Impacts of Mother Friendly Leave Benefits on Fertility Hazards in South Korea

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In this articles, we attempt to evaluate impacts of three mother friendly leave benefits menstrual leave, maternity leave and childrearing leave—of female employees on fertility hazards. Drawing on Korea Labor and Income Panel Study 2001–2015, we created first childbirth and second childbirth datasets that were fitted to Cox proportional hazards model. After accounting for an wide array of confounding variables, menstrual leave benefit and maternity leave benefit have emerged as a significant fertility boosting fringe benefits for the first childbirth. Female employees who were eligible for those benefits turned out to show enhanced fertility hazards by the factor of more than 25 percentage point. However, only menstrual leave benefit seems to have played a role of increasing fertility hazards for the second childbirth. It tended to increase fertility hazard more than a quarter of one hundred percentage point.

I. Introduction

It is widely known that South Korea (hereafter Korea) has entered the lowest-low fertility regime in 2001 and has failed to move out of it until today (Eun 2007; Kwon 2003, Statistics Korea 2016). More specifically, total fertility rate (TFR), an estimate showing how many children a woman would give birth to during her lifetime, fell into 1.297 in 2001 and has fluctuated below 1.3 to finally record 1.240 in 2015 (Statistics Korea 2016).

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It is no surprise that there have been many attempts to examine diverse factors that were associated with lowest-low fertility rates. Analyzing the decennial census from 1980 to 2000, for instance, Kim et al. (2006) attributed the emergence of low fertility to rapid urbanization and the expansion of higher education for women. Another study concluded that women from high-level socioeconomic backgrounds moved from a high to low fertility schedule after the 1997 Asian economic crisis (Kim 2009). In addition, female labor force participation has been shown to deter fertility hazards particularly of the second childbirth (Kim 2014) and there was a piece of research supporting that women's wages up to some medium level but not over that point intensified fertility hazards of the first childbirth (Kim 2015).

In this context, we try to examine whether three apparently fertility-boosting "maternity protective" leave benefits for female employees in their job would enhance fertility hazards of the first and second childbirth. The three leave benefits consist of menstrual leave, maternity leave and childrearing leave. Menstrual leave refers to the benefit that female employees can get time off when they suffer period pains. Paid one-day leave once a month was enacted as early as 1953 but the law went through a twist and turn in 2003 to be unpaid and gettable if and only if requested. Maternity leave is an absence from work during 90 days immediately before and after childbirth and childrearing leave is an absence from work for at most one year for the purpose of taking care of children who were less than eight-year old. These leaves were enacted as a partly paid right in 2001 as policy measures to balance work and family (Koo 2009).

As with other Asian countries, however, work ethics and related atmospheres of South Korea are not friendly to female employees to the extent that they can comfortably request and enjoy these leave benefits (McCurry and Leavenworth 2016). Indeed, recent survey unveiled that only 16.7, 51.0 and 29.9 per cent of business establishments with at least one employee had ever had any employees who enjoyed menstrual leave, maternity leave and childrearing leave, respectively (Kim et al. 2015). Since these leave benefits are such prohibitive benefits for female employees, we speculate that any of these measures would enhance fertility hazards.

II. Method

1. Data

To assess differential fertility hazards by eligibilities to mother friendly leave policies, we draw data from the Korea Labor and Income Panel Study (KLIPS) 2001 to 2015 waves. KLIPS

is an ongoing longitudinal survey that began collecting data from 5,000 households in 1998 and has followed respondents on an annual basis (Korea Labor Institute 2016). Because the original samples did not include Jeju island, data collectors decided to add 1,415 refresh samples in 2009 to render the survey nationally representative. Longitudinal retention rates have been quite remarkable with 68.4 per cent of the 1998 original samples responding to the annual follow-up in 2015.

The survey asked a long list of questions regarding family formation and dissolution, labour force participation, and job characteristics, to name a few. From the 2001 wave onward, questionnaires contained queries about whether respondents were eligible for maternity protective leave programs, which allowed us to utilize KLIPS from the 2001 wave. Out of the survey, we constructed two event history datasets that consisted only of female respondents who were employees. For the first childbirth dataset, the analytical time was age in years of female respondents and for the second childbirth dataset, it was the years after the first childbirth. To be consistent with the concept of childbirth risk, the first dataset had only females who did not give birth to the first child and the other dataset had only females who had born the first child but did not bear the second at the start of the study period (Kim 2014, 2015).

