B. 経済政策的インプリケーションがある実証分析

Three Years is Too Soon to Leave a Job:

Event History Analysis on Job Mobility of Japanese Graduates in the First Three Years

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Abstract

Early career turnover of young adults has attracted public attention in Japan. Past studies have addressed the issue of turnover from various perspectives, but little is known about the mechanism that affects the decision to leave/stay in the first company after graduation within three years. This study uses a nationally representative longitudinal survey data and constructs three types of event history models, including the discrete-time proportional hazards model, the frailty model with unobserved heterogeneity controls, and the time-varying coefficients frailty model, to estimate the effects of person-specific variables and company-specific variables on the decision to leave the first company within three years. The key findings show that those who got the first job that required some firm specific skills are less likely to decide to leave the first company within three years. Moreover, the risks that new employees decide to leave a company is lower at a larger company than those at a smaller company. From the empirical results obtained through this study, practical implications and policy suggestions are discussed for those who are involved with human resource management. Furthermore, two limitations inherent within this study are brought to light for future research.

Keywords: Japan, turnover, event history model, proportional hazards model, frailty model, unobserved heterogeneity, utility maximization theory, specific skills

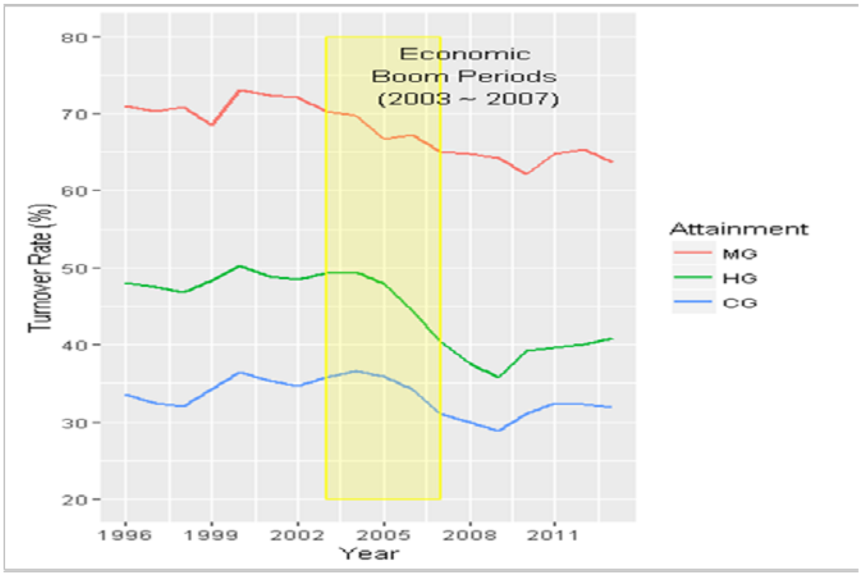
Introduction

In the present Japanese labor market, job mobility of graduates in their early career stages has drawn particular attention. The Ministry of Health, Labor and Welfare in Japan annually publicizes the records of graduates' three-year turnover rate over the past decade. Figure 1 displays the changes in the labor turnover of graduates at each school level from 1996 to 2013 (i.e. middle school graduates, high school graduates, and college graduates). The yellow shaded period represents the economic boom period due to export expansion to China. According to this Figure, labor turnover rate for each school graduates seem to fluctuate year by year, but it remains more than 30% for college graduates even during the economic boom periods ranging from 2003 through 2007. Surprisingly, it is only in 2009 that the labor turnover rate declined less than 30% after 1996. For middle school graduates, the labor turnover rate remained highest and never declined less than 60% during the observation periods. The rate of high school graduates is far lower than that of middle school graduates and goes through a sharp drop between 2008 and 2011. However, it began to increase up to 40% these days. These statistics imply that not a few graduates at each school level leave their first company every year without settling down for at least three years.

The failure of retention is a critical issue for both employers and employees. Mitchel et al. (2001) argued that turnover is costly for employers because replacement cost and hidden organizational cost are prohibitive. Moreover, it is obvious that early career turnover results in a waste of cost incurred by hiring processes and investment in human capital. In the same vein, turnover behavior burdens employees with monetary and psychological costs, too (Ehrenberg & Smith, 1985; Mitchell et al, 2001). Studies of employee retention contribute to strategizing a way to reduce these costs. Particularly, pinpointing those who are at risk of leaving an organization within three years will permit more efficient intervention strategies, which could reduce the social, organizational, and individual costs often associated with leaving an organization. Additionally, the implication from these studies also helps those who are involved with recruiting processes to screen and choose a new graduate with prospect to work for the organization longer. Some of the Japanese researchers have investigated what affects the decision to leave an organization (Kobayashi, 2016; Nakamura, 2001; Nakao, 2002). However, little is known about new graduates' early career turnover, particularly with incorporation of longitudinal information of the risk that new graduates change their first job at a particular time into the statistical models.

Therefore, the purpose of this paper is to narrow down to the Japanese labor market and to establish a predictive model of new graduates' turnover behavior within three years. Using a nationally representative longitudinal survey, referred to as the Japanese Life Course Survey for the Youth, the focus of this paper is to identify how personal attributes and the characteristics that are associated with the first job affect the decision to leave an organization within three years. For this analytical purpose, this studies uses event history models with different model specifications to use the longitudinal information fully. To the best of my knowledge, the empirical results of an event history model never before have been published to estimate what affects the three-year turnover decision of young adults. Therefore, this study will enrich turnover and retention research of the Japanese labor market. The remainder of this paper is organized as follows: First, I discuss the relevant literature regarding the studies of turnover behavior in the Japanese labor market, and the theoretical framework that is used for the analysis. Next, I elaborate the data set, variables, and empirical strategies. Then I present and discuss the results before concluding the paper with an acknowledgement of this study's limitations.

Figure 1. Within-Three-Year Turnover Rate (%) of Young Adults



1. The data in the Ministry of Health, Labour and Welfare in Japan is used. (http://www.mhlw.go.jp/stf/seisakunitsuite/bunya/0000137940.html)
2. Educational attainment is represented by:
   MG: Middle School Graduates
   HG: High School Graduates
   CG: College Graduates

Literature Review

Three key studies (Kobayashi, 2016; Nakamura, 2001; Nakao, 2002) that are reviewed for this study addressed what made individuals in the labor force more likely to leave a job. Some studies focused on employees' demographic and background characteristics to estimate the likelihood of leaving a job; others paid particular attention to external factors, such as workplace environments, organizational factors, and some indicators in the labor market. Despite the wealth of studies about the mechanism of turnover behavior, very few studies have addressed turnover behavior of the Japanese young adults, specifically their decision to leave an organization within three years after obtaining their first job. In this section, I frame an overall research design by reviewing the three key past studies and presenting an underlying econometric underpinning.

