Work-family trajectories over the life course of Japanese males and females: A transition-oriented comparison using hidden Markov models

Miki Nakai and Fulvia Pennoni

Abstract It is well known that Japan is one of the countries where expanding female employment faces significant challenges. Although the proportion of female students enrolled in tertiary education is approaching half the student body, a smaller proportion of women transition into the workforce. In this study, we analyze the work-family life courses of Japanese society through a gender lens using data from Social Stratification and Social Mobility Survey conducted in 2015. We examine career trajectories, partnership, and parenthood across different age cohorts. Using a hidden Markov model with educational level and age cohort as covariates on the initial probabilities of the latent sub-model, we can account for missing responses, non-responses, and sample weights. This approach allows us to identify distinct life stages for men and women, as well as to track varied trajectories over time. We also highlight the "motherhood penalty", whereby mothers' careers tend to lag behind those of fathers, contributing to the gender wage gap. Furthermore, using a Markov chain model with decoded states, we detect a significant effect of education on the development of women's careers.

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1 Introduction

Work and family life courses are complex processes involving a series of events that occur across the life span and are also related to the social and economic context of a specific period. This study aims to explore the interplay between paid employment and partnership and family dynamics in the life courses of Japanese men and women. We aim to identify typical patterns and transitions of employment status and family formation, examining this holistically over the life course to understand how the Japanese labor market structure, workplace norms, and gender-role expectations influence the career choices of men and women. We investigate how women's work life courses have been more intricately linked to the family domain compared to men's. In contemporary societies, women have shown greater shifts in their preferences and behaviors regarding employment and work. However, it is well known that work-family trajectories are gendered (Moen, 2016). Both advantages and disadvantages accumulate over the life course, widening inequalities across gender divides (Budig and England, 2001). Especially in Japanese society, men and women typically follow markedly different employment patterns throughout their life courses, shaped by the prevailing traditional norms of the male breadwinner and female homemaker roles (Brinton and Oh, 2019). While males in Japan, as well as in Italy, can afford parenthood with continuous employment, mothers experience highly volatile employment life courses dominated by part-time work or unemployment (Pennoni and Nakai, 2019).

In 2022, Japan's prime-age (25–54 years old) female labor force participation rate stood at 81.8 percent, surpassing the OECD average of 80.9 percent. However, the proportion of women employed in part-time jobs in Japan was 31.8 percent, significantly higher than the OECD average of 19.2 percent. Additionally, the structural and institutional contexts in countries with various state policies shape the individual career trajectories (Aisenbrey and Fasang, 2017; Nutz and Lersch, 2021). To date, life course research examining the heterogeneity of life course trajectories, especially gender differences, has predominantly focused on samples from Western affluent societies and has failed to account for East Asian context. In addition, a key focus of life course research is the variation in individual life courses in relation to a changing world. It is often emphasized that life courses are becoming increasingly differentiated and de-standardized in response to economic globalization, technological advancements, and cultural shifts (Brückner and Mayer, 2005). Studying cohort differences, while also considering gender differences, is crucial for gaining a clear understanding of social changes over time, especially in light of population aging, changing family demographics and persistent gender inequalities in old age.

To examine the evolution of trajectories and understand how events such as employment, partnership, and family life change in tandem, we propose the use of Markov and hidden Markov (HM) models. These models are widely utilized for analyzing longitudinal responses that may be continuous, discrete, or categorical, even when individual covariates are included (Bartolucci, Farcomeni and Pennoni, 2013; Pennoni and Piccarreta, 2017). They are also well-suited for multichannel sequence analysis (Raab and Struffolino, 2022) as they provide dimensionality reduction through latent states. This enables the identification of unknown cluster-based typologies, groups of individuals with similar patterns, and the analysis of how individuals transition between clusters over time. They account for the complexities of life course data due to the time, ordering, and co-occurrence of events over time, and they also account for unobserved heterogeneity (Vermunt, Langeheine and Böckenholt, 1999; Bouveyron et al., 2019; Bartolucci, Pandolfi and Pennoni, 2022). In this paper, we provide a contribution that explores the potential of Markov models for analyzing life course data, as well as a substantial analysis highlighting the persistent differences between males and females in experiencing various work and family events, while accounting for education and age cohort.

The remainder of the paper is structured as follows. In Section 2, we review the key literature on life course trajectories, with a focus on gender inequalities, describe the Japanese context, and present our hypotheses. In Section 3, we introduce the life course data. In Section 4, we outline the proposed models and their underlying assumptions. In Section 5, we present and compare the results of the analysis conducted separately for females and males in studying life course data. Finally, in Section 6, we summarize the main findings and provide concluding remarks.

2 Previous research

2.1 Arguments in previous research on work-family trajectories

In recent years, there has been a growing interest in the analysis of life course trajectories based on longitudinal data, which capture long-term individual history to emphasize the temporal dimensions of human lives. A large body of research in social sciences has investigated the properties of the interconnectedness of sequences of actions and identified ideal-typical patterns of certain processes such as transition to adulthood, intragenerational career mobility, and the partnership and parenthood transitions (Amato et al., 2015). Advanced statistical models developed in recent decades allow exploring the variation and complexity of the individual life course. Sequence analysis is one of the most widespread approaches for analyzing sequence data (Abbott, 1995; Abbott and Tsay, 1995). A considerable amount of research has illustrated employment and family trajectories patterns using longitudinal survey data, see, among others, Killewald and Zhuo (2019), Nutz and Lersch (2021). More recently, multichannel sequence analysis which focuses on the interconnections between multiple temporal processes that occur simultaneously, such as employment trajectories and family trajectories, has been applied in many research to gain a better understanding of how labor market participation and family formation are jointly constructed over the life course (Pollock, 2007; Gauthier et al., 2010). A lot of studies have identified work-family trajectories from the life course perspective. Research has suggested that socio-demographic characteristics (e.g., gender, education), historical periods, and countries' work-family policies shape individual lives and work-family trajectories, see among others, McMunn et al. (2015), Aisenbrey and Fasang (2017), Sirniö, Kauppinen and Martikainen (2017), Fasang and Aisenbrey (2022), and Uccheddu et al. (2022). For example, the interdependency between work and family lives is highly contingent on the institutional context: patterns of work-family trajectories are less gendered in the US compared to Germany (Aisenbrey and Fasang, 2017). In Great Britain, women's and men's work-family life courses have become increasingly similar over time (McMunn et al., 2015). In Finland, Sirniö, Kauppinen and Martikainen (2017) identified six distinct pathway to adulthood, characterized by educational attainment, labor market participation, and family formation. Their research highlighted that gender differences were particularly pronounced in pathways defined by low educational attainment. Additionally, Uccheddu et al. (2022) assessed how specific combination of work and family domains in early life influence physical functioning in later life for men and women in six different European welfare state clusters.

While previous research has investigated comprehensively how work-family trajectories unfold over the life course among different social groups and countries, they are predominantly in Europe and the United States. Employment and family formation trajectories have seldom been analyzed holistically in East Asian context, especially in Japan (Machü et al., 2022). Japan serves as a particularly interesting case study due to the strong persistence of traditional gendered division of labor, which makes it challenging for women to continue working after marriage. Most empirical studies in Japan have typically followed a rather static approach, focusing on particular specific life course transitions or timing of particular events, such as marriage and childbirth, labor-force exit, and determinants of these transitions rather than examining entire trajectories, see, among others, Nakai (2009), Shirahase and Ishida (2018). Some empirical studies utilizing Japanese longitudinal data have shed light on the characteristics of women's career histories and their changes observed across birth cohorts, (Iwai, 2008; Hirao, 2010; Iwai, 2015). However, these studies do not analyze individual employment trajectories as a set of sequences. Only a handful of studies have focused on building trajectories that examine timing, duration, and ordering of life events using sequence data, such as employment trajectories or family trajectories (Watanabe, 2004; Kagawa, 2021). For instance, Watanabe (2004) applied optimal matching analysis to Japanese job career data of males and identified typical males career patterns. Similarly, Kagawa (2021) used sequence analysis to identify typical employment patterns during early stages of life.