We restricted our observational period of females' age to the interval from 20 to 39 since childbirth rarely happened out of that age interval and we were concerned with the possibility that other characteristics such as unfinished schooling and early menopause would affect recovered estimates. In addition, it should be emphasized that we lagged children's birth date by 7 months to address the problem of the reverse causality between labour force participation and childbirth (Budig 2003). Pregnant women were more than likely to leave labor force when they determined to give birth to before due date (Kim 2014) so that those women would have been missed in our datasets if we did not lag childbirth date. We would have 449 and 230 births for the first and second childbirth respectively if we did not lag the birth date. After applying lagging procedure, however, our analytic data ended up with 503 and 250 births together with 6,718 and 1,602 years of observation, respectively.

2. Measures

Main explanatory variable is eligibility for three mother friendly leave benefits: menstrual leave, maternity leave, and childrearing leave. Questionnaires threw questions on whether those leave benefits were available for respondents and we created one indicator variable for each question totaling three ones that had the value 1 if available and 0 otherwise.

Confounding variables measured in this research can be divided into three groups: job characteristics, individual characteristics and household characteristics. Other job characteristics than parental leave benefits were made up of wage, working hours per week and standard job status. Wage was recorded in unit of 10,000 Korean Won (KRW) which was approximately \$ 9 USD. To report descriptive statistics, wage was classified into four categories with dividing points having the equal space of 1 million KRW. However, we used it as a continuous variable in regression models and we also included squared wage term to account for plausible inverted U-shaped relation with fertility hazards (Kim 2014).

Working hours per week was a categorical variable with four levels in descriptive statistics: less than 40 hours, 40 hours, more than 40 but less than 45 hours, and equal to or more than 45 hours. Since it was measured in unit of hours in the original question, we returned to a continuous metric in regression models. Standard job status refers to whether respondents self-reported the job as a standard job or non-standard job. Usually standard job involves various features like direct employment relation between an employer and an employee, permanent in contrast to temporary contract, established full-time working hours, high wages and enjoyable fringe benefits (Kim and Park 2006). Standard job had the value of 1 and otherwise 0.

Individual characteristics were composed of education and marital status. Educational attainment was a three-level categories: up to high school, two-year college and four-year college or more. We created two dummy variables in regression models with the first category acting as the baseline category. Marital status was a binary variable with the value 0 meaning married and 1 otherwise.

We chose three variables in the household level: home ownership, amount of yearly income and urbanicity of residential area. Home ownership has repeatedly demonstrated to be the most important factor in childbirth in South Korea (Kim 2015). This variable is a four-level qualitative variable with categories being "own home", "down payment", "rent", and "other types." A down payment is a widely used type of rent in which renters deposit an appreciable amount of money at approximately 50% to 80% of the house price and do not pay any other rent but claim the money when they vacate the house. The category "rent" means respondents paid monthly rent to home owner. Regression models had three dummy variables with the first category as the baseline one.

Income was observed in unit of 10,000 KRW in its original form and we used it as such in regression models with squared term included. For the purpose of descriptive statistics, income was categorized into three levels: less than 30 million KRW, 30 million to 50 million KRW, and equal to or more than 50 million KRW. Urbanicity of residential area was a category variable

with three levels: metropolitan area, urban area and rural area (Korean name is Gu-Si-Gun, respectively). Metropolitan area included metropolitan cities such as Seoul, the capital of South Korea, and Busan. Urban area represented small cities outside of metropolitan areas and rural area was those populated by people who worked in the primary industry. As usual, we created two dummy variables with the first category being the baseline for regression models.

Notice that we made all variables categorical for the purpose of tabulating descriptive statistics. This is because we chose to report years of waiting time, number of births and their related functions as descriptive statistics. It would be more difficult, if not impossible, to report those descriptive statistics if variables had continuous nature rather than categorical property since the latter enabled us to compared those statistics among categorized groups. However, continuous variables are not difficult to manage in Cox regression model so that we preferred using original metrics as many times as we could.

Last but not least, we note that money related variables such as wage and income were inflated or deflated to the 2010 KRW value using Consumer Price Index published by the Bank of Korea.

3. Statistical methods

Cox proportional hazards models are the most frequently used statistical methods in the literature. Various functions related to survival analyses in the statistical package R were used to produce descriptive statistics, survival graphs, and Cox model estimates (Therneau 2015; Therneau and Grambsch 2000).