Nakamura (2001) examined how a sense of mismatch derived from job dissatisfaction affected the propensity of people in the labor force toward turnover. By using a nationally representative cross sectional data set in Japan, he concluded that demographic and background variables including gender and age were associated with their intention to leave an organization. Specifically, *ceteris paribus*, the propensity of the male labor force toward turnover became lower than that of the female labor force. In addition, his study demonstrated that the propensity of people in the labor force toward turnover was likely to be lower for a one-year increase in their age. Furthermore, the findings of his study indicated that the propensity toward turnover was affected by people's satisfaction with their occupational duties and responsibilities, salaries, and other forms of rewards. This result was consistent with the arguments made by Freeman (1978) and Mobley (1977), that job satisfaction was closely related to turnover intention. While it contributed to research on what types of people in the labor force were internalized in a company or were prone to leave a job, Nakamura's study had some limitations for implementing an effective intervention strategy to keep employees retained in a company because it focused on propensity toward turnover, not actual turnover behavior.

Nakao (2002) took a different approach and investigated the experiences of changing a job in the Japanese labor market. Particularly, she focused on personal attributes of people in the labor force who had experiences of job changes in the past. First, the findings of her study demonstrated that the male labor force, who started their first career after graduation at a large company, were less likely to experience a job change than their counterparts who started their first career after at a small and medium-size company. Second, her study also showed that the younger male in the labor force (under 29 years old) had lower odds of experiencing a job change than their elderly counterparts (ages 30-69). These results lent some support to the claim that the likelihood of leaving a company tended to increase in their fifties due to the age of retirement and reemployment (Higuchi, 1988), and that the company size was associated with the decision to leave an organization (Tachibanaki, Hasegawa, & Tanaka, 1997). Third, Nakao argued that the types of skill set that were considered important in each workplace were also influential factors of turnover behavior. She showed that the male employees with specific skills that were tied to the company were more likely to stay in an organization than their counterparts without those skills. This result was also consistent with the argument made by Kobayashi (2016) that in some workplaces both employers and employees committed to investment in developing non-transferrable skills that were tied to a specific company, thus motivating the employees to stay in the company in hopes of return to this type of investment in a long run. Fourth, she presented an interesting result from investigation of the female labor force in the same way as the male labor force. According to her study, years of education significantly affected the female labor force to reduce the odds of experiencing a job change. In other words, more educated women were likely to stay in a company. Nakao’s detailed analysis is worth admiration in that it shed light on what factors affected the decision to leave a company. However, her study still has some limitations in that she did not distinguish the first job change at an initial career stage from second or more job changes at different career stages. Aggregation of these different job changes might contaminate resulting estimation when researchers are particularly interested in the first job change at an initial career stage.

A recent study conducted by Kobayashi (2016) might be the only study that exclusively focused on three-year turnover behavior of the Japanese young adults. Kobayashi used Oaxaca decomposition, and compared three-year turnover behavior of the first job between recent young adults (, who graduated from school after 1995) and past young adults (, who graduated from school before 1994). This research procedure enabled him to identify which factors accounted for the difference in three-year turnover behavior of the first job between the recent and the past young adults. The key findings displayed by his study was that the recent young adults were less likely to get a job in a large company, thus keeping them less motivated to retain there and encouraging them to decide to leave in their early career stages. Moreover, he argued the possibility that some longitudinal structural change in work environments was also conducive to an increase in the number of turnover even after controlling for various individual characteristics, labor market variables, and organizational information. His study deserves special consideration in that it exclusively focused on turnover behavior of the first job within three years, and disentangled complicated mechanism that shaped the decision to leave a job in an early career stage. However, there is still some room for improvement in his study because he did not distinguish first-year, second-year, and third-year turnover. Instead, he treated these three types of turnover as the same and created a dummy variable that turnover occurred within three years. This type of dichotomization, particularly in longitudinal data, results in some information loss (Vermunt, 1997). Allison (1984) warned that dichotomizing the dependent variable wasted information because it ignored the variation on either side of the dividing line. For instance, one might suspect that those who left a job immediately after their job entry had a higher propensity toward turnover behavior than those who left a job 24 months later.

Thus, this study places its foundation on the study conducted by Kobayashi to investigate the mechanism that affects the decision to leave the first job within three years. The remarkable difference from his study is that this study constructs event history models to prevent information loss by incorporating longitudinal information on employees' turnover behavior that were not captured by his study.

Theoretical Perspective

The past studies that were reviewed for this study did not explicitly assume a specific economics theoretical framework. However, most researchers who study one's decision making process often assume the utility maximization theory implicitly or explicitly. Thus, I follow this convention. Traditionally, this econometric perspective assumes that individuals make decisions by weighing the monetary/nonmonetary costs against the monetary/nonmonetary benefits for all possible alternatives and selecting the alternative that maximizes utility (Manski & Wise, 1983). Given that the underlying utility associated with each decision is strictly unobservable, researchers can use observable discrete choice behaviors and infer utility maximization of the choice from the observed decisions. Based on this theoretical outline, this study assumes that people in the labor force will make the decision to leave an organization when the anticipated benefits of staying in the company fail to outweigh the costs of making a decision to leave. Thus, by studying the transition of people in the labor force from entry to turnover, this study indirectly examines their benefit/cost calculations with regard to the decision to leave a job within three years.

