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Multinomial employment dynamics with state dependence and heterogeneity: Evidence from Japan☆

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ABSTRACT

The existence of state dependence, that is, the persistence of employment status in dynamic multinomial choice behavior can lead to inequality through market segmentation. Although many studies have found the existence of state dependence, poor control of heterogeneity leaves the possibility of bias in the estimator. In this study, we investigate whether state dependence exists in married women's choice of regular and non-regular work in Japan taking into account the unobserved heterogeneity as completely as possible. The empirical results suggest that significant, positive state dependence exists in the choice of regular and non-regular work and transitions between them. According to the simulation using the estimates, two important findings emerge; (1) the marginal transition probability to regular work dominates that of non-regular work and non-participation, irrespective of the initial participation state, and (2) if the first job is non-regular, a strong preference for working encourages a move to regular work.

1. Introduction

This study analyzes state dependence (persistence of employment status) in specific employment states and transitions across different employment states. In the dynamic framework of the labor supply model, the choice of employment state (regular work, non-regular work, or non-participation) depends on the individual's past experiences. For example, one who participated in non-regular work at time t tends to participate in the same work state at time $t + 1$. Heckman (1981a) provided two possible explanations for this behavior. One involves "true state dependence," in which preferences, prices, and constraints on future decisions are altered when experiencing an event. The second explanation involves "spurious state dependence," in which an individual's propensity to experience an event correlates over time, although no causation is inferred. It is important to distinguish between true and spurious state dependence in participation behavior to evaluate labor policies. As Ishikawa (2001) noted, "In the market evaluation, we say that the 'genuine wage disparity' that is problematic exists when there are workers who have the same ability and preference and yet do not obtain the same job opportunity."[1] If a positive state dependence is spurious in non-regular work under the control of unobserved heterogeneity, the choice of non-regular work is considered optimal, conditional on heterogeneity. In this case, no genuine disparity exists in the inter-temporal utilities between women who choose regular and non-regular work. Alternatively, if true state dependence exists in non-regular work, the non-regular work experience changes a worker's ability or preference; this also constrains her maximization of inter-temporal utility *ex-post* even if she intends to maximize the inter-temporal utility *ex-ante*. The non-regular work, in this case, is exclusionary (i.e., the purported "part-time trap") and may produce a genuine disparity in inter-temporal utilities between women who choose regular and non-regular work. The existence of true state dependence in regular work and "cross" state dependence from non-regular work to regular work may decrease the risk of marginalizing married women who perform non-regular work, as their regular work experience enhances their skills to conform to regular work.

While many studies have examined state dependence in general

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[1] See Ishikawa (2001), p. 246.

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economic activity (Chen and Chang, 2011; Hansen et al., 2014), numerous studies have addressed the effects of true state dependence on women's labor supply behavior (e.g., Haan, 2010; Kishi and Kano, 2017; Lee et al., 2018).[2] Haan (2010) developed a dynamic discrete choice model for married women in Germany to analyze the effects of true state dependence on the labor supply behavior along the extensive and intensive margin. Misspecification of unobserved heterogeneity and ignoring the initial states of the model can cause biases in the parameter estimation. For the modeling of the distribution of unobserved heterogeneity, they follow Heckman and Singer (1984), and on the problem of initial conditions, they follow Wooldridge (2005). This study shows that state dependence is significantly positive at the extensive margin and lower but, in general, still significant at the intensive margin. Kishi and Kano (2017) estimate dynamic multinomial logit models of the probability that an individual belongs to any of four (self-employment, fixed-term employment, permanent employment, and not working) mutually exclusive employment states controlling for observable and unobservable characteristics and the lag of each employment states. On the problem of initial conditions, similar to Haan (2010), they follow Wooldridge (2005). The finding shows the importance of handling unobserved heterogeneity when identifying state dependencies in both the Australian and Japanese labor markets. Focusing on individual heterogeneity, Lee et al. (2018) examine the causes of an individual's work status choice and the extent of state dependence in the Korean labor market. They estimate a dynamic multinomial logit model using the panel data drawn from the first to the fifteenth wave of the Korean Labour and Income Panel Study. The results suggest the presence of state dependence.

An important limitation of the aforementioned models is that they did not identify the components of serially correlated transitory errors for each employment state. Our proposed dynamic multinomial framework parallels developed by Prowse (2012) allow for time-invariant individual specific random intercepts and a first-order autocorrelation in the errors. Prowse (2012) considers the time-varying, persistent, and unobservable effects in the form of autocorrelation and random coefficients on time-varying characteristics. Prowse (2012) shows negatively correlated transitory errors for full-time workers and part-time workers in the United Kingdom using a multinomial model. Moreover, she shows evidence which suggests that ignoring random coefficients or autocorrelation can bias estimates of policy effects significantly.[3]

To briefly summarize the contributions of our analysis, using a dynamic multinomial logit framework, this study examines the existence of true state dependence in regular and non-regular work and "cross" state dependence between regular and non-regular work (e.g., effects of past non-regular work experience on the current choice of regular work). Our study contributes to current research by extending the test of state dependence in a binomial labor supply model (Hyslop, 1999; Islam, 2007; Michaud and Tatsiramos, 2011; Okamura and Islam, 2011; Hyslop and Townsend, 2020) to a multinomial one (Prowse, 2012; Kishi and Kano, 2017; Lee et al., 2018).[4] Extending a binomial model to a multinomial model increases the dimension of analysis and enables more practical decision-making, and contributes to policymaking. In general, the dynamic multinomial choice model has the following applied research stream. One is an analysis of long-term economic inequality through market segmentation. Previous studies include an analysis of segmentation among formal, informal, and not working (Funkhouser, 1997; Maloney, 1999; Gong et al., 2004; Slonimczyk and Gimpelson, 2015) and an analysis of regular, non-regular, and not working (Magnac, 1991; Prowse, 2012; Kishi and Kano, 2017; Lee et al., 2018). Second is an analysis of persistence in consumption choices, such as brand choice (Keane, 1997; Dubé et al., 2010), which has important implications for assessing a firm's discriminatory pricing. Besides these analyses, dynamic multinomial choice models have great potential in methodological extensibility and applicability to empirical studies. Along with that of Prowse (2012), our study is one of the few attempts to tackle this model using the most sophisticated analytical methods, including identifying error terms; this study will serve as an important reference point for future research in this field.

In contrast, our analysis targets the Japanese labor market. Regarding the analysis of state dependence in Japan, it is worth noting the analysis of the effects of the first job. Kondo (2007), Genda et al. (2010), and Hamaaki et al. (2013) demonstrated that the failure to obtain a regular job after graduation creates scarce subsequent opportunities for regular work. In Japan, the transition from school to employment is the primary point of entry to regular work. Failure to obtain regular work after graduation negatively portrays a student's ability or preference to potential employers and increases search costs. As a result, this produces "spurious" state dependence in non-regular work caused by individual-specific search costs that correlate over time. Esteban-Pretel et al. (2011) analyzed the transition among different employment states and the effects of the initial employment status on employment opportunities for young male workers. The authors indicated that contingent work experience in the first job does not have a long-term impact on regular work choices. Although these studies presented original findings, each has its shortcomings; Kondo (2007), Genda et al. (2010), and Hamaaki et al. (2013) only illuminate state dependence in non-regular work caused by an initial disadvantage upon entering the labor market. Esteban-Pretel et al. (2011) only shed light on male workers and lack a dynamic perspective. Our model surmounts these shortcomings by incorporating state dependence across multinomial employment states and the transition between different employment states and considering unobserved heterogeneity and serial correlation explicitly in the dynamic panel data framework.

