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Heterogeneity in Returns to Work Experience: A Dynamic Model of Female Labor Force Participation*

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Abstract

This paper provides structural estimates of heterogeneous returns to work experience for Japanese married women. A dynamic model of labor force participation is used to account for dynamic self-selection into employment. Heterogeneity is incorporated into the model in a way that allows for the multidimensional skill heterogeneity in employment and home production and for the individual-specific slope and curvature of experience effect on earnings. The structural estimates and their comparison to the reduced-form estimates highlight the importance of dynamic self-selection into employment and heterogeneity in returns to work experience.

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1 Introduction

How well can the structural approach provide reasonable parameter estimates? The structural approach has the advantages of interpreting estimated parameters in line with an economic-theoretical model and of conducting counterfactual simulation analyses. However, a concern remains about the credibility of estimation results. Indeed, early skepticism has escalated into heated discussions about methodology.[1] This paper attempts to assess the empirical performance of the structural approach in comparison to the reduced-form approach, as only a few studies have conducted systematic comparisons of parameter estimates between the two approaches.

Our analysis of this paper mainly focuses on returns to work experience. Specifically, the parameters of interest are the coefficients for the number of years of actual work experience and its square term in a standard Mincer-type earnings equation. In fact, it is of great interest to measure the returns to general labor market experience for several reasons. First, the earnings growth is important to understanding an optimal way of designing an active labor market program, as noted by Dustmann and Meghir (2005). The benefit of employment hinges on the magnitude of experience effect on earnings. Second, the estimated rate of return to experience may be used to infer the cost of non-employment in the long run as a consequence of policy distortion. Third, the rate of return to experience is a key parameter in explaining aggregate fluctuations in the labor supply, as shown by Olivetti (2005).

However, there are two econometric problems in estimating the earnings equation consistently. First, earnings data are observable only from surveys of the employed. Second, work experience may be correlated with unobserved productivity such as innate ability in a broad sense. The former problem may yield a sample-selection bias, whereas the latter may yield an omitted-variable bias. Those who have higher unobserved productivity are more likely to participate in the labor market and accumulate work experience. Thus, the ordinary least squares (OLS) estimate of the returns to experience is presumably biased upward in both cases.

One standard solution is to employ the sample-selection correction model developed by Heckman (1974, 1979). However, the sample-selection correction method tends to make little difference to wage-equation estimates, as pointed out by Moffitt (1999). Typically, results of this sort are attributed to unsuitable exclusion restrictions and a lack of identification power. Indeed, this interpretation points to the need to search for a valid instrumental variable. However, such results only suggest the failure of a static version of sample-selection correction.

The self-selection problem is intrinsically dynamic. The missing-value problem with earnings arises from the selection into employment at the present, and the omitted-variable problem with experience arises

[1] See Keane (2006) for a recent survey.

from the selection into employment in the past. The two econometric problems are boiled down to one decision-making problem in a dynamic model of labor force participation. From a dynamic perspective, labor force participation can increase not only current earnings but also future earnings through human capital accumulation. As a consequence of learning-by-doing, current participation in the labor market enhances wages offered in the future (Weiss and Gronau, 1981). Ideally, the empirical model should be consistent with such a decision-making problem in which an agent takes into account the experience effect of current labor supply on future earnings. In this paper, the dynamic structural model à la Eckstein and Wolpin (1989) is used to tackle the econometric problems stemming from self-selection into employment over the life cycle. The structural approach has the advantage of correcting for the dynamic self-selection bias, although this point has not been emphasized in the literature. The sample-selection correction model à la Heckman (1974, 1979) can be interpreted as a linear approximation to the dynamic model à la Eckstein and Wolpin (1989).

The contributions of this paper are twofold. First, this paper contributes to the assessment of dynamic structural models. Previous studies such as that by Keane and Wolpin (1997) examined the model's fit in terms of choice probabilities relative to a linearly approximated reduced-form model. However, few studies directly compare estimated parameters between the structural and reduced-form approaches.[2] By doing so, this paper highlights the importance of dynamic self-selection into employment.

Second, this paper provides structural estimates of heterogeneous earnings returns to work experience for married women. Although a number of studies have investigated a Mincer-type earnings equation, only a few papers have considered unobserved heterogeneity in the slope and curvature of experience-earnings profiles.[3] Moreover, those studies focused on young men. However, the role of heterogeneity appears also to be important for married women, especially in a country such as Japan where female labor force participation substantially varies over the life cycle. The model presented here incorporates heterogeneity in the returns to experience. Moreover, it allows for comparative advantage in terms of productivity in employment and home production. In this paper, Heckman and Singer's (1984) approach is used to account for unobserved heterogeneity along the lines of Keane and Wolpin (1989). The estimated returns to experience are indeed heterogeneous and range from zero to 0.055. Moreover, heterogeneity in the returns to experience is consistently illustrated by the structural and reduced-form approaches. Skilled workers have a concave experience-earnings profile, but unskilled workers do not.

This paper proceeds as follows. The next section describes the data used in the analysis. Section 3 lays out the reduced-form approach and provides the benchmark results. Section 4 describes the dynamic

[2] Gould (2007) provided an exception to this by analyzing the difference in the estimated urban wage premium between the structural approach and the fixed-effects approach. The seminal work by Eckstein and Wolpin (1989) also takes fixed effects into consideration.

[3] Gould (2007) used a version of the dynamic discrete-choice model and incorporates unobserved heterogeneity. Meghir and Dustmann (2005) used a control function approach to do so.

model of labor force participation. Section 5 discusses issues about estimation and identification. Section 6 provides structural estimates of the dynamic labor force participation model. The final section presents our conclusions.

2 Data

The data used in the analysis are taken from 10 waves of the Japanese Panel Survey of Consumers (JPSC) from 1993 to 2002. The JPSC has surveyed 1,500 women aged 24 to 34 since 1993 and 500 women aged 24 to 29 since 1997. At the outset of the present project, the 10th wave provided the latest available data. The estimation sample contains 4,464 observations from the data on 801 married women aged 33 or older.[4] The analysis in the present study focuses on married women in their mid-30s and older to avoid modeling marriage and fertility.[5]

The sample includes two employment status groups: workers and homemakers.[6] Based on the questionnaire item on employment status, annual earnings are calculated by monthly salary multiplied by 15 for monthly-paid workers, and by weekly/daily/hourly salary multiplied by weeks/days/hours of work a year for weekly/daily/hourly-paid workers.[7] Years of actual work experience and the current marriage duration can be calculated retrospectively from questions on work and marriage history answered at the starting year of the survey.

Table 1 reports the means and standard deviations of variables used in the analysis. The employment rate is 52% in the sample, and the sample mean of years of experience is 10.25. Table 2 displays the transition of employment at the ages of 35 and 40, for ease of reference. As is usual with transitions of this sort, the employment status is persistent. However, the transition into employment is more frequently observed than that into non-employment.

