Female Labor Participation in Iran: A Structural Model Estimation

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Abstract

Previous studies mainly focus on factors such as wage, religion, child cost, education, and culture to explain very low female participation rate in developing countries. We introduce a new channel in which discrimination in labor market conditions other than wages may explain the participation gap between men and women. In particular, we focus on job security, propensity of job finding, and search cost. We estimate a structural dynamic matching labor model of female participation choice using detailed individual panel data on labor force in Iran. We find that gender discrimination in job finding has the biggest effect in reducing the rate of women's participation. If all discrimination disappears, female participation rate will increase by 12 percent point to almost 30 percent. The main finding is that other factors outside our model such as culture have more effect on labor force participation of married woman.

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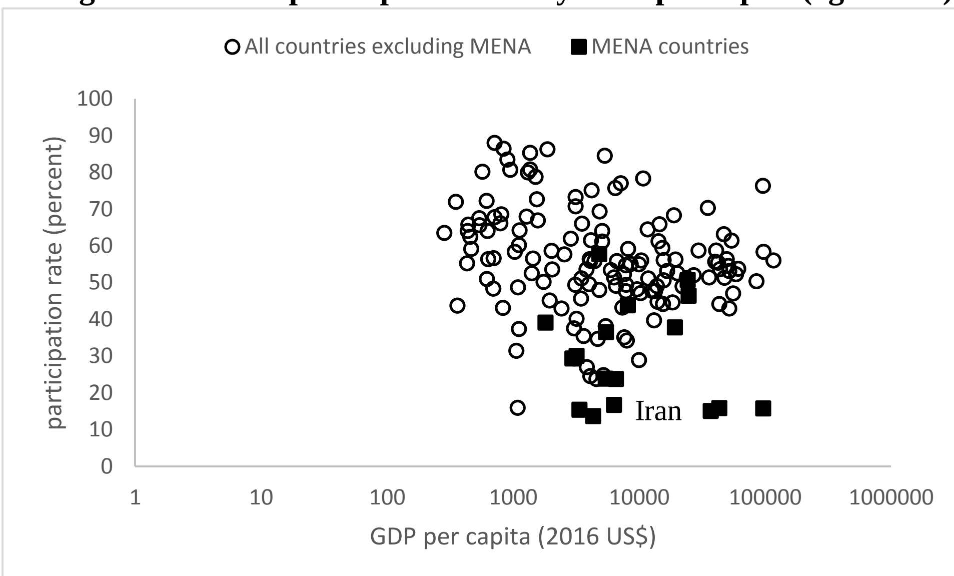
I. INTRODUCTION

Very low female employment and participation rate in Middle East and North Africa region (MENA) left behind women in these countries compared with the rest of the world (Figure 1). We know that women's participation rate in labor market is correlated with development of the country, but it is still unclear why the growth in GDP of MENA countries does not translate to their female participation rate. There are gender discriminations in labor market attitudes such as job security, job hiring, and search costs that exists in these countries, but never have been quantified to determine their impact on participation. We develop and estimate a structural model using individual panel data from Iran to quantify various factors may contribute to low female labor force participation rate.

Figure 1. Female participation rate by GDP per capita (aged +15)



Note: MENA stands for Middle East and North Africa
Source: World Bank; labor force participation rate (modeled ILO estimate); year 2014

In previous studies conducted in the area of women's labor force participation many factors have been reviewed in order to explain gender differences in participation. Some studies have examined effect of discrimination in wage on labor force participation of women; however, none of them considered other factors in labor market structure in a structural model. Probability of finding and losing a job, and search cost can play a pivotal role in a woman’s decision about labor market participation; if finding a job takes too much time and search cost, or the woman loses her job easily, she might choose leaving labor market in order to refrain paying these high costs.

The most important challenge in determining gender discrimination in labor markets of developing countries is lack of detailed micro data. Fortunately, Labor Force Survey (LFS) with detailed standard questions have conducted in Iran quarterly for a period of more than ten years. This data has rotational structure which provides opportunity of creating a panel of households’ labor market characteristics.

We used structural model estimation as a way to explore effect of various factors on labor force participation. Structural models has several advantages over other estimation methods. By using these method, we can determine effect of factors which cannot be measured directly from data, like search cost or utility of children. In addition, we can apply counterfactuals in structural models to predict effect of changes in the underlying economic environment. Thus, we can estimate how female labor force participation would change if there was not any discrimination against them in labor market.

Results have shown that gender discrimination in job finding has the biggest effect in reducing the rate of women's participation. This factor strongly affects college-educated women’s participation. Other factors, job security and wage discrimination, have lower efficacy on participation rate of women, with search cost as the least important variable. If all discrimination disappears, female participation rate will increase to almost 30 percent. Sensitivity of this analysis to urban and rural areas was examined. The main finding is that other factors outside our model such as culture have bigger effect on labor force participation of married woman.

In following sections, first, we have reviewed the underlying literature of female labor force participation, particularly papers which have used structural estimation methods. Then, in section III, we glance the stylized facts about factors affecting female labor force participation, describing the data sets we are going to use for our estimation. Afterwards, we develop a structural model for decision making of a couple about participation in labor market. This model is based on family’s characteristics and the structure of labor market, which lead us to the estimation of parameters in section IV. The estimation is divided into two parts, reduced form estimation in the first stage and then estimation of structural parameters by means of simulated method of moments. Finally, Results and counterfactuals are investigated in section V.

II. Literature Review

Numerous researches have studied factors affecting female labor force participation. Most outstanding factors are wage, education, fertility, marriage, divorce, culture and religion. Besides these factors, an important aspect of married women participation is the decision-making procedure in a household, which is influenced by culture, and it can change over time. Household labor supply models can be divided into two distinct categories: (1) conventional models and (2) game-theory based models. In the first approach, a household utility function represents utility of all its members; while, in game-theory based models, man and woman have two distinct utility functions and they maximize their own utility considering the fact that it would be a function of their spouse utility.

Only a handful of researches in this area have used structural dynamic models. Eckstein, Wolpin (1989) presented a dynamic model for explicating married women decision about participation under heterogeneous work experiences and wage differences. In each period, considering both wages and numbers of children, a women decides whether to participate in labor market or not. Participation in each period increases work experience that leads to higher future wage. It is worth noting that in this model husband always has a job, whether wife is working or not. For the purpose of estimation, they use the Maximum Likelihood Estimation

(MLE) method and find that the positive effect of work experience on wage outweighs its disutility, so women have a persistent tendency to participation when get older; in that women who participate at one age are more likely to participate at future ages. In addition, they indicated that both numbers of young children and husband's income substantially reduce participation rates while higher education has an intense positive impact on participation.

