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Three Essays in Economics of Time Use

시간 사용의 경제학에 대한 세 가지 소고

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Abstract

Three Essays in Economics of Time Use

This thesis studies individual decision-making with emphasis on time use. First, I investigate the effect of educational intervention which regulates timing of private tutoring on time use of high school students. Second, I examine the impact of expansion of Community Child Center, which alters value of non-market time, on labor supply of married women. Third, I test whether working long hours before childbirth lowers employment probability of female manager after motherhood.

The first chapter shows that implementation of the legal restriction which inhibits operation of private tutoring academies after 10PM had unexpectedly increased time spent on private tutoring. I exploit the fact that the adoption timings of curfew were different across regions and estimate the impact of the legal restriction on students' time usage using the difference in difference estimator. I find that the curfew significantly increased sleep time of high school students as well as time spent in private tutoring academies. To understand the puzzling finding, I utilize information on timings of activities in time diary data and investigate the impact of policy on time allocation before and after the designated curfew time. The results from the modified triple difference estimator and the bunching estimator suggest that the curfew was successfully implemented and time devoted to private tutoring after 10PM decreased notably. However, students significantly increased time spent in private tutoring institute before 10PM. The increase in private tutoring before the curfew time was accompanied by major reduction in after school self-study session. Average time spent on private tutoring increased as the increase in private tutoring before 10PM was greater than the decrease in private tutoring after 10PM. This result suggests the policy which restricts time use of individuals has to consider intraday substitution.

The second chapter examines how supply of Community Child Center affects labor supply of married women. The Community Child Center is expected to help mothers

to reconcile their work and family life whereas the center provides education and protection to the children under 18. The center reduces childcare cost of low-income mothers as low-income households are free to use the center. I exploit the fact that Community Child Center rapidly increased after policy of subsidizing the center was introduced. For the purpose of identification, I exploit regional variation in centers' coverage rate since after the introduction of subsidy, expansion rates of the center were notably different across regions. The result from the difference in difference estimation shows that increase in coverage rate of the Community Child Center significantly increases labor force participation of married women. I find positive labor supply effect for mothers who were likely to have primary school-aged child whereas most of the center users were primary school-aged children. I instrument regional coverage rate with regional subsidy to alleviate potential biases in estimate. The instrumental variable estimation confirms the result from the difference in difference estimation. The finding in this chapter suggests that availability of low-income targeted childcare center increases labor supply of low-income women with primary school-aged children.

The third chapter studies the impact of long working hours on maternal labor supply. I relate pre-childbirth work environment to employment probability after childbirth. Using sample of managerial women who experienced childbirth between survey year t-1 and t, I test whether working at the firm where on average employees stay at workplace more than 12 hours lowers probability of work after childbirth. The result suggests that new mothers who worked at the corporate with very long average working hours are significantly less likely to work after giving birth to child. This chapter shows that female managers with young child are sensitive to the cost of working long hours.

Keywords: Time use, Cram school curfew, Intraday time allocation, Community Child Center, Labor supply of married women, Long working hours, Female manager
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Chapter 1

A Balloon Effect: Unintended Consequences of Closing Private Tutoring Academies at 10PM

1.1 Introduction

South Korea (hereafter Korea) is one of the few countries where people are worried about young students *studying excessively*. High school students study 50.6 hours per week on average, which is very high compared with the OECD average of 44 hours (OECD, 2016). Even elementary school children study 37.7 hours on average (Statistics Korea, 2015). Over-studying is possibly caused by intensive competition to prestigious universities.[1] Thus, the demand for supplementary classes and learning in a more customized way is high. However, traditional schools are not flexible enough to satisfy such a demand. Schools in Korea are highly regulated by the government (Hanushek et al., 2013; Ho, 2006), even if they are private (Hahn et al., 2018). Private tutoring academies have accommodated this unmet demand in the market. However, private academy operation had been illegal until 2000 when the Constitutional Court decided the laws prohibiting private academies (Laws on Establishment and Operation of Private Academies, Article 3 and Article 22, Paragraph 1) to be unconstitutional. Afterward, private academies have grown substantially that even private tutoring businesses are regarded as one separate industry in Korea. As of 2018, 71.7% of school-age children participate in private tutoring, and 57.8% of students attend private tutoring academies. Household spending on private tutoring accounts for 7.4% of the total household expenditure among households with school-age

[11] It is an intriguing question how competition to top universities is remarkably prevalent to increase the effort of average students (Lee, 2007).

children. Moreover, according to Statistics Korea (2018), the total expenditure on private tutoring accounts for 1% of GDP.

The Korean government has tried to depress the market for private tutoring. The government's concern is that the growth of the private tutoring industry has been a threat to schools and public education (Lee et al., 2010). As students spend more efforts in private academies, teachers in traditional schools become less motivated. Students study ahead higher-grade curriculum in private academies; thus, they are less interested in school classes. Another concern is that competition among students is too intensive. Children in Korea are found to be deprived of physical exercise and sleep (Gradisar et al., 2011; OECD, 2016). Severe competition with peers might adversely affect children's mental health and personalities, thereby increasing problems like school violence and bullying (Akiba et al., 2002; Bibou-Nakou et al., 2012; Deb et al., 2015; Vallerand et al., 1986).

Various policies have been implemented against the private tutoring industry, for example, the restriction on business hours of private academies, which is the focus of our current study. The policy was first introduced in 2000 by Gyeongbuk, a province in the south eastern region of Korea. The province prohibited private academies from opening after 10PM. According to the 1999 Korean Time Use Survey data, which we will use in this paper, about 5.9% of high school students were participating in private academies after 10PM on weekdays. Afterward, the other provinces and metropolitan cities adopted such a policy; some chose 10PM as the curfew time and others 11PM or even midnight. By 2009, all provinces and metropolitan cities (a total of 16 in Korea) had adopted their own policy. In the same year, the national government announced the so-called "Measures for Improving School Competitiveness and Reducing Household Expenditure on Private Tutoring." The measures included the introduction of monetary reward for reporting violation of business-hour restriction. Also, local governments were recommended to strengthen their restriction and adopt the curfew time at 10PM. As a consequence, three provinces adopted the 10PM restriction between 2010 and 2012.

In our present study, we examine the effectiveness of restricting business hours of private tutoring academies. For our policy evaluation, the first-order question would be

whether the restriction could reduce students' usage of private academies. To identify the causal effect of the policy separately from any confounding factors, we utilize regional variation across provinces and cities in the timing of adopting the business-hour restriction policy. The variation provides a quasi-experimental setting for applying the difference-in-differences (DD) method. We measure students' usage of private tutoring academies using time-diary data from the Korean Time Use surveys from 1999 to 2014, which record activities in every 10-minute interval for household members aged 10 or older. The advantage of using the time-use data for the purpose of our study is that we can not only check whether students' daily use of private tutoring academies decreases after the policy but also check whether the reduction in the usage rate of private academies occurs after the curfew time. In particular, the latter finding should support our estimation of the policy's causal effect as it confirms the enforcement of the policy.

The results from the DD estimation are puzzling; the business-hour restriction policy *increases* students' usage of private academies. We find that students spend about 17.5 minutes longer per day in private academies after the implementation of the policy. Meanwhile, we also find that the policy achieves one of its intended goals: letting students sleep longer. Our estimates show that they sleep 21.5 minutes more per day, on average.

In order to explain the surprising findings from the DD model, we investigate intraday time allocation of students, comparing time-use patterns before and after the designated curfew time. The triple-difference (DDD) setting is as follows: before and after the policy, by region, and before and after the curfew time. To do so, we use hourly rather than daily time-use data and allow the treatment effect of the policy to vary within a day. In the DDD model, we allow the treatment effect to differ simply before and after the curfew time. For robustness, we also try to apply the bunching estimator in which we allow the treatment to vary hour by hour. From both models, we find the same result that students reduce their time at private academies after the designated curfew time and instead sleep longer. However, they use private academies more during their business hours, which we refer to as *the balloon effect* in this paper.

Both private tutoring and sleeping increased after the policy; however, some activities must also be decreased by the policy. Students gave up using the after-school self-study program, which was their major after-school activity prior to the policy's implementation. We find that students reduce their time spent for the after-school self-study program, and the magnitude of the reduction is almost equal to the sum of the increases in private tutoring and sleeping.

Our paper is not the first study to evaluate the business-hour restriction policy. Several studies have examined the impacts of household expenditure policy on private tutoring, average hours for private tutoring, and sleeping.[2] Although most of these studies yield consistent finding that students' sleeping time increased after the policy, the results regarding the impact on private tutoring are mixed. Some found that the policy decreased the usage of private tutoring. However, other studies found no effect or even a positive effect of the policy, and they did not explain how this unintended consequence could happen.[3] We believe that our study contributes to this literature mainly in two directions. First, we use more data, utilize all policy changes, try alternative specifications, and confirm the robustness of our result that the policy increased students' usage of private tutoring academies. Second, we attempt to provide a mechanism for the puzzling effect of the policy by examining students' activities more comprehensively and their intraday time allocation in detail.

More generally, our paper is also related to a strand of literature on government regulation in the presence of substitutes. Dinardo and Lemieux (2001) showed that increases in the minimum drinking age resulted in increases in consumption of marijuana. Their model suggests that this unintended effect is attributable to substitution effects. Shepherd (2002) studied the effect of truth-in-sentencing (TIS) legislation. The result

[2] See Appendix Table A.1.1 for the summary of the previous studies in terms of data, estimation methods, and main findings.

[3] Bae and Jin (2019) suggested that students might had changed their private tutoring classes to earlier times, but no formal analysis was conducted.

reveals that legislation reduced violent crimes. However, offenders shifted into committing property crimes. Yang (2008) examined a customs reform that increased enforcement against dodging import duties. The enforcement targeted specific illegal methods. Findings suggest that raise in enforcement decreased participation in targeted methods but significantly increased the use of other law-breaking procedures. Goulder et al. (2012) investigated the impact of adoption of limits on greenhouse gases per mile of light-duty automobiles. They found substantial offsetting emissions increase in unregulated states and in the used car market. Similar to the previous studies, our findings are consistent with the prediction from a canonical theory of consumer behavior: policies that successfully ration demand for one good will give rise to a growth in demand for the other good, given that two goods are substitutes (Dinardo and Lemieux, 2001).

The rest of the paper proceeds as follows. Section 1.2 describes the historical background of the policy of restricting business hours of private tutoring academies and its institutional setting that we exploit for our empirical identification. Section 1.3 explains the data used in the study and presents time trends of the usage of private tutoring academies and intraday distribution of time spent on private tutoring. Section 1.4 explains empirical methodologies. Section 1.5 presents the results from the DD model on the day-level aggregate impact of the policy on the time spent in private academies per day. Section 1.6 distinguishes the effects before and after the curfew time within a day in the DDD model or hour by hour in the bunching estimation model. Moreover, the effect of curfew on self-studying at school is presented. Section 1.7 presents the substantial decrease in self-study sessions at school and suggests potential explanation for the large balloon effect. Finally, Section 1.8 concludes our paper.

1.2 Institutional Background

Since the 1960s, South Korea has been considering shadow education as a challenge to public education as government put continuous effort into reducing the market for private education. Government has regulated private education and has sought to improve its

quality and eliminate competitive high stakes tests in public education. Some examples for equalization policies are "No Middle School Examination Policy," "High School Equalization Policy," and prohibition of the entrance exams managed by individual colleges. Meanwhile, the expansion of the education broadcasting system, increase in the autonomy of public education, and introduction of teacher evaluation system are examples for quality-related interventions (Lee et al., 2010). In contrast to variety of polices toward public education, few but strong restrictions have been imposed on private education.

Historically, two representative regulations on private education took place. The first was blanket ban on private tutoring following the "7.30 Educational Reform Measure," which was proposed in 1980. However, the law was abolished in 2000 upon the declaration of the South Korean Constitutional Court of the law to be unconstitutional. The second was restriction on business hours of private tutoring academies, so called cram schools (Lee et al., 2010). The curfew was imposed by some local government in the early 2000s and expanded nationwide throughout the mid-late 2000s.

The imposition of legal restriction on business hours of private tutoring academies can be divided into three distinct phases. In the early 2000s, four provinces imposed the curfew ordinance. Gyeongbuk province first inhibited operation of private tutoring academies after 10PM in 2000. Following Gyeongbuk, Seoul, Daegu, and Gangwon banned night-time cram schooling in 2001. Controversy over the ordinance was intense because the curfew could restrict workers' right to live as well as students' right to learn (Jeon, 2009).[4] In 2005, a private tutoring academy in Seoul initiated administrative litigation against the ordinance. Seoul Administrative Court declared it as illegal due to the fact that the ordinance was not grounded in law. However, this resulted in the amendment of the law to support curfew ordinance issued by local government. Following the law enforcement in 2007, all provinces and metropolitan cities imposed curfew ordinance from 2007 to 2009 (Jung, 2015). However, there was a concern that the imposed curfew times

[4] In 2009 and 2016, constitutional petitions had been filed over the curfew. In both periods, Constitutional Court of Korea judged the curfew as constitutional.

were not binding effectively. Accordingly, in 2009, government proposed the "Measures for Improving School Competitiveness and Reducing Household Expenditure on Private Tutoring," which tried to strengthen the curfew. The measure introduced financial reward for reporting the private academies violating the curfew and strengthened crackdown, and recommended local government to adjust curfew time to 10PM (KEDI, 2012). The measure induced nine provinces or metropolitan cities to modify curfew time to earlier times between 2011 and 2012.[5]

Figure 1.1 shows curfew times for high school students in 16 regions for each survey year.[6] The darkest regions are where the 10PM curfew is adopted, and the lightest regions correspond to provinces or metropolitan cities that implemented the 12AM curfew. Regions with the 11 AM curfew are denoted using medium level boldness. Between 1999 and 2004, four provinces introduced business-hour restriction on private tutoring academies. Seoul and Gyeongbuk imposed the 10PM curfew, and Daegu and Gangwon banned cram schooling after 12AM. Following amendment of the law in 2007, other 12 provinces imposed the curfew ordinance between 2004 and 2009. Ten regions, namely, Chungbuk, Chungnam, Daejeon, Gwangju, Gyeonggi, Gyungnam, Incheon, Jeju, Jeonnam and Ulsan, imposed 12AM curfew, and two regions, namely, Busan and Jeonbuk, introduced the 11PM curfew.[7] After 2009, following the educational measure, four regions altered the curfew time from 12AM to earlier times. Daegu, Gwangju, and Gyeonggi imposed the 10PM curfew, and Incheon imposed the 11PM curfew.

The sequential imposition or reinforcement of curfew provides regional variation in the timing of policy adoption, which allows us to measure the effect of policy on students'

[5] Four regions set earlier curfew times for high school students, and five regions introduced earlier curfew times for middle and elementary school students.

[6] Jung (2015) provided exact dates of imposition and curfew times for elementary, middle, and high school students.

[7] Interestingly, Gyeongbuk changed the curfew time from 10PM to later time, 12AM, during this period.

time use through DD analysis. Previous research also exploited this quasi-experimental feature of the curfew ordinance but differed from our study in an important way. Most studies used policy variations arising from reinforcement of the curfew following the measure in 2009. The only exception is the study of Jung (2015) who analyzed amendment of the law in 2007 and its reinforcement.[8] In our current study, we exploit all variations from early 2000s to early 2010s to evaluate the impact of curfew ordinance.

If the regional adoption timing of curfew ordinance is exogenous to students' time usage, then we could estimate causal effect on their time usage using DD estimation. One potential threat to the parallel trend assumption is the introduction of other policies that affect time allocation of students. Correlated timing of adoption of potentially confounding policies and the curfew ordinance could result in biased DD estimation. Two policies are of concerns, namely, "Students Human Rights Ordinance" and "Delayed School Start Time."

"Students Human Rights Ordinance" was fist imposed by Gyeonggi in 2010 and is currently enforced by five regions. The ordinance considers students' rights, including discrimination, violence, privacy, religion, and education. The right to education includes inhibiting any mandated non-school hours self-study sessions at school, such as self-study session before regular class start time or after-school self-study program (Bae and Jin, 2017). The latter is particularly important in our current setting because private tutoring is mostly taken after regular school hours. In 2007, 62.8% of students are mandated or quasi-mandated to participate in after-school self-study program (Kim, 2008). Imposition of the ordinance is expected to decrease the number of students engaging in the after-school program and might increase probability of taking private tutoring. "Delayed School Start Time" policy changed school start time from earlier time to 9AM. The policy was first applied to high school students in Gyeonggi in late 2014. This policy is not only anticipated

[8] Kim (2010) and Kim and Chang (2010) investigated the impact of the curfew before the amendment of the law, but their study designs are not quasi-experimental because no adoption or change in the curfew occurred during their sample period.

to change time devoted to sleep but also expected to affect private tutoring, presuming that students' intraday time allocation is related.

Timing of imposition of the human right ordinance and school start time policy might coincide with that of the curfew ordinance. Moreover, it is commonly believed that progressive local governments are likely to impose strict restriction on private education as well as to oppose mandating participation in school-provided self-study programs. To address the issue, we compare the standard model with the model that excludes regions or a year affected by the confounding policies or controls for the other policies. Findings suggest that progressive local governments are indeed advocating liberal policies, but the adoption of legal restriction on business hours of privates tutoring academies, especially the 10PM curfew, is exogenous to the other policies.

1.3 Data

We use Korean Time Use Survey (KTUS) for the analysis. KTUS is nationally representative household time-diary data conducted every 5 years. KTUS collects detailed information on individual characteristics and on the amount of time respondents devoted to various activities in the two consecutive days. The sample consists of every household member older than 10 years. The number of respondent households are 17,000 in 1999, 12,750 in 2004, 8,100 in 2009, and 12,000 in 2014. KTUS was conducted on September in 1999 and 2004, March and September in 2009, and on July, September, and December in 2014.

We restrict our analyses to sample of high school students because the probability of taking private tutoring after 10PM is highest for high school students.[9] Pooling of data from 1999 to 2014 yields 13,094 observations of high school students. These observations

[9] In 1999, in the absence of the legal restriction on business hours, the probability of engaging in cram schooling after 10PM is 26.7% for high school students, 1.8% for middle school students, and 0.1% for elementary school students, conditioning on attending private tutoring academies.

correspond to 6,547 high school students because all respondents are surveyed in two consecutive days in KTUS. We excluded respondents who are married or employed. In addition, students whose age does not match high school age, younger than 15 or older than 18 years, are excluded from the analysis sample. We further exclude the sample who stayed in home between 10:30 AM and 11:30 AM on school days because they were expected to be sick or likely to be in special circumstances. A total of 11,536 individual-day observation remains within the sample after the restrictions were imposed. Lastly, we confined our interest to weekday because most of the night-time cram schooling occurred on weekday. The final sample consists of 7,096 observations for 4,660 individuals.

For the sample analysis, time devoted to private tutoring institutes is defined as follows. KTUS provides information on time spent on private education but does not distinguish between private tutoring academies and other types of private education, such as private lessons or private online courses.[10] We make use of information on where individual engaged in private education. We defined time spent in private tutoring academies as time spent on private education away from respondent's home. Private tutoring academies consist 80.6% of total private education, and most private lessons and private online courses are typically conducted in students' home. Therefore, our definition of cram schooling should predict actual time devoted to private education institutes with high precision.[11] Korean students spend considerable time on study-related traveling; hence, we included the variable in the analysis. Any travel for the purpose of studying is included in the variable, such as going to school or private tutoring academies. However, if we exclude morning, then the variable should capture travel time for private education and going to school in the morning.

[10] Private online course is identifiable in 2009 and 2014 data, but we did not use this information because we pool the data from 1999 to 2014.

[11] Even under the assumption that 20% of students take private lessons or private online courses away from own home, actual cram schooling accounts for $0.806/(0.806 + ((1 - 0.806)/5) = 95\%$ of the variable.

We are also interested in time spent on sleep and after-school self-study session. A problem with defining sleep time using KTUS is that time devoted to nap and sleep are indistinguishable in the 2014 data. For consistency with the 2014 data, we aggregated nap and sleep and defined 30 minutes of subsequent "sleep or nap" as sleep time. However, from 9PM to 9AM, we did not impose the 30-minute rule.[12] KTUS provides information on time devoted to self-study session at school but do not distinguish between self-study session conducted before, during, or after regular school hours. However, similar to the study-related traveling, we can identify after-school self-study program with the help of information on time. In bunching analysis, we concentrate our attention to afternoon and night time to alleviate potential bias from measurement error in the variables.

Figure 1.2 shows the time trends of private tutoring usage. According to KTUS, in 1999, 23.6% of high school students engaged in cram schooling on weekdays. The use of private tutoring academies grew consistently as the probability of attending private tutoring academies reached 34.5% in 2014. The upward trends might reflect the ineffectiveness of restrictions on private tutoring institutes in reducing demand for private education. Survey on private tutoring (SPT) depicts slightly different time trends in 2007–2014 as percentage of student taking private tutoring classes decreased from 36.4% to 35%. However, we would like to emphasize that the participation rates from two datasets are not significantly different. This indicates that our variable definition captures actual cram schooling.

Table 1.1 shows the intraday distribution of time spent on private tutoring and other activities prior to the policy introduction. Students spend 26.7 minutes, on average, in private tutoring academies. They spend considerably long hours in cram schools because the average time spent on private tutoring is 121.8 minutes, conditioning on participating in private tutoring. Students also devote sufficiently long time, 84.4 minutes, in study-

[12] If respondent was awake more than 2 hours subsequently after less than or equal to 30 minutes of "sleep or nap," then we view this as a nap. However, simple aggregation of nap and sleep does not change the main results.

related traveling. Traveling to private tutoring institutes is time consuming; students who took private tutoring classes spend 22.5 minutes more in study-related traveling than average students. Students are likely deprived of sleep time as they engage in private tutoring because they sleep 2.9 minutes less than an average student. Students spend considerable time in self-study session at school; in particular, an average student spends 113.6 minutes in self-study session. Even though time devoted to after-school self-study session, which is 74.2 minutes, is long, an average student also spends 39.4 minutes between morning and early afternoon. This is due to the self-study session before regular school hours.[13] It is noteworthy that students significantly reduce time spent in after-school self-study session when they engage in private tutoring; students spend 42.3 minutes less on self-study session at school after 2PM. This suggests possible substitutability between after-school self-study program and private tutoring. Descriptive statistics of analysis sample is provided in Appendix Table A.1.2.

1.4 Empirical Methodologies

To measure the effect of the policy on daily time use of high school students, we employ the following DD specification:

$$\mathrm{H}_{\mathrm{idmys}}^{\mathrm{a}\epsilon\mathrm{A}} = \alpha + \beta \mathrm{D}_{\mathrm{mys}} + \varphi_{\mathrm{y}} + \tau_{\mathrm{s}} + \gamma \mathrm{X}_{\mathrm{imys}} + \delta_{\mathrm{d}} + \eta_{\mathrm{m}} + \xi_s I_s y + \varepsilon_{\mathrm{idmys}}. \quad (1)$$

$\mathrm{H}_{\mathrm{idmys}}^{\mathrm{a}}$ denotes hours spent on activity *a* for high school student *i* at survey day *d*, on month *m*, in year *y*, and in region *s*. Set A includes private tutoring, study-related traveling, sleeping, and self-study session at school. $\mathrm{D}_{\mathrm{mys}}$ is a treatment variable that is equal to 1 if high school student on month *m*, in year *y*, and in region *s* is affected by the curfew. We estimated the average effect of curfew, but we did not distinguish intensities of the curfews.

[13] Appendix Figure A.1.1 depicts the distribution of activities in a day. The figure shows that more than 40% of high school students engage in self-study session around 8AM.

We control for year-fixed effects φ_y and region-fixed effects τ_s. β provides the causal effect of curfew on daily hours spent on each activity under the identifying assumption that no differential trends existed in outcome variables across regions. δ_d and η_m represent day- and month-fixed effects, respectively. X_{imys} is the vector of individual characteristics including sex, age, parental education level, farm household, and single-parent family. ξ_s captures the effect of region-specific linear year trends. We also estimate the differential impacts of each curfew using the following specification.

$$H_{idmys}^{a\epsilon A} = \alpha + \beta_{10PM} D_{mys}^{10PM} + \beta_{11PM} D_{mys}^{11PM} + \beta_{12PM} D_{mys}^{12PM} + \varphi_y + \tau_s + \gamma X_{imys} + \delta_d + \eta_m + \xi_s I_s y + \varepsilon_{idmys}. \quad (2)$$

D_{mys}^{10PM}, D_{mys}^{11PM}, and D_{mys}^{12PM} are treatment variables that are equal to 1 if province *s* is treated by the 10PM, 11PM, or 12PM curfew on month *m* and in year *y*. Other variables are defined similarly as in equation (1).