The remainder of this paper is organized as follows: Section 2 describes the data and variables. Section 3 presents the observed pattern of transitions across three work states: regular work, non-regular work, and non-participation. In Section 4, the model's structure and empirical specifications are outlined. In Section 5, we present and discuss the results. Section 6 presents the simulation analysis. Section 7 presents the conclusions of this study.

[2] Chen and Chang (2011) investigates the transaction cost determinants of foreign market entry mode choice between wholly-owned subsidiaries and joint ventures. It shows that there is strong linkage between mode performance and future mode choice. It also shows that state dependence between current and past modes plays an important role in determining entry mode choice. Hansen et al. (2014) estimates a dynamic Probit model, controlling for endogenous initial conditions and unobserved heterogeneity, using longitudinal data extracted from the Survey of Labour and Income Dynamics (SLID) for the years 1993–2000. The empirical results suggest that the existence of structural state dependence, or a "welfare trap", appears to be more likely in provinces with relatively high benefit levels.

[3] Unlike Prowse (2012), our model does not allow different amounts of unobserved variations in the coefficients, but it allows employment state-specific coefficients. Each intercept's distribution is a robust discrete non-parametric distribution, while that of Prowse's (2012) is assumed normally distributed. Our modeling approach deviates from Prowse's (2012) in a sense that we use the Heckman (1981a,b,c) approach for initial condition instead of the Woolridge (2005) approach.

[4] We develop a model to estimate married women's labor supply decisions by combining two approaches. The first is a finite mixture approach, in which unobserved individual characteristics can be flexibly handled without imposing a parametric structure. Second, we use a simulation-based estimation method, which applies a standard approach to a simulation drawn from the specified distribution for the model with serial correlation in the errors of each labor supply alternative. For details regarding simulation-based estimation methods, see Lerman and Manski (1981), McFadden (1989), and Pakes and Pollard (1989).

Table 1
Number of respondents by cohort.

	1993 survey	1997 survey	2003 survey	2008 survey	2013 survey
Cohort A	1500	1255	980	828	732
Cohort B		500	323	261	231
Cohort C			836	560	478
Cohort D				636	450
Cohort E					648

2. Data

In this section, data from the annual Japanese Panel Surveys of Consumers for the period 1993 to 2002 are examined. These panel surveys queried 1500 women aged 24 to 34 in 1993 (Cohort A). In 1997, 500 women aged 24 to 27 were added to the survey (Cohort B). Subsequently, 836 women aged 24 to 29 were added in 2003 (Cohort C), 636 women aged 24 to 28 were added in 2008 (Cohort D), and 648 women aged 24 to 28 were added in 2013 (Cohort E). Table 1 shows the changes in the number of respondents by cohort.

We focused on the dynamic aspect of work participation by using the sample from Cohort A, which covers the period from 1993 to 2002. The sample consists of 340 continuously married couples. We used employment status as a dependent variable, categorized as regular work, non-regular work (part-time or other non-regular work), and non-participation.[5] Independent variables include age, education, number of children, permanent and transitory non-labor income, and post-school non-regular work experience (NWEP). Married women aged 24 to 34 in 1993 were included, and years of education were inputted as follows: junior high school = 9 years, high school = 12 years, special school or special training college = 12.5 years, junior college = 14 years, technical college = 15 years, university = 16 years, and graduate school = 18.5 years. Fertility variables were defined as the number of children aged 0 to 2, 3 to 5, and 6 to 17. The husband's annual earnings divided by the consumer price index (the base year is 2005) were considered non-labor income for married women. The 10-year average of non-labor income was used as permanent non-labor income (*ymp*), and deviations from permanent income were considered as transitory non-labor income (*ymt*).[6]

As aforementioned in the Introduction, stigma effects exist from the first job in the Japanese labor market. If stigmatization occurs through a failure to obtain regular employment upon entering the labor market, the subsequent search costs for such employment increases; thus, the first job affects a time-invariant, unobserved, and individual-specific component. In fact, as Cooray et al. (2017)'s findings suggest, the impact of country-specific institutions on labor supply cannot be ignored. Therefore, we considered the endogeneity of unobserved heterogeneity in the Japanese labor market by using a variable to define whether the individual failed to get regular work in the first job (failed to get regular work = 1, otherwise = 0). This is a dummy variable to indicate NWEP, or post-graduation experience in a part-time or temporary job, or joblessness otherwise.[7]

[5] Employment status is defined as the occupational status in September of each year. A part-time worker is an employee with contracted hours of work per week less than those of regular workers. Other non-regular work consists of employees who are consigned jobs (*shokutaku*) or work for an employer on contract (*haken-shain*).

[6] We followed the definition of fertility variables (Children 0–2, Children 3–5, Children 6–17) and permanent and transitory income (*ymp* and *ymt*) used by Hyslop (1999).

[7] The experience of non-regular work immediately after graduation may also delay the timing of marriage (Higuchi, 2001). By focusing on a sample of continuously married women, we can identify the effect of NWEP on subsequent work participation behavior conditional upon its effect on marriage.

Table 2
Work transition matrix for married women.

		State at Time $t+1$			
		Non-Participation (NP)	Non-Regular (NR)	Regular (R)	Total
State at Time t	Non-Participation (NP)	88.88	10.05	0.80	100
	Non-Regular (NR)	9.60	87.30	3.13	100
	Regular (R)	3.50	4.00	92.60	100

Notes: Row numbers are percentages based on 3060 observations (340 women × 9 years).

3. Observed transition patterns

Table 2 presents the transition matrix for non-participation (NP), non-regular work (NR), and regular work (R), which indicates that a substantial number of women remain in the same work state over time. A higher level of state dependence seems to exist in regular work: 92.6% of women who were regular workers in year t remained regular workers in year $t+1$. Meanwhile, 87.3% who were non-regular workers in year t remained non-regular workers in year $t+1$. Almost 10% of those who were non-regular workers in year t did not participate in year $t+1$, and almost 10% of those who were non-participating in year t transitioned to non-regular work in year $t+1$. Few cases were observed for transitions between regular and non-regular work.

Table 3 illustrates the differences in the observed characteristics among transition patterns. As anticipated, the educational level is highest in the group that experienced regular to regular work (R to R). As women who remain in the non-participation group (NP to NP) have more children aged 0 to 2 and 3 to 5, this indicates that young children restrict job opportunities for married women. Alternatively, those who remain in the non-regular workgroup (NR to NR) have more children aged 6 to 17. This result can be attributed to the special school fees required for junior high school, high school, and university entrance examinations, or home loans taken to purchase a larger residence due to an increasing number of children.[8] The husband's income (non-labor income) is higher for women who remain in the NR to NR and NP to NP work groups. These results suggest that an increase in the husband's income induces “income effects” that impact the wife's incentive to decrease her degree of participation.