[4] The raw sample contains 14,793 observations from 2,000 women. The estimation sample is selected for the subsequent analysis according to the following criteria. First, 4,009 observations are excluded as they are from single women. Second, 5,022 observations are excluded from women 32 years old or younger. Third, 989 observations are excluded that have missing values for education, experience, employment status, earnings, and residential area. Fourth, one observation is excluded that reports employment but with reported earnings of zero. Fifth, nine observations are excluded who are single and were not employed in the previous year. Sixth, 75 observations are excluded who are 42 years old due to a small cell size. Seventh, 23 observations are excluded whose work experiences were measured incorrectly. Under the current compulsory education system, age minus years of work experience has to be less than 15. Finally, 208 observations are excluded who were not consecutively observed for two years.

[5] A large part of observations will be lost when the sample is restricted to married women aged 38 or older.

[6] Workers include full-time, part-time, and temporary workers.

[7] For our analysis, this is a plausible way of calculating a measure of earnings in terms of consistent responses between employment status and earnings. The scale-up parameter is the average ratio of monthly earnings to yearly earnings calculated from other questionnaire items on previous annual earnings. In other words, this calculation takes into account bonus payments typically paid for monthly-paid workers twice a year. However, if the earnings data are created by previous annual earnings, one-year observations for each individual cannot be used.

3 Reduced-Form Approaches

3.1 Empirical Models

3.1.1 Ordinary Least Squares Model

The main equation of interest is a standard Mincer-type earnings equation for married women:

$$\ln y = \gamma_0 + \gamma_1 s + \gamma_2 x + \gamma_3 x^2 + v_1, \tag{1}$$

where s is the number of years of schooling, x is the number of years of actual work experience accumulated until the last year, v_1 is the error term.[8] The indexes for individual, time, and age are all omitted for notational simplicity in this section. The rate of return to experience is expressed as the marginal effect of experience: $\partial \ln y / \partial x = \gamma_2 + 2\gamma_3 \overline{x}$, where $\overline{x}$ is the sample mean of experience. For the OLS estimator to be consistent, the error term must be mean independent of regressors. When the error term follows the normal distribution with mean zero and some unknown variance, the OLS estimator is equivalent to the maximum likelihood estimator for a set of parameters $(\gamma_0, \gamma_1, \gamma_2, \gamma_3)$.

The observed (reported) earnings may be measured with errors:

$$\ln y^r = \ln y + v_2. \tag{2}$$

However, the OLS estimator is still consistent if the measurement error v_2 is uncorrelated with the regressors.

3.1.2 Sample-selection Correction Model

The earnings data are available only from the survey of the employed whose offered wages are higher than reservation wages. In such a case, the inverse Mills ratio appears in the right-hand side of the estimating equation (1), as shown by Heckman (1979). The selection equation for employment is necessary to construct the inverse Mills ratio. The labor supply decision may be described by the latent variable model:

$$p^* = \delta_{10} + \delta_{11}\widehat{n_1} + \delta_{12}\widehat{n_2} + \delta_{13}\widehat{y_h} + \delta_{14}t + \delta_{15}s + \delta_{16}x + e_1, \qquad p = 1\left[p^* > 0\right], \tag{3}$$

where n_1 is the number of children under the age of 7 before starting compulsory education, n_2 is the number of children aged 7 to 15 before completing compulsory education, y_h is the husband's earnings, t is age, p is the indicator variable for whether or not the subject is employed, and $1\left[\cdot\right]$ is the indicator function that equals one if the statement is true and zero otherwise. The set of excluded instruments $(\widehat{n_1}, \widehat{n_2}, \widehat{y_h}, t)$ includes the husband's earnings and the number of children under the age of 7 and aged 7 to 15 predicted

[8] Higher-order polynomials of schooling and experience were not statistically significant.

from the linear regressions described later.

In the sample-selection correction model, the identification can be achieved by either a distributional assumption on the error terms or exclusion restrictions concerning the set of instrumental variables. Under the assumption that the error terms v_1 and e_1 are assumed to have a joint normal distribution, the rate of return to experience can be consistently estimated by running the OLS regression of equation (1) after the inverse Mills ratio is incorporated as an additional regressor. The earnings equation (1) and the labor force participation equation (3) can also be jointly estimated by the maximum likelihood method, but the results obtained were similar between the two-step estimation method and the maximum likelihood method.

3.1.3 Instrumental Variable Model

The number of years of experience x is potentially correlated with the unobserved productivity contained in v_1, even after the selection correction term is incorporated. One standard solution is to apply the instrumental variable (IV) method. The reduced-form equations for employment and for experience and its square are necessary for this. The labor supply decision and the accumulation of work experience may be described as follows.

$$
\begin{aligned}
p^* &= \theta_{20} + \theta_{21}\widehat{n_1} + \theta_{22}\widehat{n_2} + \theta_{23}\widehat{y_h} + \theta_{24}t + \theta_{25}s + e_2, \qquad p = 1\left[p^* > 0\right], && (4) \\
x &= \theta_{30} + \theta_{31}\widehat{n} + \theta_{32}\widehat{y_h} + \theta_{33}t + \theta_{34}t^2 + \theta_{35}s + e_3, && (5) \\
x^2 &= \theta_{40} + \theta_{41}\widehat{n} + \theta_{42}\widehat{y_h} + \theta_{43}t + \theta_{44}t^2 + \theta_{45}s + e_4, && (6)
\end{aligned}
$$

where n is the total number of children, and e_1, e_2, and e_3 are the error terms. The error terms v_1 and e_2 are assumed to have a joint normal distribution.

Given that the rank condition holds, the main identification assumption here is exclusion restrictions concerning the set of excluded instruments $\left(\widehat{n_1}, \widehat{n_2}, \widehat{n}, \widehat{y_h}, t, t^2\right)$. The IV estimator is consistent under the assumptions. However, if the returns to experience are heterogeneous, the probability limit of the IV estimator will generally depend on the choice of instruments (Heckman, 1997).

3.1.4 Fixed-Effects Model

Another standard solution is to use a fixed-effects (FE) model:

$$
\ln y = \gamma_2 x + \gamma_3 x^2 + a + u_1, \tag{7}
$$

where a is time-invariant individual heterogeneity, and u_1 is idiosyncratic errors. The number of years of schooling s is redundant conditional on individual heterogeneity a.

In this approach, individual heterogeneity can be simply eliminated by a time-demeaning transformation using two or more periods of panel data. The fixed-effects model relies not on exclusion restrictions but on the assumption that unobserved heterogeneity is constant over time. The fixed-effects approach is useful to flexibly control for the individual-specific intercept, i.e., unobserved skill endowment. However, the fixed-effects model is not fully consistent with a theoretical model in which a temporary productivity shock drives the labor force participation decision.

In the OLS and FE models, standard errors are clustered at the individual level to account for heteroscedasticity and serial correlations of unknown form. Since the probit, sample-selection correction, and IV models involve generated regressors, standard errors are estimated using a block bootstrap technique in these models. The sampling unit is an individual to account for heteroscedasticity and serial correlations in errors.

3.1.5 Discussions

The instruments are chosen in a way that is comparable between alternative models and consistent with a structural model presented in the next section. As described later, a subset of state variables $(\widehat{n_1}, \widehat{n_2}, \widehat{y_h})$ naturally satisfies exclusion restrictions in the dynamic model of female labor force participation. This is one of the distinctive features of the model analyzed in this paper. In Belzil and Hansen's (2002) study of returns to schooling for young men, state variables perfectly overlap between wage and employment equations. In that case, identification must rely solely on distributional assumption and functional form assumption.