The mathematical discrete choice model based on the utility maximization theory has been presented by researchers (Long, 1997; Manski, 1977). For this study, I assume that there are two choices: A, represented by the decision to leave a company, and B, represented by the decision to stay in a company. The utility for choosing to leave a company is U_A and the utility for choosing to stay in a company is U_B. A person in the labor force chooses to leave a company when $U_A > U_B$, and chooses to stay in a company when $U_B > U_A$. I assume that ties do not occur. A person in the labor force is rational in the sense of choosing the alternative that maximizes the utility derived from the choice. The utility derived from choosing to leave a company for individual i equals:

$$U_{iA} = \mu_{iA} + \varepsilon_{iA}$$

[1]

where μ_{iA} is the average utility associated with choice of leaving a company for individual i, and ε_{iA} is the random error associated with that choice. The probability of choosing to leave an organization is the probability that the utility from the alternative exceeds the utility from the other:

$$\Pr(U_{iA} > U_{iB}) = \Pr(\mu_{iA} + \varepsilon_{iA} > \mu_{iB} + \varepsilon_{iB}) = \Pr(\varepsilon_{iA} - \varepsilon_{iB} > \mu_{iB} - \mu_{iA})$$

[2]

The specific form of the discrete choice model is determined by the assumed distribution of ε and the specification of how μ, the average utility term, is related to measured variables. Thus, the latent variable model of the average utility is constructed by a linear combination of the characteristics of an individual:

$$\mu_i = \boldsymbol{X_i \beta}$$

[3]

This theoretical framework enables this study to construct the hazards rate that is central to event history models. The more details are discussed in the next chapter.

Methodology

Data

The data for this analysis come from the restricted-access versions of the Japanese Life Course Panel Surveys for the Youth, hereafter the JLPS-Y, from wave 1 (2007) through wave 7 (2013). The JLPS-Y is a nationally representative longitudinal survey of young adults in Japan that has been conducted annually by the Institute of Social Science at the University of Tokyo.

Items covered in this survey are extensive in scope, including occupation, lifestyle, family background, educational attainment, social and political awareness, health status, household finance, and marriage and family life. This extensiveness makes the JLPS-Y distinct from other longitudinal surveys, and enables researchers in various fields to answer their own unique research questions.

The youth panel data were collected from people throughout Japan aged 20-34 in the base year of 2007. The respondents were selected from the Basic Resident Registration or Poll Book through a two-stage stratified random sampling based on age and gender. Furthermore, the JLPS-Y stratified the sample based on age through the three age groups: 20-24, 25-29, and 30-34, in order to secure representativeness of young adults of both genders. Self-administered questionnaires were mailed and collected by the visiting research staff. In addition, the JLPS-Y recruited additional sample in 2011 to maintain the panel size of Japanese young adults as some of them leave the panel. This replacement recruiting was conducted using the same method as the original panel.

Retention rates for each wave are shown in Table 1. The retention rate is calculated by dividing the number of respondents surveyed by the number of respondents remaining eligible for each wave. All 2007 (wave 1) respondents are eligible for the survey, with the exception of those who have been permanently dropped from the sample due to reasons such as address change, long-term absence, address unknown, death, illness or disabilities. In the wave 7 (2013) survey, 2,555 respondents out of the 4,079 eligible were surveyed, for an overall retention rate of 62.6 percent.

The data used in this study excluded the respondents who landed their first job in 2011, 2012, or 2013 because three-year observation periods were necessary in light of the purpose of this study. Moreover, those who did not specify the start year of their first job were also excluded from this study because such observations were inappropriate to answer the research question of interest and left censoring is a difficult problem to remedy both statistically and practically (DesJardins, 2003). In addition, this study limited the analytical sample to those who started their first career after graduation as regular employees because inclusion of casual employees and self-employed people might yield biased estimates. Furthermore, there were sizable proportion of missing records among the variables which were used as predictors for this study. After deleting records with missing information the effective sample size used in this study ended up being 1,321 and the data was right-censored. For estimating longitudinal events in this type of censoring data, standard regression techniques cause estimation problems such as severe bias or loss of information (Alison 1984). Thus, this study chooses to use event history models to overcome this limitation. The strength of the models is to easily incorporate information about right censored cases and therefore the technique is preferred over methods like conventional linear regression technique when analyzing longitudinal data (Yamaguchi, 1991). Elaboration of the employed statistical models is described in greater detail in the later part of this chapter.

Table 1. Sample Sizes & Retention Rates: JLPS-Y

	Base Sample		Additional Sample		Total Sample	
Year	Total	Retention Rate	Total	Retention Rate	Total	Retention Rate
2007	3,367	-	-	-	3,367	-
2008	2,716	80.7%	-	-	2,716	80.7%
2009	2,443	72.6%	-	-	2,443	72.6%
2010	2,174	64.6%	-	-	2,174	64.6%
2011	2,232	66.3%	712	-	2,944	72.2%
2012	2,121	63.0%	542	76.1%	2,663	65.3%
2013	2,038	60.5%	517	72.6%	2,555	62.6%

Note: Retention rate is defined as the percentage of base year respondents with each sample type remaining eligible who were collected in a given survey year. Included in the eligible sample are deceased and difficult to field respondents whom the JLPS-Y does not attempt to contact.

Variables

Event history model requires a binary response variable to be transformed into a specific form of probability, called the hazard rate. The hazard rate controls both the occurrence and timing of events and it is the fundamental dependent variable in an event history model (Allison, 1984). In the present example, the hazard rate is the probability of making a first job change at a particular year within three-year observation periods for those who have not yet changed jobs. Thus, the discrete time hazard rate is defined as:

$$\lambda(t) = P(T = t | T > t - 1)$$

[4]

where λ is the probability of event occurrence, t is the time interval of interest (i.e., year), and T is an integer measuring the time of the event. The first part $(T = t)$ of the right-hand side of [4] indicates that a change of state occurred in the interval t. The second part of this equation $(T \geq t)$ indicates that the hazard is conditional on a person surviving until the beginning of the time interval. Thus, in discrete-time the hazard rate is a conditional probability indicating "the probability that an event will occur at a particular time to a particular individual, given that the individual is at-risk at that time" (Allison, 1984, p16). The hazard rate [4] specifies that the dependent variable is duration until the time of turnover. In theory, it would be desirable to distinguish voluntary and involuntary turnover (Tuma, 1976; Hachen, 1990), but access to that information was limited in the JLPS-Y (the related items are available only in the surveys from wave 4 through wave 7). The failure to distinguish these two types of turnover behavior might change the resulting estimates and suggest different policy implications in the end. Thus, I will return to this limitation later for further discussion.

