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Effects of Parental Leave Policies on Female Career and Fertility Choices

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Abstract

This paper constructs and estimates a dynamic discrete choice structural model of labor supply, occupational choice, and fertility in the presence of parental leave legislation. The estimated structural model is used for an ex ante evaluation of parental leave expansions that change the duration of job protection and/or the replacement rate of the cash benefit. Counterfactual simulation results indicate that a one-year job protection significantly increased maternal employment and earnings, but extending it from one to three years and offering cash benefits have little effect. Overall, parental leave policies have little effect on fertility. I also find that policy effects are stronger for younger cohorts who observe a policy change several years before childbearing, because they adjust their career paths accordingly as soon as the policy change.

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Keywords: parental leave, female labor supply, discrete choice model, structural estimation

JEL Codes: J13, J22, J24

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1 Introduction

Parental leave is mandated in many developed countries, but the generosity of parental leave legislation greatly differs across countries. For example, in Finland, Germany, and Spain, mothers can take unpaid leave for about 3 years. In contrast, the duration of parental leave is only 12 weeks in the U.S. The cash benefit of parental leave also considerably vary across countries. While German workers receive nearly a full year of earnings, no paid leave is legislated in most U.S. states. An interesting policy question for many countries is what the consequences are if they expand their parental leave system to the level of most generous countries like Germany. Indeed, the prime minister of Japan proposed an extension of the duration of unpaid leave from 1 to 3 years, in order to promote female employment and raise the fertility rate.

Experiences of the countries that have already legislated the generous parental leave provide useful insight into the possible consequences of a parental leave expansion for other countries. However, generalizing the experience of one country to another may be misleading unless the mechanisms at which the parental leave legislation affects women's behavior in the labor market is well understood. One way to make an ex ante assessment of the effects of a parental leave expansion is to estimate a structural economic model and conduct a counterfactual policy experiment using the estimated model.

The objective of the paper is to construct and estimate a dynamic discrete choice structural model of women's labor supply in the presence of a parental leave legislation, using the panel data of Japanese women. Parental leave was first legislated in 1991 and jobs in the selected employment sector only were protected for one year without cash benefits. Japan gradually expanded parental leave, and the current legislation protects jobs in all employment sectors and cash benefits replace 50% of pre-leave earnings. This series of policy changes helps the identification of the structural model, which is more credible than identification relying solely on functional form assumptions. The estimated model is used for an ex ante evaluation of parental leave expansions including an extension of the duration of job protection and an increase of the replacement rate of the cash benefit.

Women's labor supply is modeled using the dynamic discrete choice structural framework in the style of Keane and Wolpin (1997). In each period, a woman decides on her labor force participation, occupation, whether to take up parental leave, and conception (or childbearing). When a woman works, she enjoys more consumption, but pays the disutility of cost of work. The disutility cost of work is large for mothers with young children, but decreases as her children grow. Entry costs to employment sectors incur if a woman enters to a new employment sector from home or the other employment sector. Human capital is accumulated through learning-by-doing. The earnings potential of a woman in the next year increases if she works this year, but it decreases if she stays home or is on leave due to human capital depreciation. Husband's income is modeled as stochastic processes that are correlated with observed and unobserved characteristics of women. They are also correlated with the employment choices so that policy changes affect fertility and husband's income through the employment choices.

The job protection and cash benefit of parental leave are modeled as follows. A mother is eligible for parental leave if her children are less than age one and have been employed for a year in the employment sector that is covered by the legislation. Job protection removes the entry cost to an employment sector. After the completion of parental leave, the mother can return to work in the employment sector where she was before parental leave without paying the entry cost. A mother on parental leave receives a cash benefit that replaces a fraction of the pre-leave earnings. Effects of job protection and the cash benefit are evaluated through counterfactual simulations by manipulating the policy parameters such as the eligibility rules and the replacement rate.

The estimation algorithm combines the EM algorithm for a finite mixture model developed by Arcidiacono and Jones (2003) and the sequential algorithm proposed by Kasahara and Shimotsu (2011). Unobserved heterogeneity is modeled as a finite mixture, and the method by Arcidiacono and Jones (2003) decreases computational burden significantly. Kasahara and Shimotsu (2011) propose a sequential estimation algorithm for a dynamic structural model. Their method requires only a few value function iterations per likelihood evaluation, rather than many times until convergence is achieved. Because the model includes many state variables, to further accelerate computation, the value function is approximated based on sieves Arcidiacono, Bayer, Bugni, and James (2013). Despite the complexity of the model, my algorithm makes model estimation tractable. The parameter estimates seem reasonable, and the estimated model fits to key features of the data.

The estimated model is used to evaluate effects of the legislation of job protection by counterfactual simulations. The simulation result shows that legislating a one-year job protection increases the employment rate of married women several years after childbearing age. However, extending the duration of job protection from one year to three years does not have much additional effect on the employment rate. This result is largely driven by the structure of the disutility cost of work. The disutility cost of work is very high when a mother has a newborn, but quickly drops when the child reaches age one. Because of the nonlinearity of the disutility cost of work, a one-year job protection significantly raises the employment rate, but a longer job protection does not have an additional effect.

The simulation result also shows that policy effects are stronger for a younger cohort that observe an introduction or expansion of parental leave several years before they take a parental leave. If parental leave is not legislated, young women are less willing to invest in their skills and pursue a career track job, because they know they are likely to lose their skills and jobs for childbearing. However, if their job is protected from childbearing by a parental leave legislation, young women invest in their skills and pursue a career track job before childbearing. Hence, their employment rate and earnings are higher than older cohorts throughout the life cycle. The difference in policy effects across cohorts has been paid scant attention in the literature, but it is relevant for understanding the full effects of a policy change in the long term perspective.

Most previous papers identify the effects of parental leave policies by the difference-in-differences estimator (Ruhm (1998), Baum (2003), Baker and Milligan (2008) and Asai (2012)) or by the regression discontinuity designs (Lalive and Zweimüller (2009), Schönberg and Ludsteck (2011), and Lalive, Schlosser, Steinhauer, and Zweimüller (2011)). Although these papers provide credible estimates for policy effects, the structural approach adopted by this paper sheds light on the mechanism at which the parental leave policies affect the labor supply behavior of mothers. Understanding the mechanism helps one generalize the lessons from one country to another. Another difference is that previous papers focus on the policy effects on the cohort that gives a birth in the year of a policy change so that the policy changes are unexpected to the treated individuals. This choice is made to exclude the effects of expectation, and hence, for clean identification. This paper argues that the effects of expectation are sizable for younger cohorts and relevant for understanding the full policy effects in the long run.

This paper also contributes to the literature of dynamic discrete choice structural models of female labor supply. Previous papers in the literature include, but are not limited to, Eckstein and Wolpin (1989), van der Klaauw (1996), Altug and Miller (1998), Francesconi (2002), Gayle and Miller (2006), and Keane and Wolpin (2007, 2010). The model in the current paper shares two key features in the previous contributions; (1) human capital is acquired through learning-by-doing and (2) entry costs to employment sectors exist. The current paper extends these previous models by explicitly incorporating the job protection and cash benefit of parental leave legislation.

Lalive, Schlosser, Steinhauer, and Zweimüller (2011) is closest to the current paper in that they construct and estimate a dynamic structural model of female labor supply in the presence of parental leave legislation. Their model is based on the continuous-time job search model by Frijters and van der Klaauw (2006), instead of a discrete choice framework. The current paper differs from Lalive, Schlosser, Steinhauer, and Zweimüller (2011) in that it models dynamic selections into labor force and the eligible employment sector for parental leave.The selection into labor force is relevant for countries where the female labor force participation rate is significantly lower than 100%. The selection into the eligible employment sector for parental leave is also relevant unless it is universally available. For example, Family and Medical Leave Act (FMLA) in the U.S. requires only firms who hire 50 or more employees offer a parental leave. These selection issues may not be quite relevant for some countries that offer a generous parental leave package, but relevant for other countries including Japan, Canada, and the U.S. Indeed, ex ante evaluation of a parental leave expansion is needed for these countries.

The rest of the paper is structured as follows. Section 2 describes the data and the institutional background. Section 3 lays out the structural model and shows the likelihood function. Section 4.2 describes the estimation algorithm. Section 5 presents the estimates of the structural parameters. The model's ability to fit to key aspects of the data is also demonstrated. Section 6 shows the effects of the job protection and the cash benefit of parental leave through counterfactual simulations. Section 7 concludes the paper. Details of data and additional results are available in Appendix.

2 Data and Institutional Background

2.1 Japanese Panel Survey of Consumers

The analysis is based on the data from Japanese Panel Survey of Consumers (JPSC) conducted by The Institute for Research on Household Economics. JPSC has begun in 1993 with a representative sample of 1,500 women at age 24-34 and asks respondents about marriage, fertility, and their own and spouse's work every survey year. JPSC added 500 women at age 24-27 in 1997, 836 women at age 24-29 in 2003, and 636 women at age 24-28 in 2008. As of 2008, JPSC includes 2,284 women. The parental leave legislation is effective across the country and changes over time, different cohorts are exposed to different legislation. Because multiple cohorts are in the sample, the effects of parental leave policies are identified by comparing different cohorts.

I draw a sample of married women who completed schooling and currently live in Japan. Because the model does not take into account divorce, those who have ever divorced are excluded from the sample. Given the low incidence of divorce in Japan, this restriction does not compromise generality of the analysis. I also excluded those who have ever been self-employed, because they are not covered by the parental leave legislation. After omitting observations with missing values except for own earnings, I drop observations except for the longest spell of consecutive observations for each individual. The sample includes 1,455 women and 8 observations per person (11,593 person-year observations in total). We describe detailed variable definitions in Appendix.

2.2 Institutional Background

2.2.1 Parental Leave Legislation

Parental leave was first legislated in 1991 in Japan. The parental leave legislation offered a job protection until the child reaches age one and no cash benefit. To be eligible for a parental leave, individuals must have been employed in the eligible employment sector and must be expected to return to work after the completion of parental leave.

Two different employment sectors exist in Japan, and the parental leave legislation treat them differently: regular and non-regular employment sectors. A typical job in the regular employment sector is high paid, full time, and on an indefinite term contract, while a typical job in the non-regular employment sector is low paid, part time, and on a limited term contract. Jobs in the regular employment sector have been covered by the legislation from the beginning, but those in the non-regular employment sector became covered since 2005.[1]

The cash benefit was first introduced in 1995, and the replacement rate was 25% until 2000. The replacement rate was raised to 40% from 2001, which was followed by a further increase to 50%. Note that non-regular employees did not receive the cash benefit until 2005, because they were not covered by the parental leave legislation. Table 1 summarizes the changes of the eligible employment sector and the replacement rate of the cash benefit.

Table 1: Changes in Parental Leave Policies

Years	**Eligibility**		**Replacement Rate**	**PL Take-Up Rate**			
	Non Reg	Reg		All (N=1564)	Worked (N=531)	Worked in Reg (N=317)	Worked in NonReg (N=214)
1991-1994		✓	0%	-	-	-	-
1995-2000		✓	25%	0.139 (0.011)	0.387 (0.027)	0.585 (0.036)	0.092 (0.025)
2001-2004		✓	40%				
2005-2006	✓	✓	40%	0.216 (0.018)	0.510 (0.035)	0.669 (0.042)	0.274 (0.049)
2007-2010	✓	✓	50%				

Source: Author's calculation based on JPSC.

Note: The PL take-up rate is calculated for the period from 1995 to 2004 and the period from 2005 to 2010. Standard errors are in parenthesis. The label All refers to all individuals who give a birth. The label Worked refers to the subset of the individuals who worked a year before childbirth. The labels Reg and NonReg refer to the subset of individuals who worked in the regular and non-regular sectors, respectively, a year before childbirth. Self-employed individuals are excluded from the sample.