More research utilizing detailed sequence of data on both employment and family formation is needed to further explore whether and how trajectories differ between females and males, and to understand how gender inequality in work-family trajectories develops from early adulthood through middle age. Furthermore, up to our knowledge, no existing studies have examine transitions from a specific trajectory groups. HM models are particularly suited to analyzing instantaneous transitions within the life course, as proposed in Piccarreta and Studer (2019), and identifying factors that influence the probability of experiencing these transitions.

2.2 Japanese institutional context

The Japanese labor market has been characterized by the long-time employment system, seniority-based wages, and "dual structure" formed by regular and non-regular statuses of employment under the norm of a male breadwinner, see, among others, Sato and Imai (2011), Gordon (2017). As is well known, there are disparities between regular and non-regular employment in terms of income, job stability, fringe benefits, and opportunities for development of occupational skills as well as upward mobility. Regular workers are covered by long-time stable employment and seniority-based wages and enjoy the high levels of employment protection. Compared to regular workers, non-regular workers who are outside the long-time employment framework have much less job security, are paid much lower wages and receive significantly less social insurance coverage. Furthermore, there are mobility barriers between the two; it is relatively easy to transition from regular employment to non-regular employment, whereas there is a high mobility barrier from non-regular employment to regular employment. Mobility barriers are particularly high for women. At the same time, within a corporate culture shaped by the long-time employment system, long work hours, an emphasis on face time, and unscheduled overtime and holiday work have become the norm and an indicator of loyalty and commitment to the company. This long-time employment system is inherently gender-biased favoring men while disadvantaging women (Ono, 2010). Since women bear the majority of responsibilities for housework and childcare, it becomes challenging for them to maintain full-time employment under the prevailing Japanese-style employment practices once they marry.

In addition to the above context, the practice of mass hiring of new college graduates, a uniquely Japanese custom of recruiting regular employees, makes it difficult for women to re-enter their former occupation after career interruption in the childrearing phase. As a result, although women's labor force participation rate in Japan is higher than the average among the OECD member countries, women make up a large part of non-regular workers rather than regular workers.

While Japan's parental leave policy is considered one of the most generous in the world for both men and women, many fathers choose not to take paternity leave. The bulk of childcare and domestic work responsibilities falls heavily on mothers. As a result of the above, there are considerable differences in employment profiles for men and women over the life course. Many women leave the labor force upon marriage or the birth of their first child, returning to work only after their children reach a certain age and their caregiving responsibilities decrease. This situation is expressed in the so-called M-shaped curve of female labor force participation, with the notable drop in employment around their thirties. Japanese women's quit rates at childbirth have persisted because of a combination of a corporate environment that has generally been inhospitable to working mothers and male-breadwinner/female-caregiver ideology that have been slow to change (Mun and Brinton, 2015). It is true that the female labor force participation has generally increased across age groups in recent years, but this rise does not imply that achieving a balance between work and family has become a reality. The rate of nonmarriage for younger people is increasing due to work-family incompatibility.

2.3 Research questions and hypotheses

Based on the above theoretical and empirical considerations, the first goal of our analysis is to identify typical pathways representing distinct typologies of employment and family trajectories across the life course in current Japanese society. The second goal is to examine how these trajectories are interrelated across gender over the individual life course. We reveal gender specific career trajectories and their intersections with family dynamics. Empirical studies have confirmed that transitions from employment to unemployment, and trajectories that feature long-term unemployment or non-regular job, have negative consequences for earnings (DiPrete, 2002). If women are more likely than men to experience unstable employment trajectories and lower labor force attachment throughout their lives, the gender disparity in occupational standings and earnings grow larger over the life course. This is due to different patterns of intragenerational mobility by gender. The "motherhood penalty" coupled with a "fatherhood premium" contributes significantly the remaining gender inequality (Budig and England, 2001; Correll, Benard and Paik, 2007; Hodges and Budig, 2010; Petersen, Penner and Hogsnes, 2014). Another goal is to identify transitions between trajectory patterns so that we can get in-depth understanding of the dynamics of intragenerational mobility throughout individuals' working lives, which drive the unfolding of the sequences.

Our hypotheses are as follows: We expect that family context, such as marriage and childbirth, shapes women's career trajectories in Japan. Specifically, childbearing may negatively affect women's labor force attachment, while having no effect or a positive effect on men's labor force attachment. We hypothesize that family life events influence women's likelihood of working part-time or withdrawal from the labor market. In contrast, for men, we expect little diversity or complexity in work trajectories relatively to their family situation while accounting for educational attainment and age cohort.

3 Life course data

3.1 Survey data

Data for the present study are drawn from the Social Stratification and Social Mobility survey (SSM2015), conducted in 2015 in Japan[1] (Shirahase and Miwa, 2021).

[1] For more details see the website (accessed on April 2024): https://www.l.u-tokyo.ac.jp/2015SSM-PJ/

The survey was administered through face-to-face interviews with a nationally representative sample of the Japanese population, including both men and women, aged 20 to 79 (born between 1935 and 1994). Participants were selected using a two-stage stratified random sampling method. A total of 7,817 respondents participated, 3,568 of which are men and 4,249 women, with a response rate of 50.1%.

The SSM2015 survey focused on the changes in the demographic structure of contemporary Japan, particularly the rapid aging of the population and declining birthrate. The survey collected both retrospective and current information about the status and timing of transitions in respondents' education, employment and occupation, partnership and parenthood, as well as key sociodemographic characteristics. Respondents were interviewed regarding their annual information from age 15 to present with exact time references for the start and end of each episode in their work history. This was facilitated using a life history calendar also known as the event history calendar method, which helps overcome memory problems and improves accuracy of respondents' reports (Morselli and Berchtold, 2023). The dataset enables us to examine interconnectedness of multiple life course domains such as work and family trajectories and explore patterns of similarity and difference in individual experiences. We selected men and women aged 20 and 69 in 2015 (born between 1945 and 1994) for our analytical sample in order to gain a better understanding of work-family life in Japan in decades following World War II.

To obtain typical classes of individual life course that follow similar trajectories across two life course domains, work and family, we draw on information on employment and family formation trajectories when the respondents were aged 20-40 years. This age range is chosen because people in their 20s and 30s, which is prime working and family-building age, typically experience many important life transitions that reflect changes in social roles or responsibilities[2]. The sample includes 6,332 individuals (2,885 men and 3,447 women). We also created a category for missing information in either work or family formation. The percentage of missing responses on work and family statues across all time occasions and respondents is around 13%. Demographic features such as sex, age group, geographic region, and city size were considered as auxiliary variables for post stratification weighting to correct any imbalances between the survey sample and the population. The authors acknowledge that the present analysis is based on retrospective data. Therefore, the sample is not representative of the population at the beginning of the period from which the initial conditions were derived. However, this sample is representative of the population in 1965 and 2014.

[2] The mean age at first marriage in 2022 in Japan was 29.7 for women and 31.1 for men, and the mode was 27 for both men and women. The mean age at first birth was 30.9 for women and 32.9 for men.

