HOUSEHOLD INCOME AND THE DURATION OF UNEMPLOYMENT: NEW EVIDENCE FROM JAPAN

by

Masayoshi Shibata

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

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Economists have analyzed various aspects of unemployment, such as factors that may affect individuals’ choices while unemployed. In particular, economists have examined personal characteristics that may influence an individual’s unemployment duration. I investigate the impacts of individual characteristics on the length of unemployment duration in Japan by using the 2002 Employment Status Survey. I use a household income equation for those who did not complete their unemployment spells before the date of the survey and a multiple imputation technique introduced by Rubin (1996) to generate household income for those who were employed at the time of the survey but whose unemployment spells ended before the time of the survey. I take account of the added-worker effect and assume that the longer spell of unemployment an individual has, the stronger the added-worker effect she faces. I use a Weibull parametric duration model. Furthermore, I use Heckman and Singer’s method (1984) to include unobserved heterogeneity. The results indicate that in a model that does not control for unobserved heterogeneity, unemployment duration and the level of household income are negatively associated, which is inconsistent with search theories. However, when including unobserved heterogeneity, unemployment duration and the level of household income are positively associated on the margin for some ranges of household income. The findings of this study have implications for Japanese labor market policies.
Chapter 1
INTRODUCTION

Economists have examined various elements of unemployment both from macroeconomic and microeconomic standpoints. Under microeconomic aspects, economists have analyzed factors, such as individual characteristics that may influence individuals’ decision making while unemployed.

One of the components of unemployment from microeconomic viewpoint is the length of an unemployment spell. Nickell (1979) argues that the probability of an unemployed male separating from unemployment in a particular period is negatively related to the total family income while he is unemployed and that this negative relationship becomes weaker, the longer his unemployment duration becomes. Household income may affect reservation wage where the reservation wage is the lowest wage rate at which an unemployed individual is willing to accept a given job. A higher household income of the unemployed may increase the reservation wage and may be associated with longer unemployment duration.

Unemployment duration has been internationally studied and discussed because of a consistent increase in unemployment duration in Europe in the 1980s and a lasting increase in unemployment duration in the United States during the 2008 recession (Schmieder, von Wachter, and Bender 2013). While numerous studies investigate unemployment issues in Japan (e.g., Chen et al. 2012; Kato and Miyamoto
2013; Kume et al. 2011; Murakami 2012), few studies (e.g., Sasaki, Kohara, and Machikita 2013) have examined unemployment duration in Japan.

The unemployment rate has increased consistently in Japan. According to the OECD statistics, the annual unemployment rate increased over the period of 1990 to 2002 as shown below.

Specifically, the unemployment rate increased from 2.1% to 5.4% during the period from 1990 to 2002.

Focusing on the 1990s through 2002, the unemployment rate may have risen partly due to recessions. Particularly, during the period of 1991 to 1993, unexpected drop in land and stock prices may have played a role in giving downward pressure in Japanese economy (Brunner and Kamin 1996). Moreover, during the 1990s, a

\begin{figure}
\centering
\includegraphics[width=\textwidth]{unemployment_rate.png}
\caption{Unemployment Rate in Japan (1990-2002)}
\end{figure}

\footnote{Furthermore, some studies investigate employment duration in Japan instead (e.g., Kohara, Sasaki, Machikita 2013; Tachibanaki and Taki 1996).}

\footnote{Data Source: http://stats.oecd.org/}.  

2
substantial decline in productivity may be one of the main causes of severe recessions in Japan (Hayashi and Prescott 2002).

In addition to an increase in the unemployment rate, the length of unemployment duration has also continually risen in Japan. According to the OECD statistics, 39% of the unemployed in Japan were unemployed for more than 6 months in 1980, 48% in 1990, 53% in 2000, and 63% in 2010. Hence, not only the unemployment rate but also the unemployment duration has become essential in shaping welfare policy in Japan.

In this study, I analyze the effects of personal characteristics on the length of unemployment duration in Japan. I use the 2002 Employment Status Survey conducted by the Statistics Bureau of Japan. I examine the effects of personal characteristics, including household income, on the duration of unemployment. Because household income during a period of unemployment is missing for persons who were employed at the time of the survey but were previously unemployed, I use two imputation methods to estimate their household income. Furthermore, I include the added-worker effect where the longer the unemployment duration is, the larger the added-worker effect may be when estimating or imputing missing household income values. I use a Weibull parametric model as a key model. In addition, I use Heckman and Singer’s method (1984) to take account of unobserved heterogeneity in examining the relationship between personal or family characteristics and the length of unemployment duration.

3 Data Source: http://stats.oecd.org/Index.aspx?DataSetCode=DUR_D#. According to the same source, 54% of the unemployed were unemployed for more than 6 months in 2002 and 64% in 2013 in Japan.
I find 1) that the length of unemployment spell and the level of household income are negatively related when heterogeneity is not controlled for, which is against search theories; 2) that the length of unemployment spell and the level of household income are positively related on the margin for some ranges of household income when taking account of unobserved heterogeneity; and 3) that the number of children age 0 to 14 and the length of unemployment duration are negatively related. Not controlling for unobserved heterogeneity when it is statistically significant results in biased estimates.

To the best of my knowledge, this study is the first study to investigate unemployment duration in Japan using the micro-level Employment Status Survey\(^4\), and is the first study to explicitly take account of unobserved individual heterogeneity and the added-worker effects in analyzing the duration of unemployment in the Japanese labor market. Furthermore, I examine not only linear but also non-linear effects of household income on the duration of unemployment. I find statistically significant non-linear effects of household income in the Japanese labor market. By examining essential factors connected to the length of unemployment spell, I address some policy suggestions for the Japanese labor market.

The structure of this paper is as follows: Chapter 2 consists of a literature review and describes some unique characteristics of the Japanese labor market, Chapter 3 describes the models that this study is based upon, Chapter 4 describes the methods, Chapter 5 describes the data, Chapter 6 describes the model specification, \(\ldots\)

Chapter 7 describes the results, Chapter 8 provides discussions, Chapter 9 provides policy suggestions, and Chapter 10 concludes.
Chapter 2
LITERATURE REVIEW

First, I review search theories and duration of unemployment. Specifically, I review studies that examine the effects of personal characteristics on the length of unemployment, the hazard rate (i.e., the instantaneous exit rate from unemployment), and policy parameters of unemployment, including unemployment benefits, which is part of household income of an unemployed person. I also present a history of unemployment insurance and child benefits in Japan, and the added-worker effect both in general and in Japan, which shows the effect of unemployment of one individual in a household on other household members’ labor supply. Moreover, I review studies, which take account of unobserved heterogeneity. Finally, I review unique characteristics of the Japanese labor market.

2.1 Overall Literature Review

Numerous studies have examined optimal job search strategies, such as Mortensen (1986) and Cahuc and Zylberberg (2004). Mortensen provides the fundamental framework for examining individuals’ job search activities. An unemployed individual is assumed to evaluate wage offers one by one and decide whether or not to continue her search in maximizing the present value of her lifetime utility, which a function of income and leisure. The reservation wage is the lowest wage rate at which an unemployed person is willing to accept a certain job and it
determines the condition of labor force participation (Cahuc and Zylberberg 2004). In search theories, the optimal strategy for an individual looking for a job is to accept any wage offer higher than her reservation wage. The reservation wage depends on various parameters affecting the labor market, such as the job separation rate, the job offer arrival rate, and unemployment insurance benefits (Cahuc and Zylberberg 2004). An increase in the level of benefits, which is a subset of household income of an unemployed individual, tends to increase the duration of unemployment for an eligible job seeker because it increases her reservation wage (Cahuc and Zylberberg 2004). Various empirical studies (e.g., Feldstein and Poterba 1984; Sasaki, Kohara, and Machikita 2013) show that the reservation wage and the average length of an unemployment spell are positively associated with the level of unemployment benefits.

The effect of unemployment benefits on unemployment duration has long been discussed. The Lancaster (1979) investigates econometric problems and methods used in analyzing the variation among rational behaviors of unemployed individuals seeking jobs in unemployment duration based on search theories. In particular, Lancaster presents a parametric approach for the duration distribution of unemployment where he examines temporal variation in the chances of an unemployed individual returning to work. He points out that the chance of getting a job offer may depend on at least two factors: first, individual characteristics, such as productivity, age, and health; and, second, geographical characteristics, such as the availability of jobs, i.e., the number of vacancies in relation to the number of job search competitors for these available jobs. Lancaster uses the data based on interviews with the unemployed in England conducted for the Political and Economic
Planning in 1973. His sample consists of 479 British unskilled workers. Lancaster overall finds that age negatively affects the probability of finding a new job opportunity and that the relative level of unemployment benefit negatively affects the probability of finding a new job. His second finding is consistent with search theories. Lancaster finds that the elasticity of unemployment duration due to a change in replacement ratio, which is the ratio of unemployment benefits to pre-unemployment income, is approximately 0.6. Lancaster’s findings suggest that unemployment insurance benefits may play a role of the reservation wage of an unemployed individual.

In addition to Lancaster (1979), Nickell (1979) also analyzes the relationship between unemployment insurance benefits and unemployment duration. He presents an econometric procedure for estimating conditional probability of a person separating from unemployment in any certain week of one’s jobless period. Nickell uses cross sectional data on incomplete unemployment periods. He examines the effects of unemployment benefits and the changes of these effects over the jobless period. His sample consists of 426 unemployed men from the 1972 General Household Survey in Britain. He points out that unemployment benefits are positively related to the number of dependents in Britain. Nickell finds that the expected unemployment duration of married men increases with the number of their children who are financially dependent. Nickell also finds that increasing the replacement ratio from 0.7 to 0.8 yields an expected unemployment duration elasticity of approximately unity. Furthermore, he finds that a change in the replacement ratio, which is again defined as the ratio between unemployment benefits and income, may have a negligible effect on the conditional probability of getting a job for those who are unemployed for more
than 20 weeks. Nickell points out that since the replacement ratio has a substantial impact on the chance of leaving unemployment only in the first twenty weeks, increasing the unemployment benefits of those who are long-term unemployed may be expected to have a negligible effect on the chance of leaving unemployment. Finally, Nickell shows that the probability of an unemployed male individual leaving unemployment in a particular period is negatively related to the total family income while unemployed and that this negative relationship becomes weaker, the longer one’s unemployment duration becomes. Nickell’s findings imply that not only unemployment insurance benefits but also household income may impact the reservation wage of an unemployed person.

Bover, Arellano, and Bentolila (2002) examine the relationship between unemployment benefit duration and unemployment duration, and also the relationship between business cycles and unemployment duration using longitudinal data for 1987 to 1994 from Spain. They estimate discrete-time hazard models and show that the receipt of unemployment benefits substantially decreases the hazard of separating from unemployment. Specifically, they find that the hazard for those without unemployment benefits is two times larger than the hazard for those with unemployment benefits at 3 months unemployment duration. Bover, Arellano, and Bentolila also find that favorable economic conditions result in an increase in the hazard of separating from unemployment. The effect of receiving unemployment insurance benefits on the hazard of leaving unemployment is substantially greater than the effect of favorable economic conditions on the hazard of separating from unemployment during the period of 1987 to 1994. Moreover, they apply the approach of Heckman and Singer (1984) to take account of unobserved heterogeneity. Bover,
Arellano, and Bentolila find that models without unobserved heterogeneity and models with unobserved heterogeneity produce consistent results.

Card, Chetty, and Weber (2007) examine the rates of exits from unemployment near unemployment benefit exhaustions in Austria. They use data from Austrian Social Security Registry during the period of 1981 to 2001. They focus on 1) persons age 20 to 50; 2) persons who did not voluntarily quit their jobs; and 3) persons who worked at their previous employer for at least a year. They estimate Cox proportional hazard models to analyze unemployment separation rates. Card, Chetty, and Weber find that the majority of persons who are looking for jobs separate from unemployment before their unemployment benefits are exhausted. Furthermore, they suggest that the impact of unemployment benefits on an individual’s choice between staying unemployed (i.e., searching for a job) and staying out of labor force may be substantial.

A more recent study by Farber and Valletta (2013) investigates the effect of unemployment benefits across states in the U.S. They use the Current Population Survey during the period of January 2000 to December 2012. Farber and Valletta, for example, estimate a Probit model of exit from unemployment. They find that the extension of unemployment insurance benefit leads to a statistically significant small decline in the rate of separation from unemployment. They also find that extended unemployment insurance benefits result in a small increase in the expected length of unemployment spell. Finally, Farber and Valletta suggest that extended unemployment benefits durations result in longer lengths of unemployment spells for those who are eligible for unemployment insurance benefits and at the same time may

5 Monthly data.
result in increased job opportunities for those who are not eligible for unemployment benefits.

Some empirical studies discuss the cost of staying unemployed. Schmieder, von Wachter, and Bender (2013) argue that if unemployment durations lower reemployment wages, extensions in unemployment insurance eligibility time periods may in fact worsen the prospects of the unemployed rather than help them. They estimate the effect of unemployment duration on wages using social security records during the period of 1975 to 2008 in Germany where the records provide daily information on every receipt of unemployment benefits, and corresponding wages and benefit levels. They use unemployment insurance extensions as an instrumental variable to investigate the average effect of unemployment duration in response to unemployment insurance extensions. Schmieder, von Wachter, and Bender find that unemployment duration yields a negative impact of 0.8% per month on wages. Their results imply that a long spell of unemployment duration is quite costly for those who are unemployed and are searching for new jobs. Schmieder, von Wachter, and Bender point out that longer duration of unemployment may yield lower reemployment wages because of factors, such as human capital depreciation and some stigma. These findings suggest that the cost of spending a substantial amount of time to find a job may be quite high.

Some past studies carefully examine unemployment spells. For instance, Akerlof and Main (1980) point out that the average duration of incomplete spells of unemployment may understate the average duration of completed spells of unemployment because the duration of incomplete spells tends to be shorter than the duration of completed spells. They also indicate that since the probability of an
incomplete unemployment spell getting sampled most likely depends on the length of that spell, the sampled average incomplete unemployment duration tends to overstate the completed unemployment duration due to the oversampled longer unemployment spells (Akerlof and Main 1980). Akerlof and Main use various sources of data including the Work Experience Surveys during the period of 1965 to 1977. According to the Work Experience Survey of the Bureau of Labor Statistics in 1976, 34% of the people with some unemployment experience had more than one unemployment spell and more than half of all unemployment spells were experienced by individuals with multiple unemployment spells in the United States (Akerlof and Main 1980). Akerlof and Main find that the average duration of single unemployment spells is longer than its multiple unemployment spell counterpart. Akerlof and Main further find that unemployment spell duration changes inversely with the number of unemployment spells experienced in a given calendar year. Even though the Employment Status Survey that I use only provides information on current (incomplete) unemployment spells or completed unemployment spells, I should be mindful of what Akerlof and Main indicate.

Some studies look into employment duration rather than unemployment duration in Japan. Tachibanaki and Taki (1996) analyze the effects of personal characteristics on employment duration in Japan using both parametric models (e.g., Weibull and Log-Normal models) and the proportional hazard model suggested by Cox (1972). They use the 1982 Employment Status Survey conducted by the Management and Coordination Agency. Tachibanaki and Taki look into individual age, schooling, employer’s size, occupation\(^6\), and industry as major determinants of

\(^6\) E.g., White-collar workers, blue-collar workers, services workers, and sales workers.
employment duration in Japan. Tachibanaki and Taki find that individual age and firm sizes are essential in determining hazard rate of leaving the current employment, in other words, job tenure. They find that individual age and firm size decrease the hazard rate. Furthermore, they find that a parametric approach is superior to a non-parametric approach by comparing the values of estimated log likelihood.

