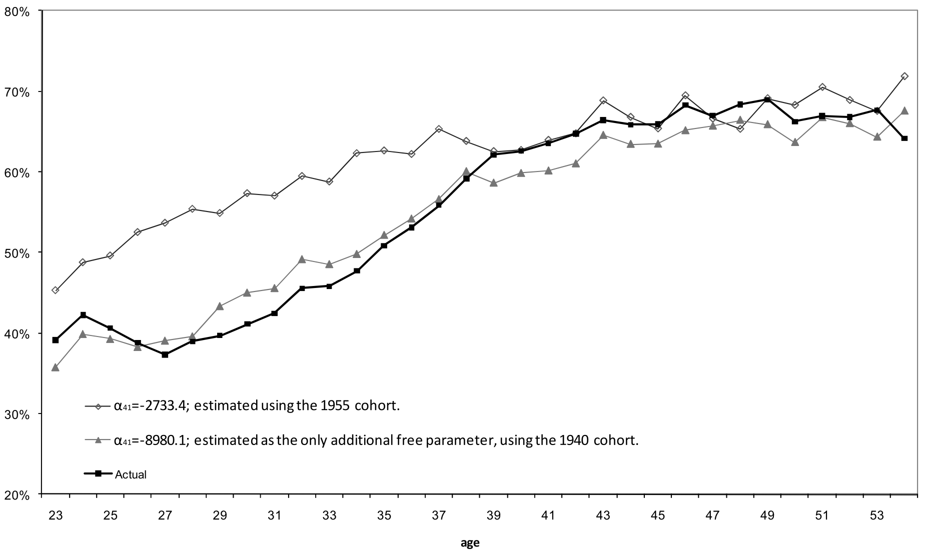

FIGURE 12A.—Actual and predicted employment rates: 1940 cohort ($\alpha_1 = -15{,}658.1$, $\alpha_{41} = -2733.4$ (estimated from the 1955 cohort); $\alpha_{41} = -8980.1$ (estimated when this parameter was unconstrained for this cohort)).

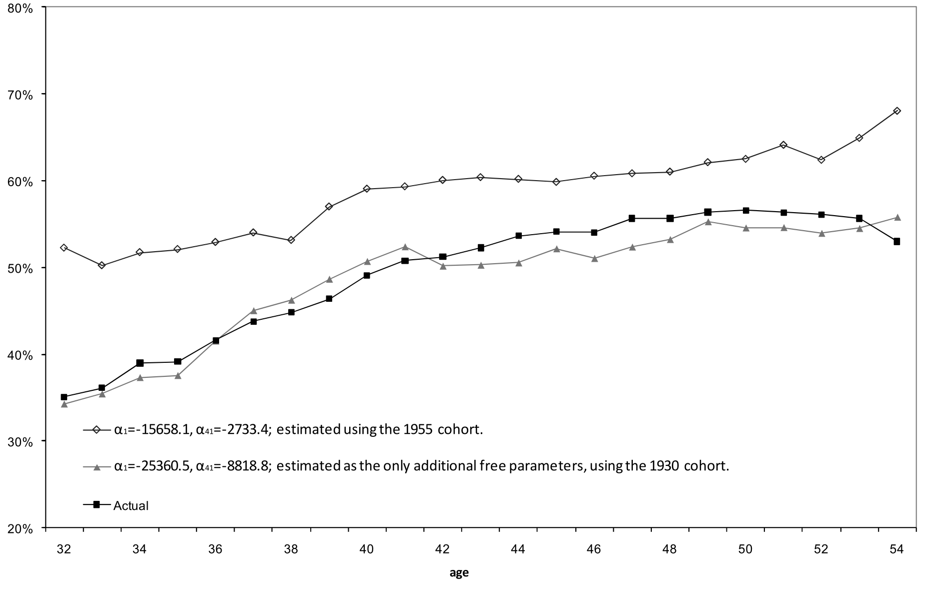

FIGURE 12B.—Actual and predicted employment rates: 1930 cohort ($\alpha_1 = -15{,}658.1$, $\alpha_{41} = -2733.4$ (estimated from the 1955 cohort); $\alpha_1 = -25{,}360.5$, $\alpha_{41} = -8818.8$ (estimated when the two parameters were unconstrained for this cohort)).

for the 1925, 1930, and 1935 cohorts. Since the model is linear, these changes can be calculated in terms of dollars per hour of work (in 2000 prices), such that working at home is about $4.50–4.90 an hour "more expensive" than working outside the home for the 1925–1935 cohorts.