In a similar framework to ours, Eckstein, Lifshitz (2011) examine the effect of several factors on the growth of female labor force participation in United States. Their model considers both single and married female; that is, each single woman has an exogenous chance of marriage in each period, and each married women is likely to go through a divorce. Same as Eckstein, Wolpin (1989), in case of being married, husband always has a job with predetermined income. To estimate the model, they use the Simulated Method of Moments (SMM) approach and find that the main factor contributed to elevating female participation in United States is education; it can explain up to 33 percent of the participation increase. Rises in women's wage and narrowing gender wage gap can account for only 20 percent. Because decline in fertility and increase in divorce rate had negligible impact, about 40 percent of rises in participation rates remained unexplained.

Moreover, Eckstein, Lifshitz (2015) examine the explanatory power of different decision-making models within a household on female labor force participation. They compared three different approaches: (1) classical household where spouses play a Stackelberg leader game with husband as the leader, (2) modern household which involves a symmetric and simultaneous game and, (3) cooperative household where couples maximize their sum of utilities. Household type is defined by couple's age and their education. Results have shown that labor supply of men is similar across all models, but women's employment rate is lower in classical households than modern ones by about 12 percentage point, and is higher in cooperative households than modern ones by 4 percentage points. They interpret modern and cooperative households to be young, better educated, and characterized by a higher degree of assortative mating. The results suggest that increase in married women labor supply has happened probably due to change in the kind of household's decision-making. Based on this finding, we believe the classical framework would be a duly fit for our benchmark modeling.

III. Data

We use two separate surveys in this paper: (a) Labor Force Survey (LFS), and (b) Household Income and Expenditure Survey (HIES). Both surveys have been conducted by the Statistical Center of Iran. Both use rotation sampling, so we can exploit panel data from them. The panel data allows us to capture the dynamics of participation and its interaction with employment. The LFS is quarterly data collected between 2005 and 2015 with the sample of roughly 50 thousand households in each survey. This survey contains detailed questions on employment, job properties, unemployment and inactivity. The HEIS is an annual survey on household income and expenditure which records individual income resources, and household expenditures on a myriad of products.

We narrow our focus down to families where both husband and wife are between the ages of 25 and 55 with predetermined levels of education. We work with this sample because the education level is often finished before 25, and about 40 percent of women are married by this age. Furthermore, in younger ages many people are single or student, and because marriage and education are considered as exogenous in our model, including younger ones in data may cause problem of sample selection. For the same purpose of having a justifiable data, we choose to ignore observations older than 55. Actually, about 45 percent of people are retired after 55. Again, because we do not have retirement in our model this feature of data for old ages can cause a problem for the estimation. Table 1 shows that the panel sample we study is a good representative of the whole data in dimensions we are interested in.

Table 1: Comparison of different subsets of data

		No. Observations (million)		**Participation Rate (%)**		**Unemployment Rate (%)**	
		male	**female**	**male**	**female**	**male**	**female**
all data		3.06	3.07	52.2	12.4	9.5	15.8
aged 25-55		1.21	1.29	89.2	20.2	7.5	12.5
married		1.44	1.48	80.3	15.6	4.7	7.2
aged 25-55 and married		1.01	1.05	91.5	17.6	4.9	6.1
our sample	All	0.14	0.14	91.9	18.3	4.3	5.6
	Urban	0.06	0.06	93.1	22.8	4.3	2.3
	Rural	0.08	0.08	91.1	15.2	4.3	8.9

Note: Our sample consists of observation of 141,000 unique families in two consecutive years. In these families both husband and wife are living together and are between the ages of 25 and 55.
Data source: LFS, quarterly data, 2005-2015

Original data consist of 6 million observations collected between 2005 and 2015. We use only panel observations of married people between ages of 25 and 55, which reduces the number of our sample to about 140 thousand people. The participation of women in the all data is about 40 percent less than men, while this gap is widen after marriage to about 65 percent. Urban women have higher participation in the labor market than rural women, but still way lower than world average rates. The unemployment rate for women is higher than men in the cities, but in rural areas there is the opposite. Table 1 indicates that there are significant differences between participation behavior of urban and rural, which we aggregated in our benchmark model. For the sake of exposition, we will also run all the estimation separately by geography.

There are four factors in previous models of female labor participation rate which we are interested in explicating their effects in this paper: age, income, education, and numbers of children. Table 2 shows participation rates for male and female across these factors.

Table 2. Participation rate by age, gender, income

age	Male	Female	education	male	female
25-30	95.4	13.4	elementary	91.0	12.6
30-35	96.0	17.1	high Sch.	90.5	10.2
35-40	95.7	18.8	Bachelor	91.7	58.1
40-45	93.2	18.8	Master	94.9	76.4
45-50	88.0	17.6	Doctoral	99.6	91.3
50-55	76.5	16.1			
family income	**Male**	**Female**	**no. child**	**male**	**female**
Q1	89.9	10.8	0	84.1	18.2
Q2	98.9	17.5	1	89.4	17.3
Q3	100.0	55.2	2	91.5	17.2
Q4	100.0	42.3	3	90.9	16.4
Q5	100.0	25.0	4+	89.9	18.3

Note: LFS, 2005-2015; HIES, 2006-2012; married; aged 25-55

There are two channels that age can influence participation rates. The performance is likely to decrease by age, so participation declines as youngsters get older (Bound, et al. [1999]). On the other hand, knowledge and experience are accumulated throughout life, which pushes for positive relationship between age and participation (Altug, Miller [1997]). It is evident from Table 2 that women participation rates is the highest in their midlife; an alternative explanation is that women enter labor market later and leave it later too.

The second factor is income. Increase in a given person's income can shift participation through both substitution and income effect. Higher income increases opportunity cost of leisure (substitution effect); on the other hand, it decreases needed hours of working to obtain same amount of income (income effect). Moreover, family income shapes the interaction between couples (Shafer [2011]). For example, when husband earns higher income, there may be less tendency for the wife to work. Table 2 shows higher income is accompanied by higher participation rate of men; in contrast, women's apex of participation is middle range of family income. Obviously, we cannot separate mutual effect and personal effect only by exploring data, so we postpone deeper analysis until we discuss modelling.

Fertility plays an important role in determining married women participation too. If a woman decides to work, she has to pay higher cost for taking care of children, such as kindergarten's cost (Haan, Wrohlich [2011]). The more children a woman has, the higher cost of participation in labor market will be. On the other hand, if a woman chooses to participate, she can increase family's income. Table 2 depicts the average participation rate of women with different numbers of children. It seems that fertility doesn't have significant effect on female participation, but this observation can be due to role of other factors that we cannot extract their effect only by observing data.