3.2 Response variables

We focus on employment trajectories and their intersections with family dynamics through the life course. It is of interest to understand how changes in family formation such as marriage and childbirth are associated with especially women's work trajectories, and how typical life courses in the work and family realm are different between women and men. We measure the employment statuses of the respondents rather than the types of jobs they hold in order to explore the ideal types of work-family patterns. In Japan, many married women either exit the labor force entirely or transition to part-time jobs with shorter working hours. We defined work trajectories using five mutually exclusive categories: "being in education (edu)", "full-time regular employment (fult)", "part-time employment (part)", "self-employed (self)", and "not in work (une)". Additionally, we include a category for missing work information: "Don't Know (DKw)".

Family formation trajectories are measured using seven mutually exclusive categories combining annual data on partnership and parenthood: "unpartnered no-child (unp0c)", "divorced/widowed no-child (div0c)", "partnered no-child (par0c)", "unpartnered with children (unpc)", "partnered with 1 child (par1c)", "partnered with 2 children (par2c)", and "partnered with 3 or more children (par3c)". We also include a category for missing family information: "Don't Know (DKf)".

3.3 Covariates: Education and age cohort

Individual educational attainment plays a significant role in shaping people's specific work-family trajectories. Those with tertiary education, particularly men, are expected to construct stable employment trajectories alongside family formation. In contrast, individuals with lower educational levels, especially young people, may face job insecurity and poor working conditions, leading to more complex trajectories with intermittent or interrupted work careers upon marriage. Respondents' educational levels are categorized as follows: "less than high school", "high school", "vocational school", "two-year college, technical college", and "four-year university or more".

Much previous research suggests that work-family trajectories differ across age cohorts. Younger cohorts are assumed to be overrepresented in non-standard work-family trajectories due to shifts in gender role attitudes and institutional reforms such as parental leave, while older cohorts tend to be overrepresented in standard or traditional work-family trajectories (Widmer and Ritschard, 2009). To account for the potential cohort effect on work-family trajectories, respondents' age is also considered into the analyses. We employ a multivariate HM model to identify typical patterns of work-family trajectories over the life course and classify respondents based on the similarity of both their work and family trajectory patterns. Separate models for men and women are estimated to account for the gendered nature of work-family dynamics, as combining men and women in a single model may obscure meaningful differences between the two gruops.

4 Hidden Markov model and Markov chain model

In the following, we introduce the multivariate HM model, which is used to analyze the available data in order to infer work-family typologies for both females and males. We also discuss the Markov chain model, employed in a two-step analysis, to better explore the effects of education on stage sequential development of work-family trajectories. In the general case, $\boldsymbol{Y}_{it}$ may contain multiple response variables of any type. The HM model assumes that, given a discrete latent process $U_{i1}, \ldots, U_{iT}$ with k states, the response vectors $\boldsymbol{Y}_{i1}, \ldots, \boldsymbol{Y}_{iT}$ are conditionally independent for $i = 1, \ldots, n$. The model consists of two sub-models: a measurement sub-model, which corresponds to the conditional distribution of each $\boldsymbol{Y}_{it}$ given U_{it}, and a latent sub-model which defines the distribution of each unit-specific latent process.

For categorical response variables, the main formulation is based on the parameters:

$$\phi_{jy,u} = p(Y_{ijt} = y | U_{it} = u), \quad j = 1, \ldots, r, \; u = 1, \ldots, k, \; y = 1, \ldots, c_j, \tag{1}$$

where Y_{ijt} denotes the j-variable in $\boldsymbol{Y}_{it}$ and c_j is the number of categories of this variable. We note that the HM model accounts for different types of missing pattern such as a partially missing response at a given time occasion and a completely missing response at a given time occasion under the missing at random assumption (Little and Rubin, 2020). For the latent sub-model we assume that the latent variable follows a Markov chain of first-order, with initial and transition probabilities denoted as follows:

$$\begin{aligned} \lambda_{i,u} &= p(U_{i1} = u), \quad u = 1, \ldots, k \\ \pi_{it,uv} &= p(U_{it} = v | U_{i,t-1} = u), \quad t = 2, \ldots, T, \; u, v = 1, \ldots, k. \end{aligned}$$

To model the dependence on the covariates we consider multinomial logits (Agresti, 2013) for the initial probabilities (Bartolucci, Farcomeni and Pennoni, 2014). These logits are defined as follows:

$$\log \frac{\lambda_{i,u}}{\lambda_{i,1}} = \alpha_u + \boldsymbol{x}_{i1}' \boldsymbol{\beta}_u, \quad u = 2, \ldots, k. \tag{2}$$

where the parameter vector is of length $(k-1)(s+1)$, and s is the number of covariates in each vector $\boldsymbol{x}_{it}$. For the transition probabilities we assume logits defined only by and intercept without covariates such as:

$$\pi_{it,uv} = \log \frac{\pi_{it,uv}}{\pi_{it,uu}} = \gamma_{uv}, \quad u, v = 1, \ldots, k, \; v \neq u, \tag{3}$$

where the logits $\pi_{it,uv}$ have, as reference state, that corresponding to the row of the transition matrix.

Estimation is based on maximization of the model log-likelihood which can be expressed as:

$$\ell(\boldsymbol{\theta}) = \sum_{i=1}^{n} \log f(\boldsymbol{y}_{i1}, \ldots, \boldsymbol{y}_{iT}),$$

involving the probability of the observed vectors of response variables denoted as $f(\boldsymbol{y}_{i1}, \ldots, \boldsymbol{y}_{iT})$, where $\boldsymbol{\theta}$ is the vector of all model parameters. The model log-likelihood may be maximized by an EM algorithm (Dempster, Laird, and Rubin, 1977) that is based on the complete data log-likelihood. The process involves alternating between two steps until the incomplete data log-likelihood $\ell(\boldsymbol{\theta})$ converges. Individual survey weights (Kaplan and Ferguson, 1999) can be accounted for by maximizing a weighted log-likelihood for the HM model (Pennoni and Nakai, 2023). Proper initialization of the estimation algorithm for a HM model is critical, as the log-likelihood is usually multimodal. Generally, for a given number of states, the inference is based on the solution that achieves the highest value of the log-likelihood upon convergence, which is typically the best optimum, see, among others, Brusa, Bartolucci and Pennoni (2023); Brusa, Pennoni and Bartolucci (2024). Information criteria such as the Akaike Information Criterion (AIC, Akaike, 1973) and Bayesian Information Criterion (BIC, Schwarz, 1978), and entropy measures are commonly used for model selection (Bacci, Pandolfi and Pennoni, 2014). However, in applications involving complex and high-dimensional data, the BIC and AIC indices typically decrease as more states are added, often up to a very large number of states. In such cases, it is advisable to choose a value of k that represents a suitable balance between goodness-of-fit and interpretability of the resulting latent states. Incorporating domain knowledge can further guide the selection of the number of states, particularly in practical applications where interpretability is crucial. To obtain asymptotic standard errors for the parameter estimates, we first fit the model to the data and derive the maximum likelihood estimates. Next, we then compute the observed information matrix by taking the negative numerical derivative of the score vector. The inverse of this matrix provides the variance-covariance matrix of the parameters estimates, and standard errors are the square roots of its diagonal elements. Inference about specific state probabilities at each time occasion is performed through local decoding. This method relies on the conditional posterior probabilities of the latent variables, given the observed responses and covariates, which are computed using backward recursions at each state and time occasion (Baum et al., 1970). The state with the maximum posterior probability is then considered the most likely for each individual at each time occasion.