To fully understand the impact of the curfew, we estimate the effect of policy before and after the curfew time. Hence, we adopt the following specification:

$$H_{itdmys}^{a\epsilon A} = \alpha + \beta_{before} D_{tmys}^{t\leq R_{mys}} + \beta_{after} D_{tmys}^{t>R_{msy}} + \varphi_y + \tau_s + \gamma X_{imys} + \rho_{ty} + \delta_d + \eta_m + \sum_{j=10PM}^{12AM} \xi_{s,j} I_{s,j} y + \varepsilon_{idmys}. \quad (3)$$

$H_{itdmys}^{a\epsilon A}$ is now a dummy variable that equals 1 if individual i at time t, at day d, on month m, in year y, and in region s engaged in activity a.[14] R_{msy} is the curfew time of province *s*, on month m, and in year y. R_{msy} is equal to 10PM, 11PM, or 12PM. Treatment variable $D_{tmys}^{t\leq R_{mys}}$ equals 1 if region s on month m and in year y is under the R_{msy} curfew and observed time t is before or equal to R_{msy}. Similarly, $D_{tmys}^{t>R_{mys}}$ equals 1

[14] Each *t* represents 10-minute time interval. For example, *t* = 1 denotes time between 12:01AM and 12:10AM, *h* = 2 denotes time between 12:11AM and 12:20AM, and *t* = 144 denotes time between 11:51PM and 12:00AM.

if region s, on month m and in year y is under the R_{msy} curfew and observed time t is after R_{msy}. If region s, on month *m* and in year *y* was not regulated by any of the curfews, then $D_{tmys}^{t\leq R_{mys}}$ and $D_{tmys}^{t>R_{mys}}$ are both equal to 0. β_{before} (β_{after}) is the average effect of the curfew on time use before (after) the regional curfew time. β_{before} (β_{after}) can be interpreted as percentage point changes in probability of doing activity within a 10-minute time interval, while estimating linear probability model. We estimate the individual-day-time level effect; hence, we additionally control for year by time-fixed effects. The term captures systematic differences in probability of engaging in an activity at each 10-minute interval. This allows likelihood of participating in each activity at each 10-minute interval to vary across the years. Furthermore, we estimate the effects of each curfew before and after the curfew times. We estimate following equation.

$$H_{itdmys}^{a\epsilon A} = \alpha + \sum_{j=10PM}^{12AM} \beta_{before,j} D_{tmys}^{t\leq j} + \sum_{j=10PM}^{12AM} \beta_{after,j} D_{tmys}^{t>j}$$

$$+\gamma X_{imys} + \varphi_y + \tau_s + \rho_{ty} + \delta_d + \eta_m + \sum_{j=10PM}^{12AM} \xi_{s,j} I_{s,j} y + \varepsilon_{itdmys} \quad (4)$$

Treatment variable $D_{tmys}^{t\leq j}$ equals 1 if region *s*, on month *m* and in year *y* is under the *j* curfew and observed time *t* is before or equal to *j*. Similarly, $D_{tmys}^{t>j}$ equals 1 if region s, on month *m* and in year *y* is under the *j* curfew and time is after *j*. If region *s* on month *m* and in year *y* is not under the *j* curfew, then $D_{tmys}^{t\leq j}$ and $D_{tmys}^{t>j}$ are both equal to 0. $\beta_{before,j}$ ($\beta_{after,j}$) denotes the effect of *j* curfew on before (after) the curfew time *j*. Equations (3) and (4) give the causal effect of curfews on students' time usage before and after the curfew times under the identifying assumption that potential trends in outcome variables were parallel across regions within hours: hours before and after the curfew times. To address the concern, we control for regional hour-specific linear year trends rather than region-specific linear year trends. $I_{s,j}$ is regional dummies that is equal to 1 if time *t* is before the curfew time *j*.

We use OLS in estimating the equations in spite of the large number of zeros in data. Zeros in time-use survey are consequence of inconsistency between diary day and period

of interest; therefore, estimates from Tobit or Cragg's (1971) two-part model are biased. OLS gives unbiased estimates for this type of data (Stewart, 2013). We estimate OLS standard errors allowing for clustering at individual level to account for serial correlation within individual.[15]

1.5 Impact on Daily Total Time

Our primary interest is the impact of the curfew on time spent in private tutoring institutes and on sleeping given that the main goal of the policy was to decrease hours of cram schooling and increase sleep time. It has to be emphasized that our prime interest is the effect of 10PM curfew. We anticipate significant effect for the 10PM curfew considering that in 1999, the likelihood of taking private tutoring classes during 10PM–4AM was 26.7%, conditioning on attending private tutoring academies. This ratio drops sharply to 11.5% and 1.6% as time changes to 11PM–4AM and 12AM–4AM. Interpretation on the estimates of 11PM and 12AM curfew is presented as these help in understanding the way students respond to the curfew.

Table 1.2 reports the DD estimation results for the time spent on private tutoring, study-related traveling, and sleeping. Panel A of Table 1.2 presents the impact of the curfew imposition regardless of curfew times, and Panel B reports the effects of each curfew. Each column in each panel presents estimates from separate regression. Columns (1) and (3) of Panel A report the impact of curfew imposition on time spent in private tutoring academies and study-related traveling. The estimates are both significantly positive, 10.6 minutes for private tutoring institutes and 4.8 minutes for study-related

[15] There exist at most 2 individual-days within individual in the DD models and at most 288 individual-day-time (10 minutes) in the DDD models.

traveling. The result is surprising because the time devoted to night-time cram schooling should be reduced presuming that the curfew was effectively imposed.

The results in Panel B of Table 1.2 indicate that 10PM, 11PM and 12AM curfews had a notably different impact on students' time usage. Column (1) reports estimates for time devoted to private tutoring institutes and Column (3) presents effects for study-related traveling. The estimates show that the 10PM curfew increases time devoted to private tutoring the most, 20.2 minutes. The 11PM curfew increases cram schooling 12.3 minutes and the 12AM curfew induces 4 minutes of additional cram schooling but the estimate is statistically insignificant for the latter. We observe similar positive effects of the policy for the study-related traveling. The 10PM, 11PM, and 12AM curfew increases traveling time for studying 8.6, 11.9, and 1.5 minutes, respectively. Again, the coefficient estimate of the 12AM curfew is statistically insignificant.

The impact of curfew imposition on sleep time is presented in Column (5) of Panel A and B. Panel A indicates that the curfew on average increases sleep time of high school students (9.7 minutes). Panel B shows that increase in sleep time is largest for the 10PM curfew (19.6 minutes). The estimated magnitude is 3–7 minutes larger than that of previous studies (Choi and Cho, 2015; Do et al., 2015). However, it is not directly comparable with the earlier studies because previous research focused on the curfew reinforcement. The 11PM curfew increases sleep time by 15 minutes, whereas the 12AM curfew increases sleep time by 3.3 minutes; however, the latter is insignificant in a statistical sense.

The results suggest that the curfew accomplished one of its intended goals, increasing sleep time, but failed to achieve the other primary policy goal, decreasing hours of cram schooling. Estimates are not only statistically significant but also economically meaningful because the average time devoted to private tutoring, study-related traveling, and sleeping are 31, 79, and 398 minutes, respectively (Appendix Table A.1.2). The curfew seems to have a substantial adverse impact on time spent on private tutoring and related traveling. However, the relationship between the curfew ordinance and the students' time spent in cram schools might be spurious because of omitted confounding factor.

The difference-in-differences model requires counterfactual trend in outcome in treated regions to be parallel to that of the untreated regions. For our current study, which has multiple treatments and periods, the analogous identifying assumption is that no province-level confounding factors existed that are coincident with the imposition of the curfew and that affected students' hours of cram schooling. To test the identifying assumption, we conduct two robustness checks. First, we control for region-specific linear year trends. This is a common practice for testing robustness of central policy relationship in similar types of settings (Wolfers, 2006; Anger et al., 2011; Lundborg et al, 2014). By doing so, we compare deviations of outcome from linear trends across regions to identify the curfew effect. Second, we run the placebo test using the sample of first and second year college and university students. No impact is anticipated for the tertiary students because they are not subjected to the curfew.

In Panel A, Columns (2), (4), and (6) present the average effects of the curfew on time devoted to cram schooling, study-related traveling, and sleeping, controlling for regional year trends. Compared with the baseline results in Columns (1), (3), and (5), the estimates vary at most 0.9 minutes for sleep time. The results in the same columns of Panel B show the estimates of each policy on each activity, after including region-specific linear trends. The estimates of the 11PM curfew are sensitive to inclusion of the linear trends. All the coefficient estimates move significantly and lose statistical significances after controlling for the linear trends. However, estimates of the 10PM and the 12AM curfew remain fairly stable with the additional trends variable. Inclusion of region-specific linear trends alter the estimates of 10PM curfew at most 2.8 minutes for cram schooling and estimates of 12AM curfew at most 2.0 minutes for sleeping. No change in statistical significance of the estimates are observed. The results suggest that the timings of adoption of 10PM and 12AM curfews are exogenous to time-varying unobservables. However, the adoption timing of 11AM curfew seems to be correlated with movement of unobserved determinants of students' time use decision.

Table 1.3 shows the results from same specifications where we confine our attention to first and second year college and university students. Panel A presents the average impact of the curfew adoption, and Panel B reports the estimates of each curfew. We find no statistically significant impact on college or university students' time usage neither in Panel A nor in Panel B. In Column (5) of Panel B, the 11PM curfew has negative impact on sleep time. However, statistical significance disappears as we control for the linear trends in column (6). This result ensures that our estimates for high school students are not driven by spurious relationship between policy variables and time-varying regional factors.

1.6 Impact on Intraday Time Allocation: Hour-by-Hour Regression

The results from DD estimation indicate that the *increase* in time spent in private tutoring institutes and on study-related traveling due to the 10PM curfew is not caused by the spurious relationship between the timing of the curfew adoption and potential contaminating factors. This raises question of whether the curfew was effectively enforced. To investigate this issue, we conduct DDD estimation wherein we allow treatment effect to vary before and after the curfew time. We should observe the negative effect of the curfew on cram schooling after the curfew time, assuming that the curfew was successfully implemented.

Panel A in Table 1.4 presents estimates for probability of engaging in each activity before and after the curfew times. In Column (1), β_{after} indicates that the curfew reduces probability of cram schooling 1.2%pt for every 10-minutes interval after the curfew time. β_{after} in Column (5) shows that the curfew increases the likelihood of sleep 1.3%pt for every 10-minutes after the curfew time. This result implies that following the introduction of the curfew, students cut time devoted to private tutoring and increase sleep

time after the curfew time. In this paper, we denote these intended effects as treatment effects.

However, we find that the presence of the curfew is associated with a significant increase in cram schooling and study-related traveling before the curfew time. β_{before} in Column (1) suggests that the curfew induces a 1.8%pt increase in time spent in private tutoring academies before the curfew time. Likewise, β_{before} in Column (3) shows that the probability of study-related traveling increases 0.7%pt before the curfew time, following imposition of the curfew. Throughout this paper, we denote these unintended positive spillover effects as balloon effects.

The results in Panel A of Table 1.4 provide an explanation for the puzzling findings in Table 1.2. After the curfew enforcement, students took more classes at the private tutoring academies before the curfew time. It is noteworthy that the balloon effect is significantly greater than the treatment effect.[16] This led to the growth in the total amount of time spent on cram schooling on a daily basis.

The effects of each curfew on time use before and after each curfew time is presented in Panel B of Table 1.4. In Column (1), we find similar patterns for probability of cram schooling as those shown in Panel A. Regardless of the curfew times, students were less (more) likely to engage in cram schooling after (before) the curfew time. The

[16] Hours before the curfew times are defined as 4:01AM–10:00PM, 4:01AM–11:00PM, and 4:01AM–12:00AM for the 10PM, 11PM, and 12AM curfew, respectively. Likewise, hours after the curfew times are 10:01PM–4:00AM, 11:01PM–4:00AM, and 12:01AM–4:00AM for each curfew. This implies that even though magnitudes of β_{before} and β_{after} are identical, the implied minute changes before the curfew time is greater than after the curfew time. For example, 1%pt increase in private tutoring before 10PM indicates $0.01 \times 10 \times 108 = 10.8$ minutes increase, and 1%pt decrease in private tutoring after 10PM means $0.01 \times 10 \times 36 = 3.6$ minutes decrease in private tutoring. The estimate of β_{before} is even greater than β_{after} in Table 1.4; therefore, the balloon effect is much greater than treatment effect.

magnitudes of balloon effects are of the same order as that of treatment effects. The 10PM curfew has the largest treatment and balloon effect, and the effects of 12AM curfew are the smallest. This observation suggests that students appear to allocate more time to private tutoring academies before the curfew time in order to compensate deprivation of time devoted to private education during regulated hours.

Our DDD estimation relies on stronger identifying assumption than the standard DDD model. Standard triple-difference estimation differences out "true" effect of the curfew in the presence of spillover effect (Bitler and Carpenter, 2016). Our empirical model identifies the effects of the imposition of curfews before and after the curfew times under the identifying assumption that potential trends of outcome were parallel across treated and untreated regions within hours; hours before and after the curfew times.

To test the robustness of the results from DDD estimation, we include linear trends of each region-hours cell; region by hours before the curfew times and region by hours after the curfew times. As a result, we compare deviations of outcome from linear trends across regions within restricted and unrestricted hours. The Column (2), (4) and (6) in each panel of Table 1.4 show the results after controlling for region-hours specific linear year trends. Even though estimates differ modestly, the main results for the 10PM curfew are robust to the inclusion of linear trends variable. The treatment and balloon effect of 10PM curfew on private tutoring is upward biased as we omit the linear trends. After controlling for the linear trends, absolute magnitudes of the estimates decrease by 0.3–0.4%pt. The estimated effect of 10PM curfew on sleep before 10PM decreases 0.3%pt but the effect on sleep after 10PM increases 1.4%pt when we consider region-hours specific linear trends.[17]

To further establish the robustness of the results, we conduct a bunching analysis. The curfew can be seen as a policy creating a notch around the curfew time because after

[17] Controlling for standard region-specific linear trends in the DDD model gives similar results.

the curfew enforcement, cost of participating in cram schooling is disproportionately higher after the curfew time. Bunching methods are applicable because the assignment variable is manipulative (Kleven, 2016).[18] We estimate the impact of the curfew on an hourly basis, under the assumption that counterfactual frequency distribution of time usage in the treated and untreated regions move in parallel. We restricted our attention to hours between 2:01 PM and 4:00 AM in order to alleviate potential bias in hours far from the curfew time. Excluding morning and early afternoon in our setting is comparable with precluding an upper tale of wage distribution in minimum wage study. Cenzig et al. (2019) estimated employment effect of minimum wage on low-wage workers under an identifying assumption analogous to our study. Moreover, by doing so, we can define the variables more accurately because (a) time devoted to going to school is excluded from the study-related traveling variable and (b) self-study session at school before regular school hours, namely, "0 hours class," is excluded from the self-study session variable. The bunching estimation is useful in a sense that we can observe distributional changes in time use around the curfew time. Moreover, the comparison of estimates from the bunching estimation and from the DDD estimation serves as valuable robustness check because bunching estimation relies on different identifying assumption, focuses on narrower time domain, and uses more accurately defined variables.

Specifically, we estimate regression equation (5). $H_{ihdmys}^{a\epsilon A}$ is now defined as

[18] Unlike most studies that adopted bunching method, we do not infer elasticity, and implicit and explicit cost changes are unobservable. However, this is not problematic in our current setting because the prime interest is to identify the causal effect on time allocation.

minutes spent on activity a during hour h.[19][20] Treatment variable $D_{mys}^{h,j}$ equals 1 if region *s* on month *m* and in year *y* is under the j curfew and hour is h. $\beta_{h,j}$ is the effect of curfew j on minutes spent on certain activity during hour h.

$$H_{ihdmys}^{a\epsilon A} = \alpha + \sum_{j=10PM}^{12AM} \sum_{h=3PM}^{3AM} \beta_{h,j} D_{mys}^{h,j} + \varphi_y + \tau_s + \gamma X_{imys} + \rho_{hy} + \delta_d + \eta_m + \xi_s I_s y + \varepsilon_{ihdmys}. \quad (5)$$

For each activity, changes before and after each curfew time j, formally $\Delta B_j = \sum_{h=2PM}^{j} \beta_{h,j}$ and $\Delta T_j = \sum_{h=j}^{3AM} \beta_{h,j}$, are calculated. We assess the effect of the curfew j on daily time use by summing treatment effect and balloon effect $\Delta B_j + \Delta T_j$. We stress that we do not only estimate total effect $\Delta B_j + \Delta T$, but we also split time allocation changes before and after curfew time.

Figure 1.3 depicts the sum of coefficient estimates for time devoted to private tutoring institutes and study-related traveling. Panel A shows the effects of 10PM curfew. The existence of treatment and balloon effect is apparent, whereas the sum of coefficients switches signs after 10PM. As suggested in DDD analysis, balloon effect is much greater in magnitude. The treatment effect is largest within 2 hours after the curfew time, and the balloon effect is largest from 2 to 3 hours before the curfew time. The balloon effect remains positive until 3 PM. Similar pattern is observed in Panel B for the 11PM curfew; however, compared with the 10PM curfew, effects are smaller in magnitude. Panel C suggests that the 12AM curfew has a modest balloon effect.

Table 1.5 compares implied changes in time spent in private tutoring academies from each estimation method. The results for the 10PM curfew is presented, considering

[19] We discretize time on hourly basis. Data are aggregated into individual-day-hour level, and using individual-day-time (10 minutes) data requires us to estimate 332 coefficients simultaneously. This will severely reduce the statistical precision of the estimates.

[20] Each h represents 1-hour time interval. For example, h = 2PM denotes time between 2:01PM and 3PM, h = 3PM denotes time between 3:01PM and 4:00PM, and h = 3AM denotes time between 3:01AM and 4:00AM.

that the 10PM has the strongest and the most robust effect. The results in Column (4) and (7) show minute changes implied by the DDD estimation and the bunching estimation. Discrepancies in implied minute changes from the DD and the bunching estimation are at most 3.44 minutes. Moreover, the results from the DD and the DDD estimation are strikingly similar. These similarities ensure that our findings on treatment and balloon effects are causal.

1.7 What is Going on?

We have shown that the existence of large balloon effect led to an increase in crams schooling despite the fact that the curfew was effectively enforced. However, this finding leaves us important questions to be answered: (a) Did an increase in cram schooling before the curfew time affected other activities during business hours? (b) Why is balloon effect much greater than treatment effect? To answer these questions, we examine the effect of curfew on after-school self-study session. Table 1.1 reveals that students devoted considerable time to after-school self-study session prior to policy introduction. Self-studying and private education are significant determinants in education production function as well as formal study (Dolton et al., 2003, Ryu and Kang, 2007); thus, students could have substituted private tutoring academies for self-study session at school.

Table 1.6 shows the effect of curfew on time devoted to after-school self-study program. The results in the table reveal that the 10PM curfew significantly reduced time spent in self-study session at school before 10PM. Column (1) and (2) present the results from DD estimation and Column (3) and (4) show the results from DDD estimation. Panel A and C in Table 1.6 give the average effect of the curfew. Panel B and D in Table 1.6 provide the effects of each curfew. Each column-panel provides the estimates from separate regressions. The estimates in the first two columns of Panel A reveal that on average, students cut 24.3 minutes of night self-study time at school. The same columns

of Panel B show that the reduction in self-study at school occurred before the curfew time. Students' probability of engaging in self-study program decreased 2.4%pt for every 10 minutes. Column (3) of Panel C indicates that the 10PM curfew decreased the self-study time 38.5 minutes. Column (4) of Panel C shows that this estimate changes to -51.3 minutes as we additionally control for the linear trends. The result from Seemingly Unrelated Regression (SUR) suggests that we cannot reject the null hypothesis that decreased self-study time at school is identical to the sum of the increase in time spent on cram schooling, study-related traveling, and sleeping.[21] Column (3) and (4) of Panel D suggest that major reduction in self-study session occurred before 10PM even though students reduced self-studying time both before and after the curfew time. This is natural because the initial probability of engaging in after-school self-study program is much higher before 10PM than after 10PM. The 10PM curfew reduces probability of the self-study 4.3%pt before the curfew time. This result explains why we observed increase in sleep before 10PM in Table 1.4. As the decrease in self-study session is larger than the increase in cram schooling before 10PM, students had substituted self-study at school with sleeping as well as private education. This explains the result from Choi and Cho (2015) that the 10PM induced growth in sleep before 10PM.

The estimates for self-study program from bunching estimation is presented in Figure 1.4. The figure clearly shows that students decreased night-time self-study at school before the curfew time. As balloon effect is largest for the 10PM curfew, reduction in self-study session is largest for the 10PM curfew.

It is evident that the curfew encouraged students to substitute self-study program at school with cram schooling. However, we would like to be sure that this result was not due to other policy changes. The "Students Human Rights Ordinance," the "Delayed School Start," and the 10PM curfew are commonly believed to be liberal policies

[21] P-value of the test is 0.9514.

supported by progressive local government. We conduct three tests to verify that substitution between activities are not driven by other policies.

We find that progressive superintendents are indeed significantly more likely to adopt liberal policies.[22] However, the estimates in Table 1.7 assure that reduction in after-school self-study program is not attributable to other policies. Panel A shows the estimates from the standard DD estimation. Panel B presents the results from DD estimation after controlling for adoption status of other liberal policies and progressivity of the local governments. The result in Panel C shows estimates of the 10PM curfew, excluding five regions where other liberal policies are adopted. We excluded the 2014 data in Panel D because other liberal policies are adopted between 2009 and 2014. In all approaches, we find a significant increase in time devoted to private tutoring academies and a decrease in after-school self-study time.

The substantial reduction in after-school program might explain why balloon effect was much greater than treatment effect. Schools face pressure from students to satisfy their demand for private education. In most schools that mandate after-school self-study session, students are allowed to not participate in the after-school program if they engage in private education. The increase in demand for cram schooling induced by 10PM curfew could have putted pressure on schools to adopt more generous policy for after-school self-study program. Students were likely to responded to increased flexibility of the self-study session because it had been costly for student to opt-out from the self-study session at school.[23] If this is true, we should observe students' behavioral response in extensive margin; students who previously engaged in self-study session at school gave up the session and took classes

[22] The results are given in Appendix Table A.1.3. Using newspaper articles, we identified progressiveness of regional superintendents. We run regressions for all possible combinations (2 × 2) because we cannot identify progressiveness of the superintendent in Gwangju and Jeonnam in 1999.

[23] Students are often asked to submit official documents proving their attendance at private tutoring institutes.

at private tutoring academies. To test the hypothesis, we run DD estimation using participation in the self-study session and in cram schooling as dependent variables. The results in Table 1.8 show that the 10PM curfew reduced probability of engaging in after-school self-study session by 11%pt and increased likelihood of taking private tutoring by 7.5%pt. This could be considered as policy affecting societal "climate." Dinardo and Lemieux (2001) found that increase in drinking age generated societal disapproval for all drug use. In our current setting, legal restriction on operation of private tutoring academies at night-time could have created societal approval for engaging in cram schooling during business hours.

1.8. Conclusion

We examined the effect of the policy that restricts business hours of private tutoring institutes on high school students' time use. Our results suggest that the legal restriction prohibiting operation of private tutoring academies after 10PM significantly increased sleep time (18.2 minutes). Nonetheless, at the same time, the curfew induced notably more time spent on private tutoring (18.3 minutes). This result holds up to various validation tests and robustness checks. To understand the mechanism behind this surprising finding, we estimate the impact of policy on student's time-use behavior before and after the curfew time. Our findings suggest that the curfew was effectively enforced and reduced 86% of time spent on cram schooling after the curfew time. However, students shifted into cram schooling before the curfew time. The increase in time devoted to private tutoring academies before 10PM was much greater than the decrease in private tutoring after 10PM; therefore, the total time spent in private tutoring institutes increased. Moreover, we found that this balloon effect was accompanied by another substitution: substitution between after-school self-study session and private tutoring academies. In order to take more private tutoring before the curfew time, students gave up self-study session at school. We provide

the anecdotal evidence that the curfew induced less restrictive after-school self-study program, and this contributed to substantial increase in private tutoring before the curfew time.

Our paper provides evidence on how effective rationing on one good, that is, private education at regulated hours, could lead to increase in demand for other good, that is, private education at unregulated hours. Previous studies suggest that substantial offsetting effect could result in zero effect of the regulation policy (Goulder et al., 2012; Yang, 2008). Our current study showed that in the presence of after-school self-study program, in which students were mandated to participate in, the policy even increased the overall demand for private tutoring. This paper suggests that intraday substitutions between activities are important in evaluating the impact of the regulation policy aiming at affecting time use of individuals.

The major limitation of our paper is that we focused exclusively on time use of individuals because of the limitations of data. A relevant topic for future research is to investigate the effect of curfew on students' welfare. The curfew is believed to have substantial welfare impact on students. For example, Do et al. (2015) suggested that the curfew decreased BMI of high school students by increasing sleep time. Some argue that the curfew enhances safety of students because it reduces probability of walking at night. Also, discussion over welfare implication of after-school self-study program is intense. It would be interesting to study how reduction in self-study session at school and increase in private tutoring affect students' well-being. The effect of curfew on academic achievement is also an important topic. The curfew might widen achievement gap considering that private tutoring affects academic achievement (Ryu and Kang, 2007).[24] Lastly, the effect of curfew on the supply side of private education market should not be ignored. The curfew

[24] We found evidence that students from highly educated parents are more likely to increase private tutoring after the curfew adoption. This result is presented in Appendix Table A.1.4.

significantly altered demand for private tutoring; hence, cram school industry could have experienced notable changes, such as employment adjustment or structural transformation.

Table 1.1 Intraday Distribution of Activities

	Unconditional					Conditional (private tutoring institute=1)				
	Day	8:01AM-2:00PM	2:01PM-10:00PM	10:01PM-4:00AM	4:01AM-8:00AM	Day	8:01AM-2:00PM	2:01PM-10:00PM	10:01PM-4:00AM	4:01AM-8:00AM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Minutes										
Private tutoring	26.7	0.3	23.1	3.3	0	121.8	1.2	105.4	15	0.2
Study-related traveling	84.4	7.4	38.1	9.1	29.7	106.9	7.4	59.5	10.7	29.3
Sleeping	399.4	1.6	3.1	246.3	148.4	396.5	0.5	1.3	243.0	151.7
Self-study session at school	113.6	27.9	69.3	4.9	11.5	71.9	30.3	31.4	0.5	9.8
Panel B. Participation (%)										
Private tutoring	21.9	0.3	20.4	5.9	0.1	100	1.3	93.1	26.7	0.3
Study-related traveling	98.9	29.0	81.1	33.5	90.1	100	31.9	96.9	42.1	90.9
Sleeping	100	3.2	4.2	99.7	99.8	100	2.7	1.9	99.8	99.8
Self-study session at school	83.2	66.8	49.5	8.5	38.0	83.5	70.9	33.3	0.9	34.9

Notes. High school sample of KTUS 1999 is used in calculation. Panel A shows average minutes spent on each activity and Panel B presents average participation rate in each activity. Column (1) to (5) show unconditional means and column (6) to (10) present means conditioning on students taking private tutoring. Column (1) and (5) present daily average and column (2) to (5) ((7) to (10)) present figures for four different time domains.