Few studies examine the duration of unemployment in Japan. Sasaki, Kohara, and Machikita (2013) investigate determinants of the duration of job search and matching functions at the individual level to evaluate search frictions in the Japanese labor market. A matching function is a measure of job matches during a given time interval. The matching function consists of the number of unemployed persons in a given area and the number of job vacancies in the same area, and the degree of area-specific search technology and/or the average search effort of unemployed persons in the same area. They use unemployment insurance data and job search data from the Ministry of Health, Labor, and Welfare. They employ both a Weibull parametric model and the proportional hazard model suggested by Cox (1972). Sasaki, Kohara, and Machikita find that the matching function indicates decreasing returns to scale\(^7\) given the number of job seekers and the number of job vacancies.

Sasaki, Kohara, and Machikita (2013) also find that the longer the duration of unemployment is, the less likely the probability that an individual will separate from unemployment is. While they do not explicitly include unobserved heterogeneity in

\(^{7}\) For example, doubling the number of persons looking for jobs and the number of job vacancies leads to fewer than two times as many job matches.
estimating the effects of personal characteristics on the duration of unemployment, I take account of unobserved heterogeneity. Sasaki, Kohara, and Machikita suggest that two different types of unemployed individuals are present: 1) those who quit their previous jobs voluntarily and are currently looking for jobs and 2) those who lost their previous jobs involuntarily and are currently looking for jobs. They show that the former group is less likely to separate from unemployment than the latter group is where the latter group may have a stronger preference for returning to work (and, therefore, may have more intensive job search) and a relatively smaller reservation wage.

Contrary to Sasaki, Kohara, and Machikita (2013) where they treat the length of unemployment duration as a dependent variable, Kohara, Sasaki, and Machikita (2013) treat the length of unemployment spell as a regressor. Kohara, Sasaki, and Machikita (2013) analyze the relationship between unemployment duration and subsequent employment duration. They use the survey data from the Ministry of Health, Labor, and Welfare. Their sample consists of those persons who separated from employment in August 2005 and found a job by the end of the survey in July 2006. Kohara, Sasaki and Machikita find that the duration of unemployment and the duration of subsequent employment are negatively associated.

Although I do not explicitly focus on unemployment insurance as a component that affects the reservation wage, knowing shifts in the unemployment benefit system

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8 Sasaki, Kohara, and Machikita (2013) include for instance age, education, and previous employment duration as personal characteristics in their analysis.

9 I focus on household income where an unemployment insurance benefit is a subset of household income.
in Japan may be helpful in understanding unemployment duration issues in Japan. Konishi (2012) provides relevant information on the Japanese unemployment benefit system. In Japan, the Unemployment Insurance Act was enacted in November 1947. Under this act, unemployment is defined as a condition where an insured individual is separated from employment and cannot find a job despite the willingness and ability to work. The current Japanese unemployment insurance system consists of three acts: 1) the Employment Insurance Act based on the principle of social insurance; 2) the Public Assistance Act covering not only unemployed individuals but also some of poor or needy individuals; and 3) the Act on Support for Job Seekers in Finding Jobs supporting job seekers. The Employment Insurance Act was enacted in December 1974. Under this act, as opposed to the Unemployment Insurance Act of 1947, the prescribed duration of benefits ranged from 90 days to 300 days depending on age, physical and mental conditions, and difficulty in finding a job because of social circumstances. The Employment Insurance Act of 1974 has been revised several times. Due to the revisions of the Act of 1974 in 1984, from 1984 to 1999, the prescribed duration of unemployment benefits depended on age, the length of the period of previous employment, and the length of the period that a person paid unemployment insurance contributions. Because of the revisions of the Act of 1974 in 2000, since 2000, the prescribed duration of unemployment benefits have depended on age, the length of the period of previous employment, the length of the period that an individual paid unemployment insurance contributions, and reasons for separation from employment. Due to lack of data availability, I focus on household income as an

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10 Both an employee and her employer pay her unemployment insurance contributions while she is employed in Japan.
element of reservation wage rather than unemployment insurance benefit\textsuperscript{11} where unemployment insurance benefits are a subset of household income.

In looking into the effect of the number of children, the child benefit system in Japan may be relevant. Child benefit was established in the 1970s in Japan and it was an income-tested benefit (Tokoro 2012). According to Tokoro (2012), the child benefit eligibility was extended from children age 3 and under to children age 7 and under in 2000.\textsuperscript{12} The monthly amount of child benefit was 5,000 Yen\textsuperscript{13} for the first child age 7 and under, 5,000 Yen for the second child age 7 and under, and 10,000 Yen for the third child age 7 and under during the period from 2000 to 2003.\textsuperscript{14} If the child benefit is an income-tested benefit, it may affect the unemployment duration of an unemployed individual in a household with children age equal to or under the age limit.

In my analyses of unemployment duration, I take account of the added-worker effect where a decline in family income due to the unemployment of one person in the

\textsuperscript{11} The amount of unemployment insurance benefit in Japan depends on the relative amount of pre-unemployment income. For example, when looking at two unemployed persons with the same characteristics where one’s pre-unemployment income is higher than the other’s pre-unemployment income the amount of the former’s benefit consists of a smaller percentage of her pre-unemployment income than the latter’s benefit does.

\textsuperscript{12} The eligibility age limit was extended to age 10 and under in 2004 according to Tokoro (2012).

\textsuperscript{13} 105 Yen = 1 Dollar as of January 2000 (not seasonally adjusted) according to the Board of Governors of the Federal Reserve System (\url{http://research.stlouisfed.org/fred2/data/EXJPUS.txt}).

\textsuperscript{14} Please refer to \url{http://www.social-policy.org.uk/lincoln/Tokoro.pdf} and/or \url{http://www.ipss.go.jp/syoushika/bunken/data/pdf/18191808.pdf}.  

\textsuperscript{16}
family may lead to a second person entering the labor market or increasing her labor supply (if this second person is already employed in the labor market) to compensate for the loss of family income. Lundberg (1985) empirically investigates the added-worker effect in the United States using data from the Seattle and Denver Income Maintenance Experiments. Instead of examining static measures of labor supply, Lundberg looks into employment transition probabilities in a dynamic simulation of changes in the rates of spousal employment and labor force participation subsequent to a change in husbands’ employment status. Furthermore, she focuses on elements, such as job uncertainty and liquidity constraints, which produce short-run patterns of labor participation and employment. Lundberg concludes that the added-worker effect is not large but it is substantial for white families in the United States.

Goux, Maurin, and Petrongolo (2014) analyze the effect of work-time regulation on spousal labor supply in France. They use French Labor Force Survey and administrative data collected by the French Ministry of Labor from 1994 to 2009. Goux, Maurin, and Petrongolo suggest that the labor supply responses of individuals, for example husbands and their wives, may not necessarily reflect only cross work-time effect because they may also reflect income effects. They overall find that husbands substantially change (i.e., decrease) their labor supply\textsuperscript{15} when their spouses’ labor hours are reduced whereas wives do not substantially change their labor supply when their spouses’ labor hours are reduced. Goux, Maurin, and Petrongolo suggest that these differences may be because of the following factors: 1) men’s working time

\textsuperscript{15} Goux, Maurin, and Petrongolo (2014) find that husbands reduce their working hours by half an hour per week when their wives’ working hours are reduced.
may be more adjustable than women’s in general and 2) spouses’ utility functions may exhibit distinctive degrees of leisure time complementarities among couples.

Kohara (2010) examines wives’ response to their husbands’ involuntary job separation and tests whether wives’ labor supply and that of husbands complement each other in Japan. Kohara uses panel data on households during the period from 1993 to 2004. Her findings suggest the presence of the added-worker effect during the mid 1990s and afterward. In particular, she finds that working spouses increase their labor hours and that non-working counterparts begin to participate in the labor market in response to their husbands’ job loss. In addition to finding the presence of the added-worker effect in Japan, Kohara also points out that the number of children in a household and wives’ labor hours are negatively correlated.16

The duration of unemployment may affect the added-worker effect. The added-worker effect may become larger, the longer individuals’ unemployment periods become. More specifically, women married to men who have been unemployed for six months or more may be substantially different from other married women not only in observable but also in unobservable characteristics (Bingley and Walker 2001). Bingley and Walker (2001) show that no difference may be present between the labor supply of women with employed husbands and the labor supply of women with short-term unemployed husbands using 15 pooled cross-sectional data of Family Expenditure Surveys from 1978 to 1992 in the United Kingdom. Bingley and Walker investigate the effects of the reduction of unemployment insurance entitlement duration from 12 months to 6 months in the UK. They define the short-term as shorter

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16 I find that the effect of the number of children age 14 and under on the length of unemployment spell is positive for women.
than 7 months, the medium-term as from 7 to 12 months, and the long-term as longer than 12 months. They allow endogenous unemployment durations of couples. Their finding suggests that the added-worker effect becomes stronger as husbands’ unemployment duration becomes longer. Lundberg (1985) also implies that if the mean of permanent income is different between two groups of unemployed persons, distinctive strengths of the added-worker effect may be present between these groups.

Stephens (2002) investigates short-run and long-run adjustments because of an earnings shock by looking at wives’ labor supply response both before and after their husbands’ job displacements. He uses 25 waves of the Panel Study of Income Dynamics during the period of 1968 to 1992 and finds that not only pre-displacement effects but also post-displacement effects are present and furthermore persistent in the United States. In addition to Stephens, Gong (2011) also shows the presence of a lasting added-worker effect. He uses panel data originating from 7 waves of Household, Income, and Labor Dynamics during the period from 2001 to 2007 in Australia and shows that the added-worker effect is persistent where women would still be willing to work longer hours than their actual hours even a year after their husbands’ job loss. Stephens’ model implies that the major effect of husbands’ displacements on their wives’ labor supply originate from a decrease in expected lifetime wealth due to a decrease in the mean of future wage offer distributions. According to a household labor supply model, a spouse changes her labor supply in response to her husband’s job displacement by permanently increasing her desired labor supply after the arrival of his job displacement (Stephens Jr 2002). Stephens’ results also suggest that the timing of wives’ labor supply responses depends on whether their husbands’ displacements are due to plant closing or permanent layoff.
Stephens finds that spouses increase their labor supply but not substantially before their husbands’ displacements and that they increase their labor supply substantially after their husbands’ displacements take place. He finds that the added-worker effect depends on the size of the husbands’ wage losses and that spouses whose husbands’ earnings are high before their displacements are more likely to produce the added-worker effect. Stephens points out that the limited duration of unemployment insurance benefits may be incapable of smoothing persistent earnings losses.

If unobserved individual heterogeneity is present and not taken account of, estimates are biased. Numerous studies (e.g., Das, Falaris, and Mulligan 2009; Bover, Arellano, and Bentolila 2002; Holmås 2002) include unobserved heterogeneity in their estimations for robustness. Holmås (2002) estimates both Gamma parametric and non-parametric hazard rate models in correcting for unobserved heterogeneity. He analyzes durations of nurses’ work in Norway using several sources of data, including data from the Norwegian Association of Local and Regional Authorities. Holmås’ final data includes 5,284 nurses who worked on January 1st, 1993. His finding shows that not only wages but also working conditions affect nurses’ separation from employment and that not taking account of the fact that the income of nurses includes compensation for working during inconvenient hours leads to a substantial downward bias of the effect of their wage (Holmås 2002).

### 2.2 Japanese Labor Market

In analyzing the unemployment duration in Japan, it may be helpful to look at some of the unique aspects of the Japanese labor market. As previously shown, the unemployment rate in Japan overall is lower than those in Europe and the United
States and may reflect unique characteristics of the Japanese labor market, such as lifetime employment. The Japanese labor market has been known for its long-term employment, seniority-wage system, and gender inequality. An employed person receives a substantial amount of training when hired and works for the same employer till she retires in the long-term employment environment in Japan. The seniority-wage system in Japan suggests that the longer an individual works for the same company, the higher her income becomes (independent of individual productivity), where in general the length of employment and promotion at work are positively related. Pregnant women may be treated as non-long-term employees and women with children may be considered as not-fully-committed employees in the Japanese labor market.

Genda, Kondo, and Ohta (2010)\(^\text{17}\) suggest that the employment system in Japan is characterized by lifetime employment from the time of completion of education to the time of retirement. This system may imply that people in Japan typically complete their education before starting their first-time jobs. Genda, Kondo, and Ohta point out two outcomes of the long-term employment system in Japan: 1) long-term job tenure and high employment continuation rates for prime-aged male workers and 2) a bipolarized working environment where some workers are regular employees who work full time and other workers are non-regular employees who work part time.

\(^{17}\) They mainly use the data from the Special Survey of the Labor Force Survey during the period of 1986 to 2001 and the Detailed Supplement to the Labor Force Survey during the period of 2002 to 2005, both of which were conducted by the Statistics Bureau of Japan.
Fujiki, Nakada, and Tachibanaki (2001)\textsuperscript{18} point out that the Beveridge curve that shows the relationship between unemployment and job vacancy has shifted upward in the Japanese labor market. They suggest that the Japanese long-term employment system and the considerable investment in training have made the labor market inflexible and this may be adversely affecting efficiency in job match when a substantial shock takes place. This inflexibility may adversely affect the ability of older unemployed individuals to find a new job due to the presence of high costs of training and employers’ perspective of hiring long-term employees.

According to Fujiki, Nakada, and Tachibanaki (2001), job creation and destruction rates tended to be lower for regular, full-time, and male employees than for temporary, part-time, and female employees during the early 1990s. Furthermore, they suggest that part-time employees tended to replace full-time employees in the 1990s. They also show that an increase in the number of part-time employees during the past 15 years is mainly because of a substantial increase in female part-time employees. In addition, Fujiki, Nakada, and Tachibanaki examine not only the supply side of the labor market but also the demand side of the labor market in Japan. According to them, the demand for part-time employees rose during the 1980s. The number of employers looking for part-time workers was greater than the number of job applicants looking for part-time work. In short, even under recessions, a shortage of part-time workers was present. Fujiki, Nakada, and Tachibanaki indicate that institutional factors, such as income tax, health insurance, and pension may play a role in having numerous part-time workers in the Japanese labor market. For instance,

\textsuperscript{18} They use various sources of data, such as Labor Force Survey conducted by the Statistics Bureau of Japan during the period of 1963 to 1999.
female part-time employees whose husbands are full-time employees may control their labor hours to set their earnings below a certain income tax threshold and/or in order not to pay their health insurance and pension contributions.

Furthermore, Fujiki, Nakada, and Tachibanaki (2001) suggest that the employment and social systems in Japan typically do not give an opportunity for an individual to reenter a regular full-time employment market once she has withdrawn from it regardless of her educational level. Lastly, according to Fujiki, Nakada, and Tachibanaki, approximately only 30% of the unemployed receive unemployment benefits, which may imply that the majority of the unemployed may depend on other sources, such as individual savings, household savings, and/or other household members’ incomes, in making their ends meet and also in searching for new jobs.

Genda and Kurosawa (2001) investigate the effects of the initial conditions of labor market and education on the prospects of employment of the youth in Japan. According to Genda and Kurosawa, some of unique characteristics of the Japanese labor market have consisted of a low unemployment rate, a low turnover rate, and a large fraction of full-time regular employment immediately after the completion of education. Genda and Kurosawa also point out that young people who are in the labor market tend not to be willing or able to find full-time jobs. Furthermore, they suggest that if workers cannot get full-time job opportunities when they enter the labor market for the first time, their probability of getting full-time job opportunities later may be significantly lower regardless of future labor market conditions given the settings of the Japanese labor market.

\[19\] They use the data from the Survey on Young Employees conducted by the Ministry of Labor in 1997.
It may be interesting to investigate differences between the behavior of unemployment duration in a full-time job market and the behavior of unemployment duration in a part-time job market in Japan. In fact, the 2002 Employment Status Survey provides the information on 1) whether an individual was looking for full-time regular work or part-time non-regular work at the time of the survey; 2) whether an individual previously had a full-time regular job or a part-time non-regular job; and furthermore 3) whether an individual had had a full-time regular job or a part-time non-regular job till the date of the survey.