After numerous specification checks, $\widehat{n}$, t, and t^2 are added into the set of excluded instruments to secure a strong correlation with endogenous variables in the reduced-form estimates. The total number of children n is simply a linear transformation of the number of children at different school-age levels, and age t is a conventional instrument for years of experience in earnings-equation estimates. The polynomials in age can be interpreted as a proxy for the future gain from working in the current period in line with the structural model. However, the inclusion of age is not technically necessary for identification and does not substantially alter the results.

3.2 Auxiliary Models

Provided that experimental data are not available, the choice of the instruments seems to be reasonable, but whether they are valid instruments may be controversial. Hence, linear regressions of the husband's earnings and fertility are conducted to correct for the potential bias.

According to the Vital Statistics of Japan, the proportion of children born outside of marriage was 0.80% in 1980 and 1.93% in 2003. Moreover, the author's calculations indicate that one half of women give birth within a year after marriage. Thus, it may not be too hard to build a *statistical* model of fertility. The biological process of fertility may be given by the polynomial form in predetermined marriage duration and age:

$$
\begin{aligned}
n_1 &= \kappa_{10} + \sum_{\iota=1}^{9} \kappa_{11,\iota} md^{\iota} + \kappa_{12} t + v_1, && (8)\\
n_2 &= \kappa_{20} + \sum_{\iota=1}^{9} \kappa_{21,\iota} md^{\iota} + \kappa_{22} t + v_2, && (9)\\
n &= \kappa_{30} + \sum_{\iota=1}^{5} \kappa_{31,\iota} md^{\iota} + \kappa_{32} t + v_3, && (10)
\end{aligned}
$$

where md is the current marriage duration until the last year. The number of polynomials in the current marriage duration is chosen to fit the data well (Table 3). Fertility decreases with age conditional on the marriage duration.

The earnings process of the husband may be described as follows:

$$\ln y_h = \kappa_{40} + \kappa_{41} s_h + \kappa_{42} t_h + \kappa_{43} t_h^2 + rd \cdot \kappa_{44} + yd \cdot \kappa_{45} + v_4, \tag{11}$$

where s_h is the number of years of the husband's schooling, and t_h is husband's age. The vectors rd and yd are the sets of 47 prefectural and 9 year dummy variables, respectively.[9] The husband's earnings vary according to labor market conditions across prefectures. Thus, regional variation in terms of macroeconomic conditions is exploited for secure identification. The returns to schooling are 5.5%, and the age-earnings profile is concave for married men (Table 4). The regional macroeconomic effects are highly statistically significant.

3.3 Extended Models

The models presented above consider heterogeneity only in the intercept, but those models can be extended to allow for heterogeneous returns to experience.

$$\ln y = \gamma_0 + \gamma_1 s + \gamma_2^S x + \gamma_3^S x^2 + v_2, \tag{12}$$

where γ^S means that the coefficients vary across four education groups: junior high school, high school, two-year college, and four-year college. Then, the coefficients for the two endogenous variables, experience and its square, vary according to years of schooling. In the first-stage regression, all the excluded instruments are interacted with the indicator variables for completed education. These excluded instruments are strongly partially correlated with the endogenous variables for a total of eight ($= 2 \times 4$) reduced-form regressions.

[9] Year dummies could be replaced with the polynomial form in time trends. However, neither linear nor polynomial time trends were statistically significant.

Furthermore, the error term can be decomposed as $v_2 = a + u_2$ in the fixed-effects approach.

3.4 Preliminary Results

The main focus of this paper is assessing the returns to experience. The OLS estimate of the returns to experience is 0.087 (column 1, Table 5). Earnings reach the maximum at the 41.8 years of experience. However, this result is presumably biased, as discussed above. Those who have higher unobserved productivity are more likely to be employed and to accumulate longer work experience. In that case, the OLS estimates suffer from an upward bias. After the sample-selection problem with employment, the endogeneity problem with experience, or both are taken into account in the empirical model, the estimated returns to experience are expected to become smaller.

However, the sample-selection correction method suggests marginally larger returns to experience, 0.096 (column 2, Table 5). The implied turning point of the experience-earnings profile is 39.3 years of experience. Indeed, the coefficient for the sample-selection correction term does not statistically significantly differ from zero, indicating no sample-selection bias. One concern about the result of no sample-selection bias is that the excluded instruments may not have a strong identification power. However, the excluded instruments used are strongly partially correlated with employment (column 1, Table 6). Another concern is that the sample-selection correction method may not be capable of controlling for dynamic self-selection into employment.

The IV estimate of the returns to experience is 0.130, which is one and one-half times as large as the OLS estimate (column 3, Table 5). The implied turning point is 16.1 years of experience. The number of years of work experience is treated as endogenous variable here. Indeed, residuals from the reduced-form regression of experience and its square are jointly significant at the 3% significance level, indicating that years of work experience are endogenous. The direction of the bias again turns out to be opposite to that expected. One concern about the analysis is a weak instrument problem. However, the results of the first-stage regression show a strong correlation between endogenous variables and excluded instruments (columns 2 to 4, Table 6).

A number of empirical studies find that the IV estimate of estimated returns to schooling is much larger than the OLS estimate (Card, 2001; Belzil, 2007). This result is interpreted as evidence that the coefficients are heterogeneous across individuals. In that case, the IV method provides the returns to schooling for those who switched years of schooling in response to the change in instrumental values (Imbens and Angrist, 1994). This interpretation would naturally apply to the context of the returns to experience. One of the implications is poor out-of-sample predictions. Another interpretation is that the IV method corrects for the attenuation bias caused by a measurement error problem. However, as discussed below, the measurement error problem cannot fully explain the result, although it can give a partial explanation. Thus, the large IV estimate may be taken as an indication of heterogeneity.

The FE estimate of the returns to experience indicates 0.060, which is smaller than the OLS estimate (column 4, Table 5). The implied turning point is 22.2 years of experience. The FE model can control for the unobserved productivity that may be correlated with experience. The result can be interpreted as indicating the correction of the omitted-variable bias.[10] However, the FE model relies on the mean independence assumption on the deviation from the mean of experience and idiosyncratic shock over time. If the change in employment status is correlated with an unobservable idiosyncratic shocks in productivity, then the FE model may still suffer from an upward bias.

The extended model further investigates heterogeneity in the returns to experience (Table 7). The findings are similar in several aspects among estimation methods. First, the estimated returns to experience are minimal for junior high school graduates. They are statistically insignificant or even negative. Second, the estimated returns to experience are positive for the other three education groups. Third, the returns to experience are larger for higher education groups. Finally, only college graduates have a concave experience-earnings profile.

More specifically, the OLS estimate of the returns to experience is clearly heterogeneous across education groups. The estimated returns to experience in the baseline model are larger than those for junior high school and high school graduates but smaller than those for two-year and four-year college graduates in the extended model. The results of the sample-selection correction model do not substantially differ from those of the OLS model. The IV estimate of the returns to experience is similar to the OLS estimate for the highest education group but larger than the OLS estimate for the middle education groups. Thus, the difference between OLS and IV estimates cannot be solely explained by the attenuation bias.