Not all eligible individuals take a parental leave for job protection and the cash benefit. One of the eligibility conditions unique to Japan is that workers must be expected to return to work after the completion of the leave. This condition applies not only to job protection, but also to the cash benefit, which is very different from other countries where individuals can receive cash benefits even if they do not intend to return to work. In Japan, parental leave takers requesting cash benefits must apply through their employers. Individuals requesting a leave need to speak to their supervisor to discuss work arrangement while they are on leave and when they return, in order to ensure that the parental leave takers will return to work.[2] In addition to this screening process,

[1]Strictly speaking, the legal eligibility for parental leave is determined by whether the employment is limited or indefinite term. JPSC does not ask the term of the employment contract, but asks whether the job is regular or non-regular employment. Because an indefinite term employment is quite often regular employment and vice versa, I determine eligibility by employment type.

[2]Although expectation to return to work is a requirement for parental leave, there is no legal penalty for not return-

employers, particularly small ones, discourage their employees from taking a parental leave to avoid the associated cost. Moreover, co-workers may not be happy with someone's parental leave taking, because that may imply more work on their shoulder. These factors explain why not all eligible workers take a parental leave.

Table 1 also reports parental leave take-up rates for two periods from 1995 to 2004 and from 2005 to 2010. If the sample period is further divided, the take-up rates cannot be estimated with reasonable precision for the sample size being small. Among all married women who give a birth and are not self-employed, 13.9% of them took a parental leave for the period 1995-2004, and the take-up rate increased to 21.6% for the period of 2005-2010. Because employment before childbirth is requirement for eligibility for parental leave, I take a subsample of individuals who have worked a year before childbearing, which decreases the sample size to a third. The take-up rate was 38.7% in 1995-2004, and it increased to 51.0% in 2005-2010. These rates suggest that eligibility does not necessarily imply the take-up of parental leave. The subsample is further divided into those who worked in the regular and non-regular sectors. In 1995-2004, the take-up rate among regular sector workers was 58.5%, whereas that was only 9.2% among non-regular workers because the legislation did not protect their jobs. In 2005-2010, the take-up rate increased to 66.9% for regular workers and to 27.4% for non-regular workers. During the two periods, regular workers enjoyed a modest increase in the replacement rate from 25-40% to 40-50%, whereas non-regular workers were granted both one-year job protection and cash benefits (i.e. the replacement rate increased from 0% to 40-50%). This greater gain for non-regular workers may account for their larger increase in the take-up rate than regular workers.

Table 2 show the estimated changes in the parental leave take-up and employment rates from the 1995-2004 period to the 2005-2010 period. The estimates are based on a linear probability model, and standard errors are robust to heteroskedasticity. Columns 1-4 show the regression results for the parental leave take-up rate in the year of childbearing. Although individual and household characteristics are controlled in the regression, the results are essentially same as the result reported in Table 1. Columns 5-8 report changes in the employment rate in the year of childbearing. Those who are employed include those who are working and on parental leave. The expansion of parental leave policies may have lead to parental leave by those who would have worked otherwise. If this is the case, no change in the employment rate is observed because both those work and those on leave are counted as the employed. The results in Columns 5-8 suggest that this did not happen. The employment rate of those who have worked increased from 2005 on. This is evident for those who have worked in the non-regular sector, but little change in the employment rate is observed for those who have worked in the regular sector. The expansion of parental leave seem to have lead to parental leave by those who would have quit their jobs

ing to work. Nevertheless, I find that about 90% of the parental leave takers in JPSC work a year after childbearing.

otherwise. Columns 9-12 show the regression results for employment a year after childbearing. The results indicate that the employment rate increased particularly for those who have worked in the non-regular sector.

2.2.2 Employment Sectors

In this paper, two different employment sectors are studied: regular and non-regular sectors. The distinction is relevant not only because they are considerably different in wages and hours, but also because the parental leave legislation treat the two employment sectors differently. The regular employment is typically under an indefinite-term contract and a full-time full-year job, while the non-regular employment is typically under a limited-term contract and a part-time job. They are also different in non-wage benefits: employers usually contribute to pension plans and health insurance premiums for their regular employees. Kambayashi and Kato (2013) find that the regular employment is more stable, pays higher hourly wages, and offers more employer-sponsored training than the non-regular employment.

Table 3 compares some of the characteristics of regular and non-regular employees. Following Kambayashi and Kato (2013), whether a job is the regular employment or not is determined according to descriptions and/or titles in the workplace. In the sample, 59.9% of all employees are non-regular employees. Compared with regular employees, non-regular employees are less educated (12.927 years vs 13.642 years) and earn much less (0.896 million yen vs 3.066 million yen). Interestingly, the husbands of non-regular employees earn more than those of regular employees, suggesting an income effect on female labor supply.

A typical Japanese woman starts her career as a regular employee after graduating from school, but she quits her job at marriage or childbearing. As her children grow older, she comes back to the labor market as a non-regular employee. Returning as a regular employee is less common once she quits her job because of a high entry barrier to the regular employment sector. This career pattern can be confirmed in the sample by comparing employment shares among those with and without children. Among married women without children, the regular employment share is 52.4%. However, it falls to 37.4% among married women with children. Regular employees have much less career interruption than non-regular employees. The average years of experience in the regular employment sector is 12.222 years, but years stayed at home is only 1.666 years and experience in non-regular sector is 1.609 years. In contrast, non-regular employees have spent 5.193 years at home. Their total work experience is comparable to that of regular employees, but they spent about the same years in the regular and non-regular sectors. These statistics are consistent with the typical career pattern mentioned at the beginning of this paragraph.

Table 2: PL Take-Up and Employment Rates

Dependent Var.	PL Take-Up				Empl. in the Year of Childbearing				Empl. One Year After Childbearing			
Population	All	Worked	Reg	NonReg	All	Worked	Reg	NonReg	All	Worked	Reg	NonReg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Years 2005-2010	0.099***	0.167***	0.082	0.202***	0.089***	0.132*	0.038	0.165*	0.096***	0.116*	0.045	0.127^{+}
	(0.019)	(0.043)	(0.058)	(0.055)	(0.021)	(0.042)	(0.051)	(0.064)	(0.025)	(0.046)	(0.058)	(0.074)
Age 30-34	0.052^{+}	0.093	0.120	0.079	0.060*	0.129*	0.154^{+}	0.180^{+}	0.016	0.043	0.098	-0.017
	(0.028)	(0.065)	(0.091)	(0.079)	(0.030)	(0.063)	(0.081)	(0.092)	(0.035)	(0.069)	(0.089)	(0.106)
Age 35-39	0.120*	0.253*	0.312^{+}	0.109	0.087	0.183	0.359*	0.044	0.068	0.109	0.325^{+}	-0.164
	(0.049)	(0.114)	(0.173)	(0.127)	(0.053)	(0.111)	(0.153)	(0.149)	(0.062)	(0.124)	(0.167)	(0.181)
Age 40+	0.162^{+}	0.308	0.184	0.064	0.141	0.376	0.372	0.344	0.216^{+}	0.340	0.471	0.000
	(0.097)	(0.259)	(0.322)	(0.451)	(0.105)	(0.252)	(0.285)	(0.526)	(0.124)	(0.310)	(0.343)	(.)
Education	0.021*	0.030^{+}	0.049*	-0.004	0.018*	0.018	0.011	0.015	0.011	0.020	0.016	0.023
	(0.007)	(0.017)	(0.023)	(0.022)	(0.008)	(0.017)	(0.021)	(0.025)	(0.009)	(0.018)	(0.023)	(0.028)
Years in Home	-0.048***	-0.028	0.033	-0.027	-0.073***	-0.091***	-0.089*	-0.069*	-0.075***	-0.096***	-0.100*	-0.055^{+}
	(0.006)	(0.019)	(0.030)	(0.021)	(0.007)	(0.018)	(0.027)	(0.025)	(0.008)	(0.021)	(0.031)	(0.029)
Years in Reg.	0.015*	0.005	-0.005	-0.004	0.021***	0.009	-0.006	-0.004	0.016*	0.007	-0.011	0.014
	(0.005)	(0.012)	(0.016)	(0.014)	(0.005)	(0.011)	(0.014)	(0.017)	(0.006)	(0.012)	(0.016)	(0.020)
Years in Non-Reg.	-0.014*	-0.057***	-0.057*	-0.011	-0.002	-0.040*	-0.034^{+}	0.005	-0.002	-0.033*	-0.038^{+}	0.021
	(0.006)	(0.014)	(0.023)	(0.017)	(0.007)	(0.014)	(0.020)	(0.020)	(0.008)	(0.015)	(0.022)	(0.023)
2 Children	0.008	0.116*	0.152*	0.115^{+}	0.067*	0.243***	0.287***	0.250***	0.103***	0.266***	0.237***	0.371***
	(0.022)	(0.049)	(0.065)	(0.061)	(0.023)	(0.048)	(0.058)	(0.072)	(0.027)	(0.052)	(0.064)	(0.082)
3+ Children	0.119***	0.175*	0.142	0.135	0.224***	0.401***	0.326***	0.423***	0.296***	0.448***	0.355***	0.504***
	(0.030)	(0.069)	(0.097)	(0.084)	(0.032)	(0.068)	(0.086)	(0.098)	(0.038)	(0.075)	(0.099)	(0.110)
Husband's Earnings	-0.011*	-0.020*	-0.035^{+}	-0.005	-0.011*	-0.015^{+}	-0.032^{+}	-0.003	-0.019*	-0.019*	-0.038*	-0.007
	(0.005)	(0.009)	(0.019)	(0.008)	(0.005)	(0.009)	(0.017)	(0.010)	(0.006)	(0.009)	(0.019)	(0.010)
Constant	-0.074	0.032	-0.062	0.173	0.014	0.268	0.661^{+}	-0.064	0.222	0.352	0.707^{+}	-0.182
	(0.121)	(0.299)	(0.409)	(0.378)	(0.130)	(0.291)	(0.362)	(0.441)	(0.150)	(0.316)	(0.397)	(0.501)
Observations	1402	480	288	192	1402	480	288	192	1261	419	253	166

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, * $p < 0.01$, *** $p < 0.001$

Note: Linear probability models are estimated. Standard errors are robust to heteroskedasticity. The sample period ranges from 1995 to 2010. The column label "All" refers to all individuals who give a birth. The label "Worked" refers to the subset of the individuals who worked a before childbearing. The label "Reg" and "NonReg" refer to the subsets of the individuals who worked a year before childbearing in the regular and non-regular employment sectors, respectively. Self-employed individuals are excluded from the sample.

Table 3: Comparison of Regular and Non-Regular Employment

	Regular Sector	Non-Regular Sector
Employment Share (among all married women)	0.401	0.599
Years of Education	13.642	12.927
Annual Earnings (mil. JPY)	3.066	0.896
Husband's Annual Earnings (mil. JPY)	4.732	5.048
Employment Share (among those w/o children)	0.524	0.476
Employment Share (among those w/ children)	0.374	0.626
Years in Home	1.666	5.193
Work Experience in Regular Sector	12.222	5.472
Work Experience in Non-Regular Sector	1.609	6.700

There is evidence that a substantial entry barrier to employment sectors exists, and it is greater for the regular employment sector. Table 4 shows the transition matrix for home and employment sectors. The rows indicate sectors in the current year, and the column indicate sectors in the next year. The switch between sectors is rare, and individuals tend to choose the same sector for two consecutive years. This persistent choice pattern can be explained by heterogeneity and state dependence. A possible sources of the state dependence is an entry barrier to employment sectors. If finding a new employment requires a significant search effort, chances of entering to a new employment sector are low. This entry barrier seems higher for the regular employment sector than for the non-regular sector. Among those who stay home this year, 10.7% start working in the non-regular employment sector, but only 0.9% find a job in the regular employment sector.