Table 4 presents the percentage of married women observed in each employment state from 1993 to 2002. On average, 19% were employed in regular work, 28% in non-regular work, and 53% were non-participating. The proportion of non-regular work constantly increased over the sample period.[9] Table 5 presents the distributions of durations of each form of employment, with pronounced peaks at 0 and 10 years in regular work and non-participation, respectively. In contrast, the duration is evenly distributed across the number of years worked in non-regular work. This represents the differences in entry and exit costs across employment states. These transition patterns are influenced by observed characteristics, such as age and education, as well as by unobserved heterogeneity. The following sections analyze the degree of true state dependence in regular and non-regular work by statistically controlling for observed characteristics and unobserved heterogeneity.

[8] These interpretations are based on the work of Okamura and Islam (2011).

[9] The aggregate proportion of non-regular work for females aged 25 to 44 in Japan, based on the Special Survey of the Labor Force (*Roudou-ryoku chousa Tokubetsu Chousa*), revealed a similar upward trend, from 0.210 in 1993 to 0.267 in 2001.

Table 3
Sample characteristics.

	Full Sample	R to R	R to NR	R to NP	NR to R	NR to NR	NR to NP	NP to R	NP to NR	NP to NP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Age	34.11	35.69	34.70	32.70	35.73	36.10	34.06	34.38	33.95	33.60
Education	12.90	13.68	12.13	13.00	12.37	12.60	12.70	12.08	12.66	12.85
No. of Children Aged 0–2	0.32	0.28	0.26	0.55	0.04	0.05	0.28	0.54	0.18	0.44
No. of Children Aged 3–5	0.44	0.37	0.39	0.40	0.42	0.24	0.27	0.38	0.45	0.58
No. of Children Aged 6–17	1.09	1.27	1.43	0.55	1.58	1.49	1.11	1.15	1.22	0.95
Husband's Earnings										
Permanent income	5.50	5.31	3.62	5.29	4.60	5.32	5.64	4.15	5.50	5.72
Transitory income	0.00	0.06	−0.04	−0.12	−0.03	0.15	0.08	−0.01	−0.03	0.08
Non-Regular Work Experience Post School	0.08	0.13	0.13	0.05	0.23	0.08	0.06	0.00	0.06	0.06
Sample Size	3400	535	23	20	26	722	79	13	173	1469

Table 4
Ratio of married women in each employment state.

Variable	Year										
	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	Average
Regular	0.203	0.188	0.185	0.182	0.188	0.188	0.185	0.188	0.191	0.191	0.189
Non-Regular	0.129	0.194	0.209	0.244	0.268	0.300	0.338	0.368	0.382	0.397	0.283
Non-Participation	0.668	0.618	0.606	0.574	0.544	0.512	0.476	0.444	0.426	0.412	0.528

Table 5
Distribution of maximum durations (%).

	Number of Years Worked											
	0	1	2	3	4	5	6	7	8	9	10	Total
Regular	73.5	2.9	1.5	1.5	1.5	1.8	0.9	0.9	1.2	0.9	13.5	100
Non-Regular	45.9	6.2	5.6	7.6	5.3	3.8	6.2	7.1	1.5	4.7	6.2	100
Non-Participation	22.4	7.9	2.6	7.4	5.6	3.8	4.4	6.5	4.4	5.9	29.1	100

4. Empirical model

This study extended the existing binary choice model proposed by Okamura and Islam (2011) to a dynamic multinomial latent-class logit model that analyzes the labor force participation behavior of married women in Japan. First, to summarize the analytical method, we estimate a multinomial logit (mixed logit) model of the probability that a married woman belongs to any of three (non-participation, regular, and non-regular work) mutually exclusive work states conditional on a vector of time-varying observable characteristics; a vector of time-invariant observable characteristics; a vector of the lag of each alternative; a vector of the lag of cross alternatives; and an unobserved individual-specific and time-invariant component. The unobserved individual-specific and time-invariant components may correlate with time-varying observable characteristics (e.g., number of children, transitory non-labor income), and thus, we follow the works of Mundlak (1978) and Chamberlain (1984). For the distribution of individual-specific unobservable characteristics, we follow the finite mixture approach as proposed by Heckman and Singer (1984) and approximate the distribution of the unobservable characteristics with a finite number of support points in each state. Further, we assume that the time-varying persistent unobservable characteristics (e.g., random shocks) are serially correlated over time in the form of autocorrelation. It is also assumed that random shocks are correlated over time, and alternatives are correlated through the probability mass function of individual-specific unobserved random factors. Thus, as in the binary model, we defined the first-order autocorrelation for the choice of non-regular work and regular work.

Further, we use simulation methods to approximate the high-dimension integral feasibly. We use a Geweke-Hajivassiliou-Keane (GHK) simulator and the simulated maximum likelihood (SML) method to estimate the model. Moreover, we calculate the serial correlation coefficients using the hyperbolic transformation to ensure that the estimated value falls within the range.[10] This study's empirical framework is described as follows.

Consider that a married woman (indexed as $i = 1, \ldots, N$) belongs to any of three mutually exclusive work states k at time t ($t = 2, 3, \ldots, T$); the reference state $k = 1$ is non-participation, the second state $k = 2$ is non-regular employment, and the third state $k = 3$ regular employment. Thus, the value function V_{ikt} for a married woman i belonging to state k at time t can be specified as follows:

$$V_{ikt} = X_{it}\beta_k^1 + Z_i\beta_k^2 + L_{it}\beta_k^3 + CL_{it}\beta_k^4 + \varepsilon_{ikt}, \tag{1}$$

where X_{it} is a vector of time-varying observable characteristics, including time dummies, age, number of children (aged 0–2, 3–5, and 6–17), and transitory non-labor income; Z_i is a vector of time-invariant observable characteristics, including educational attainment, permanent non-labor income, and the dummy variable for NWEP; L_{it} is a vector of the lag of each alternative, and CL_{it} is a vector of the lag of cross alternatives. The error term $\varepsilon_{ikt} = \mu_{ik} + \nu_{ikt}$ is composed of two terms: μ_{ik} represents an unobserved individual-specific and time-invariant component, and ν_{ikt} represents a serially correlated error term. In Equation (1), the parameter

[10] Data and Fortran code used for descriptive statistics and for estimation are available on request.

vectors β_k^l ($l = 1, 2, 3, 4$) are estimated; for identification purposes, we normalized β_1^l and μ_{i1} to zero. The probability of observing individual i in state k at time $t (t > 1)$ conditional on X_{it}, Z_i, L_{it}, CL_{it} , and μ_{ik} can be written as:

$$P_{ik}(k|\mu) = \left.\begin{aligned} &\frac{\exp\left(X_{it}\beta_k^1 + Z_i\beta_k^2 + L_{it}\beta_k^3 + CL_{it}\beta_k^4 + \mu_{ik}\right)}{1 + \sum_{k=2}^{3}\exp\left(X_{it}\beta_k^1 + Z_i\beta_k^2 + L_{it}\beta_k^3 + CL_{it}\beta_k^4 + \mu_{ik}\right)} \; for\; k = 2,3 \; and\; t = 2,3,\ldots,T P_{t1}(k_t|\mu) \\ &= \frac{1}{1 + \sum_{k=2}^{3}\exp\left(X_{it}\beta_k^1 + Z_i\beta_k^2 + L_{it}\beta_k^3 + CL_{it}\beta_k^4 + \mu_{ik}\right)} \; for\; k = 1 \; and\; t \\ &= 2,3,\ldots,T \end{aligned}\right\} . \tag{2}$$