The FE estimate of returns to experience is consistently smaller than the OLS estimate for each education group. As noted above, this can be interpreted as correcting for the omitted-variable bias. However, the estimated returns to experience are not statistically significant for the highest education group due to a large standard error. Highly educated women are more likely to stay employed, and thus, a lack of variation over time makes it difficult to achieve identification for this group in the FE model.

4 The Model

4.1 Model Description

This section considers the dynamic decision-making problem in which the *household* has two mutually exclusive and exhaustive alternatives for each period: employment (E) and non-employment (N). The

[10] Another interpretation is that the attenuation bias is magnified after a within transformation. This can partly explain the difference between the OLS and FE estimates.

model draws on seminal work by Eckstein and Wolpin (1989).[11]

The objective function in each period t, which is maximized subject to the budget constraint, is represented by

$$V_t(\Omega_t) = \max_{p_t} \mathbb{E}\left[\sum_{t=t_0}^{T} \beta^{t-t_0}\left(p_t U_t^E + (1-p_t) U_t^N\right) \middle| \Omega_t\right], \tag{13}$$

where U^j is the alternative-specific utility function for an alternative $j = \{E, N\}$, p is the indicator variable for whether the wife participates in the labor market,[12] and t indexes ages that range from 33 $(t = t_0)$ to 70 $(t = T)$. The discount factor β is set equal to 0.95. The educational choice is predetermined in the model and treated as exogenous conditional on observed and unobserved heterogeneity.

The labor force participation decision is driven by some economic variables in the state space:

$$\Omega_t = \left(s, x_{t-1}, \widehat{n_{1t}}, \widehat{n_{2t}}, \widehat{y_{ht}}, \epsilon_{1t}\right), \tag{14}$$

where ϵ_1 is an idiosyncratic shock in productivity. The household is assumed to forecast husband's earnings and fertility according to exogenous deterministic processes described earlier at the beginning of marriage.[13] The productivity shock has a normal distribution with mean zero and variance σ_1. Work experience evolves according to the law of motion:

$$x_t = x_{t-1} + p_t, \tag{15}$$

where p is the choice variable in the utility maximization problem. Years of experience are endogenously accumulated whereas years of schooling are predetermined and constant over time.

In such a discrete-choice problem, the value function can be expressed as the maximal value over all available alternatives conditional on the set of state variables:

$$V_t(\Omega_t) = \max_j \left[V_t^j(\Omega_t)\right], \tag{16}$$

where V^j is the alternative-specific utility function for an alternative $j = \{E, N\}$. The alternative-specific

[11] van der Klauww (1996) developed a dynamic discrete-choice model of employment and marital status decision. Francesconi (2002) developed a dynamic discrete-choice model of occupational and fertility choices.

[12] That is to say, $p = 1[j = E] = 1 - 1[j = N]$.

[13] The predicted values of the number of children and husband's earnings can be replaced with the actual values under the assumption that a productivity shock is orthogonal to any idiosyncratic shocks to fertility and husband's earnings. The use of actual (realized) values could increase the model fit but is vulnerable to endogeneity problems. The joint estimation of own and the husband's earnings and fertility is left for future work.

value function evolves for $t < T$ according to the Bellman equations:

$$\begin{aligned} V_t^E(\Omega_t) &= U_t^E(\Omega_t) + \beta\mathbb{E}\left[V_{t+1}(x_t = x_{t-1} + 1, \Omega_{t+1})\right], && (17) \\ V_t^N(\Omega_t) &= U_t^N(\Omega_t) + \beta\mathbb{E}\left[V_{t+1}(x_t = x_{t-1}, \Omega_{t+1})\right]. && (18) \end{aligned}$$

The decision-making problem is static at the terminal period. The terminal condition is simply given by the instantaneous utility function:

$$V_T^j(\Omega_T) = U_T^j(\Omega_T), \tag{19}$$

where T is the terminal age.

There are obviously a number of ways to extend the model. However, the use of the simple dynamic model makes it possible to conduct a fair comparison between the alternative approaches and to make a clear-cut interpretation of the results.

4.2 Model Solution

The finite-horizon dynamic programming model can be solved recursively for each value of state variables under certain functional form assumptions on the utility function and earnings equation and certain distributional assumptions on the productivity shock contained in the state space. Parametric assumptions imposed on the model are specifically described in the next subsections.

Two computational issues arise in solving the model. First, it requires to taking the expectation of the value function over the stochastic shock when calculating the second term in the Bellman equation. Second, it requires calculating the alternative-specific value function for any given value of state variables. To solve these issues, the value function is first calculated for a subset of state space, and then the second term in the Bellman equation, so-called the Emax function, is computed by means of Monte Carlo integration. Finally, the second-order polynomial interpolation method is applied to the Emax function.

4.3 Model Specifications

The instantaneous utility is assumed to be approximated by

$$U_t^j = c_t^j + \left(\alpha_{0k} + \alpha_1 s + \alpha_2 x_{t-1} + \alpha_3 n_{1t} + \alpha_4 n_{2t} + \alpha_5 c_t^j\right) p_t, \tag{20}$$

where c is consumption, and k indexes unobserved types. Then, the alternative-specific utility function can be written as follows:

$$U_t^E = \alpha_{0k} + \alpha_1 s + \alpha_2 x_{t-1} + \alpha_3 n_{1t} + \alpha_4 n_{2t} + (1 + \alpha_5)\, c_t^E, \tag{21}$$

$$U_t^N = c_t^N. \tag{22}$$

The utility is basically a function of consumption and labor supply (or leisure). The utility is linear and additively separable over time in consumption. This functional form implies that the utility maximization problem is equivalent to the income maximization problem because the timing of consumption does not matter to the value of the objective function. This is apparently a strong but common restriction, to ignore the saving decision for computational tractability.[14] The analysis of saving behavior is beyond the scope of this paper.

The employment status enters into the utility function as a binary variable and interacts with education, experience, children, and consumption. The number of children is allowed to affect the disutility of employment differently across school-age levels. When considering the diagram of the utility level and the consumption amount, the employment status shifts the intercept of utility, depending on education, experience, and children. The employment status also changes the coefficient on consumption because the preference is non-separable between consumption and leisure. Moreover, the current employment status interacts with work experience accumulated until the last period, which can be interpreted as the intertemporal non-separability in labor supply.

The parameter α_{0k} represents the unobserved (dis-)utility of employment. An alternative way to interpret this parameter is that $-\alpha_{0k}$ represents the unobserved productivity in home production. In a similar fashion, the other coefficients on employment can be interpreted either as the disutility of employment or as productivity in home production. The identification problem is discussed later.

The budget constraint states that the consumption amount is equal to the sum of own earnings y and the husband's earnings:

$$c_t^j = p_t y_t + y_{ht}, \tag{23}$$

which, of course, implies $c_t^E = y_t + y_{ht}$ and $c_t^N = y_{ht}$. Earnings follow a Mincer-type specification:

$$\ln y_t = \gamma_{0k} + \gamma_1 s + \gamma_{2k} x_{t-1} + \gamma_{3k} x_{t-1}^2 + \epsilon_{1t}, \tag{24}$$

where γ_{0k} is the unobserved skill endowment, and γ_{2k} and γ_{3k} capture heterogeneous returns to experience.