III. Results

1. Descriptive statistics

Table 1 provides descriptive statistics of two datasets that were retrieved by applying procedures as described earlier. There are four columns for summary statistics of each childbirth dataset. The first column exhibits number of years exposed to the risk of childbirth and the second displays total number of childbirths during the waiting time. The third column shows fertility rates measured by number of births per one year of exposure, namely estimates obtained by dividing the second column by the first one. These numbers can be interpreted as how many children a woman would give birth to for one year if she were exposed to the same

Table 1. Descriptive statistics

| | First childbirth (N ¹⁾ =1,888) | | | Seco | Second childbirth (N^{1} =689) | | | |
|-------------------------------------|---|--------------------|------------------------------|--------------------|-----------------------------------|------------------------|--|--|
| | Year ²⁾ | N.B. ³⁾ | Fert. ⁴⁾ $p^{5)}$ | Year ²⁾ | N.B. ³⁾ | Fert. $^{4)}$ $p^{5)}$ | | |
| Total | 6,718 | 503 | 0.075 | 1,602 | 250 | 0.156 | | |
| Job characteristics | | | | | | | | |
| Menstrual leave | | | | | | | | |
| Not eligible | 4,844 | 328 | 0.068 ** | 1,090 | 152 | 0.139 [†] | | |
| Eligible | 1,875 | 175 | 0.093 *** | 512 | 98 | 0.192 [†] | | |
| Maternity leave | | | | | | | | |
| Not eligible | 4,648 | 282 | 0.061 *** | 684 | 81 | 0.118 | | |
| Eligible | 2,070 | 221 | 0.107 *** | 918 | 169 | 0.184 | | |
| Parental leave | | | | | | | | |
| Not eligible | 5,275 | 351 | 0.067 *** | 880 | 119 | 0.135 | | |
| Eligible | 1,443 | 152 | 0.105 *** | 721 | 131 | 0.182 | | |
| Wage | | | | | | | | |
| Less than 1 million KRW | 1,462 | 71 | 0.049 ** | 256 | 37 | 0.145 | | |
| Less than 2 million KRW | 4,213 | 309 | 0.073 ** | 755 | 101 | 0.134 | | |
| Less than 3 million KRW | 899 | 104 | 0.116 ** | 443 | 91 | 0.205 | | |
| Equal to or more than 3 million KRW | 145 | 19 | 0.131 ** | 148 | 21 | 0.142 | | |
| Working hours per week | | | | | | | | |
| Less than 40 hours | 673 | 44 | 0.065 | 154 | 22 | 0.143 | | |
| 40 hours | 1,856 | 131 | 0.071 | 542 | 89 | 0.164 | | |
| 40–45 hours | 1,056 | 95 | 0.090 | 312 | 58 | 0.186 | | |
| Equal to or more than 45 hours | 3,134 | 233 | 0.074 | 594 | 81 | 0.136 | | |
| Standard job | | | | | | | | |
| No | 1,622 | 100 | 0.062 | 335 | 50 | 0.149 | | |
| Yes | 5,097 | 403 | 0.079 | 1,267 | 200 | 0.158 | | |

Note: 1) Number of women who were observed in the dataset at least once. 2) Years of waiting for childbirth. 3) Number of childbirth. 4) Fertility measured by number of childbirth per year. 5) Two-tailed, Cox model score tests for the null hypothesis that survival distributions are the same for all categories of a given variable. (0.1); (0.01); (0.

Table 1. Continued.