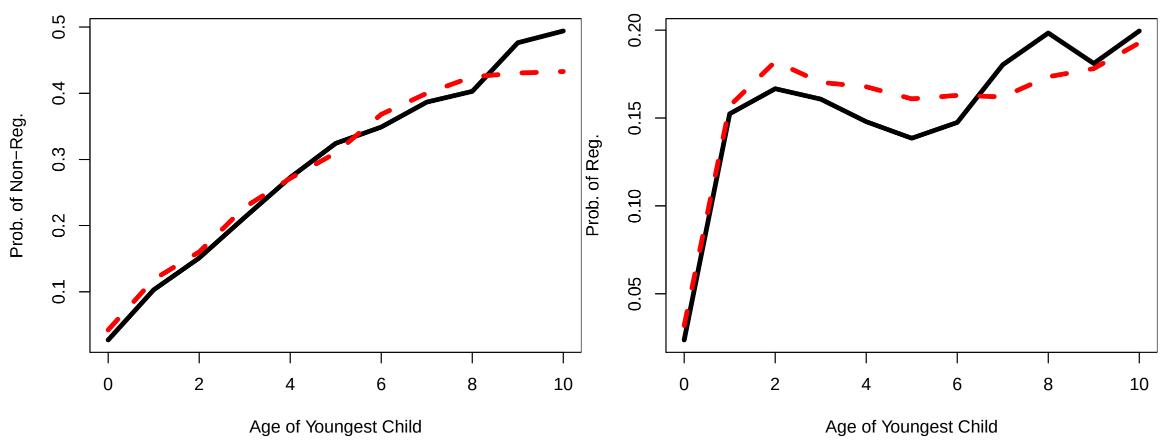
Table 4: Transition Matrix for Home and Employment Sectors

	Home	Reg. Empl.	Non-Reg. Empl.
Home	0.884	0.009	0.107
Reg. Empl.	0.064	0.890	0.046
Non-Reg. Empl.	0.110	0.042	0.848

Source: Author's calculation from JPSC.
Note: the current sectors are in the rows and the sectors in the next year are in the columns.

Figure 1 shows another piece of evidence for a high entry barrier to the regular employment sector. The left panel presents how the probability of working in the non-regular employment sector changes with the age of the youngest child. In the year when a new baby is born, very few people work, but more and more people work in the non-regular employment sector as the age of the youngest child increases. When the youngest child is age 10, about 50% of mothers work in the non-regular employment sector. The right panel presents the probability of working in the regular employment sector. In the year when a new baby is born, very few people work. When the baby grows to age one, the probability of working in the regular employment sector increases to about 15%, because mothers who took parental leave return to work. However, the probability of working in the regular employment sector only slightly increases thereafter. These two graphs suggest that (re-)entering to the regular employment sector is hard for mothers unless job is protected by parental leave and that many mothers find a new job in the non-regular employment sector.

I argue that job protection of parental leave can increases female employment when substantial entry barriers to employment exist. Many women find it hard to work and raise a new baby at the same time. If there is no or little entry barriers to employment, they do not need to take parental leave for job protection, because they can work a job that is as good as the previous one as soon as they decided to return. However, if substantial entry barriers to employment exist, mothers may need a long time to find a job that is as good as the previous one. Job protection of parental leave essentially removes this entry barrier to employment and lets mothers be off work while the child is very young.



Source: Author's calculation from JPSC.
Note: The solid lines are from the data, and the dashed lines are the model predictions.

Figure 1: Probabilities of Working in Regular and Non-Regular Sectors

3 Model

3.1 Environment

Overview The labor supply and fertility decisions of married women are modeled using the dynamic discrete choice structural framework. In each calendar year t, a married woman maximizes her present value of life time utility by making a decision on labor supply and fertility. She takes into account the consequences of her choice today to her economic states in the future. She retires from the labor market and receives the terminal value (that is zero) when she becomes 70 year old. Because parental leave policies change with calendar year, the model is non-stationary. The model allows for unobserved heterogeneity. Married women differ in their permanent skills in regular and non-regular sectors, preference for work and children, and permanent skills of their husbands.

Choices There are four labor supply or employment choices including: (1) staying home, (2) working in the regular employment sector, (3) working in the non-regular employment sector, and (4) taking a parental leave. Let $d_{h,it} = 1$ if individual i in year t stays home and $d_{h,it} = 0$ otherwise. The decision variables for working in the regular sector $d_{r,it}$, working in the non-regular sector $d_{n,it}$, and taking a parental leave $d_{l,it}$ are similarly defined. Because the employment choices are exhaustive and mutually exclusive, it must be that $\sum_{e\in\{h,r,n,l\}} d_{e,it} = 1$.

A married woman also decides on whether they conceive or not. If she conceives in year t, she will give a birth in the following year $t+1$. Let $d_{f,it} = 1$ if individual i conceives in year t and $d_{f,it} = 0$otherwise.

Because there are four employment choices and two fertility choices, there are total eight choices for a married women in each year. Define a vector of decision variables $d_{it} = (d_{h,it}, d_{r,it}, d_{n,it}, d_{l,it}, d_{f,it})$.

State Variables The current period payoff for individual i from her choice at period t is affected by a vector of her state variables S_{it} that include sector-specific experiences ($h_{h,it}$, $h_{r,it}$, and $h_{n,it}$), her own age a_{it}, age of the youngest child $a_{k,it}$, number of children n_{it}, earnings of husband $y_{h,it}$, lagged choices d_{it-1}, and lagged employment status e_{it-1}.

The employment status is distinguished from labor supply choices: Parental leave takers are not working, but considered employed. Let $e_{r,it} = 1$ if individual i is employed in the regular sector and $e_{r,it} = 0$ otherwise. The indicator for employment in the non-regular sector $e_{n,it}$ is similarly defined. The employment sectors are mutually exclusive. Define a vector of variables for employment status $e_{it} = (e_{r,it}, e_{n,it})$.

3.2 Preference

3.2.1 Consumption

The utility from consumption u is given by

$$u(C_{it}, n_{it}, d_{it}) = (\alpha_0 + \alpha_1 d_{r,it} + \alpha_2 d_{n,it} + \alpha_3 I(n_{it} = 1) + \alpha_4 I(n_{it} = 2) + \alpha_5 I(n_{it} \geq 3)) C_{it},$$

where $I(\cdot)$ is an indicator function that takes one if the condition in the bracket is satisfied and takes zero otherwise. This specification implies that the marginal utility of consumption varies with the number of children n_{it} and non-market time that is captured by the indicators for work $d_{r,it}$ and $d_{n,it}$. This non-separability of consumption and non-market time has been allowed in previous structural models of female labor supply.[3] If $\alpha_0 > 0$, $\alpha_1 < 0$, and $\alpha_2 < 0$, the labor force participation rate decreases with husband's income, which is an empirical regularity confirmed across countries.

3.2.2 Non-Pecuniary Utility from Employment Choices

Working in Regular or Non-Regular Sector Individuals derive non-pecuniary utility from work that depends on the age of the youngest child $a_{k,it}$, the number of children n_{it}, the lagged employment sectors e_{it}, and calendar year t. Because any discrete choice model identifies the difference in utility, the non-pecuniary utility from working is the deviation from that from staying home.

The age and number of children affect the non-pecuniary utility of work, because mothers may enjoy time with children more or less. The lagged employment sector is included to account for the entry cost due to labor market friction, which is consistent with the observed transition patterns for employment choices. Moreover, without the entry cost to the employment sectors, job protection does not affect the maternal employment. Calender year is also included in the non-pecuniary utility function account for time-varying macroeconomic conditions and any other institutional changes other than parental leave legislation.

The non-pecuniary utility function from work is parametrized as follows:

$$\begin{aligned} & v_j(a_{k,it}, n_{it}, e_{it-1}) \\ = \; & \gamma_{j,0} + \gamma_{j,1} I(a_{k,it} = 0) + \gamma_{j,2} I(a_{k,it} = 1) + \gamma_{j,3} I(a_{k,it} = 2) + \gamma_{j,4} I(3 \leq a_{k,it} \leq 5) + \\ & \gamma_{j,5} I(6 \leq a_{k,it} \leq 11) + \gamma_{j,6} I(a_{k,it} \geq 12) + \gamma_{j,7} I(n_{it} = 2) + \gamma_{j,8} I(n_{it} \geq 3) + \\ & \gamma_{j,9} e_{r,it-1} + \gamma_{j,10} e_{n,it-1} + \\ & \gamma_{j,11} I(2001 \leq t \leq 2004) + \gamma_{j,11} I(2005 \leq t \leq 2006) + \gamma_{j,11} I(2007 \leq t), \end{aligned}$$

[3] See Francesconi (2002), for example.

where $j = n, r$. This cost function is more flexible in the age of the youngest children than ones in previous papers. As shown below, the estimated cost is highly nonlinear in age of the youngest child, which has an important consequence in assessing the effects of extending duration of job protection.

Taking Parental Leave The data indicate that not all eligible workers take a parental leave, even though it offers job protection and cash benefits. One of the eligibility conditions unique to Japan is that workers must be expected to return to the same job after the completion of the leave. This condition applies not only to job protection, but also to cash benefits, which is very different from other countries where parental leave takers can receive cash benefits even if they do not intend to return to work. In Japan, parental leave takers requesting cash benefits must apply through their employers. This setup discourages eligible workers from taking a parental leave. Workers requesting a leave need to speak to their supervisor to discuss work arrangement while they are on leave and when they return. Co-workers may not be happy with someone's parental leave taking, because that may imply more work on their shoulder particularly in a smaller establishment. This psychic cost of taking a parental leave is a possible explanation for why not all eligible workers take a parental leave.

While not all eligible workers take a parental leave, some seemingly ineligible workers take a parental leave. This is because some employers offer a parental leave package that requires less stringent eligibility conditions than the legislation. For example, the duration of job protection is 1 year under the current legislation, but some employers offer an extended parental leave for more than 1 year. Non-regular employees were not legally eligible for parental leave until 2005, but some employers offer parental leave to them before 2005. In the data, no one takes a parental leave if she stayed home last year or has no children age one or younger. Hence, I assume that those who do not satisfy the legal eligibility conditions may take a parental leave if they were employed in the last year and have a child age one. All other workers are not able to take a parental leave.

The cost of taking a parental leave depends on whether the worker satisfies the legal eligibility conditions or not. Let D_{it}^{EE} be an indicator that takes one if individual i is able to take a parental leave and takes zero otherwise. Let D_{it}^{LE} be an indicator variable that takes one if individual i satisfies the legal eligibility conditions and takes zero otherwise. The cost of taking a parental leave is given by

$$v_l(D_{it}^{EE}, D_{it}^{LE}) \quad = \quad \gamma_{l,0} + \gamma_{l,1} D_{it}^{LE} + \gamma_{l,2} d_{l,it-1} - \infty(1 - D_{it}^{EE}),$$

where

$$D_{it}^{EE} = \begin{cases} 1 & \text{if } (e_{r,it-1} = 1 \text{ or } e_{n,it-1} = 1) \text{ and } 0 \leq a_{k,it} \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$D_{it}^{LE} = \begin{cases} 1 & \text{if } (e_{r,it-1} = 1 \text{ and } a_{k,it} = 0) \text{ or } (e_{n,it-1} = 1 \text{ and } a_{k,it} = 0 \text{ and } t \geq 2005) \\ 0 & \text{otherwise.} \end{cases}$$

Parental leave is not available for those who were not employed in the last year or those who do not have a child age one or less. Hence, their payoff from taking a parental leave is $-\infty$. The indicator variable D^{LE} reflects the fact that workers in the non-regular sector became legally eligible in the 2005 reform. The lagged indicator variable for parental leave is included to account for possibility that renewing or extending a parental leave is easier than starting a new one. Indeed, this feature improves the model fit to the data.

