Estimation of the Effects of Statistical Discrimination on the Gender Wage Gap

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Abstract

How much of the gender wage gap can be attributed to statistical discrimination? Applying an employer learning model and Instrumental Variable (IV) estimation strategy to Japanese panel data, I examine how women's generally weak employer-employee attachment affects wages when employers cannot easily observe an individual's intentions regarding remaining at the firm. To overcome endogeneity issues, I use survey information on individual workers' intentions to continue working in the same firm after having children and Japanese panel data with exogenous variation in average job turnover rates for female workers. I find that the extent of statistical discrimination is greatest for young age cohorts, ages 24 to 35, and that it diminishes for older cohorts. I also find that if employers could observe individuals intentions, the gender wage gap could be reduced from 17% to 5% for workers aged 24 to 29, after controlling for their work intentions, education, and occupation choice.

JEL Code: J24, J31, J63, J71

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1 Introduction

Despite the advances in labor force participation and labor market earnings of females in developed economies, sizable wage gaps relative to males persist even after accounting for observable human capital characteristics. Among the potential explanations is statistical discrimination.[1] Statistical discrimination is discriminatory but rational behavior under asymmetric information, based on group characteristics rather than individual characteristics. Statistical discrimination has been studied extensively in the theoretical literature. However, quantifying how much statistical discrimination actually drives observed wage inequality is challenging; it is difficult to tell whether a correlation between wages and an easily-observed worker characteristic arises because: 1) an imperfectly-informed employer uses the observable trait to discriminate (i.e. statistical discrimination), or because 2) the observable trait (e.g. gender) is correlated with unobserved worker productivity, which would not imply discrimination.[2] The literature on discrimination, including statistical discrimination, commonly uses decomposition methods developed by Blinder (1973), Oaxaca (1973), and Juhn et al. (1993), but these methods have some important limitations with respect to differentiating between true discrimination and unobserved heterogeneity. Decompositions attribute all of the group differences unexplained by observables to discrimination, thereby making discrimination subject to overestimation.

This paper adds to the literature by addressing the overestimation of discrimination using the method proposed by Altonji and Pierret (2001). Applying their method and exploiting the unique features of the Japanese Panel Survey of Consumers (JPSC) data, this paper aims to quantify the effect of statistical discrimination on the gender wage gap in the Japanese labor market. I study statistical discrimination based on the average employer-employee attachment of a group, theoretically illustrated in Barron et al. (1993). Attachment between employers and employees would influence wage compensation if a cost arises when firms hire a new employee, and employers do not observe individual workers' intentions regarding remaining at the firm. The employer's best initial prediction of a worker's job turnover rate is the job turnover behavior of the group of workers with the same observable characteristics. Given that young women's job turnover rates are on average higher than those of men, the expected cost for the employer to hire a woman is higher. Thus, a young female worker could receive lower wages than an otherwise identical male worker, at least upon entry into the labour market. After controlling for workers' observable characteristics such as education, occupation, and work history, I compare the monthly earnings of these highly

[1] Statistical discrimination is also known as systemic discrimination in the field of sociology.

[2] In fact, few studies empirically quantify the contribution of statistical discrimination to observed wage gaps. The scarcity of non-laboratory empirical analysis is also pointed out in Moro (2009). Indeed, many experimental papers have contributed to our understanding of statistical discrimination by providing results from a laboratory or field environment designed to generate random assignments. To name a few, List (2004), Bertrand and Mullainathan (2004), Carlsson and Rooth (2007), and Oreopoulos (2011) have all produced influential studies. However, these experimental papers focus on statistical discrimination in hiring decisions, not wage determinants.

educated women with those of corresponding men over time up to age 40. I analyze how much of the gender earnings gap can be attributed to the average characteristics of the group instead of the individual characteristics of each worker.

There are two main empirical results. First, I find that the effect of the average turnover rates on the wages decreases with tenure, and the effect of the estimated individual turnover rate on the wages increases with tenure. These findings serve as evidence of statistical discrimination. Second, I find that 70% ($= (17-5)/17$) of the observed male-female wage gap is due to statistical discrimination for young workers aged 24 to 29 who chose a career-oriented job course with four-year college degrees and strong employer-employee attachment.

The basic idea behind the method of Altonji and Pierret (2001) is employer learning;[3] the hypothesis that if an individual's productivity is really independent of the group she/he belongs to, then repeated observation of individual performance should allow employers to correctly estimate her/his true productivity, sooner or later. By examining whether statistical discrimination diminishes as workers stay in the same firm longer, we can tease out how much of the observed wage gap is attributable to statistical discrimination. The key requirement for their method is access to a measure of workers' productivity that is unobserved to the employer. I can construct such a measure by using survey questions asking individual workers' "willingness to continue working after childbirth" and "willingness to stay in the same firm in the next year." Both survey questions are asked of female respondents in the JPSC data at intervals of two to three years. I assume that the information about individual women's intentions may be harder for employers to obtain at the onset of the employment, but will gradually become known to the employers over time. If statistical discrimination exists, then the average job turnover rate will be a strong wage determinant at the beginning of career for female workers, but the wage effect of the average turnover rate will diminish as their tenure grows.

The Altonji and Pierret (2001) identification strategy itself, however, does not tell the causal direction of the correlation between the average job turnover rate and wage; not only does a high average job turnover rate lead to women's low wages through statistical discrimination but also low wages or poor labor market opportunities at the firm results in a high average job turnover rate by discouraging women from staying with the firm.

In order to identify the causal effect of the average job turnover rate on wages, I use variation in the accessibility of accredited child-care as an instrumental variable (IV) for women's average job turnover rate. In Japan, most of young women have a child and rely on child-care service in order to work. Weak employer-employee attachment of young women is mostly attributed to their weak labor force attachment following childbirth. I instrument the average job turnover rates by the child-care accessibility across different residential areas. As discussed later in this paper, there has been a severe shortage of child-care since the early 2000's in Japan, mainly due to

[3] The employer learning model was first formulated by Farber and Gibbons (1996).

government regulation in the child-care market and a recent rapid increase in demand for child-care services. I argue that child-care accessibility is correlated with mothers' labor force participation provided that most urban households consist of a nuclear family (they do not live with a child's grandparents). Since most female workers have a child, we can regard child-care accessibility as correlated with young women's labor force participation. Under the assumption that the child-care shortage only affects wage payment through women's job turnover rate, child-care accessibility serves as a valid instrument for women's employer-employee attachment and thus identifies the wage effect of statistical discrimination studied in this paper.

The rest of the paper is organized as follows: Section 2 introduces the institutional background and the challenges of identifying statistical discrimination. Section 3 describes the data. Section 4 introduces the conceptual framework of the statistical discrimination studied in this paper. Section 5 presents and estimates an empirical model. Section 6 shows the results and tests for the presence of statistical discrimination. Section 7 concludes.

2 Background

2.1 Women's Heterogeneous Work Preference and Labor Supply Patterns

In Japan from 1990 to 2005, most women get married and have a child; approximately 90% of young Japanese women get married and 85% of them have a child by age 45, according to the Census. Men typically work without interruption until the legal retirement age of 65. Young women's labor supply patterns are dichotomous—over the past 20 years, more than 90% of single women work full-time, and roughly 60% of working women quit their jobs and a half of working women left the labor force at the time of marriage or motherhood (Cabinet Office, Government of Japan 2012). Once leaving the labor force, women never return as full-time workers. In contrast, those women who continue to work after child-birth work in the same firm as long as their male counterparts.

Japanese female workers have large heterogeneity in their preferences toward work life. According to the Annual National Survey of Lifestyle Preferences (NSLP), in 1998 and 2008 only about 20% of married women wished to continue to work, 25% of them wished to permanently leave the labor market at marriage or childbirth, and 50% of them wished to leave the labor market temporarily and return when their children grew older.

Women's overall weak labor force attachment translates into shorter average job tenure. As of 2008, average job tenure in Japan is 13.1 years for men and 8.6 years for women.[4] Men's tenure is the longest among OECD countries while women's is just above the OECD average for women. The voluntary separation rate per year for full-time workers is 10.9% for men and 24.6% for women.[5]

For a substantial proportion of young women in Japan, job turnover comes as labor force withdrawal. Since most women who quit their job also withdraw from the labor force, this paper does not distinguish the difference between returns to job tenure and labor market experience as in other literature such as Topel (1993) and Audrey Light (1995).

2.2 High Worker Replacement Cost

The key assumption in this study is that replacing workers is costly, and that, as a consequence, workers' employer-employee attachment would affect wage compensation. This assumption is justified because worker replacement cost is substantially high in Japan. Japanese firms intensively finance and invest in employee training. According to the 2010 survey by SANRO Research Institute Inc,[6] the cost of employee training per employee before employment is on average $43,798$ Japanese yen (approximately \$437) and the average cost of on-the-job training is $165,191$ Japanese yen (\$$1,651$).[7] On-the-job training for white-collar and professional careers can last from a half year to two years. The training period is especially lengthy in large firms, where, during the training periods, employees are assigned to different sectors of the company in order to learn how the company operates. In fact, the survey reports that, in large firms with more than 3,000 employees, the cost of on-the-job training per employee amounts to as much as $252,036$ Japanese yen (US\$2,520). Thus, hiring new workers is remarkably costly. Given the great costs of employee training, Japanese firms attempt to protect this investment by minimizing employee turnover.

[4] The difference in the average tenure, 4.5 years, is the largest figure among developed countries in 2008, exceeding the second largest gender gap, observed in Ireland, by 1.5 years. The average of the gender gap among other OECD countries—excluding the U.S.—is 1.05 years. (Source: OECD) For reference, the median tenure in the U.S. is 4.4 years for men and 4.1 years for women as of 2010. (Source: Bureau of Labor Statistics)

[5] I calculate the separation rates as the number of workers (called regular workers in the survey) who left the job within a year divided by the number of workers who worked at the beginning of the year, using the data from the Survey on Employment Trends.