First, coping with the endogenous nature of individual-specific effects and lagged variables is important in the formulation of the dynamic panel data model. At the first point, the unobserved individual-specific and time-invariant components may correlate with the number of children, transitory non-labor income, and NWEP. Thus, following the works of Mundlak (1978) and Chamberlain (1984), we assumed that the unobserved individual-specific and time-invariant components μ_{ik} correlate with the mean values (over t) of the number of children, transitory non-labor income, and NWEP.[11] We then defined the correlated random effects as follows:

$$\begin{aligned} \mu_{ik} &= \delta_1 mean(\#Children0-2)_{ik} + \delta_2 mean(\#Children3-5)_{ik} \\ &+ \delta_3 mean(\#Children6-17)_{ik} \\ &+ \delta_4 mean(Ymt)_{ik} + \delta_5 mean(NWEP)_{ik} + \eta_{ik} \end{aligned} \tag{3}$$

where η_{ik} represents the unobserved individual-specific components and is uncorrelated with the number of children and transitory non-labor income.[12]

On the second point, at the initial observation, a person may be endogenous in the dynamic model (i.e., initial observations may correlate with unobserved components). Thus, we adopted the procedure suggested by Heckman (1981b) to address the initial condition. Let the value for individual i in state k at the initial period ($t = 1$) be specified as

$$V_{ik1} = X_{i1}\theta_k^1 + \varepsilon_{ik1} \tag{4}$$

where $\varepsilon_{ik1} = \tau_{ik} + \nu_{ik1}$.

The parameter θ_k^1 is to be estimated; as before, we normalized θ_1^1 and τ_{i1} to zero. The probability of observing individual i in state k at time $t (t = 1)$, conditional on X_{i1} and τ_{ik}, can be written as:

$$\left.\begin{aligned} &P_k(k|\mu) = \frac{\exp\left(X_{it}\theta_k^1 + \tau_{ik}\right)}{1 + \sum_{k=2}^{3}\exp\left(X_{it}\theta_k^1 + \tau_{ik}\right)} \; for\; k = 2,3 \; and \\ &t = 1 \quad P_1(k_t|\mu) = \frac{1}{1 + \sum_{k=2}^{3}\exp\left(X_{it}\theta_k^1 + \tau_{ik}\right)} \; for\; k = 1 \; and\; t = 1 \end{aligned}\right\} \tag{5}$$

Accordingly, the sample likelihood for the multinomial logit model with random intercepts has the following form:

$$L = \prod_{i=1}^{n} \int_{-\infty}^{\infty} \prod_t \prod_k \left\{ \begin{aligned} &\begin{pmatrix} \dfrac{\exp\left(X_{it}\theta_k^1 + \tau_{ik}\right)}{1 + \sum_{k=2}^{3}\exp(X_{it}\theta_k^1 + \tau_{ik})} \; for\; k = 2,3 \\ \\ \dfrac{1}{1 + \sum_{k=2}^{3}\exp(X_{it}\theta_k^1 + \tau_{ik})} \; for\; k = 1 \end{pmatrix}^{d_{ikt}} \; for\; t = 1 \\ &\begin{pmatrix} \dfrac{\exp\left(X_{it}\beta_k^1 + Z_i\beta_k^2 + L_{it}\beta_k^3 + CL_{it}\beta_k^4 + \mu_{ik}\right)}{1 + \sum_{k=2}^{3}\exp(X_{it}\beta_k^1 + Z_i\beta_k^2 + L_{it}\beta_k^3 + CL_{it}\beta_k^4 + \mu_{ik})} \; for\; k = 2,3 \\ \\ \dfrac{1}{1 + \sum_{k=2}^{3}\exp(X_{it}\beta_k^1 + Z_i\beta_k^2 + L_{it}\beta_k^3 + CL_{it}\beta_k^4 + \mu_{ik})} \; for\; k = 1 \end{pmatrix}^{d_{ikt}} \; for\; t = 2,3,\ldots,T \end{aligned} \right\} f(\vartheta)d\vartheta \tag{6}$$

where $d_{ikt} = 1$ if individual i chooses alternative k at time t, and equals zero otherwise.[13]

We need a distributional assumption to capture the unobservable random effect (ϑ_i), or the vector of unobserved factors. We followed the finite mixture approach as proposed by Heckman and Singer (1984) and approximated the distribution of the unobservable with a finite number J of support points in each state.[14] We assumed that J types of individuals exist and that each is endowed with a set of unobserved characteristics ϑ_i^j (consisting of τ_{ik}^j and η_{ik}^j for $k = 1, 2, 3$) for $j = 1, 2 \ldots, J$. The model allows an arbitrary correlation between unobserved effects in the initial period and unobserved effects in other periods, with the probability distribution of support points from initial and other periods. As in many previous studies (e.g., Ham and Lalonde, 1996; Eberwein et al., 1997; Stevens, 1999; Cameron and Heckman, 2001; Hansen and Lofstrom, 2009), our

[11] Rivers and Vuong (1988) suggested a two-stage probit model as an alternative method to control for unobserved heterogeneity and control the variable's endogeneity.

[12] Xin et al. (2021) is an epoch-making research that incorporates time-varying individual-specific effects in the female labor supply. In contrast, our model assumes individual-specific effects to be time-invariant, but allows correlate with socio-economic factors. Estimating a dynamic labor supply model that incorporates time-varying individual-specific effects is a challenging study in the future.

[13] Without a loss of generality, the normalization $V_{i1t} = 0$ can be imposed (or similarly, the estimates of V_{i2t} and V_{i3t} can be observed as the differences between the utility of alternatives 2 and 3 with the utility of the benchmark alternative $j = 1$).

[14] One can choose a normal distribution instead of a finite mixture. It is noteworthy that the addition of time-invariant, individual-specific, and unobservable characteristics breaks the Independence of Irrelevant Alternatives property, as they naturally align with the lag of employment status. Therefore, we do not need to test for independence from irrelevant alternatives; for detailed examples, see Train (2009) Section 6.3 and Prowse (2012).

Table 6
Women's participation outcomes with the dynamic multinomial logit model.