3.2.3 Conception

A married woman derives utility from conception. This utility component is the utility difference from non-conception and can be interpreted as the present value of utility flows from children as they grow. The utility from conception depends mother's age, age of the youngest child, the number of existing children, lagged labor supply choices, and time. It is parametrized as follows;

$$\begin{aligned}
& v_f(a_{it}, a_{k,it}, n_{it}, d_{it}, t) \\
= \ & \delta_0 + \delta_1(a_{it} - 30)I(a_{it} \geq 30) - \infty I(a_{it} \geq 45) + \\
& \delta_2 I(a_{k,it} = 0) + \delta_3 I(a_{k,it} = 1) + \delta_4 I(a_{k,it} = 2) + \delta_5 I(3 \leq a_{k,it} \leq 5) + \\
& \delta_6 I(6 \leq a_{k,it} \leq 11) + \delta_7 I(a_{k,it} \geq 12) + \delta_8 I(n_{it} = 2) + \delta_9 I(n_{it} \geq 3) + \\
& \delta_{10} d_{r,it} + \delta_{11} d_{n,it} + \delta_{12} I(2001 \leq t \leq 2004) + \delta_{12} I(2005 \leq t \leq 2006) + \delta_{13} I(2007 \leq t),
\end{aligned}$$

Mother's age a_{it} is included to account for the fact that fecundity decreases from age 30. A woman becomes infecund at age 45, and hence, the utility from conception from age 45 on is negative infinity. To allow for the number and age distribution of children to differently affect the utility, the utility function includes the number of children n_{it} and the age of the youngest child $a_{k,it}$. Because non-market time may affect the utility from conception, the current labor supply choices $d_{r,it}$ and $d_{n,it}$ are included. Lastly, to account for changes in policies and environment for children and family over time, calender year t also affects the utility from conception.

3.3 Budget Constraint

The household consumes all the income earned in a given year. The budget constraint is

$$C_{it} = y_{h,it} + d_{r,it}y_{r,it} + d_{n,it}y_{n,it} + d_{l,it}b_{it},$$

where $y_{h,it}$ is earnings of husband, $y_{r,it}$ is earnings in the regular employment sector, $y_{n,it}$ is earnings that individual i would make in year t if she works in the non-regular employment sector, and b_{it} is the cash benefit for parental leave.

Earnings of Husband The earnings of husband are given by a function of the wife's age, lagged husband's earnings, age of the youngest child, and number of children,

$$\begin{aligned} y_{h,it} = {} & \omega_{hi,0} + \omega_{h,1}a_{it} + \omega_{h,2}a_{it}^2 + \omega_{h,3}a_{it}^3 + \omega_{h,4}y_{h,it-1} + \omega_{h,5}I(a_{k,it}=0) + \omega_{h,6}I(a_{k,it}=1) + \\ & \omega_{h,7}I(a_{k,it}=2) + \omega_{h,8}I(3 \le a_{k,it} \le 5) + \omega_{h,9}I(6 \le a_{k,it} \le 11) + \omega_{h,10}I(n_{it}=1) + \\ & \omega_{h,11}I(n_{it}=2) + \omega_{h,12}I(n_{it} \ge 3) + \omega_{h,13}d_{r,it} + \omega_{h,14}d_{n,it} + \omega_{h,15}d_{l,it} + \omega_{ht,16} + \varepsilon_{yh,it}, \end{aligned}$$

where the intercept $\omega_{hi,0}$ varies across households to allow for difference in husband's unobserved permanent skills and $\omega_{ht,16}$ captures time effects. The last term $\varepsilon_{yh,it}$ is an i.i.d. income shock that follows a normal distribution with zero mean and variance σ_{yh}^2. Note that this last term is not a measurement error, and hence, variation in observed husband's income affects women's employment and parental leave take-up decisions.

Own Earnings The earnings functions are sector-specific and given by

$$\begin{aligned} y_{r,it} = {} & \omega_{ri,0} + \omega_{r,1}h_{r,it} + \omega_{r,2}h_{r,it}^2 + \omega_{r,3}h_{n,it} + \omega_{r,4}h_{h,it} + \omega_{r,5}d_{r,it-1} + \omega_{r,6}d_{n,it-1} + \\ & \omega_{r,7}I(2001 \le t \le 2004) + \omega_{r,8}I(2005 \le t \le 2006) + \omega_{r,9}I(2007 \le t) + \varepsilon_{y,it}. \end{aligned} \tag{1}$$

$$\begin{aligned} y_{n,it} = {} & \omega_{ni,0} + \omega_{n,1}h_{n,it} + \omega_{n,2}h_{n,it}^2 + \omega_{r,3}h_{r,it} + \omega_{n,4}h_{h,it} + \omega_{n,5}d_{r,it-1} + \omega_{n,6}d_{n,it-1} + \\ & \omega_{n,7}I(2001 \le t \le 2004) + \omega_{n,8}I(2005 \le t \le 2006) + \omega_{n,9}I(2007 \le t) + \varepsilon_{y,it}. \end{aligned} \tag{2}$$

where $h_{n,it}$ is the non-regular employment sector-specific experience, $h_{r,it}$ is the regular employment sector-specific experience, and $h_{h,it}$ is years spent at home after age 18. Lagged choices $d_{j,it-1}$ are included to account for a temporal human capital depreciation, while years at home account for permanent human capital depreciation. To account for changes in macroeconomic conditions and any institutions that may affect women's earnings, sector-specific time effects are included. Earnings are measured with error $\varepsilon_{y,it}$ that follows a normal distribution with zero mean and variance σ_y^2. Lastly, the sector-specific intercept $\omega_{ji,0}$ $(j = n, r)$ varies across individual to allow for difference in unobserved permanent skills.

Cash Benefit To be eligible for the cash benefit, a parental leave taker must (1) be legally eligible for parental leave and (2) have worked in the last year. The replacement rate of the cash benefit R_t is summarized in Table 1, and it is zero for ineligible individuals.

The cash benefit replaces a fraction R_t of pre-leave earnings net of bonus up to 5.112 million yen per year. In the data, gross labor earnings including bonus are reported. According to Basic Survey on Wage Structure 2008, regular workers' bonus per year is worth their three-month earnings,[4] while that of non-regular workers is worth their one-month earnings. The cash benefit of parental leave is given by

$$b_{it} \quad = \quad R_t \min\left[5.112,\ d_{r,it-1}\frac{12}{15}\hat{y}_{r,it} + d_{n,it-1}\frac{12}{13}\hat{y}_{n,it}\right],$$

where $\hat{y}_{j,it} = y_{j,it} - \varepsilon_{y,it}$ $(j = i,n)$ is earnings less an measurement error. Because the exact pre-leave salary is not included in the state variable to reduce computational burden, it is approximated by the predicted earnings in year t.

3.4 Dynamic Choice

The objective of a married woman is to maximize the present discount value of her lifetime utilities. Her value function V is recursively defined as

$$V(S_{it},\varepsilon_{it}) \quad = \quad \max_{j\in\{h,r,n.l\},f\in\{0,1\}} U_j^f(S_{it}) + \varepsilon_{j,it}^f + \beta E[V(S_{it+1},\varepsilon_{it+1})|S_{it},d_{it}] \tag{3}$$

where β is a discount factor. Her current payoff is also affected by a preference shock $\varepsilon_{j,it}^f$ specific to a choice $j \in \{h,r,n,l\}$ and $f \in \{0,1\}$. The choice-specific shock follows a generalized extreme value distribution so that the choice probability can be modeled by a nested logit model. Specifically, four employment choices when $d_{f,it} = 0$ and four employment choices when $d_{f,it} = 1$ form two different nests.

I derive the conditional choice probability given the state variables S_{it}. Omit the state variables for notational simplicity, let $\bar{V}_j^f$ be the choice-specific value less the preference shock $\varepsilon_{j,it}^f$, where $f = 0$ means non-conception and $f = 1$ means conception. The conditional choice probability

[4]For regular workers, the average monthly earnings without bonus was 243,900 JPY and the average bonus in 2008 was 724,000 JPY. For non-regular workers, the average monthly earnings without bonus was 170,500 JPY and the average bonus in 2008 was 140,800 JPY.

implied by the structural model is given by

$$l^d(d_{j,it}=1, d_{it}^f|S_{it}) \quad = \quad \frac{\exp\left(\bar{V}_j^f/\lambda_f\right)\cdot\left(\sum_{j\in\{h,r,n,l\}}\exp\left(\bar{V}_j^f/\lambda_f\right)\right)^{\lambda_f-1}}{\sum_{m=0}^{1}\left(\sum_{j\in\{h,r,n,l\}}\exp\left(\bar{V}_j^m/\lambda_m\right)\right)^{\lambda_m}},$$

where λ_f is a dissimilarity parameter that takes values between 0 and 1: a lower value of λ_f implies more correlation between the error terms in a given nest. When $\lambda_f = 1$ for $f = 0,1$, this nested logit model is reduced to the multinomial logit model.

3.5 Unobserved Heterogeneity

Permanent unobserved heterogeneity is modeled as a finite mixture. Individuals are one of K types, but the type of an individual is not observed. Let θ_k be a vector of the parameters of the model for type k. Following Wooldridge (2005), to address the initial condition problem, I allow for the probability of being type k to depend on the observed choice in the first year when individual i is observed in the data. Let τ_i be the first year when individual i is observed in the data. Define $x_{i\tau_i}$ as the vector of observed characteristics and choice in year τ_i: $x_{i\tau_i} = (d_{i\tau_i}, S_{i\tau_i}, edu_i)$ where edu_i is years of education.

The probability that individual i is type k is given by

$$p_k(d_{i\tau_i}, S_{i\tau_i}, edu_i) \quad = \quad \frac{\exp(g_{k,i})}{\sum_{\kappa=1}^{K}\exp(g_{\kappa,i})},$$

where

$$g_{\kappa,i} \quad = \quad \pi_\kappa' x_{i\tau_i}.$$

For normalization, the parameters for the first type is set 0 so that $\pi_{\kappa=1} = 0$.

4 Model Estimation

4.1 The Likelihood

Define d_i as a sequence of choices made by individual i from $\tau_i + 1$ to T_i where τ_i and T_i are the first and last years when individual i is observed in the data, respectively, i.e., $d_i = (d_{i\tau_i+1}, d_{i\tau_i+2}, \cdots d_{iT_i})$. Sequences of own and husband's earnings are similarly defined and given by y_i and $y_{h,i}$, respectively. Let $\theta = (\theta_1, \cdots, \theta_K)$ be a vector of parameters for all K types where θ_k is a vector of parameters for type k individual. Let $\pi = (\pi_1, \cdots, \pi_K)$ be a vector of parameters for type probability. The likelihood of observed sequences of choices, own earnings, and husband's earnings conditional on the observed characteristics and choices in year τ_i is

$$
\begin{aligned}
& \mathscr{L}(d_i, y_{h,i}, y_i \mid d_{i\tau_i}, S_{i\tau_i}, edu_i; \theta, \pi) \\
= & \sum_{k=1}^{K} p_k(d_{i\tau_i}, S_{i\tau_i}, edu_i; \pi) L(d_i, y_{h,i}, y_i \mid d_{i\tau_i}, S_{i\tau_i}; \theta_k),
\end{aligned}
$$

where $p_k(\cdot)$ is the probability of being type k and $L(\cdot)$ is the conditional likelihood of the sequences given being type k and the observed choices and state variables in the first year.

Given the first order Markov structure of the model, the likelihood of the observed sequences can be rewritten as a product of probability functions. The parameter vector for type k consists of the sub parameter vectors such that $\theta_k = (\theta_k^y, \theta_k^{yh}, \theta_k^u)$, where θ_k^y is a parameter vector for own earnings functions, θ_k^{yh} is a parameter vector for husband's earnings function, and θ_k^u is a parameter vector for the utility function

$$
\begin{aligned}
& L(d_i, y_{h,i}, y_i \mid d_{i\tau_i}, S_{i\tau_i}; \theta_k) \\
= & \prod_{t=\tau_i+1}^{T_i} l(d_{it}, y_{h,it}, y_{it} \mid S_{it-1}, d_{it-1}; \theta_k) \\
= & \prod_{t=\tau_i+1}^{T_i} l^d(d_{it} | S_{it}; \theta_k^d, \theta_k^y, \theta_k^{yh}) \cdot l^y(y_{it} | S_{it}, d_{it}; \theta_k^y) \cdot l^{yh}(y_{h,it} | S_{it-1}, d_{it-1}; \theta_k^{yh}),
\end{aligned}
$$

where $l^d(\cdot)$ is the conditional choice probability given the structural model and state variables in year t, $l^y(\cdot)$ is the likelihood of earnings given the state variables and choice in year t, and $l^{yh}(\cdot)$ is the conditional likelihood for earnings of husband in year t, respectively, given the choice and state variables in the previous year $t-1$.