[14] Japan's national saving rate has been dramatically declining for recent years.

A departure from standard specifications is to allow for unobserved heterogeneity in terms of the slope and curvature of experience effect.

4.4 Heterogeneity

The model accounts for potentially multidimensional unobserved heterogeneity in employment and home production. In other words, the theoretical framework accommodates comparative advantage in terms of productivity in the market and at home.

The first type of persistent skill heterogeneity is captured by the intercept, slope, and curvature of the experience-earnings profile, γ_{0k}, γ_{2k}, and γ_{3k}. Thus, the earnings equation can be interpreted as a random-coefficients model in which not only the intercept but also coefficients can vary across individuals. The second type of heterogeneity is captured by the intercept of home production value, $-\alpha_{0k}$, in the utility function.

5 Estimation and Identification

5.1 Model Estimation

Incorporating the measurement error, the earnings equation can be written as follows.

$$\begin{aligned} \ln y_t &= \gamma_{0k} + \gamma_1 s + \gamma_{2k} x_{t-1} + \gamma_{3k} x_{t-1}^2 + \epsilon_{3t}, && (25) \\ \epsilon_{3t} &= \epsilon_{1t} + \epsilon_{2t}, && (26) \end{aligned}$$

where the total error term ϵ_3 is defined as the sum of the productivity shock ϵ_1 and the measurement error ϵ_2.

Suppose that the productivity shock and the measurement errors are independently normally distributed: $\epsilon_1 \sim \mathcal{N}\left(0, \sigma_1^2\right)$ and $\epsilon_2 \sim \mathcal{N}\left(0, \sigma_2^2\right)$. Then, the total error term has a normal distribution: $\epsilon_3 \sim \mathcal{N}\left(0, \sigma_3^2\right)$, where $\sigma_3^2 = \sigma_1^2 + \sigma_2^2$. The conditional distribution of the total error term given the productivity shock also follows a normal distribution: $\epsilon_1 | \, \epsilon_3 \sim \mathcal{N}\left(\rho^2 \epsilon_3, \sigma_1^2 \left(1 - \rho^2\right)\right)$, where $\rho = \sigma_1 / \, \sigma_3$.

The distributional assumption on the productivity shock is imposed to solve the dynamic-programming model. Combined with the distributional assumption on the measurement error, the log likelihood function can be constructed as the summation, over the observations, of the log of the individual contribution:

$$\begin{aligned} L_i &= \sum_{k=1}^{K} \pi_k \prod_{t=t_0}^{T} \Pr\left(p_{it} = 1, \ln y_{it} | \, \Omega_{it}, \text{type} = k\right)^{p_{it}} \Pr\left(p_{it} = 0 | \, \Omega_{it}, \text{type} = k\right)^{1-p_{it}} \\ &= \sum_{k=1}^{K} \pi_k \prod_{t=t_0}^{T} \left[\left(1 - \Phi\left(\frac{\epsilon_{1kit} - \rho^2 \epsilon_{3kit}}{\sigma_1 \sqrt{1-\rho^2}}\right)\right) \frac{1}{\sigma_3} \phi\left(\frac{\epsilon_{3kit}}{\sigma_3}\right) \right]^{p_{it}} \Phi\left(\frac{\epsilon_{1kit}}{\sigma_1}\right)^{1-p_{it}} && (27) \end{aligned}$$

where π_k is the probability of being type k (Heckman and Singer, 1984). The number of types K is set equal to three.[15] The process of updating parameters to maximize the likelihood function involves solving the dynamic programming model. The solution to the dynamic-programming model is used as an input to construct a likelihood function for the estimation of structural parameters. The estimation does not require balanced panel data. The standard errors can be computed using the outer product of the gradients.

5.2 Identification

The dynamic discrete-choice model of labor supply is essentially an extended version of the standard sample-selection correction model. The identification of structural parameters can be achieved by a combination of exclusion restrictions, variation of state variables in the data, distributional assumption, and functional form assumption. The exclusion restrictions are the key to identification although they are not necessarily required. The restrictions imposed on the model are summarized as follows. The number of children and the husband's earnings, which are determined by the marriage duration, the woman's own and her husband's age, and regional macroeconomic conditions, affect the labor supply decision only through the change in reservation wages. Experience squared affects the labor supply decision only through the change of productivity in employment. Moreover, both cross-section and time-series variations in covariates such as years of experience facilitate identification. Consequently, structural analysis, in contrast to the reduced-form analysis, allows us to separately identify the experience effect on preference and earnings.

Neither the linear form of the utility function nor the logarithmic form of earnings equation is necessary for identification. The distributional assumption on the productivity shock is required to solve the model and help to identify structural parameters. Indeed, the solution to the dynamic-programming model generates an additional source of identification. Then, the normality assumption is exploited to construct the likelihood function. Moreover, the productivity shock and the measurement error are identifiable due to the distributional assumption. Importantly, a finite mixture distribution, which is an approximation of a more general distribution, is used to account for unobserved heterogeneity.

As in standard discrete-choice models, the parameters in the instantaneous utility represent not the absolute but rather the relative effects of each variable, i.e., the difference in the two absolute effects. More specifically, the model cannot separately identify the disutility of employment and the productivity in home production. Moreover, the monetary cost of raising children is not identified separately from the psychological disutility of employment pertaining to children. For this reason, such a cost is not included in the budget constraint, but the interpretation of estimation results requires caution.

[15] This is a conservative and conventional choice in the literature. An increase in the number of types from 3 to 4 did not improve the estimation in terms of log-likelihood value or model fit.

6 Results

6.1 Utility Function

The structural estimates suggest substantial heterogeneity in productivity in the market and at home (Table 8). The intercept of the productivity in home production is positive ($-\alpha_0 > 0$). In other words, the intercept of the utility of employment is negative ($\alpha_0 < 0$). The productivity for the high type is 2.6 times higher than the productivity for the middle type in terms of home production. Schooling enhances the productivity in home production ($-\alpha_1 > 0$).

Years of work experience increase the disutility of employment ($\alpha_2 < 0$). The effect of children on employment changes across different school-age levels. The number of children under the age of 7 decreases the probability of employment ($\alpha_3 < 0$), whereas the number of children aged 7 to 15 increases the probability of employment ($\alpha_4 > 0$). This implies that the disutility of employment increases with the number of preschool children, but that the number of children elementary school-aged and older raises the productivity of home production. The relationship between consumption and employment status is negative and marginally significant ($\alpha_5 < 0$). The value of consumption is lower in employment than in non-employment. In other words, consumption and leisure are complements in utility. Overall, the signs of estimated parameters other than α_4 are the same as those in Eckstein and Wolpin (1989) and Francesconi (2002). However, the estimated parameter α_3 does not statistically significantly differ from zero, as in the probit model of labor force participation.

6.2 Earnings Equation

The weighted average of estimated rate of return to experience across types is 0.039. The estimated returns to experience substantially differ across types: 0.055, 0.032, and 0.000. The slope and curvature of experience effect imply a concave experience-earnings profile for type 1. Earnings reach the maximum at the 31.9 years of experience. The coefficient on the quadratic term in experience is small and statistically insignificant for type 2.