Variable Name	Regular Work	Non-Regular Work
	Coefficient	Coefficient
Constant	−20.722***	−16.625***
	(7.122)	(3.472)
Own-Lagged Variable	6.631***	2.920***
	(0.623)	(0.227)
Cross-Alternative Lagged Variable	3.505***	1.814***
	(0.555)	(0.474)
Age	0.919	0.596**
	(0.577)	(0.292)
Age Square	−1.051	−0.811*
	(0.778)	(0.417)
Years of Education	0.315*	−0.117
	(0.172)	(0.084)
Non-Regular Work Experience Post-School	0.366	0.471*
	(0.337)	(0.258)
No. of Children Aged 0–2	−0.898	−1.483***
	(0.561)	(0.266)
No. of Children Aged 3–5	−0.5	−0.615***
	(0.583)	(0.229)
No. of Children Aged 6–17	−0.173	−0.155
	(0.553)	(0.229)
Permanent Non-Labor Income	−0.453***	−0.221***
	(0.169)	(0.067)
Transitory Non-Labor Income	−0.217	−0.12
	(0.160)	(0.080)
AR (1) Coefficient	0.472***	0.316***
	(0.028)	(0.028)
$Corr(\overline{\theta}_R^I, \overline{\theta}_{NR}^I)$	0.518	
$Corr(\overline{\theta}_R^C, \overline{\theta}_{NR}^C)$	0.424	

Notes. Both specifications include unrestricted time effects. Standard errors are noted in parentheses. * indicates significance at the 10% level., ** indicates significance at the 5% level, *** indicates significance at the 1% level. $Corr(\overline{\theta}_R^I, \overline{\theta}_{NR}^I)$ and $Corr(\overline{\theta}_R^C, \overline{\theta}_{NR}^C)$ are correlation coefficients of the mass points between regular and non-regular work for the initial and current periods, respectively.

model is only a proper fit with the three classes, although we have estimated it with three, four, and more classes. Therefore, we report the estimates based on three support points for each alternative and their pairs of associated values, denoted by $\theta_{\text{Regular}}(j = 1, 2, 3)$ and $\theta^{l}_{\text{Non-Regular work}}(l = 1, 2, 3)$ with nine distinct probabilities π_k^{jl} summing to one.[15]

Our model assumes that random shocks' effects correlate over time, and alternatives correlate through individual unobserved random factors (μ_{ik}). Thus, as in the binary model, we defined the first-order autocorrelation for the choice of non-regular work, $\varepsilon_{i2t} = \rho_2 \varepsilon_{i2t-1} + \nu_{i2t}$, $\nu_{i2t} \sim N(0, \sigma^2_{\nu_2})$, and regular work, $\varepsilon_{i3t} = \rho_3 \varepsilon_{i3t-1} + \nu_{i3t}$, $\nu_{i3t} \sim N(0, \sigma^2_{\nu_3})$.[16]

The likelihood function with a first-order autocorrelation can then be defined as follows:

$$L = \prod_{i=1}^{n} \frac{1}{R} \sum_{r=1}^{R} \sum_{j=1}^{J} \pi_{jk} \prod_t \prod_k \left\{ \begin{array}{ll} \left(\begin{array}{l} \dfrac{\exp\left(X_{it}\theta_k^1 + \tau_{ik}\right)}{1 + \sum_{k=2}^{3} \exp\left(X_{it}\theta_k^1 + \tau_{ik}\right)} \; for\ k = 2, 3 \\ \\ \dfrac{1}{1 + \sum_{k=2}^{3} \exp\left(X_{it}\theta_k^1 + \tau_{ik}\right)} \; for\ k = 1 \end{array} \right)^{d_{ikt}} & for\ t = 1 \\ \left(\begin{array}{l} \dfrac{\exp\left(X_{it}\beta_k^1 + Z_i\beta_k^2 + L_{it}\beta_k^3 + CL_{it}\beta_k^4 + \mu_{ik}\right)}{1 + \sum_{k=2}^{3} \exp\left(X_{it}\beta_k^1 + Z_i\beta_k^2 + L_{it}\beta_k^3 + CL_{it}\beta_k^4 + \mu_{ik} + \rho\varepsilon^r_{ik,t-1}\right)} \; for\ k = 2, 3 \\ \\ \dfrac{1}{1 + \sum_{k=2}^{3} \exp\left(X_{it}\beta_k^1 + Z_i\beta_k^2 + L_{it}\beta_k^3 + CL_{it}\beta_k^4 + \mu_{ik} + \rho\varepsilon^r_{ik,t-1}\right)} \; for\ k = 1 \end{array} \right)^{d_{ikt}} & for\ t = 2, 3, \ldots, T \end{array} \right\} \tag{7}$$

Further, we used simulation methods to approximate the high-

[15] See Heckman and Singer (1984) and Chay and Hyslop (1998) for more information regarding choosing the number of mass points.

[16] One caveat of our model is that perhaps higher order correlation exists but it is not verified. This could be investigated in further research. In our view, because it is a model of annual household decision-making, AR(1) is a sufficient approximation, even if there is weak higher order correlation.

Table 7
Joint and marginal distributions of the individual-specific, unobserved characteristics of regular and non-regular work.

	Non-Regular Work				
Regular Work	Mass Point	$\theta_{NR}^{c1} = -22.273^{***}$ (0.0285)	$\theta_{NR}^{c2} = 8.302^{***}$ (1.8075)	$\theta_{NR}^{c3} = 6.985^{***}$ (1.8429)	
	$\theta_{R}^{c1} = -9.183^{***}$ (0.5469)	$\pi^{11} = .000021$	$\pi^{12} = .000004$	$\pi^{13} = .000005$	$\pi^{1l} = .00003$
	$\theta_{R}^{c2} = -7.269^{**}$ (3.2996)	$\pi^{21} = 0.159$	$\pi^{22} = 0.295$	$\pi^{23} = 0.233$	$\pi^{2l} = 0.687$
	$\theta_{R}^{c3} = -3.807$ (3.5146)	$\pi^{31} = 0.124$	$\pi^{32} = 0.147$	$\pi^{33} = 0.042$	$\pi^{3l} = 0.313$
		$\pi^{j1} = 0.283$	$\pi^{j2} = 0.442$	$\pi^{j3} = 0.275$	$\sum_{j=1}^{3}\sum_{l=1}^{3}\pi^{jl} = 1$

Notes. All calculations are based on the current period. The marginal distributions π^{j1}, π^{j2}, π^{j3} and π^{1l}, π^{2l}, π^{3l} are the sum of each row and column. Standard errors are noted in parentheses. ** indicates significance at the 5% level, *** indicates significance at the 1% level.

Table 8
Effect of variables that correlate with unobserved heterogeneity.

Variable Name	Regular Work	Non-Regular Work
	Coefficient	Coefficient
Transitory Non-Labor Income	1.138 (0.882)	−1.265 (1.305)
No. of Children Aged 0–2	1.151 (1.129)	−0.140 (0.461)
No. of Children Aged 3–5	−0.590 (1.655)	0.134 (0.411)
No. of Children Aged 6–17	0.800 (0.529)	0.406 (0.321)
Non-Regular Work Experience Post School	0.669** (0.337)	−0.257 (0.256)

Notes. Standard errors are noted in parentheses. ** indicates significance at the 5% level.