Table 1.2 DD Estimation

	Dependent variables: time spent on each activity on a daily basis					
	Private tutoring		Study-related traveling		Sleep	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Avergae effect						
β	10.058**	10.307**	4.807*	4.883*	9.673**	8.762*
	(4.406)	(4.437)	(2.809)	(2.833)	(4.854)	(4.898)
B. Effects of each policy						
β_{10}	20.217***	17.493***	8.567**	9.584**	19.602***	21.455***
	(5.616)	(6.588)	(3.451)	(4.117)	(5.847)	(6.807)
β_{11}	12.264*	14.016	11.938***	9.182	15.000**	-10.471
	(6.483)	(10.023)	(4.223)	(6.728)	(7.324)	(11.545)
β_{12}	4.037	5.662	1.509	1.503	3.251	5.264
	(4.510)	(4.738)	(2.892)	(3.083)	(5.189)	(5.436)
Control variables						
Observables; day, month fixed effects	√	√	√	√	√	√
Regional fixed effects	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√
Time x year fixed effects	√	√	√	√	√	√
Regional specific linear trends		√		√		√

Notes. Sample=7,096 individual-day observations in Panels A and B. Panel A reports average effect of the curfew regardless of the curfew times. Panel B shows the effects of each policy. Column (1), (3), (5) use hours spent on private tutoring, study-related traveling, and sleeping as dependent variables respectively. Year and regional fixed effects are included as control variables in each specifications. Unreported "Observables" include sex, age, parental education, farm household, single(or no)-parent. Column (2), (4), (6) additionally controls for regional specific linear trends. Standard errors in parentheses, are clustered by individual.

***, **, and * Statstically significant at 1%, 5%, 10%.

Table 1.3 Placebo DD using College Sample

	Dependent variables: time spent on each activity on a daily basis					
	Private tutoring		Study-related traveling		Sleep	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Average effect						
β	2.848	1.382	-2.300	2.305	-5.981	0.561
	(2.960)	(2.679)	(4.153)	(5.864)	(8.793)	(10.775)
B. Effects of each policy						
β_{10}	5.494	4.882	1.639	9.884	-1.027	2.671
	(4.040)	(4.556)	(4.745)	(7.548)	(10.268)	(14.867)
β_{11}	-0.394	4.774	-7.648	3.032	-30.642*	-21.912
	(4.388)	(8.735)	(5.702)	(13.563)	(16.383)	(23.554)
β_{12}	0.349	-4.189	-5.954	-7.170	-8.352	6.806
	(2.845)	(3.060)	(5.212)	(8.472)	(11.571)	(14.834)
Control variables						
Observables; day, month fixed effects	√	√	√	√	√	√
Regional fixed effects	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√
Time x year fixed effects	√	√	√	√	√	√
Regional specific linear trends		√		√		√

Notes. Sample=2,233 individual-day observations in Panels A, B. Panel A reports average effect of policy. Panel B shows the effects of each regulation policiy. Column (1), (3) and (5) use hours spent on private tutoring, study-related traveling and sleeping as dependent variables respectively. Year and regional fixed effects are included as control variables in each specifications. Unreported "Observables" include sex, age, farm household. Column (2), (4), (6) additionally controls for regional specific linear trends. Standard errors in parentheses, are clustered by individual.
***, **, and * Statstically significant at 1%, 5%, 10%.

Table 1.4 DDD Estimation

	Dependent variables: participation in each activity (every 10 minutes)					
	Private tutoring		Study-related traveling		Sleep	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Averages effects						
β_{before}	0.018***	0.017***	0.007***	0.006**	0.003	0.000
	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
β_{after}	-0.012***	-0.009***	-0.003	-0.002	0.013**	0.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
B. Effects of each policy						
$\beta_{10,before}$	0.025***	0.021***	0.010***	0.010***	0.013***	0.010**
	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
$\beta_{10,after}$	-0.018***	-0.015***	-0.006*	-0.002	0.016*	0.030**
	(0.005)	(0.006)	(0.003)	(0.004)	(0.010)	(0.012)
$\beta_{11,before}$	0.014***	0.016**	0.012***	0.009*	0.006	-0.015*
	(0.005)	(0.007)	(0.003)	(0.005)	(0.005)	(0.008)
$\beta_{11,after}$	-0.014***	-0.013*	-0.007**	-0.004	0.029*	0.022
	(0.005)	(0.007)	(0.003)	(0.005)	(0.015)	(0.018)
$\beta_{12,before}$	0.005	0.006*	0.001	0.001	0.001	0.002
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
$\beta_{12,after}$	-0.008**	-0.008**	0.000	0.000	0.010	0.014
	(0.003)	(0.003)	(0.002)	(0.002)	(0.010)	(0.011)
Control variables						
Observables; day, month fixed effects	√	√	√	√	√	√
Regional fixed effects	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√
Time x year fixed effects	√	√	√	√	√	√
Region-hours specific linear trends		√		√		√

Notes . Sample=1,021,824 individual-day-time observations in Panels A and B. Panel A reports average effect of policies regardless of the curfew times. Panel B shows the effects of each regulation policy. Column (1), (3) and (5) use hours spent on private tutoring, study-related traveling, and sleeping as dependent variables. Year and regional fixed effects are included as control variables in each specifications. Interaction of time and year dummy is included. Unreported "Observables" include sex, age, parental education, farm household, single(or no)-parent. Column (2), (4) and (6) additionally controls for region-hours specific linear trends. Standard errors in parentheses, are clustered by individual.
***, **, and * Statstically significant at 1%, 5%, 10%.

Table 1.5 Implied Minutes Change by the 10PM Curfew

	Estimation methods						
	Standard DD	DDD : before and after 10PM (10 minutes bin, 24 hours)			Bunching methods (1hour bin, 2:01PM-4:00AM)		
	total	before	after	total=before+after	ΔB_{10PM}	ΔT_{10PM}	$\Delta B_{10PM} + \Delta T_{10PM}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Private tutoring outside	17.49***	22.79***	-5.29***	17.49***	23.3***	-4.99**	18.31***
Study related moving	9.58**	10.32***	-0.74	9.58**	10.78***	-1.49**	9.29***
Sleep	21.46***	10.73**	10.73**	21.46***	8.53***	9.63**	18.16***

Notes. The leftest column shows the estimates from the standard DD estimation. Column (2) and (3) present implied minutes change before and after 10PM from the DDD estimation. Column (5) and (6) show calculated minutes change before and after 10PM from the bunching estimation. Differences between minutes change are presented in column (4) and (7).

Table 1.6 Effect on Self-study Session

	DD		DDD	
	(1)	(2)	(3)	(4)
PanelA. Average effect-total daily time				
β	-24.397***	-24.312***		
	(6.559)	(6.608)		
Panel B. Average effect-before and after				
β_{before}			-0.024***	-0.025***
			(0.006)	(0.006)
β_{after}			-0.005	-0.003
			(0.003)	(0.003)
Panel C. Effect of each policy-total daily amount				
β_{10}	-38.503***	-51.304***		
	(7.755)	(8.743)		
β_{11}	-45.752***	-16.732		
	(9.569)	(15.452)		
β_{12}	-12.938*	-10.793		
	(6.979)	(7.441)		
Panel D. Effect of each policy-before and after				
$\beta_{10,before}$			-0.034***	-0.042***
			(0.006)	(0.007)
$\beta_{10,after}$			-0.005	-0.017***
			(0.004)	(0.005)
$\beta_{11,before}$			-0.037***	-0.018
			(0.008)	(0.012)
$\beta_{11,after}$			-0.014***	0.014
			(0.004)	(0.009)
$\beta_{12,before}$			-0.008	-0.009
			(0.005)	(0.006)
$\beta_{12,after}$			-0.012***	-0.002
			(0.003)	(0.003)
Control variables				
Observables; day, month fixed effects	√	√	√	√
Regional fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Time x year fixed effects	√	√	√	√
Regional specific linear trends		√		
Region-hours specific linear trends				√

Notes. Sample=7,096 individual-day observations in Panels A, C and 1,021,824 individual-day-time observations in Panel C and D. Column (1) and (3) report estimates from the DD estimation. Column (2) and (4) presents estimates
from the DDD estimation. Column (3) additionally controls for regional specific linear trends and column (4) additionally controls for region-hours specific linear trends. Year and regional fixed effects are included as control variables in each specifications. Unreported "Observables" include sex, age, parental education, farm household, single(or no)-parent. In Column (3) and (4), interaction of time and year dummy is included. Standard errors in parentheses, are clustered by individual.
***, **, and * Statstically significant at 1%, 5%, 10%.

Table 1.7 Unconfoundedness of the Curfew

	Province specific linear year trend: X				Province specific linear year trend: O			
	Private tutoring	Study-related traveling	Self-study sessoin	Sleep	Private tutoring	Study-related traveling	Self-study sessoin	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Standard model								
β_{10}	20.217***	8.567**	-38.503***	19.602***	17.493***	9.584**	-51.304***	21.455***
	(5.616)	(3.451)	(7.755)	(5.847)	(6.588)	(4.117)	(8.743)	(6.807)
Panel B. Control for other policies								
β_{10}	20.094***	8.157**	-38.152***	16.521***	21.292***	8.507**	-50.622***	19.548***
	(5.943)	(3.606)	(8.034)	(6.110)	(7.067)	(4.211)	(8.871)	(6.994)
Panel C. Excluding 5 provinces								
β_{10}	16.707**	7.004	-38.778***	19.519**	16.241*	7.636	-39.749***	12.815
	(7.262)	(5.818)	(13.278)	(8.795)	(8.295)	(6.934)	(15.197)	(9.761)
Panel D. Excluding 2014								
β_{10}	21.338***	12.239***	-41.457***	13.649**	34.234***	11.324*	-54.749***	14.797
	(6.435)	(4.071)	(8.988)	(6.783)	(9.018)	(6.544)	(13.859)	(9.891)
Control variables								
11PM curfew treatment dummy	√	√	√	√	√	√	√	√
12AM curfew treatment dummy	√	√	√	√	√	√	√	√
Observables; day, month fixed effects	√	√	√	√	√	√	√	√
Regional fixed effects	√	√	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√	√	√
Regional specific linear trends					√	√	√	√
Human Right Ordinance dummy		included in Panel B				included in Panel B		
Delayed School Strat Time dummy		included in Panel B				included in Panel B		

Notes. Sample=7,096 invidiaul-day observations in Panels A and B, 4,129 observations in Panel C and 5,781 observations in Panel D. Panel A shows estimates for 10PM curfew from standard DD presented in Table 4. Panel B are estimates of 10PM curfew from standard DD controlling for 'Human Right Ordinance' and 'Delayed School Start Time' policies. Panel C depicts effects of the 10PM curfew from DD estimation excluding 5 provinces with 'Human Right Oridnance' policy or 'Delayed School Start Time'. Panel D reports effect of 10PM curfew excluding 2014 data. Treatment dummies for 11PM and 12AM curfew are included in all specifications. Column (1), (2), (3) and (4) use the hours spent on private tutoring, study related moving,self night study and sleeping as dependent variables respectively. Year and regional fixed effects are included as control variables in each specifications. Unreported "Observables" include sex, age, parental education, farm household, single(or no)-parent. Column (5), (6), (7), (8) presents estimates after controlling for regional specific linear trends. Standard errors in parentheses, are clustered by individual.

***, **, and * Statstically significant at 1%, 5% and 10%.

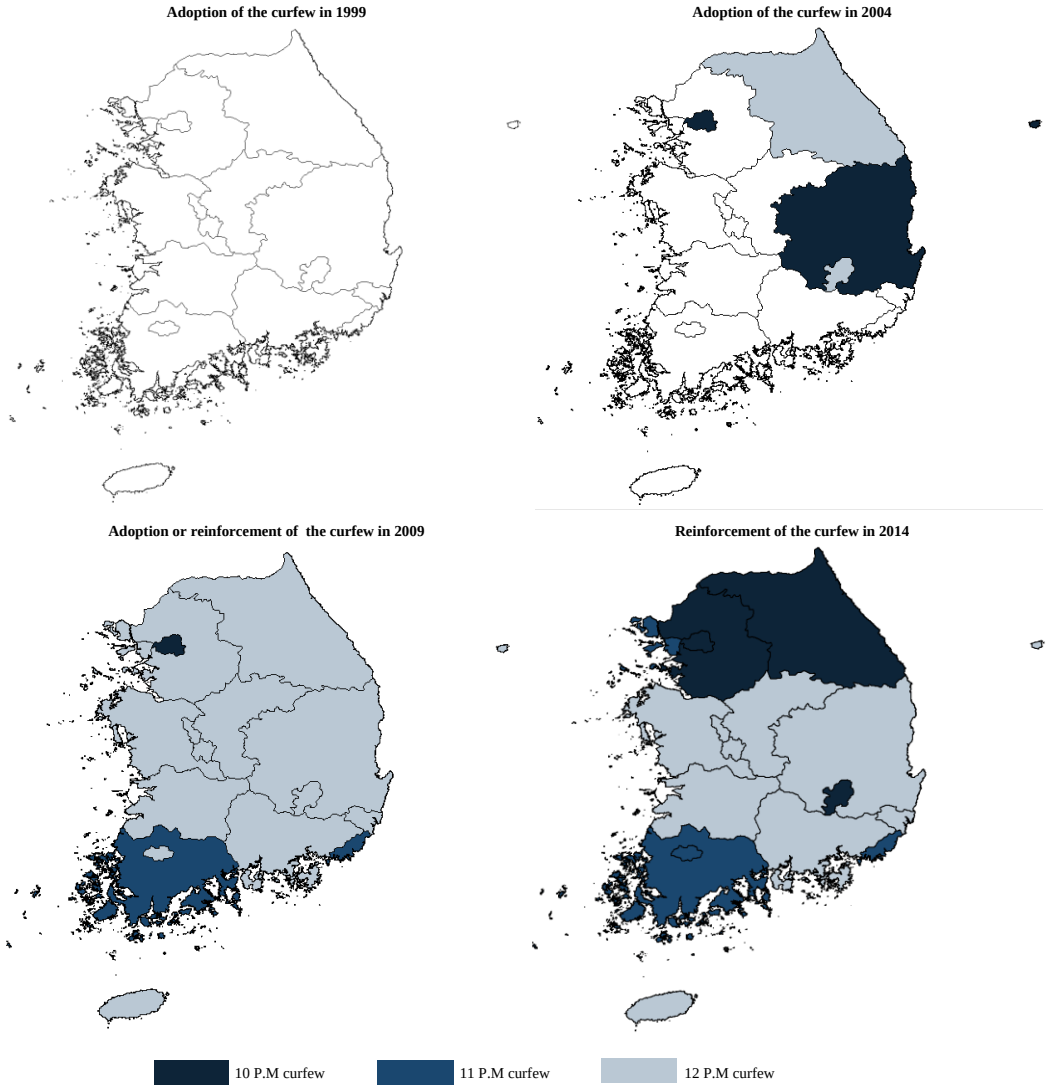
Table 1.8 Effect of each Cufrew on Participation

	Private tutoring		Study-related traveling		Self-study session		Sleep	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_{10}	0.103***	0.075*	-0.015	-0.011	-0.090***	-0.110***	0	0
	(0.04)	(0.04)	(0.01)	(0.01)	(0.03)	(0.04)	0	0
β_{11}	0.066	0.095	-0.002	-0.013	-0.061	0.034	0	0
	(0.05)	(0.07)	(0.01)	(0.02)	(0.04)	(0.06)	0	0
β_{12}	0.007	0.022	-0.012	-0.013	0.011	0.006	-0.001	-0.001
	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)	(0.00)	(0.00)
Control variables								
Observables; day, month fixed effects	√	√	√	√	√	√	√	√
Regional fixed effects	√	√	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√	√	√
Regional specific linear trends		√		√		√		√

Notes. Sample=7,096 individual-day observations. Column (1) and (2) report effects of the curfews on participation in private tutoring. Panel (3) and (4) show the effect of the curfews on participation in Study-related traveling. Column (5) and (6) report effects of the curfews on participation in self-study session and Column (7) and (8) present effects of the curfews on sleeping. Year and regional fixed effects are included as control variables in each specifications. Unreported "Observables" include sex, age, parental education, farm household, single(or no)-parent. Column (2), (4), (6) and (8) additionally controls for regional specific linear trends. Standard errors in parentheses, are clustered by individual.

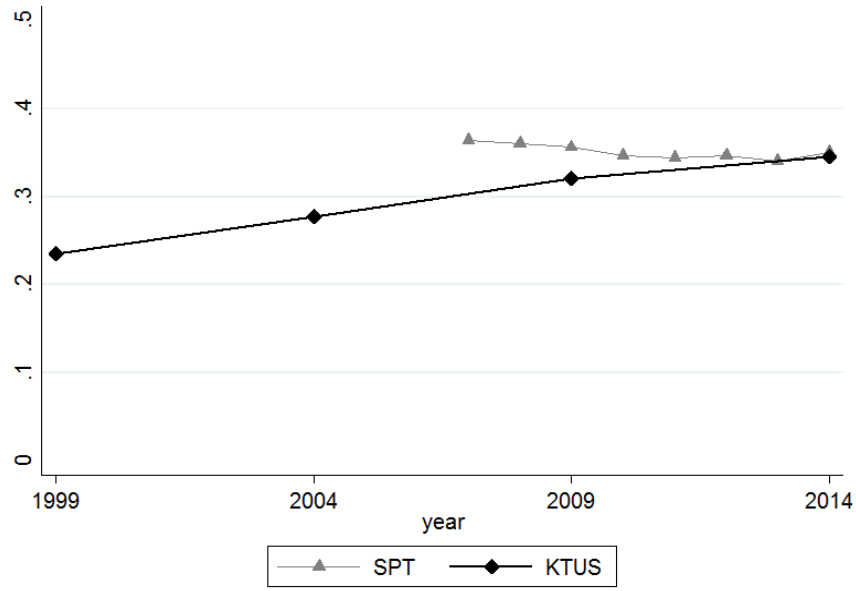
***, **, and * Statstically significant at 1%, 5%, 10%.

Figure 1.1 Adoption of the Curfews



Notes. Adoption of the curfew in each survey years. The graphs shows the regional adoption or reinforcement status of the curfew in each survey years of Korean Time Use Survey(KTUS). Adopted or reinforced status of curfew in certain year does not necessarily mean that curfew was adopted or reinforced exactly in that year. It shows that the curfew was adopted or reinforced after last survey year and before or in current survey year. 17 administrative divisions of South Korea are distinguished in the figure using black lines. Intensities of the curfews are denoted by different colors. The darker the regions are, the more restrictive the curfews are. Curfew of 11:50 p.m. was reinforced in province North Jeolla but we denoted it as 12 p.m. in the figure for simplicity.

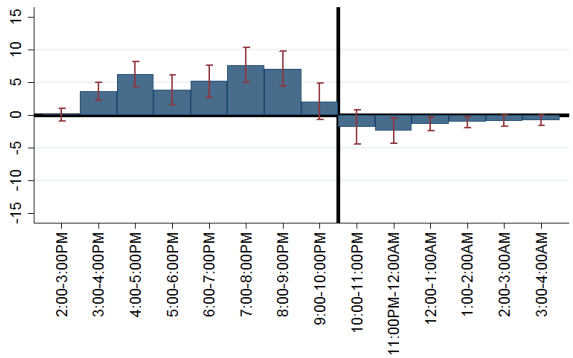
Figure 1.2 Time Trends in Cram Schooling



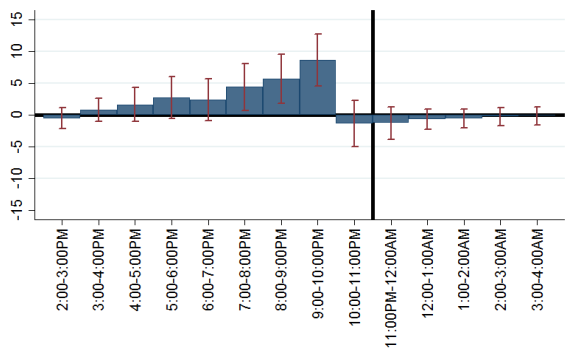
Notes. The figure depicts time trends in participation in private tutoring academies. Rhombus represents the participation rate calculated using KTUS and triangle represents the participation rate calculated using Survey on Private Tutoring (SPT). KTUS 1999, 2004, 2009, and 2014 and SPT 2007-2014 is used.

Figure 1.3 Hour-by-Hour regression : Impact on Cram Schooling and Study-related Traveling

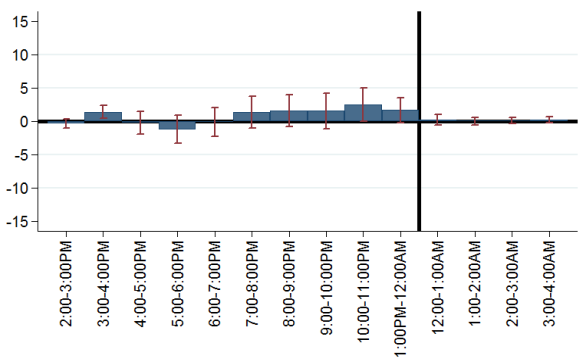
Panel A. 10PM curfew



Panel B. 11PM curfew

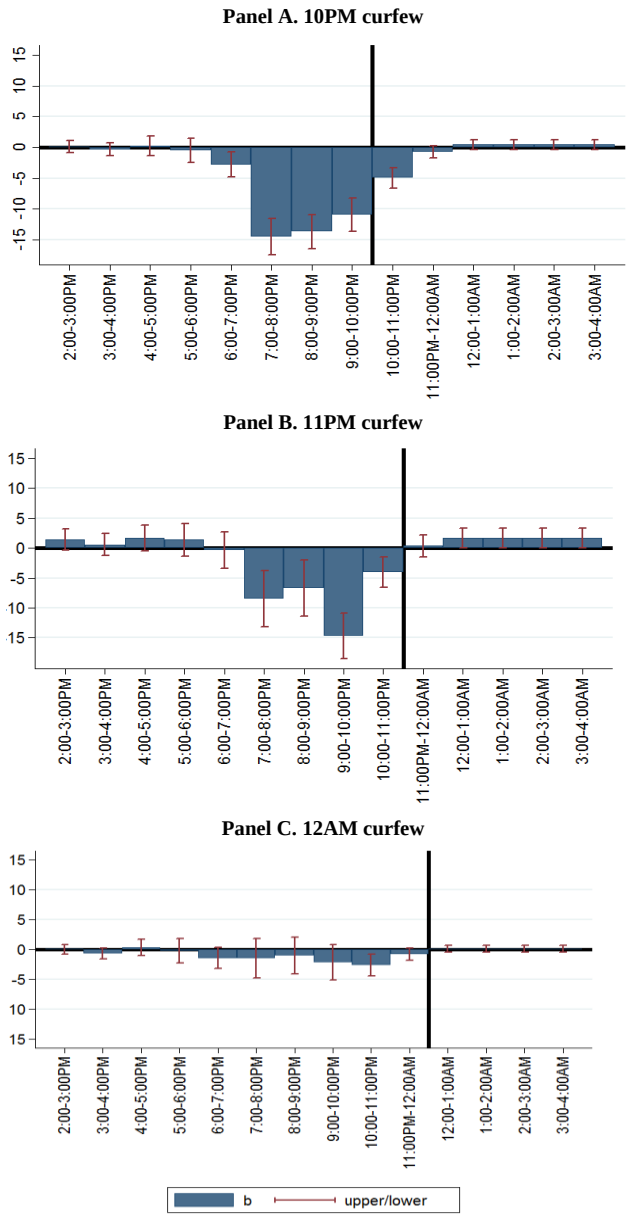


Panel C. 12AM curfew



Notes. The figure depicts estimated coefficients from the hour-by-hour regression. Blue bars denote the estimated impacts of the curfew on time devoted to cram schooling and study-related traveling for each hour. Red lines represent 95% confidence interval. Panel A, B and C show the impact the 10PM curfew, the 11PM curfew and the 12AM curfew respectively.

Figure 1.4 Hour-by-Hour regression : Impact on Self-study Session at School



Notes. The figure depicts estimated coefficients from the hour-by-hour regression. Blue bars denote the estimated impacts of the curfew on time devoted to self-study session at school for each hour. Red lines represent 95% confidence interval. Panel A, B and C show the impact the 10PM curfew, the 11PM curfew and the 12AM curfew respectively.

Chapter 2

Supply of Community Child Centers and Labor Supply of Married Women

2.1 Introduction

Time devoted to children makes up a significant proportion of the total cost of children (Gustafsson and Urban, 1994).[1] Providing subsidized child care has been presumed to increase the labor force participation of mothers of young children by promoting reconciliation of work and family life (Bauernschuster and Martin, 2015). In this paper, we investigate the effect of publicly subsidized Community Child Centers targeted at low-income families on the supply of female labor. Recent research has suggested that the low level of female labor force participation in Korea is associated with the time cost of primary school children (Kim, 2018). An increase in the number of Community Child Centers is expected to lower the time and money cost of mothers of primary school children and raise their labor supply.

Researchers have found that preschool care and out-of-school care have two crucial roles. The first is to increase the chances of the child's parent being employed. The second is to improve child development, especially for underprivileged children (Blau & Currie, 2006). Regarding the analysis of the role of child care on parental employment, earlier studies focused on the effect of the price of child care on maternal employment. However, these estimates suffered from a lack of exogenous variation since they were based on a non-experimental setting (Blau, 2003). A growing body of studies has exploited

[1] Gustafsson and Urban (1994) investigated the Swedish family and suggested that the time cost of children accounts for half of the total cost of children.

quasi-experiments to identify the causal effect of child care on the labor supply of women (Bauernschuster & Martin, 2015). This paper contributes to this line of research.