[6] The survey asked 230 randomly-picked companies how much they spend on their newly-hired employees.

[7] Among the most common kinds of training are 1) fostering workers' business attitudes (95.4%); 2) developing workers' communication skills—including, but not limited to, presentation, information exchange, and counseling skills (89.0%); and 3) teaching employees company operations and philosophy (87.7%).

2.3 Employer Learning and Dual Job Course System

Another key assumption is that employers do not directly observe individual workers' labor force intentions at hiring. I provide evidence that employers in fact do not directly observe individual workers' labor force intentions. In theory, firms could offer training only to workers who accept a contract in which they promise to pay penalties upon leaving their job. However, such arrangements are not commonly observed in the Japanese data.[8]

What we do observe in Japan is the two track career system. Since the 1986 Equal Employment Opportunity Law, Japanese firms cannot discriminate against workers in an explicit manner based on gender. Differences in hiring rates or wages solely based on gender are hard to justify. Being concerned about female employee turnover, many Japanese firms started to offer a dual job course system, which consists of two distinct career paths called "Sogo-shoku" (career course) and "Ippan-shoku" (non-career course). These two courses are characterized by different wage growth as well as differences in the difficulty of tasks, chance of promotion and chance of job transfer. While career courses are associated with large wage growth, chances for promotion, and demanding tasks, non-career courses are associated with little wage growth, little promotion and relatively easy tasks. At the beginning of a job application, workers self-select into a course. After choosing, they are rarely allowed to switch courses. The non-career courses, which assign workers to tasks that do not require specialized skills, attract almost no male workers but predominantly consist of female workers who plan to leave the labor market upon marriage or motherhood. This job course system has been explicitly and commonly adopted by Japanese companies, at least from 1993 to 2008, which is the period studied in this paper.

Women who self-select into the non-career track are revealing their weaker attachment to the labour force. The focus of this analysis is on women who select into the career track. Even for those who select into the career track, there is a substantial male-female wage gap after several years of employment. The regression analysis takes job course choice into account and analyze gender wage gap within and across career tracks.

Given diversity in work-family life preferences among young female workers, if individuals' labor force intentions are unobservable to their employers, a larger degree of heterogeneity within a group could lead to more inefficiency due to statistical discrimination. If employers cannot observe an individual's quitting intention, they may utilize information on the average quit rate by

[8] A signaling mechanism is another solution to ameliorate the information problem, but common signaling devices such as education and hours worked seem too noisy to clearly convey labor force intentions. I run logit regressions of employee turnover on various indicators and find that neither education nor overtime work predicts worker turnover rates. These findings are not surprising considering that many women go to college for purposes other than work-related investment and the number of hours worked for full-time jobs is not typically flexible in Japan. Difficulty for employers to identify employer-employee attachment was explored in Light and Ureta (1992) in the context of American labor market. They estimate proportional hazard models and find that employers had more difficulty identifying female non-quitters than male non-quitters.

an early-observable characteristic, such as gender, to maximize their profits. This is an example of statistical discrimination.

3 Data

3.1 Data Sources

I use three data sources: the Japanese Panel Survey of Consumers (JPSC), the Census, and aggregate data on child-care services provided by Zenhoren (The Institute for Research on Child-Care). The main source of the sample of women and their spouses used in this study comes from the JPSC data from 1993 to 2008. The JPSC, offered by the Institute for Research on Household Economics, is a data set widely used to study young women in Japan with respect to consumption, savings, labor supply, and family formation over the respondents' life-cycle. The survey started with a cohort of 1,500 women age 24 to 34 randomly chosen from across Japan in 1993; sample members have been surveyed annually since then. Hundreds of young adult women have been added to the data every 3 to 5 years. The oldest cohort was 49 years old as of 2008. The JPSC contains their province of residence and the population of their city, which inform us about the child-care accessibility that each woman faces.[9]

In addition to the household panel data, I use data on child-care services provided by Zenhoren (The Institute for Research on Child-Care),[10] containing information on the availability of child-care by each prefecture and municipality. Using this variation in the accessibility of accredited child-care as an instrumental variable for women's quit rates, I address the endogeneity problem in estimating the wage regression.

While the JPSC provides information that is indispensable to the identification strategy used in this analysis, there are also several disadvantages that arise from using the JPSC. The first problem is that the attrition rate is not low. If the survey sample exhibits properties different from the population with respect to variables of our interest, then results from analyzing the raw data cannot be generalized from a sample to the population. The second problem is that the data only contains respondents' husbands, rather than men more generally. Obviously, married men are not representative of all Japanese men. To avoid inaccurate or misleading implications, I apply a

[9] Information about women's place of residence are restricted, but available after one year of use of the unrestricted data. We observe samples from all 47 prefectures. The number of observations by prefecture in the sample data is proportional to that of population data.

[10] The official name of the institute is Zenkoku Hoiku Dantai Renrakukai. The website is found at: http://hoiku-zenhoren.org/

sampling weight adjustment to the JPSC data by comparing it to statistics in the national Census. Details regarding the construction of sampling weights are described in the Appendix.[11]

3.2 Main Variables

The actual individual labor force attachment is measured by respondents' answers to the survey questions. The JPSC data contains several questions that ask workers about their career plans. One of the questions asked of all women in the sample is whether they want to continue to work at their current job, switch the job for one with shorter hours worked, or stop working when they have a child. The survey in the panel data show that only 35% of women with college degrees plan to continue to work full-time beyond childbirth. Regardless of educational attainment, more than 10% of female workers leave their firm, while only 1.5% of male workers who work in the same firm do so. In both genders, the average quit rates fall as workers age. A remarkable decline is observed over time, especially in the turnover rates of female workers. The one exception to this pattern is for the age range of 42–47, where the sample size is small due to sample attrition.

For the cohorts born between 1958 and 1973, the survey asks for information about women's labor force intentions every two to three years. The JPSC data asked all the respondents whether they plan to work after childbirth and whether they plan to stay in the same firm in the following year in 1994, 1997, and 2000. The possible answers are: "continue their current job," "continue working but change a job such as a part-time job," "stop working," and "continue not working." The JPSC also asks the married respondents who were working at the time of the interview about their career plans in 1994 and from 1997 to 2002. The possible answers are: "plan to continue their current job," "leave the labor market temporarily," "continue to work, but switch to another job," "quit this job immediately (do not wait till childbirth)," and "quit sometime later regardless of having a child."[12]

3.3 Sample Universe

My sample universe is men and women aged 24 to 49 who work full-time and have never had a spell of non-employment longer than six months at the time of the interview. In conducting this analysis, I restrict myself to the sample of respondents with four-year college degrees who were younger than age 29, single, and worked in their first firm when they were first observed in the data set. I made such selection because this selected group of women are thought to be the most subject

[11] The data do not include cohabitation status. However, the nature of cohabitation is very different from marriage in Japan. Most cohabiting couples are financially independent from each other. Also, there are few out-of-wedlock children. Therefore, I ignore the influence of cohabitation on household budget and labor allocation.

[12] Since the third cohort (born from 1974 – 1979) was added in 2003, these questions are only asked of the first two cohorts, Cohort A and B.

to statistical discrimination.[13] I further restrict the sample to the women who have answered the survey question regarding their labor force intentions at least once. Among those who provided the data on their labor force intentions, 67% work full-time. Among full-time female workers, 81.9% are single, so the sample size shrinks to 1,035 women. All variables (including control variables), sources, and descriptive statistics are documented in the Appendix.

3.4 Source of Exogenous Variation: the Shortage of Child-Care Service

Another advantage of studying the Japanese labor market is that it provides exogenous variation in women's quitting behavior around the time of childbirth. Without exogenous variation, we cannot separate the effect of the average employer-employee attachment on wage from the effect of wage (or poor opportunity at work place) on the average employer-employee attachment. As exogenous variation of women's quitting behavior, I use differences in child-care accessibility over time and across prefecture in Japan.

In the following, I describe how the child-care market is regulated by the government and how the shortage of child-care services affects women's work decisions regardless of women's willingness to work. I also argue that the child-care market consists of relatively homogenous services as a result of stringent regulation.

In a market without government intervention, child-care accessibility is likely to be correlated with women's labor force intentions: the supply of child-care would respond to its demand, which comes from the frequency with which both parents work. Therefore, mothers who live in areas with better accessibility may have stronger labor force intentions than the other areas; this would violate the key assumption I rely on for identification. However, this is not the case in Japan, where the child-care market is strictly regulated by the government.

In Japan, the government intervenes in the child-care market for quality control purposes.[14] The government requires that all child-care services caring for six or more children register in a database and satisfy certain quality measures. The government monitors the quality of these child-care services in order to eliminate what it considers to be poor child-rearing environments, which it believes may ultimately result in the death of a child.

The use of child-care in Japan concentrates on the accredited type, which is heavily subsidized by the government. In order to obtain accreditation, a child-care facility must satisfy strict cri-

[13] During the period of this study, from 1993 to 2008, many four-year college graduates chose jobs with career advancement, but about half of them left the labor market at the time of marriage or motherhood. Once they leave, they typically do not come back as a full-time worker.