Kato (2001) examines transformation of lifetime employment in Japan using quantitative and qualitative data from national surveys and finds that overall lifetime employment is still prevalent. As opposed to Kato (2001), Ono (2010) finds that less than 20% of workers in Japan are likely to be employed under informal lifetime employment contracts. He also finds that job mobility remains considerably lower in Japan than in other industrialized countries. Ono’s finding also suggests that the economic stagnation of the 1990s disproportionately affected women and young people. Moreover, Hamaaki, Hori, Maeda, and Murata (2012) find that lifetime employment has declined among young generations with bachelor’s degrees because of low expectations for age-based wage increase (i.e., seniority wage) since early

Preliminary results indicate that overall the effect of household income is similar in both full-time and part-time labor markets in Japan.

He uses various data sources, including the Wage Census for various years during the period from 1980 to 2005 conducted by the Ministry of Health, Labor, and Welfare in Japan.

They use the data from the Basic Survey on Wage Structure conducted by the Ministry of Health, Labor, and Welfare in Japan.
2000s and that old generations tend to stay in their current employment because of difficulty in finding alternative opportunities.

Fukuda (2006) finds that both the effects of getting married and giving birth on female labor supply are negative in Japan. Furthermore, he indicates that the negative effects of getting married and giving birth on the labor supply of women are substantially larger in Japan than in the U.S. Nakamura and Ueda (1999) show that both schooling and access to childcare services determine whether a married woman continues her work when she gives birth. They indicate that even higher wages and/or shorter working hours may not have a substantial effect on whether a female worker continues her work when experiencing childbirth.
Chapter 3

MODEL

This study is based on a search model provided by Cahuc and Zylberberg (2004). I choose the model introduced by Cahuc and Zylberberg since their model implies that the duration of unemployment and household income are positively associated as discussed later. The optimal strategy for an individual looking for a job is to select a reservation wage where the reservation wage is the lowest wage rate at which she accepts a given job offer. Various factors, such as unemployment benefits, which belong to a subset of household income of an unemployed person, job offer arrival rates, availability of jobs, and the quality of the match, affect the reservation wage.

An unemployed individual is assumed to know the distribution of wage offers; this distribution is assumed to be constant and each successive random wage offer is assumed to be an independent draw. In addition, an unemployed individual is assumed to be risk-neutral and the disutility of work is disregarded.

Let $F(·)$ denote the cumulative distribution function of wage offers. An unemployed individual’s discounted expected utility (Cahuc and Zylberberg 2004, p112) is then given by

$$ rV_U = z + \lambda \int_{w_R}^{\infty} [V_E(w) - V_U]dF(w) $$

(1)
where \( r \) is a real interest rate, \( V_U \) is the discounted expected utility of an unemployed individual, \( z \) is the net income while looking for a job\(^{23} \), which includes unemployment insurance benefits, \( \lambda \) is the job offer arrival rate, \( w^R \) is the reservation wage, \( V_E(w) \) is an expected utility of an individual while employed with wage, \( w \).\(^{24} \)

The job offer arrival rate, \( \lambda \), is a function of personal characteristics of an unemployed individual, including age and schooling, and also her effort level of job search.\(^{25} \) The left hand side of Equation (1) is the level of utility that an unemployed person receives by staying unemployed and the right hand side is the sum of the net income from looking for a job \( z \) and the average gain from changing from unemployment to employment at wage, \( w \). In short, Equation (1) shows a tradeoff between staying unemployed, and searching and accepting a given job offer.

The following equation characterizes the reservation wage \( (w^R) \).

\[
(2) \quad w^R = z + \frac{\lambda}{r+q} \int_{x}^{w} (w - w^R) dF(w)
\]

where \( q \) is the rate at which any given wage offer disappears. The left hand side of Equation (2) is the reservation wage and the right hand side is the sum of the net income during job search \( z \) and the capital gain from job search. Hence, Equation

\[\]

\(^{23} z = b - c \) where \( b \) is the sum of factors, including unemployment benefits, consumption of domestic production, and leisure and \( c \) is the sum of factors, including financial cost of looking for a job and the opportunity cost of looking for a job (e.g., foregone leisure). I assume one of the main elements of \( b \) is household income. Please note that both \( b \) and \( c \) are assumed to be greater than 0.

\(^{24} V_E(w) \) increases with \( w \).

\(^{25} \) For instance, if an unemployed person puts a higher level of effort into job search, the value of the job offer arrival rate increases.
(2) balances the marginal cost of job search and the marginal benefit of job search. The hazard rate (i.e., the separation rate from unemployment) is given by

\[ (3) \quad \lambda [1 - F(w^R)] \]

where \([1 - F(w^R)]\) is the probability of an unemployed individual accepting a wage offer given that the wage offer is equal to or greater than her reservation wage. Hence, the average duration of unemployment is given by

\[ (4) \quad T_U = \frac{1}{\lambda [1 - F(w^R)]}. \]

Equation (4) indicates that the average length of unemployment spell increases with the reservation wage \((w^R)\), which suggests that when searching for a job if the reservation wage of an unemployed individual increases the duration of job search increases on average.

Equation (2) can be rewritten as follows.

\[ (5) \quad \phi(w^R, z, r, \lambda, q) = w^R - z - \frac{\lambda}{r + q} \int_{w^R}^{\infty} (w - w^R) dF(w) \]

where \(\phi(w^R, z, r, \lambda, q) = 0\). Equation (5) suggests the following relationships:

\[ (6) \quad \frac{\partial w^R}{\partial z} > 0, \quad \frac{\partial w^R}{\partial r} < 0, \quad \frac{\partial w^R}{\partial \lambda} > 0, \quad \text{and} \quad \frac{\partial w^R}{\partial q} < 0. \]

As seen in Equation (6), 1) an increase in the net income, which includes household income, while unemployed \((z)\) results in an increase in the reservation wage \((w^R)\); 2) an increase in the real interest rate \((r)\), which means an unemployed person values the current wage offer more\(^{26}\), leads to a decrease in the reservation wage \((w^R)\); 3) an increase in the job offer arrival rate \((\lambda)\), which means an unemployed person is now more likely to face a new job offer (i.e., she faces a job offer more quickly), results in an increase in the reservation wage \((w^R)\); and 4) an increase in the rate at which a job

\(^{26}\) If the real interest rate increases, the value of the current state (e.g., the value of money today) increases.
offer disappears \((q)\), which means a job offer disappears more quickly, results in a decrease in the reservation wage \(w^R\).

Furthermore, Equation (4) and Equation (5) together suggest that

\[
(7) \quad \frac{\partial T_U}{\partial z} > 0, \quad \frac{\partial T_U}{\partial r} < 0, \quad \text{and} \quad \frac{\partial T_U}{\partial q} < 0.
\]

Equation (7) implies that 1) an increase in household income \((\propto z)\) leads to an increase in the average duration of unemployment \((T_U)\); 2) an increase in the real interest rate \((r)\) leads to a decrease in the average duration of unemployment \((T_U)\); and 3) an increase in the rate at which a job offer disappears \((q)\) results in a decrease in the average duration of unemployment \((T_U)\).

I assume that household income of an unemployed person at least partially influences her reservation wage. More specifically, I assume that the higher the household income level of an unemployed individual is, the higher the reservation wage of an unemployed person is and the longer her unemployment duration is.

This study is also based on a model describing labor supply and the added-worker effect. Lundberg (1985) provides fundamental aspects of the added-worker effect. In a static model of household labor supply, an unemployment spell of a household head affects the labor supply of non-participating household members who are eligible to work through transitory fall in household income and rise in the household head’s non-labor time, which may together result in a decrease in the relative value of the non-participant household members’ non-labor time. In a life-cycle setting, the added-worker effect is crucial only if households face liquidity constraints. The wealth effect of short unemployment duration tends to be negligible if households do not face credit constraints; therefore, contemporaneous changes in
the labor supply of a household head and non-participant household members may not be substantial.\(^\text{27}\)

Let a household of two individuals (i.e., a husband and a wife) maximize its expected value of utility. The utility function of the household is given by a summation of the utility flow, which is discounted, in each time period. The utility flow function is strictly concave. The utility flow is given by

\[
U(c_t, l_{1t}, l_{2t}),
\]

which is a function of 1) commodity consumption in time period \(t\), \(c_t\), 2) a husband’s leisure time, \(l_{1t}\), and 3) a wife’s leisure time, \(l_{2t}\) assuming that commodities and leisure are complements and that the leisure time of the husband and that of the wife are either complements\(^\text{28}\) or substitutes.

Each household member enters either of the three states: 1) employment, 2) unemployment, or 3) non-participation. Employment of household member \(i\) involves a certain portion of total time available, \(m_i\), spent on market labor where leisure time is

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\(^{27}\) This corresponds to the assumption that the longer the length of unemployment spell is, the stronger added-worker effect is. I take account of the added-worker effect based on this assumption.

\(^{28}\) Kohara (2010) states that the added-worker effect exists even under the assumption of complementary between husband’s and wife’s leisure time. Specifically, Kohara explains as follows. When a husband loses his job, his non-market-labor time, such as time devoted to home production, increases. As the husband’s time devoted to home production increases, his wife’s reservation wage decreases since the relative value of home production for the wife decreases. The wife’s lower reservation wage leads to an increase in her labor supply. Furthermore, as discussed earlier, Goux, Maurin, and Petrongolo (2014) suggest that even under the assumption of leisure time complementarity wives may not substantially change their leisure time when their husbands’ leisure time changes.
given by remaining time, \( l - m_i \). Unemployment involves a certain amount of time, \( n_i < m_i \), devoted to finding a job. An employed individual faces a budget constraint, which depends on her wage and non-labor income, each time period.

The couple faces numerous events, which are random, including a change in the value of leisure time, employment separation, and a random wage (job) offer arrival to an unemployed individual. The optimal strategy of the couple is to maximize a value function consisting of utility flow in the current period and the expected value of utility flow in the future, which is discounted. Let \( V_s(w_h, w_w) \) be the sum of utility flow in the current period where the spouse is in state \( s \) and earns a wage, \( w_w \), and her husband earns, \( w_h \), and the expected gain of utility in the future given the allocation of the spouse’s time in the current period. The couple’s strategy, which determines the decisions on the spouse’s participation in the labor market and job offer acceptance, is composed of two functions of reservation wage equating the value of the spouse’s employment to the value of the spouse’s job search and the value of the spouse’s non-participation. Let \( w^r_w(w_h) \) be the solution to

\[
V_e[w_h, w^r_w(w_h)] = V_u(w_h, 0)
\]

and \( w^l_2(w_1) \) be the solution to

\[
V_e[w_h, w^l_2(w_h)] = V_n(w_h, 0).
\]

\( w^r_w(\cdot) \) is the value of the spouse’s job search (i.e., unemployment) and \( w^l_2(\cdot) \) is the value of the spouse’s non-participation.

\[\text{-------------------------}\]

\( ^{29} \) The total time available is normalized to 1.

\( ^{30} \approx \) a reservation wage in a job search model.

\( ^{31} \approx \) a reservation wage in a labor force participation model.
An unemployed spouse accepts a wage (i.e., job) offer, $\bar{w}_w$, if the value of being employed at $\bar{w}_w$ is greater than the value of further job search,

$$V_e[w_h, \bar{w}_w] > V_u(w_h, 0).$$

Moreover, the unemployed spouse accepts a wage offer, $\bar{w}_w$ if

$$\bar{w}_w > w^*_w(w_h).$$

In determining the spouse’s labor-market participation, assuming she is not attached to any particular job, the couple compares $V_u(w_h, 0)$ and $V_n(w_h, 0)$. The spouse participates in the labor market if the cost of search, which is represented by the utility loss due to a decrease in leisure time, is smaller than the expected return to job search. A parallel condition of labor-market participation can be given by $w^*_w(w_h) > w^*_w(w_h)$. Furthermore,

$$\frac{\partial w^*_w}{\partial w_h} > \frac{\partial w^*_w}{\partial w_h} > 0.$$ 

If the wage of the husband increases, the spouse’s reservation wage increases and she becomes more reluctant to participate in the labor market. If the wife participates, she is more reluctant to accept a wage (i.e., job) offer. The spouse is more eager to find a job and accept a certain job offer if her husband is not employed. By switching the husband and the wife, a similar exposition for the husband can be found.

The two reservation wages, i.e., the value of looking for a job and the value of not participating in the labor market, ceteris paribus, are smaller for wives whose husbands are unemployed. The added-worker effect can be shown by various rates of state transition. Let the state of each couple be represented by a pair $(JK)$ where $J$ represents the husband’s employment status and $K$ represents the wife’s employment status. Controlling for both wages and non-labor income, the following predictions can be found:
where \( \pi \) denotes the probability of making a transition from state 1 to state 2 and the subscripts, \( e, u, \) and \( n \) stand for employment, unemployment, and non-participation. Equation (14) implies that employed wives are less likely to separate from employment\(^{32} \) if their partners are not employed.

\[
\begin{align*}
\pi_{ee\rightarrow eu} &> \pi_{ue\rightarrow uu}, \\
\pi_{ee\rightarrow en} &> \pi_{ue\rightarrow un}.
\end{align*}
\]

Equation (15) suggests that non-participating wives are more eager to participate in the labor market if their spouses are not employed.

\[
\begin{align*}
\pi_{en\rightarrow eu} &< \pi_{un\rightarrow uu}, \\
\pi_{en\rightarrow ee} &< \pi_{un\rightarrow ue}.
\end{align*}
\]

Equation (16) implies that wives searching for jobs accept available job offers more and start working more quickly when their spouses are unemployed.

\[
\begin{align*}
\pi_{uu\rightarrow ue} &> \pi_{eu\rightarrow ee}.
\end{align*}
\]

Kohara (2010) also describes essential aspects of the added-worker effect. The added-worker effect is based on the behavior of risk-sharing within a household. A household maximizing its expected lifetime utility subject to its lifetime constraints faces an inter-temporally optimal condition in which the value of consumption and leisure in the current period is set equal to the value of consumption and leisure in the future, which is discounted, assuming constant marginal utility (i.e., constant expected wealth of lifetime) across time period. A household also faces an intra-temporally optimal condition in which the marginal utility of leisure divided by wage is set equal to the marginal utility of consumption. This intra-temporally optimal condition

\(^{32} = \text{Move to either unemployment or non-participation.}\)
involves identical marginal utilities of leisure divided by wage among household members who are eligible to work. Complementarity and/or substitutability between consumption and leisure, and between, for example, leisure time of husband and that of wife, determines the household members’ optimal allocation of leisure and market labor. Particularly, if a husband separates from his employment and household income decreases, his spouse may increase her working hours in response to his job loss. In short, if a main breadwinner of a household separates from employment, other individuals in the household may increase their labor supply in order to compensate for the main income earner’s employment separation.
Chapter 4
METHODS

I estimate duration models of unemployment using maximum likelihood methods. Specifically, I consider duration models where \( n \) individuals are included and data of the form \((T_i^0, c_i, \mu_i), i = 1, \ldots, n\) are collected. \( T_i \) is a random variable denoting the length of a spell of unemployment of \( i \)th individual. \( c_i \) is an indicator variable equals 0 if \( i \)th individual is censored, in other words, has not completed her unemployment spell and equals 1 if \( i \)th individual has completed her unemployment spell. \( \mu_i \) is a row vector of covariates associated with the \( i \)th individual. The duration model is specified with a parameter vector \( \theta \) and the survival function for the \( i \)th individual is \( S(T_i^0; \theta, \mu_i) \) with corresponding density function, \( f(T_i^0; \theta, \mu_i) \), where \( T_i^0 \) represents the length of a spell of unemployment of the \( i \)th individual, which may or may not be observed due to censoring (Kalbfleisch and Prentice 2011).