Our study furthers our understanding of the role of child care in maternal employment by examining a policy experiment that resulted in a marked increase in Community Child Centers. To the best of our knowledge, this study is the first attempt to evaluate the effect on the labor supply of an increase in Community Child Centers in the Korean context. Even though the capacity of Community Child Centers is fairly small relative to the young population, findings in previous studies have suggested that we should anticipate a positive impact of the centers on the maternal labor supply. It is due to the fact that (a) Community Child Centers are virtually free to use; (b) the labor force participation rate of women from the mid-30s to mid-40s has been notably low;[2] and (c) low-income families were targeted. A reading of the previous literature has shown that the labor supply of single women and the labor supply of individuals with low-income or low education are more sensitive to the child care cost (Anderson & Levine, 2000; Baum, 2002; Connelly & Kimmel. 2000; Fronstin & Wissoker, 1994; Han, Nollenberger, & Rodriguez-Planas, 2014; Waldfogel, 2001; U.S. GAO, 1994b).[3]

Community Child Centers are child care facilities that provide basic care, protection, and education to children from low-income families. A legal claim was made in 2004 to subsidize Community Child Centers. The number of Community Child Centers

[2] Bauernschuster and Martin (2015) summarized the pre-conditions for public child care to enhance the maternal labor supply: insufficient supply of child care, low maternal employment rate, and high subsidization rate. Moreover, they pointed out that previous findings suggested the rationing of public child care and availability of private child care programs are other important factors in determining the effectiveness of public child care provision on maternal labor supply.

[3] To the best of our knowledge, two exceptions are the estimates of Kimmel (1998) and Yoon (2010). Kimmel (1998) suggested that in the US the elasticity for married women was -0.92 compared to -0.22 for single women is. Yoon (2010) suggested that the elasticity for Korean women with a high school education or less was -0.852 and for women with a college education or more it was -3.751.

has expanded continuously since the introduction of the policy alongside consistent increases in the subsidy. Before the legalization, the centers were privately operated in the absence of the subsidy. Figure 2.1 illustrates the total number of facilities and the number of users of Community Child Centers from 1995 to 2017. The centers markedly increased following the legal claim in 2004. However, the pace of expansion differs significantly among the provinces. We exploited this province-level variation to estimate the effect of Community Child Centers.

We used variations in changes in the province-level coverage rate of the centers to estimate the employment effect. Our primary assumption for the identification of this effect was that supply variations across provinces are exogenous to women's labor force participation decisions. The estimate from the difference-in-differences estimator showed that growth in the coverage of Community Child Centers significantly increased the probability of employment for non-single women aged 35–44. This result was reasonable given that most of the users of the centers are primary school-aged children and non-single women aged 35–44 are most likely to have children of that age.

Potential threats to our identification strategy were unobserved, time-varying regional factors correlated with the labor supply of women and the capacity of the centers. In particular, if decisions on the supply of the centers were endogenous to regional variables then the difference-in-differences estimator might have yielded biased estimates. For example, the supply of centers in a certain province could increase due to a rapidly growing or dampening economy. We used the level of subsidy provided to a province as an instrument to eliminate the potential bias. The findings in this paper suggest that subsidies significantly increase the supply of centers. We believe that the amount of subsidy paid to Community Child Centers is plausibly exogenous to unobserved factors since it is subject to the budget of the respective provincial government, which is determined in the previous year. We found that the estimates from the instrumental variable regression are comparable to the estimates from the difference-in-differences estimation. Furthermore, we conducted a placebo experiment using single men and women. The availability of Community Child Centers was found to have no effect on the employment

probability of single men and women. The results indicate that our estimates did not stem from a spurious relationship between the growth in the number of centers and time-varying, regional unobservables. We also used the level of lagged subsidy (subsidy in year *t-1*) as an instrument in robustness check. The results from the instrumental variable regression using the lagged subsidy confirms the findings from the difference-in-differences estimation and the instrumental variable estimation using the level of subsidy in year *t*.

The empirical findings in this paper provide evidence of the effect of highly subsidized child care centers on maternal labor supply. Papers studying the impact of the supply of public child care on maternal supply have usually shown a significantly positive effect (Baker et al., 2005; Cascio, 2009; Gelbach, 2002; Han, Nollenberger & Rodriguez-Planas, 2014; Bauernschuster & Martin, 2015). Our paper contributes to this line of research. To the best of our knowledge, in the Korean context, this is one of the few papers to evaluate the effect of the expansion of child care centers on the supply of women's labor. Most of the previous papers focused on the price of child care or child care subsidy programs. Moreover, this paper suggests that policy which reduces the cost of *primary* school children might enhance the labor force participation of mothers. The existing literature has predominantly examined the policy impact of the labor supply of women with preschool children. Our finding is important since women with primary school children have a significantly low employment rate in Korea.

The findings will be of interest to those who want to compare the effect of the child care subsidy program[4] with other types of policies encouraging the employment of low-income parents such as the Earned Income Tax Credit. The relative effectiveness of the child care subsidy as a policy tool for increasing the employment of low-income families has been deemed an important issue (Blau, 2003). In addition, our results imply that the *quantity* of child care facilities would be particularly important for *low-income* mothers. It is notable that the quality of Community Child Centers has been considered

[4] Giving access to public child care can be considered as providing price subsidy for child care (Gelbach, 2002).

low in general (Kim, 2015). The significant and large labor supply effect of Community Child Care centers shows the potentially high substitutability between the market for child care and maternal child care for low-income mothers. Mothers might not be able to access the market for child care for various reasons, such as credit constraints. Kreyenfeld and Hank (2000) argued that the provision of public child care might be more important than the price of the child care when the supply of public child care is insufficient.

The rest of the paper proceeds as follows. Section 2.2 presents labor supply of Korean women over time and describes the institutional background of Community Child Center. Section 2.3 introduces the data used in the study and explains how we constructed the variables in detail. Section 2.4 describes the empirical methodologies. Section 2.5 presents results from the difference-in-differences estimation and the instrumental variable estimation. Robustness check is provided in Section 2.6 and the conclusion of the paper is given in Section 2.7.

2.2 Institutional Background

In this section we first provide basic facts about the labor supply of women in Korea. Community Child Centers and the subsidy program are then introduced. We expected a positive employment effect of Community Child Centers due to the fact that the use of Community Child Centers is concentrated on primary school children. The labor force participation rate of women starts to fall rapidly in their mid-20s and then begins to rise in their late-30s. This M-shaped life cycle trend of labor force participation has often been referred to as the M-curve and considered a distinctive feature of female employment in Korea (Kim, 2008). Panel A of Figure 2.2 depicts the clear M-shaped pattern of labor force participation. The average labor force participation rate of women increased from 46.3% in 1980 to 59% in 2017 (OECD labor statistics). We found considerable upward movement of the M-curve, as illustrated in Panel A of Figure 2.2 Nonetheless, changes in the labor force participation rate significantly differed by age. Panel B of Figure 2.2 shows changes in the labor force participation rate compared to 1980. The labor force participation rate of

women aged 25 to 34 continuously increased but the rate for women aged 35 to 44 began to stagnate in the late 1990s. The probability of having primary school-aged children was much higher for women aged 35 to 44 compared to women aged 25 to 34.

Kim (2018) analyzed the phenomenon carefully using three datasets and showed that primary school children significantly restrict the labor supply of married women. Moreover, Kim (2018) decomposed the factors contributing to the stagnation and found that the estimated effect of primary school children on restrictions on the labor supply of married women increased during 2006–2016. Choi (2008) also suggested that a mother of a primary school child spends 5.2 hours educating her children per week. Considering the non-negligible amount of time spent on primary school children, some have expected the reduction in time cost for mothers of primary school children could result in increased labor force participation for the mothers (Kim, 2018). Moreover, estimates for American women have suggested that the child care cost elasticity for the employment of women with primary school children is comparable to that of women with preschool children. For example, structural estimates of the uncompensated paid care cost elasticities in Ribar (1995) were identical for women with children under 15 years old and women with children under 6 years old. Anderson and Levine's (2000) estimates of elasticities for women with children under 13 years old were of magnitudes of 65%~81% of elasticities for women with children under the age of 6. These results suggest that we could expect the policy to have a considerable labor supply effect which reduces the cost of child care for women with primary school-aged children.

The Community Child Center is a non-profit organization that provides education and protection to children in local communities.[5] The center was privately operated

[5] Community Child Centers are able to receive money from the children of families that are not considered low-income. However, only 1.8% of the centers received fees from a child's family in 2015. Among those centers, fees were paid by 19% of enrolled children and the centers received 42,079 won on average, which corresponds to 36.81 U.S. dollars in 2019. (Headquarters for the Community Child Center, 2015)

before 2004. On January 29, 2004, a legal claim was made to subsidize the Community Child Center. We expect that the introduction of the subsidy will result in an increase in the number of Community Child Centers since the subsidy reduces the fixed cost of the centers. Subsidy-eligible centers receive a fixed amount of money on a monthly basis. The amount of the subsidy has continuously increased since its introduction. In 2008, the subsidy accounted for 36% of total income for Community Child Centers. However, in 2015, the subsidy accounted for 70.7% of the total income for the centers (Headquarters for the Community Child Center, 2015).

Table 2.1 shows the amount of subsidy for Community Child Centers in 16 provinces. Unfortunately, information on the subsidy is only available from 2008. The provinces have spent 105.8 hundred million South Korean won on Community Child Centers on average since 2008. The amount allocated to the centers increased from 36.1 hundred million won in 2008 to 147.4 hundred million won in 2017.[6] Panel A of Figure 2.3 depicts the relationship between the total subsidy and the number of eligible centers. The figure indicates that the subsidy is not distributed among a fixed number of centers since the number of eligible centers increases as the subsidy expands. This suggests that the subsidy has affected the quantity as well as the quality of the centers. Panel B of Figure 2.3 shows that the subsidy allocated to each center has increased as the total subsidy grows. In 2008, 0.16 hundred million won were given to a center and the amount increased to 0.57 hundred million won in 2017.

Community Child Centers provide near full-time care for children. The centers are mandated to operate at least five days a week. Hours of operation must exceed eight hours a day. The centers are forced to open before 2 p.m. and close after 7 p.m. during the semester. During vacations, the centers are not allowed open after noon or close before 5 p.m. On average, the centers open at 10:20 a.m. and close at 8 p.m. The centers operate for an average of 5.6 days per week. The provision of sufficiently long hours of care is believed

[6] One hundred million South Korean won corresponds to approximately 86,487 U.S. dollars in 2019.

to have a positive impact on the labor force participation of mothers. It is known that demand for Community Child Centers is sufficiently high. Figure 2.4 shows the number of users compared to the capacity during 2008-2017. 'Users' in provided statistics is defined as the children who used the Community Child Center for more than 70% of the operating days. The figure shows that on average 92.8% of capacity is utilized and the utilization rate is stable across years.

Community Child Care centers are targeted at children from low-income families. Panel A of Table 2.2 summarizes the eligibility conditions. 'Children under primary protection' are children from low-income or disadvantaged households. The centers must keep the ratio of 'children under primary protection' above 60%. Among the 'children under primary protection', priority is given to beneficiary children. Panel B of Table 2.2 shows the number of children in centers by their economic status. On average, 'Children under primary protection' account for more than 80% of users. The number of beneficiary children and children from near-poor families in each center decreased from 2007 to 2015 and there was an increase in the number of children selected from families with an income equivalent to less than 70% of the national median income. This implies that the children using Community Child Centers became relatively wealthier in 2015 compared to 2007. However, the table confirms that the majority of the children using Community Child Centers were from low-income families.

Table 2.3 provides information on the grades of children using the centers from 2004 to 2017. The table shows that primary school children accounted for nearly 80% of the total users during 2004–2017. Middle school children made up the second largest proportion of users, at nearly 15%. Preschool and high school children account for only a small proportion of the total users. In 2007, preschool and high school children comprised only 4.9% of the total number of children using Community Centers. The rapid decrease in the number of preschool children may be a consequence of the large expansion of kindergarten and daycare centers during the period. The number of primary school children shows declining trends even though they account for the majority of users. This is believed to be the result of the large increase in the 'Elementary School Care Class' which provides

care to primary school children at school.[7] To summarize, Community Child Centers are free facilities that provide education and care to children in local communities. The centers have experienced a large expansion due to the introduction of the subsidy policy and the majority of users are low-income primary school children.

2.3 Data

We combined two datasets—the Regional Employment Survey (RES) and Community Child Center microdata— to analyze the effect of Community Child Centers on maternal labor supply. In this section, we first introduce RES and then describe in detail how we constructed variables of interest using Community Child Center microdata.

We used the RES from 2008 to 2017 for individual characteristics and employment status. The capacity and number per province of Community Child Centers were constructed from microdata provided by the headquarters for the Community Child Center. By merging the province-level Community Child Center information with the RES, we were able to estimate the impact of changes in the Community Child Centers at the provincial level on maternal employment. The RES contains information on 20 million households in Korea. Since 2008 was the first survey year of the RES and information on the relevant subsidy is available from 2008, we used the RES dating back to 2008. The RES contains detailed information on the individual characteristics of individuals. Control variables used in the analysis were age, sex, head of household, marital status, education and province of residence. Unfortunately, the RES lacks information on the number or age of children. Moreover, we were not able to use information on children or spouses since the household was not identifiable in the data. Hence, we focused on a sample of women aged 35–44 who were most likely to have primary school-aged children.

The headquarters of the Community Child Center collects basic information on each center annually. Microdata were available from 2006 to 2017. Microdata hold

[7] Appendix Figure A.2.1 shows the proportion of the children using the center graphically.

information on each center's location, date of opening and number of users. The number of available slots of each center was not available before 2009, and is only available from 2009 to 2017. Since we were interested in the province-level coverage rate, the lack of information on number of slots in 2008 was problematic. We tried to manage the problem by constructing the predicted capacity for the centers in 2008. In order to do this, we multiplied the inverse of the province-level utilization rate in 2009 by the number of users in 2008.[8] Under the assumption that the province-level utilization rate is stable across years, the predicted slots could approximate slots. Figure 2.5 shows the province-level utilization rate across years. The figure compares the number of users in each province to the number of available slots in each province during 2008-2017. Different provinces are denoted by different colors. The province-level utilization rate (distance of the circle from the straight line) is stable across years.[9] Moreover, to validate our assumption, we compared the actual province-level capacity with the predicted capacity in 2009–2016. Predicted capacities were constructed using the inverse of the utilization rate in 2010–2017 and the actual number of users in 2009–2016.

Figure 2.6 shows the predicted and actual capacity in 2009–2016. The straight red line denotes 45-degree line. The figure shows that the actual number of slots can be well approximated by the predicted number of slots calculated using the inverse of the posterior utilization rate. Since we were interested in the impact of the centers on the employment of mothers of primary school children, the variable of interest was the provincial capacity of the centers compared to the population aged 6–12 in the province. The constructed province-level variables were matched to the RES for the analysis. For descriptive purposes, we supplemented the RES with census microdata.

Table 2.4 provides descriptive statistics of the variables of interest and control variables at the provincial level. The mean employment rate of women aged 35-44 is 57.8

[8] $\widehat{capacity}_{j2008} = user_{j2008} \times [\frac{capacity_{j2009}}{user_{j2009}}]$ for each province j.

[9] Appendix Figure A.2.2 depicts municipality-level utilization rate. Similar to the province-level utilization rate, the municipality-level utilization rate is also high and stable.

between 2008 and 2017. As Figure 2.2 suggested, employment rate of women aged between 35 and 44 is stagnated. The employment rate is decreased between 2008 and 2017. The number of Community Child Center for each province is 355.5 on average. The number of center for each province increased from 277.3 to 371.8 during 2008-2017.As number of the center increased, available slots also increased from 8606.4 to 11051.2 during the sample period. On average, provinces receive 16 billion Won each year. The figure indicates that more than 93% of women aged 35-44 are married. Appendix Table A.2.1 presents the province-level subsidy, number of the centers and the number of slots in 2008 and 2017. The table shows that there exists heterogeneity in level of variables across provinces as well as heterogeneity in changes in variables across provinces.

2.4 Empirical Strategy

The introduction and expansion of the relevant subsidy led to two important results: (a) a rapid increase in the supply of Community Child Centers; and (b) disproportionate growth in Community Child Centers across provinces. Subsidization provides incentives to supply the centers as it lowers the centers' fixed operating costs. Figure 2.7 depicts the evolvement of the employment rate of non-single women aged 35-44, the growth of the coverage of Community Child Centers for 6 to 12-year-old children, [10] and the subsidy for Community Child Center for 6 to 12-year-old children. The figure shows strong heterogeneity in the growth of variables across provinces. The employment rate of non-single women aged 35-44 decreased between 2008 and 2017 in eleven provinces. Five provinces experienced increase in the employment rate of non-single women aged 35-44. Both the subsidies and the available slots increased during 2008-2017. Increase in the subsidy and the slots for 6 to 12-year-old children was fastest in the Gwangju. Increase in the subsidy and the slots for 6 to 12-year-old children was slowest in the Ulsan, where

[10] Here, the coverage rate was defined as province-level slots divided by the number of 6 to 12-year-old children in the province.

experienced fastest decline in the employment rate. In this chapter, we try to relate the changes of the employment rate and the coverage.

To estimate the impact of the changes in the coverage of Community Child Center on the maternal employment rate, we estimated the following difference-in-differences equation for non-single women aged 35–44.

$$emp_{c(j,t,X)} = \alpha + \beta\ coverage_{jt} + \gamma X + \varphi_t + \tau_j + \varepsilon_{c(j,t,X)} \quad (1)$$

In the equation above, $emp_{c(j,t,X)}$ is the mean employment rate of non-single women aged 35-44 for each cell $c(j,t,X)$. Each cell $c(j,t,X)$ is combination of province j (16 provinces), year t (10 years; from 2008 to 2017) and elements of the vector X. The vector X consists of marital status (3-categories: married, divorced, bereaved), education (8-categories: none, elementary, middle, high, college, university, master and PhD), 5-year age bins (2-categories: age 35-39 and age 40-44) and head of household (2-categories: head of household=1 and head of household=0). X represents the set of dummies for marital status, education, 5-year age bins and head of household. φ_t and τ_j denote the year and the province fixed effect respectively. $coverage_{jt}$ is the number of Community Child Centers relative to the number of children aged 6–12 in province j in year t or number of Community Child Center slots relative to the number of children aged 6–12 in province j in year t.[11] β captures the impact of a 1%pt increase in coverage in province j on the employment probability of the non-single women aged 35–44. The identifying assumption was that changes in the coverage across provinces were exogenous to the employment rate of mothers, conditional on control variables; potential trends in the provincial employment rates of women aged 35–44 were expected to be parallel across provinces.

[11] More precisely, $coverage_{jt}(\%) = \frac{CCC\ slots_{jt}}{population\ 6-12_{jt}} \times 100$ or $coverage_{jt}(‰) = \frac{number\ of\ CCC_{jt}}{population\ 6-12_{jt}} \times 1000$

However, if the entry or exit decision of the centers were correlated with time-varying, province-specific economic conditions then our difference-in-differences estimates would be biased. To alleviate the potential biases, we estimated β using instrumental variable estimation. We instrumented $coverage_{jt}$ using $subsidy_{jt}^{6-12}$. $subsidy_{jt}^{6-12}$ is defined as the level of subsidy in province *j* in year *t* divided by the number of children aged 6–12 in province *j* in year *t*. However, if the subsidy is systematically correlated with other provincial subsidy policies that affect the labor supply of women and determined in previous year then the exogeneity assumption would be violated. For example, a province with a generous Community Child Center subsidy could have offered other types of welfare programs, such as cash transfers to mothers of young children. Thus, we used the lagged subsidy variable, $subsidy_{jt-1}^{6-12}$ as an instrument in robustness check. $subsidy_{jt-1}^{6-12}$ is defined as the level of subsidy in province *j* in year *t-1* divided by the number of children aged 6–12 in province *j* in year *t-1*. The estimates from the instrumental variable regression using the level of subsidy in the previous year confirmed the results from the difference-in-differences estimation and the IV estimation using the subsidy in year *t*

To make sure that the correlation between the coverage rate and the subsidy relative to young population did not stem from population changes, we regressed the coverage rate on the level of subsidy. Appendix Figure A.2.3 shows the relationship between changes in the province-level subsidy and changes in the number of centers as well as changes in the number of available slots. There exists significant positive relationship between the changes in two variables.

2.5 Estimation Results

In order to estimate the impact of the Community Child Center on non-single women's employment, we first adopt difference in differences estimation. Identifying assumption is

that changes in employment rate of non-single married women were parallel between the provinces with rapid growth in coverage rate and the province with slow growth in coverage rate. The estimation strategy is similar to the strategy used in Card (1992)'s minimum wage study, as it is the difference-in-differences estimation with continuous treatment variable which varies at regional level. [1 2]

The difference-in-differences estimation requires that the employment rates of non-single women aged 35-44 move in parallel across the provinces. It is difficult to test the hypothesis directly as we do not have pre-treatment period and there is no province without treatment. We split the sample into two groups according to the growth rate of the Community Child Centers availability between 2013 and 2017. We define the provinces with the top 50% growth rate as "high growth group" and define the rest of provinces as "low growth group". Then we compare the employment rates changes for two groups during 2008-2012. If there were no endogenous entry of the Community Child Center then the employment rates should had moved in parallel.

Figure 2.8 depicts time trends in employment rates of two groups. As we expected, regions with low mean employment rate in pre-period (2008-2012) experienced higher growth in Community Child Centers in post-period (2013-2017). However, even though there existed systematic differences in the mean employment rate across the provinces, the difference-in-differences estimation yields unbiased estimates as long as the employment rates of provinces move in parallel. In Panel A, we split the sample into two groups according to the growth rate of the number of the centers. The changes in employment rates are parallel between two groups. In Panel B, we split the sample into two groups according to the growth rate of the center slots. Similar to the Panel A, we observe the parallel trends between two groups. The figure supports the identifying assumption of the difference-in-differences model.

[1 2] Card (1992) evaluated the impact of changes in minimum wage on the state-level employment. Card (1992) exploited the variations in state-level fraction of teen affected by the minimum wage increase.

Table 2.5 shows the estimates from the difference-in-differences estimation. Panel A shows the impact of the number of Community Child Centers and Panel B presents the impact of the available Community Child Care slots. We find substantial reduction in magnitude of estimates as we control for year fixed effects and province fixed effects. Column (3) of Panel A and B present the difference-in-differences estimates without control variables. Increase in 0.1%pt of the number of Community Child Center increases the probability of employment of non-single women aged 35-44 0.127%pt. Similarly, increase in 1%pt of the number of Community Child Care slots increases the employment probability of non-single women aged 35-44 0.447%pt. As we control for additional variables, magnitudes of estimates become slightly smaller. Column (7) of Panel A and B shows the estimates from the difference-in-differences estimation which controls for full set of control variables. Growth in 0.1%pt of the number of Community Child Center increases the chance of employment of non-single women aged 35-44 0.111%pt. Similarly, increase in 1%pt of the number of Community Child Care slots increases the employment probability of non-single women aged 35-44 0.4%pt. The estimates of 0.4%pt is comparable to the estimates from the previous studies. Bauernschuster and Martin (2015) showed that 1%pt increase in the coverage rate of universal child care increases the employment probability of women with child aged 3-4 0.366%pt. The estimated effect is also comparable to the impact of implementation of free kindergarten in U.S on single mothers' labor supply in Cascio (2009). Considering that our sample consists of non-single women aged 35-44 and majority of Community Child Center users are primary school age children, the estimates presented in the table is likely to capture the impact of the center on the employment probability of women who have primary school age children. Substantial impact of Community Child Center on women with primary school age children suggests that primary school age children restricting the labor supply of married women considerably. The other reason for the significant employment impact is that Community Child Center supports low-income family.

Potential threat to the difference-in-differences specification is unobservable time-varying regional factors which affect both Community Child Center availability and

employment of non-single women. For example, some governors of the provinces supported Community Child Centers as well as other policies which enhances employment of non-single women. To eliminate the potential biases, we run the instrumental variable regression. We use the level of subsidy for Community Child Center as an instrument. Since subsidy budget is predetermined in the previous year, the subsidy should not be affected by the number of newly available Community Child Centers.

We first establish the reduced form relationship between the level of subsidy and the availability of the centers. Table 2.6 presents the estimates from the difference-in-differences estimation. The variable of interest is province-level subsidy. Column (3) shows the difference-in-differences estimate without control variables. Additional ten thousand Won per children aged between 6 and 12 increases the employment rate of non-single women aged 35-44 0.203%pt. Column (7) presents the estimate from the regression which controls for full set of control variables. Increasing the subsidy per children aged 6-12 10,000 Won results in 0.187%pt increase in the probability of employment of non-single women aged between 35 and 44. On average, the number of children using the center accounts for 2.8% of total number of children aged 6-12. Increase in ten thousand Won per children aged 6-12 is equivalent to increase in 352,000 Won per children using the centers.

Relevance of the instrument is presented in Table 2.7. Panel A-1 of Table 2.7 shows the impact of the subsidy on the number of Community Child Center and Panel A-2 of Table 2.7 presents the effect of the subsidy on the number of center slots. Increase in 10,000 Won per children aged 6-12 increases the number of the centers per children aged 6-12 0.281%pt. This implies that 355,872 Won per children aged 6-12 Increase in ten thousand Won per children aged 6 to12 years increases the center slots per children aged between 6 and 12 1.016%pt. This implies that every child aged between 6 and 12 could use the center if subsidy of 984,251 Won is provided per children aged 6-12. The table indicates that the subsidy substantially increases the availability of Community Child Center.