The predictor variables that are used in this study are twofold: person-specific variables (i.e., gender, educational attainment, college major, and occupation category), and company-specific variables (i.e., industry classification, and company size). These variables were chosen based on theoretical consideration and previous research on turnover behavior. First, it is commonly recognized that individual characteristics have been correlated with his/her activities in later life (Mehan, Hertweck, & Meihls, 1986). For example, many studies have indicated that the female workers are more likely to leave a job than the male counterparts (Marsh & Mannari, 1977; Yanadori & Kato, 2009). The difference in their job mobility pattern is considered due to gender discrimination in Japanese companies (Peltokorpi, 2013), glass ceiling career track (Ogasawara, 1991; Wortheley et al., 2009), and imposition of the role to wife and mother (Wortheley et al., 2009). Thus, gender difference deserves particular attention. Second, accumulation of human capital also deserves consideration because individuals with more human capital are highly productive (Becker, 1964). With higher productivity, it is reasonable to expect that their company makes the best efforts to keep productive workers retained while it ditches less productive workers. Indeed, individuals with a high level of education are less likely to change a job (Borsch-Supan, 1990). Another explanation might be possible that productive workers are more likely to leave an organization because its competitor headhunts them with a better job offer; on the other hand, less productive workers are less likely to leave an organization because they have nowhere to go. This is so because more educated workers should be better able to collect and process information. They tend to be more efficient job searchers and have lower transaction costs. If workers move when their perceived utility difference between new job and present job outweighs moving and other transaction costs, they should therefore move and change jobs more easily (Greenwood, 1975). In either way, the empirical models should account for the distinction of those with more productivity from those with less. In order to capture it, a binary status of college graduates/non-college graduates is appropriate. In relation to human capital theory, college major also deserves consideration because the earning is a critical factor for people in the labor force to make a decision to leave or stay, and past studies have found substantial variation in earnings by major. Arcidi-acono (2004) found that large earnings premiums existed for some majors. In particular, studies have found that more-technical fields receive a higher earnings premium compared to less-technical fields (Grogger & Eide, 1995; James et al., 1989; Loury & Garman, 1995). Therefore, college major is also worthwhile for investigation. Finally, the characteristics of the first company or first job are considered critical factors for people in the labor force to decide to leave or stay. Indeed, Higuchi (1991) demonstrated that turnover behavior differed by industry, occupation, and company size. In JLPS-Y, the information on the industry, occupation, and company size that are associated with the first job is available. In order to reduce the dimensions and thus to make the analysis simpler, I collect the relevant categories and create a larger category that encompasses them. This aggregation procedure is inspired by the study conducted by Kobayashi (2016). The more detailed information is provided in Table 2.

Table 2. List of Aggregated Categories of Industry, Occupation, and Company Size

Variables	Aggregated Category	JLPS-Y Category
Industry	Manufacturing, Mining, and Construction	Mining Industry, Construction Industry, Manufacturing Industry
	Logistics & Transportation, Wholesaling, Retailing, and Restaurant	Logistics & Transportation Industry, Travel Industry, Wholesaling Industry, Retailing Industry, Restaurant
	Service	Information Communication Service Industry, Medical Welfare Service Industry, Education Research Service Industry, Law Accounting Service Industry, Other Services Industry, Clam School, Human Development, Health
	Others	Agricultural Industry, Forest Industry, Fishing Industry, Infrastructure, Finance and Insurance Industry, Property Industry, Newspaper Industry, Publishing Industry, Television Industry, Film Industry, Advertising Industry, Postal Savings and Postal Life Insurance, Unclassified Industries
Occupation	Business/Financial Operations, and Engineering	Business/Financial Operations, and Engineering
	Office/Administrative Support	Office/Administrative Support
	Sales, Service, Transportation, and Security	Sales, Service, Transportation, and Security
	Others	Management, Factory Workers, Technician, Others, Fishery, Farmer
Company Size	"~ 100"	"1", "2 ~4", "5 ~ 9", "10 ~ 29", "30 ~ 99"
	"100 ~ 299"	"100 ~ 299"
	"300 ~ 999"	"300 ~ 999"
	"1000 ~"	"1000 ~"

Model Specification

The hazard rate that is specified as [4] is only a function of time. Typically, researchers attempt to explain hazard probabilities as a function of a set of covariates that are thought to explain event occurrence. When I add predictor variables to the model the hazard is defined as:

$$\lambda(t|\boldsymbol{X}) = P(T = t|T > t - 1, \boldsymbol{X})$$

[5]

where $\boldsymbol{X}$ is a vector of variables that are elaborated in the previous section and the hazard is now conditional on a person surviving until the beginning of the time interval and on the covariates specified in the model.

Based on this setup, event history models are constructed. These statistical models are used for the analysis of length of time until the occurrence of some event and utilize information from longitudinal data to full extent. For the analytical purpose of this study, I specify three empirical models: the discrete-time proportional hazards model, the frailty model with Gamma UH control, and the frailty model with time-varying coefficients.

The discrete-time proportional hazards model is the standard method to estimate an event history model without having to specify or parametrize time dependency. Thus, the results from this is used as a benchmark against which another model specification can be compared. This model is expressed mathematically as:

$$P(T = t|T > t - 1, \boldsymbol{X}) = 1 - exp\big(-exp(\alpha_t + \boldsymbol{\beta X})\big)$$

[6]

where $\boldsymbol{\beta}$ is a vector of time-invariant coefficients that measure the effects of a vector of the time-fixed explanatory variables ($\boldsymbol{X}$) and α_t is a time-varying constant term ($t = 1, 2, 3$). While it is straightforward and widely used in various fields, this statistical model has two restrictions: (1)

this does not include an unobserved heterogeneity (UH) control, and (2) it does not allow for time-varying coefficients.

Unobserved heterogeneity is variability between individuals that is due to unmeasured characteristics. Desjardins (2003) warned that without controlling for unobserved heterogeneity and resulting omitted variables caused model misspecification and yielded biased estimates in any regression model. The standard approach to cope with this problem is to include in the empirical model a random effect, referred to as frailty, which is derived from unobserved characteristics that are specific to an individual and fixed over time. Researchers usually assume some distributional form for the random effects. Here, this study focuses on the frailty model with Gamma UH control because the Gamma distribution is one of the most often applied distributional family in the frailty model (Wienke, 2003). The revised model is mathematically expressed as:

$$P(T = t|T > t - 1, \boldsymbol{X}) = 1 - exp(-exp(\alpha_t + \boldsymbol{\beta X})\theta)$$

[7]

where θ is unobserved and distributed independently of $\boldsymbol{X}$.