| | First childbirth (N ¹⁾ =1,888) | | | Second childbirth $(N^{1}=689)$ | | |
|--------------------------------------|---|--------------------|------------------|---------------------------------|--------------------|-------------------|
| | Year ²⁾ | N.B. ³⁾ | Fert. 4) p^{5} | Year ²⁾ | N.B. ³⁾ | Fert. 4) p^{55} |
| Total | 6,718 | 503 | 0.075 | 1,602 | 250 | 0.156 |
| Other covariates | | | | | | |
| Education | | | | | | |
| Up to high school | 1,573 | 132 | 0.084 | 507 | 58 | 0.114 |
| Two-year college | 2,378 | 146 | 0.061 | 366 | 71 | 0.194 |
| Four-year college or more | 2,768 | 225 | 0.081 | 728 | 121 | 0.166 |
| Marital status | | | | | | |
| Married | 684 | 248 | 0.362 | 1,495 | 243 | 0.163 |
| Not married | 6,034 | 255 | 0.042 | 107 | 7 | 0.066 |
| Home ownership | | | | | | |
| Own home | 4,058 | 251 | 0.062 | 677 | 118 | 0.174 |
| Down payment | 1,471 | 186 | 0.126 | 692 | 98 | 0.142 |
| Rent | 841 | 41 | 0.049 | 153 | 21 | 0.137 |
| Etc. | 349 | 25 | 0.072 | 80 | 13 | 0.163 |
| Income | | | | | | |
| Less than 30 million KRW | 2,288 | 163 | 0.071 | 350 | 50 | 0.143 |
| Less than 50 million KRW | 2,107 | 144 | 0.068 | 533 | 78 | 0.146 |
| Equal to or more than 50 million KRW | 2,323 | 196 | 0.084 | 719 | 122 | 0.170 |
| Urbanicity | | | | | | |
| Metropolitan area | 4,836 | 356 | 0.074 | 1,116 | 165 | 0.148 |
| Urban area | 1,735 | 131 | 0.076 | 425 | 73 | 0.172 |
| Rural area | 148 | 16 | 0.108 | 61 | 12 | 0.198 |

Note: 1) Number of women who were observed in the dataset at least once. 2) Years of waiting for childbirth. 3) Number of childbirth. 4) Fertility measured by number of childbirth per year. 5) Two-tailed, Cox model score tests for the null hypothesis that survival distributions are the same for all categories of a given variable. (0.1); (0.00); (0.00); (0.00)

risk of childbirth as observed in the dataset. Finally, the last column registers p-value signs for the Cox model score test for the null hypothesis that survival distributions are the same across all categories of a given variable (Therneau 2015). Log rank test is more frequently used in this context of nonparametric test of different survival curves but we used score test from a Cox model since the former is not available for left truncated data and the latter can be considered the same as the former (Therneau 2009).

First row of Table 1 displays that female employees under study spent 6,718 years waiting for the first child, which can be translated into an average of 3.6 years per woman since the dataset contains 1,888 women. The number of births per year for the first childbirth is 0.075, meaning that one thousand women gave birth to 75 children per year on average during the age interval of 20 - 39. Moving to the second childbirth, we find that 689 women contributed 1,602 years to the waiting time winding up with average 2.3 years per woman. The number of births per year of waiting time was 0.156 which is higher than fertility of the first childbirth.

Accessibility to mother friendly leave benefits seems to have had fertility enhancing impacts regardless of their types and birth parity. For instance, female employees who were eligible for menstrual leave delivered 0.093 first children, approximately 36.8 per cent higher fertility rate than that of 0.068 of female employees who were not eligible for the benefit. It is interesting to note that the differences of fertility rates by entitlement to leave benefits appear to be similar across benefit types in the first childbirth dataset. We also observe that these differences are all statistically significant with all p-values of Cox score tests being less than 0.01.

A bit different picture emerges if we move to the second childbirth dataset. Across all leave benefits, we find eligibility to any leave benefit have boosted fertility rates. For instance, fertility rate of female employees eligible for menstrual leave was 0.192 and that of those who were not eligible was 0.139, resulting in roughly 38.1 per cent higher fertility rate in the former group. Similar difference is noticeable for childrearing leave and substantially higher difference existed for maternity leave. However, those differences failed to reach statistical significance in the conventional α -level of 0.05. The difference for menstrual leave would be statistically significant only if we extended the α -level to 0.1 (more precise p-value was 0.061).

Survival curves depicted in Figure 1 present more vivid description of fertility differentials of first childbirth by eligibility of leave benefit types. Y-axis of these graphs represents probability to survive, namely proportion of female employees who were yet to give birth to a baby. To put in into another perspective, the gap from the unity line to the specific point means the proportion of female employees who gave birth to a child by a given time point. All solid lines stand for survival curves of female employees eligible for leave benefits and all dotted lines those of the other female employees. We added different symbols to set apart different types of



Figure 1. Survival curves of first childbirth by leave eligibility

leave benefits.