Furthermore, as shown in Table 2 higher education is correlated with participation, either because education is required for jobs so people that want to participate target for higher education, or high skilled workers can obtain higher degrees with less efforts. Interestingly, Table 2 shows that unlike men, university education elevates female participation rate substantially.

Importantly, job market characteristics including job finding and destruction rate; play a pivotal role in people's participation decisions. Theoretically, in the presence of even small search costs, the lower the probability of finding a job is, people are less likely to participate in labor market. Particularly, for women that may need to enter and exit the labor market multiple times because of pregnancy, the opportunity cost of time spent to find a new job may be burdensome (Pries, Rogerson [2004]). In our sample, between men who are looking for a work in a given year, 65 percent will find a job in the subsequent year, 19 percent will remain unemployed, and 16 percent will leave labor market. These numbers for married women are respectively 11, 19 and 70 percent; indicating job finding rate for women in Iran is extremely low, and most of them stop searching in less than one year. Moreover, if people lose their jobs with a high probability and in a short span of time, the expected value of job for them will decrease, and with the awareness of high probability of job loss, people are less likely to pay any search costs for just a temporary job, so they will choose not to enter labor market. In the data, probability of job destruction in one year for a man is just 8 percent. Surprisingly, in Iran, job destruction rate for women is enormously high, about 42 percent. Interestingly, for observations with doctoral degree the likelihood to lose a job is about 0 and 2.5 percent for male and female, respectively. It seems that there is much less gender discrimination in firing for workers with graduate degrees. For calculating these rates, we excluded exogenous conditions in which women leave their job because of pregnancy. In addition, since our sample does not include marriage and divorce, none of these factors play role in job destruction rates reported above.

This explanation may shed light on the transition of female labor force participation over decades in developed countries. Many factors have probably contributed to the higher propensity to find a job for women and lower destruction rates for their jobs. Mainly, by the improvement in technology, workplace required less skills that male are superior, so more jobs are opened for women over decades. In this paper, by constructing a structural model we investigate the impact of differences in job market characteristics on the gap in participation between male and female.

IV. Model

In this paper, to examine the factors affecting participation rate of married women, structural model estimation method is used. Structural modeling has several merits relative to other methods which justifies its superiority (Reiss and Wolak [2007]):

- A structural model can be used to estimate unobservable economic parameters or behavioral responses from non-experimental data.
- Structural models can be used to simulate changes in equilibrium outcomes resulting from changes in the underlying economic environment (counterfactual).

– Structural models can be used to compare the predictive performance of two competing theories.

The model which employed in this paper is a dynamic discrete-choice model. In this, society is composed of a number of families in each of them there are a woman, a man, and several or no children. Husband and wife jointly decide about participation in the labor market. Only married people aged 25-55 are examined, and marriage, divorce and death does not occur.

The time period of the decision-making for each couple is 30 years; each interval is equivalent to one year. At the age of 25, we assume people have finished their education and it will not change.[2] The children of each family are divided into two categories: children who are aged 0-5, and the ones aged 6-24. This division is due to differences between two categories of children's care costs.

In this model similar to the literature, such as Eckstein, Lifshitz (2011) and Fehr, Ujhelyiova (2012), fertility and education are considered as exogenous parameters, mainly because this assumption results in a substantial simplification. Moreover, starting from the age of 25, many individuals have finished studying, and last but not least, several recent studies with endogenous schooling and fertility (such as Keane, Wolpin [1997,2006]; Cameron, Heckman [2001]; Ge [2011]) document that innate ability and family background are the main explanations for schooling level. Two levels of education for each individual are considered: (1) high education: people who have a university degree, and (2) low education: people with education less than university level.

The only Endogenous variables within model are participation of man (p^m) and woman (p^f). In case of participation, these variables equal one, otherwise they equal zero. Husband and wife adopt a decision in order to maximize family's utility in the current period plus expected utility for all the courses ahead (classical model of household decisions such as Van Soest [1995]).

Similar to Eckstein, Wolpin (1989), current utility is considered to be:

$$U_t\left(c_t, l_t^m, l_t^f, S^m, S^f, N_t^y, N_t^o\right) = c_t + \sum_{i=m,f} \left(\alpha_1{}^i + \alpha_2^i S^i\right) l_t^i + \sum_{j=y,o} f(N_t^j) \tag{1}$$

Where S^m, S^f represent respectively education level of man and woman, and c_t, N_t^y and N_t^o respectively represent consumption, numbers of children in 0-5 years group, and numbers of children in 6-24 years group in time t. l_t^m and l_t^f indicate man or woman employment in time t.

$f(N_t^j)$ is a function that captures utility gain from children for whole family. It is defined by:

$$f\left(N_t^j\right) = \gamma_0 N_t^j + \gamma_1 (N_t^j)^2$$

The following is budget constraint for the family:

$$\sum_{i=m,f} y_t^i l_t^i = c_t + \sum_{j=y,o} (b_1^j + b_2^j l_t^f) N_t^j \tag{2}$$

[2] We drop observations that the education changes after age 25 (only 1.6% of total observations)

Left side of this equation shows family income, and spending is in the right side. b_1^i represents the cost of a child in age group j if the mother is a housewife, and b_2^j is extra cost as a result of mother's employment.

Family income equals to sum of man's and woman's income if either of them has a job. The income of the couple is a function of their characteristics and a random element i.e. $y_t^m(S^m, A_t^m, N_t^y, N_t^o, \varepsilon_t^m)$ and $y_t^f(S^f, A_t^f, N_t^y, N_t^o, \varepsilon_t^f)$, where ε_t^i is a random value. For sake of numerical calculation, we assume that ε_t^i has only two values for each of the men and women and the Markov processes are stated by two distinct transition matrixes for men and women.

In each period, with the probability of $p_t^0(A_t^m, A_t^f, S^m, S^f, N_t^y, N_t^o)$, a child will be born, with the probability of $p_t^1(A_t^m, A_t^f, S^m, S^f, N_t^y, N_t^o)$, a child aged 0-5 grows to 6-24, and with the probability of $p_t^2(A_t^m, A_t^f, S^m, S^f, N_t^y, N_t^o)$, a child aged 6-24 will leave this family.