Furthermore, the frailty model [7] is revised again by relaxing the assumption of the proportional hazards model and then allowing for time-varying coefficients.

$$P(T = t|T > t - 1, \boldsymbol{X}) = 1 - exp(-exp(\alpha_t + \boldsymbol{\beta_t X})\theta)$$

[8]

where $\boldsymbol{\beta_t}$ measures the time-varying effect of $\boldsymbol{X}$ in period $(t = 1, 2, 3)$. By allowing for time-varying coefficients, the statistical model becomes more suitable for the real world analysis. Consequently, rich practical implications are anticipated because an appropriate intervention strategy for improving retention is proposed by tracking down the changes in effects of a specific predictor variables on the decision to leave a company.

Note that R is used to estimate the coefficients in the model [6], model [7], and model [8]. Copies of the programming code are available from the author.

Results

Descriptive Statistics

The information provided in the Table 3 shows that the initial at-risk pool of employees consists of the cohort of all young adults in the effective sample (N = 1,321). In addition, a subset of those who had a college degree before their entry into the job market is also provided (N = 438). The risk periods are defined as three employment years. With regard to the risk set, as time passes the number of employees at risk of turnover diminishes because they have the event of interest, and these employees are excluded from the at-risk pool at the time of each year. Therefore, the relevant risk set in any given time period is comprised of employees who still stay in their first company because they are still subject to the decision to leave the first company. For example, in employment year second in the case of all young adults the sample is reduced to 1,048 employees because 273 employees left the first company. Thus, the risk set for year second is calculated by subtracting the number of turnover at year first from the initial cohort of employees. Using Table 3, the empirical hazards rate of turnover can also be calculated. Empirical hazard rates are calculated by dividing the number of employees who experienced the event in question in a particular employment year by the number of employees at risk in that year. For instance, the hazard rate of turnover in the subset in the third employment year is 50/310 or 0.161. This empirical hazards rate indicates that employees who leave until the three employment year have about 16 percent probability of turnover in that year. The vector of predictors specified in the previous section is summarized in Table 4. Because all of the independent variables are time-constant, the number and the proportion in the employment year first are presented.

Table 3. Distribution of Turnover and the Hazard Rates

	All Young Adults			
Year	Risk Set	Turnover	Empirical Hazard Rate	Cumulative Hazard Rate
1	1321	273	0.207	0.207
2	1048	160	0.153	0.359
3	888	161	0.181	0.541
	College Graduates			
Year	Risk Set	Turnover	Empirical Hazard Rate	Cumulative Hazard Rate
1	438	77	0.176	0.176
2	361	51	0.141	0.317
3	310	50	0.161	0.478

Table 4. Descriptive Statistics of the Sample

		All Young Adults		College Graduates	
Variables	Names	#	%	#	%
Gender	Male	640	0.484	258	0.589
	Female	681	0.516	180	0.411
Academic Status	Non College Graduates	793	0.600	-	-
	College Graduates	528	0.400	-	-
College Major	Health Field	-	-	18	0.041
	Humanities	-	-	85	0.194
	Others	-	-	64	0.146
	Social Science	-	-	162	0.370
	STEM	-	-	109	0.249
		-	-		
Industry	Manufacturing, Mining, and Construction	370	0.280	102	0.233
	Logistics & Transportation, Wholesaling, Retailing, and Restaurant	309	0.234	98	0.224
	Service	497	0.376	174	0.397
	Others	145	0.110	64	0.146
Occupation	Business/Financial Operations, and Engineering	410	0.310	161	0.368
	Office/Administrative Support	342	0.259	129	0.295
	Sales, Service, Transportation, and Security	374	0.283	118	0.269
	Others	195	0.148	30	0.068
Company Size	~ 100	540	0.409	132	0.301
	100 ~ 299	235	0.178	82	0.187
	300 ~	236	0.179	81	0.185
	1000 ~	310	0.235	143	0.326

Empirical Results – All Young Adults –

As mentioned in the earlier section, there are three different model specifications with respect to the time to first turnover for the full sample of all young adults and the subset of college graduates. The results displayed in Table 5 are the raw coefficient estimates, standard errors, and their statistical significance.

Initially, this study began by estimating the discrete-time proportional hazards model without unmeasured heterogeneity controls (Column 1), and followed by the frailty model with Gamma unobserved heterogeneity controls (Column 2) and the frailty model with Gamma unobserved heterogeneity controls and time-varying coefficients (Column 3 ~ Column 5). All these three statistical models meet the assumption of proportionality (See the second row from the bottom). The estimates produced by the discrete-time proportional hazards model and the frailty model with Gamma unobserved heterogeneity controls do not vary to a great degree. With respect to model fit, the AIC drops very slightly as the model specification goes from the discrete-time proportional hazards model ($AIC = 8178.6$) to the frailty model with Gamma unobserved heterogeneity controls ($AIC = 8178.5$). These results suggest that the effects of unobserved heterogeneity are almost ignorable. In addition, the AIC inflates as the model specification goes from the frailty model with Gamma unobserved heterogeneity controls ($AIC = 8178.5$) to the frailty model with Gamma unobserved heterogeneity controls and time-varying coefficients ($AIC = 8204.6$). This result is quite reasonable because the time-varying coefficients model has more parametrization and thus adds to more complexity to the previous model. This study found that those who got the first job that was associated with “Business/Financial Operations, and Engineering” have the risk of turnover within three years

0.64 $\left(= exp(-0.452)\right)$ times or 36% lower than those who got the first job that was associated with “Sales, Service, Transportation, and Security.”

The results from the time-varying coefficients model indicates that the comparative advantage of “Business/Financial Operations, and Engineering” over “Sales, Service, Transportation, and Security” in terms of the risk of turnover lasts up until the second year. In other words, those who got the first job that was associated with “Sales, Service, Transportation, and Security” have the risk of first-year turnover 1.57 times or 56% higher, and the risk of second-year turnover 1.93 times or 93% higher than those who got the first job that was associated with “Business/Financial Operations, and Engineering.” However, the risk of third-year turnover does not vary between these two occupations. These results might be explained by the types of skill set that were considered important in each workplace, which was argued by Nakao (2002) in the earlier section. In comparison with “Sales, Service, Transportation, and Security,” the occupations that are associated with “Business/Financial Operations, and Engineering” and “Office/Administrative Support” generally need specific skills that are tied to a specific company. Indeed, there is a conventional wisdom that firm specific skills and knowledge that needed for specific types of occupations discourage employees from leaving an organization (Jovanovic, 1979).