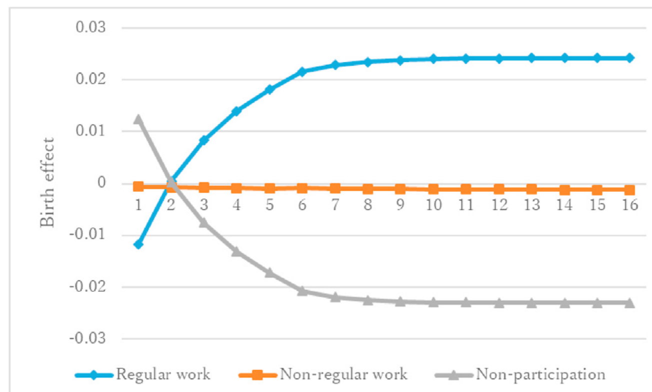


Fig. 1. Dynamic participation response to the age of the child for a woman who was a regular worker at $t = 1$.

dimension integral feasibly.[17] We used a Geweke-Hajivassiliou-Keane (GHK) simulator and the simulated maximum likelihood (SML) method to estimate the model.[18] Moreover, we calculated the serial correlation coefficient by using the hyperbolic transformation to ensure that the estimated value of ρ_k (k = 2, 3) falls within the range.[19] The estimated coefficient $\hat{\rho}_k$ is then transformed, as follows:

$$\rho_k = \left(\exp\left(2\times\hat{\rho}_k\right) - 1\right) \Big/ \left(\exp\left(2\times\hat{\rho}_k\right) + 1\right) \tag{8}$$

5. Empirical results

Table 6 presents women's participation outcomes with the dynamic multinomial logit model. These results indicate that, on the one hand, permanent income—rather than transitory non-labor income—has significant, negative effects on participation. This effect is stronger in regular than non-regular work. On the other hand, the number of children aged 0 to 2 and 3 to 5 significantly and negatively affects the choice of non-regular work, while it has no significant effect on the choice of regular work. As anticipated, the NWEP positively affects the current choice of non-regular work.

Our main concern involves testing for true state dependence based on the coefficients of the lagged dependent variable by controlling for unobserved heterogeneity. If the coefficient of the lagged dependent variable is significantly positive, we infer that a true state dependence exists in married women's participation behavior. Table 5 indicates that the coefficients of own lagged participation for regular work (6.631) and the coefficient of own lagged participation for non-regular work (2.920) are significantly positive. The cross-lagged variables—the effect of lagged participation of non-regular work on the current choice of regular work (3.505) and the effect of lagged participation of regular work on the current choice of non-regular work (1.814)—are also significantly positive. Unexpectedly, this result indicates that both the own-lagged and cross-lagged effects are stronger for regular than non-regular work.[20] Unlike the above results, Okamura and Islam's (2011) binomial estimation shows insignificant state dependence in the participation behavior. The difference between the results of the binomial and multinomial model on the estimates of state dependence lies in the sample distribution. In the sample of Okamura and Islam (2011), more than half have experienced a transition between "participation" and "non-participation" at least once, which has led to the empirical result that there is no state dependence. In contrast, our multinomial model specifies "non-participation" as a base category, and as Table 2 shows, the proportion of samples who experienced transition between "regular (non-regular) work" and "non-participation" is relatively small compared to the proportion of those who were continuously choosing "regular (non-regular) work." As a result, we obtained the outcome indicating the state dependence in regular and non-regular work. The existence of true state dependence in non-regular work implies that non-regular work experience decreases the ability or preference of married women to conform to

[17] See Hajivassiliou and Ruud (1994) for a detailed discussion.
[18] See Train (2009) on how to use the GHK simulator and SML to estimate the multinomial probit model. We applied Lee's (1997) procedures to first generate independent and uniform [0, 1] random variables for the GHK simulator.
[19] We followed the delta method approach (Haan and Uhlendorff, 2006) to calculate the standard error of ρ.

[20] There is a caveat for these findings. As Ellwood (1982) observed, the existence of true state dependence depends on the choice of "artificial" analysis periods. When the chosen period is long, relative to the average length of stay in a state (e.g., non-regular work), the existence of true state dependence may be overstated.

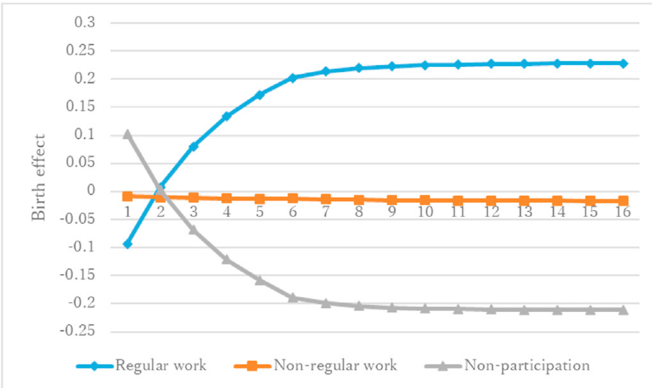


Fig. 2. Dynamic participation response to the age of a child for a woman who was a non-regular worker at $t = 1$.

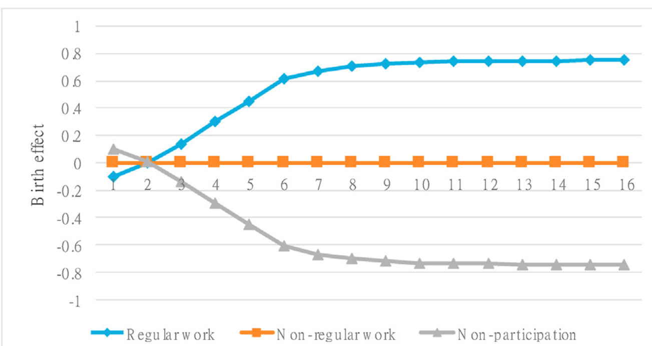
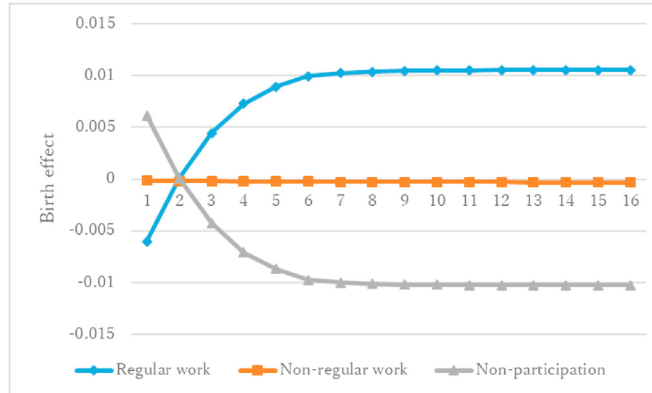
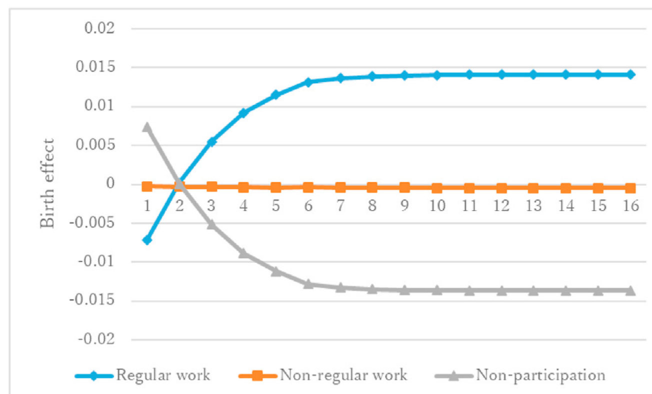


Fig. 3. Dynamic participation response to the age of a child for a woman who was a non-participation worker at $t = 1$.