[14] Child-care, hereafter, is interpreted as care for and supervision of children from birth to three years of age, mainly to facilitate maternal employment in either the public or private sector. Child-care services for pre-school children aged four to six are not discussed because the accreditation system is significantly different from those of services for younger children. The criteria to obtain accreditation are much less stringent for these pre-schools and kindergartens.

teria.[15] The prices of child-care services in accredited facilities are generally regarded to be far below the market price, partly because of the massive subsidy and mainly because of the suggested prices posted by municipal governments.[16] The Japanese government regulates the quality of non-accredited child-care, too, though less rigorously than for accredited child-care. Due to the overall quality control, the service quality varies little: there is no cheap or poor-quality child-care service available.[17] Hiring a baby-sitter is also expensive in Japan, since, as mentioned above, labor costs are generally quite high.

One problem of accredited child-care is that it requires substantial time investment to obtain accreditation, and therefore its supply responds very slowly to changes in demand. Due to a recent rapid increase in demand for child-care services, there has been a severe shortage of child-care since the early 2000's. This shortage primarily affects accredited child-care, which serves 90% of all children in child-care facilities. This has led to excess demand for child care and, as of 2011, the total occupancy rate of child care facilities exceeds 100%, with as many as 25,556 children on waiting lists (See Figure 1 in the Appendix).[18] This shortage for affordable child care is so severe that some women have to quit their jobs despite their willingness to continue to work in order to take care of their children. According to the Annual National Survey by the Ministry of Labour, Health and Welfare, 15-20% of women leave the labor market at their first childbirth every year. Conditional on continuing working, 70-83% of women take child-care leave; this proportion has been increasing over the past decade. Among workers who take child-care leave, more than 97% of those are women. Conditional on taking child-care leave, 8-11% of women do not return to the work place, which is partly attributed to the recent shortage of child-care service.

[15]To be specific, a child-care facility must satisfy the following criteria: 1) the capacity is larger than 20; 2) the space per child is larger than 3.3 square meters (35.5 square feet); 3) the local government collects pre-fixed fees; 4) applications must go through the local government; and 5) the provider must operate fewer than 11 hours per day.

[16]While the central government provides subsidies for accredited facilities, local governments also supply additional subsidies and set the final prices that consumers pay.

[17]While some non-accredited child-care providers offer high-quality services, very few households use such high-end child-care services. These services generally charge two to four times the price of public child care: indeed, prices for non-accredited child care amount to more than half the average monthly salary for young female workers. Thus, there are rarely cheap, low-quality child-care services available in either the formal or informal sector.

[18]Child care hereafter is interpreted as caring for and supervising children from 0 to 3 years of age, mainly to facilitate maternal employment in both the public and private sectors. Child-care services for pre-school children aged 4 to 6 are not discussed because the accreditation system is greatly different from those of services for younger children. The criteria to obtain accredition are much lower for pre-schools and kindergartens.

3.5 Validity of the Exclusion Restriction Condition: Labor Mobility of Women with a Small Child

In addition to claiming that the supply side is insensitive to demand changes in the Japanese child-care market, I also argue that the demand side of the child-care market is not sensitive to the child-care shortage during the periods examined in this study.

It appears that many mothers were not aware of the seriousness of the child-care shortage while they were employed. The JPSC data in 1993 and 1997 show that more than 80% of all women had little information on child-care facilities in their current residential area before settling down, which implies that few women aged 24 to 34 chose their residential area based on child-care accessibility. For the sample of women working full-time, about 13% of women moved for reasons related to their child (e.g. they moved because they had a baby or their number of children increased). Even when the sample is restricted to married women who moved with a child aged less than two, only 21% of the movers answered that they moved for reasons related to their children. Among those 21% who moved due to their child, only 37% answered that they knew about the accessibility or quality of child-care facilities around their new residential area. For the rest, who moved due to other reasons, 25% answered that they had information about child-care facilities. While the data on moving is only available for these two years (1993 and 1997), this exclusion restriction is plausible in Japan at least until 2008, the last period currently available in the JPSC data. In fact, the child-care shortage had not been widely covered by media until 2011, and many of the mothers reported that they did not expect to have difficulty in accessing child-care services until they actively sought them.

Second, I argue that moving costs are high for married women with a small child. Even when they face a shortage of child-care services, that shortage does not seem to provide mothers with the incentive to move to a place with better accessibility over leaving the labor force. Such a claim is convincing given that the proportion of women living in owned homes among married women is relatively high. Within my sample observations, 86% of married women live in owned homes at the time of the survey. Given that owning a house makes moving substantially more costly, the low percentage of moves for child-related reasons may seem to be reasonable even amidst a child-care shortage, given the high percentage of homeowners. Thus, young women with a child are rarely observed relocating between cities based on child-care accessibility. Asai et al. (2015) also discuss that mothers with a small child rarely relocate themselves in Japan.

Assuming that most women were unaware of the extent of the local child-care shortage and that they do not relocate, I argue that the recent shortage of child-care exogenously affects the labor force participation of women at child-birth. In Section 5, I will further discuss how I use this exogenous variation in the labor force participation of young women in order to estimate statistical discrimination.

4 Conceptual Framework

This section provides a conceptual framework to illustrate how average quit rates affect equilibrium wages using a simple model of employer learning and statistical discrimination. Presenting the conceptual framework provides us with a theoretical rationale behind the relationship of interest to guide the interpretation of regression results. The framework also helps justify empirical specifications.

I apply the employer learning model of Farber and Gibbons (1996) to study statistical discrimination. This model was first theoretically examined in Barron et al. (1993) in the context of the U.S labor market and later empirically analyzed by Gayle and Golan (2012). The key assumptions of my model are that replacing workers is costly and that employers do not directly observe individual workers' labor force intentions, but do gradually learn about the individual's true intentions to remain at the firm (employer learning). The model implies that an individual belonging to an identifiable group has a wage offer that is influenced by the average job turnover rate of their group (statistical discrimination).

4.1 A Model of Employer Learning, Labor Force Attachment, and Statistical Discrimination

The model setup is as follows. The labor market is competitive with identical firms that compete for workers with heterogeneous labor force intentions in terms of remaining with the same firm unobservable to the employers. There is a continuum of male workers, denoted as m, and female workers, denoted as f, with a size of one, respectively. Workers live for T periods, and identical firms live infinitely. The firms maximize profits and the workers maximize their discounted lifetime labor income.

The log of the quantity of output produced by worker i with t_i years of experience is denoted as $y_{it}(X)$, where X is a vector of determinants of the quantity of output. A fixed hiring cost γ occurs when a firm replaces a worker who has left the firm. Assume that firms must immediately fill a job vacancy. Hiring costs can be interpreted as mobility costs, such as replacement costs, including recruitment, training, start-up, administrative costs, and loss in revenue.[19]

Each period, workers choose whether to remain in the labor force or stay at home. Assume that nobody changes firms. Thus, staying in the labor force is equivalent to remaining in the same firm. Denote $d_t = 1$ if a worker remains in the same firm and $d_t = 0$ otherwise. A worker is born with time-invariant labor force intentions with respect to continuing working. Labor force intentions can be interpreted as the ex-anti probability of leaving the labor force. That is, workers

[19]The examples of replacements are given here based on the eligible expenses for a company to claim business overhead expense (BOE) disability insurance.

have different outside options and draw shocks to the outside options every period. If the shock is high enough that the value of realized outside options exceeds the wage at the labor market, the worker decides to stay at home.

As in the employer learning model of Farber and Gibbons (1996), employers update their beliefs about workers' productivity based on observation over time. Unlike the preceding employer learning models, in my model, labor force intentions also affect the expected productivity of each worker due to the presence of a hiring cost. The additional key assumption here is that employers do not observe individual workers' labor force intentions but know the quitting probability of workers as a group defined by an observable characteristic. Employers are rational and form beliefs about workers' labor force intentions by calculating the probability that a worker with gender j and characteristics X will remain in the firm in period t. Denote the employers' belief by $\mu_{it}^{j}(X)$.

In every period, the following process repeats:

1. At the beginning of each period, employers update their beliefs based on workers' observable characteristics and offer each worker wages.

2. The workers, knowing their own quitting probability in future periods, decide whether to work or leave the labor force.

3. Production occurs and the agents consume.

From a firm's perspective, workers with characteristics X can be decomposed into newly-hired workers this period and workers who stay in the firm from the previous period. I call them "new" and "old" workers, hereafter.

The dynamic problem is solved backwards as follows: in the last period, a newly-hired worker brings a value of

$$V_T^{new} = -\gamma + y_{iT}(X) - w_{iT}(X)$$

while an old worker brings a value of

$$V_T^{old} = y_{iT}(X) - w_{iT}(X).$$

In a competitive market, the wage in the last period is derived by setting the potential employer's expected profit from a worker equal to zero for all workers:

$$w_{iT}(X) = -\gamma + y_{iT}(X)$$

Thus, the firm's profit from a new worker is zero, but due to the hiring costs, the current employers earn a rent of γ in each period when workers remain in the firm. Similarly, the profit-zero condition in the second to last period is derived by setting the potential employer's expected profit equal to zero:

$$V^{new}_{T-1}(X) = -\gamma + y_{iT-1}(X) - w_{iT-1}(X) + \beta \mu^j_{iT}(X) V^{old}_T(X) = 0$$

where $\mu^j_{iT}(X)$ is the probability that the worker with gender j and characteristics X will remain in the firm in period T calculated by the employer. The second to last period's salary is thus:

$$w_{iT-1}(X) = -\gamma + y_{iT-1}(X) + \beta \mu^j_{iT}(X) V^{old}_T(X).$$

By induction, the competitive equilibrium wage at period t is written as:

$$w_{it}(X) = -\gamma + y_{it}(X) + \beta \mu^j_{it+1}(X) V^{old}_{t+1}(X), \tag{1}$$

where the per-period net surplus that an old worker generates is γ. For presentation purposes, the above wage equation (1) can be reduced and approximated by the following equation:

$$w_{it}(X) = -\gamma + y_{it}(X) + \mu^j_{it+1}(X)\Phi. \tag{2}$$

where $\Phi \equiv \beta V^{old}_{t+1}(X)$. A modified version of Equation (2) will be estimated in the empirical section below.