It is, however, readily noticeable that variations in survival probability among leave benefit types were no bigger than those between eligible and ineligible female employees. Even though there was no detectable difference in survival curves until age 26, the gaps began emerging after that age point and got wider as time went by. In other words, female employees eligible for leave benefits were less likely to survive risk of bearing the first child, or more likely to bear the first child than their counterparts. The age of 26 when leave benefits began cracking the gap of the first childbirth is starkly consistent with the age when most women with 4-year college degree found jobs in labor market by that age.

Survival curves in Figure 2 fell steeply in early years after the first childbirth such that more than a half of female employees gave birth to the second child until four years after the first childbirth. We fail to observe any distinguishable difference in survival curves among groups formed by eligibility of leave benefits by that time. However, the gaps in fertility hazards began emerging around four years under the risk, got wider for some time, and a bit closed after eight years. As with the survival curves for the first childbirth, those for the second one are remarkable in that leave benefit types did not carve as salient impacts as eligibility of those leave benefits.



Figure 2. Survival curves of second childbirth by leave eligibility

Getting back to Table 1, some observations are worth mentioning regarding associations between confounding variables and fertility rates. One interesting feature overshadowing Table 1 is that most variables showed nontrivial fertility differentials but those differences failed to reach statistical significance. It is particularly true for the second childbirth dataset in which no variable succeeded to pass the conventional α -level of 0.05. We suspect that these patterns might be due to small number of observed female employees, short observational period and small numbers of childbirth in that dataset, all of which are explicable by the fact that women tended to get out of labor force as soon as they got married or gave birth to the first child (Lee et al. 2008).

The finding is consistent with the previous research that women's wage enhanced the first childbirth hazards while it did not the second childbirth hazards (Kim 2015). The most striking result would be the statistically significant difference in fertility rates by marital status for the first childbirth but not for the second childbirth. Some readers who were familiar with the conservative Korean context in which bearing a child outside marriage is almost unheard of

| | Excluding other job characteristics | | | |
|-----------------------------------|-------------------------------------|----------------|------------------|--------------|
| | Model 1 | Model 2 | Model 3 | , Model 4 |
| Iob characteristics | 11104011 | 1000012 | 10100015 | 1110401 |
| Menstrual leave | 0 300 ** | | | 0.228 * |
| Maternity leave | 0.500 | 0.260 ** | | 0.184 |
| Darental leave | | 0.200 | 0.102 1 | -0.043 |
| Other opvariates | | | 0.192 | -0.045 |
| Education (vs. up to high school) | | | | |
| Two weer cellege | 0.050 | 0.000 | 0.000 | 0.067 |
| Two-year college | -0.059 | -0.068 | -0.068 | -0.067 |
| Four-year college or more | -0.048 | -0.077 | -0.075 | -0.065 |
| Marital status (vs. married) | -1.994 | -1.965 | -1.988 | -1.972 |
| Home ownership (vs. own home) | | | | |
| Down payment | 0.002 | -0.019 | -0.014 | -0.007 |
| Rent | -0.318 | -0.333 + | -0.327 | -0.326 |
| Etc. | -0.055 | -0.079 | -0.068 | -0.072 |
| Income | 0.000 | 0.000 | 0.000 | 0.000 |
| Income squared | 0.000 | 0.000 | 0.000 | 0.000 |
| Urbanicity (vs. metropolitan) | | | | |
| Urban | -0.051 | -0.042 | -0.042 | -0.050 |
| Rural | -0.099 | -0.126 | -0.125 | -0.109 |
| | | | | |
| | It | ncluding other | job characterist | ics |
| | Model 5 | Model 6 | Model 7 | Model 8 |
| Job characteristics | | | | |
| Menstrual leave | 0.277 ** | | | 0.221 * |
| Maternity leave | | 0.243 * | | 0.176 |
| Parental leave | | | 0.160 | -0.037 |
| Wage | 0.004 | 0.004 | 0.004 | 0.003 |
| Wage squared | 0.000 | 0.000 | 0.000 | 0.000 |
| Working hours | 0.001 | 0.001 | 0.001 | 0.001 |
| Standard job | -0.009 | -0.028 | 0.000 | -0.034 |
| Other covariates | 0.009 | 0.020 | 0.000 | 0.021 |
| Education (vs. up to high school) | | | | |
| Two-year college | -0.063 | -0.070 | -0.072 | -0.067 |
| Four-year college or more | -0.003 | -0.070 | -0.072 | -0.007 |
| Marital status (vs. married) | 2 001 *** | 1074 *** | 1 006 *** | 1 021 *** |
| Home experience (vs. manieu) | -2.001 | -1.774 | -1.990 | -1.901 |
| Down normant | 0.006 | 0.000 | 0.024 | 0.000 |
| Down payment | -0.006 | -0.022 | -0.024 | -0.008 |
| | -0.331 | -0.344 | -0.341 | -0.330 ' |
| EIC. | -0.066 | -0.086 | -0.081 | -0.078 |
| Income | 0.000 | 0.000 | 0.000 | 0.000 |
| Income squared | 0.000 | 0.000 | 0.000 | 0.000 |
| Urbanicity (vs. metropolitan) | | | | |
| Urban | -0.046 | -0.040 | -0.036 | -0.049 |
| Rural | -0.114 | -0.141 | -0.137 | -0.126 |