By Insertion of budget constraint into current utility function, it becomes:

$$U_t(l_t^m, l_t^f, y_t^m, y_t^f, S^m, S^f, N_t^y, N_t^o) = \sum_{i=m,f} y_t^i l_t^i - \sum_{j=y,o} (b_1^j + b_2^j l_t^f) N_t^j + \sum_{i=m,f} (\alpha_1{}^i + \alpha_2^i S^i) l_t^i + \sum_{j=y,o} f(N_t^j) \tag{3}$$

In each period, man and woman jointly make a decision about participation in the job market in order to maximize discounted expected utility of all the following periods. Therefore, the optimization problem is:

$$\max_{p_t^m=\{0,1\}, p_t^f=\{0,1\}} E_t \left[\sum_{k=0}^{T} \beta^k U(l_t^m, l_t^f, y_t^m, y_t^f, S^m, S^f, N_t^y, N_t^o) \right]$$

Participation in the labor market does not necessarily leads to employment. A non-employed person who decides to participate must pay a cost for searching job, which is called "search cost". This cost is different for men and women (s^m for men and s^f for women). In case of searching for a job, he or she will find a job with the probability of respectively $\lambda^m(S^m, A_t^m, N_t^y, N_t^o)$ and $\lambda^f(S^f, A_t^f, N_t^y, N_t^o)$.

An employed person who decides to participate faces the possibility of losing his job, and it varies by education. The "job destruction rate" is $\delta_i^m, i = l, h$ for men and $\delta_i^f, i = l, h$ for women, where i is an index which indicates education. $i = h$ represents high education and $i = l$ for low education.

Hence, timing of the events in any period can be expressed as follows:

- In the beginning of each period the numbers of children in each family and the wage of wife and husband are realized.
- Spouses decide about their participation in the labor market with regard to their status of ages, employment, wages and the number of children.

– At the end of the period, the employment status of people who have contributed will be realized.

Solution of the dynamic programming optimization problem is obtained by backward induction method. $V_t(l_{t-1}^m, l_{t-1}^f, \varepsilon_t^m, \varepsilon_t^f, \Omega_t)$ is discounted expected utility of all years ahead untill age 55 for given values of previous employment and the random part of the income of man and woman, and other relevant state variables (Ω_t). Vector of state variables in time t is $\Omega_t = \{S^m, S^f, A_t^m, A_t^f, N_t^y, N_t^o\}$. Value function is defined as:

$$V_t(l_{t-1}^m, l_{t-1}^f, \varepsilon_t^m, \varepsilon_t^f, \Omega_t) = \max \begin{Bmatrix} V_t^{1,1}(l_{t-1}^m, l_{t-1}^f, \varepsilon_t^m, \varepsilon_t^f, \Omega_t), V_t^{1,0}(l_{t-1}^m, l_{t-1}^f, \varepsilon_t^m, \Omega_t) \\ , V_t^{0,1}(l_{t-1}^m, l_{t-1}^f, \varepsilon_t^f, \Omega_t), V_t^{0,0}(l_{t-1}^m, l_{t-1}^f, \Omega_t) \end{Bmatrix} \quad (4)$$

Where $V_t^{1,1}(.)$, $V_t^{1,0}(.)$,$V_t^{0,1}(.)$ and $V_t^{0,0}(.)$ respectively represent maximum discounted expected utility for states of participation of both woman and man ($p_t^m = p_t^f = 1$), participation of only man ($p_t^m = 1, p_t^f = 0$), participation of only woman ($p_t^m = 0, p_t^f = 1$) and participation of none ($p_t^m = p_t^f = 0$).

If a person was employed in the previous period and chooses to participate in the labor market, he has the risk of losing his job. However, a person who was not employed in the previous period, must pay a search cost to participate, after that, he is likely to find a job with a probability explained before. The search cost differs by gender and education (s_h^m: search cost for man with university education, s_l^m: search cost for man with education lower that university level, and s_h^f s_l^f defined similarly). So $V_t^{1,1}(.)$ is as follows:

$$\begin{aligned} V_t^{1,1}&(l_{t-1}^m, l_{t-1}^f, \varepsilon_t^m, \varepsilon_t^f, \Omega_t) \\ &= (\lambda^m(1 - l_{t-1}^m) + (1 - \delta_i^m) l_{t-1}^m)\big(\lambda^f(1 - l_{t-1}^f) + (1 - \delta_i^f) l_{t-1}^f\big)(U_t(1,1,\Omega_t) \\ &+ \beta E_t[V_{t+1}(1,1,\Omega_{t+1})]) \\ &+ (\lambda^m(1 - l_{t-1}^m) + (1 - \delta_i^m) l_{t-1}^m)\big((1 - \lambda^f)(1 - l_{t-1}^f) + \delta_i^f l_{t-1}^f\big)(U_t(1,0,\Omega_t) \\ &+ \beta E_t[V_{t+1}(1,0,\Omega_{t+1})]) \\ &+ ((1 - \lambda^m)(1 - l_{t-1}^m) + \delta_i^m l_{t-1}^m)\big(\lambda^f(1 - l_{t-1}^f) + (1 - \delta_i^f) l_{t-1}^f\big)(U_t(0,1,\Omega_t) \\ &+ \beta E_t[V_{t+1}(0,1,\Omega_{t+1})]) \\ &+ ((1 - \lambda^m)(1 - l_{t-1}^m) + \delta_i^m l_{t-1}^m)\big((1 - \lambda^f)(1 - l_{t-1}^f) + \delta_i^f\ l_{t-1}^f\big)(U_t(0,0,\Omega_t) \\ &+ \beta E_t[V_{t+1}(0,0,\Omega_{t+1})]) - s_i^m(1 - l_t^m) - s_i^f(1 - l_t^f), \quad i = l, h \end{aligned}$$

$V_t^{1,0}(.)$,$V_t^{0,1}(.)$ and $V_t^{0,0}(.)$ similarly can be obtained. Therefore, participation choice of every men and women according to their state variables will be determined.

V. Estimation

Estimation of models parameters is separated into two steps; in the first step, we determine parameters that can be directly estimated using state variables and agent choices; then, we estimate the left parameters using Simulated Method of Moments (SMM) by solving the structural model. The main advantage of this technique is its computational simplicity.

However, it has an important limitation. It is asymptotically inefficient because its asymptotic variance depends on the variance of parameters estimated in the first stage.

A. First Stage: Reduced Form Parameters

Items which are estimated directly are income functions (y^m and y^f), probability functions of finding jobs (λ^m and λ^f), job destruction rate ($\delta_h^m, \delta_l^m, \delta_h^f$ and δ_l^f) and probability of change in numbers of children in each age. Discount factor is assumed to be 0.985 for its seasonal value, so the yearly value of β in our model will be 0.94.