In the following, we introduce the Markov chain model, to explore in a stepwise approach the influence of education on switching between decoding patterns over time. We define u_{it} as a single categorical response variable with k states representing the decoded sequence for individual i at each time occasion $t, t = 1, \ldots, T$. The Markov model assumes that u_{it} is conditionally independent of $u_{i1}, \ldots, u_{i,t-2}$. The model parameters are the initial and the transition probabilities, denoted by $\pi_{i,u}$

and $l_{it,uv}$, respectively. We assume that these parameters may depend on a set of individual covariates, denoted by $\boldsymbol{w}_{it}$, which are different from those in $\boldsymbol{x}_{it}$. For the initial probabilities the parametrization assumes that

$$\log \frac{\pi_{i,u}}{\pi_{i,1}} = \alpha_u + \boldsymbol{w}'_{i1}\boldsymbol{\beta}_u, \quad u = 2, \dots, k. \tag{4}$$

For the transition probabilities the parametrization assumes

$$\log \frac{l_{it,uv}}{l_{it,uu}} = \gamma_{uv} + \boldsymbol{w}'_{it}\boldsymbol{\delta}_{uv}, \quad u, v = 1, \dots, k, \ v \neq u. \tag{5}$$

The logits $l_{it,uv}$ use the row of the transition matrix as the reference state. The Newton-Raphson algorithm is employed to perform maximum likelihood estimation, and the standard errors are computed as illustrated for the HM model.

5 Results

In Subsection 5.1, we present the results of the HM model estimated using the female data, along with the results of the Markov chain model used to analyze the decoded states. Then, in Subsection 5.2, we present the results of the HM model estimated with male data. Finally, in Subsection 5.3, we compare the results for males and females. The models are estimated using the `LMest` package (Bartolucci, Pandolfi and Pennoni, 2022) in the `R` software environment (R Core Team, 2024). The code and complete results of the analyses are available from the authors upon request.

A HM model with nine latent states is selected based on the estimated relative differences in the BIC index from models with increasing number of latent states for both females and males. The maximum log-likelihood values at convergence are -80,329.88 for females and -53,806.07 for males, with both models having 188 parameters. The estimated conditional response probabilities, given the latent states, are reported in Table 1 for females, and Table 2 for males. These probabilities are also illustrated in Figure 1, along with the acronyms assigned to each state. These estimates characterize the different work-family typologies described in the following subsections.

5.1 Results of the multivariate model for females

According to the estimated conditional probabilities reported in Table 1, we identify two groups of women who are consistently working full-time (8th and 3rd states). We also find three trajectories associated with various patterns of insecure positions in the labor market following marriage and/or childbirth (5th, 7th, and 9th states). One trajectory is primarily characterized by self-employment, combined with differ-

Table 1 *Estimated conditional probabilities under the HM model with $k = 9$ hidden states for females: first six columns related to work and the other eight columns to family.*

	$\hat{\phi}_{jy,u}$													
u	fult	part	self	une	DKw	edu	unp0c	div0c	par0c	unpc	par1c	par2c	par3c	DKf
1 UW-S0CH	0.00	0.72	0.00	0.28	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2 SELF-VARF	0.00	0.00	1.00	0.00	0.00	0.00	0.20	0.01	0.12	0.00	0.14	0.33	0.19	0.00
3 SF-P12CH	0.97	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.40	0.59	0.00	0.01
4 NW-P2CH	0.00	0.27	0.00	0.73	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
5 UW-P0CH	0.39	0.21	0.00	0.40	0.00	0.00	0.00	0.00	0.98	0.01	0.00	0.00	0.00	0.00
6 NW-P1CH	0.02	0.18	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
7 UW-P3CH	0.21	0.24	0.00	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
8 SF-S0CH	0.86	0.00	0.00	0.02	0.01	0.12	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9 UW-S1CH	0.38	0.26	0.08	0.27	0.00	0.02	0.00	0.06	0.00	0.39	0.00	0.00	0.00	0.55

Table 2 *Estimated conditional probabilities under the HM model with $k = 9$ hidden states for males: first six columns related to work and the other eight columns to family.*

	$\hat{\phi}_{jy,u}$													
u	fult	part	self	une	DKw	edu	unp0c	div0c	par0c	unpc	par1c	par2c	par3c	DKf
1 SELF-VARF	0.00	0.00	0.88	0.00	0.13	0.00	0.42	0.00	0.10	0.00	0.14	0.23	0.00	0.11
2 SF-S0CH	0.99	0.00	0.00	0.01	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3 SF-P0CH	0.95	0.03	0.00	0.01	0.00	0.01	0.00	0.00	0.97	0.03	0.00	0.00	0.00	0.00
4 EDU-S0CH	0.00	0.00	0.00	0.03	0.00	0.97	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5 SF-P2CH	0.98	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
6 UW-S0CH	0.00	0.72	0.00	0.28	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7 SW-P3CH	0.78	0.05	0.15	0.01	0.01	0.00	0.00	0.09	0.00	0.21	0.00	0.00	0.70	0.00
8 SF-P1CH	0.97	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9 SW-DKF	0.79	0.10	0.00	0.05	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

ent family stages (2nd state). Another trajectory reflects precarious, unstable work without family involvement (1st state). Lastly, there are two trajectories primarily related to homemaking and childrearing (4th and 6th states). In the following, we describe these results in more detail.

The 8th state characterizes the beginning of work trajectories, including females still in education, those primarily working full-time, and those in the single, childless family stage. Individuals in this group reflect highly work-oriented women who experience a smooth transition from school to stable employment upon entering the labor market and continue to maintain this employment. This state can be labeled as the “stable full-time employment (SF), single, no child (S0CH), (SF-S0CH)" group.

The 3rd state represents another group characterized by a strong attachment to the labor force. Unlike the 8th state, this group combines continuous full-time employment with parenthood, experiencing stable, continuous working lives after childbirth. It can be labeled as the “stable full-time employment (SF), partnered with one or two children (P12CH), (SF-P12CH)" group. While there are people with stable continuous work lives combined with parenthood as seen for the 3rd state, many groups of women adapt their work patterns in response to marriage and the birth of a child. This indicates that women’s work-family life course types are diverse and complex (McMunn et al., 2015).

The 5th state is characterized by mixed working patterns combined with partnerships. This group reflects women who either exit the labor force or shift to a subsidiary part-time job upon marriage, aligning with gender expectations in the context of a strong male-breadwinner/female-homemaker tradition. This group is labeled as “unstable work (UW), partnered, no parenting (P0CH), (UW-P0CH)".

The 7th state is characterized by fragmented work trajectories combined with having three or more children. Respondents in this group are likely to stay out of workforce for a considerable period for childrearing, and returned to work after family-related interruptions, demonstrating weak labor market attachment. This group is labeled as “unstable work (UW), partnered, 3+ children (P3CH), (UW-P3CH)" . The 9th state includes individuals who experience mixed work trajectories with children but no partner. This group is labeled as “unstable work, single, 1+ children (S1CH), (UW-S1CH)". These individuals are likely to have interrupted work careers; with many women exiting the labor force after marriage or childbirth to care for their children. When they attempt to re-enter the workforce after separation, they often find themselves limited to part-time jobs upon their return.

The 2nd state consists almost exclusively of individuals who are self-employed across various family stages, including those who are still single and childless, as well as those with a partner and children. This group is labeled as “self-employed (SELF), various family stages (VARF), (SELF-VARF)" .

The 1st state represents unstable career trajectories, with a significant portion of individuals working part-time or being out of the labor force. This group consists mostly of respondents who are single and childless in terms of family trajectories. This state may be labeled as “unstable labor force attachment (UW), single and childless (S0CH), (UW-S0CH)" .