4.2 The Algorithm

The estimation algorithm is based on Kasahara and Shimotsu (2011). Their algorithm sequentially updates the parameter estimates and the value function estimate. For each likelihood evaluation, the value function is iterated for a small number of times rather than until convergence, which significantly reduces computational time. To accelerate the computation for the value function iteration in evaluating the likelihood, the value function is approximated based on sieves, using the method proposed by Arcidiacono, Bayer, Bugni, and James (2013). When the state space is large, this sieve approximation can reduce the computational time dramatically.

To account for unobserved heterogeneity modeled as a finite mixture, I combine the sequential algorithm by Kasahara and Shimotsu (2011) and the Expectation-Maximization algorithm with a sequential maximization step (ESM) developed by Arcidiacono and Jones (2003). Combining these two sequential algorithms makes the model estimation tractable.

In the following, I first describe the estimation algorithm for the model in which individuals are homogeneous. I then explain how this estimation algorithm can be applied to the model in which individuals are heterogeneous.

4.2.1 Homogeneous Individuals

When individuals are homogeneous, the log-likelihood is given by

$$
\begin{aligned}
& \ln L\left(\{d_i, y_{h,i}, y_i\}_{i=1}^N | \{d_{i\tau_i}, S_{i\tau_i}\}_{i=1}^N; \theta\right) \\
= & \sum_{i=1}^N \sum_{t=\tau_i+1}^{T_i} \ln l^d(d_{it}|S_{it}; \theta^d, \theta^y, \theta^{yh}) + \ln l^y(y_{it}|S_{it}, d_{it}; \theta^y) + \ln l^{yh}(y_{h,it}|S_{it-1}, d_{it-1}; \theta^{yh}).
\end{aligned}
$$

Consistent estimates for the parameter vectors θ^y and θ^{yh} are given by

$$
\begin{aligned}
\hat{\theta}^y & \equiv \arg\max_{\theta^y} \sum_{i=1}^N \sum_{t=\tau_i+1}^{T_i} \ln l^y(y_{it}|S_{it}, d_{it}; \theta^y) \\
\hat{\theta}^{yh} & \equiv \arg\max_{\theta^{yh}} \sum_{i=1}^N \sum_{t=\tau_i+1}^{T_i} \ln l^{yh}(y_{it}|S_{it}, d_{it}; \theta^{yh})
\end{aligned}
$$

Note that the consistent estimates for the parameters $\hat{\theta}^y$ and $\hat{\theta}^{yh}$ can be obtained separately from the parameters in the utility function. Because estimation of these parameters $\hat{\theta}^y$ and $\hat{\theta}^{yh}$ is straightforward, I focus on the algorithm for estimating θ^d in the following.

The Bellman equation (3) can be rewritten in terms of the expectation of the value function

$$
\begin{aligned}
EV(S_{it}) & = E\left[\max_{j,f} U_j^f(S_{it}) + \varepsilon_{j,it}^f + \beta E[V(S_{it+1}, \varepsilon_{it+1})|S_{it}, d_{it}]\right] && (4) \\
& = E\left[\max_{j,f} U_j^f(S_{it}) + \varepsilon_{j,it}^f + \beta \int EV(S_{it+1}) dF(S_{it+1}|S_{it}, d_{it})\right]. && (5)
\end{aligned}
$$

Define the Bellman operator given by the right hand side of the above equation as

$$
[\Gamma(\theta, EV)](S_{it}) \equiv E\left[\max_{j,f} U_j^f(S_{it}) + \varepsilon_{j,it}^f + \beta \int EV(S_{it+1}) dF(S_{it+1}|S_{it}, d_{it})\right].
$$

The Bellman equation (5) is compactly rewritten as $EV = \Gamma(\theta, EV)$.

The choice-specific value $\bar{V}_j^f(S_{it})$ less the preference shock ε_{it} is given by

$$\bar{V}_j^f(S_{it};EV,\theta) \quad = \quad U_j^f(S_{it};\theta)+\beta\int EV(S_{it+1})dF(S_{it+1}|S_{it},d_{it};\theta).$$

The likelihood of choosing employment choice $j\in\{h,r,n,l\}$ and fertility choice $f\in\{0,1\}$ can be expressed as

$$\begin{aligned}
& l^d(d_{j,it}=1,d_{it}^f|S_{it};EV,\theta^d,\hat{\theta}^y,\hat{\theta}^{yh}) \\
= \quad & \frac{\exp\left(\bar{V}_j^f(S_{it};EV,\theta)/\lambda_f\right)\cdot\left(\sum_{j\in\{h,r,n,l\}}\exp\left(\bar{V}_j^f(S_{it};EV,\theta)/\lambda_f\right)\right)^{\lambda_f-1}}{\sum_{m=0}^1\left(\sum_{j\in\{h,r,n,l\}}\exp\left(\bar{V}_j^m(S_{it};EV,\theta)/\lambda_m\right)\right)^{\lambda_m}},
\end{aligned}$$

where $\hat{\theta}^y$ and $\hat{\theta}^{yh}$ are consistent estimates. Define the mapping $\Lambda(\theta,EV)$ as

$$\begin{aligned}
& [\Lambda(EV,\theta)]\,(d_{j,it}=1,d_{it}^f|S_{it}) \\
\equiv \quad & \frac{\exp\left(\bar{V}_j^f(S_{it};EV,\theta)/\lambda_f\right)\cdot\left(\sum_{j\in\{h,r,n,l\}}\exp\left(\bar{V}_j^f(S_{it};EV,\theta)/\lambda_f\right)\right)^{\lambda_f-1}}{\sum_{m=0}^1\left(\sum_{j\in\{h,r,n,l\}}\exp\left(\bar{V}_j^m(S_{it};EV,\theta)/\lambda_m\right)\right)^{\lambda_m}}.
\end{aligned}$$

The consistent estimate for the parameter vector θ^d is given by

$$\hat{\theta}^d \quad = \quad \arg\max_{\theta^d}\frac{1}{N}\sum_{i=1}^N\ln\Lambda(EV,\theta^d,\hat{\theta}^y,\hat{\theta}^{yh}) \text{ subject to } EV=\Gamma(\theta,EV).$$

Computation of the likelihood function by the nested fixed point algorithm by Rust (1987) requires solving the fixed points of $EV=\Gamma(\theta,EV)$ at each trial parameter value in maximizing the objective function with respect to θ^d. The q-NPL algorithm proposed by Kasahara and Shimotsu (2011) iterates the Bellman operator for only q times rather than finding fixed points.

Define a q-fold operator of Γ as $\Gamma^q(\theta,EV)$. Starting from an initial estimate $\widetilde{EV}(0)$ for the expectation of the value function, the q-NPL algorithm iterates the following steps until EV and θ^d converge:

1. Given $\widetilde{EV}(m-1)$, update θ^d by

$$\tilde{\theta}^d(m) \quad = \quad \arg\max_{\theta^d}\frac{1}{N}\sum_{i=1}^N\ln\Lambda(\theta^d,\hat{\theta}^y,\hat{\theta}^{yh},\Gamma^q(\theta,\widetilde{EV}(m-1))).$$

2. Update EV using the obtained estimate $\tilde{\theta}^d(m)$

$$\widetilde{EV}(m) = \Gamma^q(\tilde{\theta}(m), EV(m-1)),$$

where $\tilde{\theta}(m) = (\tilde{\theta}^d(m), \hat{\theta}^y, \hat{\theta}^{yh})$.

Kasahara and Shimotsu (2011) prove that this sequence converges when q is large enough and yields a consistent estimate for θ^d. I tried different values for q and find $q = 6$ seems to minimize the computational time for the model and data in this paper.

The Bellman operator Γ could be applied to the discretized state space, but that can be computationally intractable when the state space is large. Following Arcidiacono, Bayer, Bugni, and James (2013), to reduce computational burden, the Bellman operator is approximated by a higher order polynomial function. Let $W(S_{it})$ be a vector of polynomials of the state variables. Let ρ be a vector of parameters that approximate the value function. For any state variable S_{it}, the sieve approximation satisfies

$$\begin{aligned} W(S_{it})'\rho &\approx EV(S_{it}). \\ &= \ln\left[\sum_{f\in\{0,1\}}\left(\sum_{j\in\{h,r,n,l\}}\exp\left(\frac{U_j^f(S_{it}) + \beta E\left[W(S_{it+1})'\rho|S_{it}, d_{it}\right]}{\lambda_f}\right)\right)^{\lambda_f - 1}\right] \\ &= \ln\left[\sum_{f\in\{0,1\}}\left(\sum_{j\in\{h,r,n,l\}}\exp\left(\frac{U_j^f(S_{it}) + \beta E\left[W(S_{it+1})|S_{it}, d_{it}\right]'\rho}{\lambda_f}\right)\right)^{\lambda_f - 1}\right]. \end{aligned}$$

A key convenience of this approach based on a polynomial function is that the parameter ρ can be taken out of the expectation operator $E(\cdot)$ as it can be seen in the last equality. This can save the computational time, because the expectation of $E(W(S_{it+1})|S_{it}, d_{it})$ needs to be calculated only once as long as the parameters for transition probabilities remain the same.

4.2.2 Heterogeneous Individuals

In this subsection, I describe the estimation method for the case in which individuals are heterogeneous. The method described in the last subsection is combined with the EM algorithm developed by Arcidiacono and Jones (2003).

Expectation Step In the expectation step, I calculate the conditional probability of being in each unobserved type given the values of the parameters, choices, earnings, and observed state variables. Let $\tilde{\theta}(m-1)$ and $\tilde{\pi}(m-1)$ be the vectors of parameters obtained from the $(m-1)$ th iteration.

The estimates for the expectation of the value function is denoted by $\widetilde{EV}(m-1)$. The likelihood of the observations on individual i given the parameters at the $(m-1)$ th iteration is found by

$$L_i^{(m-1)} = \mathscr{L}(d_i, y_{h,i}, y_i | d_{i\tau_i}, S_{i\tau_i}, edu_i; \widetilde{EV}(m-1), \tilde{\theta}(m-1), \tilde{\pi}(m-1)).$$

Similarly, I denote by $L_{ik}^{(m-1)}$ the joint likelihood of the observations and being type k given the parameters at the $m-1$ th iteration. At iteration m, following from the Bayes rule, the probability of individual i being type k, $q_{ik}(m)$ is given by

$$q_{ik}(m) = \frac{L_{ik}^{(m-1)}}{L_i^{(m-1)}}.$$

Maximization Step The parameter vector is updated to $\tilde{\theta}(m)$ by maximizing

$$\begin{aligned}
&\sum_{i=1}^{N}\sum_{k=1}^{K} q_{ik}(m) \ln \mathscr{L}(d_i, y_{h,i}, y_i \mid d_{i\tau_i}, S_{i\tau_i}, edu_i; \widetilde{EV}(m-1), \tilde{\theta}(m-1), \tilde{\pi}(m-1)) \\
= &\sum_{i=1}^{N}\sum_{k=1}^{K} q_{ik} \Big(\ln p_k(d_{i\tau_i}, S_{i\tau_i}, edu_i; \tilde{\pi}(m-1)) + \sum_{t=\tau_i+1}^{T_i} \ln l^d(d_{it}|S_{it}; \widetilde{EV}(m-1), \tilde{\theta}_k(m-1)) + \\
&\ln l^y(y_{it}|S_{it}, d_{it}; \tilde{\theta}_k^y(m-1)) + \ln l^{yh}(y_{h,it}|S_{it-1}, d_{it-1}; \tilde{\theta}_k^{yh}(m-1)).
\end{aligned}$$