I estimate a Weibull parametric model of unemployment duration. Das, Falaris, and Mulligan (2009) indicate that a Weibull parametric model allows for an increase or a decrease in the hazard function over time. The hazard function is the instantaneous exit rate, i.e., the instantaneous rate of leaving the current state. If an estimate of the Weibull scale parameter is less than 1 then the hazard function is monotonically increasing with time and vice versa. The model that I use for the time until an unemployed individual \( i \) leaves her unemployment (i.e., she finds a job) is

\[
\log T_i = \beta'X_i + \sigma \varepsilon_i.
\]
$X_i$ is a vector of independent variables and it includes the intercept. $\epsilon_i$ is the error term that is assumed to follow the Weibull distribution. I look into a Weibull distribution case because it allows for duration dependence where the duration of unemployment spell depends on how long the spell has been. $\beta$ and $\sigma$ are parameters. $T_i$ is the length of unemployment duration and $X_i$ includes years of schooling, years of work experience, experience squared, gender, the number of children age 0 to 14 or the number of children age 0 to 5, and household income. I estimate Equation (17) with and without correction for censoring to investigate the impacts of censoring.

I estimate both models in two specifications using 1) a continuous linear measure of household income and 2) a non-linear model with several household-income interval variables. I estimate the income interval models to investigate if any non-linear effects of household income exist. Specifically, I use a spline function where intervals are given by: 1) ≤ 4 million Yen, 2) 4-8 million Yen, 3) 8-12 million Yen, and 4) > 12 million Yen.

In failure time studies, clearly identifying an origin and an endpoint are essential (Kalbfleisch and Prentice 2011). I consider the beginning of unemployment spell as an origin and the end of unemployment spell as an end. I treat the unemployment duration as a continuous random variable that is subjected to censoring. Some past studies, such as Dawkins, Shen, and Sanchez (2005), also estimate continuous time duration models using the length of unemployment duration measured in months.

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33 I do not include previous employment tenure as one of the regressors since relevant information was only available for roughly half of my sample.
Heckman and Singer (1984) introduce a method that minimizes the impact of distributional assumptions in duration data econometric models with heterogeneity. The standard approach uses specified parametric functional forms for the structural duration distribution conditional on heterogeneity component with its distribution function. The functional forms of the heterogeneity component are chosen for computational tractability rather than their realism in characterizing the data. These parametric heterogeneity distributions may lead to substantially biased estimates of key structural parameters. In short, the standard approach may over-parameterize duration models (Heckman and Singer 1984). The effects of observables on the time until an unemployed individual leaves unemployment may depend on the type of each individual (i.e., unobserved individual heterogeneity). Kiefer (1984) points out that heterogeneity may originate from explanatory variable omission, functional form misspecification, and/or unobservable variations.

To take account of heterogeneity, I use the estimator suggested by Heckman and Singer (1984) given as follows, assuming a Weibull model for the time until an unemployed individual leaves unemployment,

\[ \log T_i = \delta_j + \beta'X_i + \sigma W_i. \]

\(X_i\) is a vector of independent variables and it does not include the intercept. \(T_i\) is again the length of unemployment duration and \(X_i\) includes the same variables as those for Equation (17). \(W_i\) is the error term that is assumed to follow the Weibull distribution. \(\beta\) and \(\sigma\) are once again parameters. \(\delta_j\) are parameters chosen from a discrete

---

34 For example, frailty models use distributions, such as the Gamma distribution and the Inverse Gaussian distribution (Hougaard 1995). Frailty models are random effect models that can be used in capturing unobserved heterogeneity for survival data.
distribution with points of support $P_j$ and $\sum P_j = 1$. There are $j$ types of unemployed individuals but I do not know deductively which unemployed individual belongs to which type. Hence, I assume that the probability that an unemployed individual is of type $j$ is $P_j$. Larger positive values of $\delta_j$ indicate longer duration of unemployment and smaller positive values of $\delta_j$ indicate shorter duration of unemployment.

Heterogeneity parameters $\delta_j$'s and their corresponding probabilities $P_j$'s are considered parameters, which can be estimated together with the other coefficients by maximum likelihood.\(^{35}\)

The log likelihood function is

\[\log (L) = \sum_{i \in U} \left( \log \left( \sum_j P_j f_i(\delta_j + \beta'X_i) \right) - \log (\sigma) \right) + \sum_{i \in C} \left( \log \left( \sum_j P_j (1 - F_i(\delta_j + \beta'X_i)) \right) \right).\]

The subscript, $U$, denotes uncensored observations and the subscript, $C$, denotes censored observations. $F$ and $f$ respectively are the distribution and density functions given by the assumed Weibull distribution of $W$. I empirically take account of the optimal number of points of support of the heterogeneity. Trussell and Richards (1985) indicate that the number of points of support should be successively added till no further improvement in the fit of the model occurs. Heckman and Walker (1990) suggest that the model of the best fit with heterogeneity in general has a small number of points of support. In choosing a preferred model, I conduct the Vuong tests to compare the Weibull models. Standard tests of nested hypotheses (e.g., likelihood ratio tests) cannot be used in the case of this study since conventional tests involve testing hypotheses on the estimates of the probabilities of the points of support at the

\(^{35}\) I estimate these parameters, $\delta_j$'s (i.e., points of support), and their corresponding probabilities, $P_j$'s, together with other parameters by maximum likelihood.
limit of the parameter space. Vuong (1989) introduces a bi-directional test. The
Vuong test can be used to test non-nested hypotheses and can be applied to this study
in selecting a model among alternatives.
In this study, I use the Employment Status Survey conducted by the Statistics Bureau of Japan in 2002. The survey was taken as of October 1st, 2002. The survey collected both national and regional-level primary data on the conditions of employment structure, changes in labor force status in past 12 months, willingness to work, and other related elements. It provides information on 413,707 individuals 15 years old and above.

The 2002 survey includes individual-level data and household-level data. For those who were unemployed at the date of the survey, information on the length of job search duration is available. For those who found jobs between November 2001 and September 2002, the survey includes information on the length of period before finding a current job, but not on whether an individual was actively searching for work throughout this interval. I assume that these individuals searched throughout their jobless spell and therefore use this spell as a measure of their unemployment duration.

The following personnel are not included: foreign diplomats, foreign consular staff, foreign military personnel, foreign military civilians, their dependents, personnel staying in camps or ships of the Self-Defense Forces, personnel staying in prison or detention houses, and personnel staying in reformatory institutions or guidance homes.

I am mindful of the fact that some of those who found jobs between November 2001 and September 2002 might not have searched for a job during the whole period.
For those who were currently unemployed at the time of the survey, the duration of job search spell is measured in months for durations through 3 years and as more than 3 years for longer spells. On the other hand, for those who separated from unemployment between November 2001 and September 2002 (i.e., those who were employed at the time of the survey) but were previously jobless, the duration of jobless spell is measured in months through 11 months, in 1 year and 11 month intervals from 1 year to 4 years and 11 months, in 5 to 6 years, in 7 to 9 years, in 5 year intervals from 10 to 19 years, and as more than 20 years for longer spells.

Individual-level data also include gender, educational attainment, age, the current work status of being employed or jobless, change in work status within the last twelve months, and annual personal earnings\(^{38}\). The annual personal earnings are individuals’ earnings during the past year (i.e., the period of October 2001 to September 2002). For those who changed their jobs or those who got their jobs for the first time during this period, their self-estimated annual personal earnings are reported.\(^{39}\) Educational attainment is given by either the completion of elementary school and middle school, the completion of high school, the completion of 2-year college, or the completion of 4-year college and/or graduate school. Age is given by 5-year age category, such as 15 to 19 years old and 80 to 84 years old.\(^{40}\) Change in

\(^{38}\) Inclusive of tax and given by either ¥500,000-¥990,000, ¥1,000,000-¥1,490,000, ¥1,500,000-¥1,990,000, ¥2,000,000-¥2,490,000, ¥2,500,000-¥2,990,000, ¥3,000,000-¥3,990,000, ¥4,000,000-¥4,990,000, ¥5,000,000-¥5,990,000, ¥6,000,000-¥6,990,000, ¥7,000,000-¥7,990,000, ¥8,000,000-¥8,990,000, ¥9,000,000-¥9,990,000, ¥10,000,000-¥14,990,000, or > ¥15 million Yen. For those who were unemployed at the time of the survey, the value of the personal income equals ¥0.

\(^{39}\) For the former group, personal earnings from the current jobs are reported.

\(^{40}\) I use the mean age for each age category.
work status within the last twelve months is given by either 1) working for the same employer; 2) switching employers; 3) not working till a year ago but finding a job within the last 12 months; 4) working till a year ago but leaving employment within the last 12 months; or 5) not working a year ago and still not working.

In addition to individual-level data, household-level data include information on household structure such as the number of household members, the number of household members of the age of 5 and under, the number of employed household members, the number of household members searching for jobs, the age of the youngest child in a household, sources of household income, and the amount of annual household income during the past year (i.e., during the period from October 2001 to September 2002). The annual household income includes annual personal earnings of household members who worked continuously throughout the period of October 2001 to September 2002 without switching jobs. For persons who changed their jobs or who found their jobs for the first time during this period, only earnings from the current (i.e., the most recent) job is included and if they worked for less than 12 months for the current employer their estimated annual earnings from the current job are included.\(^4\) For persons who left their employment during this period and were jobless at the time of the survey, no earnings information is available and, therefore, their earnings if they had any during this period are not included. The household income consists of not only employed household members’ personal earnings but also other sources, such as unemployment insurance benefits, rental income, and interest.

\(^4\) For example, if an individual worked for only 3 months for the current employer during this period then this individual’s earnings is converted into annual earnings by multiplying the 3 months earnings by 4.
income. The amount of household income is inclusive of tax and is given in ¥1,000,000-wide brackets through ¥10,000,000 and by ¥2,500,000-wide brackets through ¥15,000,000.

Reported household income includes the earnings of all persons who were employed at the time of the survey. Persons who were previously unemployed but found a job between November 2001 and September 2002 were employed at the time of the survey and thus their reported household income includes their estimated annual personal earnings in their current job. Hence, their household income during the period when they were unemployed, which would not include their own personal earnings, is missing.\textsuperscript{42} My sample consists of 20,536 individuals who had an unemployment spell of 1 to 35 months. I impute household income for 9,970 observations\textsuperscript{43}. The average duration of unemployment for 9,970 individuals who completed their unemployment spell before the time of the survey was 6.5 months while the average duration of spells still in progress at the time of the survey was 8.5 months. Kmenta (1978) points out that missing values may result in an efficiency loss in estimation. A substantial number of missing observations may lead to less efficient results where standard errors and confidence intervals tend to be large, and statistical test powers tend to be small. Especially when the portion of data excluding missing values does not represent the population, estimated parameters are biased.

\textsuperscript{42} Again, I assume that for those who found their current jobs between November 2001 and September 2002 their job search time period and their jobless time period before finding the current jobs are identical.

\textsuperscript{43} = 49\% of the sample.
I use two methods to handle the household income observations for those who separated from unemployment. Specifically, first I use a regression equation estimating household income of those who were unemployed at the time of the survey to predict the values of household income for those who found jobs between November 2001 and September 2002 assuming that the individuals whose unemployment spells ended before October 2002 are not systematically different from the individuals whose unemployment spells did not end before October 2002. Second, I use a multiple imputation (MI) approach to generate the values of household income of those who were no longer unemployed at the time of the survey. Hence, the sample of this study includes both those who did not complete an unemployment spell and those who completed an unemployment spell before the time of the survey.

MI is a technique that imputes missing data by imputing a multiple set of plausible values (StataCorp LP 2013). I discuss this MI technique in detail below. I denote the first method as a non-MI (i.e., regression) approach and the second method as a MI approach.

Under the non-MI approach, I estimate the following equation:

\[
\ln(Y_i^h) = c + \beta'X_i + \epsilon_i
\]

where \( \ln(Y_i^h) \) is the natural log of an individual \( i \)'s household income when she is unemployed, \( X_i \) includes years of schooling, age, age squared, and the number of

---

44 Please refer to Appendix A for summary statistics of observable characteristics (which are used for imputing household income) of these two groups of individuals: 1) those who were unemployed at the time of the survey and 2) those who were employed at the time of the survey but were previously jobless. As shown in Appendix A, the mean values of the observable characteristics are similar between these two groups.
household workers, \( c \) is the intercept, and \( \varepsilon_i \) is the error term.\(^{45}\) Past studies, such as Lillard and Panis (1998), include age, education, and marital status in their household income equation as regressors. I exponentiate the natural log of the household income once I estimate the household income equation to derive the values of household income.

As the second approach in managing household income observations for those who found jobs between November 2001 and September 2002, I use a MI approach suggested by Rubin (1996). MI includes the sampling variability due to the missing observations, i.e., the variability between each imputation (Little and Rubin 1987). MI is a flexible statistical method based on simulation and it is composed of three steps: 1) \( i \) imputations of complete datasets are generated under a given imputation model, 2) the analysis is performed separately on each imputation \( i = 1, \ldots, I \), and 3) the results obtained from \( I \) data analyses are combined into a single output. Statistical validity may be satisfied if point estimates are approximately unbiased\(^{46}\) and confidence

\(^{45}\) Please refer to Appendix B for the estimation results of Equation (20). As shown in Appendix B, all of the effects of the regressors are statistically significant at the 1% level and furthermore the signs of the effects are as expected (i.e., the effects of age, the number of years of schooling, and the number of household members who are employed are positive, and the non-linear effect of age is negative).

\(^{46}\) Allison (2000) states that since random errors are introduced under multiple imputation, multiple imputation results in approximately unbiased estimates of parameters. Requirements for approximately unbiased estimates are as follows: 1) missing data are missing at random (i.e., the probability of missing data on a given variable does not depend on that variable itself); 2) the model used to impute missing values (i.e., the imputation model) is a correct model; and 3) the imputation model and the analysis model are congruous with each other in some way while they do not have to be identical (e.g., Allison 2000; Rubin 1987). Sterne and et al. (2009) note that if the missing values and observed values are not systematically different, missing data are missing completely at random. Furthermore, they note that if any systematic differences between missing values and observed values are explained by observables,
intervals originate from nominal coverage averaged over the randomization
distributions influenced by sampling and posited structures of missing observations
(Rubin 1996).

MI involves specification of two models: the imputation model and the
analysis model where the former is the model used to generate imputations in the
imputation step and the latter is the completed data model used to get completed data
estimates, $\hat{X}$, of parameters of focus, $X$, and the estimate, $Z$, of sampling variability
associated with $\hat{X}$ in the analysis step (StataCorp LP 2013). The individual completed
data estimates ($\hat{X}, Z$), are combined into ($\hat{X}_{MI}, V$) to construct one repeated imputation
inference in the pooling step, i.e., the third step, where $\hat{X}_{MI}$ are the combined
parameter estimates and $V$ is their associated sampling variance estimate. Each
missing element of $X$ is replaced by an element randomly chosen from the distribution
of $P(X_M|X_O, \bar{\eta})$ where $X_M$ is a set of imputed values of missing values of $X$, $X_O$ is a set
of non-missing (i.e., observed) values of $X$, $\bar{\eta}$ is an element randomly drawn from the
non-missing data distribution of $P(\eta|X_O)$. In producing $I$ sets of imputations, which
are mutually independent and are conditional on $X_O$, $I$ values of $\eta$, which are simulated
and are mutually independent, are chosen from the distribution of the observed data of
$\bar{\eta}_i$ for $i = 1, \ldots, I$. For each element of $\bar{\eta}_i$, a set of imputed elements of $X_M$ is randomly
drawn from each corresponding distribution of $P(X_M|X_O, \bar{\eta}_i)$ (Zhang 2003).
Considering a case where both the imputation and the analysis models are identical

missing data are missing at random. Assuming that those who were unemployed at
the time of the survey and those who were employed at the time of the survey but
previously jobless are not systematically different, the first requirement of missing at
random is satisfied.
Bayesian models, $V$ is the approximation to the posterior variance of $X$. $V$ consists of $WV$ and $BV$ where $WV$ denotes the variability within each imputation and $BV$ denotes the variability between imputations.