The 4th and the 6th states are characterized by a lack of employment combined with being partnered parents. These two states are differentiated primarily by the number of children. The 6th state is labeled as “no paid work (NW), partnered, 1 child, (P1CH), (NW-P1CH)" , while the 4th is labeled as “no paid work (NW), partnered, 2 children (P2CH), (NW-P2CH)". Women in these groups assume the roles of caregiver or homemaker and are characterized by economic dependence on men throughout their marriage.

The first row of Table 3 shows the estimated initial probabilities for each state: when respondents were 20 years old, the 1st state comprises 13% of the population, while the 8th state accounts for 73% of the population. The transition matrix between states shown in Table 3, reveals two pathways leading to a decrease in strong labor force attachment during the observation period, when respondents were between 20 and 40 years old. Approximately 9% of women transitioned from the 8th to the 5th state, indicating that some left the labor force or shifted to intermittent or part-time

Fig. 1 *Estimated conditional probabilities for females and males under the HM model with $k = 9$ hidden states. Colors in shades of pink are family-related states, while shades of blue refer to employment.*

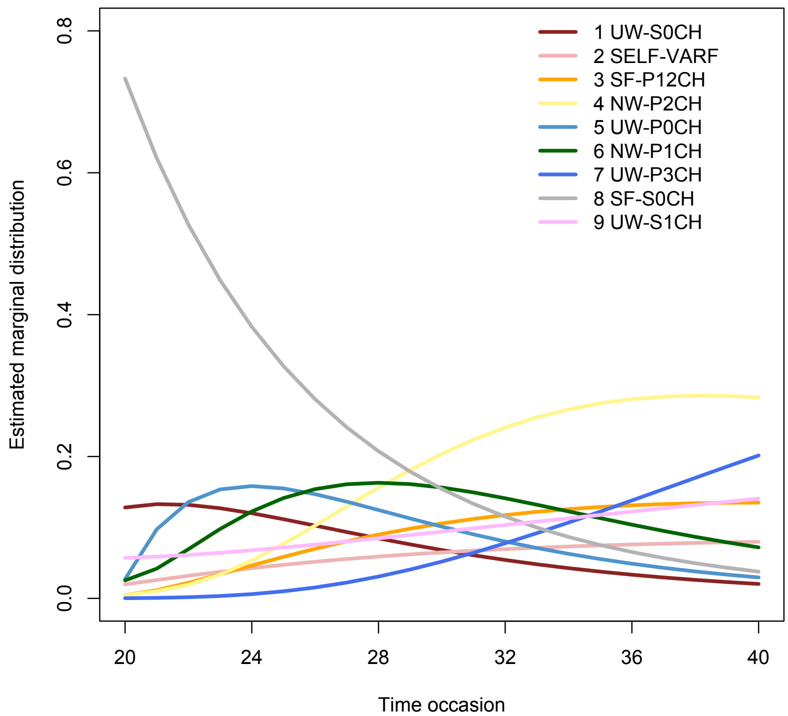

Fig. 2 *Representation of the estimated probabilities at each age for each latent state under the hidden Markov model with $k = 9$ for females.*

work after marriage. The other pathway involves 4% of women moving from stable full-time employment to insecure part-time work while remaining single (1st state). Ten percent of single women with unstable part-time employment (1st) transitioned to disrupted work trajectories upon marriage (5th). Married, childless women with mixed work attachment (5th) are more likely to move to "no paid work, partnered, 1 child" (6th), which accounts for 23% of the transitions. A smaller proportion, 6%, return to stable full-time employment after childbirth (3rd). From "no paid work, partnered, 1 child" (6th), 21% transition to "no paid work, partnered, 2 children" (4th). These transitions suggest that family events, such as marriage or childbirth, are commonly associated with changes in women's work trajectories. A significant proportion of women tend to leave the labor force or shift to non-regular jobs once they have a partner and/or children.

By examining the estimated marginal distributions by age, depicted in Figure 2, we gain a clearer understanding of how the distribution of states evolves over time and how work-family typologies behave in the long run. This approach sim-

Table 3 *Average initial and transition probabilities under the HM model $k = 9$ hidden states estimated for females.*

	$\hat{\bar{\pi}}_{uv}$								
u	$v = 1$	$v = 2$	$v = 3$	$v = 4$	$v = 5$	$v = 6$	$v = 7$	$v = 8$	$v = 9$
$\hat{\bar{\lambda}}_u$	0.13	0.02	0.00	0.00	0.03	0.03	0.00	0.73	0.06
1 UW-S0CH	0.79	0.01	0.00	0.00	0.10	0.03	0.00	0.06	0.00
2 SELF-VARF	0.00	0.97	0.00	0.00	0.01	0.01	0.00	0.00	0.00
3 SF-P12CH	0.00	0.00	0.94	0.02	0.00	0.01	0.02	0.00	0.01
4 NW-P2CH	0.00	0.00	0.02	0.92	0.00	0.00	0.05	0.00	0.01
5 UW-P0CH	0.00	0.01	0.06	0.00	0.68	0.23	0.00	0.00	0.01
6 NW-P1CH	0.00	0.00	0.01	0.21	0.00	0.76	0.00	0.00	0.01
7 UW-P3CH	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.01
8 SF-S0CH	0.04	0.01	0.01	0.00	0.09	0.02	0.00	0.84	0.00
9 UW-S1CH	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99

Table 4 *Estimated regression coefficients for the initial probabilities ($\hat{\alpha}_u$, $\hat{\boldsymbol{\beta}}_u$) of the HM model with $k = 9$ hidden states for females (significance indicated at the †10%, *5%, and **1% level).*

Covariate	u=2	u=3	u=4	u=5	u=6	u=7	u=8	u=9
Intercept	-5.05^{**}	-3.55^{**}	$-1.53^{\dagger}$	-3.45^{**}	-1.37^{**}	2.30^{**}	-0.83^{**}	-1.97^{**}
Age cohort	0.07^{**}	0.01	$-0.04^{\dagger}$	0.05^{**}	0.00	-0.54^{**}	0.05^{**}	0.02^{**}
Edu. 1	−0.24	$1.25^{\dagger}$	1.40^{*}	−0.17	0.83^{*}	9.60^{**}	-0.68^{**}	0.29
Edu. 2	0.27	−1.30	-5.37^{**}	-1.15^{*}	-1.47^{**}	-0.45^{**}	0.52^{**}	−0.12
Edu. 3	$-1.27^{\dagger}$	−1.47	-5.28^{**}	-1.59^{**}	-2.51^{**}	0.11^{**}	0.50^{**}	−0.08
Edu. 4	0.56	-2.83^{**}	−2.86	-4.21^{**}	0.28	1.79^{**}	3.92^{**}	2.90^{**}

Education: 1 less than high school; 2 vocational school; 3 two-year college, technical college; 4 four-year university or more.

plifies the interpretation of results by focusing on the temporal dynamics of state probabilities. The estimated probabilities at each age indicate that the 1st and 8th states represent typical early career trajectories. While the 1st state shares similar family-stage characteristics with the 8th state, its defining feature is its association with entry into a precarious and insecure labor market.