Thus, those who had chances to develop specific skills through their occupation might be more likely to stay in a company than those who did not. With respect to the company size, the key findings are that the comparative advantage of larger companies over smaller companies in terms of the risk of turnover within three years does exist. Particularly, those who got the first job at a company with “1000 ~” employees have the risk of first-year turnover 0.48 times or 52% lower, the risk of second-year turnover 0.50 times or 50% lower, and the risk of third-year turnover 0.65 times or 35% lower than their counterparts at a company with "~ 100" employees. These results suggest that employees are much more sensitive to monetary/non-monetary benefits than I initially expected. In general, larger companies can afford to reward employees with various benefits such as bonus, flexible work schedule, emphasis on compliance, and etcetera. It is probable that the lack of these benefits at smaller companies ends up reducing employees' utility, thus affecting the decision to leave an organization in their early-career stage.

Other interesting results are that years of education do not affect the risk of turnover. This implies that when college graduates enter into a specific company, their risk of three-year turnover and turnover at a particular year is not different than non-college graduates' risk. Therefore, the characteristics that are associated with the first job (i.e., occupation category and company size) are more influential on the decision to leave/stay within the first three years than years of education. Counterintuitively, gender also does not affect the risk of turnover in early career stages. The rationale for this result is that the female workers are not likely to encounter the risk factors that researchers think influence on the decision to leave a company (e.g., birth of a child, marriage, and glass ceiling of promotion) within three years at the first company. Thus, the risk of turnover does not change between the male and the female workers. Figure 2 is a post-hoc estimation of the survivor rate when I only allow the occupation category and the company size to vary respectively. The implication obtained from this result is consistent with what is obtained from Table 5.

Table 5. Estimates of Turnover for All Young Adults

Variables		No U. H.	Gamma U. H.	Year 1	Year 2	Year 3
Coefficients/(se)		*Coef.*	*Coef.*	*Coef.*	*Coef.*	*Coef.*
Personal Attributes	College Graduates	0.147	0.147	0.158	0.144	0.116
		(0.090)	(0.090)	(0.131)	(0.173)	(0.173)
	Female	0.033	0.033	-0.037	0.070	0.106
		(0.094)	(0.094)	(0.138)	(0.183)	(0.183)
Industry (1)	Manufacturing, Mining, and Construction	-0.039	-0.039	0.058	-0.050	-0.201
		(0.136)	(0.136)	(0.197)	(0.264)	(0.262)
	Service	0.044	0.044	-0.061	0.198	0.080
		(0.119)	(0.119)	(0.176)	(0.226)	(0.230)
	Others	-0.149	-0.149	0.083	-0.150	-0.567
		(0.170)	(0.170)	(0.241)	(0.329)	(0.347)
Occupation (2)	Business/Financial Operations, and Engineering	-0.452 ***	-0.452 ***	-0.448 ***	-0.656 ***	-0.255
		(0.120)	(0.120)	(0.172)	(0.236)	(0.236)
	Office/Administrative Support	-0.315 **	-0.315 **	-0.615 ***	-0.156	0.005
		(0.123)	(0.123)	(0.189)	(0.228)	(0.239)
	Others	-0.144	-0.144	-0.286	-0.084	0.073
		(0.152)	(0.152)	(0.218)	(0.292)	(0.305)
Company Size (3)	100 ~ 299	-0.318 ***	-0.318 ***	-0.362 **	-0.207	-0.379
		(0.116)	(0.116)	(0.171)	(0.210)	(0.236)
	300 ~ 999	-0.447 ***	-0.447 ***	-0.476 ***	-0.743 ***	-0.156
		(0.120)	(0.121)	(0.180)	(0.254)	(0.215)
	1000 ~	-0.651 ***	-0.651 ***	-0.744 ***	-0.691 ***	-0.436 *
		(0.121)	(0.121)	(0.183)	(0.234)	(0.225)
	Proportionality Assumption	○	○	○		
	AIC	8178.6	8178.5	8204.6		