Because of the linear separability, I can maximize the objective function sequentially. Specifically, the updated sub-vectors are given by

$$\begin{aligned}
\tilde{\pi}(m) &= \arg\max_{\pi} \sum_{i=1}^{N}\sum_{k=1}^{K} q_{ik}(m) \ln p_k(d_{i\tau_i}, S_{i\tau_i}, edu_i; \pi) \\
\tilde{\theta}^y(m) &= \arg\max_{\theta^y} \sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{t=\tau_i+1}^{T_i} q_{ik}(m) \ln l_k^y(y_{it}|S_{it}, d_{it}; \theta^y) \\
\tilde{\theta}^{yh}(m) &= \arg\max_{\theta^{yh}} \sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{t=\tau_i+1}^{T_i} q_{ik}(m) \ln l_k^{yh}(y_{h,it}|S_{it-1}, d_{it-1}; \theta^{yh}) \\
\tilde{\theta}^d(m) &= \arg\max_{\theta^d} \frac{1}{N} \sum_{i=1}^{N} q_{ik}(m) \ln \Lambda(\theta^d, \tilde{\theta}^y(m-1), \tilde{\theta}^{yh}(m-1), \Gamma^q(\theta, \widetilde{EV}(m-1))).
\end{aligned}$$

In updating θ^d, the Bellman operator Γ is approximated by a higher order polynomial function as outlined above for the case of homogeneous individuals. Finally, the estimate of the expectation of the value function is updated by

$$\widetilde{EV}(m) = \Gamma^q(\tilde{\theta}(m), \widetilde{EV}(m-1)).$$

5 Estimation Results

5.1 Parameter Estimates

The parameter estimates are shown in Appendix B. In the current version, no standard errors are reported due to computational burden, but they will be calculated by the bootstrap. In the following, I discuss the parameters that are of particular interest.

5.1.1 Utility Function

Table 10 reports the parameter estimates for the utility function. Marginal utility of consumption decreases with non-market time, given that average hours of work is longer for regular than non-regular employment. This implies that the labor force participation rate and the probability of work in the regular employment sector decreases with husband's income. Marginal utility of consumption increases with the number of children, implying that women with children are more likely to participate in the labor market than women without children.

Children play an important role in deciding labor force participation. The non-pecuniary utility of working in the regular employment sector substantially decreases in the year when the new baby is born (i.e. the age of the youngest child is zero), but it quickly increases when the child reaches age one and continues to increase as the youngest child grows older. The non-pecuniary utility of working in the non-regular sector similarly changes with the age of the youngest child. The non-pecuniary utility from working in the regular sector increases with the number of children, while that from working in the non-regular sector is very small.

The choice transition matrix shown in Table 5 indicates that individuals tend to choose the same alternative from year to year, which can be explained by heterogeneity and state dependence. The estimates for the utility function shows that the preference for work and PL varies considerably across types (see the intercept of each choice). In addition, state dependence also accounts for the observed persistent choice patterns over time. The entry cost to the employment sectors is large, which implies that the persistence in the choice patterns is due to state dependence. For both employment sectors, the entry cost is higher when individuals stayed home in the last year than the entry cost when individuals worked in a different employment sector.

The estimates for the non-pecuniary utility of taking a parental leave indicate that the transaction cost is reduced when the legal eligibility is granted. The non-pecuniary utility for non-regular workers with a new baby (child age 0) is -1.028 when they are not legally eligible, but it increased to -0.559 after 2005 when parental leave is mandated for non-regular workers. The estimates also show that the transaction cost is higher for non-regular workers than regular workers, and for mothers with older children (age 1-2) than new babies (age 0).

The parameter estimates related to non-pecuniary utility from conception are reported in Table 12. The non-pecuniary utility from conception decreases with age after 30, which is consistent with the finding in the medical literature that fecundity decreases after age 30. Women are unlikely to have a child for two or more consecutive years.

5.1.2 Earnings Function

Table 13 reports the parameter estimates for the log earnings function. Individuals have considerably different skills, as shown in the difference in the constant term across individuals. In both sectors, earnings increase with and are concave in the experience in the own sector. The experience in the other employment sector also increases earnings.

Earnings capacity decreases while individuals stay home. This detrimental effect is is not only temporary (captured by lagged home), but also lasts permanently (captured by years in home). Interestingly, the negative effect on earnings capacity in the regular employment sector is very little unless one stays home for more than five years, while that on earnings capacity in the non-regular employment sector increases with years in home.

5.1.3 Earnings Function for Husband

Table 14 reports the parameter estimates for the earnings function for husband. Earnings of husband are highly and serially correlated and increase with age of the wife. They do not change with the number of children and the age of the youngest child.

5.1.4 Type Probability Function

Table 15 reports the parameter estimates for the type probability function. The variables in the table are evaluated at the first year in the sample.

5.2 Model Fit

In this subsection, I present evidence on how well the model is able to fit the data from different viewpoints. The model prediction is based on the model simulation. For each individual in the data, her employment choice, earnings, earnings of her husband, and fertility are simulated given her initial conditions until the year when she last appears in the data.

5.2.1 Profiles Along Own Age

Figure 2 show the actual and predicted age profiles of choice probabilities, earnings, earnings of husband, and the fertility probability. In all of the seven panels in the figure, the predicted age

Table 5: Choice-Transition Matrix

	Home	Reg	Non-Reg	PL
Data				
Home	0.882	0.010	0.108	0.000
Reg	0.062	0.821	0.051	0.065
Non-Reg	0.108	0.041	0.845	0.007
PL	0.094	0.667	0.139	0.100
Model				
Home	0.886	0.010	0.104	0.000
Reg	0.062	0.817	0.051	0.071
Non-Reg	0.108	0.042	0.843	0.008
PL	0.102	0.712	0.130	0.056

profiles are very similar to the actual age profiles. Note that neither the utility functions nor the earnings function include own age. Hence, the similarity between the actual and predicted age profiles for the choice probabilities and earnings is not by construction.

5.2.2 Choice-Transition Matrix

The fit of the model with respect to the extent of serial correlation in the choice is also matched quite well. Table 5 compares the actual and predicted transition matrices for choices. The model is able to the choice transition pattern very closely.

6 Policy Simulations

6.1 Setup

Using the estimated model, I simulate labor supply and fertility decisions of married women under different policy scenarios. Simulated individuals begin their decision making in age 25, which is the youngest age in the sample. Their initial conditions are taken from the empirical distribution. Policies are fixed at age 25 and invariant throughout the lives of the simulated individuals.

I simulate the following four policy scenarios in ascending order in terms of generosity. In the first scenario, no parental leave is mandated. In the second scenario, one-year job protection is mandated in both regular and non-regular sectors, but no cash benefit is paid. In the third scenario, in addition to one-year job protection in both regular and non-regular sectors, cash benefit is mandated for one year and the replacement rate is 50%. This policy scenario corresponds to

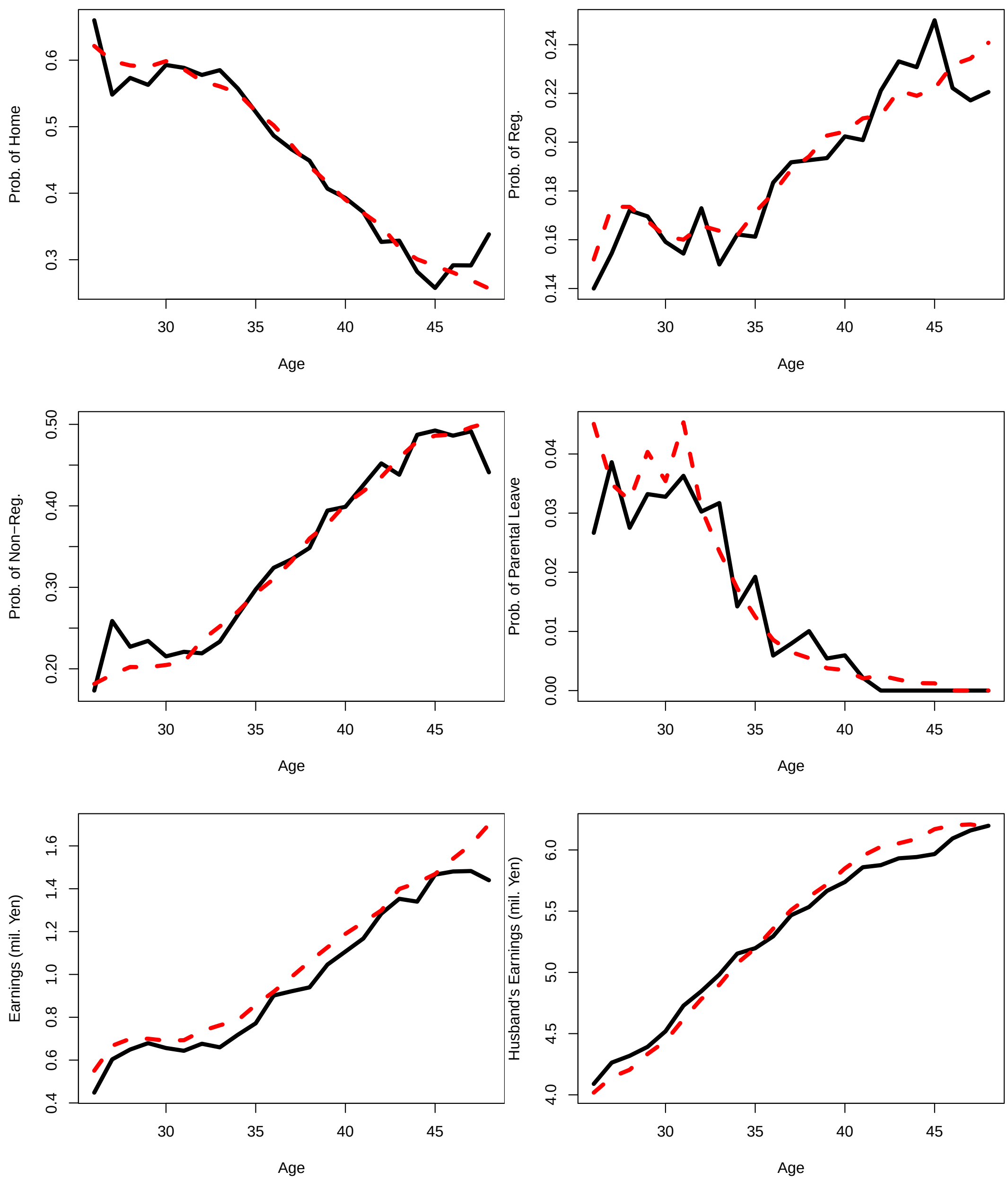


Figure 2: Age Profiles For Labor Market Outcomes

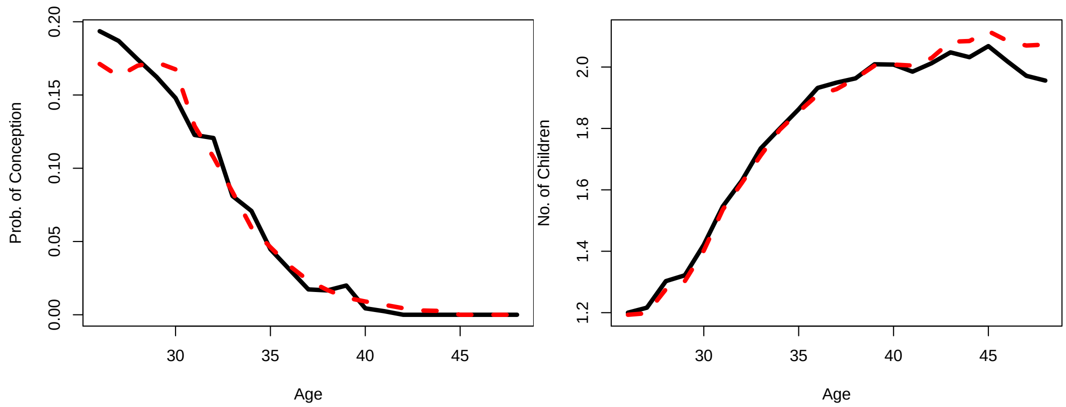


Figure 3: Age Profiles For Fertility Outcomes

the current parental leave system in Japan. In the fourth scenario, the duration of job protection is extended to three years, while cash benefit stays the same as the third scenario in which the duration of payment is one year and the replacement rate is 50%. This policy scenario corresponds to the one proposed by the Japanese Prime Minister. By comparing the third and fourth scenarios, I can evaluate the effects of the proposed parental leave expansion on women's labor supply and fertility decisions.