Each husband's and wife's income in time t considered as a function of his/her characteristics in model in that time; these items are age, education and number of children in each age group. These functions estimated by employing ordinary least square (OLS) method using HIES data. Equation (5) and (6) demonstrate income function for woman and man respectively.

$$\begin{aligned} y^m = \underset{(.144)}{16.25} + \underset{(.0120)}{.585}\ S^m + \underset{(.00756)}{.0626}\ A^m - \underset{(.0000940)}{.000665}\ (A^m)^2 \\ - \underset{(.00837)}{.0437}\ N^y - \underset{(.00767)}{.0206}\ N^o + \varepsilon^m \end{aligned} \tag{5}$$

$$n = 21307, R^2 = .092$$

$$\begin{aligned} y^f = \underset{(.811)}{13.17} + \underset{(.0495)}{1.378}\ S^f + \underset{(.0435)}{.148}\ A^f - \underset{(.000557)}{.00145}\ \left(A^f\right)^2 \\ + \underset{(.0464)}{.0431}\ N^y - \underset{(.0401)}{.0682}\ N^o + \varepsilon^f \end{aligned} \tag{6}$$

$$n = 1433, R^2 = .390$$

Equation (7) and (8), demonstrate the evolution of $\varepsilon^m, \varepsilon^f$ with the higher persistency for woman, while being more volatile.

$$\varepsilon_t^m = \underset{(.00542)}{-.0328} + \underset{(.0128)}{.522}\ \varepsilon_{t-1}^m + \xi_t^m \tag{7}$$

$$n = 10600, R^2 = .289$$

$$\varepsilon_t^f = \underset{(.0228)}{.0230} + \underset{(.0324)}{.664}\ \varepsilon_{t-1}^f + \xi_t^f \tag{8}$$

$$n = 666, R^2 = .518$$

We consider two possible states for ε, and discretize them as introduced by Adda, Cooper (2003). Results of this method give us two states with a transition matrix for random part of each income function.

Moreover, job finding functions are estimated directly from data using the logistic regression. Equation (9) and (10) shows the estimation results for men and women respectively.

$$\lambda^m = 1/(1 + \exp(-(\underset{(.197)}{1.965} - \underset{(.124)}{.442}\ S^m - \underset{(.00503)}{.0381}\ A^m + \underset{(.0510)}{.0969}\ N^y + \underset{(.0430)}{.145}\ N^o)) \tag{9}$$

$$\lambda^f = 1/(1 + \exp(-(\underset{(.541)}{-2.243} + \underset{(.185)}{.00933}\, S^f + \underset{(.0169)}{.00590}\ A^f - \underset{(.143)}{.0691}\ N^y + \underset{(.136)}{.113}\ N^o)) \tag{10}$$

We also estimate a function for the entering and leaving two categories (0-5 and 6-25 years) for a child. The possibility of entering a child into 0-5 category is equivalent to the probability of a new baby. These probabilities are estimated by logistic regression and presented in the Appendix A.

B. Structural Parameters

We use Simulated Method of Moments which has first introduced by McFadden (1989) and, Pakes and Pollard (1989) to estimate the structural parameters. Moments are quantitative measures of data points that explain their shape. In this method, optimal parameters are the ones which minimize the distance between moments derived from model to data moments. Therefore, objective function will be:

$$(m_S - m_D).\mathbf{w}\,(m_S - m_D)$$

Where m_S and m_D respectively represent vectors of simulated and data moments, and **w** is a positive weight matrix. This matrix is required when some moments are more sensitive to some parameters than other ones. Weight can be obtained by reversing variance-covariance matrix of data moments (Gourieroux et al., 1993). The variance-covariance matrix is constructed by the bootstrap method from data.

Twenty moments were used for estimation of 14 parameters (6 utility parameters, 4 budget constrain parameters, and 4 search costs); these moments are men's and women's rate of participation for all, high and low educated, without children, with 0-5 children, with 6-24 children, and some combination of these states. To perform optimization we use Particle Swarm Optimization in MATLAB software. In this algorithm, at first, some candidates are considered for answer (particles). These particles are moving in the search space; their direction is toward the best detected point, and their speed depends on their distance to that point. In this paper, 50 particles and 500 iteration were considered for optimization.

VI. Results and Counterfactuals

Table 3 demonstrates results of structural estimation. Estimated parameters indicate that employment creates negative utility for both low-educated men and women. Education decreases men tendency to work, in contrast to high-educated women who gain high utility from working. Expectedly, the utility from numbers of children is quadratic, and children with age less than 6 cost more than older ages. Interestingly, the cost of a child would be almost double when the mother is employed. Search cost is higher for educated people, probably because they seek high-wage jobs related to their profession.

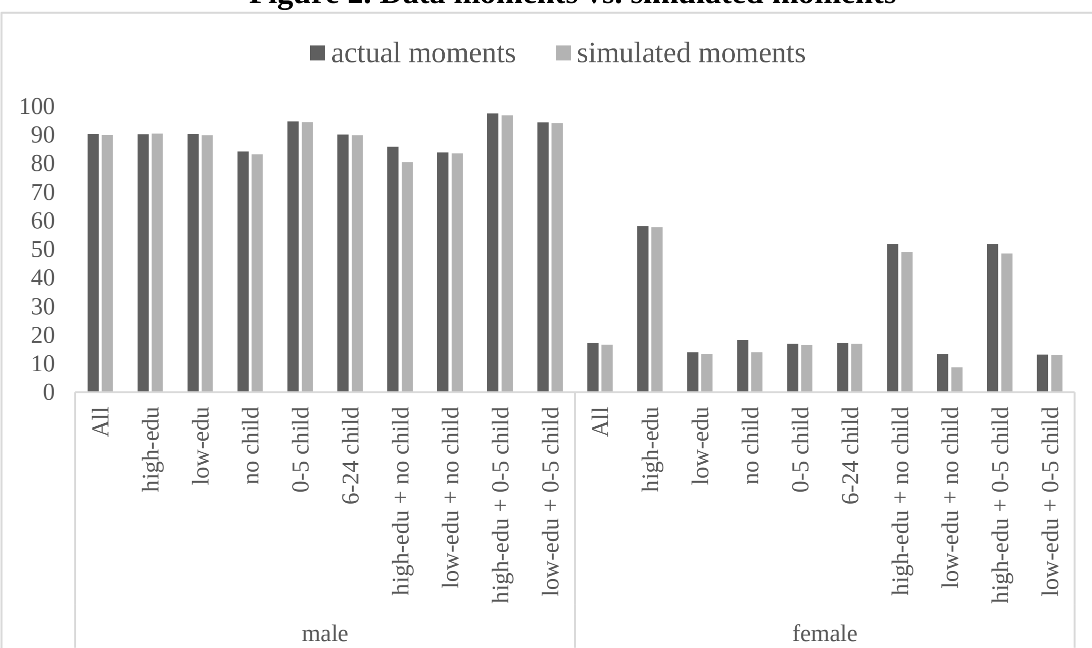
Table 3. Structural Parameters (Utility, Budget Constrain, and Market Characteristics)