In the model with full information, where employers directly observe each individual worker's labor force intentions, the employer's belief is equal to each individual's probability of staying with the firm, denoted as p_{it}. In the model with imperfect information, the employer's belief is calculated as the average probability of staying with the firm over workers with the same gender (j) and the same observable characteristics (X), denoted as $\bar{p}^j_t(X)$.

Suppose the employer's belief about an individual worker's probability of staying is a weighted linear function of the actual individual probability and the average probability: i.e.

$$\mu^j_{it}(X) = (1 - \theta_t)\bar{p}^j_t(X) + \theta_t p_{it} \tag{3}$$

where θ_t is bounded between 0 and 1, and captures how much the firm knows about individual workers' labor force intention at time t.

Thus, equilibrium wages can be expressed as a function of the weighted average of overall labor force attachment (captured by $\bar{p}^j_t(X)$) and individual labor force attachment (captured by p_{it}) as follows:

$$w_{it} = -\gamma + y_{it}(X) + \Big((1-\theta_t)\bar{p}_t^j(X) + \theta_t p_{it}\Big)\Phi. \tag{4}$$

I will estimate the empirical analogue to this equation in the estimation section.

5 Empirical Specification

5.1 Identification

I estimate the empirical analogue to the theoretical relationship presented in Equation (4) in Section 4. As in Altonji and Pierret (2001), assume that θ_t is 0 when hiring because employers are assumed to know nothing about differences in individuals' employer-employee attachment conditional on observable characteristics (X).

The conditional expectation function of log wage at time t is:

$$E(\ln w_{it}|\bar{p}_t^j, p_{it}, X_{it}) = b_{st}\bar{p}_t^j + b_{zt}p_{it} + \mathbf{X}_{it}' b_X. \tag{5}$$

Given that the wage evolves as employers learn, the coefficients of average quit rates and of individual quit rates (b_{st} and b_{zt}) change over time. According to Equation (3), such changes can be expressed as:

$$b_{st} = (1-\theta_t)\Phi_\mu$$

$$b_{zt} = \theta_t\Phi_\mu,$$

where Φ_μ is a vector of the coefficients of the regression of log wage on the quit rates in Equation (2).

If statistical discrimination exists to a non-negligible extent, the coefficient b_{st} diminishes as the worker stays in the labor market longer while the coefficient b_{zt} grows. Such a test reflects their hypothesis that under statistical discrimination, the signaling effect decreases and workers' true productivity is more reflected in earnings as employers learn. I summarize this testable implication in the following proposition:

Proposition 1.

Under the assumptions of the model, the estimate of coefficient b_{st} in Equation (5) is non-decreasing in t and that of the regression coefficient b_{zt} is non-increasing in t.

5.2 Estimation

As in Altonji and Pierret (2001), I identify statistical discrimination by examining the way in which employers' prior beliefs are correlated with observed quit rates (the average quit rates in this study) over time.[20] I will estimate these two coefficients of interest. To estimate statistical discrimination, I estimate Equation (5).

I estimate the wage function for gender j as follows:

$$\ln w_{it} \quad = \quad b_0 + b_{st}\bar{p}_t + b_{zt}p_{it} + \mathbf{X}'_{\mathbf{it}}b_X + \nu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

where ν_i is the time-invariant individual fixed effect, λ_t is time-fixed effect that captures changes in the economic climate, and ε_{it} is normally-distributed measurement error. The estimates of interest are the coefficients for the terms that contain average quit rates $\bar{p}_t$ and individual quit rates p_{it}. I define the productivity determinants as $X_{it} = (\text{hours}_{it}, \text{hours}^2_{it}, \text{age}_{it}, \text{age}^2_{it}, \text{age}_{it} \times \text{edu}_i, \text{married}_{it}, \text{number of young kids}_{it})$. Such specification of the production function follows the empirical literature [e.g. Eckstein and Wolpin (1989); Altug and Miller (1998); Gayle and Golan (2012)].

5.3 Instruments

As discussed earlier, naive regression analysis using OLS can result in biased estimates of the parameters in Equation (5) due to endogeneity issues. To identify the causal effect of statistical discrimination, I use variation in the accessibility of accredited child-care as an instrumental variable for women's quit rates.[21]

For the instrument to be valid, both the non-weak correlation and exclusion restrictions must be satisfied. I argue that the first condition is satisfied by showing that our instrument is non-weakly correlated with the effect of interest (labor force intentions). In particular, I present evidence that labor force participation is correlated with the accessibility of public child-care in Table 1.

Table 1 reports OLS estimation results and the F-statistics that show correlation between child-care access and women's labor force participation probability. Columns (1) and (2) use the sample of married women who have a child between zero and two years old. The standard errors reported

[20] In this study, the variable observed by employers, which corresponds to the way Altonji and Pierret (2001) used schooling or race in their study, is the average quit rate of each gender; the variable unobserved by employers, which corresponds to the AFQT test or father's education is the individual quit rate. I first estimate the average quit rates and the individual quitting probabilities directly from the data. The average quit rate is calculated conditional on gender, age, education, occupation, and work history. For details on the actual derivation of the quit rates, see the appendix.

[21] Although data on child-care expenses and usage for each household are available in JPSC data, I only observe accepted prices of child care, which would bias estimation results. Instead of the actual expenses, therefore, I utilize a variation in the availability and costs of public child care across municipalities.

in Column (2) are clustered by prefecture level. A child-care access (CCA) index is constructed as the number of children who are in child-care divided by the total number of children whose age falls in the category eligible for child-care. All the F-statistics in the first stage of the IV exceed the Stock and Yogo (2005) 10% critical value. The coefficient on the interaction term shows that women who do not live with a parent are 59% more likely to participate in the labor force when the child-care access index is higher by one. The results are robust when logit regression is used, and when the sample is expanded to married women with a child aged zero to five. Such correlation between child-care access and labor force participation is not surprising given that more than 80% of households with a child younger than three in urban areas are nuclear families,[22] which need child-care service if both parents work. Up to one year of child-care leave is available to parents.[23] While grandparents can provide child care, grandparents serve as a main caregiver to only 8 to 10% of children aged 1 to 2 (Source: Longitudinal Survey of Newborns in the 21st Century 2002-2003).

Second, I argue that the second condition necessary for a valid IV method, the exclusion restriction, is thought to be plausible in Japan. The exclusion restriction is satisfied when the instrument (child-care accessibility) does not affect women's compensation through any channel other than women's average quit rates. The major concerns about the validity of the exclusion restriction are that child-care accessibility in a particular residential area may affect women's residential choice. However, as discussed in Section 3, very few women move due to child-care accessibility. This is demonstrated by two survey questions in the JPSC data: First, women were not aware of the local child-care shortage at the time they choose their residential area. Second, even after they become aware of it, they do not move to seek better child-care accessibility.

Based on this analyses, I assume that these two conditions for the IV method hold and that the IV method is therefore valid for identifying the degree of statistical discrimination. In particular, I utilize the fact that the accessibility of accredited child-care, as measured by the degree of rationing, varies greatly across municipalities in order to estimate the effect of women's average quit rate on their earnings.

[22]Data Source: Longitudinal Survey of Newborns in the 21st Century 2001-2003

[23]An extension is possible for up to additional six more months.

Table 1: The First Stage Parameter Estimates

Dependent Variable	LFP	LFP	LFP	LFP
Sample: Married women	w/ 0–2 yrs old		w/ 0–5 yrs old	
	(1)	(2)	(3)	(4)
Child-care access (CCA)	-1.13***	-1.13	-0.55*	-0.55
	(0.41)	(0.70)	(0.33)	(0.50)
CCA × living w/o a parent	0.59***	0.59**	0.43***	0.43*
	(0.17)	(0.25)	(0.13)	(0.25)
High school grad	0.04**	0.04	0.04***	0.04
	(0.02)	(0.04)	(0.01)	(0.04)
2 yr college	0.07***	0.07**	0.03**	0.03
	(0.02)	(0.03)	(0.01)	(0.03)
4 yr college	0.11***	0.11***	0.08***	0.08*
	(0.02)	(0.04)	(0.02)	(0.04)
Age 30–34	0.01	0.01	-0.00	-0.00
	(0.02)	(0.02)	(0.01)	(0.02)
Age 35+	0.01	0.01	0.00	0.00
	(0.02)	(0.04)	(0.02)	(0.03)
Living with a parent(s)	0.21***	0.21***	0.19***	0.19***
	(0.04)	(0.05)	(0.03)	(0.06)
Husband's income	-0.17***	-0.17***	-0.18***	-0.18***
	(0.03)	(0.05)	(0.02)	(0.04)
Mother's work years	0.05***	0.05**	0.06***	0.06***
	(0.02)	(0.02)	(0.01)	(0.02)
Unemployment rate	0.03	0.03	0.02	0.02
	(0.02)	(0.03)	(0.02)	(0.03)
Number of children 0 yrs old	-0.01	-0.01	-0.04	-0.04
	(0.06)	(0.04)	(0.04)	(0.04)
Number of children 1–2 yrs old	0.05	0.05	0.02	0.02
	(0.06)	(0.03)	(0.04)	(0.04)
Number of children 3–5 yrs old	0.12**	0.12***	0.14***	0.14***
	(0.05)	(0.03)	(0.04)	(0.04)
Number of children 6–12 yrs old	0.16***	0.16***	0.18***	0.18***
	(0.05)	(0.03)	(0.04)	(0.04)
Number of children 13–18 yrs old	0.12*	0.12**	0.18***	0.18***
	(0.06)	(0.06)	(0.04)	(0.05)
Number of children living together	-0.12**	-0.12***	-0.15***	-0.15***
	(0.05)	(0.03)	(0.04)	(0.03)
Observations	4,286	4,286	7,364	7,364
R-squared	0.13	0.13	0.14	0.14
S.E. Clustered by Prefecture	No	Yes	No	Yes
F statistics for weak identification	17.8	13.7	51.8	35.2

Sample: JPSC 1993–2008. Married women aged 24 to 49 with small children.
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1. The sample includes married women with a child younger than two for (1) and (2), and those with a child younger than five for (3) and (4). Each regression also includes year dummies and prefecture dummies.