In Figure 3, we show the decoded individual sequences over time. When examining the estimated typologies of work-family patterns, ordered by the final state at age 40, we find that the 4th represents the largest group at that age. The proposed methodological approach successfully identifies distinct pathways. In Table 4, we present the estimated regression coefficients of the covariates in the model for the initial probabilities for females. The trajectory representing the most insecure career pathways, along with never-partnered childless individuals, was used as the reference category for females, as this group was assumed to represent one of the typical

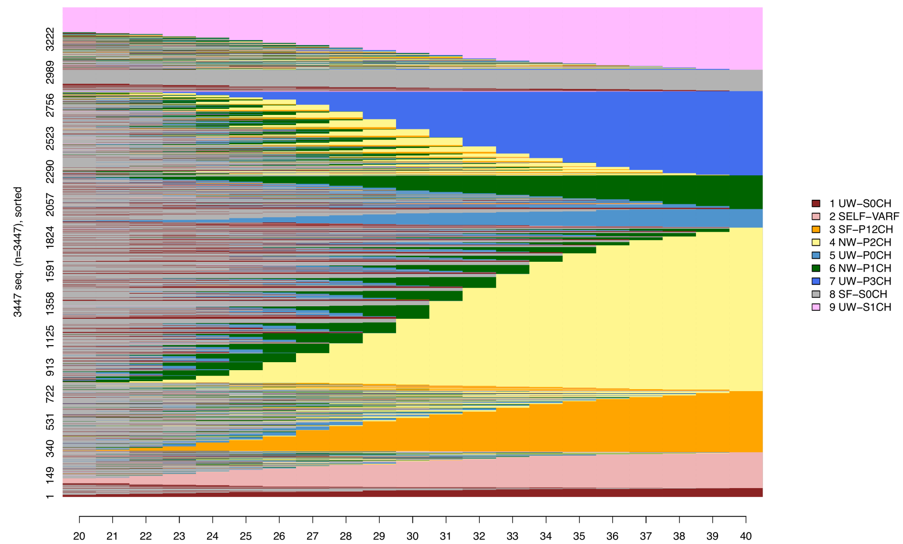

Fig. 3 *Estimated typologies of work-family patterns ordered from the ending state under the hidden Markov model with $k = 9$ hidden states for females.*

early career trajectories when respondents were 20 years old. We observe a general tendency towards the 1st state (UW-S0CH, considered as baseline), compared to the other states, with the exception of the 7th state. Moreover, having a low educational level significantly increases the likelihood of being in the 7th state, as indicated by a positive and significant estimated regression coefficient. In contrast, estimates for four-year college graduates suggest that individuals with a four-year degree are significantly more likely to enter stable full-time employment (8th state) compared to the 1st state, relative to high school graduates at age 20. Higher educational qualifications reduce the risk of following a temporary and insecure job trajectory during the early stages of a career.

The coefficients of cohort effects for females suggest that more recent cohorts faces high risks of experiencing unstable, non-standard work trajectories, rather than stable early career paths, compared with their older counterparts at age 20. Younger entrants to the labor market may be particularly vulnerable. In Japan, a significant generational divide exists, driven by a a dual labor market system that favors older workers at the expense of younger ones. Older workers benefit from substantial employment protections, making it difficult for younger workers to secure regular jobs, often forcing them into non-regular work arrangements.

We also focused in more detail on certain groups of women, which are of particular interest for better understanding the role of educational level. For example, by

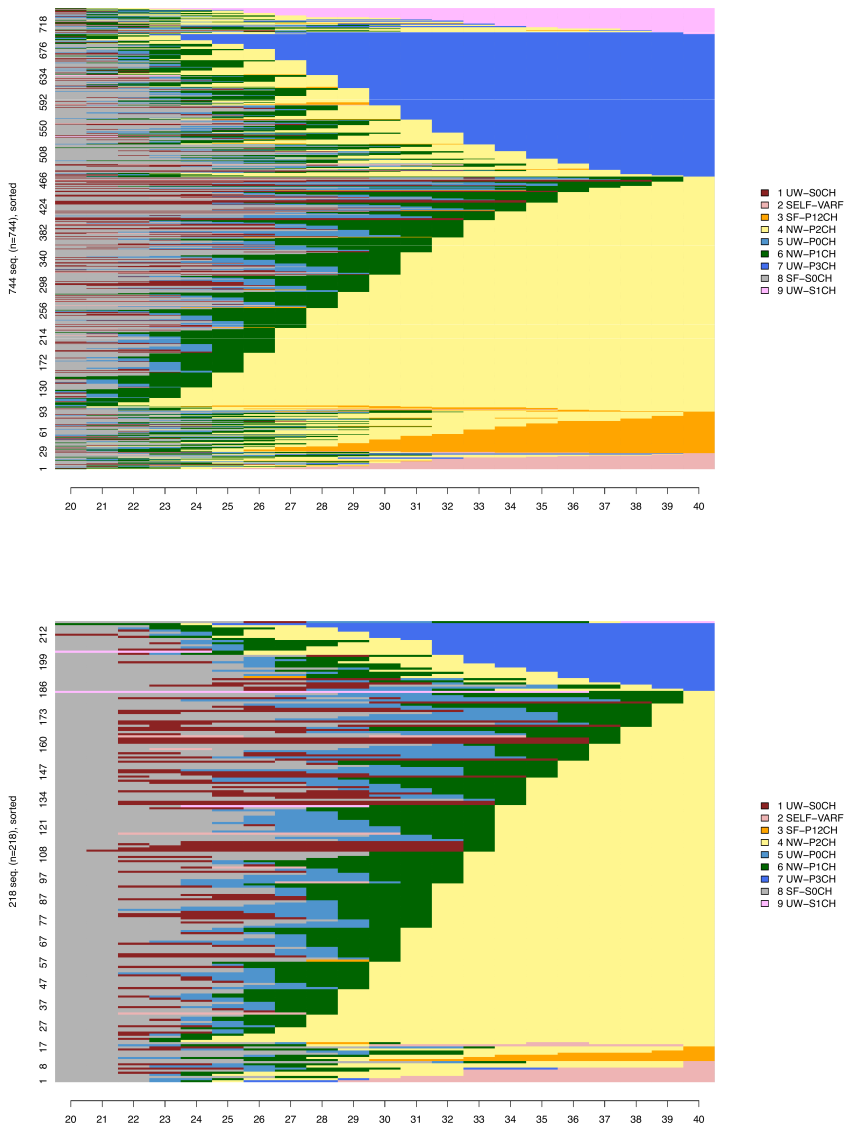

Fig. 4 *Estimated typologies of work-family patterns ordered from the ending state under the hidden Markov model with $k = 9$ hidden states for females having a transition from the 6th state to the 4th state. Females with a low level of education (top panel), females with a high educational level (bottom panel).*

examining the decoded states, we observe that there are 1,590 women transitioning from the 6th state (NW-P1CH) to the 4th state (NW-P2CH), that is, from having one child to having two children while still not working. Figure 4 compares the decoded patterns of those (among women transitioning from the 6th to the 4th state) with lower educational levels to those with the highest. To quantify this effect, we estimated a Markov chain model for the categorical response variable representing state membership at each time point, as introduced in Equation (4), and (5), considering educational level as a covariate affecting the initial and transition probabilities. The model reached a log-likelihood of -16,022 at convergence, using 400 parameters. Examining the distribution of the estimated parameters related to the initial probability, we observe that, at the beginning of the survey, females with more years of education are less likely to belong to the 6th state compared to those with fewer years of schooling. Specifically, the log-odds for individuals with a four-year university degree are -2.833 (s.e. 1.048), using those with a high school education or less as the baseline. Examining the effects of education on the probability of transitioning from the sixth to the fourth state, we observe that the estimated for females log-odds are 0.325 (s.e. 0.1691) with a four-year university degree and 0.460 (s.e. 0.1355) for those with a high school education.