Utility				Budget Constraint		Search	
parameter	value	parameter	value	parameter	value	parameter	value
α_1^m	-0.01 (0.00000003)	γ_0	3.18 (0.0010)	b_1^1	2.58 (0.0014)	s_h^m	3.01 (0.0037)
α_2^m	-0.48 (0.000079)	γ_1	-1.94 (0.00023)	b_2^1	2.29 (0.0017)	s_l^m	2.19 (0.00027)
α_1^f	-1.01 (0.00048)			b_1^2	1.74 (0.00021)	s_h^f	3.29 (0.0068)
α_2^f	3.02 (0.00030)			b_2^2	1.48 (0.00023)	s_l^f	1.55 (0.00045)

Note: Standard errors are in parenthesis. Estimation bases on Simulated Method of Moments, with 20 moments for 14 parameters. The algorithm used for the estimation is Particle Swarm Optimization with 50 particles and 500 iterations. The optimal weight is computed using bootstrap method on actual data.

To verify the accuracy of estimated parameters, simulated moments calculated by optimal parameters are compared with actual data moments. Figure 2 shows these two sets of moments and indicate that the simulated moments are precisely fitted with the actual ones.

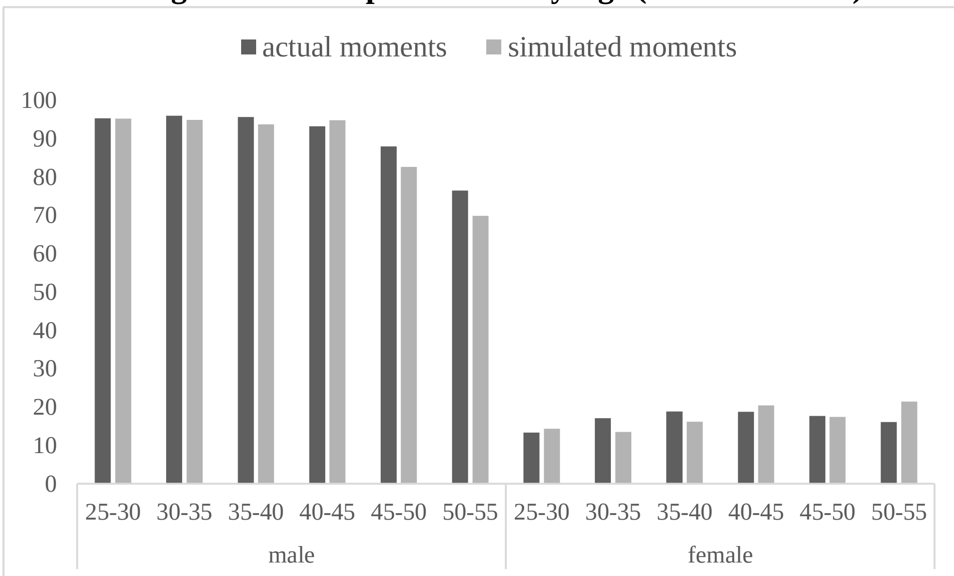
Figure 2. Data moments vs. simulated moments



To validate estimated parameters, we should compare out-of-estimation moments from model (moments that we don't use for the estimation) to their actual counterparts. Importantly, we only use cross-sectional moments to estimate our parameters, i.e. there are no age-specific moment in Figure 2. Therefore, this would be a strict test to check the fitness of dynamic moments in data and model. To do so, we compare age specific participation rates of men and women in Figure 3 and similar moments for different levels of education and numbers of children in Appendix B.

Interestingly, the prediction of the model almost accurately coincides with the participation rates for various ages of male and female.

Figure 3. Participation Rate by Age (Model vs. Data)



The main purpose of this research is determining how much potentials factors play role in lower participation rate of married women with a particular focus on labor market characteristics. For this purpose, a number of counterfactual tests are done by altering one parameter at a time for female to the same amount as men; in order to find out how much women participation would change if the circumstances were same for both genders. These experiments are changing parameters related to job security, job finding function, income function and search costs. Results are shown by Table 4.

Table 4. Female Participation Rate for Counterfactuals

	all	high-education	low-education	no child	only 0-5 aged children
Data	17.28	58.11	13.92	18.21	16.93
Model	16.65	57.61	13.28	13.95	16.46
Job security	18.49	73.51	13.95	13.84	20.07
Job finding	20.91	99.62	14.42	20.24	21.61
Wage discrimination	18.24	57.39	15.01	14.70	16.96
High educated search cost	17.77	58.84	14.38	14.60	16.14
Low educated search cost	17.52	57.24	14.24	14.23	16.13
Education	16.45	15.12	14.22	57.63	17.53
No Labor Market Discrimination	28.75	19.05	19.32	99.75	25.45

Note: No labor market discrimination is when all search costs, job finding, job security, and wage equations for women are the same as male.

The first row of Table 4 shows the participation rates of all female, educated and low-educated women, husband with no child, and mothers with child not older than age five. The second row reports the same moments simulated by our benchmark model in which its parameters reported in Table 3. As mentioned above, our estimates provide a precise fit to the actual moments. Other rows report similar moments but for each counterfactual. For example, the fifth row show the moments when women are paid the same wage as male. Notice that all counterfactuals but education are related to labor market characteristics.

Results indicate that eliminating gender discrimination in job finding between male and female has a significant effect on lowering participation rate of married women. If this rate rises to the same level as men, the married female participation rate would increase by 4.3 percentage points. Interestingly, roughly all increase in participation rate comes from higher participation rates of educated female. We can conclude that the low probability of job finding deter educated women from participating in labor market. Moreover, the results indicate that the job finding is much less important for low educated women. However, for women with no-college education the wage discrimination contribute the most in their low participation rate. If they are paid the same amount as male with no-college education, their participation rate will increase by 1.1 percentage point.

Job security and wage discrimination have almost same amount of efficacy on declining participation. Changing each one of these parameters to men's values would increase total participation rate of women by about 2 percentage points. Interestingly, mothers with a child younger than five are very concern with their job security, and if their job security would be as large as male they participation rate increase by 3.1 percentage point. Search cost plays least important role; in estimated parameters there was not so much difference between men and women. If one eliminates all labor market discrimination, so male and female would have similar wage structure, the same labor search cost, the same propensity to hire and fire, then the female labor force participation increase to about 29 percent, that is much lower than 90% of male participation rate. The main conclusion of our experiment is that no market conditions in Iran can explain the low participation rates of women. Therefore, probably the culture and other social economic factors that are outside our model can explain the low participation rates of women in Iran.