The cost of raising children aged 0–5 for working women varies monotonically for all cohorts.[45] Thus, it is more than three times higher for the 1945 and earlier cohorts than for the 1955 cohort and a quarter of that for recent cohorts (Table V). In terms of dollars per hour, these estimates imply that the cost of rearing children below 6 years of age while working is higher by $2.10 for the 1950 cohort and about $3.20 higher for cohorts born prior to that. For cohorts born later than 1955, it is about $1 less.

The estimated parameters needed to adjust the cost/utility of housework and of raising young children when working outside the home to produce a good fit to female employment for these cohorts are consistent with the explanations provided in the literature (see Section 2). Furthermore, the modifications are of significant magnitude and are consistent with those presented in recent studies. However, we are unable to determine whether these changes in parameters by cohort should be interpreted as technical change in home production and in rearing young children or as a change in preferences due to shifts in social norms.

Aggregate Fit

It is important to determine whether the estimated model for the 1955 cohort is able to predict the increase in the employment rate for married women and the stability in the rate for unmarried women. This is done by checking whether the simulated aggregation by cohort provides a good fit to the aggregate employment rates of married and unmarried women. Thus, the predictions from the accounting analysis are used to forecast the aggregate employment rate for married and unmarried women from 1980 to 2007, as well as the change in the parameters needed to close the unexplained gap.[46] Figure 13 shows that the aggregate fit to the married and unmarried female employment rates is remarkably good. The only significant deviation is a small overprediction of married female employment rates from 2003 to 2007 and a small underprediction of unmarried female employment rates from 1995 to 2004.[47] Is the fit maintained across cohorts and age groups? Table VI shows that the dynamic model provides a good fit to the employment rates of both married

[45] α_{41} cannot be estimated for the 1925 and 1930 cohorts since they did not include enough observations for young women. Therefore, we imposed the parameter estimated for the 1935 cohort.

[46] The reason for starting in 1980 is the lack of data for earlier cohorts.

[47] The underprediction for unmarried women may be due to the welfare-to-work program introduced in the mid-1990s, which was aimed at single low-paid mothers and is ignored in the estimated model.

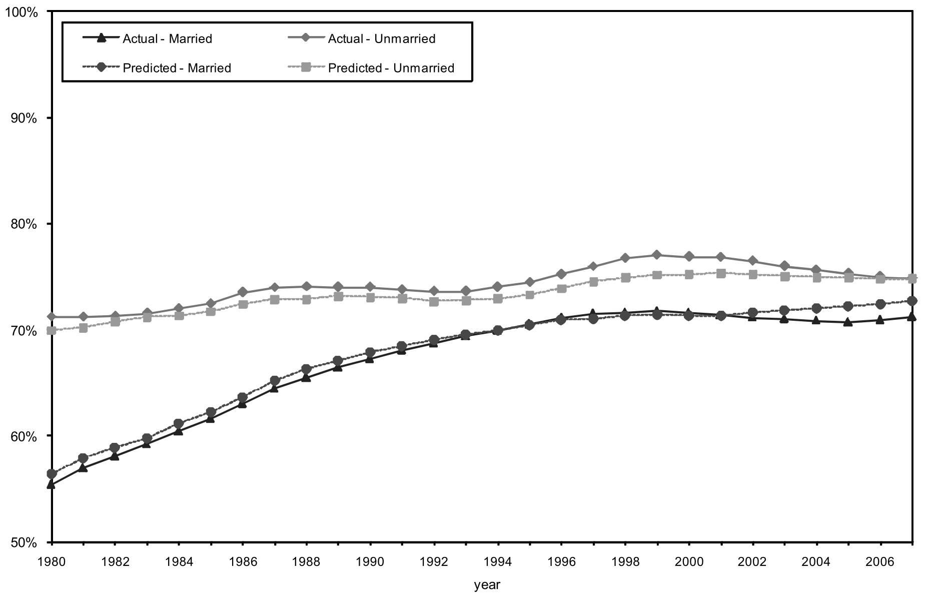

FIGURE 13.—Aggregate employment rates of females, aged 83–54.

and unmarried females for all cohorts and for all age groups. There are very few cells in which the deviation is above 2 percent and many in which it is zero.

8. CONCLUDING REMARKS

The dynamic model provides a superior fit and interpretation for the observed female employment rate. The majority of the increase in married female employment is explained by the increase in years of schooling, while the rise in women's wages also explains a significant proportion. Somewhat surprisingly, changes in fertility and marital status do not have much of an impact. Furthermore, the unexplained portion is quite large and positive; in other words, for cohorts born before 1955, the simulations overpredict female employment and for more recent cohorts, underpredict it. Therefore, there must have been other changes taking place among married women by cohort. We have shown above that it is consistent with the model to claim that technological progress in household production or a change in social norms has brought down the costs of working outside the home. Moreover, the claim that the cost of raising young children (aged 0–5) has also declined significantly for all cohorts born after 1935 is also consistent with the estimated model.