I use univariate MI to impute a single variable, household income. For univariate imputation, I consider a univariate variable $X = (x_1, x_2, ..., x_n)'$ that follows a normal linear regression model

$$
(21) \quad x_i | a_i \sim N(a_i' \beta, \sigma^2)
$$

Where $a_i = (a_{i1}, a_{i2}, ..., a_{iq})'$ represents values of regressors of $X$ for observation $i$, $\beta$ represents the $q \times 1$ vector of unknown regression coefficients, and $\sigma^2$ represents the unknown scalar variance. Note that when a constant term is included in the linear regression model $a_{i1} = 1$ for $i = 1, ..., n$. Considering a partition of $X = (X'_O, X'_M)$ into $n_O \times 1$ and $n_M \times 1$ vectors containing complete and incomplete observations and considering a similar partition of $A = (A_O, A_M)$ into $n_O \times 1$ and $n_M \times 1$ submatrices, univariate MI follows the following steps: 1) fit a regression model (21) to the observed data $(X_O, A_O)$ to obtain estimates $\hat{\beta}$ and $\hat{\sigma^2}$; 2) simulate new parameters $\beta^*$ and $\sigma^{*2}$ from their joint posterior distribution under the conventional non-informative improper prior $P(\beta, \sigma^2) \propto \frac{1}{\sigma^2}$ where this step is done in two steps:

(i) $\sigma^{*2} \sim \frac{\hat{\sigma^2}(n_O-q)}{X^2_{O-q}}$, and

(ii) $\beta^* | \sigma^{*2} \sim N(\hat{\beta}, \sigma^{*2} (A'_O, A_O)^{-1})$;

3) obtain a set of imputed values $X'_M$ by simulating from $N(A_M \beta^*, \sigma^{*2} I_{NM \times NM})$; and 4) repeat step 2) and step 3) to obtain $I$ sets of imputed values of $X'_M, X'_M, ..., X'_M$

47 = The average value of the completed data variance estimates, $Z$.

48 = The variance estimate of $X'_M$ over repeated imputations.
Assuming that the subsequent mean and variance are satisfactory summaries of the subsequent distribution, the repeated-imputation inference based on these combined estimates may be accepted by either a purely Bayesian standpoint or by a purely frequency-based standpoint (StataCorp LP 2013). In practice, the analysis model and the imputation model tend to be different (i.e., neither of them is explicitly a Bayesian model). However, statistical validity still holds because of repeated-imputation inference (Rubin 2009). In this study, the imputation model is, as previously noted, given by an equation like Equation (20) where regressors are given by years of schooling, years of work experience, years of work experience squared, gender, the number of children age 14 and under, the number of children age 5 and under, the number of household members, the number of household workers, and the natural log of unemployment duration. On the other hand, the analysis models are given by either an equation identical to Equation (17) or an equation identical to Equation (18) depending on whether I include unobserved individual heterogeneity or not.

During the process of MI, initially the value of household income is natural-log transformed to avoid any possibility of generating negative imputed values of household income. Once the values of missing observations of natural log of household income are imputed, I exponentiate this natural-log transformed household income value to the power of $e$.

\[49\text{ According to the Stata manual (2013), an outcome variable for analysis should be also included in the imputation equation.}\]
While Rubin (1987) suggests that a sufficient number of imputations under a MI approach is 5 in order to reach valid inference, the Stata manual (StataCorp LP 2013) proposes 20 imputations. I use various numbers of imputations, including 5, 20, and 100. There are several factors that I have to be mindful when using a MI technique. For example, likelihood does not have straightforward interpretation in a MI environment where standard likelihood-ratio tests cannot be applied to MI results (StataCorp LP 2013).

A MI technique has been empirically used for the imputation of missing observations of income variables. For instance, Schenker, Raghunathan, Chiu, Makuc, Zhang, and Cohen (2006) apply a MI approach to impute missing values for household income and individual earnings variables in the National Health Interview Survey (NHIS) during the period from 1997 to 2004. A substantial number of data points for previous year household income and previous year individual earnings are missing in the NHIS (Schenker et al. 2006). In imputing family income and personal earnings, they use, for instance, age, race, region of residence, a variable for not having health insurance, a variable for having activity limitations, and a variable for country of birth (i.e., either the United States or not) as regressors. They find that a MI method corrects for estimate biases and that it also leads to efficiency gains (Schenker et al. 2006).
Chapter 6

MODEL SPECIFICATION

The dependent variable is the length of unemployment duration measured in months. The 2002 Employment Status Survey provides the job search period of the currently unemployed, the jobless period of those who were currently jobless but previously employed, and the jobless period of those who found jobs between November 2001 and September 2002. I include the following individuals: 1) those who were unemployed at the time of the survey without previous employment where I can observe their incomplete job search (unemployment) durations; 2) those who were unemployed at the time of the survey and who were previously employed where again I can observe their incomplete job search (unemployment) durations; and 3) those who found their current jobs between November 2001 and September 2002 (i.e., employed at the time of the survey), and who were previously jobless after leaving their previous employment where I assume that their jobless period equals their job search (unemployment) period. For this last group of individuals, I can observe completed unemployment durations where their unemployment spells ended when they found

---

50 I exclude discouraged workers who gave up searching for jobs. The 2002 Employment Status Survey includes a question to find out whether a jobless person stopped searching for a job because of various reasons, such as 1) no expectation of finding a job opportunity that she was interested in, 2) injury, 3) illness, and 4) advanced age.
their current jobs. For the unemployment duration of the first group, I use the job search period and I drop the first category of less than 1 month and the last category of more than 3 years due to their ambiguity. Hence, the shortest length of unemployment spell is 1 month and the longest length of unemployment spell is 35 months for this group. For the unemployment duration of the second group, if the job search period is equal or shorter than their jobless period, their unemployment duration is given by the job search period just like the first group, and, on the other hand, if the job search period is longer than the jobless period, their unemployment duration is given by the jobless period. Note that if an individual’s job search period is shorter than her jobless period then she might not have spent the entire jobless time period on job searching. In addition, note that if an individual’s job search period is longer than her jobless period then she might have started looking for an alternative job even when she was still employed by her previous employer. For the jobless period, I exclude the first category of 0 month (because of no presence of unemployment duration measured in months), I drop the categories of more than 3 years, and as for categories given by intervals, including 1 year to 1 year and 11 months, I use their mean values. Thus, the shortest length of unemployment spell is 1 month and the longest length of unemployment spell is either 35 months or 29.5 months depending on whether their job search period was shorter than or equal to their jobless period for the second group. For the unemployment duration of the third group, I use the jobless period. For this third group, I assume that their jobless period equals their job search period even though I am aware that it is possible that those who found jobs between November 2001 and September 2002 might not have spent their entire jobless period on searching for new jobs.
The independent variables include years of schooling, years of work experience, years of work experience squared, gender, the number of children age 14 and under, the number of children age 5 and under, and household income. The number of years of schooling is calculated by using the information of four categories provided by the survey: 1) completing elementary and middle schools, which corresponds to 9 years of schooling; 2) completing high school (12 years of schooling); 3) completing 2-year college (14 years of schooling), and; 4) completing 4-year college and/or graduate school, (16.4 years of schooling)\(^{51}\).

The number of years of work experience equals age minus the number of years of schooling minus 6 (Mincer 1974) where age is given by the mean value of each age category. For instance, for the age category of 15 to 19 years old, I use 17 years old, which is the mean value between 15 and 19. Furthermore, I focus on the sample of age 22 to 57 to take account of non-student and non-retired individuals. The variable of household income is given by either the level of household income or household income intervals. The level of household income is measured in ten thousand Yen and I use the mean value of household income for each category.

The values of the independent variables need to be measured at the beginning of unemployment spell that varies across individuals since I use duration models for

\(^{51}\) According to the Ministry of Education, Culture, Sports, Science, and Technology, the ratio of graduate students to undergraduate students increased to 8.3% by 2000 (Fuess 2003). Hence, for the highest level of educational achievement, i.e., completing 4-year college and/or graduate school, I use the following calculation: 
\[ 12 + (1 - .083) \times 4 + .083 \times (4 + 5) = 16.415 \] 
where 12 represents 12 years of elementary school, middle school, and high school, 4 represents 4 years of 4-year college, and 4 + 5 represents 4 years of 4-year college plus the maximum number of years of graduate school, i.e., 5 years (PhD program).
analysis. Thus, I adjust independent variables accordingly. Specifically, for years of schooling, I assume that every individual completes her education before finding and starting her first job and therefore no adjustment is made. This assumption may be reasonable in the case of the Japanese labor market because education and career may not be as age-flexible in Japan as in other countries, such as the United States. In Japan, typically people finish their education before entering the labor market for the first time and they do not go back to school, and the older an individual gets, the more difficult it is to change her job. I adjust years of work experience for the length of unemployment. Gender is time invariant; therefore, no adjustment is made.

I adjust the current number of children age 14 and under to reflect the number at the beginning of the spell of unemployment. For example, for the number of children age 14 and under, for those who were currently unemployed for 1 year or more and less than 2 years, I deduct the number of children age 0 from the total number of children age 14 and under. The number of children age 5 and under is also similarly adjusted.

As a measure of household income, I use the past-year annual household income net of past-year earnings of those who were unemployed at the time of the survey (if they had any earnings during the past year). Hence, it represents household income, which does not include the personal earnings of unemployed household members.

52 Please note that for currently unemployed persons at the time of the survey but were previously jobless, I adjust their years of work experience based on the sum of their current employment duration and their previous unemployment duration.
If the unemployment duration is long, other household members of the unemployed may increase their labor supply and earn higher earnings in order to compensate for the loss of earnings of the unemployed. In taking account of the added-worker effects, I assume that there are the following unemployed individuals: 1) those individuals facing short-term unemployment durations and short-term earnings losses; and 2) those individuals facing long-term unemployment durations and long-term earnings losses. I define the unemployment duration of 6 months or less as short-term unemployment duration and that of 7 months or more as long-term unemployment duration. When imputing household income for those whose unemployment spells already ended before the time of the survey (i.e., those who were employed at the time of the survey but were previously jobless), I divide the sample into four groups: i) those who were unemployed at the time of the survey and were unemployed for 6 months or less, ii) those who were unemployed at the time of the survey and were unemployed for 7 months or more, iii) those who were employed at the time of the survey but were unemployed for 6 months or less before finding their current jobs between November 2001 and September 2002, and iv) those who were employed at the time of the survey but were unemployed for 7 months or more before finding their current jobs between November 2001 and September 2002. I use the group i to impute the group iii’s household income and I use the group ii to impute the group iv’s household income. I investigate not only unemployment duration without taking account of the added-worker effects (where the sample is not divided into the groups in imputing household income) but also unemployment duration after taking account of the added-worker effects as described above (where the sample is divided
into the groups in imputing household income) to find differences between a model without the added-worker effects and a model with the added-worker effects.
Chapter 7

RESULTS

Before presenting detailed results, I briefly summarize overall results. I find that when unobserved individual heterogeneity is included the effect of household income on the length of unemployment duration of an unemployed individual is positive on the margin for some ranges of household income. In addition, the effect of household income is non-linear where, depending on which interval the level of household income of an unemployed person belongs to, the sign and the magnitude of the effect of household income changes. Overall, the effects of schooling and experience are positive, which may reflect inflexibility in the Japanese labor market in which new employees may experience extensive training and so education and experience may in fact have adverse effect on job finding. The effect of the number of children age 0 to 14 is overall negative, which suggests that an unemployed individual may search for a job more intensively if an unemployed individual has children. However, when analyzed separately by gender, the effect of the number of children age 0 to 14 is positive for unemployed women and still negative for unemployed men.

53 And/or unemployed persons with more years of schooling and/or more years of work experience may spend more time on job search.
First, I present summary statistics of my sample using Table 7.1. Second, I show results from non-censored and censored regressions using Table 7.2. Third, I present results from censored regressions with and without allowing for the added-worker effects using Table 7.3. Lastly, I show results from censored household income interval regressions with and without allowing for the added-worker effects, and with and without allowing for unobserved individual heterogeneity using Tables 7.4 and 7.5. Since I find that unobserved heterogeneity is statistically significant, I do not discuss specific sizes of effects of personal characteristics on the unemployment duration for Tables 7.2 and 7.3 in which unobserved individual heterogeneity is not taken account of. I discuss magnitudes of effects of individual characteristics on the length of unemployment spell for Tables 7.4 and 7.5.

Table 7.1 below illustrates summary statistics for the 2002 survey of persons age 22 to 57 and with the unemployment duration between 1 and 35 months.
As shown in Table 7.1 above, the sample includes 20,536 persons who experienced a spell of unemployment. The average duration of unemployment was 7.5 months. Approximately half (i.e., 49%) of the observed spells were censored, i.e., in progress at the time of the survey. An average unemployed person had

\[ \text{Number of Observations} = 20,536 \]

\[ \text{Standard deviations are presented in parentheses.} \]

\[ \text{a} \text{ Measured at the time of the survey and cannot be adjusted based on the unemployment duration because of data availability.} \]

\[ \text{b} \text{ Same as above.} \]

\[ \text{c} \text{ 124 Yen = 1 Dollar as of October 2002 (not seasonally adjusted) according to the Board of Governors of the Federal Reserve System (http://research.stlouisfed.org/fred2/data/EXJPUS.txt).} \]

\[ \text{d} \text{ Adjusted via regression; see text for details.} \]

\[ \text{e} \text{ Adjusted using the MI technique; see text for details. Based on the MI of 100 imputations and measured at the 100th imputation (note that all of the MIs of 5, 20, and 100 imputations produce similar average values of household income where the MI of 5 imputations gives the average household income value of 626.1 and the MI of 20 imputations 616.6).} \]

\[ \text{54 Dropping censored observations leads to the loss of half the sample. In investigating if any differences between the models with and without dropping} \]
approximately 12 years of schooling and 20 years of work experience. The average number of children was quite low, which reflects recent low fertility rates in Japan. More than half of the unemployed persons in the sample were female. The average value of unadjusted household income was approximately 5.1 million Yen. The average value of non-MI adjusted (i.e., regression-adjusted) household income was approximately, 6.1 million Yen. The average value of MI-adjusted household income was also approximately 6.1 million Yen. Hence, both the non-MI and MI adjustments result in similar average values of household income.

censored observations are present, I have attempted estimating models with heterogeneity in which I drop censored observations. However, the maximum likelihood estimations do not converge even when using different starting values for points of support and their corresponding probabilities. I include estimation results of a model without taking account of unobserved heterogeneity where I drop uncensored observations (i.e., where I do not impute any household income values) in Appendix C for reference.
Table 7.2: Non-Censored and Censored Weibull Duration Models

<table>
<thead>
<tr>
<th>Variables</th>
<th>1. Non-Censored</th>
<th>2. Censored</th>
<th>3. Censored</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Schooling</td>
<td>-.0093**</td>
<td>.0072</td>
<td>-.0029</td>
</tr>
<tr>
<td></td>
<td>(.0039)</td>
<td>(.0057)</td>
<td>(.0064)</td>
</tr>
<tr>
<td>Experience</td>
<td>.0333***</td>
<td>.0301***</td>
<td>.0368***</td>
</tr>
<tr>
<td></td>
<td>(.0028)</td>
<td>(.0044)</td>
<td>(.0049)</td>
</tr>
<tr>
<td>Experience Squared</td>
<td>-.0006***</td>
<td>-.0002***</td>
<td>-.0004***</td>
</tr>
<tr>
<td></td>
<td>(.0001)</td>
<td>(.0001)</td>
<td>(.0001)</td>
</tr>
<tr>
<td>Male</td>
<td>-.1552***</td>
<td>-.3521***</td>
<td>-.3628***</td>
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<tr>
<td></td>
<td>(.0148)</td>
<td>(.0224)</td>
<td>(.0249)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 14</td>
<td>-.0841***</td>
<td>-.1328***</td>
<td>-.1185***</td>
</tr>
<tr>
<td></td>
<td>(.0091)</td>
<td>(.0134)</td>
<td>(.014)</td>
</tr>
<tr>
<td>Annual Household Income</td>
<td>-.0002***</td>
<td>-.0006***</td>
<td>-.0003***</td>
</tr>
<tr>
<td>Non-MI Imputeda (Ten Thousand Yen)</td>
<td>(.00002)</td>
<td>(.00001)</td>
<td>(.00005)</td>
</tr>
<tr>
<td>Annual Household Income MI Imputeda (Ten Thousand Yen)</td>
<td></td>
<td></td>
<td>.0366</td>
</tr>
<tr>
<td>Constant</td>
<td>1.5048***</td>
<td>2.7833***</td>
<td>2.66***</td>
</tr>
<tr>
<td></td>
<td>(.0565)</td>
<td>(.0881)</td>
<td>(.0974)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>20,536</td>
<td>20,536</td>
<td>20,536</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-23,710.065</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.0366</td>
<td>1.0907***</td>
<td>1.0896***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0086)</td>
<td>(.009)</td>
</tr>
</tbody>
</table>

Standard errors are presented in parentheses.
* indicates P-value < .1, ** P-value < .05, and *** P-value < .01.
Standard errors are in parentheses.
* MI of 100 imputations (note that all of the MI of 5, 20, and 100 imputations produce similar results, i.e., similar magnitudes of coefficients, standard errors, and scale parameters).