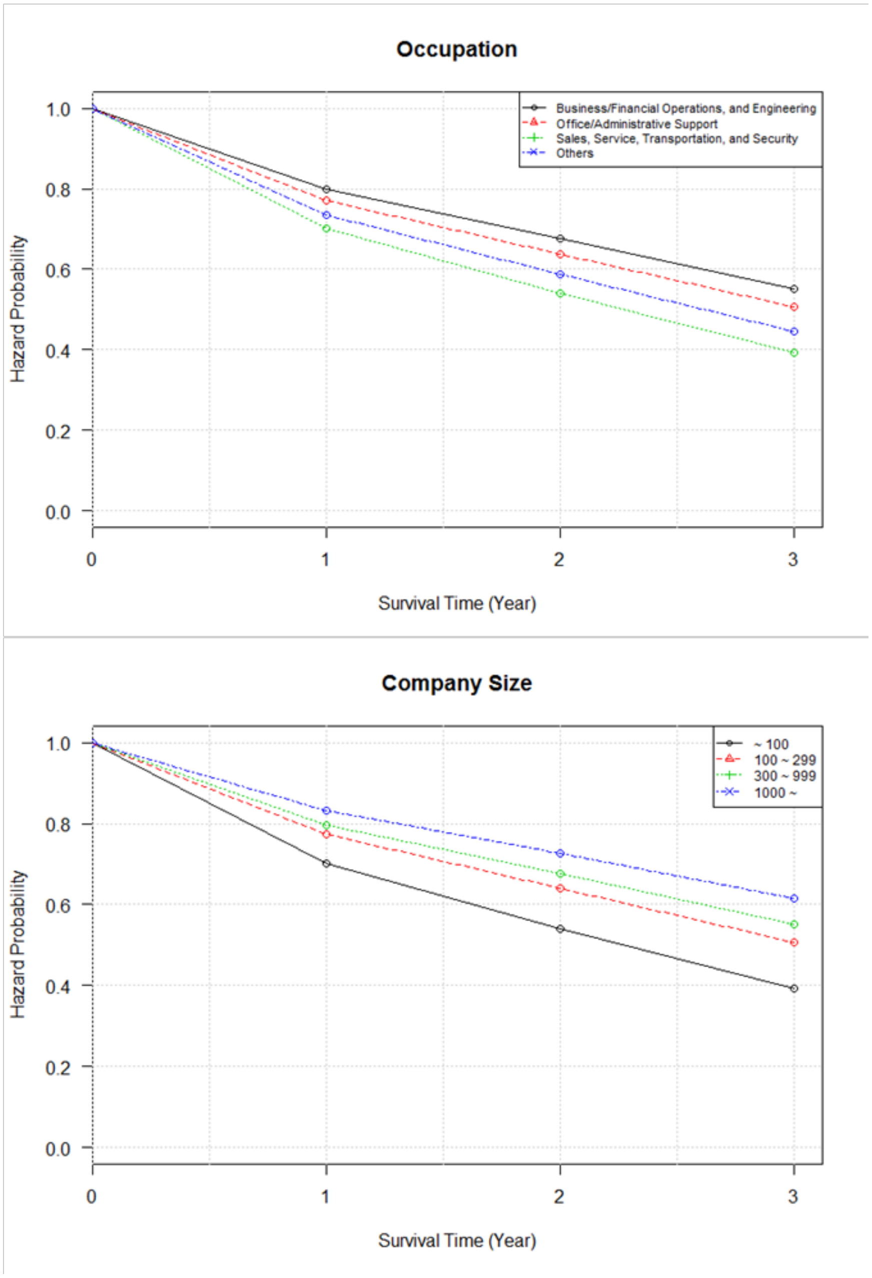
* p < 0.10; ** p < 0.05; *** p < 0.01

(1) The base category is "Logistics & Transportation, Wholesaling, Retailing, and Restaurant"

(2) The base category is "Sales, Service, Transportation, and Security"

(3) The base category is "~ 100"

Figure 2. Post-hoc Estimation for All Young Adults



Empirical Results – College Graduates –

In the same vein, the results displayed in the Table 6 are produced by estimating from the subset of college graduates only. The overall results obtained from this analysis are almost consistent with the previous ones. However, there are still striking results. For example, the coefficient of "Others" in the occupation category becomes statistically significant. That is, those who got the first job that was associated with “Others” have the risk of turnover 0.34 times or 66% lower than their counterparts who got the first job that was associated with “Sales, Service, Transportation, and Security.”

One of the rationale for this result is that actual occupations included in the “Others” category is different between college graduates only and all young adults. As Table 2 illustrated, the “Others” category included “Management,” “Factory Workers,” “Technician,” “Fishery,” and “Farmers.” Remember, the coefficients in this section were estimated from the subset of college graduates. For college graduates, it is unlikely to get a job other than “Management.” Generally speaking, an occupation that is associated with “Management” also requires some specific skills, which might glue employees to a specific company. Thus, the comparative advantage of “Others” over “Sales, Service, Transportation, and Security” in terms of the risk turnover exists at least up until the first year.

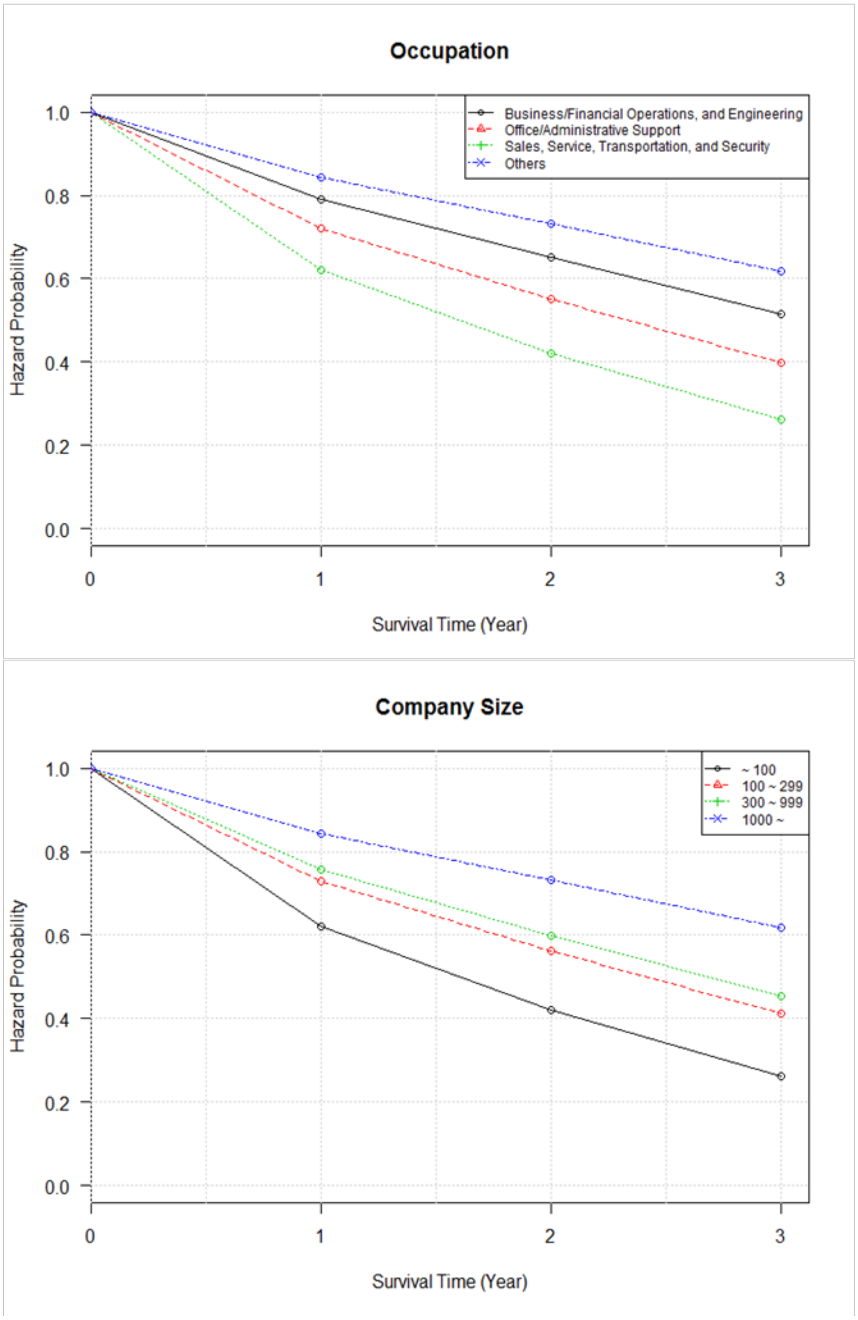
Furthermore, those who studied “Social Science” at college have the risk of third-year turnover 0.48 times or 52% lower than their counterparts who studied “Humanities” at college. It is challenging to devise a convincing rationale for this result because it seems unreasonable that the coefficient of “Social Science” only at third year is statistically significant while the coefficients of STEM, which is thought to yield more productive employees than “Social Science” are not statistically significant throughout the observation periods. One possible, and sensible explanation for this result might be a statistical artifact due to reduction of sample sizes or some biases in the collection or manipulation of data. Future researchers might want to double check it for more accuracy. As in the previous section, Figure 3 shows a post-hoc estimation of the survivor rate when I only allow the occupation category and the company size to vary respectively. The implication obtained from result is consistent with what is obtained from the Table 6.