(a)



(b)

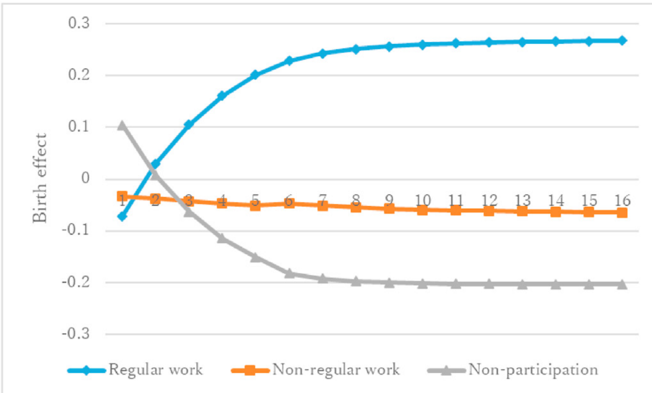
Fig. 4. (a). Dynamic participation response to the age of a child for a strongly motivated working woman who was a regular worker at $t = 1$ 0.4(b). Dynamic participation response to the age of a child for a weakly motivated working woman who was a regular worker at $t = 1$.

non-regular work. This seems to suggest the possibility of a genuine disparity in inter-temporal utilities between married women who are engaged in regular work and those engaged in non-regular work. However, because of the existence of true state dependence in regular work, the transition from non-regular work to regular work changes the abilities or preferences of married women to conform to regular work, and it is thought to decrease the genuine disparity.

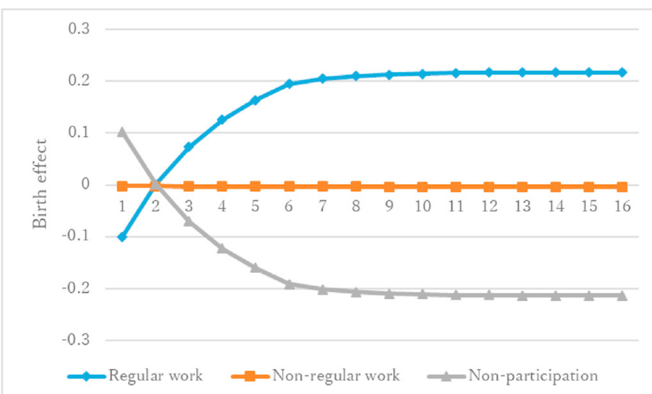
Additionally, the effect of lagged participation of non-regular work on the current choice of regular work is significantly positive. Interpreting this result in the economic context shows that non-regular work is not necessarily exclusive, but plays a stepping-stone role for regular work through factors such as skill enhancement effect based on work experience. It is noteworthy that this result is in contrast with that of Kishi and Kano's (2017), which suggested that fixed-term employment does not have any significant effects on permanent and ongoing employment in the next period. As mentioned earlier, the decisive difference between Kishi and Kano's (2017) estimation model and ours lies in controlling serial correlation in each employment status. If the inertia of working in non-regular work is enhanced by positive AR (1) in non-regular employment, the models that do not control serial correlation are expected to underestimate the probability of moving from non-regular work to other states. In fact, the coefficients of AR (1) and the standard errors indicate that serially correlated transitory errors significantly and positively affect the choice of regular and non-regular work. This is consistent with the significantly positive effect of past non-regular work experience on the current choice of regular work.

The specification used for the distribution of unobserved heterogeneity (mass points) allows for unrestricted correlations between the unobserved characteristics (such as an ability, taste, or preference) for regular work (determined by θ_R^{cl}), and for non-regular work (determined by θ_{NR}^{cl}). The empirical correlation coefficient between regular and non-regular unobserved preference for work is 0.518 for the initial period and 0.424 for the current period (see Table 6). This suggests that, holding observable characteristics constant, preference for regular work is positively associated with non-regular work. Table 7 presents a joint distribution of the individual-specific, unobserved characteristics of regular and non-regular work. The mass points of unobserved heterogeneity for regular and non-regular work are noted as $\theta_R^{c3} > \theta_R^{c2} > \theta_R^{c1}$ and $\theta_{NR}^{c2} > \theta_{NR}^{c3} > \theta_{NR}^{c1}$, respectively. The highest value of θ represents the strongest preference, the middle value of θ represents the more modest value, and the lowest value of θ represents the weakest preference for work. Further, π^{jl} are the joint distributions for each mass point, and π^{j1}, π^{j2}, π^{j3} and π^{1l}, π^{2l}, π^{3l} are the marginal distributions. The results indicate that 31% ($\pi^{3l} = 0.313$) of women exhibit a strong preference for regular work, and 44% ($\pi^{j2} = 0.442$) strongly prefer non-regular work. Alternatively, 69% ($\pi^{2l} = 0.687$) modestly prefer regular work, and 28% ($\pi^{j3} = 0.275$) have a modest preference for non-regular work. On the weakly preference, only 0.03% ($\pi^{1l} = 0.0003$) weakly prefer regular work, while a considerable number: 28% ($\pi^{j1} = 0.283$) have weak preference for non-regular work.

Fertility, non-labor income, and NWEP possibly correlate with individual-specific, unobserved characteristics; if true, then the estimated coefficients produce biases and inconsistent results. We consider this issue by estimating the correlated random effects specification as defined in Equation (3). Table 8 presents the correlated random effects model results wherein the coefficients of the mean values (over t) of the



(a)



(b)

Fig. 5. (a). Dynamic participation response to the age of a child for a strongly motivated working woman who was a non-regular worker at $t = 1$. 5(b). Dynamic participation response to the age of a child for a weakly motivated working woman who was a non-regular worker at $t = 1$.

number of children, transitory non-labor income, and NWEP are not statistically significant; that is, omitted unobserved heterogeneity does not correlate with fertility and earnings variables.

6. Simulation analysis

In this section, we simulate the transition probabilities of regular work, non-regular work, and non-participation from their initial working states using the parameter estimates above. This simulation investigates how childbirth effects on dynamic state choices differ by initial working states and unobserved choice preferences. We perform this simulation by first predicting the sequence of each employment state's transition probabilities over 16 years for women who experienced or did not experience childbirth in year one. We then calculated the marginal effects of child age—or the effects of the child becoming one year older—on the transition probabilities of work states. This was accomplished by deducting the predicted transition probabilities of employment states for women who did *not* experience childbirth in year one from those for women who *did*. In summary, we calculated the marginal effects of child age on the transition probabilities of working states for women who experienced childbirth, relative to those who did not.[21] As childbirth only occurs in year one, this simulation demonstrates how the disadvantage in the choice of employment state changes with the child's age.