5.2 Results for males

According to the estimated conditional probabilities for males, shown in Table 2 and depicted in the lower panel of Figure 1, we identify one group enrolled in education (4th state), six groups of men continuously working full-time at various family stages (1st, 2nd, 3rd, 5th, 7th, 8th, and 9th states), one trajectory primarily involving self-employment combined with different family stages (1st state), and one group characterized by precarious, unstable work with no family involvement (6th state). Unlike women's work-family patterns, which often include family-related work interruptions and exits from the labor market, the majority of men maintain continuous commitment to paid work throughout the life course, regardless of family life stages. The estimated distribution of each latent state, depicted in Figure 5 indicates that the 2nd and 4th states represent the most typical early career trajectories at age 20. In the following, we better describe the estimated work-family typologies.

The 4th state is characterized by the beginning of the careers for those with tertiary education as they are enrolled in education and being single childless family stage. This state may be labeled as "enrolled in education (EDU), single, no child (S0CH), (EDU-S0CH)" . The initial probability suggests that it accounts for 34% of the population when the respondents were 20 years old.

The 2nd state is characterized by continuous full-time work and never-partnered childless family stage. The initial probabilities reported in the first row of Table 5 suggest that it accounts for 45% of the population when the respondents were 20 years old. This is a typical early career stage for those with a lower level of educational attainment (less than tertiary education) at the beginning of the observation period,

Table 5 *Average initial and transition probabilities under the HM model $k = 9$ hidden states estimated for males.*

	$\hat{\bar{\pi}}_{uv}$								
u	$v = 1$	$v = 2$	$v = 3$	$v = 4$	$v = 5$	$v = 6$	$v = 7$	$v = 8$	$v = 9$
$\hat{\bar{\lambda}}_u$	0.04	0.45	0.01	0.34	0.00	0.08	0.01	0.01	0.06
1 SELF-VARF	0.95	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00
2 SF-S0CH	0.01	0.89	0.08	0.00	0.00	0.01	0.00	0.02	0.00
3 SF-P0CH	0.01	0.00	0.67	0.00	0.01	0.00	0.01	0.30	0.00
4 EDU-S0CH	0.01	0.28	0.01	0.65	0.00	0.05	0.00	0.00	0.00
5 SF-P2CH	0.01	0.00	0.00	0.00	0.94	0.00	0.05	0.00	0.00
6 UW-S0CH	0.02	0.10	0.02	0.01	0.00	0.85	0.00	0.01	0.00
7 SW-P3CH	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00
8 SF-P1CH	0.01	0.00	0.00	0.00	0.23	0.00	0.01	0.76	0.00
9 SW-DKF	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99

Table 6 *Estimated regression coefficients for the initial probabilities ($\hat{\alpha}_u$, $\hat{\boldsymbol{\beta}}_u$) of the HM model with $k = 9$ hidden states for males (significance indicated at the †10%, *5%, and **1% level).*

Covariate	u=2	u=3	u=4	u=5	u=6	u=7	u=8	u=9
Intercept	2.58^{**}	-0.94	-5.09^{**}	0.38	3.13^{**}	-0.16	1.74^{*}	2.60^{**}
Age cohort	0.00	-0.02	-0.04^{**}	-0.08^{*}	-0.05^{**}	-0.04^{*}	-0.08^{**}	-0.05^{**}
Edu. 1	-0.26	0.11	-3.07^{**}	1.13	0.05	0.93	0.97	0.00
Edu. 2	0.50	-0.76	8.30^{**}	-4.10^{**}	0.51	-5.30^{**}	-1.07	0.23
Edu. 3	0.19	0.86	8.57^{**}	-2.59^{**}	0.31	-3.87^{**}	-4.11^{**}	-0.19
Edu. 4	-0.83	$1.45^{\dagger}$	12.60^{**}	-2.64^{**}	0.88	-3.95^{**}	-4.02^{**}	2.48^{**}

Education: 1 less than high school; 2 vocational school; 3 two-year college, technical college; 4 four-year university or more.

approximately 28% of men transitioned from the 4th state to this state, as reported in Table 5, indicating a smooth school-to-work transition for university graduates. This state is labeled as the “stable full-time employment (SF), single, no child (S0CH), (SF-S0CH)”.

The 3rd, 5th, 7th, and 8th states are characterized by a strong attachment to the labor force combined with family formation. The 3rd state is labeled as “stable full-time employment (SF), partnered, no parenting (P0CH), (SF-P0CH)”. The 8th is labeled as “stable full-time employment (SF), partnered, one child (P1CH), (SF-P1CH)”. The 5th is labeled as “stable full-time employment (SF), partnered, two children (P2CH), (SF-P2CH”). The 7th state is characterized by stable participation in either full-time employment or self-employed along with parenthood. This state is labeled as “stable work (SW), partnered, three or more children (P3CH), (SW-P3CH)”.

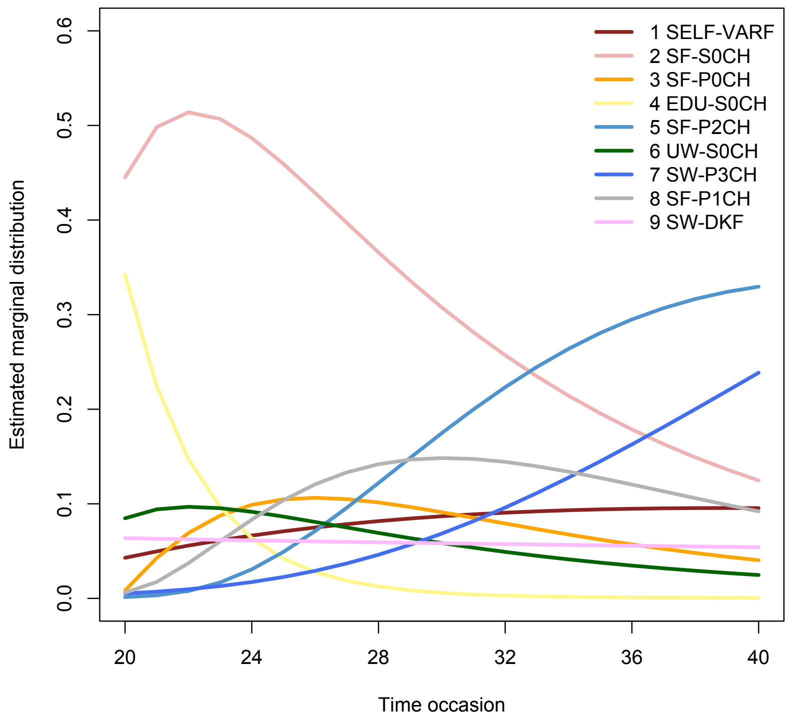

Fig. 5 *Representation of the estimated probabilities at each age for each latent state under the hidden Markov model with* $k = 9$ *for males.*

The 9th state is also characterized by continuous employment, primarily full-time, along with some non-regular part-time jobs, although their life stages in the family domain are unknown. This state is labeled as the "stable work (SW), family stage unknown (DKF), (SW-DKF)".