Table 2.8 compares the estimates from the instrumental variable estimation to the estimates from the difference-in-differences estimation. Column (1) and (2) show the

impact of the number of the centers and column (3) and (4) present the impact of the number of the center slots. The magnitudes of the estimates from the instrumental variable regressions, presented in column (2) and (4), are systematically greater than the magnitudes of the estimates from the difference-in-differences regressions, presented in column (1) and (3). The IV estimation indicates that 0.1%pt increase in the number of Community Child Center increases the employment rate of non-single women aged 35 to 44 years 0.187%pt, while the DD estimation suggests that 0.1%pt increase in the number of the centers increases the employment rate 0.111%pt. Similarly, the IV estimation shows that 1%pt increase in the number of Community Child Center slots increases the employment rate of non-single women aged 35-44 0.701%pt. However, the DD estimation indicates that 1%pt increase in the number of the center slots increases the employment rate 0.4%pt. This result indicates that the estimates from the difference-in-differences estimation is downward-biased. Strong positive effect of the availability of Community Child Center on the labor supply of non-single women suggests that the availability of the childcare is especially important for the women in low-income family. Low-income household might have limited access to the market childcare. Provision of childcare is effective when childcare is not readily accessible (Kreyenfeld and Hank, 2000). Moreover, the positive effect of the center on maternal labor supply shows the high substitutability between market and maternal child care for low-income mothers.

Table 2.9 presents the effects of the centers by marital status. Column (1) and (2) shows the estimates for the married women and column (3) and (4) presents the estimates for the divorced or bereaved women. The impact of the center on married women's employment probability is almost identical to estimates for the full sample. The IV estimation suggests that 0.1%pt increase in the number of Community Child Center increases the employment rate of married women aged 35 to 44 years 0.186%pt and 1%pt increase in the number of Community Child Center slots increases the employment rate of married women 0.695%pt. The estimates for divorced or bereaved women are greater than the estimates for married women. However, the estimates for divorced or bereaved women are not significant in a statistical sense.

2.6 Robustness Check

Concern for the estimation strategy which uses subsidy in year *t* as an instrument is that the subsidy in year *t* might not be fully exogenous to the availability of the centers in year *t*. Even though subsidy budget is predetermined in the previous year, it might be function of the local government's expectation of the availability of Community Child Centers in year *t*. Moreover, other predetermined province-level budgets might be correlated with the subsidy for Community Child Centers and the budgets might affect the employment rate of non-single women in year *t*. For example, provinces with generous welfare benefits might invest in Community Child Centers as well as other childcare policies which promotes reconciliation of work and family life, such as 'Elementary School Care Class'. To alleviate the potential bias from using the subsidy in year *t* as an instrument, we use lagged subsidy as an instrument. Since the amount of subsidy budget in year *t-1* is predetermined in year *t-2* and distributed during year *t-1*, the subsidy in year *t-1* would not be affected by the availability of Community Child Centers in year *t*.

The estimates from the reduced form estimation presented in Appendix Table A.2.2 show that lagged subsidy has significant impact on employment rate of non-single women. Moreover, Panel B of 2.7 indicates that subsidy in year *t-1* predicts the availability of Community Child Center in year *t*. Table 2.10 compares estimates from the instrumental variable estimations using subsidy in year t as an instrument to the instrumental variable estimations using subsidy in year *t-1* as an instrument. Panel A shows the impact of the number of Community Child Centers on employment and Panel B presents the impact of the available slots on employment. For the sample of non-single women, we find the impact of Community Child Center on employment rate is slightly bigger as we use lagged subsidy as an instrument. For the married women, we find that the estimates are strikingly identical. The estimates suggest that 0.1%pt increase in the number of Community Child Center relative to the number of children aged 6 to 12 years increases the employment probability of married women 0.186%pt. Likewise, 1%pt increase in the number of available Community Child Center slots relative to the number of children aged between

6 and12 increases likelihood of employment 0.695%pt. The similarity between the estimates using the subsidy in year *t* and the subsidy in year *t-1* ensures that the endogeniety of instrument does not drive the results.

To make sure that our estimation results did not from spurious relationship between province-level unobservable factors affecting the Community Child Center availability and women's labor force participation decision, we use the employment rate of single men and women as dependent variable. Out-of-wedlock birth is unusual in Korea. In 2015, single men or women with children accounts only 0.1% of total population (Choi & Ahn, 2019). As probability of having child is extremely low for single population, we expect no impact of Community Child Center on the employment of single men and women.

Table 2.11 shows the estimated impact of the Community Child Center on single men and women. Panel A reports the impact of the number of the centers and Panel B presents the impact of the Community Child Center slots. Column (1), (2) and (3) present the estimates for the single women and column (4) to (6) show the estimates for the single men. Column (1) and (4) shows the results from the DD estimation. The availability of the center has positive effect on the employment rates of single men and women but estimates are statistically not significant. In column (2) and (5), we observe that magnitudes of the estimates become smaller as we instrument the availability of the centers using the subsidy level. Moreover, column (5) and (7) suggest negative impact of the centers on probability of employment. In column (5) and (7), we use the lagged level of subsidy as an instrument for the availability of Community Child Center. In all specifications, we found no statistically significant effect of the centers on employment probability of single men and women. The results from the placebo experiment reassures that the estimates for non-single women captures the actual impact of the Community Child Center on employment.

2.7 Conclusion

In this paper we evaluated the labor supply effect of Community Child Centers. The

number of Community Child Centers increased rapidly following the legal claim to subsidize the organization in 2004. We exploit the province-level variation in coverage rate of the centers. The estimates from the difference-in-differences estimation and the instrumental variable estimation showed that the supply of Community Child Centers had a large employment effect for non-single mothers with a high chance of having primary school-aged children. To the best of our knowledge, this paper is the first attempt to evaluate the impact of highly subsidized child care facilities on maternal employment using a quasi-experiment in the Korean setting.

Also, this paper extends the previous literature on the impact of public child care on maternal supply by using the quasi-experiment in two ways. The previous literature tends to concern the labor supply of mothers with pre-school children. However, our estimates suggest that the effect of highly subsidized child care centers on the employment probability of mothers with primary school children could be large. In addition, our estimates show the labor supply impact of a low-income targeted program. Even though the literature regarding the impact of public child care provision on maternal supply using quasi-experiments is sizable and rapidly growing, we believe that few studies have examined the effect of the provision of low-income targeted public child care centers.

We did not conduct a cost-benefit analysis of the centers. However, since information on the amount of the subsidy is available, evaluating the net benefit of the program would be useful. Policymakers should also be interested in the effectiveness of Community Child Centers compared to other policy tools aimed at increasing the maternal labor supply. However, to fully evaluate the impact of Community Child Centers, other aspects should be considered. Baker et al. (2005) showed that the universal child care program in Canada increased the maternal supply significantly but had negative effects on various measures of outcomes for children. Considering the low-quality of Community Child Centers, the impact on children's outcomes should be investigated. Moreover, substitutability between the government interventions targeted at primary school-aged children is important. The 'Elementary School Care Class' expanded rapidly during the sample period. Further study is required to evaluate the impact of Community Child

Centers compared to the ‘Elementary School Care Class’.

Table 2.1 Subsidy for Community Child Center in each Province

	Overall	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Seoul	172.4	56.4	90.6	112.7	141.3	164.7	198.8	221.4	237.1	249.6	251.6
Busan	85.0	31.6	51.3	57.8	72.5	84.4	99.7	106.6	114.3	115.9	116.1
Daegu	64.8	11.1	22.2	32.4	47.9	59.8	77.5	86.8	96.9	104.6	108.8
Incheon	75.5	33.8	50.8	57.4	49.6	79.4	89.0	94.7	97.7	102.5	99.8
Gwangju	110.2	26.3	50.3	65.3	89.3	102.4	131.7	149.0	155.7	162.0	169.7
Daejeon	66.0	24.8	41.6	51.5	61.6	69.9	78.9	79.6	82.7	85.1	84.5
Ulsan	24.4	12.3	15.7	18.3	22.5	25.5	28.3	29.7	31.3	31.1	29.7
Gyenggido	321.5	114.2	181.2	229.6	277.6	325.0	373.7	404.9	423.9	438.2	447.1
Gangwondo	77.1	26.6	39.8	54.6	68.8	82.7	92.4	93.9	98.9	106.4	107.4
North Chungbuk	82.2	30.3	49.0	58.9	73.6	85.4	98.6	104.1	106.9	108.5	107.1
South Chungbuk	96.2	27.3	46.7	64.1	82.3	94.7	115.1	127.9	133.4	136.1	134.1
North Jeolla	119.1	43.6	64.3	78.9	106.0	124.5	140.8	152.3	154.7	165.5	160.2
South Jeolla	163.1	62.6	91.6	114.8	148.5	173.8	196.3	203.3	210.8	217.0	212.6
North Gyeongsang	102.2	30.0	50.4	62.5	87.9	104.2	124.9	131.3	136.6	145.5	148.9
South Gyeonsang	101.9	35.1	55.0	69.1	90.2	105.7	124.6	128.4	134.7	135.7	140.8
Jeju	31.3	11.0	18.7	21.0	28.5	33.6	39.1	39.4	40.3	41.1	40.3
Overall	105.8	36.1	57.4	71.8	90.5	107.2	125.6	134.6	141.0	146.5	147.4
	(81.3)	(25.3)	(39.2)	(49.6)	(60.6)	(70.1)	(80.6)	(88.0)	(92.3)	(95.7)	(97.6)

Notes. Table presents the province-level subsidy in each year.

Table 2.2 Economic Status and Community Child Center

Panel A. Eligibility Conditions

Children under primary protection (>60%)	
1st	Beneficiary children
2nd	Children from near-poor families
	Protection required children from single-parent families
	Children from grandparent families
	Children from multicultural families
	Children from disabled famlies
3rd	Selected children from household income lower than 0.7 * median houshold income (need approval from the head of municipality)
Children in general	
	Example. Children from dual earner families

Panel B. Proportion of children using the center by economic status

	2007	2008	2009	2010	2011	2012	2013	2014	2015
All	29.1	29	28.2	27.2	26.3	26.8	26.9	26.8	26.7
Beneficiary children	8.3 (29%)	9.2 (32%)	7.8 (28%)	7.2 (27%)	6.6 (25%)	6.7 (23%)	5.4 (20%)	4.9 (18%)	4.5 (17%)
Children from near-poor families	11.8 (40%)	8.9 (31%)	9.2 (33%)	10.2 (38%)	10.2 (38%)	9.6 (32%)	7.3 (27%)	6.3 (24%)	5.5 (21%)
Selected children from household income lower than 0.7 * median houshold income	3.9 (13%)	4.8 (17%)	5 (18%)	6 (22%)	6 (23%)	10.7 (33%)	10.6 (39%)	11.9 (44%)	12.9 (48%)
Children in general	5.2 (18%)	6.1 (21%)	6.2 (22%)	3.8 (14%)	3.7 (14%)	5.4 (13%)	3.5 (13%)	3.7 (14%)	3.8 (14%)

Notes . Table shows the eligibity conditions (Panel A) and proportion of the children using the center by their economic status (Panel B).

Table 2.3 Proportion of each Grade

Year	Pre	Primary	Middle	High
2004	6.7%	78.6%	12.3%	2.4%
2005	6.9%	79.1%	11.7%	2.2%
2006	7.0%	79.1%	11.6%	1.9%
2007	5.4%	80.1%	12.1%	1.9%
2008	5.3%	79.2%	13.0%	2.1%
2009	4.9%	78.7%	13.9%	2.1%
2010	4.4%	77.9%	15.0%	2.3%
2011	4.4%	75.9%	16.5%	2.9%
2012	3.7%	74.2%	18.5%	3.4%
2013	3.4%	73.6%	19.1%	3.7%
2014	3.2%	74.4%	18.5%	3.7%
2015	2.9%	75.1%	17.8%	4.0%
2016	1.8%	77.0%	17.0%	4.1%
2017	1.0%	78.0%	16.2%	3.9%

Notes. Table shows the proportion of each grade enrolled in Community Child Center

Table 2.4 Province-level Descriptive Statistics

	All (2008-2017)		2008		2017	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Employment rate	57.8	5.5	58.5	4.6	57.1	5.3
Number of Community Child Centers	355.5	219.2	277.3	182.8	371.8	232.8
Number of the center slots	10555.0	7097.4	8606.4	6121.7	11051.2	7565.8
Subsidy (unit : 100,000,000 Won)	160	110	53	35	210	140
Size of population aged 6-12 (unit : 10,000)	38	35	45	39	35	32
(Number of the centers / population 6-12) X 1000	1.3	0.7	0.8	0.4	1.5	0.7
(Number of slots / population 6-12) X 100	3.7	1.9	2.4	1.1	4.2	2.0
Subsidy / population 6-12 (unit : 10,000 won)	6.0	3.8	1.5	0.8	8.5	4.2
Proportion married	93.2	0.8	93.1	1.0	93.6	0.6
Mean education	13.3	0.5	12.6	0.4	13.8	0.4
Mean Age	39.8	0.1	39.5	0.1	39.8	0.1
Number of observations	160	160	16	16	16	16

Notes. Table shows the province-level descriptive statistics. Left two columns show the average during 2008-2017. Column (3) and (4) present the average in 2008. Column (5) and (6) show the mean values in 2017. Education variable has 8 categories (0: none, 1: elemantary, 2: middle, 3:high, 4:college, 5: university, 6: Master, 7: PhD).

Table 2.5 Difference in Differences Estimation: Impact of Community Child Center on Employment Rate of Non-single Women Aged 35-44

	Dependent variable: cell-mean employment rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Impact of number of the centers							
Total number of the centers in province in year t	0.570***	0.656***	0.127**	0.122**	0.150***	0.131**	0.111**
divided by the number of children aged 6-12 in province in year t	(0.048)	(0.050)	(0.056)	(0.054)	(0.055)	(0.055)	(0.056)
Panel B. Impact of available slots							
Total available slots in province in year t	1.999***	2.296***	0.447**	0.441**	0.542**	0.466**	0.400*
divided by the number of children aged 6-12 in province in year t	(0.168)	(0.177)	(0.214)	(0.207)	(0.209)	(0.209)	(0.209)
Control variables							
Year fixed effects		√	√	√	√	√	√
Province fixed effects			√	√	√	√	√
Marital status dummies				√	√	√	√
Education level dummies					√	√	√
5-year age bin dummies						√	√
Head of household dummy							√

Notes. The table shows the impact of Community Child Center on employment rate of women aged 35-44. Each cell represents combination of year (10), province (16), marital status (3), education (8), 5-year age bin (2), and head of household (2). For the regressions presented in the table, we confine our attention to This gives us 15,360 cells. Howeve due to the missing cells, total number of cells is 8,365. Panel A shows the impact of number of Community Child Center and Panel B presents the impact of number of available slots. Column (1) presents the results from the bivariate regression and column (2) controls for year fixed effects. Column (3) to (7) present results from the difference in differer estimation as we control for year and province fixed effects. Standard errors in parentheses, are clustered at year-province level.

*, ** and *** significant at 1%, 5%, 10% level.

Table 2.6 Reduced Form Regression: Impact of the Community Child Center Subsidy on Employment Rate of Married Women Aged 35-44

	Dependent variable: cell-mean employment rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total subsidy in province divided by	0.754***	1.299***	0.203***	0.189***	0.223***	0.203***	0.187***
number of children aged 6 to 12 years at the province (unit: 10,000 Won)	(0.075)	(0.111)	(0.065)	(0.064)	(0.064)	(0.064)	(0.066)
Divorced				20.250***	20.160***	18.539***	7.247***
				(0.856)	(0.819)	(0.802)	(0.683)
Bereaved				18.844***	18.690***	17.689***	7.077***
				(0.729)	(0.686)	(0.678)	(0.551)
Elemantary					20.680***	20.477***	19.778***
					(2.333)	(2.354)	(2.309)
Middle					24.465***	24.208***	23.193***
					(2.087)	(2.143)	(2.076)
High					19.630***	21.005***	19.936***
					(2.125)	(2.163)	(2.093)
College					18.304***	21.250***	20.149***
					(2.087)	(2.128)	(2.067)
University					18.023***	20.483***	19.261***
					(2.182)	(2.234)	(2.167)
Master					32.054***	34.646***	33.210***
					(2.132)	(2.185)	(2.124)
PhD					46.623***	48.974***	47.127***
					(2.445)	(2.482)	(2.396)
Age 40-44						10.143***	9.791***
						(0.268)	(0.274)
Head of household							13.824***
							(0.590)
Constant	53.525***	56.508***	54.008***	52.530***	32.494***	25.763***	25.933***
	(0.732)	(1.236)	(0.644)	(0.624)	(2.223)	(2.255)	(2.195)
Year fixed effects		√	√	√	√	√	√
Province fixed effects			√	√	√	√	√
Obervations	8,365	8,365	8,365	8,365	8,365	8,365	8,365
R-squared	0.055	0.101	0.183	0.331	0.391	0.55	0.645

Notes. The table shows the impact of Community Child Center Subsidy on cell-mean employment rate of women aged 35-44. Each cell represents combination of year (10), province (16), marital status (3), education (8), 5-year age bin (2) and head of household (2). This gives us 15,360 cells. However, due to the missing cells, total number of cells is 8,365. The variable of interest is province-level subsidy divided by the number of children aged 6 to 12 years in the province. Column (1) shows bivariate relationship between subsidy and employment rate and colum (2) additionally controls for year fixed effects. Column (3) to (7) present difference in differences estimates as we control fo year and province fixed effects. Standard errors in parentheses, are clustered at year-province level.

*, ** and *** significant at 1%, 5%, 10% level.

Table 2.7 First Stage Relationship: Relationship between (Lagged) Subsidy and Community Child Center Availability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Relationship between subsidy and Community Child Center availability							
Panel A-1. Dependent variable: Total Community Child Center slots in province in year t divided by number children aged 6 to 12 year in the province in year t (x100)							
Total subsidy in province in year t divided by number of children aged 6 to 12 years in the province in year t (unit: 10,000 Won)	0.428***	0.553***	0.279***	0.279***	0.283***	0.283***	0.281***
	(0.013)	(0.013)	(0.015)	(0.015)	(0.017)	(0.016)	(0.015)
Panel A-2. Dependent variable: Total number of Community Child Centers in province in year t divided by number children aged 6 to 12 year in the province in year t (x 10,000)							
Total subsidy in province in year t divided by number of children aged 6 to 12 years in the province in year t (unit: 10,000 Won)	1.539***	1.973***	1.020***	1.019***	1.017***	1.021***	1.016***
	(0.044)	(0.041)	(0.047)	(0.050)	(0.059)	(0.054)	(0.051)
Panel B. Relationship between lagged subsidy and Community Child Center availability							
Panel B-1. Dependent variable: Total Community Child Center slots in province in year t divided by number children aged 6 to 12 year in the province in year t (x 100)							
Total subsidy in province in year t-1 divided by number of children aged 6 to 12 years in the province in year t-1 (unit: 10,000 Won)	0.421***	0.570***	0.168***	0.163***	0.161***	0.163***	0.161***
	(0.017)	(0.019)	(0.016)	(0.016)	(0.018)	(0.018)	(0.017)
Panel B-2. Dependent variable: Total number of Community Child Centers in province in year t divided by number children aged 6 to 12 year in the province in year t (x 10,000)							
Total subsidy in province in year t-1 divided by number of children aged 6 to 12 years in the province in year t-1 (unit: 10,000 Won)	1.507***	2.039***	0.618***	0.601***	0.580***	0.593***	0.588***
	(0.061)	(0.062)	(0.060)	(0.060)	(0.068)	(0.066)	(0.063)
Control variables							
Year fixed effects		√	√	√	√	√	√
Province fixed effects			√	√	√	√	√
Marital status dummies				√	√	√	√
Average education level					√	√	√
Average age						√	√
Proportion of head of household							√

Notes . Total 160 province-year observations for Panel A and total 144 province-year observations for Panel B. Panel A-1 presents the relationship between subsidy and centers slot and Panel A-2 shows the relationship between subsidy and the number of center . Panel B-1 shows the relationship between lagged subsidy and center slots and Panel B-2 presents relationship between lagged subsidy and the number of centers. Column (1) shows the results from bivariate regression and colum (2) additionally controls for year fixed effects. Column (3) to (7) present difference in differences estimates as we control for both year and province fixed effects. Standard errors in parentheses, are clustered at year-province le
*, ** and *** significant at 1%, 5%, 10% level.

Table 2.8 OLS and IV Regression: Impact of Community Child Center on Employment Rate of Non-single Women Aged 35-44

	Dependent variable: cell-mean employment rate			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Total number of the centers in province in year t divided by the number of children aged 6 to 12 years in province in year t (x 1000)	0.111**	0.187***		
	(0.056)	(0.066)		
Total available slots in province in year t divided by the number of children aged 6 to 12 years in province in year t (x 100)			0.400*	0.701***
			(0.210)	(0.249)
Divorced	7.250***	7.252***	7.249***	7.251***
	(0.684)	(0.681)	(0.684)	(0.681)
Bereaved	7.080***	7.081***	7.080***	7.081***
	(0.552)	(0.550)	(0.553)	(0.550)
Elemantary	19.794***	19.774***	19.796***	19.775***
	(2.316)	(2.301)	(2.316)	(2.301)
Middle	23.219***	23.195***	23.220***	23.193***
	(2.084)	(2.070)	(2.084)	(2.070)
High	19.973***	19.937***	19.974***	19.935***
	(2.103)	(2.087)	(2.102)	(2.087)
College	20.186***	20.149***	20.187***	20.147***
	(2.076)	(2.061)	(2.076)	(2.061)
University	19.294***	19.260***	19.294***	19.259***
	(2.176)	(2.161)	(2.176)	(2.161)
Master	33.236***	33.208***	33.236***	33.205***
	(2.133)	(2.118)	(2.132)	(2.118)
PhD	47.150***	47.124***	47.152***	47.124***
	(2.406)	(2.390)	(2.406)	(2.390)
Age 40-44	9.792***	9.791***	9.791***	9.790***
	(0.275)	(0.274)	(0.275)	(0.274)
Head of household	13.824***	13.822***	13.825***	13.823***
	(0.591)	(0.589)	(0.591)	(0.589)
Constant	25.475***	25.376***	25.409***	25.251***
	(2.204)	(2.193)	(2.203)	(2.199)
Year fixed effects	√	√	√	√
Province fixed effects	√	√	√	√
Obervations	8,365	8,365	8,365	8,365
R-squared	0.645	0.645	0.645	0.645
Montiel-Pflueger first-stage F-statistics		538.226		511.267

Notes. The table shows the impact of Community Child Center on employment rate of women aged 35-44. Each cell represents combination of year (10), province (16), marital status (3), education (8), 5-year age bin (2), and head of household (2). This gives us 15,360 cells. However, due to the missing cells, total number of cells is 8,36 Column (1) and (2) shows the impact of number of centers in provinces and column (3) and (4) presents the effect of available slots in provinces. Both variables are divid by the number children aged 6-12 in provinces. Column (1) and (3) show the results from DD estimations and column (2) and (4) present the results from the instrumenta variable regressions. Province-level subsidy divided by number of children aged 6-12 is used as an instrument. Standard errors in parentheses, are clustered at year-provin level.

*, ** and *** significant at 1%, 5%, 10% level.

Table 2.9 Impact of Community Child Center on Employment Rate of Non-single Women Aged 35-44 - Heterogeneous Impact by Marital Status

	Dependent variable: cell-mean employment rate			
	Married		Divorced/Bereaved	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Panel A. Impact of number of the centers				
Total number of the centers at province in year t	0.111**	0.186***	0.073	0.213
	(0.054)	(0.065)	(0.155)	(0.178)
Montiel-Pflueger first-stage F-statistics		537.277		544.573
Observations	4,175	4,175	4,190	4,190
Panel B. Impact of available slots				
Total available slots at province in year t	0.412**	0.695***	0.12	0.795
	(0.203)	(0.244)	(0.609)	(0.665)
Montiel-Pflueger first-stage F-statistics		511.969		494.864
Observations	4,175	4,175	4,190	4,190
Control variables				
Year fixed effects	√	√	√	√
Province fixed effects	√	√	√	√
Marital status dummies	√	√	√	√
Education level dummies	√	√	√	√
5-year age bin dummies	√	√	√	√
Head of household dummy	√	√	√	√

Notes. The table shows the impact of Community Child Center on employment rate of women aged 35-44. Each cell represents combination of year (10), province (16), marital status (1 for marrid and 2 for divorced/bereaved), education (8), 5-year age bin (2) and head of household (2). This gives us 5,120 cells for married women and 10,240 cells for divorced/bereaved women. However, due to the missing cells, total number of cells is 4,175 for married women and 4,190 for divorced/bereaved women. Panel A shows the imp of numberof Community Child Center and Panel B presents the impact of number of available slots. For each sample, left column presents the estimates from the DD estimation and right column shows the results from the IV regression. Standard errors in parentheses, are clustered at year-province level.

*, ** and *** significant at 1%, 5%, 10% level.