The structural estimates suggest a flatter experience-earnings profile than do reduced-form estimates in the previous section (Figure 1). The structural estimate of the returns to experience is smaller than the OLS estimate, as opposed to the sample-selection correction and IV estimates. Indeed, it is slightly smaller than the FE estimate. The results obtained here imply that the structural approach is capable of correcting for dynamic self-selection bias, whereas the reduced-form approach is not.

The structural estimate of the returns to schooling (γ_1) is 0.047, which is much smaller than the reduced-form estimates reported in Table 5. The reduced-form estimate of the returns to schooling may also suffer from an upward bias caused by non-random sample selection into employment. This finding also highlights the importance of dynamic self-selection into employment in the estimating earnings equation.

The general skill endowment (γ_0) also differs across types. The productivity for the high type (type 1) and the middle type (type 2) are respectively 4.52 times and 2.54 times higher than the productivity for the low type (type 1) in terms of the level of earnings. The implied standard deviation of the measurement error (σ_2) is 0.348, which is 2.63 times larger than the standard deviation of the productivity shock (σ_1).

6.3 Skill Heterogeneity

The model developed here accounts for comparative advantage of skill heterogeneity. Thus, the ranking of unobserved heterogeneity in each dimension is of interest. However, the results suggest that heterogeneity is one-dimensional (Table 9). The probability of being types 1 or 2 accounts for 92%. Type 1 (Type 3) has the highest (lowest) productivity in home production and employment and the highest (lowest) returns to experience. An interesting implication is that people with high productivity in employment may not necessarily be more likely to participate in the labor market, as they also have high productivity at home.

6.4 Model Fit

This paper places emphasis on the discussion about causal inference relative to forecasting or model fitting. As discussed above, the estimated parameter values are reasonably interpretable from economic and econometric perspectives, which may suffice to justify the model. However, to look further at the validity of the structural model, the model prediction is compared to the data here. The employment rate predicted from the structural model is close to the actual employment rate for women in their 30s, whereas the model does not perfectly fit the data for women in their 40s, where the sample size is small (Table 10). Overall, the Pearson χ^2-statistic indicates that the null hypothesis is securely accepted that the model prediction equals the observed data. Figure 2 shows that all the predicted values are within 95% confidence intervals.

7 Conclusion

This paper investigates the earnings returns to general experience in the labor market using several methods. By doing so, the empirical performance of the structural approach has been examined in comparison to the reduced-form approach. Despite a considerable proportion of non-employed women among married women, the sample-selection correction method makes little difference to earnings-equation estimates. The instrumental variable estimate of the returns to experience is higher than the OLS estimate, although the OLS estimate is presumably biased upward. The fixed-effects estimate corrects for the upward bias, but the fixed-effects model is not consistent with the structural model in which an idiosyncratic shock determines the employment status. This study uses Eckstein and Wolpin's (1989) model to account for dynamic self-selection into employment. Indeed, the structural estimate of the returns to experience is smaller than the reduced-form estimates. It also reduces the so-called ability bias, i.e., the upward bias in the OLS estimate of the returns to schooling. The findings obtained in this paper suggest the importance of dynamic self-selection.

Heterogeneity and selection are the keys to understanding the earnings-equation estimates. The reduced-form approaches reveal substantial heterogeneity in the returns to experience across education groups. This study also employs Heckman and Singer's (1984) approach along the lines of Keane and Wolpin to allow for unobserved heterogeneity in a flexible way. The model developed here accounts for comparative advantage in employment and home production and for heterogeneity in the returns to experience. Consequently, the structural estimates of the returns to experience range from zero to 0.055. Skilled workers have a concave experience-earnings profile, but unskilled workers do not.

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Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Obs.
Age	36.33	2.51	
Years of work experience	10.25	4.83	
Years of schooling	13.23	1.42	
Years of schooling, husband	13.75	2.11	
Number of children	1.99	0.90	4464
Number of children aged 0-6	0.72	0.81	
Number of children aged 7-15	1.16	0.93	
Current marriage duration	11.29	4.32	
Employment: = 1 if employed	0.52	0.50	
Annual earnings	2.10	1.62	2303
Annual earnings, husband	5.49	1.89	3839

Notes: Annual earnings are measured in 1 million Japanese yen. Missing values in own and husband's earnings are due to non-employment. Missing values in husband's earnings are due to non-response.

Table 2: Transition of Employment

<table>
<tr><th>Age</th><th>Obs.</th><th>Year</th><th colspan="4">E: Employment, N: Non-Employment</th></tr>
<tr><td rowspan="4">35</td><td rowspan="4">539</td><td rowspan="2">t</td><td colspan="2">E</td><td colspan="2">N</td></tr>
<tr><td colspan="2">257 (47.7%)</td><td colspan="2">281 (52.3%)</td></tr>
<tr><td rowspan="2">t+1</td><td>E</td><td>N</td><td>E</td><td>N</td></tr>
<tr><td>235 (91.4%)</td><td>22 (8.6%)</td><td>38 (13.5%)</td><td>243 (86.5%)</td></tr>
<tr><td rowspan="4">40</td><td rowspan="4">194</td><td rowspan="2">t</td><td colspan="2">E</td><td colspan="2">N</td></tr>
<tr><td colspan="2">124 (63.9%)</td><td colspan="2">70 (36.1%)</td></tr>
<tr><td rowspan="2">t+1</td><td>E</td><td>N</td><td>E</td><td>N</td></tr>
<tr><td>114 (91.9%)</td><td>10 (8.1%)</td><td>10 (14.3%)</td><td>60 (85.7%)</td></tr>
</table>

Notes: The figures in columns 4 to 7 are the numbers of employed and non-employed women. The employment and non-employment rates are in parentheses.

Table 3: Fertility Process

Dependent Variables:	# children 0-6		# children 7-15		# children	
Explanatory Variables:	(1)		(2)		(3)	
Marriage duration	0.802	(0.186)	-0.488	(0.123)	0.030	(0.091)
Marriage duration squared	-0.638	(0.172)	0.515	(0.121)	0.051	(0.023)
Marriage duration cubic	0.262	(0.067)	-0.225	(0.051)	-0.007	(0.002)
Marriage duration 4th power/10	-0.534	(0.135)	0.489	(0.111)	0.003	(0.001)
Marriage duration 5th power/10^2	0.604	(0.159)	-0.592	(0.139)	-0.001	(0.000)
Marriage duration 6th power/10^3	-0.402	(0.113)	0.423	(0.104)	—	—
Marriage duration 7th power/10^4	0.158	(0.047)	-0.178	(0.046)	—	—
Marriage duration 8th power/10^5	-0.034	(0.011)	0.041	(0.011)	—	—
Marriage duration 9th power/10^7	0.031	(0.010)	-0.040	(0.011)	—	—
Age	-0.023	(0.008)	-0.026	(0.009)	-0.052	(0.012)
Intercept	1.061	(0.292)	1.135	(0.305)	2.395	(0.419)
R-squared	0.372		0.541		0.184	

Notes: Standard errors in parentheses are clustered at the individual level.