The 1st state consists mostly of self-employment at various family stages, such as being single and childless, or having a partner and children. This group is labeled as "self-employed (SELF), various family stages (VARF), (SELF-VARF)". The 6th state represents insecure relatively early career stage, as the majority work in non-regular part-time jobs, while some are out of labor force. In terms of family trajectories, they are single and childless. This state may be labeled as "unstable labor force attachment (UW), single, no child (S0CH), (UW-S0CH)". Referring to the initial probability when the respondents were 20 years old, this state makes up 8% of the population. Additionally, 5% of individuals from "enrolled in education, single, no child" (4th state) enter into this unstable and insecure work environment in terms of both the continuity and quantity of work during their early careers. We also find that 10% of

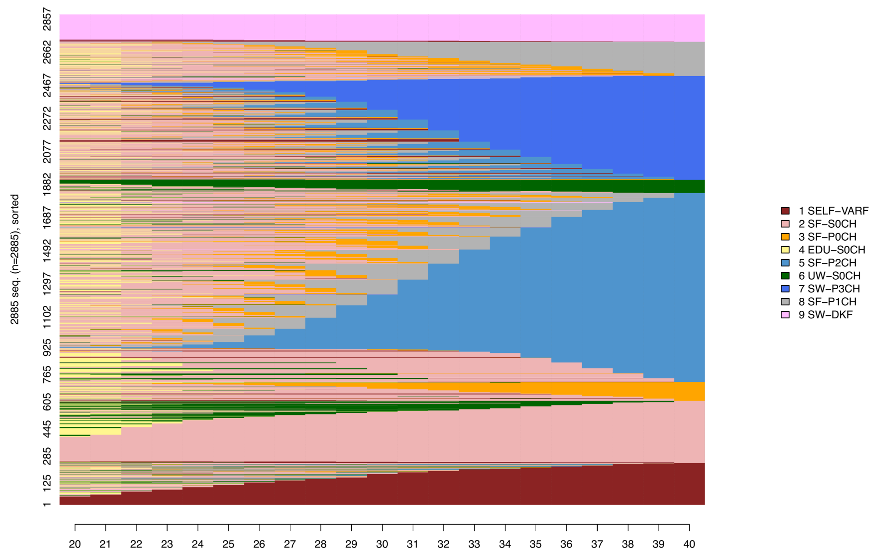

Fig. 6 *Estimated typologies of work-family patterns ordered from the ending state under the hidden Markov model with $k = 9$ hidden states for males.*

men in the precarious trajectory (6th state) move into the stable work trajectory (2nd state). Although it is often said that more and more young people are finding jobs characterized by precarious employment, low wages, and a lack of social security, men are more likely than women to move from non-regular to regular employment.

As can be observed from Figure 5, the probability of the 2nd state increases until the time when the respondents reach 22 years old, and then gradually decreases. About 8% of single men in the stable work trajectory transition into a family stage of marital union, which corresponds to the 3rd state. Over the course of their careers, 30% of men in the stable full-time employment and partnered childless family trajectory (3rd state) move to the trajectory characterized by employment stability combined with parenthood (8th state). Subsequently, 23% of males in this state transition to the 5th state, which is characterized by employment stability combined with two children. In Figure 6 we show decoded singular sequences over time.

Table 6 shows the effects of age cohort and educational attainment on the trajectories when the male respondents were 20 years old. Compared to the 1st state, or the self-employed trajectory at various family stages, several other states (the 4th, 5th, 6th, 7th, 8th, and 9th) are more likely to be the initial states for younger cohorts. Postsecondary education increases the likelihood of entering the trajectory characterized by the 4th state, indicating that most individuals in this group are enrolled in education at age 20, as opposed to those in the 1st state. Conversely, those who completed postsecondary education are less likely to be in stable full-time employment with two or more children (5th state) compared to those in the 1st state at age 20.

5.3 Gendered work-family trajectories

A clear contrast exists between female and male trajectories, particularly after family-related life events. For women, we identify two work-family trajectories involving parenthood combined with extensive nonworking periods and three groups marked by disrupted work patterns and high employment instability. This suggests that women tend to adapt their work patterns in response to family transitions. In contrast, we find no evidence of nonworking or disrupted work states for men in response to family formation. Instead, men are more likely to maintain stable employment trajectories throughout marital and parenthood transitions.

Furthermore, in women's employment trajectories, the share of stable employment paths is substantially lower and gradually declines over the observation period. Mothers are often found in trajectories characterized by unstable, predominantly part-time jobs or exiting the workforce, often in response to marriage and family formation. This reflects the persistent reality that women bear the primary responsibility for housework, childcare, and other family obligations. As a result, women continue to earn significantly less than men and remain underrepresented in higher occupational statuses. These findings align with existing research on the "motherhood penalty" (Budig and England, 2001). Conversely, fatherhood is often associated with a pay premium, termed the "fatherhood premium" or "fatherhood bonus", meaning men experience wage increase after becoming fathers, likely to support their families (Correll, Benard and Paik, 2007; Hodges and Budig, 2010; Petersen, Penner and Hogsnes, 2014). Parenthood thus plays a key role in perpetuating gender inequality through gendered work-family life course trajectories.

6 Conclusions

The aim of this study is to explore the interplay of paid employment and family processes in the life courses of Japanese men and women born between 1945 and 1994, and to identify typical patterns in transitions of employment status and family formation—referred to as work-family trajectories. To examine how employment, partnership, and family life evolve together over time, we apply hidden Markov (HM) models. Adopting a life-course perspective and a multichannel sequence analysis approach allows us to better understand how labor market participation and family formation are interwoven. Additionally, this approach highlights transitions between trajectory groups, and also the effects of education and age cohort.

The empirical analysis identified nine typical work-family trajectories for women. Two trajectories were characterized by stable full-time employment, three by uncertain, unstable, and insecure work following marriage and/or childbirth, one primarily by self-employment combined with various family stages, one by precarious, unstable work with no family involvement, and two by parenthood coupled with extensive periods of nonworking. In contrast, nine trajectories were also identified for men, but these exhibited much greater employment stability across marital and parenthood transitions compared to those of women. As expected, work-family trajectories for women are more complex and heterogeneous than those for men.

From the analyses illustrated above, we observe gender specific career trajectories and their intersections with family dynamics. Our findings confirmed the persistent gender disparity in life course patterns within Japanese society, where family context such as marriage and childbirth impede women's career progress. This result aligns with previous studies (Kalleberg, Hewison, and Shin, 2021). In Japan, non-regular employment is closely linked to gender. Women are seldom part of the patriarchal lifetime employment system and are most likely to occupy non-regular positions, making them among the most vulnerable of workers. Thus, although women's labor force participation has been increasing, it remains gendered. Additionally, a significant number of women still exit the labor market with the birth of their first child.

Balancing work and family life has been a pervasive challenge for women in most societies. Comparative literature has shown, however, that a woman's ability to achieve a healthy work-life balance often depends on social policy measures in her country and that the differences between various welfare regimes is important for that issue. Compared to other major industrialized countries, Japan's tax and social security systems are strongly oriented towards male-breadwinner/female-homemaker family model. The tax and social insurance schemes in Japan favor households with a full-time housewife or working part-time earning below a certain threshold. As a result, there are strong incentives for married women to adjust their employment accordingly. Overall, compared to many Western advanced societies, Japanese women's work-family trajectories differ significantly from those of men.

The difficulty in balancing work and child-rearing for females is closely related to trends such as late marriage or remaining unmarried, as well as the declining birth rate among married individuals. A woman might postpone or even forgo childbearing due to the substantial opportunity costs associated her professional career. Although Japan offers one of the most generous family leave systems in the world, workplace norms and the prevailing social expectation that women are primarily responsible for housework and childcare make it challenging for women to pursue a stable career or balance work and family.

Several points merit further investigation. First, it is important to examine whether early adult work-family life trajectories affect earnings in mid- and later-life, and how combined work-family trajectories relate to subjective well-being at these life stages. Because our primary aim was to identify combined work-family trajectories within Japanese populations, we did not focus on economic or subjective well-being or health outcomes of respondents. However, further research focusing on the lasting effects of trajectories on well-being is recommended to address persistent gender inequalities. This approach could also help clarify whether early-life trajectories (e.g.,early negative career experiences) have lasting impacts, such as scarring effects (Gangl , 2006; Mugiyama, 2017). Future studies should also systematically investigate the socioeconomic factors that may explain differences in transitions among work-life trajectories over time, using longer follow-up periods and more detailed data on both employment and family formation.

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