Table 2.10 Impact of Community Child Center on Employment Rate of Non-single Women Aged 35-44 - Using Lagged Subsidy as an Instrument

	Dependent variable: cell-mean employment rate			
	Non-single		Married	
	IV	IV-lagged	IV	IV-lagged
	(1)	(2)	(3)	(4)
Panel A. Impact of number of the centers				
Total number of the centers in province in year t	0.187***	0.209**	0.186***	0.186**
divided by the number of children aged 6-12 in province in year t	(0.066)	(0.089)	(0.065)	(0.090)
Montiel-Pflueger first-stage F-statistics	538.226	170.239	537.277	171.956
Observations	8,365	8,365	4,175	4,175
Panel B. Impact of available slots				
Total available slots in province in year t	0.701***	0.782**	0.695***	0.695**
divided by the number of children aged 6-12 in province in year t	(0.249)	(0.329)	(0.244)	(0.334)
Montiel-Pflueger first-stage F-statistics	511.267	165.142	511.969	166.415
Observations	8,365	8,365	4,175	4,175
Control variables				
Year fixed effects	√	√	√	√
Province fixed effects	√	√	√	√
Marital status dummies	√	√	√	√
Education level dummies	√	√	√	√
5-year age bin dummies	√	√	√	√
Head of household dummy	√	√	√	√

Notes. The table shows the impact of Community Child Center subsidy on cell-mean employment rate of women aged 35-44. Each cell represents combination of year (marital status (3), education (8), 5-year age bin (9), sex (2), and head of household (2). This gives us 15,360 cells. However, due to the missing cells, total number of c 8,365. Likewise, we have 4,175 cells for married women . For each sample, the left column shows the estimates from the IV regression using subsidy as an instrument right column shows the estimates from the IV regression using the lagged subsidy as an instrument. Panel A shows the impact of number of Community Child Center a Panel B presents the impact of number of available slots. Standard errors in parentheses, are clustered at year-province level.

*, ** and *** significant at 1%, 5%, 10% level.

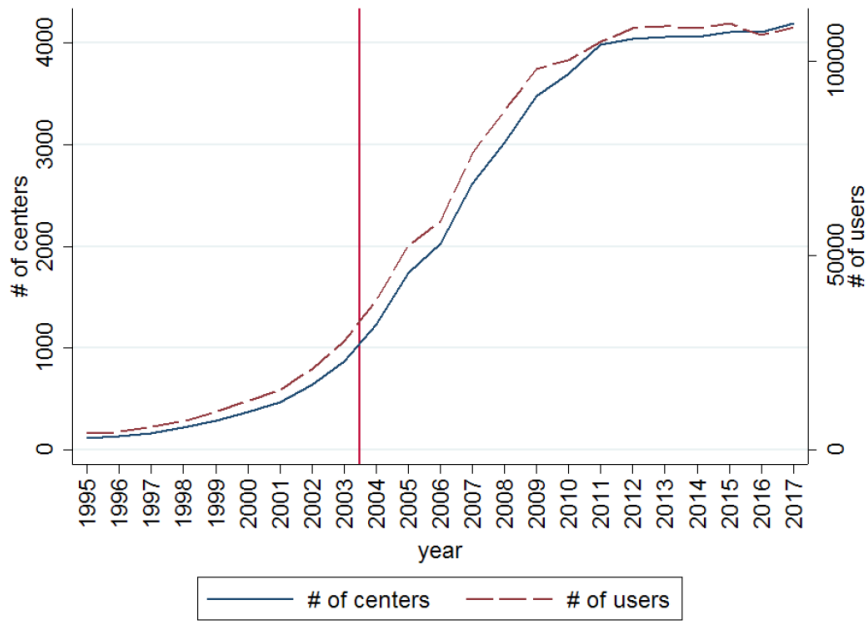
Table 2.11 Impact of Community Child Center on Employment Rate of Single Men and Women Aged 35-44

	Dependent variable: cell-mean employment rate					
	Single women			Single men		
	OLS	IV	IV-lagged	OLS	IV	IV-lagged
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Impact of number of the centers						
Total number of the centers in province in year t divided by	0.136	0.072	-0.172	0.12	0.093	-0.027
the number of children aged 6 to 12 years in province in year t (x 1000)	(0.197)	(0.228)	(0.291)	(0.097)	(0.107)	(0.151)
Montiel-Pflueger first-stage F-statistics		521.337	166.169		513.255	154.546
Observations	3,555	3,555	3,555	4,016	4,016	4,016
Panel B. Impact of available slots						
Total available slots in province in year t divided by	0.379	0.269	-0.645	0.49	0.348	-0.101
the number of children aged 6 to 12 years in province in year t (x 100)	(0.760)	(0.858)	(1.093)	(0.363)	(0.402)	(0.567)
Montiel-Pflueger first-stage F-statistics		480.812	159.021		494.253	146.337
Observations	3,555	3,555	3,555	4,016	4,016	4,016
Control variables						
Year fixed effects	√	√	√	√	√	√
Province fixed effects	√	√	√	√	√	√
Marital status dummies	√	√	√	√	√	√
Education level dummies	√	√	√	√	√	√
5-year age bin dummies	√	√	√	√	√	√
Head of household dummy	√	√	√	√	√	√

Notes. The table shows the impact of Community Child Center Subsidy on cell-mean employment rate of single men and women aged 35-44. Each cell represents combination of year (10), province (16), education (8), 5-year age bin (2), and head of household (2). This gives us 5,120 cells for single women and men. However, due to the missing cells, total numbers of cells are 3,555 and 4,016 for women an Panel A shows the impact of number of Community Child Center and Panel B presents the impact of number of available slots. Column (1) and (4) presents the results from the standard difference in differe estimation and column (2) and (5) shows the estimates from the IV regressions which use subsidy per children aged 6-12 as an insturment. Column (3) and (6) shows the estimates from the IV regressions w use the lagged subsidy as an insturment. We control for marital status, educational level, 5-year age bin, and head of household dummies as well as year and province fixed effects in all regressions. Standar in parentheses, are clustered at year-province level.

*, ** and *** significant at 1%, 5%, 10% level.

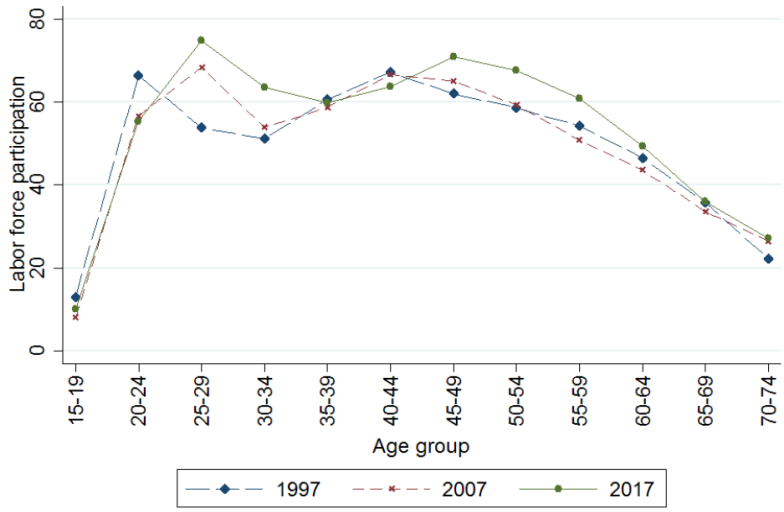
Figure 2.1 Increase in Community Child Center



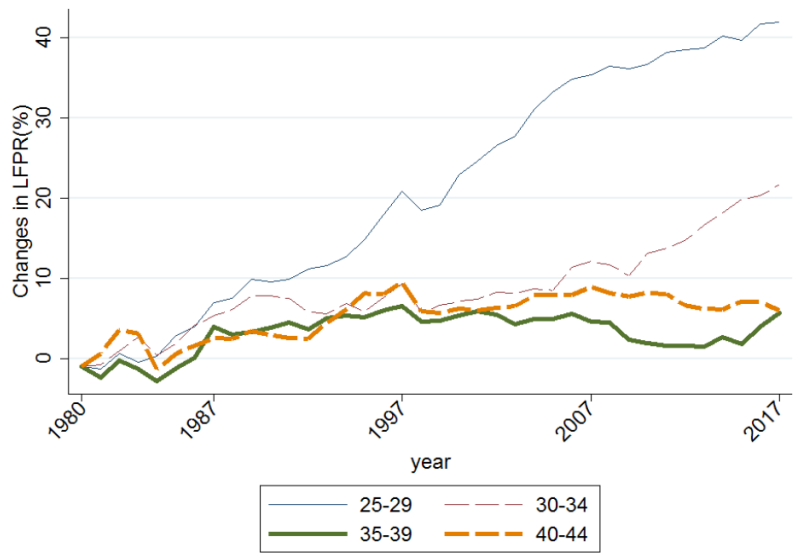
Notes. The figure depicts the number of Community Child Centers from 1995 to 2017. The number are calculated using Community Child Center microdata. Due to the fact that microdata is available from 2006, we constructed the number of centers before 2006 using information on location and opening date of the centers in 2006 microdata.

Figure 2.2 Labor Supply of Women in Korea

Panel A. Women's labor supply by 5-year age bins



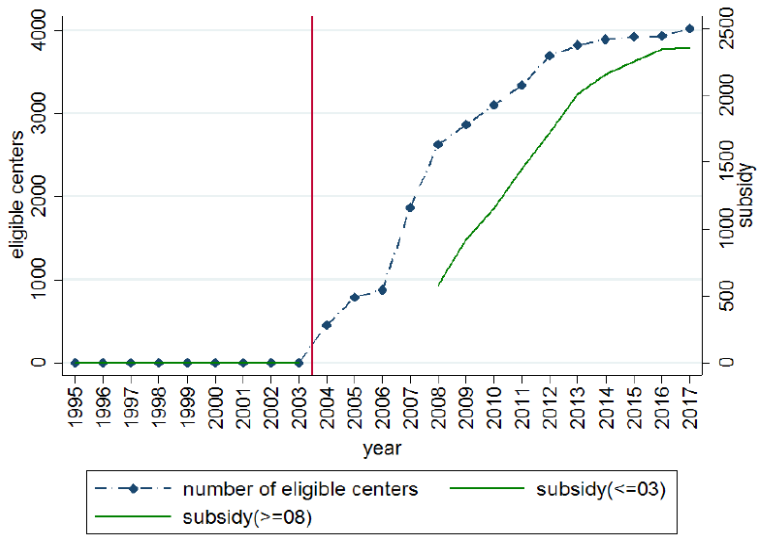
Panel B. Changes in Women's labor supply relative to 1980



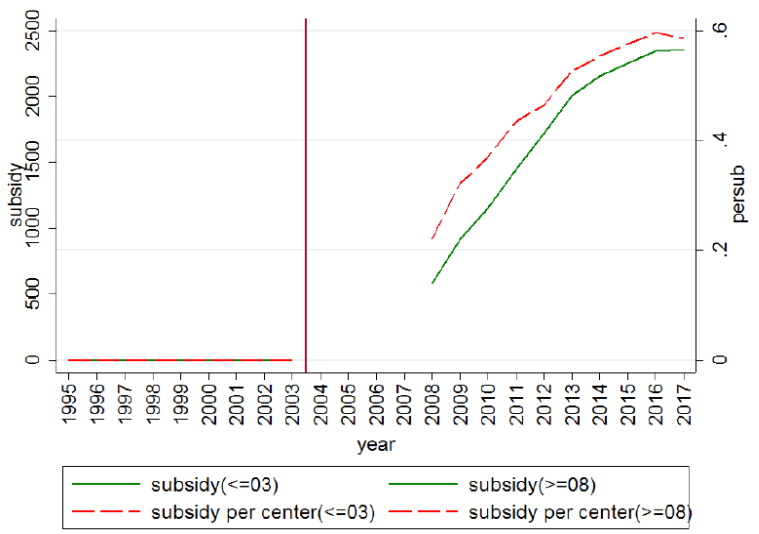
Notes. The figure shows the labor supply of women in Korea. Panel A shows labor force participation rate for each 5-year age bins in 1997, 2007 and 2017. Panel B depicts changes in labor force participation relative to 1980. Data from OECD labor statistics is used.

Figure 2.3 Increase in the Subsidy for Community Child Center

Panel A. Increase in subsidy and subsidy-eligible centers

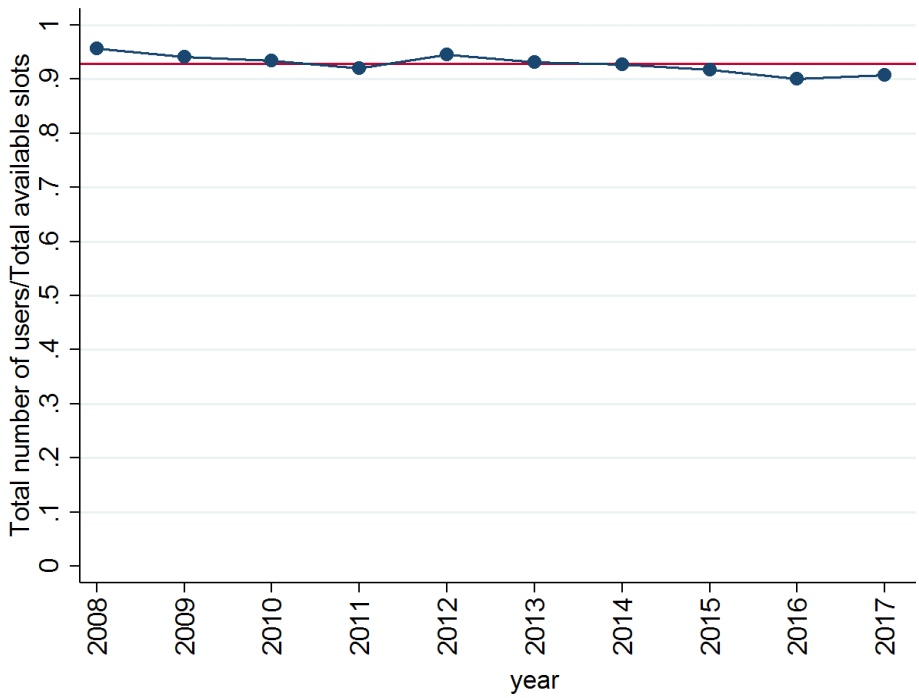


Panel B. Changes in subsidy per the center



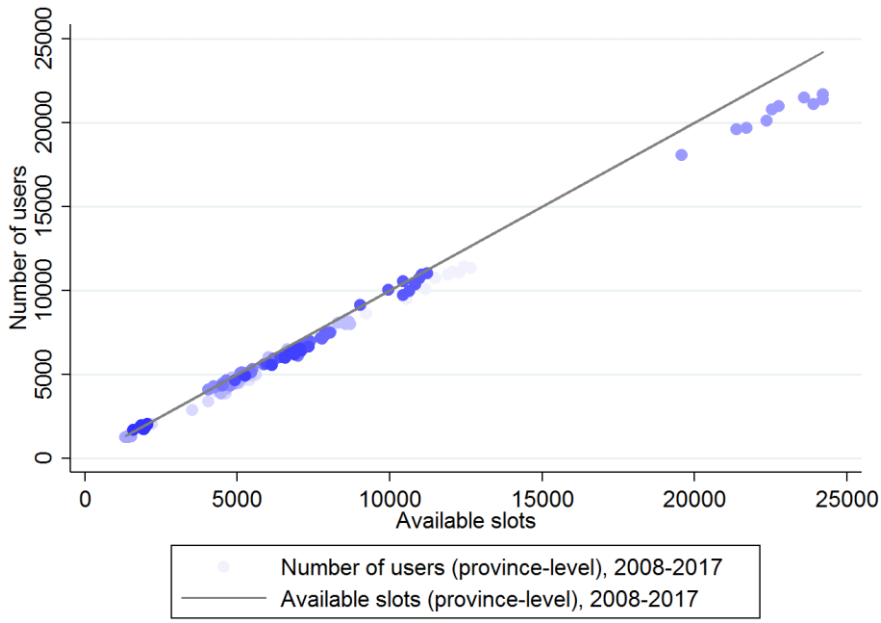
Notes. The figure depicts changes in subsidy for Community Child Center. Panel A shows the changes in number of subsidy-eligible centers and total subsidy. Panel B presents the growth in subsidy per Community Child Center. Unit is 100,000,000 Won.

Figure 2.4 Utilization Rate of the Community Child Centers during 2008-2017



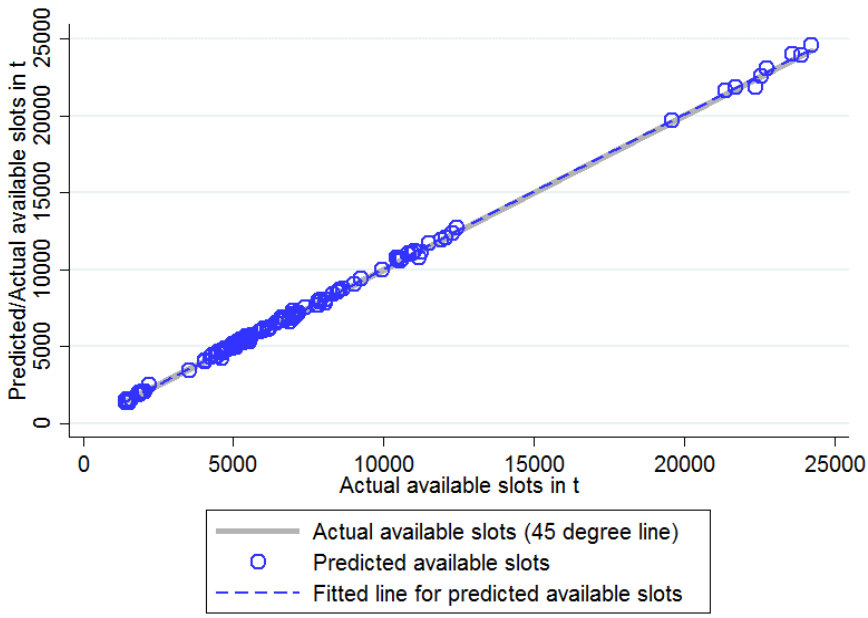
Notes. The figure depicts utilization rate of the Community Child Centers between 2008 and 2017. Dotted-blue line denotes the utilization rates for each year and straight-red line represents the mean utilization rate of the Community Child Centers.

Figure 2.5 Number of Users and Available Slots in each Province



Notes. The figure shows the number of users in each province. Blue circles represent the number of users in each province in 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016 and 2017. There are 16 provinces in each year. Each province is denoted using different colors. 45 degree line depicts the available slots in each year.

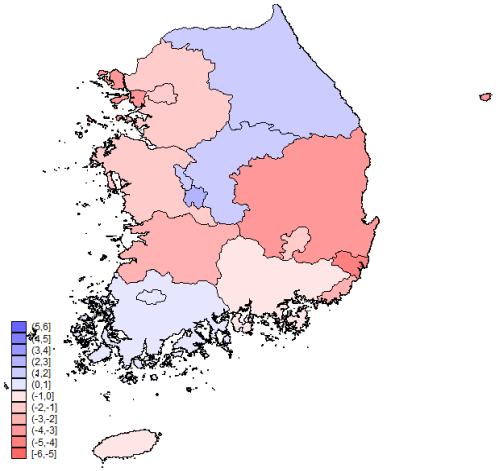
Figure 2.6 Predicted and Actual Slots



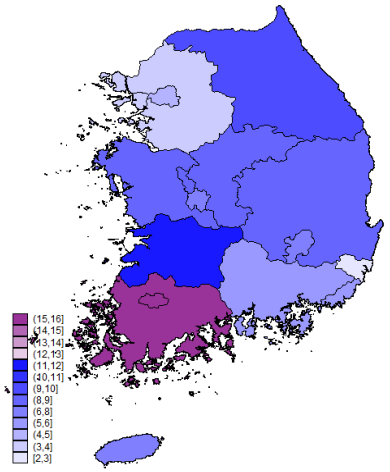
Notes. This figure shows the predicted and actual available slots in each province in 2009, 2010, 2011, 2012, 2013, 2014, 2015 and 2016. There are 16 provinces in each year. 45 degress line shows the actual available slots and blue-hollow circles represents the predicted number of slots in each province.

Figure 2.7 Changes in Province-level Employment Rate of Non-single Women Aged 35-44, Subsidy Divided by Number of Children Aged 6-12, and Community Child Center Slots Divided by Number of Children Aged 6-12

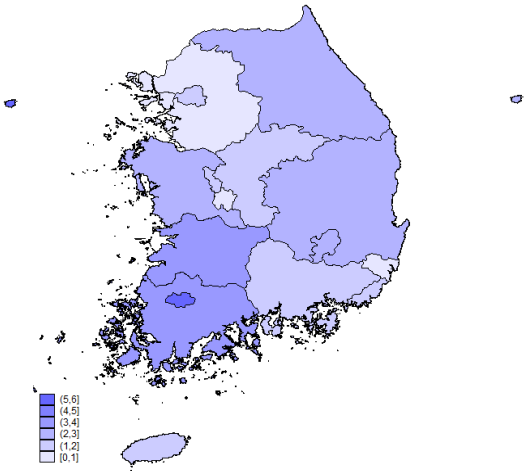
Panel A. Changes in Employment Rate of Non-single Women Aged 35-44 between 2008-2017



Panel B. Changes in Subisdy Divided by Number of Children Aged 6-12 between 2008-2017



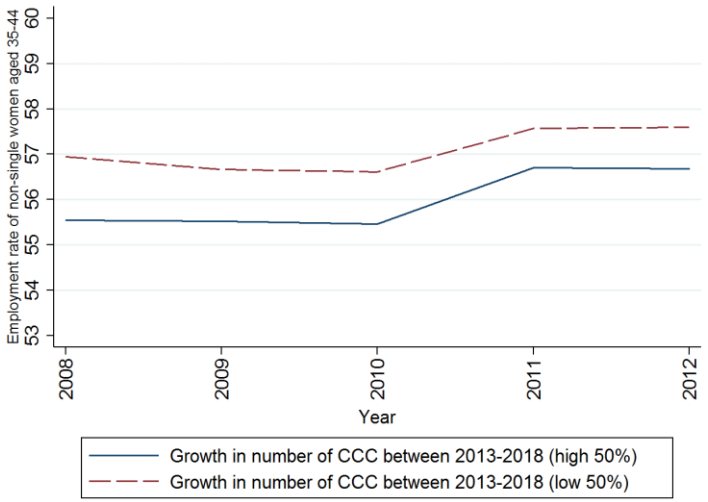
Panel C. Changes in Available Community Child Center Slots Divided by Number of Children Aged 6-12 between 2008-2017



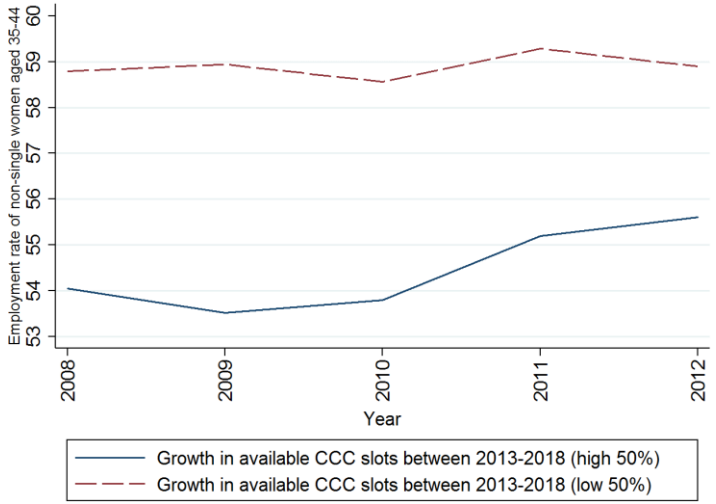
Notes. The Panel A depicts the changes in employment rate of non-single women aged 35-44 in each province. The Panel B shows the changes in subsidy divided by the number of children aged 6 to 12 in each province. The Panel C presents the changes in number of available Community Child Care divided by the number of children aged 6 to 12 in each province. Changes are calculated by substracting province-level variable mean in 2008 from province-level variable mean in 2017. All variables are denoted in percentage terms.

Figure 2.8 Time Trends in Employment Rate of Non-single Women aged 35-44 during 2008-2012 by Changes in Community Child Center Availability between 2013 and 2018

Panel A. Time Trends in Employment Rates of Non-single Women aged 35-44 between the Provinces with Rapid Growth in CCC Numbers per children aged 6-12 during 2013-2018 and the Provinces with Slow Growth in CCC Numbers per children aged 6-12 during 2013-2018



Panel B. Time Trends in Employment Rates of Non-single Women aged 35-44 between the Provinces with Rapid Growth in Available CCC Slots per children aged 6-12 during 2013-2018 and the Provinces with Slow Growth in Available CCC Slots per children aged 6-12 during 2013-2018



Notes. The figure shows the time trends in employment rate of non-single women aged 35-44 during 2008-2012. Panel A compares the provinces experienced rapid growth in number of Community Child Centers between 2013 and 2018 t provinces undergone slow growth in number of Community Child Centers between 2013 and 2018. Panel B compares the provinces experienced rapid growth in available slots at Community Child Centers between 2013 and 2018 to the provinces undergone slow growth inavailable slots at Community Child Centers between 2013 and 2018.

Chapter 3

Working Long Hours and Female Managerial Employment after Motherhood

3.1 Introduction

The low female labor force participation rate in Korea is an important issue that is affected by motherhood. Specifically, a low probability of entering or returning to work after childbirth significantly contributes to the low supply of female labor (Kim, 2008). Previous studies suggest that the low female labor force participation of married women is attributable to numerous factors, such as the substitutability of market child care compared with maternal child care (Hwang et al., 2018), discrimination (Charles et al., 2018), social norms (Jayachandran, 2019), bargaining (Knowles, 2013), human capital depreciation (Mincer & Polachek, 1974), and workplace flexibility (Goldin & Katz, 2011; Herr & Wolfram, 2012). This chapter focuses on the effect of workplace flexibility, especially long working hours, on the probability of working after motherhood for female managers.