Note that we are unable to separate between utility and costs, and therefore impose on the model that changes are for the lifetime of each cohort. Therefore, it may well be a change in social norms that provides the explanation

TABLE VI

MARRIED AND UNMARRIED, ACTUAL AND FITTED FEMALE EMPLOYMENT RATES BY COHORT AND AGE: DYNAMIC MODEL

	Cohort																			
	1925		1930		1935		1940		1945		1950		1960		1965		1970		1975	
Age Group	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted	Actual	Fitted
23–27																				
Married							0.32	0.30	0.39	0.39	0.48	0.48	0.60	0.61	0.64	0.63	0.66	0.64	0.65	0.65
Unmarried							0.74	0.70	0.73	0.72	0.71	0.69	0.71	0.69	0.72	0.72	0.72	0.72	0.76	0.74
28–32																				
Married					0.30	0.31	0.36	0.40	0.43	0.45	0.55	0.57	0.65	0.68	0.68	0.69	0.69	0.68	0.66	0.67
Unmarried					0.71	0.70	0.69	0.71	0.70	0.69	0.73	0.71	0.72	0.71	0.73	0.73	0.79	0.75	0.76	0.75
33–37																				
Married			0.36	0.38	0.41	0.41	0.47	0.49	0.56	0.59	0.63	0.64	0.70	0.71	0.70	0.71	0.68	0.71		
Unmarried			0.68	0.67	0.67	0.66	0.67	0.67	0.72	0.71	0.75	0.73	0.74	0.71	0.77	0.75	0.76	0.74		
38–42																				
Married	0.40	0.42	0.45	0.47	0.51	0.50	0.59	0.59	0.66	0.65	0.71	0.70	0.73	0.74	0.72	0.73				
Unmarried	0.72	0.73	0.69	0.67	0.67	0.66	0.72	0.73	0.75	0.76	0.78	0.75	0.78	0.75	0.76	0.75				
43–47																				
Married	0.48	0.46	0.51	0.49	0.58	0.57	0.64	0.63	0.72	0.71	0.75	0.74	0.75	0.75						
Unmarried	0.70	0.71	0.68	0.69	0.71	0.71	0.73	0.75	0.77	0.76	0.78	0.76	0.76	0.75						
48–52																				
Married	0.48	0.49	0.53	0.53	0.59	0.58	0.65	0.65	0.71	0.71	0.74	0.74								
Unmarried	0.66	0.70	0.67	0.67	0.69	0.68	0.73	0.73	0.76	0.75	0.76	0.77								

rather than a change in costs. Thus, it is possible that the value of home production is determined by social norms, which in turn are determined by the values held by individuals. This leads to unobserved heterogeneity which can change over time and thus shift social norms. The model is also not able to capture the possibility of an intrafamily game used by households to internally allocate resources (Chiappori (1997)). This conceptual framework has been prominent in the recent literature and is used to develop an estimable dynamic model of household labor supply. This line of research stems from the need for models of household behavior that can potentially endogenize and quantify the complicated decisions involving labor supply, fertility, children, education, and divorce (Lifshitz (2004), Brown and Flinn (2007), DelBoca and Flinn (2009), and Tartari (2005)).

Can this framework predict the future increase in per capita U.S. GDP due to the employment of married women? There are good reasons to believe that female levels of schooling will continue to rise and that female wages will approach those of men, in addition to any increase due to economic growth. Furthermore, it is likely that technological change will continue to affect household activities, including the reduction in the cost of raising young children, and that social norms will continue to change in the direction of greater equality between men and women in household decisions. On the other hand, Figure 2 indicates that female employment has been stable during the past decade. This is due to the surprising reduction in the employment of PC women and an increase in the employment of HSD women, which together have resulted in a stable employment rate. Meanwhile, the data on schooling (Figure 3) show some signs of convergence. Thus, it would be a real challenge to predict future changes in female employment using the model. Nonetheless, in the most likely scenario for coming years, the contribution of women to the growth in per capita GDP will be significantly less than that pictured in Figure 1.