6.2 Simulation Results

Simulation results for labor supply and fertility decisions are summarized in Tables 6 and 7, respectively. I start with evaluating effects of the introduction of one-year job protection by comparing the first policy scenario (no mandated parental leave) and the second policy scenario (one-year job protection without cash benefit). The introduction of one-year job protection increases the employment rate at age 30 from 0.281 to 0.338. This positive employment effect lasts for many years, and the employment rate increases from 0.670 to 0.700 at age 45. Individuals are considered employed if they work in either employment sector or are on parental leave. The introduction of one-year mandated leave increases the employment rate not only through a higher parental leave take-up rate, but also through higher rates of work. However, policy effects are very different between the regular and non-regular sectors. The probability of work in the regular sector increases from 0.085 to 0.120 at age 30, and the positive effects lasts even at age 45. The probability of work in the regular sector increases from 0.117 to 0.146 at age 45. In contrast, very little policy effects are seen on the probability of work in the non-regular sector. The increase in the probability of work in the regular sector is transmitted to the increase in earnings. Note that earnings do not include the cash benefit for parental leave. The average earnings increases from 0.393 million yen (= 10,000 USD) to 0.510 million yen at age 30 and from 0.911 yen to 1.110 yen at age 45. While effects on labor supply are substantial, effects on fertility seems very little. The conception rate at age 30 slightly increases from 0.135 to 0.137. The completed fertility rate (= number of children at age 45) for married women slightly increases from 2.241 to 2.262, while the childlessness rate for married women at age 45 slightly decreases from 0.029 to 0.022.

Next, I evaluate the effects of the introduction of cash benefit by comparing the second and third policy scenarios. In both scenarios, the duration of job protection is one year in both the regular and non-regular sectors, but cash benefit is legislated only in the third scenario. The replacement rate of the cash benefit is 50%. The results indicate that cash benefit increases the employment rate, the probabilities of work, and earnings only modestly. The employment rate at age 30 slightly increases from 0.338 to 0.350, but the positive effect almost disappears by age 45. The effects on fertility decisions are negligibly small.

Finally, I evaluate the effects of an extension of job protection period, which is proposed by the Japanese Prime Minister. Namely, the duration of job protection is extended from one to three years, while the duration of cash benefit remains at one year and the replacement rate also remains at 50%. The effects of the proposed expansion are estimated by comparing the third and fourth policy scenarios. The extension of job protection period increases the employment rate at age 30 from 0.350 to 0.378. Note that this positive effect is largely due to the higher parental leave take-up rate and the probabilities of work do not increase very much. The effect on the employment rate at age 45 is very small: it increases from 0.704 to 0.711. Because the expansion has only small effects on labor supply, its effects on fertility are also very small. The completed fertility rate for married women increases 2.266 to 2.287.

Table 6: Policy Effects on Labor Market Outcomes

Age	30	35	40	45
Employed				
No PL	0.281	0.432	0.592	0.670
1-Yr JP + 0%	0.338	0.477	0.626	0.700
1-Yr JP + 50%	0.350	0.486	0.633	0.704
3-Yr JP + 50%	0.378	0.512	0.645	0.711
Work in Reg				
No PL	0.085	0.087	0.110	0.117
1-Yr JP + 0%	0.120	0.125	0.143	0.146
1-Yr JP + 50%	0.126	0.133	0.149	0.150
3-Yr JP + 50%	0.130	0.141	0.155	0.153
Work in Non-Reg				
No PL	0.190	0.343	0.482	0.553
1-Yr JP + 0%	0.194	0.346	0.481	0.553
1-Yr JP + 50%	0.197	0.346	0.482	0.553
3-Yr JP + 50%	0.201	0.350	0.485	0.556
Earnings (10,000 USD)				
No PL	0.393	0.503	0.732	0.911
1-Yr JP + 0%	0.510	0.687	0.926	1.110
1-Yr JP + 50%	0.530	0.720	0.962	1.139
3-Yr JP + 50%	0.526	0.735	0.987	1.154

Table 7: Policy Effects on Fertility

Age	30	35	40	45
Conception				
No PL	0.135	0.032	0.005	0.000
1-Yr JP + 0%	0.137	0.032	0.005	0.000
1-Yr JP + 50%	0.137	0.032	0.006	0.000
3-Yr JP + 50%	0.139	0.034	0.006	0.000
No. of Children				
No PL	1.740	2.142	2.224	2.241
1-Yr JP + 0%	1.759	2.164	2.245	2.262
1-Yr JP + 50%	1.762	2.168	2.249	2.266
3-Yr JP + 50%	1.766	2.184	2.270	2.287
Childless Rate				
No PL	0.098	0.040	0.031	0.029
1-Yr JP + 0%	0.088	0.032	0.024	0.022
1-Yr JP + 50%	0.087	0.031	0.023	0.021
3-Yr JP + 50%	0.084	0.031	0.023	0.021

The results indicate that introducing a one-year job protection is effective, but extending it to two or three years does not significantly increase the employment rate. Why is that? A possible explanation is the labor force participation cost of young children. As shown in Table 10, the disutility cost of work is very high when the new child is born, but it sharply drops when the child reaches age 1. A one-year job protection is useful for mothers because the disutility cost of work is very high, but a three-year job protection is not as beneficial, because the disutility cost of work is dramatically reduced.

Note that this sharp drop in the cost of children for labor force participation after the child grows to age 1 is also found in the U.K. Prowse (2012) estimates a dynamic discrete choice reduced-form model of female labor force participation using British Household Panel Survey. She finds that the employment probability sharply drops in the year of childbearing, but it quickly recovers when the child grows age 1. Combined with finding by Prowse (2012), my finding suggests that extending the job protection period from one to three years would little affect the maternal employment rate in the U.K.

Is the model's predictions about the effects of three-year job protection reasonable? Answering this question is not easy, because the policy has never been implemented in the past. Nevertheless, examining a related policy might provide insight into possible policy effects of three-year job protection. Although majority of female workers are in the private sector and their job protection period is one year, public sector employees are already offered a 3-year job protection.[5] They are not fully comparable with private sector employees, but their experience may be useful to see if the model predictions are reasonable. Table 8 shows the distributions of the duration of parental leave for local and the national government employees and the predicted distribution for the private sector employees. Local government employees tend to take a longer parental leave than the national government employees. The model predicts that the fraction of short (1-12 months) parental leave takers is greater in the private sector than in the public sector. Given that local and national governments provide more family-friendly working environment than the private sector employers, this prediction seems reasonable. The fraction of parental leave takers in the public sector decreases with duration. The model prediction is different from this pattern. At this point, I am not entirely sure about why this is happening in the model, but the model prediction seems reasonable otherwise. The comparison here suggests, but by no means prove, that the model predictions are reasonable.

Table 8: Distributions of Parental Leave Duration Among Public Sector Workers

PL Duration	Local	National	Model
1 to 12 months	38%	54%	59%
13 to 24 months	40%	34%	8%
25 to 36 months	22%	12%	32%

Sources: The National Personnel Authority.

6.3 Long-Term Policy Effects

Most previous studies that estimate the effects of parental leave on female labor supply take the reduced-form estimation approach. More specifically, their identification strategy is based on the difference-in-differences estimator or the regression discontinuity designs. While their identification strategy is credible, the estimated policy effects are valid for very specific groups: women who give birth around the time of a policy reform. For example, Lalive, Schlosser, Steinhauer, and Zweimüller (2014) identify the policy effects by comparing those who give birth right before a policy reform (control group) and those who do so right after a policy reform (treatment group) using the regression discontinuity designs.

While the effects on this group are of interest to policy makers, effects on other women should also be understood to evaluate the full effects of a policy. In particular, the effects on young women

[5] Ideally, the policy effect should be estimated using the data that contain a large number of public sector employees. Unfortunately, I am not aware of any data that enable me to do so.

without a child are relevant to understand the long-term effects of a policy, because they are likely to respond to a policy change by changing their labor supply and fertility decisions several years before they give birth and take a parental leave. Consider a young woman who does not have a child, but plans to have one in the future. If no mandated parental leave exists, she does not pursue and invest in her career in the regular employment sector, because she knows that she will lose her career at childbearing. However, if parental leave is mandated, the same women is willing to pursue and invest in her career, because her career is protected from childbearing and child rearing, thanks to the parental leave legislation. Parental leave policies can affects the career path, not only after childbearing, but also several years before childbearing. Hence, the life cycle career paths may vary across cohorts, because they are informed of a policy change at different ages in their lives. The effects on young cohorts are relevant for understanding how parental leave policies change the life cycle career path of a woman in the long run.

To see how policy effects vary, I examine two cohorts. One cohort is informed of a policy change at their age 30, while another cohort is informed of a policy change at their age 25. Because a policy change takes place in the same calendar year for both cohorts, the former is referred to as the old cohort and the latter is referred to as the young cohort. I examine the effects of the introduction of one-year job protection. The baseline policy is no mandated parental leave, while the new policy is one-year job protection without cash benefit. Both cohorts are simulated from their age 25 and their initial conditions are identical. The only difference between the two cohorts are the timing of the policy change that is unexpected by individuals.

Table 9 presents simulation results. Until age 29, the choice probabilities and earnings of the old cohort do not change under the two policy scenarios, because they do not expect a new policy. At age 30, one-year job protection is legislated unexpectedly, which increases the employment rate from 0.281 to 0.292. As is shown in the last section, the new policy has lasting effects so that the employment rate and the probability of regular work increases by about one percentage point, although the probability of work in the non-regular sector does not change.

The career path of the young cohort is very different from that of the old cohort. One-year job protection is legislated when the young cohort is at age 25. Because they respond to the new policy as soon as it is legislated, their employment rate is higher than that of the old cohort even at age 29. Moreover, the employment rate of the young cohort is higher than that of the old cohort at age 45. This exercise shows that policy effects are stronger on the young cohort. Although this group has received scant attention in the literature, the policy effects on this group is relevant for understanding who parental leave policies can change women's career in the long run in a given economy.

Table 9: Differential Policy Effects Across Cohorts

Age	29	30	35	40	45
Employed					
No PL	0.280	0.281	0.432	0.592	0.670
1-Yr JP + 0% at Age 30	0.280	0.292	0.449	0.605	0.681
1-Yr JP + 0% at Age 25	0.336	0.338	0.477	0.626	0.700
Work in Reg					
No PL	0.095	0.085	0.087	0.110	0.117
1-Yr JP + 0% at Age 30	0.095	0.088	0.100	0.122	0.128
1-Yr JP + 0% at Age 25	0.128	0.120	0.125	0.143	0.146
Work in Non-Reg					
No PL	0.177	0.190	0.343	0.482	0.553
1-Yr JP + 0% at Age 30	0.177	0.191	0.344	0.481	0.553
1-Yr JP + 0% at Age 25	0.181	0.194	0.346	0.481	0.553
Earnings (10,000 USD)					
No PL	0.415	0.393	0.503	0.732	0.911
1-Yr JP + 0% at Age 30	0.415	0.405	0.555	0.798	0.980
1-Yr JP + 0% at Age 25	0.514	0.510	0.687	0.926	1.110

7 Conclusion

I construct a dynamic discrete choice structural model of female labor supply in the presence of parental leave legislation. The model highlights the roles of entry costs to employment sectors and costs of children for labor force participation. The model is estimated by the sequential estimation algorithm that combines the EM algorithm by Arcidiacono and Jones (2003) and q-NPL algorithm by Kasahara and Shimotsu (2011). The sieve approximation for the value function by Arcidiacono, Bayer, Bugni, and James (2013) was also applied to further reduce computational burden. The estimated model seems to fit to key features of the data.