6 Results

6.1 Stylized Facts

I present the main estimation results with and without instruments. As a baseline, I first estimate the naive OLS specification for the effect of statistical discrimination on the wage gap. Table 1 reports the coefficient estimates from the OLS specification with individual fixed effects in Columns (1) and (2) and without fixed effects in Columns (3) and (4).

The coefficient estimate on wages presented in Column (1) indicates that increases in the average quit rates are associated with a decrease in wages. In particular, the regression results tell us that workers whose average quit rate is higher by 10 percentage points receive wages 6.03 percentage points lower, on average, at their time of hire (with zero job tenure), but the correlation between average quit rates and wages diminishes as job tenure grows. In fact, with ten years of job tenure, workers with average quit rates 10 percentage points higher receive wages only 2.29 (= 6.03 - 3.74) percentage points lower. However, the coefficient of the interaction term between individual quit rates and job tenure is negative, which implies that individual quit rates are correlated with wages more strongly as tenure increases.

Similar analysis is conducted in Column (2) by adding the occupation dummies into the regression. The occupation dummies allow us to take into consideration whether the gender wage gap is driven by occupational differences. While occupation choices are not studied as outcome variables in this paper, occupation enters the regression model as an important control in estimation. The regression results presented in Column (2) are similar to those in Column (1) except that the coefficient of the interaction term on individual quit rates and tenure years becomes insignificant. Thus, the results indicate that, compared to (1), changes in individual quit rates over time have weaker power in predicting the observed wage differences. Such a change makes sense given that individual quit rates are negatively correlated with the newly added dummy of occupation choice, which can account for wage differences better than individual quit rates.

However, without individual-fixed effects, the estimated coefficient on individual quit rates is significant, regardless of the model specification. Two of the main results are presented in Columns (3) and (4). The finding that individual quit rates affect wages significantly without fixed-effects but insignificantly with fixed-effects implies that individual labor force attachment affects wages, but that labor force intentions do not vary over time (i.e. the wage effects of individual quit rates are not ignorable, but are absorbed in the time-invariant fixed terms in a fixed effects model). Note that I find that a 1 percentage point reduction in the average quit rate increases monthly wage by 0.83 to 1.13 percentage points with a zero-job tenure year, but the effect diminishes over tenure.

Throughout the OLS model analysis presented in Table 2, the negative correlation between the average quit rate and wage is found to gradually diminish as tenure grows. This finding is consistent with the hypothesis that statistical discrimination exists for young age cohorts but diminishes for older cohorts in Japan. In other words, we find data features that are consistent with the hypothesis of statistical discrimination presented as Proposition 1.

Table 2: OLS Results: Wage Function

	Dependent var.: Log monthly wage			
Variables	(1)	(2)	(3)	(4)
Avg. quit	-0.60***	-0.60***	-1.13***	-0.83***
	(0.14)	(0.14)	(0.20)	(0.20)
Avg. quit × job tenure	0.04***	0.04***	0.02*	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Individual quit	0.14	0.13	1.9***	1.9***
	(0.26)	(0.25)	(0.38)	(0.37)
Individual quit ×job tenure	-0.53*	-0.47	-2.9***	-2.7***
	(0.30)	(0.29)	(0.38)	(0.37)
Never changed a firm (dummy)	0.03	0.03	0.01	0.05***
	(0.02)	(0.02)	(0.02)	(0.02)
Hours worked	0.009***	0.009***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
(Hours worked)^2	-4.6e-05***	-4.4e-05**	-0.0002***	-0.0002***
	(0.00)	(0.00)	(0.00)	(0.00)
Career course		0.10***		0.19***
		(0.03)		(0.03)
Career course × female		0.02***		0.015***
		(0.00)		(0.00)
Observations	4639	4639	4639	4639
R-squared	0.26	0.27	0.42	0.45
Number of id	841	841		
Individual fixed-effects	Yes	Yes	No	No

Note 1) Standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1.
Note 2) Each regression also includes dummies for occupation, education, age, firm size, family type (co-residence with a woman's parent or her parent-in-law), the number of children, and type of firms.

6.2 Instrumental Variables Method

To address the endogeneity biases, in addition to the Altonji and Pierret (2001) identification strategy, I estimate the effect of the average quit rate on female workers' earnings using the Heckman two-step method (Heckman (1979)). To identify the effect of the average quit rates on wages, I instrument the average quit rates by the child-care accessibility across different residential area.[24] In the first stage, I include the child-care shortage, prefecture dummies, and the same controls used in Table 1. Under the assumption that the child-care shortage only affects wage payment through women's job-quitting rate, child-care accessibility serves as an instrument for women's labor force participation and thus addresses the endogeneity problem. The estimates from the second stage are presented in Table 3.

In my preferred specification, selection bias in the wage equation is corrected by the Heckman two step method with average quit rates instrumented for by child-care accessibility in one's residential prefecture. Details of the estimation method are presented in the Appendix. Using child-care accessibility as an instrument for labor force participation, I estimate the effects of statistical discrimination on wage. The key assumption is that child-care accessibility only affects wage compensation through its effect on the average quit rates. Table 3 presents the regression results. Columns (5) and (6) present the results when all the samples are used. The regression analysis using the Heckman method shows similar results to the OLS analysis. I find that a 1 percentage point reduction in the average quit rate increases monthly wages by 0.81 to 1.09 percentage points, but that the effect diminishes over tenure (the coefficient on the interaction term of the average quit rate and job tenure is positive). Again, we find that individual quit probabilities adversely affect earnings and their impact grows with tenure, regardless of the model's specification. These results are consistent with Proposition 1: the estimates of b_{st} (the coefficient of the average quit rates) is non-decreasing in job tenure and the estimate of regression coefficient b_{zt} (the coefficient of individual quit rates) is non-increasing in job tenure.

The results from Heckman's correction model are comparable to the OLS results presented in Table 2. The estimated wage effects of the average quit rates (-0.81 and -1.09) are smaller (the magnitude is smaller) than the OLS estimates (-0.83 and -1.13). This comparison indicates that the OLS estimates are downward-biased, which is consistent with the criticism in the literature that OLS estimators often over-estimate the effect of statistical discrimination.

The wage effects of average quit rates are thought to be significant in explaining the gender wage gap given that the average quit rate of women (aged 24 to 29 with a four year college degree who work in the first firm in a career-oriented course) is 18.6% while that of corresponding men is only 1.4%.[25] The estimation results imply that women's wages would increase by roughly 14 to 19% for women whose employer-employee attachment is as strong as that of corresponding men. A 15% increase in these women's wages reduces the gender wage gap from 17% to 5%, after controling differences in worker attributes.[26]

[24] There is significant variation in child-care accessibility across prefecture as shown in Table 6 in the Appendix.

[25] Calculated from JPSC data. See Table 7 in the Appendix for the details of the statistics.

[26] The number is calculated from the JPSC data (17%=(2,761 - 2,279) / 2,761).

Such results support the hypothesis that statistical discrimination against weak labor force attachment exists and results in lower wages for young female workers. Thus, the data features are consistent with the model of statistical discrimination where employers use the average quit rates (the observed traits that are correlated with the actual workers' quit rates) at the beginning of hire, but update their belief as they observe an individual's labor force intentions over time.

Next, I estimate the model for two different age cohorts: those who are 35 or younger and those who are older than 35. The results are shown in Columns (7) and (8) of Table 3. The groups are divided at age 35 because, generally speaking, fertility rates drop suddenly around this age. Since child-birth is the main reason that young female workers leave the labor force, one can expect significant structural changes in the female labor market, including employers' perception toward women's labor force attachment, at this age. By estimating age groups separately, I allow for different coefficients based on worker age in the wage regression. I do not use a finer stratification for age group since the sample size would become untenably small.[27] The average quit rate significantly affects wages for workers younger than age 35, and its effects diminish as workers' tenure grows for both age groups. The rate at which it diminishes is larger for the younger group.

[27] I also estimate the model using all age groups with all controls interacting with age group, but found similar results.

Table 3: IV Results (Stage 2) : Wage Regressions

Dependent Var.: Log monthly wage				
Variables	(5)	(6)	(7)	(8)
Sample	All	All	Age $\leq$ 35	Age $>$ 35
Avg. quit	-1.09***	-0.81***	-0.65***	-1.33***
	(0.20)	(0.20)	(0.21)	(0.50)
Avg. quit × tenure	0.02*	0.03***	0.08***	0.01
	(0.01)	(0.01)	(0.02)	(0.02)
Individual quit	1.8***	1.8***	0.94**	3.62***
	(0.38)	(0.37)	(0.41)	(0.70)
Individual quit ×tenure	-2.8***	-2.7***	-1.41***	-4.93***
	(0.38)	(0.37)	(0.39)	(0.76)
Never changed firm	0.01	0.05***	0.05**	0.04
	(0.02)	(0.02)	(0.02)	(0.06)
Hours worked	0.03***	0.03***	0.02***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
(Hours worked)^2	-0.0002***	-0.0002***	-0.0002***	-0.0003***
	(0.00)	(0.00)	(0.00)	(0.00)
Career course		0.18***	0.19***	0.22***
		(0.03)	(0.03)	(0.06)
Career course × female		0.02***	0.02***	0.01**
		(0.00)	(0.01)	(0.01)
No. Observation	26,037	26,037	15,978	10,059

Note 1) Standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1.
Note 2) Each regression also includes dummies for occupation, education, age, firm size, family type (co-residence with a woman's parent or her parent-in-law), the number of children, and type of firms.