Table 7.2 above presents my regression estimates for the duration of unemployment. I present results from three models: 1) non-censored model in which duration is set equal to the maximum observed as of the date of the survey (Col 1); 2) a censored Weibull duration model in which household income is imputed through the non-MI (i.e., regression) approach (Col 2); and 3) a censored Weibull duration model in which household income is imputed through the MI approach (Col 3).

As shown in Table 7.2, censoring does not affect the signs of the effects of all the variables whose effects are statistically significant at the 5% level. Specifically, all of the three models indicate that the effect of years of work experience is positive and
the effects of experience squared, gender\textsuperscript{55}, the number of children 0 to 14, and household income are negative. For years of schooling, only the non-censored model (Col 1) indicates a statistically significant negative effect of schooling on the length of unemployment spell.

In addition, both the censored non-MI model (Col 2) and the censored MI model (Col 3) show similar statistically significant effects of experience, gender, and the number of children age 14 and under. The magnitude of the effect of household income is different between the censored non-MI model (Col 2) and the censored MI model (Col 3) where the former shows a stronger negative effect of household income on the unemployment duration than the latter does. Moreover, according to both the censored non-MI and the censored MI regression results (Col 2 and Col 3), the effect of household income on the unemployment duration of an unemployed individual is negative. The negative effect of household income is not consistent with search theories.

Finally, since both the censored non-MI and MI regressions (Col 2 and Col 3) show consistent signs of the effects of personal characteristics on the length of unemployment duration and also since the MI regressions involve some complications in estimating unobserved heterogeneity models discussed later, from the following section on, I focus on the non-MI approach and models that adjust for censoring.\textsuperscript{56}

\textsuperscript{55} Gender = 1 for male and gender = 0 for female.

\textsuperscript{56} For instance, with the MI approach, I have attempted to estimate frailty models with both the Gamma and the Inverse Gaussian distributions; however, both maximum likelihood estimations with the Gamma distribution and with the Inverse Gaussian distribution do not converge. In addition, with the MI approach, I have also attempted to estimate discrete time proportional hazard models using hshaz commands suggested by Jenkins (2005) to take account of unobserved heterogeneity; however, maximum
Table 7.3: Weibull Duration Model with Censored Non-MI with and without Added-Worker Effects

<table>
<thead>
<tr>
<th>Variables</th>
<th>1. With Added-Worker Effects</th>
<th>2. Without Added-Worker Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Schooling</td>
<td>.004 (.0057)</td>
<td>.0072 (.0057)</td>
</tr>
<tr>
<td>Experience</td>
<td>.0331*** (.0044)</td>
<td>.0301*** (.0044)</td>
</tr>
<tr>
<td>Experience Squared</td>
<td>-.0003*** (.0001)</td>
<td>-.0002** (.0001)</td>
</tr>
<tr>
<td>Male</td>
<td>-.3512*** (.0226)</td>
<td>-.3521*** (.0224)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 14</td>
<td>-.1316*** (.0135)</td>
<td>-.1328*** (.0134)</td>
</tr>
<tr>
<td>Annual Household Income Imputed Including Added-Worker Effects (Ten Thousand Yen)</td>
<td>-.0005*** (.00001)</td>
<td></td>
</tr>
<tr>
<td>Annual Household Income Imputed not Including Added-Worker Effects (Ten Thousand Yen)</td>
<td></td>
<td>-.0006*** (.00001)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.7342*** (.0885)</td>
<td>2.7833*** (.0881)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>20,536</td>
<td>20,536</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-23,832.944</td>
<td>-23,710.065</td>
</tr>
<tr>
<td>Scale Parameter</td>
<td>1.0977*** (.0087)</td>
<td>1.0907*** (.0086)</td>
</tr>
</tbody>
</table>

Table 7.3 presents my regression estimates from 1) a censored model in which household income is imputed by the non-MI approach and the added-worker effects are included (Col 1); and 2) a censored model in which household income is imputed by the non-MI approach and the added-worker effects are not included (Col 2).57

As explained previously, to take account of the added-worker effects, I use a household income equation for those persons who were unemployed at the time of the survey for 6 months or less to impute household income for those persons who were employed at the time of the survey but previously unemployed for 6 months or less.

likelihood estimations again do not converge where I have used various starting values of points of support and probabilities. Finally, I have also attempted to estimate generalized linear latent and mixed models (GLLAM) suggested by Rabe-Hesketh (2005). Again, estimations do not converge while using different starting values.

57 The second column of Table 7.3 is same as the second column of Table 7.2.
Furthermore, I use a household income equation for those persons who were unemployed at the time of the survey for 7 months or more to impute household income for those persons who were employed at the time of the survey but previously unemployed for 7 months or more. I assume that the longer the unemployment duration is, the stronger the added-worker effects are.

As shown in Table 7.3 above, the signs of the effects of variables whose effects are statistically significant at the 5% level are identical between the non-MI models with and without the added-worker effects. Specifically, both models show a positive effect of years of work experience and negative effects of experience squared, gender, the number of children 0 to 14, and household income. As a whole, the magnitudes of the effects of the independent variables are similar between the two models. Furthermore, when the added-worker effects are included (Col 1), the negative effect of household income on the unemployment duration is smaller. Lastly, the two models presented above together suggest a negative effect of household income on the length of unemployment spell, which is conflicting with search theories.

As already shown, models with a linear measure of household income in Tables 7.2 and 7.3 imply a negative effect of household income on the length of unemployment spell, which is not congruent with search theories. I suspect non-linearity in the effect of household income where specifically in some ranges of household income a negative effect on the unemployment duration may exist and in other ranges of household income a positive effect may exist. Thus, I examine models with household income intervals to find out if any non-linear effect of household income...
income is present.\textsuperscript{58} I use a four household income interval model\textsuperscript{59} and three points of support. The four household income intervals are given by either 1) $\leq 4$ million Yen, 2) 4-8 million Yen, 3) 8-12 million Yen, or 4) $> 12$ million Yen. I also allow for unobserved individual heterogeneity.

\textsuperscript{58} I have estimated a model, which includes both a linear term and a quadratic term of household income. The effects of both the linear and quadratic terms are statistically significant at the 1\% level. However, the sign of the effect of the linear term is negative, which is conflicting with search theories. I suspect that the non-linearity of household income effect cannot be completely captured by the model with the linear and quadratic terms of household income.

\textsuperscript{59} I have estimated a three income interval model with three points of support. However, according to the log likelihood ratio test (Gourieroux, Holly, and Monfort, 1982), the four income interval model is preferred. In addition, I have estimated a four income interval model with two points of support. According to the Vuong test (Vuong 1989), the four income interval model with three points of support is preferred. Moreover, I conducted the Vuong test to compare a three income interval model with three points of support and its counterpart with two points of support. I find the former model is preferred. Finally, I have also attempted to estimate a four income interval model with four points support. However, the maximum likelihood estimation does not converge even when different starting values for points of support and their corresponding probabilities are used.
Table 7.4: Weibull Duration Model with Household Income Intervals, with and without Added-Worker Effects, and Heterogeneity

<table>
<thead>
<tr>
<th>Variables</th>
<th>1. Without Added-Worker Effects and without Heterogeneity</th>
<th>2. With Added-Worker Effects and without Heterogeneity</th>
<th>3. With Added-Worker Effects and with Heterogeneitya</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Schooling</td>
<td>.0328*** (.0058)</td>
<td>.0328*** (.0058)</td>
<td>.1219*** (.003)</td>
</tr>
<tr>
<td>Experience</td>
<td>.0243*** (.0044)</td>
<td>.0254*** (.0044)</td>
<td>.0827*** (.0002)</td>
</tr>
<tr>
<td>Experience Squared</td>
<td>-.0002* (.0001)</td>
<td>-.0002* (.0001)</td>
<td>-.0012*** (.000004)</td>
</tr>
<tr>
<td>Male</td>
<td>-.4541*** (.0224)</td>
<td>-.4621*** (.0224)</td>
<td>-.4117*** (.0011)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 14</td>
<td>-.0958*** (.0135)</td>
<td>-.0877*** (.0135)</td>
<td>-.0974*** (.0005)</td>
</tr>
<tr>
<td>Household Income ≤ 4 M$^b$ Yen</td>
<td>-.0087*** (.0003)</td>
<td>-.0093*** (.0003)</td>
<td>.0067*** (.0001)</td>
</tr>
<tr>
<td>Household Income &gt; 4 M Yen and ≤ 8 M Yen</td>
<td>.0004*** (.0001)</td>
<td>.0002*** (.0001)</td>
<td>-.0019*** (.0001)</td>
</tr>
<tr>
<td>Household Income &gt; 8 M Yen and ≤ 12 M Yen</td>
<td>-.001*** (.0001)</td>
<td>-.0008*** (.0001)</td>
<td>-.0001*** (.0002)</td>
</tr>
<tr>
<td>Constant</td>
<td>5.387*** (.1268)</td>
<td>5.5997*** (.1297)</td>
<td></td>
</tr>
<tr>
<td>$\delta_1$</td>
<td></td>
<td></td>
<td>-.4681*** (.0044)</td>
</tr>
<tr>
<td>$\delta_2$</td>
<td></td>
<td></td>
<td>-1.9999*** (.0059)</td>
</tr>
<tr>
<td>$\delta_3$</td>
<td></td>
<td></td>
<td>-3.000005*** (.0092)</td>
</tr>
<tr>
<td>$P_1$</td>
<td></td>
<td></td>
<td>.4167*** (.0044)</td>
</tr>
<tr>
<td>$P_2$</td>
<td></td>
<td></td>
<td>.200002*** (.004)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>20,536</td>
<td>20,536</td>
<td>20,536</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-22,800.7414</td>
<td>-22,734.0325</td>
<td>-128,295.1871</td>
</tr>
<tr>
<td>Scale Parameter</td>
<td>1.084*** (.0085)</td>
<td>1.0818*** (.0085)</td>
<td>.0786*** (.0002)</td>
</tr>
</tbody>
</table>

* Three points of support.

b = Million.

Table 7.4 presents my regression estimates for the duration of unemployment from three models: 1) a model in which neither the added-worker effects nor unobserved heterogeneity is taken account of (Col 1); 2) a model in which the added-
worker effects are taken account of, but without allowing for unobserved heterogeneity (Col 2); and 3) a model in which both the added-worker effects and unobserved heterogeneity (i.e., with three points of support) are taken account of (Col 3).

As indicated in Table 7.4 above, the model including both the added-worker effects and unobserved heterogeneity (Col 3) indicates that the effects of the three points of support and their corresponding probabilities are all statistically significant at the 1% level, which suggests that unobserved individual heterogeneity exists. When both the added-worker effects and unobserved heterogeneity are included, the effect of household income is positive at lower household income levels and negative at higher household income levels and statistically significant at the 1% level.

Comparing the model with the added-worker effects and unobserved heterogeneity (Col 3) and the model with the added-worker effects and without unobserved heterogeneity (Col 2), the former model shows larger positive effects of years of schooling and experience on the length of unemployment duration than the latter model shows. The former model (Col 3) implies a weaker negative effect of gender$^{60}$ and a stronger negative effect of the number of children age 14 and under on the length of unemployment duration than the latter model (Col 2) does. Furthermore, the former model (Col 3) overall shows a positive non-linear effect of household income on the length of unemployment spell on the margin for some ranges of household income and the latter model (Col 2) overall shows a negative non-linear effect of household income on the length of unemployment spell.

$^{60}$ Again, gender = 1 for male and gender = 0 for female.
Comparing the model with both the added-worker effects and unobserved heterogeneity (Col 3) and the model without the added-worker effects and without unobserved heterogeneity (Col 1), the former model suggests stronger positive effects of years of schooling and experience than the latter model suggests. In addition, the former model (Col 3) suggests a weaker negative effect of gender and a stronger negative effect of the number of children age 14 and under than the latter model (Col 1) does. Moreover, the former model (Col 3) overall suggests a positive non-linear effect of household income on unemployment duration on the margin for some ranges of household income and the latter model (Col 1) overall suggests a negative non-linear effect of household income on unemployment duration.

The model with the added-worker effects and the three points of support (Col 3) shows that as the number of years of schooling increases by 1 the unemployment duration becomes longer by 12%. The same model also implies a non-linear effect of the experience where the degree of increase in the unemployment duration decreases as the number of years of work experience increases. The model with the added-worker effects and the three points of support, moreover, shows that if an unemployed person is male, the unemployment duration decreases by 41%. It also shows that as the number of children age 14 and under increases by 1 the unemployment duration decreases by 9.7%.

According to the model with the added-worker effects and the three points of support (Col 3), the effect of household income on unemployment duration is positive at the lowest household income interval and negative on the margin at higher household income levels. If an unemployed individual’s household income equals 4 million Yen, then as an unemployed person’s household income increases from 0 Yen
to 4 million Yen then her unemployment duration increases by approximately 14.59 months.\(^{61}\) If an unemployed individual’s household income increases from 0 Yen to 8 million Yen, then the length of her unemployment spell increases by approximately 6.82 months. If an unemployed person’s household income increases from 0 Yen to 12 million Yen, then her unemployment duration increases by approximately 6.55 months. If an unemployed person’s household income increases from 0 Yen to 16 million Yen, then the length of her unemployment spell increases by approximately 6.53 months. The level of household income of the unemployed persons in my sample is less than or equal to 4 million Yen for approximately 35.73% of them, greater than 4 million Yen and less than or equal to 8 million Yen for approximately 42.79%, greater than 8 million Yen and less than or equal to 12 million Yen for approximately 14.47%, and greater than 12 million Yen for approximately 7.01%. The positive overall effect of household income on unemployment duration becomes smaller as the level of household income increases. This is perhaps because, for example, job offer arrival rates are systematically different in different segments of the labor market.

Lastly, in examining the scale parameters\(^{62}\), the models without unobserved heterogeneity (Col 1 and Col 2) show scale parameters greater than 1 and the model with unobserved heterogeneity (Col 3) shows a scale parameter smaller than 1. Thus, when unobserved heterogeneity is not included, the baseline hazard decreases over time. On the other hand, when unobserved heterogeneity is controlled for, the baseline hazard increases over time.