APPENDIX A: THE CONTRIBUTION OF FEMALE EMPLOYMENT TO GDP

The following assumptions were made in calculating per capita GDP for the various specifications of female employment (quantity and quality): First, a standard Cobb–Douglas function of the form $Y_t = (A_t K_t)^{\alpha} \cdot (L_t^{F*} + L_t^{M*})^{1-\alpha}$ was assumed, where $\alpha = 0.33$, A_t is the level of productivity, K_t is the capital stock, L_t^{F*} is female aggregate labor supply for ages 22–65, and L_t^{M*} is male aggregate labor supply for ages 22–65. Since we wish to simulate changes in male and female employment, 90 subgroups (types) of employees were defined according to schooling, marital status, and experience as follows: education (five groups: HSD, HSG, SC, CG, PC); marital status (three groups: married, single, others); experience (six groups, by years of experience: 0–5, 6–10, 11–20, 21–30, 31–40, 40+).[48] The aggregate labor supply for each gender is then

[48]We define years of potential experience as the difference between age and years of schooling, where years of schooling is defined to be 18 years for the HSD group, 19 years for the HSG group,

defined by $L_t^* = \sum_{j=1}^{90} L_{tj} \cdot H_{tj} \cdot W_{tj}$, where L_{tj} is the number of employees of type j in period t, H_{tj} is the mean number of weekly hours for an employee of type j in period t, and W_{tj} is the mean hourly real wage of employees of type j in period t (as a proxy for productivity or quality). We use the CPS data to calculate the values of L_t^* for men and women and then plug them into the production function. We then estimate the productivity and capital contribution as a residual when using actual per capita GDP and labor input, as defined.[49] We then simulate two different scenarios for female labor input as follows:

Simulation 1—Female Employment Fixed at Its 1964 Level: We assume that female employment remains constant, that is, $L_t^{F*} = L_{1964}^{F*}$, and then calculate per capita GDP using the estimated productivity and capital contributions. In this scenario, per capita GDP reaches \$33,375 in 2007, which is 40 percent less than actual per capita GDP in that year.

Simulation 2—Quality of Female Labor Fixed at Its 1964 Level: We assume that women's wages relative to those of men remain constant at their 1964 levels for each subgroup defined above. In other words, female employment with fixed quality is given as $L_t^{F*} = \sum_{j=1}^{90} L_{tj} \cdot H_{tj} \cdot W_{1964j}$. In this scenario, per capita GDP increases to \$37,954 in 2007, which is 23 percent less than the actual per capita GDP in that year.

APPENDIX B: THE CPS DATA FOR THE STANDARD MODEL

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

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

Weekly wages are constructed by taking the previous year's wage and salary income and dividing it by the number of weeks worked in the previous year. Hourly wages are defined as the weekly wage divided by the number of hours worked in the previous week in all jobs, while annual (annualized) wages are

22 years for the SC group, and 23 years for the CG and PC groups (including the 6 years before school).

[49]Real per capita GDP in 2006 dollars for the period 1964–2007.

defined as the weekly wage multiplied by 52. Wages are multiplied by 1.75 for top-coded observations until 1995. Nominal wages are deflated using the Personal Consumption Expenditure (PCE) index from National Income and Product Account (NIPA) Table 2.3.4 (http://www.bea.gov/national/nipaweb/index.asp). Since wages refer to the previous year, we use the PCE for year $X-1$ for observations in year X and, therefore, all wages are expressed in constant 2006 dollars.

Information on number of children under 6 for the period 1968–1975, which is missing from the survey data, is completed where possible using the distributions of this variable in 1967 and 1976 for each gender, marital status, and cohort separately. The completed information can be used to construct an aggregate trend, but not to identify the number of children for a specific individual.

APPENDIX C: HUSBAND'S WAGE AND HUMAN CAPITAL

This appendix explains how the data on husbands' wages, schooling, and experience have been generated for the estimation and simulation of the model in Section 3. If a woman is married, we simulate her husband's human capital (i.e., education and accumulated experience) according to the actual distribution for the cohort. In particular, we use the actual distribution of husbands' level of education (HSD, HSG, SC, CG, PC) and accumulated experience (0–10, 10–20, 20–30, and 30+ years)[50] for each particular group of women. To construct a couple, we kept only heads of households and spouses (i.e., households with two families were dropped), and dropped households with more than one male or more than one female. We then merged women and men based on year and household identification, and dropped problematic couples such as those with two heads or two spouses, more than one family, or inconsistent marital status or number of children. This is done separately for each education group and cohort, and a random draw is then made for the husband's characteristics. We also simulate whether the husband is employed using the employment rate of husbands for this specific group of women. We then simulate the husband's wage using the coefficient estimated from a standard Mincer/Ben-Porath wage equation for men married to women of that particular cohort. Here again, we use a separate wage equation for each cohort and education group of women. The characteristics of the husband and the wage regression estimators can be found in the Supplement Material.