Table 2. Coefficients Estimates from First Childbirth Cox Models

Note: [†]<0.1;^{*} *<0.05^{*}; **<0.01^{**}; **<0.001.

would be surprised by the sheer number of first childbirths born to unmarried women (Raymo et al. 2015). Reminding that our data were collected with one year spacing and we lagged birth date by seven months, marital status of women who gave birth to a baby were measured approximately 15 months before the actual birth so that there were plenty of room for them to get married and bear the first child. In addition, the statistical insignificance for the second childbirth appears to be attributable to the small size of births born to unmarried women.

2. First childbirth Cox models

Table 2 presents coefficients and p-values of diverse Cox hazards models that can be singled out by conditioning of specific sets of covariates. We did not include other job characteristics except for availability of leave benefits in Model 1 through 4 but we did in Model 5 through Model 8. Each model within the block is distinguished by which leave benefits acted as the main explanatory variables.

The coefficient on menstrual leave in Model 1 is 0.300, implying that female employees who were eligible for the menstrual leave were more likely to give birth to the first child than their counterparts after controlling for all confounding variables excluding other job characteristics. The coefficient 0.300 can be converted to the hazard ratio by taking exponential, leading to $\exp(0.300) \approx 1.350$. This quantity means that, on average, fertility hazards of women eligible for menstrual leave benefit were, on average, 35 per cent higher than fertility hazards of women ineligible for menstrual leave benefit. Using the same method, we see that entitlements to maternity leave and childrearing leave were associated with 29.7 and 21.1 per cent increases in fertility hazards respectively. All these estimates are statistically significant with the α -level of 0.1.

Including all three leave benefits in one model (Model 4) substantially decreased magnitudes of all coefficients and the coefficient on childrearing leave turned negative. However, only menstrual leave remains statistically significant. These results suggest that menstrual leave benefit was the most influential mother friendly leave benefit to the extent that eligibility for the benefit enhanced fertility hazards by more than a quarter times ($\exp(0.228)-1\approx0.25.6$) even for female employees who were eligible for the other two leave benefits. The other leave benefits were found to boost fertility hazards but the impacts were not statistically significant once the other leave benefits were eligible.

Those coefficients on leave benefits dwindled in absolute terms and a couple of statistical significance disappeared upon including the other job characteristics such as wage, wage