Table 6. Estimates of Turnover for College Graduates

Variables		No U. H.	Gamma U. H.	Year 1	Year 2	Year 3
Coefficients/(se)		*Coef.*	*Coef.*	*Coef.*	*Coef.*	*Coef.*
Gender	Female	0.047	0.043	-0.018	0.276	-0.104
		(0.181)	(0.188)	(0.275)	(0.333)	(0.351)
College Major (1)	Health Field	0.532	0.544	0.486	0.364	0.740
		(0.423)	(0.442)	(0.705)	(0.738)	(0.773)
	Others	-0.016	-0.011	0.1778	-0.447	0.1128
		(0.261)	(0.273)	(0.419)	(0.500)	(0.457)
	Social Science	-0.263	-0.276	-0.054	-0.157	-0.732 *
		(0.215)	(0.225)	(0.339)	(0.381)	(0.430)
	STEM	-0.136	-0.129	0.3974	-0.606	-0.447
		(0.279)	(0.292)	(0.419)	(0.555)	(0.541)
Industry (1)	Manufacturing, Mining, and Construction	0.274	0.268	0.350	-0.401	0.599
		(0.239)	(0.250)	(0.347)	(0.528)	(0.457)
	Service	-0.044	-0.060	-0.321	-0.065	0.407
		(0.215)	(0.224)	(0.333)	(0.382)	(0.432)
	Others	-0.072	-0.074	0.237	-0.215	-0.463
		(0.277)	(0.288)	(0.392)	(0.518)	(0.613)
Occupation (2)	Business/Financial Operations, and Engineering	-0.702 ***	-0.740 ***	-0.765 **	-0.360	-1.000 **
		(0.246)	(0.256)	(0.357)	(0.456)	(0.500)
	Office/Administrative Support	-0.376 *	-0.405 *	-0.581 *	-0.365	-0.118
		(0.212)	(0.221)	(0.325)	(0.399)	(0.409)
	Others	-1.028 ***	-1.085 ***	-1.510 **	-0.975	-0.466
		(0.377)	(0.390)	(0.633)	(0.779)	(0.612)
Company Size (3)	100 ~ 299	-0.414 *	-0.428 *	-0.226	-0.513	-0.655
		(0.215)	(0.225)	(0.310)	(0.391)	(0.468)
	300 ~ 999	-0.531 **	-0.553 **	-0.328	-1.343 ***	-0.169
		(0.218)	(0.227)	(0.309)	(0.511)	(0.416)
	1000 ~	-1.020 ***	-1.064 ***	-1.445 ***	-0.953 **	-0.528
		(0.215)	(0.222)	(0.364)	(0.382)	(0.402)
	Proportionality Assumption	◯	◯	◯		
	AIC	2064.9	2061.8	2091.0		

* p < 0.10; ** p < 0.05; *** p < 0.01
(1) The base category is "Humanities"
(2) The base category is "Logistics & Transportation, Wholesaling, Retailing, and Restaurant"
(3) The base category is "Sales, Service, Transportation, and Security"
(4) The base category is "~ 100"

Figure 3. Post-hoc Estimation for College



Conclustion

Early career turnover of young adults has attracted public attention in Japan because this burdens both employers and employees with various costs. By using JLPS-Y, this study has shed light on the mechanism of early career turnover of young adults. For the analytical purpose, I constructed three types of event history models: the discrete time proportional hazards model, the frailty model with Gamma UH control, and the frailty model with Gamma UH control and time-varying coefficients. The resulting estimates from these three event history models provide practitioners with some implications. First, given that given that those who have chances to develop firm specific skills through their occupation are more likely to stay in the first company, people in HR division might want to plan training sessions or workshop to equip participants with some specific skills that are directly related to their job or workplace. The coherence of skill sets with where employees belong to is a critical factor for young adults to decide to leave/stay in the first company. Furthermore, given that those at a larger company have lower risks of turnover in their early career stages than their counterparts at a smaller company, employers must be ready to provide employees with monetary/nonmonetary benefits to prevent their utility from declining. For example, maintaining long-hours work culture or taking a pay cut to keep competitive might be worse than the ill. Rewarding employees in various ways sometimes incurs costs; however, letting employees' utility decline and forcing them to make a decision to leave the first company in the early career stage results in a waste of more money in the long run. Thus, those who are involved with human resource management need to take it seriously to maximize employees' utility within limited budget.

While I believe that this study enriched turnover and retention research of the Japanese labor market to some extent, several limitations still exist. First, this study does not distinguish "voluntary" and "involuntary" turnover. People leave an organization for various reasons such as a part of restructuring, family issues, career development, dissatisfaction with wages and work environments, and etcetera. It is obvious that one might get very different results, and there may be very different policy implications, if the destination state is simply "turnover" compared to disaggregating turnover into “voluntary” and “involuntary” turnover. Optimally, if I knew whether an employee left an organization voluntarily or involuntarily, an estimation could be corrected. However, in JLPS-Y such information becomes available only after the wave 4 survey. For fear of reducing the effective sample sizes, this study chose to use a simple binary status to represent turnover behavior. However, as JLPS-Y collects more records researchers will be able to distinguish voluntary and involuntary turnover without sacrificing statistical powers. Second, this study used only time-constant variables (i.e., gender, educational attainment, college major, characteristics that are associated with the first job) and did not include time dependent variables. Because one of the advantages from event history models is to incorporate time-dependent variables into the model, the failure to include time-dependent variables means that this study does not take full advantage of event history models. However, those who got the first job and experienced the first job change before the wave 1 does not have such time-varying information to estimate the first-time turnover. If I exclude such respondents from the analytical sample, the effective sample sizes end up being 156. Thus, inclusion of time dependent variables will also become possible when JLPS-Y collects more longitudinal information. These two limitations are left for future research.

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