APPENDIX D: MOMENTS AND IDENTIFICATION

We divide the sample into cohorts for 1925–1975, where each cohort consists of women born over a 5-year interval (thus, the 1925 cohort consists of women

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

born in the period 1923–1927, the 1930 cohort consists of women born in 1928–1932 and so on, up until the 1975 cohort).

For each education group within each cohort, we use the CPS data for 1964–2007 to calculate the following moments at each age from 23 to 54 (for CG and PC women, we start at age 24): (i) *employment rate*—for the entire population, including absences and with no restrictions on weekly work hours (T*5 moments); (ii) *average hourly wages*—real hourly wage for employed women with nonzero wage (T*5 moments); (iii) *marriage rate*—including women with an absent spouse (T*5 moments); (iv) *divorce rate* (T*5 moments); (v) *distribution of number of children under 6*—no children, one child, two children, and three or more children (T*5*4 moments); (vi) *distribution of the number of children aged 6–18*—no children, one child, two children, and three or more children, defined as the difference between the number of children under 18 and the number under 6 (T*5*4 moments).

We used the T*5*12 ($T = 32$) moments above to identify the model parameters. We then compared these moments to those simulated by the model. Since we have 45 parameters, the model is identified. Each group of parameters is identified from a different set of moments. Thus, the 9 utility parameters and 8 job-offer probability parameters are identified using the employment rate moments. The 8 wage parameters are identified using the average hourly wage moments. The 8 probability-of-another-child parameters are identified using the distribution of the number of children in the two age group moments. The 12 marriage and divorce probability parameters are identified using the marriage rate moments.

APPENDIX E: DESCRIPTION OF THE ACCOUNTING EXERCISE

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

Schooling

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

Wages

To estimate the influence of the change in wages on female employment, we modify both the wages of the women and those of their husbands. For the husbands, we estimate reduced form wage regressions for each cohort and for each education group, and use the repressors to simulate the husbands' wages. For the wives, we reestimate the parameters β_1, β_2, and β_3 from equation (3.3) for each cohort and use the new parameters to simulate female employment for each cohort.

Fertility

To estimate the influence of the number of children, their ages and the age of the women at childbirth on female employment, we reestimate the parameters λ_1, λ_2, and λ_3 separately for each cohort from the probability function for having another child. We use the new parameters to simulate female employment.

Marital Status

For each cohort, we reestimate the parameters ς_0, $\varsigma_{1,}$, and ς_2 from the probability function for marriage and the parameters ξ_0, ξ_1, and ξ_2 from the probability function for divorce. We use the new parameters to simulate female employment.

APPENDIX F

TABLE F.I

LOGIT PROBABILITY FUNCTIONS FOR FERTILITY, DIVORCE, AND MARRIAGE[a]

	Probability of Another Child[b]			Probability of Divorce[c]			Probability of Marriage[d]	
	Dynamic	Static		Dynamic	Static		Dynamic	Static
λ_0	−2.33	−2.44	ξ_0	−3.87	−3.68	ς_0	−4.16	−3.21
	(0.03)	(0.04)		(0.03)	(0.04)		(0.02)	(2.16)
λ_1	0.21	0.22	ξ_1	0.02	0.02	ς_1	0.001	0.001
	(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
λ_2	−0.01	−0.01	ξ_2	0.003	0.004	ς_2	−0.00003	−0.00004
	(0.00)	(0.00)		(0.00)	(0.01)		(0.00)	(0.00)
λ_3	0.00002	−0.00001	ξ_3	−1.54	−1.39	ς_3	−3.88	−3.91
	(0.00)	(0.00)		(0.03)	(0.09)		(1.48)	(1.54)
λ_4	−0.34	−0.36	ξ_4	0.00003	0.00004	ς_4	−0.0002	−0.0003
	(0.12)	(0.05)		(0.00)	(0.00)		(0.00)	(0.00)
λ_5	0.08	0.09	ξ_5	0.03	0.04			
	(0.01)	(0.04)		(0.02)	(0.05)			
λ_6	−0.52	−0.52	ξ_6	−2.43	−2.47			
	(0.04)	(0.07)		(2.64)	(1.34)			
λ_7	0.23	0.24						
	(0.12)	(0.10)						

[a]Standard errors appear in parentheses.
[b]See equation (3.9).
[c]See equation (3.11).
[d]See equation (3.10).

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