6.3 Robustness Check

Since I implement the estimation using regression analysis, I paid careful attention to a non-linear relationship in the wage equation, and conducted various sets of regression analyses with and without quadratic terms, cubic terms, and interaction terms. I found in each case that the sign of the regression coefficients of interest are the same as the main results presented above. I also used a different cut-off for the age grouping, such as age 40, but consistently found a strong effect of statistical discrimination for the younger cohort and an insignificant effect for the older cohort.

I have also conducted the same set of analyses with sampling weights constructed from Census data. The regression results are similar to those obtained without sampling weights, regardless of how the sampling weights were constructed.

Last, I address the issue of measurement error. Both the average quit rates and individual quit rates, the key variables used in the analysis, are estimated from the data. (See the Appendix for details of calculation.) Instead of using these variables, I use the gender dummy, as observable traits and individual labor force intentions as unobservable traits, in order to estimate the model of statistical discrimination. The dummy for gender in the regression now captures how employers update their beliefs toward women's labor force attachment as tenure grows; it enters the regression equation along with its interaction term with years of job tenure. Individual labor force intentions are constructed from the survey answers collected in the raw JPSC data. I assign one to workers who answered that they plan to leave the labor force or switch to part-time after childbirth, and zero to those who answered they plan to continue to work full-time. Thus, I use the female dummy instead of the average quit rates, and the dummy for weak labor force attachment instead of the predicted value of individual quit rates.

The spirit of the estimation strategy is the same as before. Table 4 presents the regression results. As before, Columns (9) and (10) use all workers in the sample. Column (11) uses only younger workers and (12) uses only older workers. While the effects of individual labor force intentions on wages become insignificant in some specifications, the female dummy affects wages negatively and its adverse effects diminish over time (for model specifications (9) through (11)). If we assume that returns to tenure are not significantly different between male and female workers, conditional on their work history and occupation, then the diminishing wage gap between the genders over time is difficult to explain. One rationale is statistical discrimination against young female workers due to their high quitting probability. In fact, if the sample is restricted to workers age 35 or younger, the extent of statistical discrimination is found to be larger and more statistically significant. In contrast, for workers older than age 35 the effect of statistical discrimination is found to be insignificant. The signs on the coefficients do not support the presence of statistical discrimination for these older workers.

Table 4: Wage Regressions

Dependent variable: Log monthly wage

Variables	(9)	(10)	(11)	(12)
Sample	All	All	Age $\leq$ 35	Age $>$ 35
Female	-0.26***	-0.26***	-0.33***	0.20***
	(0.03)	(0.03)	(0.04)	(0.06)
Female $\times$ tenure	0.01***	0.01***	0.01*	-0.02***
	(0.002)	(0.002)	(0.00)	(0.00)
Labor force intention	0.01	-0.01	0.05*	-0.37***
	(0.02)	(0.02)	(0.03)	(0.08)
Labor force intention$\times$tenure	-0.007**	-0.001	-0.01	0.02***
	(0.002)	(0.002)	(0.00)	(0.01)
Never changed firm	0.06***	0.05***	0.03*	0.07***
	(0.01)	(0.02)	(0.02)	(0.01)
Hours worked	0.01***	0.01***	0.07***	0.06
	(0.0003)	(0.0003)	(0.02)	(0.04)
(Hours worked)^2	-1.56e-05***	-1.84e-05***	0.01***	0.00***
	(4.16e-06)	(4.16e-06)	(0.00)	(0.00)
Married $\times$ female	-0.07***	0.00**	-0.02	-0.20***
	(0.01)	(0.00)	(0.02)	(0.04)
Career course		0.17***	0.12***	-0.14
		(0.03)	(0.04)	(0.12)
Career course $\times$ female		0.01	0.02***	0.01
		(0.00)	(0.01)	(0.01)
	28,268	28,045	16,107	16,107

Note 1) Standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1.
Note 2) Each regression also includes dummies for occupation, education, age, firm size, family type (co-residence with a woman's parent or her parent-in-law), the number of children, and type of firms.

Throughout a set of regression analyses, I controlled for possible changes in productivity by including dummy variables for events that trigger productivity changes (i.e. child-care leave, layoff). The coefficients on the productivity determinant variables are allowed to vary with employment spell and residence in an urban area.

Regardless of model specification, I found that an interaction term of the average quit rates (or gender) and tenure is negative in the wage regressions and that the effect of the average quit rates on wage becomes smaller as workers stay in the firm longer. In contrast, individual quit rates (or workers' labor force intentions) affect wages more adversely as job tenure grows. Since the fixed-effects analysis controls for unobserved differences in workers' productivity, this decrease in the gender wage gap over the lifecycle is puzzling. One rationale is that firms delay investing in female workers until these workers are old enough that pregnancy is unlikely. Over this period, the employer learns about the individual worker's labor force intentions and reevaluates, or alternatively, quit rates drop as pregnancy rates decline with age and so makes theses women statistically less likely to quit. Firms do not have to wait to invest in male workers because men's career orientation varies radically less than that of women.

There are other ways to interpret the regression results. One explanation is that the returns to training change over time between gender. However, the possibility of time-variant returns to training is hard to test empirically, as Altonji and Pierret (2001) points out. Separating the effect of returns to training is out of the scope of this paper.

The findings that a significant portion of wage gaps can be attributed to employer-employee attachment reinforces the importance of job tenure and labor market experiment as wage determinants. Such an implication is consistent with the findings in the literature that gender wage gaps are less pronounced among continuously employed workers than among the full sample in the U.S. labor market [e.g. Light and Ureta (1990) and Gayle and Golan (2012)].

6.4 Discussion: Other Endogeneity Issues

In the model, individuals' intentions to quit, hours worked, and fertility decisions are taken as exogenous. Indeed, these outcomes may be affected by more limited opportunities in the labor market. However, I take all these outcomes as exogenous mainly because these outcome variables are thought to be less sensitive to changes in work place opportunities in the short term in the context of the Japanese labor market. Especially in this analysis, the change in labor market opportunities is driven by the extent of child-care shortages, which are assumed to be unexpected by female workers. In such a situation, worker's decisions, such as intention to continue to work, may not change much if workers make decisions in a dynamic framework insofaras current and future decisions depend on the series of past decisions that have influenced the current state. For example, human capital accumulation takes place over more than a decade of schooling, and women form a plan for career, marriage, and childbearing accordingly.

Hours worked are also taken as exogenous in this paper. I focus on full-time workers, most of whom are required to work at least 40 hours per week. While hours worked, or the intensive margin of labor supply, would illuminate some aspects of the story regarding discrimination effects, I find that the relationship between hours worked and other labor market variables in my data is too complex to impose a convincing model assumption. For example, I do not see the systematic relationship between hours worked and labor force intentions or actual quit rates, even when I look at over-time work hours with pay and without pay separately. Similarly, I did not find any correlation between hours worked and hourly wages for full-time workers. Therefore, throughout the analysis, I assume that female workers are not allowed to freely choose hours worked.

Among the outcomes that change very slowly in Japan is occupation choice. First, I emphasize that changing a firm—let alone an occupation—does not necessarily benefit a worker's career in Japan, at least during the period of this study, from 1993 to 2008. In fact, switching firms rarely happens for female full-time workers in Japan. While labor mobility has increased over the past two decades, the majority of people stay in the same firm to climb up the career ladder. Career advancement in Japan overwhelmingly happens within one's company in the form of promotion and wage raises according to a seniority-based payment system. Changing one's type of task (or occupation) within a firm is a theoretically possible option, but is practically-speaking a very rare event.

I also ignore the short-term discrimination effects on marriage and fertility choices and take these decisions as exogenously given. While these are likely endogenous decisions that are affected by labor market discrimination, I do not evaluate them because the adjustment takes a longer time and the treatment effects kick in with significant lags. Compared to preferences towards work life, women's preferences towards family life have little heterogeneity in Japan; in the JPSC data, 87% of never-married women at age 25 answered that they want to get married some day while 10% answered they do not necessarily want to get married, and only 3% answered they do not want to get married. Conditional on wanting to get married, 90% of women at age 25 answered their desired age of marriage is 30 or younger and 98% answered 35 or younger.[28] Within my data set, preferences towards marriage and childbearing are consistent over time. Marriage and fertility could go out of control; factors other than labor market opportunities often affect these choices. Notably, more than 25% of couples have already had a child or conceived a child when they got married (i.e. shotgun marriage) in Japan (Source: Specified Report of Vital Statistics by the Ministry of Labour, Health and Welfare, 2005, 2010). These stylized facts cast doubt on the idea that women's fertility responds to discrimination in a timely manner during the 16 years of my data set.

In addition to the issues above, some may argue that endogeneity arises because of the causal relationship between average quit rates and individual quit rates. Indeed, if there is any significant causal relationship between control variables, this will bias estimated coefficients; this concern is commonly known as the problem of "bad controls" (Angrist and Pischke (2008)). However, I rely on the assumptions posed in the model presented in Subsection 4; I assume that the labor market is competitive and, thus, each individual's labor supply decision has no impact on the average statistics. Also, the model specifies that all individuals make decisions simultaneously without interaction. Under these assumptions, I presume that individuals' labor force intentions do not directly affect average quit rates and that average quit rates only affect individual labor force intentions through their effect on wage rates.