Table 4: Husband's Earnings Process

Dependent Variable:	log of Husband's Earnings	
Explanatory Variables		
Schooling, husband	0.055	(0.005)
Age, husband	0.077	(0.022)
Age squared/10^2, husband	-0.078	(0.028)
Intercept	-0.982	(0.451)
F-statistic: prefectural dummies	5.77	{0.000}
F-statistic: year dummies	1.42	{0.184}
R-squared	0.254	

Notes: Standard errors in parentheses are clustered at the individual level. *p*-values are in curly brackets. *F*-statistic is the test statistic under the null hypothesis that all the coefficients on prefectural dummies or year dummies are zero.

Table 5: Earnings-equation Estimates

Estimation Models:	OLS		Sample Selection		IV		FE	
Dependent Variable:	log of Earnings							
Explanatory Variables	(1)		(2)		(3)		(4)	
Experience	0.115	(0.023)	0.129	[0.031]	0.343	[0.139]	0.108	(0.020)
Experience squared/10^2	-0.137	(0.089)	-0.164	[0.100]	-1.065	[0.522]	-0.244	(0.063)
Schooling	0.179	(0.021)	0.178	[0.021]	0.161	[0.022]	—	—
Intercept	-3.114	(0.314)	-3.289	[0.377]	-4.227	[0.707]	—	—
Inverse Mills ratio, employment	—	—	0.099	[0.121]	0.193	[0.183]	—	—
Residual, experience	—	—	—	—	-0.252	[0.145]	—	—
Residual, experience squared	—	—	—	—	1.055	[0..543]	—	—
Returns to experience	0.087	(0.007)	0.096	[0.012]	0.130	[0.042]	0.060	(0.008)
Wald statistic {p-value}	—	—	—	—	6.760	{0.034}	—	—
R-squared	0.308		—		—		—	

Notes: Work experience and its square are treated as endogenous variables in the IV model. Standard errors in parentheses are clustered at the individual level. Standard errors in square brackets are estimated by block bootstrap. The Wald test statistic is χ^2-statistic under the null hypothesis that experience and its square are endogenous.

Table 6: Reduced-form Estimates for Employment and Work Experience

Estimation Models:	Probit		Probit		Sample Selection			
Dependent Variables:	Employment		Employment		Experience		Experience Squared	
Explanatory Variables	(1)		(2)		(3)		(4)	
# children 0-6	-0.010	[0.060]	-0.046	[0.058]	—	—	—	—
# children 7-15	0.271	[0.042]	0.088	[0.034]	—	—	—	—
# children	—	—	—	—	-2.617	[0.553]	-0.649	[0.162]
Husband's earnings	-0.046	[0.017]	-0.097	[0.018]	-1.540	[0.315]	-0.369	[0.089]
Age	-0.022	[0.007]	0.025	[0.007]	0.686	[0.420]	0.077	[0.120]
Age squared	—	—	—	—	0.007	[0.015]	0.006	[0.004]
Schooling	0.032	[0.013]	0.013	[0.012]	0.035	[0.134]	-0.003	[0.037]
Experience	0.072	[0.004]	—	—	—	—	—	—
Intercept	—	—	—	—	13.842	[3.861]	0.413	[0.438]
Inverse Mills ratio	—	—	—	—	2.480	[1.644]	2.846	[1.087]
Wald statistic {p-value}	107.9	{0.000}	100.4	{0.000}	166.8	{0.000}	145.0	{0.000}
Pseudo *R*-squared	0.254		0.054		—		—	

Notes: Marginal effects are reported in the probit model of employment. The first column displays first-step estimates for the sample-selection correction model. The next three columns display reduced-form estimates for the IV model, where work experience and its square are treated as endogenous variables. Standard errors in square brackets are computed by block bootstrap. The Wald test statistic is the χ^2 statistic under the null hypothesis that all the coefficients on excluded instruments are zero. *p*-values are in curly brackets.

Table 7: Heterogeneous Returns to Experience across Education Groups

Estimation Models:	OLS		Sample Selection		IV		FE	
Dependent Variable:	log of Earnings							
Explanatory Variables	(1)		(2)		(3)		(4)	
Experience								
junior high school	-0.040	(0.100)	-0.029	[0.281]	0.572	[10.452]	0.574	(0.120)
high school	0.046	(0.028)	0.057	[0.035]	0.378	[0.178]	0.103	(0.024)
2-year college	0.162	(0.029)	0.172	[0.034]	0.350	[0.136]	0.124	(0.032)
4-year college	0.301	(0.059)	0.309	[0.063]	0.294	[0.232]	0.105	(0.098)
Experience squared/10^2								
junior high school	0.191	(0.591)	0.168	[1.956]	-2.207	[128.999]	-4.058	(0.675)
high school	0.084	(0.112)	0.063	[0.119]	-1.201	[0.670]	-0.222	(0.077)
2-year college	-0.282	(0.116)	-0.300	[0.123]	-1.145	[0.507]	-0.297	(0.102)
4-year college	-0.709	(0.258)	-0.715	[0.270]	-0.779	[0.859]	-0.228	(0.328)
Schooling	-0.247	(0.096)	-0.245	[0.100]	0.266	[0.487]	-0.508	(0.142)
Intercept	2.464	(1.263)	2.314	[1.352]	-5.632	[6.553]	—	—
Inverse Mills ratio, employment	—	—	0.070	[0.119]	0.141	[0.173]	—	—
Residual, experience							—	—
junior high school	—	—	—	—	0.370	[26.806]	—	—
high school	—	—	—	—	-0.372	[0.183]	—	—
2-year college	—	—	—	—	-0.184	[0.147]	—	—
4-year college	—	—	—	—	-0.113	[0.280]	—	—
Residual, experience squared								
junior high school	—	—	—	—	-2.178	[121.723]	—	—
high school	—	—	—	—	1.450	[0.686]	—	—
2-year college	—	—	—	—	0.924	[0.549]	—	—
4-year college	—	—	—	—	0.659	[1.151]	—	—
Returns to experience								
junior high school	-0.007	(0.030)	0.000	[0.0629]	0.197	[1.830]	-0.116	(0.011)
high school	0.064	(0.008)	0.070	[0.0121]	0.121	[0.037]	0.056	(0.010)
2-year college	0.105	(0.009)	0.112	[0.0144]	0.121	[0.042]	0.065	(0.013)
4-year college	0.167	(0.015)	0.173	[0.0206]	0.146	[0.067]	0.062	(0.036)
Wald statistic {*p*-value}	—	—	—	—	14.57	{0.068}	—	—
R-squared	0.330		—		—		—	

Notes: Standard errors in parentheses are clustered at the individual level. Standard errors in square brackets are estimated by block bootstrap. The Wald test statistic is the χ^2 statistic under the null hypothesis that experience and its square are endogenous.