Goldin and Katz (2011) suggest that workplace flexibility is multidimensional concept. It includes a) long working hours, b) the possibility of job interruption, c) availability of part-time work, and d) flexible work timing arrangements during the day. Workplace flexibility in Korea is perceived to be low in all four aspects. Even though the Korean government has expanded maternity leave and child care leave to reduce interruptions to the workplace as a result of childbirth, the utilization rate is still low, and there is significant heterogeneity in utilization rates across sectors (Park, 2016). Availability of part-time work and flexibility in work timing are also considered low. Keum (2014) shows that in 2012, part-time work accounted for 10.2% of all work in Korea, which is 5.2% less than the OECD average. Figure 3.1 compares the hours worked by full-

time employed workers by gender. Panel A shows the results for single workers and Panel B depicts results for individuals with a child under six years of age. For each panel, the left figure shows the distribution in Korea compared with that in the United States on the right. For single men and women, no differences are evident in the distribution of working hours for both countries. However, from Panel B it is evident that mothers work consistently fewer hours than fathers during a work day in the United States. This is because mothers adjust the timing of work and spend time with children during the day (Cubas et al., 2019).[37] However, a difference in working hours between mothers and fathers in Korea is not emphasized. Importantly, working hours are almost identical between 10:00 am and 3:00 pm. This result suggests that it is difficult for Korean mothers to adjust their working hours flexibly. Lastly, Korea is known for having exceptionally long working hours. In 2018, Korean employees worked an average of 1993 h per year, which is the third highest in the world (OECD, 2020). Such long working hours might be costly for new mothers, presuming that they are willing to allocate considerable time to their child. Among the many elements of workplace flexibility, this study focuses on the effect of long working hours on the labor supply of women after motherhood.

Figure 3.2 shows that the trend of estimated mothers' time with their child declines as the child grows older (Brilli, 2017).[38] It is noteworthy that maternal time with the child is significantly high until the child reaches the age of three years, and then it reduces sharply. This suggests that women with children under the age of three would be

[37] The figures for the United States are borrowed form Figure 2 of Cubas et al. (2019), which shows that US full-time employed mothers spend significant time with their children during the day. However, there is large heterogeneity in flexibility across occupations. For example, Healthcare practitioners can easily adjust their timing of work but lawyers are not able to adjust their work timing. Also, flexible use of time in the workplace is associated with a reduction in wages as well as occupation selection decisions. For a detailed explanation, see Cubas et al. (2019).

[38] The figure is borrowed from Figure 1 in Brilli (2017).

more likely to avoid long work hours if they have no alternative child care arrangements to substitute maternal care. In this chapter, the Korean Women Manager Panel (KWMP) is used to estimate the impact of working long hours on the labor supply of women after motherhood. Specifically, I relate the work environment of survey year t-1 with work status in survey year t. Since the KWMP is a biennial survey and I focus on women who gave birth between survey year t-1 and t, the analysis sample consists of managerial women who have at least one child younger than two years. I test whether female managers who worked at a firm (where on average employees work for more than 12 h per day) are less likely to work after childbirth. The KWMP suggests that managerial women in Korea spend considerable time in the workplace. For example, in 2014, female managers worked 10 h and 39 min on average per day, which is 1 h and 52 min longer than non-managerial full-time employed women spent at work.[39] This implies that managerial women would find it even more difficult to reconcile work and child care than the average employed woman.[40]

This study exploits the fact that managerial women in the KWMP are a subsample of selected firms and that information about these firms is available. The estimation result using the constructed firm-level working hours suggests that managerial women who worked at a firm where average employees remain for more than 12 h are 8.5% –9.5% more likely to leave the labor market after giving birth. This result is robust in its inclusion of various individual and firm characteristics.

To the extent of my knowledge, in a Korean context, this is the first study to evaluate the impact of long working hours on the labor supply of mothers. In addition,

[39] I calculated how long full-time employed women stayed at work using the Korean Time Use Survey 2014. In 2014, female full-time employees stayed at work 8 hours and 46 minutes on average.

[40] Here I am simply assuming that the managerial women and the average employed women have same preference for time with children. However, it is an empirical question as to which group has higher preference for time with children.

even though many studies have examined the effect of flexibility on female labor supply, few studies have explicitly investigated the effect of long working hours on the opt-out rate of women after motherhood. Recent literature suggests that women take the cost of working long hours into account when they select their occupation (Cortes & Pan, 2017). However, women systematically underestimate the cost of motherhood before childbirth, and this underestimation is higher for women who are educated to a higher level (Kuziemko et al., 2018). In this chapter, I suggest that managerial women in Korea (who are highly educated) might underestimate the cost of long working hours on their motherhood. The results suggest that policies that reduce the cost of long working hours could be an effective way of increasing the labor force participation rate of highly educated women after childbirth.

The rest of the chapter proceeds as follows. Section 3.2 describes the conceptual framework related to labor supply and minimum hours requirements. Section 3.3 explains the KWMP and presents descriptive statistics for the sample (for individuals and firms). Section 3.4 demonstrates the empirical strategy used in this chapter. Section 3.5 presents the results from the estimation, and the conclusions are presented in Section 3.6.

3.2 Conceptual Framework

I use firm-level working hours to estimate the effect of long working hours on female labor supply. I conceptualize the required working hours at the workplace as a minimum hours' requirement. This is a similar approach to that used by Herr and Wolfram (2012), who viewed the inflexibility of the pre-childbirth work environment as a minimum hours' constraint. Theoretically, firms are likely to have strong preferences for working hours due to worker-specific costs and nonlinearities between hours worked per worker and outputs (Deardorff & Stafford, 1976). Empirical findings show that the constraint on hours worked

imposed by the demand side significantly affects employment (Altonji & Paxson, 1990; Ham, 1977, 1982, 1986; Moffitt, 1984).[41]

In this paper, I modify the simple conceptual framework suggested in Herr and Wolfram (2012). A standard labor supply model can be expressed using following two equations:[42]

$$w_{it} = a_0 + a_{1c}D_{ic} + a_2E_{it} + Z_{it} + \theta_{it} \quad (1)$$

$$w_{it}^{*} = \beta_0 + \beta_1 h_{it} + \beta_2 X_{it} + v_{it} \quad (2)$$

Hourly wage w_{it} is a function of work experience, E_{it}, and a vector of other factors, Z_{it}, which affects hourly wage. D_{ic} is a dummy variable, which equals 1 if women i work at firm c. Her reservation wage w_{it}^{*} is determined by hours worked, h_{it}, and other individual characteristics, X_{it}, such as number of children, husband's salary, and non-labor income. Women will participate in the labor market only if their reservation wage at $h_{it} = 0$ is lower than hourly wage w_{it}. If they decide to participate in the market then they will choose an optimal level of working hours where the two equations are equal.

However, if there is a minimum number of hours required by the firm c, then the comparison is made between hourly wage and reservation wage at minimum hours constraint. More explicitly, the reservation wage equation wage can be expressed in the following form:

$$w_{it}^{*}(h_c^{min}) = \beta_0 + \beta_1 h_c^{min} + \beta_2 X_{it} + \beta_3 w_{it} h_c^{min} + v_{it} \quad (3)$$

This implies that women i in firm c will work only if following inequality holds. This inequality suggests that if a minimum hours requirement for firm c, h_c^{min}, is lower than

[41] Minimum hours constraint could also arise from the supply side. See Cogan (1981) for detail.

[42] Herr and Wolfram (2009)'s model is based on Heckman (1976)'s canonical labor supply model, in which individuals compare the value of marginal hours at work with the value of marginal time at home.

the requirement for firm c', $h_{c'}^{min}$, then the probability of working is higher for firm c, assuming that all other things are equal.

$$\mathrm{P}(h_{it}>0|D_{ic}) = \mathrm{P}(w_{it}(D_{ic}) > w_{it}^{*}(h_c^{min}))$$

$$= \mathrm{P}(a_0 + a_2 D_{ic} + a_2 E_{it} + Z_{it} + \varepsilon_{it} > \beta_0 + \beta_1 h_c^{min} + \beta_2 X_{it} + \beta_3 w_{it} h_c^{min} + v_{it}) \quad (4)$$

In this chapter, I test the hypothesis that higher h_c^{min} results in lower female labor supply after motherhood. Since motherhood shifts the reservation wage upward, mothers working in the firm with higher h_c^{min} are more likely to opt out from the labor market.

A potential problem for this identification is the possible correlation between preference for their child and working long hours. We can decompose the error term v_{it} in Equation (3) into two parts as follows. Here, ξ_i stands for individual preference for the child and μ_{it} is pure error uncorrelated with other factors.

$$w_{it}^{*}(h_c^{min}) = \beta_0 + \beta_1 h_c^{min} + \beta_2 X_{it} + \beta_3 w_{it} h_c^{min} + \xi_i + \mu_{it} \quad (5)$$

Theoretically, we can expect both positive and negative relationships between ξ_i and h_c^{min} (Herr & Wolfram, 2009). For individuals with insufficiently high ξ_i, I expect a negative relationship between two variables. Women with a higher preference for their child will choose the firm with lowest minimum hours requirement to reconcile work and child care. However, if the sample is restricted to individuals with very high ξ_i, then it might be anticipated that there is a positive correlation between minimum hours and preference for the child. This is because women with a very high preference for their child would expect to leave the labor market after motherhood. Given that opting out from the labor market after childbirth is an optimal strategy, they would work sufficiently long hours before childbirth to maximize their lifetime earnings. However, for our analysis sample, such a positive relationship is unlikely. Herr and Wolfram (2009) suggest it is hard to believe that women with a high preference for their child would invest so much into

their own human capital. Since our sample of female managers are highly educated[43], it is unexpected that the sample also consisted of very high ξ_i. Ruling out the possibility that sample comprised of individuals with very high ξ_i, unobserved preference for the child would attenuate the potential negative effect of h_c^{min} on female labor supply after motherhood.

There is also a possibility that the estimate of the effect of h_c^{min} on labor force participation could be inflated. In the regression analysis, I restrict the sample to female managers who gave birth between survey year t-1 and t. If a non-family-friendly work environment negatively affects the decision to have a child, then preference for their child will be higher for mothers who work in an inflexible workplace.[44] Appendix Table A.3.1 shows that women who work in firms with long working hours are 3.3% less likely to have a child. This implies that restricting the sample to mothers will overstate the potential negative impact of long working hours on labor supply. It is an empirical question of which effect dominates the other.[45]

3.3 Data

I conducted the analysis using the KWMP, which is a panel survey that collects detailed information on Korean managerial women and their firms. The KWMP started in 2007 as

[43] In the KWMP for 2007, 2008, 2010, 2012, 2014, and 2016, 89.5% of the sample of female managers held a college degree or higher.

[44] Mothers with low preference for the child will give up childbearing as they work in non-family-friendly environment.

[45] Even though the conceptual framework given in this section does not explicitly consider the women's expectations, I would like to emphasize that women's career decisions at different moments are made under imperfect knowledge about family responsibilities, as well as the cost of inflexibility at workplace (Goldin and Katz, 2011; Herr and Wolfram, 2012). This implies that opting-out from the labor market might not be fully anticipated before the childbirth.

an annual survey; however, in 2008 it changed to a biennial survey. This study utilized KWMP data from 2007, 2008, 2010, 2012, 2014, and 2016. The initial sample consisted of 2,361 female managers working in 341 firms. The KWMP was considered suitable for investigating the impact of the pre-childbirth work environment on the labor supply, because a large proportion of the sample had a child during the sample period. Figure 3.3 presents the age distribution of the sample in 2007, and shows that the average age is 32.7 years with a standard deviation of 4.5. Table 3.1 shows the number of women who had a child during the sample period. Panel A illustrates that during the sample period, 1,009 female managers had a child. This corresponds to 12.4% of the total sample. Since we need information on the work environment of the firms where women worked before having a child, we confined our interest to the sample who worked in the last survey year.[46] Panel B shows that the childbirth probability for this sample is 13.6%. As this study focused on the sample of women who gave birth between survey year t-1 and t, this gave a sample of 699 managerial women.

Sample observations were reduced, as some respondents did not provide information on main variables such as working hours or education. Due to these missing variables, our final sample consisted of 347 female managers. Table 3.2 presents descriptive statistics for the sample, in which working hours are defined as "time stayed at workplace: from the usual arrival time to the usual departure time". Because the flexibility of work time in Korea is low, the length of time that individuals stay at work would be more important than their regular working hours. Analysis from the sample shows that an average of 10 h and 47 min was spent at the workplace (before having a child). On average, they arrived at their workplace by 8:24 am and departed by 7:11 pm. The average monthly wage for the sample of female managers was 3.46 million won. Average work experience was 12 years, which implies that most female managers entered the labor market after graduating from university. The average age for the sample was 36 years. It was found that

[46] Additional female managers are included in the survey from KWMP 2012 to deal with the attrition problem. I used respondents from the first survey and those who participated from 2012.

spouses of female managers had a high probability of working, as more than 97% of spouses were working at t-1. Since the average age was 36 years, most women managers had already had a child; only 12% of workers had given birth for the first time. Among our analysis sample, 96.3% have college degrees (or higher). This was 6.8% higher than the KWMP average.[47] The majority of female managers majored in the social sciences, science, or engineering. It is noteworthy that more than 63% of women had graduated from universities or colleges located in Seoul. This reflects the potentially high ability of these female managers.[48]

Table 3.3 presents the descriptive statistics for firms where sample individuals worked before having a child. Firm-level average working hours, average arrival time at the workplace, and average departure time from the workplace are presented.[49] On average, workers arrived at 8:28 am and departed at 7:14 pm. It is interesting to note that even though average working hours are almost identical to the firm-level average, sample individuals arrived and departed earlier. This might imply that night time costs are greater than morning costs for young mothers. Since the KWMP survey incorporates firms with more than 99 employees, there was only a very small proportion of firms with less than 100 employees. Interestingly, 86.5% of firms were located in Seoul. This is partly because our analysis sample went to universities located in Seoul. However, it also reflects the fact that large firms and corporations with female managers are concentrated in Seoul. Table 3.3 presents details about corporate childcare policies. Respondents identified the availability of short time work, childcare centers at the workplace, maternity leave, and parental leave in their answers. Because maternity leave is enforced by law, maternity leave was available at 98.5% of firms. Parental leave was also available at 84.5% of firms.

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[47] This may reflect the positive selection of motherhood based on education or ability, since we restricted our interest to the sample who gave birth to a child.

[48] In Korea, most top universities are concentrated in Seoul. The competition to enter the so called "in-Seoul" university is intense.

[49] Individual i's data is not used in calculating the firm-level average.

However, shorter work hours were not accessible, with less than 20% of corporates allowing female managers to reduce their working hours after motherhood. The probability of working at a firm with a childcare center is very low, because only 10% of firms had such childcare facilities in the workplace.

Flexibility-related corporate culture is presented in the table. The KMWP asks respondents various questions about workplace flexibility. Averages for each 5-point Likert-scale question closely related to overtime work are presented in Table 3.3.[50] The questions used are as follows: "Leaving work on time is like walking on eggshells," "Having vacation on weekdays due to a personal matter is hardly allowed," "Working until late at night is the best way to get a good performance evaluation," "To survive, I have to put my work as a first priority," and "Missing company nights out is like walking on eggshells."[51]

3.4 Empirical Strategies

In this chapter, I estimate the impact of pre-childbirth workplace flexibility on post-childbirth labor force participation. Specifically, I estimate the following regression equation:

$$Nowork_{i,t} = \gamma_0 + \gamma_1 Longwork_{-i,c,t-1} + \gamma_2 E_{i,t-1} + \gamma_3 X_{i,t-1} + \varphi_t + \epsilon_{it} \quad (6)$$

$Nowork_{i,c,t}$ is a dummy variable that equals 1 if the female manager i did not work at time t. $Longwork_{-i,c,t-1}$ is a dummy variable that equals 1 if the average working hours of the firm c where the female manager i worked at time $t-1$ is greater than 12 h. When constructing the average working hours, I did not include the individual i's working hours. Term $E_{i,t-1}$ is a vector that contains individual i's work experience at $t-1$ and

[50] Individual i's data is not used in calculating the firm-level average.

[51] Scales are 1) not at all, 2) unlikely, 3) of average, 4) likely, 5) very likely.

its square. Term $X_{i,t-1}$ is vector of individual characteristics at $t-1$, which includes age, age squared, number of children, education, log wage, spouse's education, and spouse's work status.

Since the empirical model controls for year fixed effects φ_t, the opt-out rate for new mothers who worked at their workplace on average for less than 12 h per day is compared to the opt-out rate of new mothers who were employed at the firm where on average workers stayed for more than 12 h within each survey year. Term γ_1 provides the average differences in opt-out rate between two groups as a result of working more than 12 h. Comparing female managers who became mothers in different years, estimates could be biased, presuming that differential trends in flexibility existed between the family-friendly and family-unfriendly firms. Panel A of Appendix Figure A.3.1 shows the time trend of availability for family-friendly policies and the flexibility-related culture of firms. The figures in Panel A suggest that work environment becomes more flexible as time passes. Panel B of Appendix Figure A.3.1 depicts differences in both availability and culture between firms with long and short working hours. The figures in Panel B show that changes in flexibility are not same across firms. In particular, corporate norms together with long working hours seems to change slowly.

To prevent potential bias from the omitted factors, I included a rich set of control variables and estimated the following regression equation:

$$Nowork_{i,c,t} = \gamma_0 + \gamma_1 Longwork_{-i,c,t-1} + \gamma_2 E_{i,t-1} + \gamma_3 X_{i,t-1} + \gamma_4 A_i + \gamma_5 Z_{-i,c,t-1} + \varphi_t + \epsilon_{it} \quad (7)$$

I first added the location of university or college where female managers graduated as a control variable. Individuals with high ability might select into an inflexible workplace, whereas family-unfriendly workplaces offer higher wages due to the compensating wage differentials. Ability-based selection into marriage or motherhood is also a concern. Since prestigious universities are concentrated in Seoul, graduates from universities located in the capital city are expected to have higher ability and earnings potential. For this reason, I controlled for whether the female manager attended university in Seoul. Moreover, I controlled for their major, since it is well known that wage potential is highly related to

major choice. Vector A_i includes individual i's major and location of the university or college.

Second, I controlled for the various firm-level variables. I included size and location of the firm as well as corporate norms related to long working hours. The latter is particularly important, because corporate norms could affect working hours as well as the probability of returning to work after having a child. Previous studies suggest that flexibility-related corporate culture significantly affects employees' work-life balance and life satisfaction (Son and Park 2014; Yoo, 2008). In addition,, I verified whether controlling for the availability of family-friendly policies alters the estimated impact of long working hours on post-motherhood labor supply. To ensure that the estimate captured the effect of working long hours rather than the effect of the length of time working, I also controlled for the average arrival time at work.[52] When constructing the firm-level variables, I calculated the average of colleagues' reported values, except for individual i. Term $Z_{-i,c,t-1}$ stands for the vector of corporate characteristics.

3.5 Results

First, I present the relationship between long working hours and the opt-out rate. Figure 3.4 shows the probability of working at t-1, conditional on firm-level working hours at t. The depicted lines illustrate the nonparametric relationship between opt-out rate and working hours. The bold line represents the female managers who worked at survey year t-1 and had a child between survey year t-1 and t. The dashed line represents all women who worked at t-1. The probability of working at time t for women who worked standard hours (8–9 h) at t-1 is the same for new mothers and average female managers. However, the quit rate increased for female managers who had a child as average working hours increased from 8 h to 9 h. The probability of new mothers returning to work remained

[52] A recent study suggests that workers are more likely to avoid nighttime work (Mas & Pallais, 2017).

stable as average working hours increased from 9 h to 12 h. This increased notably as average working hours exceeded 12 h. For female employees who worked during year t-1 at a firm where (on average) colleagues worked for more than 13 h per day, and who experienced childbirth between t-1 and t, they were more than 20% less likely to work at the same firm as they did at time t compared to women who did not have a child. The figure suggests that even though long working hours and work probability have a generally negative relationship, new mothers are much more sensitive to long working hours.

Table 3.4 shows the impact of long working hours on the probability of working after childbirth. The estimation results are based on Equation (6). Column (9) controls for a full set of individual characteristics, $X_{i,t-1}$. Column (1) of Table 3.4 presents the results from the simple regression, which only controls for year fixed effects. The estimate shows that female managers who worked at a firm where (on average) colleagues worked for more than 12 h per day were 10.6% less likely to work after having a child. It was evident that the estimate remained stable as we included individual level characteristics such as log wage, experience, age, education level, spouse's education, and spouse's work status. Including the number of children at year t-1 reduced the estimate by 2.4%. This implies that female managers who had a child at t-1 already selected to work at a firm with short working hours since it is clear that these mothers are more likely to work after having a child. It is understood that the cost of motherhood would be higher for those managers having their first child than for managers who have already had a child.

Table 3.4 suggests that working at a firm requiring more than 12 h work per day has a remarkable impact on the probability of returning to work after having a child. However, the estimate might be biased, as factors that simultaneously affect working hours and probability of returning to work were omitted. For this reason, I controlled for the location of the university and the major as well as for various firm-level characteristics. These include size and location of the firm, flexibility-related corporate norms, and availability of family-friendly policies. Table 3.5 compares the estimate from the basic regression to the estimates controlling for the proxies of abilities and firm characteristics.

Column (2) of Table 3.5 controls for the location of the university and the major. Female managers who graduated from universities in Seoul were 9.8% less likely to opt out from the labor market after having a child. This might reflect an increased preference for working by individuals with higher ability. Moreover, it was evident that the estimated impact of long working hours increased after controlling for the proxies for abilities. Given that female managers who graduated from universities in Seoul were more likely to work after having a child, this finding suggests that high ability managers positively selected into the inflexible work environment.

Column (3) additionally controlled for the corporate norms related to an inflexible work environment. Interestingly, working at a firm with a high average score for question 3: "Working until late at night is the best way to get a good performance evaluation" significantly increased opt-out probability. This suggests that the corporate culture (which compels individuals to work longer) affects actual working hours as well as labor supply decisions after motherhood. Females managers' position at t-1, location of the firm, and size of the firm are added in Column (4). Position and size had no effect on female labor supply. However, female managers who worked at firms in Seoul were much more likely to work after having a child.

Column (5) controlled for availability of family-friendly policies. No policies (except for parental leave) had a significant effect on female labor supply decisions. Female managers who could utilize parental leave were 13.7% more likely not to work after having a child. This result aligned with the findings presented in Kim (2012), who showed that expansion of parental leave benefit has had a negative impact on female labor supply.

The result from the estimation that controlled for rich set of individual and firm characteristics suggests that female managers avoid inflexible work environments after motherhood. Unexpectedly, family-friendly policies seem to have a limited effect on female labor supply decisions. However, it is difficult to conclude that family-friendly policies are an ineffective method of enhancing the labor force participation of new mothers. This is because availability of short time work and childcare centers in the

workplace is very low during the sample period.[53] Furthermore, the actual utilization rate of these policies was not examined. The result suggests that corporate norms forcing long working hours (as well as working hours) is an important determinant of labor supply decisions for mothers. Policies to reduce the cost of long working hours might be a concern in terms of the cultural aspects of firms.

3.6 Conclusion

In this chapter, the impact of long working hours on the female labor supply was analyzed. Using the KWMP, I estimated the effect of working before having a child at firms where (on average) colleagues stay in the workplace more than 12 h per day, based on the probability of working after having a child. The results of this study suggest that working in a firm that requires long working hours significantly reduces the probability of working after the having a child. For female managers who have had a child, an inflexible workplace environment reduces the probability of working after motherhood by at least 8.2%. I was able to control for detailed firm-level information provided in the KWMP. The result was robust, even after including corporate norms and availability of family-friendly policies. This finding suggests that new mothers are sensitive to the cost of long working hours. Recent studies emphasize the role of imperfect information when individuals make their career decisions. Women might systematically underestimate the cost of motherhood (Kuziemko et al., 2018). It is also possible that labor market frictions reduce job-match quality as more traditional models suggest. In either case, the observed pattern of opting out from the inflexible workplace might not reflect socially optimal choices. It would be interesting to study possible ways to decrease the opt-out rate caused by working long hours and to estimate the expected social welfare changes.

The major limitation of this study is that it is not possible to rule out potential selection into the flexible work environment. I tried to control for the large set of individual

[53] See Appendix Figure 3.1.

and firm characteristics. However, unobserved factors might affect both selection decision and labor supply decisions after having a child. Future studies might exploit quasi-experimental methods to validate the findings presented here.[54] This study focuses on a relatively short time span. However, opting out from the labor market could have long-term consequences as human capital depreciates (Mincer and Polachek, 1974). Future studies might investigate the long-term impact of leaving the labor market due to long working hours. Lastly, recent studies suggest that flexibility is the key element to explain the gender wage gap (Goldin, 2014). It would be important to understand how life-time earnings change as individuals opt-out from the inflexible environment.

[54] Note that this chapter does not employ the traditional selection technique whereas it is difficult to find the instrument. Traditional selection models such as recursive bivariate probit could identify the parameter of interest as long as we have exogenous regressors for each equation. However, without an additional instrument, identification hinges on function from assumption (Li et al., 2019)

Table 3.1 Childbirth Probability

Childbirth between t-1 and t	Year (t)					
	2008	2010	2012	2014	2016	Total
Panel A. All sample						
Total	1,767	1,542	1,948	1,544	1,330	8,131
No	1,708	947	1,815	1,424	1,228	7,122
Yes	59	595	133	120	102	1,009
Percentage (%)	3.3%	38.6%	6.8%	7.8%	7.7%	12.4%
Panel B. Sample worked at t-1						
Total	1,755	1,140	991	734	535	5,155
No	1,697	724	874	679	482	4,456
Yes	58	416	117	55	53	699
Percentage (%)	3.3%	36.5%	11.8%	7.5%	9.9%	13.6%

Notes. KWMP 2007, 2008, 2010, 2012, 2014 and 2016 are used in calculation. Panel A shows the number of female managers who experienced childbirth during survey year t-1 and t. Panel B presents the number of female managers who gave birth between survey year t-1 and t.