Living conditions and culture is different for rural and urban areas. As we have seen in the data section, participation and unemployment rates are significantly different for them. Thus, we should estimate our model and run counterfactuals separately for both groups. Table 5 demonstrates result of the counterfactuals.

Table 5. Counterfactuals for Urban and Rural

	participation rate of female (married; aged 25-55)									
	all		higher education		lower education		no child		only 0-5 aged children	
	urban	rural	urban	rural	urban	rural	urban	rural	urban	rural
Data	14.08	21.99	57.96	49.67	8.17	21.58	15.80	16.65	13.68	18.70
Model	15.73	23.09	62.40	64.89	9.45	22.47	14.74	16.58	13.06	21.12
Job security	16.72	22.34	82.66	80.57	7.85	21.48	23.05	19.24	16.48	19.54
Job finding	15.20	22.71	58.32	48.38	9.40	22.33	16.27	20.35	13.93	19.54
Wage discrimination	13.80	21.99	56.59	45.01	8.05	21.65	15.27	18.27	13.44	19.26
High educated search cost	14.03	22.02	57.55	48.89	8.17	21.62	15.39	18.04	13.55	19.29
Low educated search cost	14.31	22.09	58.03	49.64	8.43	21.69	15.70	18.79	13.46	19.41
Education	21.49	60.52	85.59	78.16	12.87	60.26	23.72	16.98	17.85	56.38
No Discrimination	14.08	21.99	57.96	49.67	8.17	21.58	15.80	16.65	13.68	18.70

Note: No labor market discrimination is when all search costs, job finding, job security, and wage equations for women are the same as male.

Generally, participation rate of women in rural areas is more than urban areas. Specifically, in urban areas, lower share of non-college educated women participate; women with lower education participate less than 150 percent of urban women. In case of the participation, job security and job finding have the most important role in rural and urban areas respectively. In both areas, labor market discrimination affects educated women more; increase in participation rate of whole women is due to increase in participation of college-educated ones. Unlike rural areas, search cost is lower for women than men in urban areas, so changing women's search cost to men's values decreases their participation.

VII. Conclusion

In this paper, we estimate a structural dynamic discrete-choice model about participation decision in a household using simulated method of moments. We consider common factors affecting participation that have been reviewed in literature in our model; age, education, income and fertility. Moreover, we capture the effect of discrimination in labor market other than wage on participation. We do this by including risk of finding and losing a job, and search cost in our model.

Results of estimation indicate that risk of finding job has biggest effect on lowering participation rate of married woman. On second level, job destruction and wage discrimination lower female participation rate, and search costs have negligible effect. If all discrimination disappears, female participation rate will increase by 12 percent point to almost 30 percent. This result indicates that other factors outside our model have more effect on labor force participation of married woman.

To further investigate effect of labor market discrimination on female labor force participation, other kind of families with game-theory approach for decision-making in a household should be examined. A variable which we excluded from model because of extensive complexity it results is job experience. Considering its effect on wage and utility from working can provide more detailed results.

VIII. Appendix A

Table A1. Child probability regressions results using the logit method

VARIABLES	p^0	p^1	p^2
A^m	-0.0609***	0.0164***	0.0212***
	(0.00376)	(0.00255)	(0.00252)
A^f	-0.113***	-0.000926	0.00170
	(0.00408)	(0.00268)	(0.00265)
S^m	0.0934**	-0.00275	-9.31e-05
	(0.0458)	(0.0364)	(0.0360)
S^f	0.0680	-0.253***	-0.265***
	(0.0515)	(0.0445)	(0.0441)
L^m	0.0133	0.121***	0.119***
	(0.0488)	(0.0355)	(0.0350)
L^f	0.0781**	0.253***	0.258***
	(0.0384)	(0.0279)	(0.0276)
N^y	-0.742***	2.103***	2.178***
	(0.0250)	(0.0177)	(0.0178)
N^o	-0.227***	-0.0633***	-0.0674***
	(0.0217)	(0.0153)	(0.0151)
Constant	3.538***	-4.637***	-4.918***
	(0.115)	(0.0905)	(0.0899)
Observations	141,304	141,304	141,304

IX. Appendix B

Figure B1. Validity test: participation rate of high-educated people by age (married; aged 25-55)

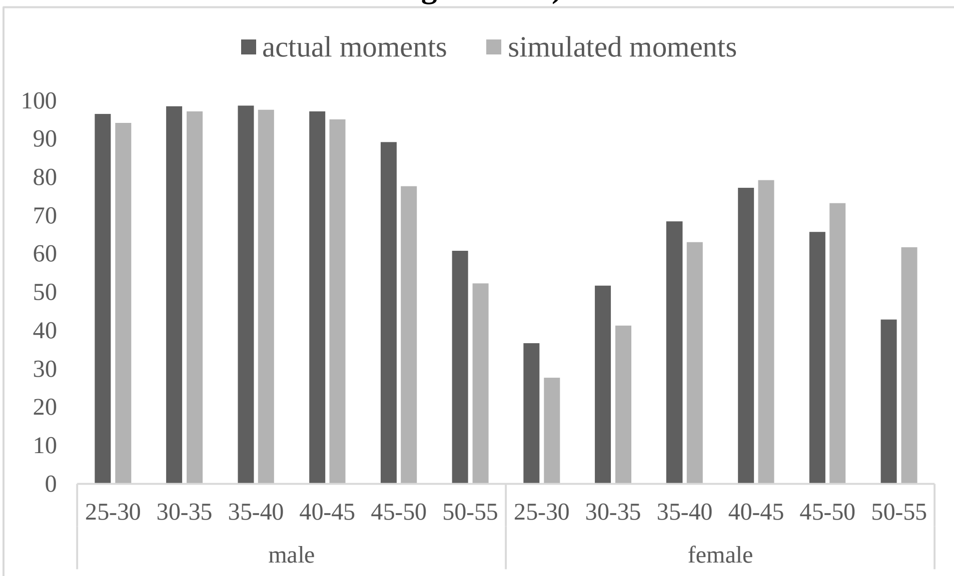


Figure B2. Validity test: participation rate of low-educated people by age (married; aged 25-55)