---

\(^{61}\) \(14.59 \approx e^{(0.0067 \times 400)}\).

\(^{62}\) If the scale parameter < 1, then the baseline hazard increases over time. On the other hand, if the scale parameter > 1, then the baseline hazard decreases over time.
Estimating models separately by gender allows us to investigate differences in the effects of personal characteristics on the unemployment duration for women and men.

Table 7.5: Weibull Duration Model with Household Income Intervals, with Added-Worker Effects, and with and without Heterogeneity, by Gender

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Schooling</td>
<td>.1524*** (.0004)</td>
<td>.0565*** (.009)</td>
<td>.1231*** (.0003)</td>
<td>.0204*** (.0076)</td>
</tr>
<tr>
<td>Experience</td>
<td>.0791*** (.0003)</td>
<td>.0337*** (.0059)</td>
<td>.1017*** (.0003)</td>
<td>.0132** (.0065)</td>
</tr>
<tr>
<td>Experience Squared</td>
<td>-.0007*** (.00001)</td>
<td>-.0002 (.0001)</td>
<td>-.0017*** (.00001)</td>
<td>-.0001 (.0002)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 14</td>
<td>.047*** (.0011)</td>
<td>.0585*** (.0181)</td>
<td>-.2963*** (.0008)</td>
<td>-.2926*** (.02)</td>
</tr>
<tr>
<td>Household Income ≤ 4 M Yen</td>
<td>.0084*** (.00002)</td>
<td>-.0085*** (.0004)</td>
<td>.0052*** (.00001)</td>
<td>.0099*** (.0004)</td>
</tr>
<tr>
<td>Household Income &gt; 4 M Yen and ≤ 8 M Yen</td>
<td>-.0047*** (.00002)</td>
<td>-.0001 (.0001)</td>
<td>-.0035*** (.00001)</td>
<td>.0004*** (.0002)</td>
</tr>
<tr>
<td>Household Income &gt; 8 M Yen and ≤ 12 M Yen</td>
<td>.002*** (.00002)</td>
<td>-.0008*** (.0002)</td>
<td>.0023*** (.00002)</td>
<td>-.0008*** (.0002)</td>
</tr>
<tr>
<td>Household Income &gt; 12 M Yen</td>
<td>-.0001*** (.00005)</td>
<td>-.0001* (.00004)</td>
<td>-.0001*** (.00001)</td>
<td>-.0001 (.0001)</td>
</tr>
<tr>
<td>Constant</td>
<td>4.79*** (.1912)</td>
<td></td>
<td>5.7387*** (.1731)</td>
<td></td>
</tr>
<tr>
<td>( \delta_1 )</td>
<td>-1.467*** (.007)</td>
<td></td>
<td>-4.566*** (.0073)</td>
<td></td>
</tr>
<tr>
<td>( \delta_2 )</td>
<td>-2.51*** (.009)</td>
<td></td>
<td>-9.999*** (.0099)</td>
<td></td>
</tr>
<tr>
<td>( \delta_3 )</td>
<td>-3.9948*** (.0087)</td>
<td></td>
<td>-2.5*** (.0065)</td>
<td></td>
</tr>
<tr>
<td>( P_1 )</td>
<td>.462*** (.0064)</td>
<td></td>
<td>.416*** (.0074)</td>
<td></td>
</tr>
<tr>
<td>( P_2 )</td>
<td>.2499*** (.0055)</td>
<td></td>
<td>.2001*** (.0055)</td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>12,164</td>
<td>12,164</td>
<td>8,372</td>
<td>8,372</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-58,996.1143</td>
<td>-12,979.7759</td>
<td>-59,854.1552</td>
<td>-9,612.7193</td>
</tr>
<tr>
<td>Scale Parameter</td>
<td>.0871*** (.0003)</td>
<td>1.0634*** (.0112)</td>
<td>.0879*** (.0003)</td>
<td>1.0915*** (.0126)</td>
</tr>
</tbody>
</table>

* Three points of support.

Table 7.5 presents my regression estimates for the duration of unemployment by gender. I present results from four models: 1) a model for women in which both
the added-worker effects and unobserved heterogeneity are included (Col 1); 2) a model for women in which the added-worker effects are included, but without allowing for unobserved heterogeneity (Col 2); 3) a model for men in which both the added-worker effects and unobserved heterogeneity are included (Col 3); and 4) a model for men in which the added-worker effects are included, but without allowing for unobserved heterogeneity (Col 4).

As shown in Table 7.5 above, according to all of the four models presented, the effect of the number of children age 14 and under\textsuperscript{63} is statistically significant at the 1% level and positive for unemployed women and is statistically significant at the 1% level and negative for unemployed men. Specifically, the model with the added-worker effects and unobserved heterogeneity with three points of support for unemployed females (Col 1) shows that as the number of children age 0 to 14 increases by 1, the length of unemployment duration increases by 4.7%. On the other hand, its male counterpart (Col 3) indicates that as the number of children age 14 and under increases by 1 the length of unemployment duration decreases by 29.6%.

In addition, according to the models with the added-worker effects and the three points of support (Col 1 and Col 3), a positive effect of years of schooling is larger for unemployed females than for their male counterparts. On the other hand, the same models imply that a positive effect of years of work experience is larger for unemployed men than for their female counterparts. More specifically, as the number of years of schooling increases by 1 the length of unemployment spell increases by 15% for unemployed women and 12% for unemployed men. Moreover, the same two

\textsuperscript{63} Note that the effect of the number of children age 5 and under is similar where overall it is positive for unemployed females and negative for unemployed males.
models indicate that all of effects of household income interval variables are statistically significant at the 1% level where all of the three points of support and their corresponding probabilities for both models are statistically significant at the 1% level, which suggest that unobserved heterogeneity is prevalent.

According to the model with the added-worker effects and the three points of support for women (Col 1), the effect of household income on the length of unemployment spell for unemployed women is positive at the lowest household income level, negative on the margin at the second household income interval, positive on the margin at the third household income interval, and negative on the margin at the highest household income interval. In addition, according to the model with the added-worker effects and the three points of support for men (Col 3), the effect of household income for unemployed men is positive on the margin at the lowest household income interval, negative on the margin at the second household income interval, positive on the margin at the third household income interval, and negative on the margin at the highest household income interval. Again, this non-linear effect of household income may be due to, for instance, systematically different job offer arrival rates for different segments of the labor market.

In looking into the scale parameters, again, the models without unobserved heterogeneity indicate scale parameters, which are greater than 1, and the models with unobserved heterogeneity show scale parameters, which are smaller than 1. Therefore, when unobserved heterogeneity is not controlled for, the baseline hazard decreases over time. On the other hand, when unobserved heterogeneity is controlled for, the baseline hazard increases over time.
I conduct the log likelihood ratio test to find out if the effects of personal characteristics on the length of unemployment spell are different between unemployed women and unemployed men. The test statistic is given by

\[-2(L_w - L_s)\]

where $L_w$ is a log likelihood from a model including the whole sample (i.e., both unemployed women and unemployed men) and $L_s$ is the sum of a log likelihood from a model including only unemployed women and a log likelihood from a model including only unemployed men. The null hypothesis states that no gender difference exists.\(^{64}\) The degrees of freedom are given by

\[U_1 + U_2 - U\]

where $U_1$ denotes the sum of the number of regressors and the intercept term from the model including only unemployed women, $U_2$ represents the sum of the number of regressors and the intercept term from the model including only unemployed men, and $U$ denotes the sum of the number of regressors and the intercept term from the model including both unemployed women and unemployed men.

I use the models with the four household income intervals and the three points of support (Col 3 in Table 7.4, and Col 1 and Col 3 in Table 7.5). The test statistic is 18,889.84.\(^{65}\) The critical value with the degrees of freedom of 9 is 16.92 at the 5% level.

\(^{64}\) I.e., The model including both unemployed females and unemployed males suffices and the two separate models by gender are not needed.

\(^{65}\) $= -2 \times (-128,295.1871 - (-58,996.1143 - 59,854.1552)) = 18,889.84$ where $L_U$ is taken from Table 7.4 and $L_R$ is taken from Table 7.5.
significance level. Hence, gender differences in the effects of personal characteristics on the length of unemployment duration are statistically significant.

The degrees of freedom = $U_1 + U_2 - U = (9+9) - 9 = 9$. 

---

66 The degrees of freedom = $U_1 + U_2 - U = (9+9) - 9 = 9$. 
Chapter 8
DISCUSSION

I find that household income and the reservation wage of the unemployed appear to be negatively associated when not allowing for unobserved individual heterogeneity, but they appear to be positively associated on the margin for some ranges of household income when I control for unobserved individual heterogeneity. Ignoring the presence of unobserved heterogeneity leads to not only a biased estimate of the effect of household income but also biased estimates of the effects of other personal characteristics. I find that the models with the added-worker effects and unobserved individual heterogeneity suggest positive effects of household income on the unemployment duration on the margin for some ranges of household income. In comparing an unemployed person with household income of zero Yen and an unemployed person with household income of a positive value, I find that the length of unemployment spell of the latter individual is longer than that of the former individual, which is consistent with search theories. The non-linear effect of household income shows that the positive overall effect of household income on the length of unemployment spell becomes smaller as the level of household income increases. However, I find that the models without unobserved individual heterogeneity show negative effects of household income on the unemployment duration, which is conflicting with search theories.
Unfortunately it is not possible to quantify the magnitudes of the added-worker effects of my sample given the availability of data. However, according to the 2002 Employment Status Survey, approximately 34% of the wives whose husbands were jobless at the time of the survey indicated that they were working because they needed some earnings. Roughly 7% of the employed spouses whose husbands were jobless at the date of the survey did not work one year before the date of the survey. In addition, approximately 13% of the wives whose husbands were jobless at the time of the survey indicated that they wanted to increase their working hours. These findings may partially imply the presence of the added-worker effects. Moreover, I test the equality of the effects of personal characteristics from the two household income equation regressions where one household income equation is estimated on those persons who were unemployed for 6 months or less at the time of the survey and the other household income equation is estimated on those persons who were unemployed for 7 months or more at the time of the survey.\textsuperscript{67} I find that the effects of personal characteristics are different between these two groups. This difference may be partially due to the added-worker effects. The group of unemployed individuals who were unemployed for 7 months or more may be facing stronger added-worker effects than the group of the unemployed individuals who were unemployed for 6 months or less. Nevertheless, since again I cannot quantify the sizes of the added-worker effects a further analysis is needed on this issue.

\textsuperscript{67} The regressions results are given in Columns 2 and 3 in Table B in Appendix B. Please refer to http://www.stata.com/support/faqs/statistics/test-equality-of-coefficients/ for the procedure testing whether coefficients from two equation regressions estimated on two different samples are equal or not.
Overall, the effect of number of children age 14 and under on the length of unemployment duration is negative. The cost of raising children may be high in Japan. Some past studies (e.g., Oyama 2004) find that the rising cost of raising children is one of the main causes of the recent low fertility rate in Japan. Many couples may choose not to have children due to high costs of childrearing. Those individuals who have children may look for new jobs intensively once they separate from employment because of high costs of raising children.

Using the model with the added-worker effects and the three points of support where one of the regressors is the number of children age 0 to 5 instead of the number of children age 0 to 14, I find that the negative effect of the number of children age 5 and under is not statistically significant.\(^68\) This statistically insignificant effect of the number of children age 0 to 5 may be reasonable since the opportunity cost of searching a job may be higher the younger children an unemployed individual has. First, it may require more time and focus in taking care of children age 0 to 5 than children age 6 to 14 where children with age 6 to 14 are included in the number of children age 0 to 14. Second, the younger its children are, the more eligible a household is for child benefits in Japan. Households with children age 0 to 3 were eligible for child benefits based on their household incomes before the year of 2000 and households with children age 0 to 7 were eligible for child benefits again based on their household incomes since 2000.\(^69\)

\(^68\) The estimation results with the number of children age 0 to 5 are reported in Appendix D (Tables D1 and D2).

\(^69\) As explained previously in the literature review chapter, for example, the monthly child benefit was 5,000 Yen for the first child age 0 to 7, 5,000 Yen for the second
I find positive effects of schooling on the duration of unemployment. Sasaki, Kohara, and Machikita (2013) on the other hand find negative effects of schooling on the duration of job search by the unemployed in Japan. In general, an unemployed person with higher education may spend more time on searching for a job given her skills till she finds her match. From this aspect, the reservation wage of a highly educated unemployed person may be higher than that of a not highly educated counterpart. In addition, Sasaki, Kohara, and Machikita use the data during the period of August 1st 2005 to July 13th 2006 while I use the data from 2002. According to the OECD statistics70, the unemployment rate was 4.7% in 2000, 5% in 2001, 5.4% in 2002, 4.4% in 2005, and 4.1% in 2006. Job vacancy rate was approximately 2% in 2000-2002 and approximately 3% in 2005 (Ito, Takei, Fellman and Wright 2009). Hence, an unemployed person might have had a higher probability of finding a better job match within a given time interval during the time period that Sasaki, Kohara, and Machikita examine than during the time period investigated here.

In comparing behaviors of unemployed females and those of unemployed males, I find that the effect of the number of children age 0 to 14 becomes positive for women and the effect stays negative for men. One possible explanation is that the opportunity cost of searching for a job is higher for female individuals than for their male counterparts if they have children in Japan. Furthermore, the division of labor among couples may be present in Japan where men are typically breadwinners and

70 Please refer to: http://stats.oecd.org/index.aspx?queryid=36324#.
women are mainly child caretakers if they have children. A deeper analysis is needed on this issue.

In addition to gender differences in the effects of the number of children, the effects of years of schooling and experience of unemployed females may differ from those of unemployed males. Overall, the positive effect of years of schooling on the length of unemployment duration is stronger for unemployed females than for their male counterparts according to the models with the added-worker effects and the three points of support. On the other hand, the positive effect of years of work experience is stronger for unemployed males than for their female counterparts according to the same models. As some past studies, including Fujiki, Nakada, and Tachibanaki (2001), imply, in the Japanese labor market, overall inflexibility for labor force reentry may exist irrespective of education and previous work experience. The positive effects of education and experience may partially reflect the finding of Fujiki, Nakada, and Tachibanaki.

As shown in Tables 7.4 and 7.5, when I control for unobserved heterogeneity the positive effects of years of schooling and years of work experience become larger where all of the effects of the points of support and their corresponding probabilities are statistically significant at the 1% level. Unobserved individual heterogeneity may originate from various factors, such as the eagerness to find a job, individual savings, wealth, and/or liquidity constraints. Some individuals may be more eager to find jobs than others are after controlling for all the observables. The lower level of individual savings and/or the lower level of wealth an unemployed person has, she may be more eager to find a job during a given time interval. In addition, the more liquidity constrained an unemployed person is, she may be more eager to look for a job during a
given time interval. For example, as presented in Table 7.4, the largest negative value of the point of support (i.e., \(\delta_3\)) is -3 and the smallest negative value of the point of the support (i.e., \(\delta_1\)) is -.5. Those unemployed persons with \(\delta_3\) may be more eager to find jobs than those unemployed persons with \(\delta_1\) are because of unobserved factors including the ones discussed here.

I look into expected time until separation from unemployment at the means of all the independent variables. The expected time till an unemployed individual leaves unemployment is given by

\[
E[t_i|X] = \exp(\delta_j + \beta'X_i)\Gamma(\sigma + 1)
\]

where the Gamma function, \(\Gamma(\cdot)\), with a positive constant, \(P\), is given by

\[
\Gamma(P) = \int_0^\infty t^{P-1}e^{-t}dt.\]

In examining an unemployed individual with the mean values of personal characteristics, I use the model with the four household income intervals, the added-worker effects, and the three points of support, which is a preferred model according to the results of Vuong and log likelihood ratio tests. The model with the three points of support presents behaviors of three different types of unemployed individuals. Let 

Type 1  denote the first type of an unemployed individual, Type 2 the second type, and 

Type 3 the third type where \(\delta_1, \delta_2, \text{ and } \delta_3\) respectively represent their corresponding constant terms in the regressions. These three types exhibit unobserved individual heterogeneity, such as again eagerness to find a job.