Table 8: Structural Estimates of Dynamic Labor Force Participation Model

Variables	Parameters	Estimates	S.E.
Utility Function			
	α_{01}	-4.1284	*0.1347*
intercept	α_{02}	-1.9941	*0.1096*
	α_{03}	0.1184	*0.0665*
schooling	α_1	-0.0242	*0.0030*
experience	α_2	-0.0023	*0.0007*
# children 0-6	α_3	-0.0126	*0.0105*
# children 7-15	α_4	0.0603	*0.0089*
consumption	α_5	-0.0045	*0.0024*
Earnings Equation			
	γ_{01}	-0.2555	*0.0399*
intercept	γ_{02}	-0.8297	*0.0380*
	γ_{03}	-1.7631	*0.0948*
schooling	γ_1	0.0469	*0.0027*
	γ_{21}	0.0805	*0.0015*
experience	γ_{22}	0.0328	*0.0010*
	γ_{23}	0.0206	*0.0111*
	γ_{31}	-0.1263	*0.0046*
experience squared/10^2	γ_{32}	-0.0054	*0.0051*
	γ_{33}	-0.1045	*0.0428*
Stochastic Shock			
productivity shock	σ_1	0.1322	*0.0103*
ratio of shock to total errors	ρ	0.3547	*0.0283*
Type Probability			
type 1	π_1	0.4882	*0.0162*
type 2	π_2	0.4354	*0.0149*
log likelihood		4614.9	
Returns to experience			
type 1		0.0553	
type 2		0.0317	
type 3		-0.0003	

Notes: Standard errors are in italic.

Table 9: Ranking of Type-specific Parameters

Unobserved Heterogeneity		Type 1	Type 2	Type 3
			Ranking	
Productivity in home production	$-\alpha_{0k}$	1	2	3
Productivity in employment	γ_{0k}	1	2	3
Returns to experience	$\gamma_{1k}+2\gamma_{2k}\overline{x}$	1	2	3
			type probability	
	π_k	0.4882	0.4354	0.0764

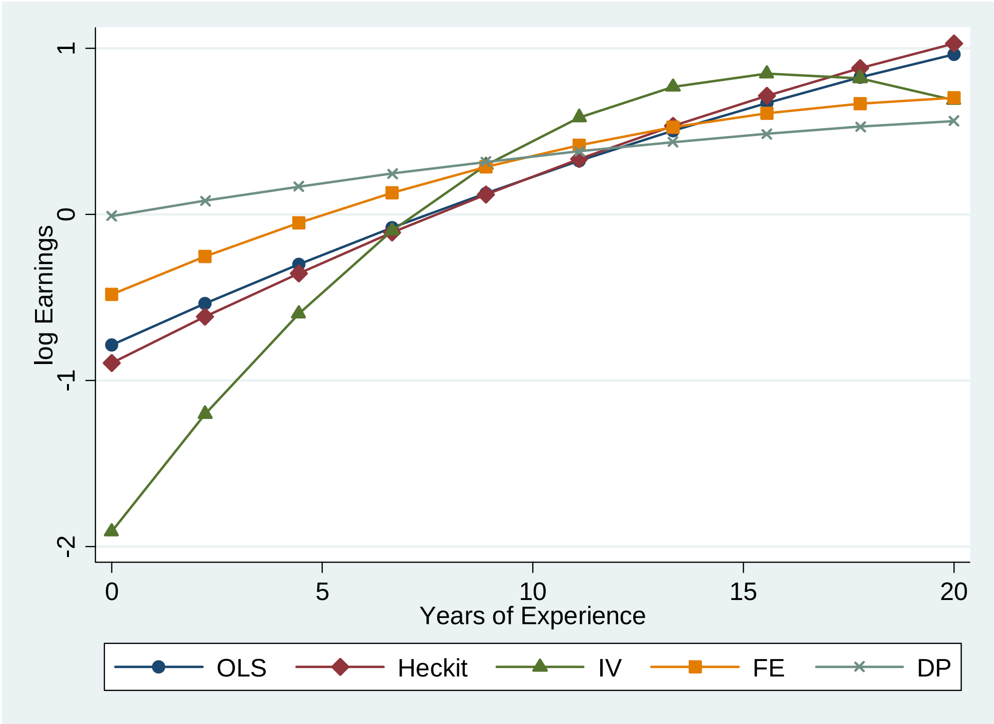
Notes: The bar represents the sample mean.

Table 10: Employment Rate

Age	Obs.	Data	Model
33	599	0.407	0.380
34	728	0.448	0.425
35	652	0.475	0.474
36	569	0.510	0.514
37	511	0.550	0.553
38	432	0.565	0.582
39	367	0.597	0.599
40	274	0.620	0.592
41	198	0.636	0.604
42	134	0.694	0.626
χ^2-statistic {p-value}		1.463	{0.003}

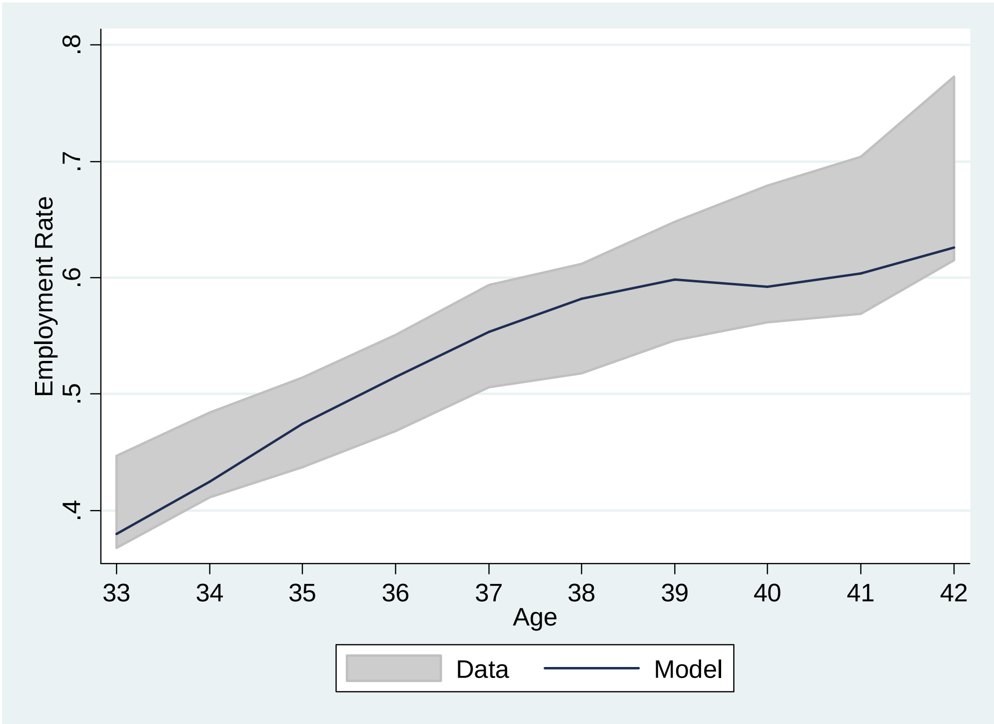
Notes: χ^2-statistic is the test statistic under the null hypothesis that the employment rate in the data equals the rate predicted by the dynamic programming model.

Figure 1: Experience-earnings Profile



Notes: DP is the structural estimate of experience-earnings profile. The sample mean of experience is about 10.

Figure 2: Employment Rate



Notes: The shaded area represents the 95% confidence intervals calculated from the data.