Fig. 1 illustrates the dynamic participation response to the age of the child for a woman who was a regular worker. When a child is born in year one, the marginal transition probability to non-participation increases by nearly 0.012, and the marginal probability of retaining regular work decreases by the same amount. However, when the child reaches three years of age, the marginal transition probability to regular work increases by almost 0.008 and remains at almost 0.024 after the seventh year when the child is six years of age. The marginal transition probabilities to non-regular work are almost zero throughout the period.

The participation response to the child's age for a non-regular worker (Fig. 2) and non-participant (Fig. 3) share a similar pattern of transition probabilities with the regular worker. However, the magnitudes of the probabilities differ markedly. As Fig. 2 indicates, the marginal transition probability of a non-regular worker to non-participation increases by nearly 0.102 in year one, while the marginal probabilities of retaining non-regular work and moving to regular work decrease by 0.018 and 0.093, respectively, in the same year. After the seventh year, the marginal transition probability to regular work increases by almost 0.220, or approximately nine times that of a regular worker. In the case of the non-participant (Fig. 3), the magnitude of marginal transition probabilities toward regular work becomes higher than that in the non-regular worker's case; after the seventh year, the marginal transition probability to regular work increases to almost 0.740, or approximately three times that of the non-regular worker. Reflecting the estimated results, the strong state dependence in regular work and cross-effects from non-regular work to regular work, a mother's participation response to having a child compared with those who do not is dominated by regular work in the long-term, irrespective of the initial employment state.

These results seem strange from the common perspective on the reality of the labor market for married women in Japan. However, they suggest a hidden reality uncovered by serial correlation-controlled estimates that could not be observed in previous studies. The result can be interpreted in two possible ways. First, as pecuniary child-rearing costs increase with the child's age, mothers are willing to engage in regular work. Second, as child-rearing becomes less time-consuming with the child's age, the opportunity cost of the work activity decreases, and mothers become more willing to engage in regular work. Further, as mentioned above, serially correlated transitory errors significantly and positively affect the choice of regular and non-regular work, and the effect size is larger in regular work than in non-regular work. Interpreting the simulation results based on this finding suggests that an event, such as purchasing a new home as the child grows up, may result in intertemporal labor force participation correlations.

Subsequently, we identify the unobserved heterogeneity effects on the participation response to the age of child using the estimated parameter in Table 7. We calculate the weak and strong preferences for the participation response by using one support point: the unobserved heterogeneity distribution. The participation responses with weak (the mass point's lowest value) and strong (the mass point's highest value) preferences reflect the parameter estimates of the first and third support points, respectively.[22] Fig. 4(a) and (b) illustrate the participation response to child age for regular workers with different participation preferences. There is almost no difference noted in the marginal probabilities of moving to non-regular work among women with strong or weak preferences. Instead, weak preference decreases the marginal transition probability to non-participation more than the strong preference does.

Fig. 5(a) and (b) display the participation response to a child's age for non-regular workers with different participation preferences. We find

[21] Because it is calculated as the *marginal* transition probability in terms of child age, the sum of probabilities among states is zero.

[22] We also calculated the participation response with a "modest" preference, which corresponds to the second support point. This reference has not been cited in the text.

that the decrease in the marginal probability of retaining non-regular work is larger for women with strong preferences than for those with weak preferences. Simultaneously, a strong preference increases the marginal transition probability to regular work more than the weak preference does.

In summary, this study finds that there is an "intrinsic" tendency for a mother to choose regular work after childbirth regardless of her initial employment status, and if the first job is non-regular, a strong preference for working increases the probability of her choosing regular work. Above all, the latter simulation result has important policy implications. The result suggests that even if a worker happens to have to engage in non-regular work due to a bad economy at the time of graduation, there is room to step up to regular work if they have a strong preference for working. This provides important evidence for designing employment policies for workers who were forced to find employment unwillingly during the "Employment Ice Age."

7. Conclusion

We investigated whether true state dependence exists in married women's choice of regular and non-regular work in Japan. As a general and original contribution to previous studies, we made estimates with as much control as possible about unobserved factors. In Particular, we estimated a dynamic multinomial logit model that allows for correlated random effects and serially correlated transitory errors, and controlling a factor related to the country-specific labor market system using Japanese panel data. The empirical results suggest that significant true state dependence exists in the choice of regular and non-regular work, which is similar to the results of Haan (2010), Prowse (2012), and Kishi and Kano (2017). We also find a significantly positive "cross" state dependence from non-regular to regular work and a positive correlation of transitory errors in the choice of regular and non-regular work. This result is different from previous studies that do not control the autocorrelation of error terms, and suggests the importance of controlling heterogeneity as much as possible in the estimation of state dependence. The estimated results show that state dependence in regular work is positive and significant and that past non-regular employment increases the probability of current regular employment. This allows us to conclude that non-regular work functions are far from exclusionary for married women in the Japanese labor market. The Introduction discussed the genuine disparity in inter-temporal utilities between married women who continue regular work and those who transition to non-regular work after childbirth. In line with this argument, our findings suggest that the genuine disparity in these groups' inter-temporal utilities is seemingly trivial. On the serially correlated transitory errors, earlier research revealed ambivalent results; on the one hand, some results of the previous binomial model (Hyslop, 1999; Michaud and Tatsiramos, 2011) provided evidence of negatively correlated transitory errors in the United States, Denmark, France, Germany, the Netherlands, Italy, Spain, and the United Kingdom. On the other hand, Islam (2007) and Okamura and Islam (2011) showed evidence of positively correlated transitory errors in Sweden and Japan using the same binomial model. Further, Prowse's (2012) multinomial model indicated negatively correlated transitory errors for full- and part-time workers in the United Kingdom. Important avenues for further research involve identifying the components of serially correlated transitory errors for each employment state and clarifying the sources of cross-country differences in state dependence and the effects of serial correlation.[23]

We used the aforementioned parameter estimates to simulate the effect of childbirth and the age of child on dynamic state choice, with different initial states and heterogeneity in preference. Childbirth initially decreases the marginal transition probability to regular work and increases the marginal transition probability to non-participation. However, as the child reaches three years of age, the marginal transition probabilities to regular work dominate the marginal transition probabilities to non-regular work and non-participation, *irrespective* of the initial participation state. We also identify the effects of preference heterogeneity on the dynamic state choice by simulation. Our findings suggest that if the first job is non-regular, a strong preference for working encourages the move to regular work. With the exception of Prowse (2012), there are no studies to our knowledge that simulate in detail the effects of heterogeneity on dynamic labor supply. It can be said that our research has presented a way to derive policy implications from the identification of heterogeneity.

Our analysis only focused on females and is based on annual data from a specific cohort. Considering the current situation wherein an increase in non-regular "males" is becoming a social issue, the state dependence in male non-regular employment should be analyzed. Further research based on monthly data, including multiple cohorts, is necessary to confirm our findings.

[23] Del Boca and Sauer (2009) discovered cross-country differences in the first-order state dependency in Italy, Spain, and France. They also found that the differences in state dependency among these countries are consistent with the order of the country-level measures of the labor market's flexibility and child-care availability.

Declaration of competing interest

The authors declare that they have no conflict of interest.

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