The model is used to conduct counterfactual simulations for evaluating parental leave policies. Effects of one-year job protection on maternal labor market outcomes are significant, but extending the duration of job protection from one to three years has little effect on maternal employment. This is because the cost of children for labor force participation drops when the child grows up to age 1.

The simulation results indicate that effects of parental leave are stronger for younger cohorts who observe an introduction of parental leave policies several years before childbearing. They invest in their skills and pursue a career-track job, because they know that their acquired skills and careers will be protected from a childbearing shock by the parental leave legislation. Although this effect has been paid scant attention in the literature, it is relevant for understanding the full effects of the parental leave legislation in the long run.

Although the empirical results in this paper are based on the Japanese data and legislation, the model and estimation method are applicable to other countries where the parental leave policies could be expanded. For example, the FMLA offers only 12 weeks of unpaid parental leave in the U.S. The model could be used to conduct ex ante evaluation of extending job protection period and an introduction of cash benefits.

One area of future work will examine the interaction effects with other pro-family policies such as childcare expansion that are intended to support working mothers. Such policies are likely to affect the cost of children for labor force participation, and hence, the effects of parental leave policies.

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A Details of Data

A.1 Variable Definitions

A.1.1 Labor Market Status

The choice variable for labor market status has four possible mutually exclusive states. It is determined by the following hierarchical rule. First, I determine if a woman is on parental leave. If not, I examine whether she works in the regular or non-regular sector. If she is not on leave or works, I examine whether she stay at home.

Parental Leave Take-Up For those who report childbearing, JPSC asks whether an individual took a parental leave or not. If yes, she is considered on parental leave for the year. If not, I check her employment status as of October and whether she delivers a baby. The employment status as of October include information on whether the respondent is on parental leave or not, but this answer alone does not seem reliable. Women are considered on parental leave, if they (1) give a birth and (2) are on parental leave or other leave than parental, caregiving, and medical leave as of October.

A Woman may be on parental leave even when she does not deliver a baby, because the leave can be for older children. To determine if their reported parental leave is correct, I check if they have a child and the age of the youngest child. Ten women report parental leave as of October, but they have no child. These respondents seem to be on pregnancy leave, because they deliver a baby in the next year. They are not considered to be on parental leave.

For those who have a child and report parental leave, the age of the youngest child is 4 or less. For those who have a child age 4, the reported parental leave seems false, because they deliver a baby in the following year and the child is too old for a parental leave. They are likely to be on pregnancy leave, not on parental leave. For 2 out of 3 women who have a child age 3, the reported parental leave seems false for the same reason as above. One exception is the woman with ID number 766. She does not deliver a baby in the following year and work full-time full-year. I consider her parental leave is true. For those who have children age 1 or 2, I consider their reported parental leave is all true, because the child is reasonably young for parental leave and they report parental leave in the previous year.

Work in the Regular and Non-Regular Employment Sectors If a woman is considered not on parental leave according to the criteria above, I determine if she works in the regular or non-regular sector. If a woman works and employed as a regular or non-regular employee as of October, I consider she works in the reported employment sector for the year. If a woman is employed, report parental leave or other leave than parental, caregiving, and medical leave, and gives a birth in the next year, she is considered to work in her reported employment sector. This is because she is likely to be on short pregnancy leave in October and work most of the year.

Stay at Home If a woman is considered not on parental leave and not at work according to the criteria above, I determine if she stays at home. If a woman was on leave, a homemaker, or did not do any work as of October, she is considered to stay at home.

A.1.2 Sector-Specific Experiences

Retrospective labor market status from age 18 is available for the 1997 and newer cohorts in the year they first appear in the survey. It is also available for the 1993 cohort in 1997. Part-time job, dispatched work, and sideline work at home are all considered as the non-regular work. The labor market status constructed subsection A.1.1 is used to construct the sector specific experiences for years when individuals are surveyed.

A.1.3 Other Variables

The following lists definitions of other variables.

- Childbearing is identified if an individual report that she delivered a baby or if the report age of the youngest child is zero.
- In constructing the number of children and the age of the youngest child, I count all children regardless of whether they live with the survey respondent. This is relatively innocuous, because most children age 10 or younger live with their mothers.
- Own and husband's labor income are deflated by the 2010 CPI.
- Years of education is constructed from the completed education level. Junior high-school is 9 years, high school is 12 years, 2-year college are vocational school 14 years, 4-year university is 16 years, and advanced degree is 18 years.

B Additional Tables

Table 10: Utility Function (Consumption and Choice-Specific Shocks)

	Estimate	S.E.
Consumption		
Intercept	0.063	0.009
Reg.	0.026	0.008
Non-Reg.	0.047	0.007
1 Child	0.026	0.003
2 Children	0.033	0.005
3+ Children	0.034	0.005
Dissimilarity		
Non Conception	−0.697	0.171
Conception	−0.475	0.217

Table 11: Utility Function (Work and PL)

	Reg.		**Non-Reg.**		**PL**	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Intercept (Type 1)	−0.154	0.043	−0.151	0.050	−0.088	0.334
Intercept (Type 2)	0.009	0.065	0.072	0.037	−0.133	0.317
Intercept (Type 3)	−0.199	0.087	−0.781	0.195	0.502	0.262
Intercept (Type 4)	0.202	0.052	0.146	0.069	−0.242	0.171
Child Age 0	−1.231	0.185	−1.199	0.171		
Child Age 1	−0.389	0.121	−0.281	0.083		
Child Age 2	−0.027	0.109	−0.224	0.073		
Child Age 3-5	−0.185	0.089	−0.117	0.052		
Child Age 6-11	−0.095	0.077	−0.062	0.052		
Child Age 12+	−0.039	0.080	−0.003	0.059		
2 Children	0.070	0.046	0.078	0.023		
3 or More Children	0.021	0.043	0.059	0.025		
Home Last Year	−2.185	0.262	−1.197	0.144		
Reg. Last Year			−0.599	0.100		
Non-Reg. Last Year	−1.080	0.140				
Year 2001-2004	−0.065	0.065	−0.025	0.034		
Year 2005-2006	0.066	0.074	0.072	0.044		
Year 2007-	−0.061	0.050	−0.071	0.024		
Child Age 0 + Non-Reg					−1.028	0.210
Child Age 0 + Non-Reg + After 2005					−0.559	0.144
Child Age 1-2 + Reg					−0.829	0.431
Child Age 1-2 + Non-Reg					−1.287	2.162
PL Last Year					−0.138	0.345

Table 12: Utility Function (Fertility)

	Estimate	S.E.
Intercept (Type 1)	−0.154	0.226
Intercept (Type 2)	−0.037	0.258
Intercept (Type 3)	0.040	0.361
Intercept (Type 4)	−1.049	0.321
Age - 30	−0.282	0.026
Child Age 0	−1.517	0.496
Child Age 1	0.187	0.459
Child Age 2	0.369	0.468
Child Age 3-5	0.167	0.463
Child Age 6-11	−0.402	0.508
Child Age 12+	0.161	0.706
2 Children	−0.276	1.040
3 or More Children	−0.704	0.579
Year 2001-2004	−0.131	0.133
Year 2005-2006	−0.278	0.166
Year 2007-	0.043	0.144
Work in Reg	−0.015	0.257
Work in Non-Reg	−0.625	0.189

Table 13: Log Earnings Function

	Reg.		Non-Reg.	
	Estimate	S.E.	Estimate	S.E.
Intercept (Type 1)	0.216	0.101	−0.973	0.049
Intercept (Type 2)	−0.335	0.101	−1.589	0.048
Intercept (Type 3)	0.657	0.092	−0.176	0.174
Intercept (Type 4)	0.101	0.102	−2.416	0.048
Years in Reg.	0.028	0.011	0.039	0.002
SQ of Years in Reg.	−0.029	0.033		
Years in Non-Reg.	0.020	0.004	0.101	0.006
SQ of Years in Non-Reg.			−0.273	0.030
1 Year at Home	−0.038	0.046	0.335	0.043
2 Years at Home	0.090	0.070	0.011	0.045
3 Years at Home	−0.031	0.072	−0.013	0.042
4-5 Years at Home	0.034	0.089	−0.104	0.037
6+ Years at Home	−0.118	0.067	−0.345	0.038
Year 2001-2004	0.045	0.069	0.012	0.023
Year 2005-2006	0.049	0.069	0.023	0.030
Year 2007-	0.031	0.052	−0.002	0.026
Reg. Last Year	0.483	0.056	0.946	0.065
Non-Reg. Last Year	0.285	0.079	0.719	0.024

Note: The dependent variable is log earnings.

Table 14: Earnings Function for Husband

	Estimate	S.E.
Intercept (Type 1)	1.805	0.244
Intercept (Type 2)	1.797	0.246
Intercept (Type 3)	1.850	0.249
Intercept (Type 4)	1.914	0.248
Age	−0.142	0.015
Age-sq	0.559	0.051
Age-cu	−0.062	0.007
Husband's Earnings	0.851	0.004
Child Age 0	−0.082	0.059
Child Age 1	−0.012	0.057
Child Age 2	−0.011	0.056
Child Age 3-5	−0.044	0.053
Child Age 6-11	−0.072	0.053
Child Age 12+	−0.069	0.060
2 Children	−0.014	0.031
3 or More Children	−0.032	0.036
Reg.	−0.147	0.040
Non-Reg.	−0.091	0.033
PL	−0.029	0.118
Year 2001-2004	−0.030	0.037
Year 2005-2006	0.002	0.044
Year 2007-	−0.102	0.038
Std. Dev. of Error Term	1.022	0.003

Note: The dependent variable is the level of earnings so that zero earnings can be included.

Table 15: Type Probability Function

	Type 2		Type 3		Type 4	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Intercept	14.212	8.879	20.220	8.650	1.100	12.546
Some College	0.182	0.388	−0.048	0.389	1.334	0.719
4-Yr College	0.299	0.668	−0.873	0.768	1.769	1.066
Age	−0.788	0.580	−1.278	0.561	−0.562	0.811
Age-sq	1.422	0.913	2.136	0.876	1.540	1.321
Years at Home	0.081	0.208	0.054	0.195	−1.018	0.422
SQ of Years at Home	0.761	1.593	−0.276	1.608	8.121	2.914
Years in Reg.	−0.230	0.153	−0.032	0.156	−0.375	0.248
SQ of Years in Reg.	0.365	0.669	−0.464	0.596	0.221	1.052
Years in Non-Reg.	−0.432	0.181	−0.219	0.183	−0.807	0.327
SQ of Years in Non-Reg.	2.464	1.539	1.089	1.575	5.186	3.316
Husband's Earnings	−0.361	0.114	−0.126	0.108	0.446	0.159
Child Age 0	−0.932	0.507	−0.600	0.510	−0.191	1.247
Child Age 1	0.089	0.531	0.414	0.521	1.355	0.808
Child Age 2	0.588	0.624	0.444	0.617	1.412	1.345
Child Age 3-5	−0.727	0.512	−0.068	0.458	0.673	0.917
Child Age 6+	−0.735	0.621	0.255	0.551	−0.790	1.043
2 Children	0.626	0.384	0.527	0.369	−0.061	0.734
3 or More Children	−0.339	0.556	0.205	0.512	−2.068	1.137
Reg. in 1st Year	−0.681	0.535	−1.262	0.497	3.002	1.116
Non-Reg. in 1st Year	−0.123	0.407	0.649	0.386	−1.893	2.673
PL in 1st Year	0.373	1.103	−0.054	1.033	4.664	1.627
Conceived in 1st Year	−0.088	0.371	−0.040	0.386	−0.664	0.565