| Excluding other job characteristics | | | |
|-------------------------------------|---|---|--|
| Model 1 | Model 2 | Model 3 | Model 4 |
| | | | |
| 0.258 [†] | | | 0.250 † |
| | 0.155 | | 0.100 |
| | | 0.033 | -0.099 |
| | | | |
| | | | |
| 0.321 [†] | 0.302 | 0.317 [†] | 0.324 † |
| 0.107 | 0.086 | 0.106 | 0.110 |
| -0.388 | -0.391 | -0.429 | -0.381 |
| | | | |
| -0.172 | -0.165 | -0.160 | -0.177 |
| 0.087 | 0.111 | 0.108 | 0.086 |
| -0.096 | -0.088 | -0.098 | -0.096 |
| 0.000 | 0.000 | 0.000 | 0.000 |
| 0.000 | 0.000 | 0.000 | 0.000 |
| | | | - |
| 0.286 * | 0.286 * | 0.283 † | 0.292 * |
| 0.216 | 0.206 | 0.189 | 0.235 |
| | | | |
| Inc | cluding other j | ob characteris | tics |
| Model 5 | Model 6 | Model 7 | Model 8 |
| - | | | |
| 0.268 † | | | 0.240 |
| | 0.213 | | 0.168 |
| | | 0.039 | -0.104 |
| 0.002 | 0.002 | 0.003 | 0.002 |
| 0.000 | 0.000 | 0.000 | 0.000 |
| -0.007 | -0.007 | -0.006 | -0.007 |
| -0.261 | -0.290 | -0.232 | -0.284 |
| | | | |
| | | | |
| 0.293 | 0.267 | 0.293 | 0.286 |
| 0.038 | 0.010 | 0.034 | 0.032 |
| -0.410 | -0.405 | -0.459 | -0.386 |
| | | | |
| -0.169 | -0.166 | -0.159 | -0.176 |
| 0.088 | 0.109 | 0.113 | 0.086 |
| -0.135 | -0.127 | -0.138 | -0.131 |
| 0.000 | 0.000 | 0.000 | 0.000 |
| 0.000 | 0.000 | 0.000 | 0.000 |
| 0.000 | 0.000 | 0.000 | 0.000 |
| | | | |
| 0.301 * | 0.300 * | 0.302.* | 0.306 * |
| | $\begin{array}{r} \mbox{Model 1} \\ \hline 0.258 ^{\dagger} \\ \hline 0.321 ^{\dagger} \\ \hline 0.107 \\ -0.388 \\ \hline 0.107 \\ -0.388 \\ \hline 0.172 \\ \hline 0.087 \\ -0.096 \\ \hline 0.000 \\ \hline 0.000 \\ \hline 0.000 \\ \hline 0.286 ^{\ast} \\ \hline 0.216 \\ \hline \\ \mbox{Model 5} \\ \hline 0.268 ^{\dagger} \\ \hline 0.268 ^{\dagger} \\ \hline 0.002 \\ \hline 0.000 \\ -0.007 \\ -0.261 \\ \hline 0.293 \\ \hline 0.000 \\ -0.007 \\ -0.261 \\ \hline 0.293 \\ \hline 0.038 \\ -0.410 \\ \hline 0.169 \\ \hline 0.088 \\ -0.135 \\ \hline 0.000 \\ \hline 0.000 \\ \hline \end{array}$ | Model 1 Model 2 0.258^{+} 0.155^{-} 0.321^{+} 0.302^{-} 0.107^{-} 0.086^{-} -0.172^{-} -0.165^{-} 0.087^{-} 0.111^{-} -0.096^{-} -0.088^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.286^{-*} 0.286^{-*} 0.216^{-} 0.206^{-} Including other j. Model 6 0.268^{-+} 0.213^{-} 0.002^{-} 0.002^{-} 0.002^{-} 0.002^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} 0.000^{-} | $\begin{tabular}{ c c c c c c } \hline Model 1 & Model 2 & Model 3 \\ \hline 0.258 ^{\dagger} & & & & & & & & & & & & & & & & & & &$ |

Table 3. Coefficients Estimates from Second Childbirth Cox Models

Note: [†]†<0.1; * *<0.05; **<0.01; **<0.001;

squared, working hours, and standard job status (Model 5 through Model 8). For instance, the coefficient on the childrearing leave benefit is no longer statistically significant in Model 7. Nevertheless, those coefficients on the menstrual leave and maternity leave remain substantially large and statistically significant, supporting the conclusion that these benefits carved distinguishable impacts on fertility hazards of the first childbirth by the neighborhood of 25 per cent increases.

3. Second childbirth Cox models

Table 3 exhibits statistical estimates from Cox models fitted to the second childbirth dataset. The results reveal similar patterns with those from the first childbirth models with depreciated magnitudes of coefficients and their attenuated statistical significance. For instance, menstrual leave benefit was likely to intensify fertility hazards of the second childbirth by approximately 30 per cent by itself but its statistical significance faded away as soon as the other leave benefits along with the other job characteristics were conditioned on (Model 8). The other two leave benefits failed to attain statistical significance even though it seems not a big stretch to conclude that maternity leave benefit was a meaningful fertility boosting factor of the second childbirth.

IV. Summary

We can summarize our findings from statistical analyses of KLIPS 2001–2015 as follows. Menstrual leave benefit and maternity leave benefit have emerged as a significant fertility boosting fringe benefits for the first childbirth. Female employees who were eligible for those benefits turned out to show enhanced fertility hazards by the factor of more than 25 percentage point. However, only menstrual leave benefit seems to have played a role of increasing fertility hazards for the second childbirth. It tended to increase fertility hazard more than a quarter of one hundred percentage point.

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