[28] In calculating these statistics, I ignore the small fraction (0.19% of the whole population) who have divorced in the JPSC data.

7 Conclusion

This paper has used the employer learning and statistical discrimination model and the variation in child-care accessibility to estimate statistical discrimination against young female workers in the Japanese labor market. Utilizing a unique feature of the Japanese panel data, I quantify the wage effects of a textbook case of statistical discrimination, where employers, who cannot directly observe individual productivity, could give a female employee a lower wage than a male employee with the same potential productivity because higher turnover rates among women make them less profitable hires. Owing to the inability of employers to distinguish individual worker characteristics, productive inefficiency arises when all women receive the same amount of wage compensation, despite the fact that women with weaker labor market attachments are potentially less productive than other women. I find that a 10 percentage point decrease in the average quit rates of young female workers increases their wages by 0.8 to 1.1 percentage points, but that these effects diminish as job tenure increases. In contrast, individual quit rates less-adversely affect wages at the beginning of employment. This finding is consistent with the hypothesis that statistical discrimination exists. That is, employers cannot directly observe individual labor force intentions, but they can learn, gradually. As a result, wages become more dependent on the actual productivity of the individual (i.e. labor force intention) and less dependent on easily-observed worker traits (i.e. the average labor force intentions of the corresponding gender group). I find that such statistical discrimination exists and is especially serious for young age cohorts (those at age 24 to 29) but that it diminishes for older cohorts in Japan.

I overcome difficult identification issues by applying the methodology developed by Farber and Gibbons (1996) and Altonji and Pierret (2001) in order to address overestimation of discrimination. The idea behind this method is that, assuming that employers can observe individual workers' performance over time, statistical discrimination can be detected by examining the diminishing returns of group characteristics and the increasing returns of individual characteristics on wage compensation over time. While some of the assumptions made by Altonji and Pierret (2001) are considered too strong, the assumptions made in this paper about employers' missing knowledge are more reasonable. In applying their testing method, I use labor force intentions as the variable that is revealed to employers only gradually.

Several limitations to this paper also need to be acknowledged. First, this paper ignores changes in taste-based discrimination and productivity differences between genders as tenure grows. Indeed, the identification still relies on the relatively strong assumption that the gender gap in taste-based discrimination and productivity, unobserved in my data set, remains the same over time. However, there is no theoretical or empirical evidence to suggest that gender productivity differences, such as physical and/or intellectual ability, have changed over the study period, so the principle finding—the importance of statistical discrimination—remains valid.

Another issue that was not addressed in this paper is the potential underestimation of discrimination, which occurs when the model lacks a self-fulfilling mechanism (Arrow (1973); Coate and Loury (1993)): wages may be correlated with labor force attachment not only because weaker labor force attachment leads to lower payment but also because a lack of opportunity in the labor market discourages workers from staying in the labor market. To address the issues of underestimation, the model would need to incorporate a self-fulfilling mechanism by modeling how workers' types are formulated and evolve as well as how they affect women's choices regarding education, marriage, and labor force participation over time. This is beyond the scope of this paper. Therefore I leave estimation of the equilibrium effects of child care to future/forthcoming work. In fact, much of the empirical literature on statistical discrimination leaves the underestimation issue unresolved, with the exception of Moro (2003) and Gayle and Golan (2012). I do not structurally estimate a model with such a self-fulfilling prophecy, but I informally test whether low payment actually discourages women from continuing to work by examining changes in labor force intentions over time. I find little evidence of discouragement in that sense.

While the empirical implications of this project are specifically tailored to the current Japanese labor market, the type of statistical discrimination studied in this paper can be observed elsewhere. In fact, the statistical discrimination examined in this paper was first theoretically examined in Barron et al. (1993) in the context of the U.S. labor market. Therefore, providing evidence of statistical discrimination in the case of Japan, even though its labor market is distinct, might still serve as an illustrative example of how much of the gender wage gap can be attributed to the oft-cited "glass ceiling" that female workers face around the world. Even for countries whose labor market structure is significantly different from Japan, the Japanese labor market conditions may more closely resemble their historic conditions. For example, as pointed out and studied by Gayle and Golan (2012), a decline in statistical discrimination can partly explain the narrowing gender wage gap observed in North America in past decades. Quantifying statistical discrimination in today's Japan helps us to understand historical macro-trends in the female labor market in the U.S. and in other countries with declining gender wage gaps. Additionally, the framework presented in this paper is general enough to be applied to this specific type of statistical discrimination in other countries. The key requirement for the identification method is information on worker's labor force intentions. In sum, this paper illustrates a way to estimate statistical discrimination, and the findings in this paper shed new light on statistical discrimination as the driving force behind the gender wage gap.

Appendix

Data

The empirical analysis is based on JPSC1993 – 2008. The individuals surveyed in the 1993 – 2008 wave of the JPSC are divided into four cohorts: Cohort A (born from 1958 – 1969), Cohort B (born from 1970 – 1973), Cohort C (born from 1974 – 1979), and Cohort D (born from 1980 – 1984). The cohorts are divided thusly because they entered the sample at a different time using a slightly different sampling design.

My sample universe consists of the first two cohorts (born from 1958 – 1973), whom the survey has asked for information about women's labor force intentions. I exclude those women who have a spell of unemployment longer than a half year.

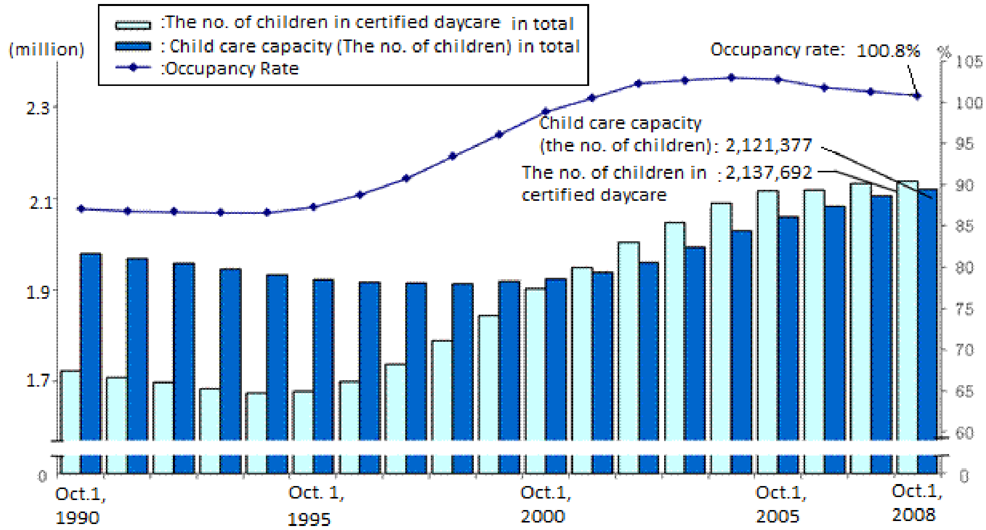
In the following, I present summary statistics to characterize features of my sample universe.

Table 5: Summary Statistics

Female Cohort Born in 1958-1973					
Variable	Observations	Mean	S. D.	Min	Max
% Married	7364	74.7%			
Age	7364	34.6	5.7	24	49
Education (Years)	7364	13.1	1.7	9	16
Work Experience (Years)	7364	10.2	5.8	0.2	34.1
Job Tenure (Years)	7364	5.7	5.3	0	31
Monthly Wage (Thousand Japanese Yen)	7364	220.9	100.7	0	1800
Number of Children	7364	1.4	1.1	0	7
Child-Care access (CCA)	7364	0.20	0.09	0.05	0.55
Education years	7364	13.11	1.65	9	16
Age	7364	31.97	3.76	24	46
Living with a parent(s)	7364	0.32	0.47	0	1
Husband's monthly income	7364	250.57	180.13	0	1500
Unemployment	7364	4.13	1.17	1.7	8.4
Number of children 0 yrs old	7364	0.19	0.39	0	1
Number of children 1–2 yrs old	7364	0.44	0.52	0	2
Number of children 3–5 yrs old	7364	0.73	0.58	0	3

(Source: JPSC 1993–2008; The Institute for Research on Child-Care 1996–2000)
Note 1) The mean of the number of children at age 35 conditional on being married by age 35
Note 2) The numbers in parenthesis are standard deviation

Figure 1: Child Care Shortage



(Data: Annual Report by the Ministry of Health, Labor and Welfare)

Notes: This shortage for affordable child-care is so severe that a number of women have to quit their jobs despite their willingness to continue to work in order to take care of their children. According to the Annual National Survey by the Ministry of Labour, Health and Welfare, 15-20% of women leave the labor market at their first childbirth every year. Conditional on continuing working, 70-83% of women take child-care leave. This proportion has increased over the past decade. Among workers who take child-care leave, more than 97% of those are women. Conditional on taking child-care leave, 8-11% of women do not return to the work place, which is partly attributed to the recent shortage of child-care service.