I find that a Type 1 female with the mean values of personal characteristics faces the expected length of unemployment duration of 48.93 months\textsuperscript{72}, its Type 2

\textsuperscript{71} Greene (2008), p. 1092.
counterpart faces 17.24 months, and its *Type 3* counterpart faces 3.91 months. Thus, the average expected length of unemployment duration of these three types of unemployed women is 23.36 months. On the other hand, I find that a *Type 1* male with the mean values of personal characteristics faces the expected length of unemployment duration of 32.63 months, while *Type 2* has an expected duration of 18.94 months, and *Type 3* has an expected duration of 4.23 month. Hence, the expected average length of unemployment duration for these three types of unemployed men is 18.6 months.

In examining scale parameters, all of the models controlling for unobserved individual heterogeneity suggest that the baseline hazard increases over time.\textsuperscript{73} Hence, I find that the hazard rate shows positive time dependency when controlling for unobserved heterogeneity. One of the possible explanations for the positive time dependency is that while the intensity of job search is different among, for example, three types of unemployed individuals based on the model with the four household income intervals and the three points of support, overall the longer the length of

\textsuperscript{72} Please refer to Table E in Appendix E for the mean values of personal characteristics, and Table 7.5 for the effects of personal characteristics and points of support. 

\[ 50.8 \approx [\exp(0.1524 \times \text{(the mean of years of schooling for women)} + 0.0791 \times \text{(the mean of experience for women)} - 0.007 \times \text{(the mean of experience-squared for women)} + 0.047 \times \text{(the mean of the number of children age 0 to 14 for women)} + 0.0084 \times 400 + (-0.0047) \times \text{(the mean of household income for women} - 400) + \delta_f] \times \Gamma(\sigma+1) \]

where the mean of years of schooling for women equals 12.5, the mean of experience for women equals 19.5, the mean of experience-squared for women equals 513.7, the mean of the number of children age 0 to 14 for women equals .57, the mean of household income for women equals 628.3, the value of $\delta_f$ for women equals −1.467, the value of $\sigma$ for women equals .0871, and the value of $\Gamma(\sigma+1)$ for women equals .9567.

\textsuperscript{73} I.e., the scale parameter < 1.
unemployment spell of an individual is, she may become less hesitant about accepting a job offer available. Sasaki, Kohara, and Machikita (2013), on the other hand, find that the hazard rate shows negative time dependency. They suggest that factors, such as skill depreciation may cause the negative time dependency. When not including unobserved individual heterogeneity, I also find negative time dependency of the baseline hazard. However, I find that unobserved heterogeneity is statistically significant. While Sasaki, Kohara, and Machikita do not include unobserved individual heterogeneity, I take account of unobserved individual heterogeneity.
In considering policies for the Japanese labor market, unobserved heterogeneity should be included in an analysis in order to produce unbiased estimates of the effects of personal characteristics on unemployment duration. Not considering unobserved individual heterogeneity leads to policies that may not apply to the labor market in Japan.

The opposite effects of the number of children age 0 to 14 on unemployment duration between unemployed women and unemployed men need to be addressed. The positive effect of the number of children age 0 to 14 indicates that especially in alleviating the unemployment of women who raise children, more supportive working environment may be necessary. The shortage of childcare services has been discussed in Japan. Zhou, Oishi, and Ueda (2003) indicate that a long-standing shortage of licensed childcare services has been present in Japan where, for example, a large number of children are on waiting lists. Zhou, Oishi, and Ueda indicate that the privatization of public daycare centers in improving efficiencies of daycare services has been supported by some economists (e.g., Fukuda 2000). Howard and Usui (2008) point out that while expanded privatization and private-public partnerships in

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74 For example, the number of children who were on waiting lists was 35,144 in 2001 according to Zhou, Oishi, and Ueda (2003).
child daycare services have increased the availability of diversified child daycare services in Japan, the diversification of daycare services in fact has led to inequality in access to desired services where the higher the quality of services is, the higher the costs for parents may be. They indicate, moreover, that for daycare services provided by municipalities, parents are paying a large portion of the cost of child daycare service. Finally, Howard and Usui suggest that the culture of using women in a secondary role at work and considering women as main caregivers of children is still prevalent in Japan. To sum up, further reform of childcare services may be needed to reduce women’s job search intervals.

The aspect of inflexible labor market for unemployed individuals with higher educational backgrounds and longer work experiences needs to be examined. For both women and men, I find that the number of years of schooling is positively associated with the length of unemployment spell.

Finally, the household income may affect the reservation wage of an unemployed person in the Japanese labor market. Household income may include subcomponents, such as unemployment insurance benefits, which influence the reservation wage of an unemployed individual. In short, in investigating reservation wages of unemployed individuals in the Japanese labor market, household income should be included as one of the factors that affect their reservation wages.
Chapter 10
CONCLUSION

Economists have analyzed various aspects of unemployment that are associated with individuals’ choices while unemployed. Specifically, economists have examined individual and family characteristics that may affect an unemployed person’s duration of unemployment. I examine the effects of personal characteristics on the length of unemployment spell in the Japanese labor market by using the 2002 Employment Status Survey. I use a household income equation for those who did not complete their unemployment spells before the date of the survey and a multiple imputation technique introduced by Rubin (1996) to impute household income for those who were employed at the time of the survey but whose unemployment spells ended before the time of the survey. I include the added-worker effect and assume that the longer spell of unemployment a person has, the stronger the added-worker effect she experiences. I use a Weibull parametric duration model. Moreover, I use Heckman and Singer’s method (1984) to take account of unobserved heterogeneity.

I find that the unemployment duration and household income are positively associated on the margin for some ranges of household income when both the added-worker effects and unobserved individual heterogeneity are taken account of. Hence, household income affects the reservation wage of an unemployed individual in Japan. Furthermore, a non-linear relationship between the level of household income and the level of reservation wage is present.
For future studies, other approaches of handling the household income variable may lead to more valid and efficient estimations. In addition, using various years of surveys, including those of 2007 and 2012 whenever they are available makes it possible to look into the unemployment duration in Japan more thoroughly.
REFERENCES


Appendix A


<table>
<thead>
<tr>
<th>Variable</th>
<th>Unemployed at the Time of the Survey</th>
<th>Employed at the Time of the Survey</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
</tr>
<tr>
<td>Years of Schooling</td>
<td>12.3 (2.1)</td>
<td>12.5 (2)</td>
</tr>
<tr>
<td>Years of Work Experience</td>
<td>21.5 (12)</td>
<td>17.9 (11.34)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 14</td>
<td>.47 (.84)</td>
<td>.52 (.88)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 5</td>
<td>.18 (.48)</td>
<td>.2 (.5)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>10,566</td>
<td>9,970</td>
</tr>
</tbody>
</table>
Appendix B

TABLE B: HOUSEHOLD INCOME NON-MI IMPUTATION EQUATION ESTIMATES

<table>
<thead>
<tr>
<th>Variables</th>
<th>1. Unemployment Duration 1 to 35 Months</th>
<th>2. Unemployment Duration ≤ 6 Months</th>
<th>3. Unemployment Duration ≥ 7 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Schooling</td>
<td>.0683*** (.0051)</td>
<td>.0654*** (.0044)</td>
<td>.0685*** (.005)</td>
</tr>
<tr>
<td>Age</td>
<td>.0456*** (.0001)</td>
<td>.042*** (.0064)</td>
<td>.0477*** (.0089)</td>
</tr>
<tr>
<td>Age Squared</td>
<td>-.0005*** (.0001)</td>
<td>-.0005*** (.0001)</td>
<td>-.0006*** (.0001)</td>
</tr>
<tr>
<td>Number of Household Workers</td>
<td>.5669*** (.0074)</td>
<td>.5267*** (.0095)</td>
<td>.6166*** (.0115)</td>
</tr>
<tr>
<td>Constant</td>
<td>3.4659*** (.105)</td>
<td>3.6188*** (.1289)</td>
<td>3.3473*** (.1859)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>10,566</td>
<td>5,918</td>
<td>4,648</td>
</tr>
<tr>
<td>R²</td>
<td>.3789</td>
<td>.358</td>
<td>.4039</td>
</tr>
</tbody>
</table>
### Table C: Weibull Duration Model with Only Uncensored Unemployment Spells (No Household Income Imputation)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Schooling</td>
<td>-.0076</td>
<td>(.0047)</td>
</tr>
<tr>
<td>Experience</td>
<td>.0365***</td>
<td>(.0034)</td>
</tr>
<tr>
<td>Experience Squared</td>
<td>-.0006***</td>
<td>(.0001)</td>
</tr>
<tr>
<td>Male</td>
<td>-.0468**</td>
<td>(.019)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 14</td>
<td>-.0513***</td>
<td>(.0115)</td>
</tr>
<tr>
<td>Household Income (\leq 4) Million Yen</td>
<td>-.0005***</td>
<td>(.0001)</td>
</tr>
<tr>
<td>Household Income (&gt; 4) Million Yen and (\leq 8) Million Yen</td>
<td>-.00001</td>
<td>(.0001)</td>
</tr>
<tr>
<td>Household Income (&gt; 8) Million Yen (\leq 12) Million Yen</td>
<td>-.0001</td>
<td>(.0002)</td>
</tr>
<tr>
<td>Household Income (&gt; 12) Million Yen</td>
<td>.0002</td>
<td>(.0005)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.6413***</td>
<td>(.0733)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>10,566</td>
<td></td>
</tr>
</tbody>
</table>

R²: .0315
### Appendix D

**TABLE D1: WEIBULL DURATION MODEL WITH CENSORED NON-MI, AND WITH AND WITHOUT ADDED-WORKER EFFECTS, EFFECT OF NUMBER OF CHILDREN AGE 0 TO 5**

<table>
<thead>
<tr>
<th>Variables</th>
<th>With Added-Worker Effects</th>
<th>Without Added-Worker Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Schooling</td>
<td>.0057 (.0058)</td>
<td>.0088 (.0057)</td>
</tr>
<tr>
<td>Experience</td>
<td>.0206*** (.0042)</td>
<td>.0176*** (.0042)</td>
</tr>
<tr>
<td>Experience Squared</td>
<td>.00003 (.0001)</td>
<td>.0001 (.0001)</td>
</tr>
<tr>
<td>Male</td>
<td>-.3237*** (.0226)</td>
<td>-.3253*** (.0224)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 5</td>
<td>-.0388* (.0227)</td>
<td>-.0451** (.0226)</td>
</tr>
<tr>
<td>Annual Household Income Imputed Including Added-Worker Effects (Ten Thousand Yen)</td>
<td>-.0005*** (.00001)</td>
<td></td>
</tr>
<tr>
<td>Annual Household Income Imputed not Including Added-Worker Effects (Ten Thousand Yen)</td>
<td></td>
<td>-.0006*** (.00001)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.7263*** (.0897)</td>
<td>2.7793*** (.0892)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>20,536</td>
<td>20,536</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-23,875.035</td>
<td>-23,754.853</td>
</tr>
<tr>
<td>Scale Parameter</td>
<td>1.101*** (.0087)</td>
<td>1.0944*** (.0086)</td>
</tr>
</tbody>
</table>
TABLE D2: WEIBULL DURATION MODEL WITH HOUSEHOLD INCOME INTERVALS, WITH AND WITHOUT ADDED-WORKER EFFECTS, AND HETEROGENEITY, EFFECT OF NUMBER OF CHILDREN AGE 0 TO 5

<table>
<thead>
<tr>
<th>Variables</th>
<th>With Added-Worker Effects without Heterogeneity</th>
<th>Without Added-Worker Effects without Heterogeneity</th>
<th>With Added-Worker Effects with Heterogeneity*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Schooling</td>
<td>.0343*** (.0058)</td>
<td>.344*** (.0058)</td>
<td>.1003*** (.0004)</td>
</tr>
<tr>
<td>Experience</td>
<td>.0165*** (.0042)</td>
<td>.0148*** (.0042)</td>
<td>.054*** (.0002)</td>
</tr>
<tr>
<td>Experience Squared</td>
<td>.00003 (.0001)</td>
<td>.0001 (.0001)</td>
<td>-.0007*** (.000005)</td>
</tr>
<tr>
<td>Male</td>
<td>-.444*** (.0224)</td>
<td>-.435*** (.0224)</td>
<td>-.3751*** (.00011)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 5</td>
<td>-.0039 (.0225)</td>
<td>-.0121 (.0226)</td>
<td>.0013 (.0012)</td>
</tr>
<tr>
<td>Household Income ≤ 4 Million Yen</td>
<td>-.0094*** (.0003)</td>
<td>-.0088*** (.0003)</td>
<td>.0057*** (.00001)</td>
</tr>
<tr>
<td>Household Income &gt; 4 Million Yen and ≤ 8 Million Yen</td>
<td>.0002** (.0001)</td>
<td>.0003*** (.0001)</td>
<td>-.0015*** (.00002)</td>
</tr>
<tr>
<td>Household Income &gt; 8 Million Yen and ≤ 12 Million Yen</td>
<td>-.0007*** (.0001)</td>
<td>-.001*** (.0001)</td>
<td>.00004 (.00001)</td>
</tr>
<tr>
<td>Household Income &gt; 12 Million Yen</td>
<td>-.0001*** (.00003)</td>
<td>-.0002*** (.00003)</td>
<td>.00004*** (.00001)</td>
</tr>
<tr>
<td>Constant</td>
<td>5.6208*** (.1303)</td>
<td>5.4095*** (.1275)</td>
<td></td>
</tr>
<tr>
<td>$\delta_1$</td>
<td>0.5253*** (.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_2$</td>
<td>2*** (.0062)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_3$</td>
<td>3*** (.0068)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P_1$</td>
<td>2.583*** (.0025)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P_2$</td>
<td>2*** (.0034)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>20,536</td>
<td>20,536</td>
<td>20,536</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-22,754.443</td>
<td>-22,824.934</td>
<td>-131,038.8721</td>
</tr>
<tr>
<td>Scale Parameter</td>
<td>1.0843*** (.0085)</td>
<td>1.0863*** (.0085)</td>
<td>.0742*** (.0002)</td>
</tr>
</tbody>
</table>

* Three points of support.
Appendix E

TABLE E: AVERAGE VALUES OF PERSONAL CHARACTERISTICS BY GENDER

<table>
<thead>
<tr>
<th>Variable</th>
<th>Women</th>
<th>Men</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment Duration (Months)</td>
<td>7.8 (7.5)</td>
<td>7.1 (7.2)</td>
</tr>
<tr>
<td>Years of Schooling</td>
<td>12.5 (1.9)</td>
<td>12.4 (2.3)</td>
</tr>
<tr>
<td>Years of Work Experience</td>
<td>19.5 (11.5)</td>
<td>20 (12.3)</td>
</tr>
<tr>
<td>Years of Work Experience Squared</td>
<td>513.7 (495.3)</td>
<td>551 (541.7)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 14</td>
<td>.57 (.9)</td>
<td>.38 (.77)</td>
</tr>
<tr>
<td>Number of Children Age 0 to 5</td>
<td>.2 (.5)</td>
<td>.16 (.47)</td>
</tr>
<tr>
<td>Non-MI-Adjusted Annual Household Income</td>
<td>628.3 (449.7)</td>
<td>572.9 (477.7)</td>
</tr>
<tr>
<td>(Ten Thousand Yen)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>12,164</td>
<td>8,372</td>
</tr>
</tbody>
</table>

Standard deviations are presented in parentheses. The number of years of schooling, the number of years of work experience, and the number of children are adjusted based on unemployment duration.