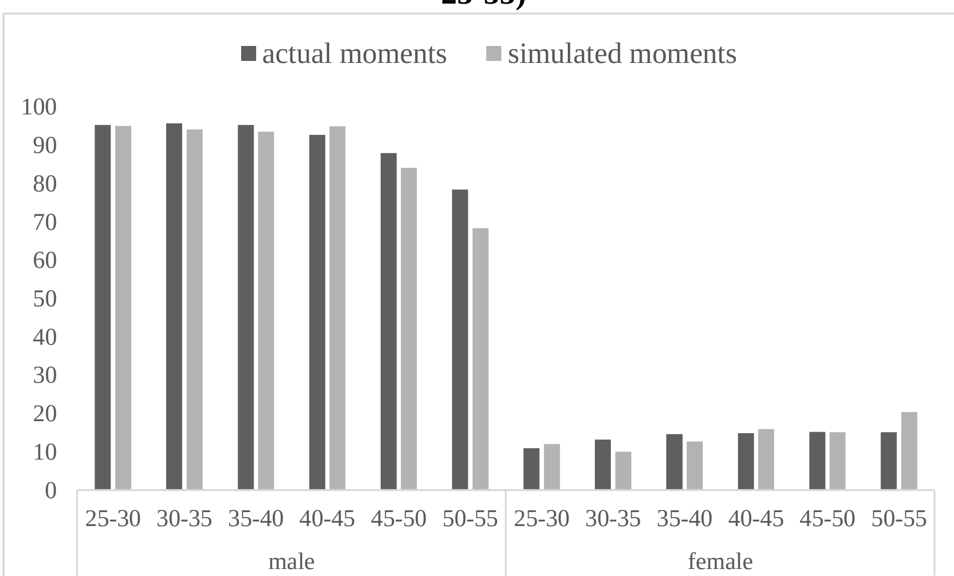
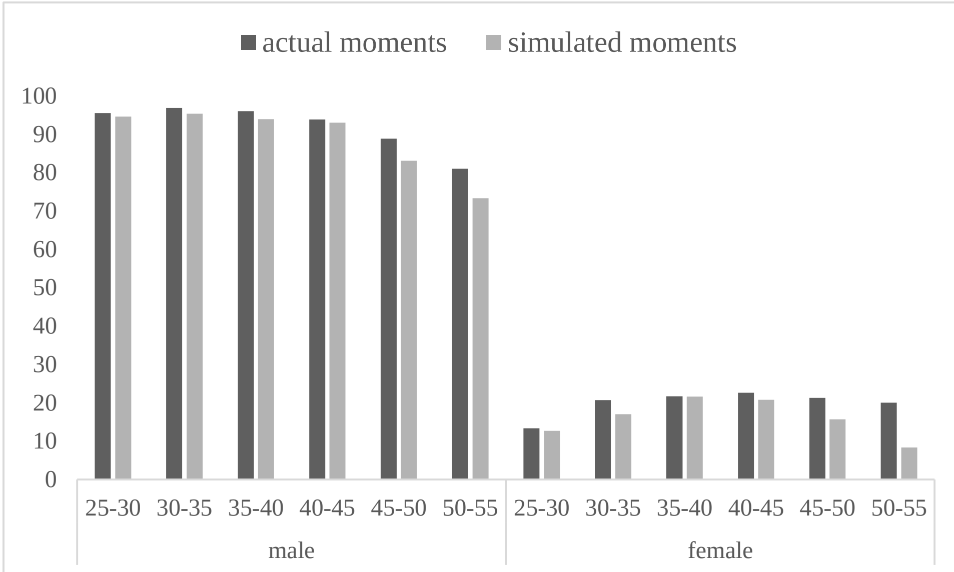


Figure B3. Validity test: participation rate of people with no child by age (married; aged 25-55)



References:

Adda, Jerome, and Russell W. Cooper. *Dynamic economics: quantitative methods and applications*. MIT press, 2003.

Altuğ, Sumru, and Robert A. Miller. "The effect of work experience on female wages and labour supply." *The Review of Economic Studies* 65.1 (1998): 45-85.

Bound, John, et al. "The dynamic effects of health on the labor force transitions of older workers." *Labour Economics* 6.2 (1999): 179-202.

Cameron, Stephen V., and James J. Heckman. "The dynamics of educational attainment for black, hispanic, and white males." *Journal of political Economy*109.3 (2001): 455-499.

Eckstein, Zvi, and Kenneth I. Wolpin. "Dynamic labour force participation of married women and endogenous work experience." *The Review of Economic Studies* 56.3 (1989): 375-390.

Eckstein, Zvi, and Osnat Lifshitz. "Dynamic female labor supply."*Econometrica* 79.6 (2011): 1675-1726.

Eckstein, Zvi, and Osnat Lifshitz. "Household Interaction and the Labor Supply of Married Women." *International Economic Review* 56.2 (2015): 427-455.

Fehr, Hans, and Daniela Ujhelyiova. "Fertility, Female Labor Supply, and Family Policy." *German Economic Review* 14.2 (2013): 138-165.

Fernández, Raquel. "Cultural change as learning: The evolution of female labor force participation over a century." *The American Economic Review* 103.1 (2013): 472-500.

Ge, Suqin. "Women's college decisions: how much does marriage matter?."*Journal of Labor Economics* 29.4 (2011): 773-818.

Haan, Peter, and Katharina Wrohlich. "Can child care policy encourage employment and fertility?: Evidence from a structural model." *Labour Economics* 18.4 (2011): 498-512.

Keane, Michael P., and Kenneth I. Wolpin. "The career decisions of young men." *Journal of political Economy* 105.3 (1997): 473-522.

Keane, Michael P., and Kenneth I. Wolpin. "The role of labor and marriage markets, preference heterogeneity, and the welfare system in the life cycle decisions of black, hispanic, and white women." *International Economic Review* 51.3 (2010): 851-892.

McFadden, Daniel. "A method of simulated moments for estimation of discrete response models without numerical integration." *Econometrica: Journal of the Econometric Society* (1989): 995-1026.

Pakes, Ariel, and David Pollard. "Simulation and the asymptotics of optimization estimators." *Econometrica: Journal of the Econometric Society*(1989): 1027-1057.

Pries, Michael J., and Richard Rogerson. *Search frictions and labor market participation*. mimeo, Maryland University, 2004.

Reiss, Peter C., and Frank A. Wolak. "Structural econometric modeling: Rationales and examples from industrial organization." *Handbook of econometrics* 6 (2007): 4277-4415.

Shafer, Emily Fitzgibbons. "Wives' Relative Wages, Husbands' Paid Work Hours, and Wives' Labor-Force Exit." *Journal of Marriage and Family* 73.1 (2011): 250-263.

Van Soest, Arthur. "Structural models of family labor supply: a discrete choice approach." *Journal of human Resources* (1995): 63-88.