Table 6: Child-Care accessibility for mothers with 0-year old children

Prefecture	Accessibility (%)	Prefecture	Accessibility (%)
Hokkaido	93.8	Kyoto	92.0
Aomori	95.0	Osaka	83.1
Iwate	96.1	Hyogo	90.4
Miyagi	84.9	Nara	90.9
Akita	93.8	Wakayama	94.4
Yamagata	88.5	Tottori	93.7
Fukushima	93.8	Shimane	90.9
Ibaraki	91.7	Okayama	91.4
Tochigi	91.8	Hiroshima	93.6
Gunma	95.7	Yamaguchi	99.5
Saitama	88.9	Tokushima	91.8
Chiba	95.7	Kagawa	92.7
Tokyo	80.5	Ehime	97.4
Kanagawa	84.8	Kochi	89.6
Niigata	98.4	Fukuoka	92.9
Toyama	98.7	Saga	96.2
Ishikawa	98.7	Nagasaki	92.6
Fukui	95.2	Kumamoto	93.3
Yamanashi	99.5	Oita	91.8
Nagano	99.6	Miyazaki	99.1
Gifu	99.8	Kagoshima	95.5
Shizuoka	92.9	Okinawa	70.5
Aichi	94.7		
Mie	94.8		
Shiga	92.5	Total	92.8

(Source: The Institute for Research on Child-Care 1996–2000)
Note 1) All 47 prefectures are reported.
Note 2) Child-care accessibility is calculated as the ratio of the total number of children in use divided by (the total number of children in use + the number of children on the waiting list)
Note 3) This table is presented to show that there is sufficient variation in child-care accessibility across prefecture.

Average Quit Rates

I choose the variables that the employers use to calculate the average quit rates as whether a worker has a college degree and whether she has ever changed her job. That is, $\Psi =$ (education, work history) where Ψ consists of the variables that affect the average quit rate.

Denote $\bar{q}_{\tau t+1}$ as the average quit rate of worker i in occupation τ for gender j. The average quit rate is calculated directly from the data as follows:

$$\bar{q}^{j}_{\tau t+1}(d_{it-1} = 1; \Psi_{it}) = 1 - \frac{\sum_{i \in \{i_j\}|\Psi_{it}} d_{it} d_{it+1}}{\sum_{i \in \{i_j\}|\Psi_{it}} d_{it}}$$

$$\bar{q}^{j}_{\tau t+1}(d_{it-1} = 0; \Psi_{it}) = 1 - \frac{\sum_{i \in \{i_j\}|\Psi_{it}} (1 - d_{it-1}) d_{it+1}}{\sum_{i \in \{i_j\}|\Psi_{it}} (1 - d_{it-1})}$$

The calculated average quit rate is summarized in Table 7. The sample is divided by gender, occupation, and work history. There is a stark contrast in the average quit rate between male and female workers. Regardless of educational attainment, more than 10% of female workers leave the firm while only 1.4–1.5% of male workers who work in the same firm do so. In both genders, the average quit rates fall as workers age. A remarkable decline is observed over time, especially in the turnover rates of female workers, except for the age range of 42–47, where the sample size is small.

Table 7: The Average Quit Rate

The Average Quit Rate ($\bar{q}^{f}_{i\tau t}(d_{it-1}; \Psi)$): Female Cohort Born in 1959-1973							
		Professional		Non-Professional			
Age	Overall	College		College		Less Than College	
		Never quit	Changed a job	Never quit	Changed a job	Never quit	Changed a job
24–29	36.1%	18.6%	43.0	11.0%	19.4	13.4%	22.0
30–35	39.8	6.4	29.3	5.6	9.1	5.5	14.9
35–41	39.6	3.8	28.1	2.4	10.5	3.5	15.4

The Average Quit Rate ($\bar{q}^{m}_{i\tau t}(d_{it-1}; \Psi)$): Married Male					
Age	Overall	College		LT College	
		Never quit	Changed a job	Never quit	Changed a job
24–29	36.1%	1.4%	–	1.5	14.3
30–35	39.8	0.6	12.9	0.4	7.3
35–41	39.6	0.3	7.6	0.3	3.1

(Source: JPSC 1993–2008)
Note: Blank entries "–" indicate that there are no respondents who quit their job in the category.

Then, the average probability that workers with characteristics Ψ_t and work history $d_{\tau t}$ stay in the occupation τ in the next period $t+1$ is $\bar{p}_{i\tau t+1} = 1 - \bar{q}_{\tau t+1}(d_{it-1}; \Psi_{it})$.

Individual Quit Rates

The probability that worker i will remain in the same firm $p^{j}_{i\tau t}$ is estimated as: $\hat{p}^{j}_{i\tau t} = 1 - \sum_{i\in\{i_j\}} \hat{q}_{i\tau t}$. I estimate individual quit probabilities using the Cox proportional hazard model. Univariate hazard analysis demonstrates a different relative probability of exit rates among workers. The hazard function for the Cox proportional hazard model is written as:

$$\lambda(t|X) = \lambda_0(t)\exp(\Gamma'\mathbf{X})$$

where $\mathbf{X} = (\Phi, \theta)$, and thus the quit rate is calculated based on individual labor force intentions. By maximizing the partial likelihood

$$L(\Gamma) = \Pi_{i:C_i=1}\frac{\mathbf{X}_i}{\sum_{j:Y_j\geq Y_i}\mathbf{X}_j}$$

the estimates for the hazard ratio can be obtained.

The summary statistics of the estimates of the Cox proportional hazard model are presented in Table 8. The first/second columns in Table 8 are the proportion of workers who stay/do not stay in the firm in the next period. Most estimates of the hazard model are not surprising, except for the one for four-year college graduates. The estimation results show that women with four-year college degrees are more likely to leave their firm, even after controlling marital status, husband's income, and the number of children.

Labor force intentions, presented in the third and fourth row of the table, show that those who are planning to leave are 149% more likely to do so. Thus, the information in the JPSC provides a good predictor of individual quitting probabilities, conditional on observables.

Table 8: Individual Labor Force Intention for Married Workers

Variables	Distribution of outcome		Estimates	Distribution of outcome		Estimates
Sample	Age	24–35		Age	36–49	
	Stay ($d_{t+1}=1$)	Leave ($d_{t+1}=0$)		Stay ($d_{t+1}=1$)	Leave ($d_{t+1}=0$)	
Age	–	–	0.69***	–	–	0.44***
Intention						
Plan to stay (ref)	86.9%	13.1	1.00	93.3	6.7	1.00
Plan not to stay	77.3	22.7	2.49***	90.4	9.6	1.69
Education						
LT high school (ref)	76.8	23.2	1.00	88.1	11.9	1.00
High school	78.6	21.4	1.70**	91.0	9.0	3.71*
2 yr college	82.0	18.0	1.34	92.2	7.8	0.69
4 yr college	73.7	26.3	3.51***	97.3	2.7	2.54
Single (ref)	81.7	18.3	1.00	93.0	7.0	1.00
Married	70.0	30.0	1.35	90.0	10.0	0.50
# child	–	–	1.18	–	–	
Occupation						
Non-professional (ref)	93.8	6.2	1.00	92.9	7.1	1.00
Professional	93.7	6.3	1.80**	94.6	5.4	5.84**
History						
Ever quit a job (ref)	81.3	18.7	1.00	85.6	14.4	1.00
Never quit a job	96.2	3.8	0.26*	98.6	1.4	0.21**
Log wage	–	–	0.28***	–	–	0.15**
Husband's income	–	–	1.0003	–	–	1.0002

Note 1) The sample is females aged 24 to 49 who work full-time in JPSC 1993–2008.

How informative the women's labor force intention data are about their actual quitting outcomes is also presented in the next tables. Table 9 presents the estimated hazard ratios conditional on observables Ψ= (age, occupation, work history). We see a variation in quitting probabilities for each group. I then divide the group by the survey data on their labor force intention.

Table 9: Estimated Individual Female Workers' Quitting Probability

Individual Quitting Probability ($\hat{q}_{it}$)

Professional Occupation

	Never quit					Have changed a job				
Age	Sample	Mean	S. D.	Min	Max	Sample	Mean	S. D.	Min	Max
24–29	142	0.01	0.03	2.36E-42	0.16	70	0.04	0.06	4.4E-17	0.16
30–35	109	0.01	0.02	2.02E-31	0.16	112	0.04	0.05	1.3E-35	0.16
35–41	72	0.00008	0.0004	7.91E-13	0.003	64	0.03	0.05	9.1E-48	0.16

Non-Professional Occupation

	Never quit					Have changed a job				
Age	Sample	Mean	S. D.	Min	Max	Sample	Mean	S. D.	Min	Max
24–29	1565	0.01	0.028	1.4E-60	0.16	877	0.04	0.06	9.1E-48	0.16
30–35	978	0.001	0.006	3.0E-100	0.16	1056	0.03	0.05	8.8E-73	0.16
35–41	450	1.2E-04	0.001	5.8E-157	0.02	845	0.03	0.05	3.0E-100	0.16

(Source: JPSC 1993–2008)

Exclusion restrictions in the employment equation

My reduced form model of employment is:

$$U_{it}^{*} = \mathbf{X}_{it}'\beta_x + \beta_z Z_{it} + \varepsilon_{it} \tag{7}$$

where U_{it}^{*} is the latent variable that represents the utility from working. Worker i works if $U_{it}^{*} > 0$. The last term ε_{it} captures taste for work. The vector Z_{it} includes exclusion restrictions. They affect the likelihood of participating in the labor force, but do not affect the wage, conditional on $\mathbf{X}_{it}$. I use child-care accessibility as an exclusion restriction for the estimation of the wage parameters.

After estimating (7), the inverse Mills ratio is calculated as $\lambda(\mathbf{X}, Z) = \phi(\mathbf{X}, Z)/\Phi(\mathbf{X}, Z)$, where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the p.d.f. and c.d.f. of the standard normal distribution, respectively. Using the inverse Mills Ratio, I estimate the wage equation as

$$\ln w_{it} = b_0 + b_{st}\bar{p}_t + b_{zt}p_{it} + \mathbf{X}_{it}'\mathbf{b_X} + \sigma\lambda(\mathbf{X}, Z) + \upsilon_{it}$$

where σ is the correlation between unobserved determinants of propensity to work ε_{it} and unobserved determinants of wage offers υ_{it}, using the sample of workers who work at time t. The estimation results are reported in Table 3.

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