Table 3.2. Sample Descriptive Statstics: Individuals

	Mean	SD
Working hours at t-1 (unit: minutes)	647.3	69.3
Go work	08:24AM	31.8
Come work	19:11PM	61.9
Wage at t-1 (unite: 10000 Won)	345.9	128.8
Experience at t-1 (unite: year)	12.3	4.6
Age	36.7	3.8
Education		
High school or lower	0.3%	5.4%
College	18.4%	38.8%
University	64.3%	48.0%
Master	16.7%	37.4%
PhD	0.3%	5.4%
Spousal education		
High school or lower	3.7%	19.0%
College	7.5%	26.4%
University	64.0%	48.1%
Master	21.6%	41.2%
PhD	3.2%	17.5%
Spousal work status		
Yes	97.7%	15.0%
No	2.3%	15.0%
Number of child at t-1		
0	12.1%	32.7%
1	50.7%	50.1%
2	33.4%	47.2%
3 or more	3.7%	19.0%
Marital status		
Single	100.0%	-
Married	0.0%	-
Other	0.0%	-
Major		
Languages and humanities	13.5%	34.3%
Social Sciences	31.7%	46.6%
Sciences and engineerings	37.8%	48.5%
Medicine	0.3%	5.4%
Other	16.7%	37.4%
University (college) location		
Other region	36.9%	48.3%
Seoul	63.1%	48.3%

Notes. KWMP 2008, 2010, 2012, 2014 and 2016 is used in calculation. Female managers who worked at survey year t-1 and experienced childbirth between survey year t-1 and t are used (N=347).

Table 3.3 Sample Decriptive Statistics: Firms

	Mean	SD
	(1)	(2)
$Working\ hour_{c,-i}$(unit: minutes)	646.7	46.2
$Go\ to\ work_{c,-i}$	8:28AM	20.4
$Come\ to\ work_{c,-i}$	7:14PM	42.2
Corporate size		
$N \leq 99$	0.6%	7.9%
$100 \leq N \leq 299$	40.3%	49.1%
$300 \leq N \leq 999$	25.3%	43.5%
$1000 \leq N \leq 1999$	18.1%	38.6%
$2000 \leq N$	15.6%	36.4%
Corporate location		
Other region	13.5%	34.3%
Seoul	86.5%	34.3%
Short work availability		
Not available	65.3%	47.7%
Don't know	15.5%	36.3%
Availabe	19.2%	39.5%
Childcare facility at workplace		
Not available	90.0%	30.0%
Don't know	0.0%	0.0%
Availabe	10.0%	30.0%
Maternity leave		
Not available	1.1%	10.5%
Don't know	0.4%	6.1%
Availabe	98.5%	12.1%
Parental leave		
Not available	3.0%	17.0%
Don't know	12.5%	33.2%
Availabe	84.5%	36.3%
$Corporate\ Culture_{c,-i}$		
Leaving work on time is like walking on eggshell	3.01	0.57
Having vacation on weedays due to the personal matters is hardly allowed	2.60	0.54
Working until late night is the best way to get a good performance evaluation	2.86	0.53
To survive, I have to put my work as first priority	3.20	0.47
Missing company night out is like walking on eggshell	3.14	0.49

Notes. KWMP 2008, 2010, 2012, 2014 and 2016 is used in calculation. Female managers who worked at survey year t-1 and experienced childbirth between survey year t-1 and t are used (N=347).

Table 3.4 Effect of Working Long Hours at t-1 on the Probability of Not Working at t: Standard Specification

	Dependent variable: work status at t (not working at t =1, other cases=0)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Working\ hour_{c,-i} \geq 12$	0.101**	0.099**	0.095**	0.113**	0.111**	0.106**	0.104**	0.105**	0.085*
	(0.048)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.048)	(0.047)
$Go\ to\ work_{c,-i}$	0.046	0.047	0.049	0.046	0.041	0.048	0.043	0.045	0.046
	(0.049)	(0.048)	(0.049)	(0.048)	(0.049)	(0.048)	(0.049)	(0.049)	(0.048)
Year									
2010									
2012	0.163***	0.159***	0.174***	0.163***	0.159***	0.172***	0.169***	0.167***	0.185***
	(0.040)	(0.040)	(0.041)	(0.040)	(0.040)	(0.040)	(0.041)	(0.041)	(0.040)
2014	0.026	0.026	0.043	0.034	0.032	0.047	0.047	0.048	0.09
	(0.054)	(0.053)	(0.054)	(0.053)	(0.055)	(0.054)	(0.055)	(0.056)	(0.056)
2016	0.123*	0.180**	0.175**	0.169**	0.167**	0.206***	0.203***	0.209***	0.245***
	(0.068)	(0.074)	(0.072)	(0.072)	(0.072)	(0.075)	(0.076)	(0.077)	(0.076)
Education									
High school or lower									
College		0.109		0.132	0.133	0.108	0.106	0.094	0.09
		(0.313)		(0.312)	(0.315)	(0.312)	(0.314)	(0.316)	(0.308)
University		0.216		0.243	0.244	0.217	0.216	0.205	0.203
		(0.311)		(0.311)	(0.313)	(0.310)	(0.312)	(0.314)	(0.307)
Master		0.08		0.117	0.119	0.092	0.093	0.08	0.079
		(0.314)		(0.314)	(0.316)	(0.313)	(0.315)	(0.317)	(0.309)
PhD		-0.021		0.074	0.073	0.044	0.044	0.025	0.041
		(0.431)		(0.431)	(0.433)	(0.430)	(0.433)	(0.435)	(0.425)
Experience		-0.002*	0.003			0.002	0.003	0.003	0.002
		(0.001)	-0.003			(0.003)	(0.003)	(0.003)	(0.003)
Experience squre/1000			-0.002			-0.001	-0.001	-0.001	-0.001
			(0.001)			(0.001)	(0.001)	(0.001)	(0.001)
Log(wage)				-0.114**	-0.114**	-0.098*	-0.100*	-0.091	-0.103*
				(0.052)	(0.054)	(0.053)	(0.054)	(0.059)	(0.058)
Spousal education									
High school or lower									
College					-0.055		-0.059	-0.063	-0.007
					(0.105)		(0.105)	(0.106)	(0.104)
University					-0.025		-0.025	-0.03	-0.007
					(0.088)		(0.088)	(0.089)	(0.087)
Master					-0.019		-0.024	-0.029	-0.023
					(0.093)		(0.093)	(0.094)	(0.091)
PhD					-0.082		-0.076	-0.082	-0.066
					(0.127)		(0.127)	(0.128)	(0.125)
Spousal work status					0.016		0.041	0.037	0.072
					(0.111)		(0.112)	(0.113)	(0.111)
Age								0.005	-0.004
								(0.043)	(0.042)
Age square/1000								-0.096	0.02
								(0.572)	(0.560)
Number of child at t-1									
0									
1									-0.231***
									(0.055)
2									-0.189***
									(0.057)
3 or more									-0.074
									(0.097)
Constant	-0.349	-0.494	-0.228	0.105	0.161	0.145	0.19	0.092	0.407
	(0.419)	(0.519)	(0.420)	(0.595)	(0.618)	(0.597)	(0.620)	(0.966)	(0.946)
Observations	347	347	347	347	347	347	347	347	347
R-squared	0.056	0.101	0.072	0.104	0.106	0.116	0.118	0.119	0.169

Notes. KWMP 2008, 2010, 2012, 2014 and 2016 is used. Female managers who worked at survey year t-1 and experienced childbirth betwe survey year t-1 and t are used (N=347). Each column presents the result from separate regression. Huber/White heteroskedasticity robust standard errors in parentheses.

*, **, *** Statistically significant at 1%, 5%, 10%.

Table 3.5 Effect of Working Long Hours at t-1 on the Probability of Not Working at t: Additional Controls

	Dependent variable: work status at t (not working at t =1, other cases=0)				
	(1)	(2)	(3)	(4)	(5)
$Working\ hour_{c,-i} \geq 12$	0.085*	0.089*	0.088*	0.095*	0.093*
	(0.047)	(0.047)	(0.047)	(0.048)	(0.049)
$Go\ to\ work_{c,-i}$	0.046	0.034	0.028	0.026	0.011
	(0.048)	(0.048)	(0.050)	(0.055)	(0.056)
Year					
2010					
2012	0.185***	0.176***	0.161***	0.154***	0.154***
	(0.040)	(0.040)	(0.042)	(0.042)	(0.043)
2014	0.09	0.094*	0.08	0.056	0.054
	(0.056)	(0.055)	(0.056)	(0.065)	(0.065)
2016	0.245***	0.240***	0.216***	0.081	0.081
	(0.076)	(0.076)	(0.078)	(0.112)	(0.112)
Major					
Language and liberal arts					
Social sciences		0.084	0.076	0.105*	0.117**
		(0.052)	(0.053)	(0.057)	(0.057)
Sciences and engineering		0.031	0.022	0.037	0.051
		(0.053)	(0.054)	(0.057)	(0.057)
Medicine		0.119	0.034	0.086	0.075
		(0.306)	(0.311)	(0.321)	(0.320)
Other		0.047	0.035	0.051	0.061
		(0.059)	(0.061)	(0.065)	(0.065)
University location					
Other					
Seoul		-0.098***	-0.088**	-0.061	-0.067*
		(0.035)	(0.035)	(0.037)	(0.037)
Flexibility-related culture					
question 1			-0.018	-0.015	-0.019
			(0.040)	(0.041)	(0.041)
question 2			-0.044	-0.06	-0.046
			(0.040)	(0.042)	(0.042)
question 3			0.076**	0.076*	0.077*
			(0.037)	(0.040)	(0.039)
question 4			-0.007	0.007	0.002
			(0.043)	(0.046)	(0.047)
question 5			-0.007	-0.011	-0.024
			(0.044)	(0.046)	(0.046)
Position at t-1					
rank_l=2					
rank_l=3				0.043	0.04
				(0.043)	(0.043)
rank_l=4				0.048	0.049
				(0.070)	(0.070)
rank_l=5				0.035	0.049
				(0.111)	(0.111)
rank_l=6				0.053	0.047
				(0.199)	(0.229)
Corporate size					
$N \leq 299$					
$300 \leq N$				-0.018	-0.014
				(0.038)	(0.039)
Corporate location					
corpwhere_l=0					
corpwhere_l=1				-0.123**	-0.119**
				(0.055)	(0.055)
Family-friendly policies					
Maternity leave					
Not available / don't know					
Available					-0.053
					(0.379)
Parental leave					
Not available / don't know					
Available					0.137**
					(0.055)
Short time work					
Not available / don't know					
Available					-0.064
					(0.060)
Child care facility					
Not available / don't know					
Available					0.003
					(0.078)
Constant	0.407	0.514	0.565	0.864	1.049
	(0.946)	(0.945)	(0.969)	(0.660)	(0.773)
Controls;					
Individual chracteristics	√	√	√	√	√
Observations	347	347	347	322	322.000
R-squared	0.169	0.195	0.207	0.232	0.251

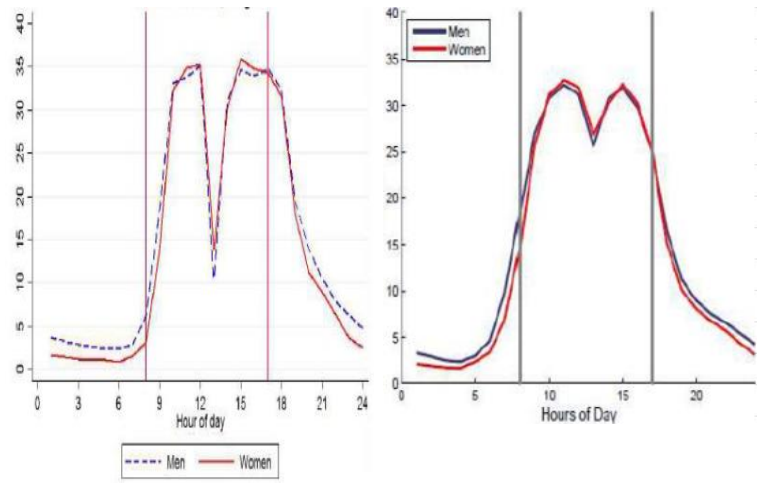
Notes. KWMP 2008, 2010, 2012, 2014 and 2016 is used. Female managers who worked at survey year t-1 and experienced childbirth between survey year t-1 and t are used (N=347). Each column presents the result from separate regression. Huber/White heteroskedasticity robust standard errors in parentheses. Individaul charateristics include education, age, age square, experience, experience square, log wage, spousal education and spousal work status.

*, **, *** Statistically significant at 1%, 5%, 10%.

Figure 3.1 Gender Difference in Working Hours

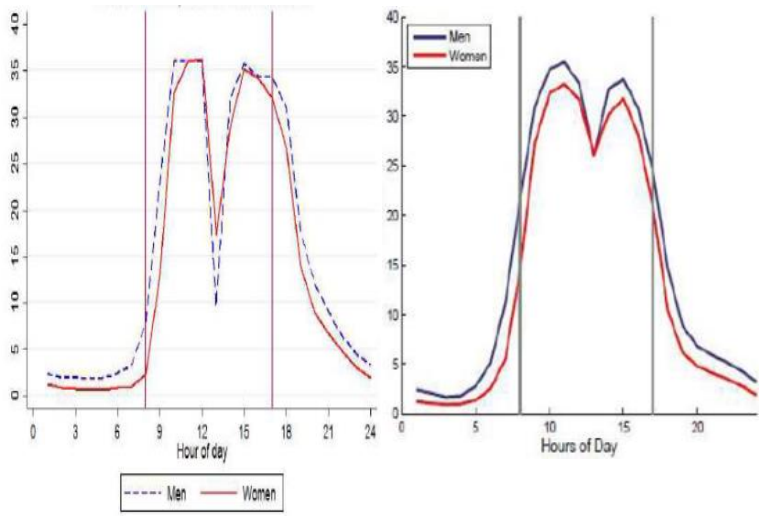
Panel A. Single men and women

A-1. Korea A-2. US



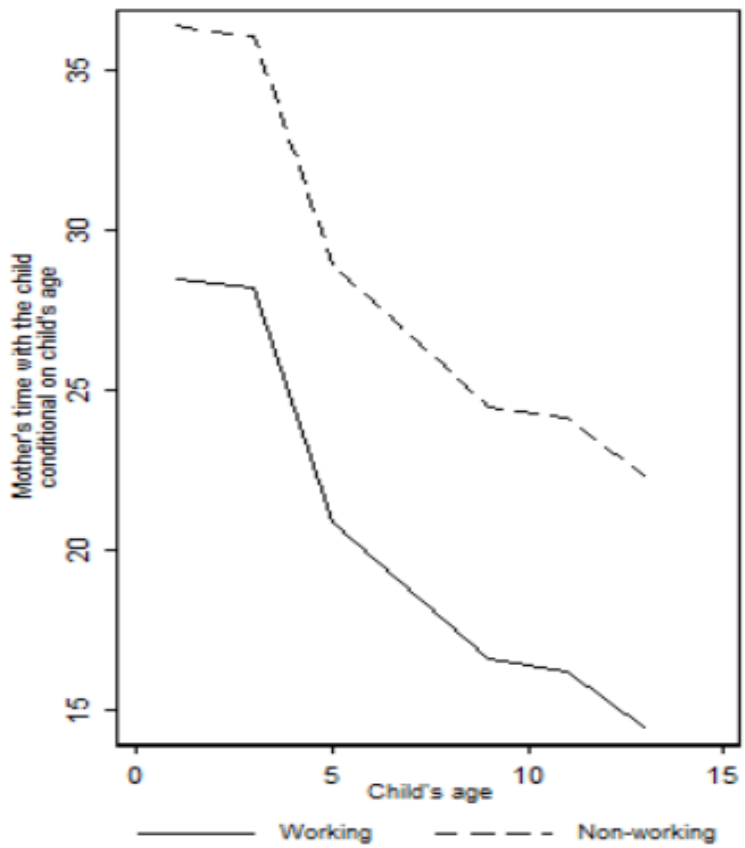
Panel B. Individuals with child under 6

B-1. Korea B-2. US



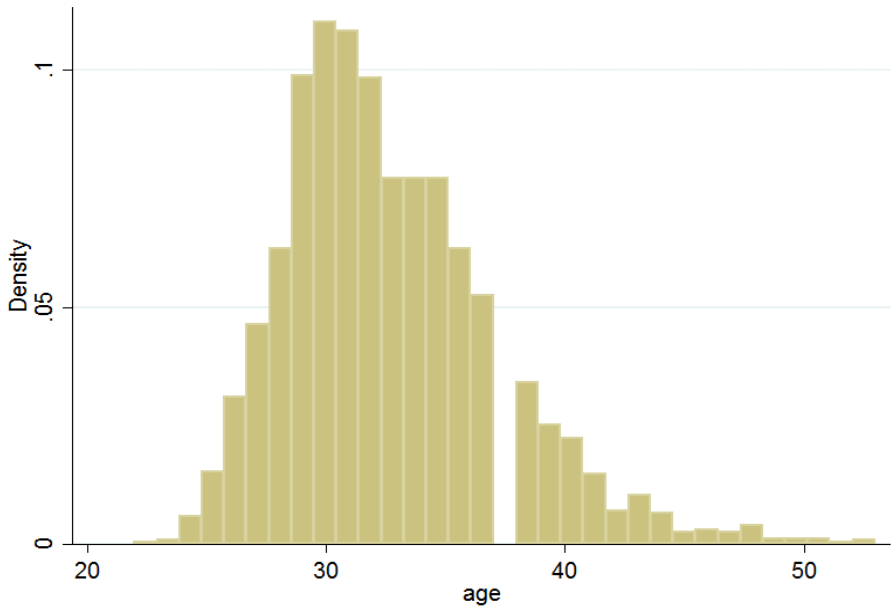
Notes. The figure shows gender difference in average minutes spent on working on a hourly basis. Panel A depicts results for the single men and women and Panel B shows results for individuals with child under 6. For each panel, left figure is distributions in Korea and right figures are distributions in US. Korean Time Use Survey (KTUS) 2004, 2009 and 2014 is used in drawing distributions in Korea. Figure A2 and B2 are borrowed from the Figure 2 of Cubas et al. (2019). American Time Use Survey (ATUS) 2003-2014 is used in drawing the figures for US. The figures are based on 18-65 years old full-time employees. Both weekdays and weekends are included.

Figure 3.2 Maternal Time with Child Conditional on Child's Age



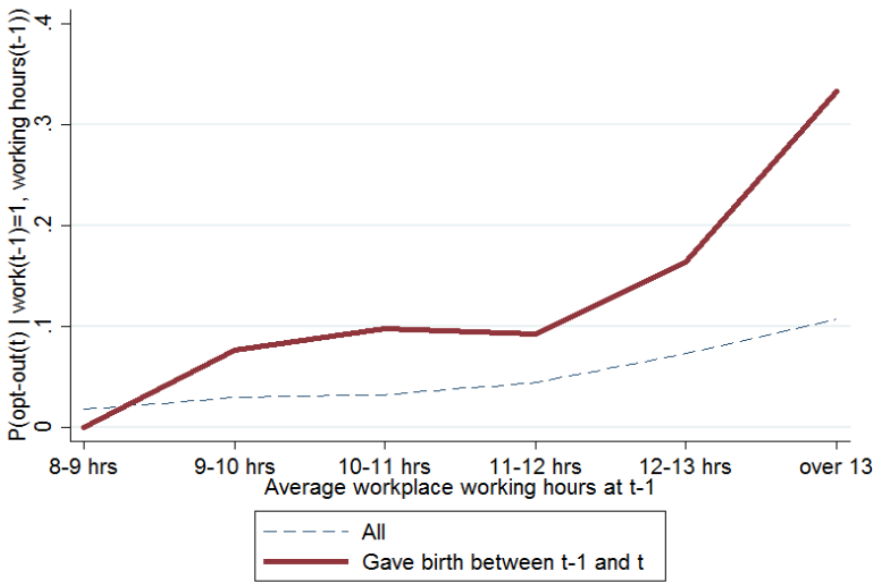
Notes. The figure is borrowed from the Figure 1 in Brilli (2017). Using PSID-CDS data (N=572), Brill (2017) estimated the impact of child's age and working status on maternal time with child. The figure shows the fitted value from the regression. See Brilli (2017) for the detailed explanation.

Figure 3.3. Age Distribution in KWMP 2007



Notes. This figure shows age distribution of the sample in KWMP 2007. All 2,367 samples are used in drawing the figure.

Figure 3.4 Opt-out Rate of New Mothers Conditional on Pre-childbirth Firm-level Working Hours



Notes. KWMP 2008, 2010, 2012, 2014 and 2016 is used. Graph shows probability of *not* working at survey year t for the female manage who worked at survey year t-1, conditional on firm-level working hours at survey t-1. Thick red line depicts the opt-out rates for the new mothers who gave birth to the child between survey year t-1 and t (N=557), and dashed blue line shows the opt-out rates for the all female managers who worked at survey year t-1 (N=5,372). The trends are nonparmetrically fitted from the locally weighted regression, using th lowess command in Stata.

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Appendix

Appendix Table A.1.1 Findings in Previous Studies

Study	Data	Sample	Policy of Interest	Research Design and Estimation Method	Main Findings
Kim (2009)	Korean Education and Employment Panel (KEEP) , 2005-2007	High school student cohort attended 1st year in 2005	Ordinances without legislation (before 2007)	Betwwen comparison	10, 11PM curfews reduce 1-1.5 hours weekly cram schooling and reduce monthly expenditure on cram schooling negligibly .
Kim and Chang (2010)	Survey questionnaire distributed in 2005	Third year high school student in 2005	Ordinances without legislation (before 2007)	Between comparison	10PM curfew reduces montly expenditure on cram schooling negligibly.
Choi (2013)	Survey of Private Education Expenditure (SPEE) , 2009-2012	Elementary, middle and high school students in 2009-2012	Reinforcements between 2011-2012	Difference-in-differences	Curfews on average has positive but statistically insignificant effects on monthly expenditure/weekly hours spent on private tutoring.
Jung (2015)	Korean Longitudinal Survey of Women & Families (KLoWF), 2007, 2008, 2010 and 2012	Elementary, middle and high school students in 2007, 2008, 2010, 2012	Enforcements following legislation in 2007	Difference-in-differences	(1) 12AM curfew has positive effect on weekday hours and negative effect on monthly expenditure on cram schooling but effects are statistically insignificant (2) 10PM and 11PM curfew have positive effects on weekday hours and monthly expenditure on cram schooling for high school students, but estimates are statistically insignificant in general.
Choi and Cho (2015)	Korean Youth Risk Behaviours web-Based Survey (KYRBS), 2009-2012 and Survey on Private Tutoring (SPT), 2009-2012	High school students in 2009-2012	Reinforcements between 2011-2012	Difference-in-differences	(1) 10PM curfew decreases monthly expenditure and increases weekly hours on private tutoring but effects are statistically insignificant (2) 10PM curfew increases 12.5 minutes of sleep and 15 minutes of internet usage
Do et al. (2015)	Korean Youth Risk Behaviours web-Based Survey (KYRBS), 2009-2012	First and second year high school students in 2009-2012	Reinforcements between 2011-2012	Difference-in-differences	10PM curfew increases 16.8 minutes of sleep and reduces BMI 0.11kg/m2
Choi and Choi (2016)	Survey of Private Education Expenditure (SPEE) , 2009-2012	Middle and high school students in 2009-2012	Reinforcements between 2011-2012	Difference-in-differences	Curfews on average has negative but statistically insignificant effects on weekly hours spent on cram schooling and negative and statistically significant effect on monthly expenditure on cram schooling.
Kim (2016)	Youth Panel (YP) 2007-2010	High school students in 2007-2010	Reinforcements between 2011-2012	Before and after comparison	10PM curfew increases monthly expenditure on private tutoring and 11PM curfew decreases monthly expenditure on private tutoring.
Kim and Kang (2017)	Korean Labor & Income Panel Study (KLIPS) , 2010 and 2011	Elementary, middle and high school students in 2010 and 2011	Reinforcements in 2011	Difference-in-differences	10PM curfew decreases monthlyl expenditure on cram schooling but statistically insignificant
Go and Jung (2018)	Korean Time Use Survey (KTUS) 2009, 2014	Elementary, middle and high school students in 2009 and 2014	Reinforcements between 2011-2012	Difference-in-differences	10PM and 11PM curfews increase private tutoring time 9.11~13.6 minutes and 11~19.9 mintues respectively.
Bae and Jin (2019)	Korean Time Use Survey (KTUS) 2009, 2014	High school students in 2009 and 2014	Reinforcements between 2011-2012	Difference-in-differences	(1) 10PM curfew decreases time spent on private tutoring near 0.5~2 minutes between 10PM and 12AM but estimates are statistically insignificant (2) 10PM curfew increases sleep time between 10PM and 8AM but estimate is statistically insignificant

Notes. This table shows the empirical findings of the previous studies. Maing findings for high school students are listed.

Appendix Table A.1.2 Descriptive Statistics of High School Students

	All	1999	2004	2009	2014
	(1)	(2)	(3)	(4)	(5)
Private tutoring (outside)	31.3	26.7	30.3	34.5	39.9
	(63.7)	(58.7)	(59.9)	(65.7)	(75.1)
Sleep(not nap)	398.2	399.4	395.5	390.2	406.5
	(79.7)	(82.8)	(78.2)	(68.7)	(83.0)
Study hall session	111.2	113.6	115.2	123.7	89.1
	(103.8)	(110.2)	(104.5)	(92.9)	(94.2)
Study related move	79.0	84.4	79.9	76.3	68.5
	(43.2)	(44.6)	(42.5)	(38.9)	(42.8)
Surveyed times					
Surveyed 2 day	68.7%	68.8%	67.2%	69.4%	69.5%
Surveyed 1 day	31.3%	31.2%	32.8%	30.6%	30.5%
Age					
15	17.5%	16.9%	11.6%	23.6%	20.8%
	(38.0%)	(37.5%)	(32.0%)	(42.5%)	(40.6%)
16	34.5%	33.2%	35.0%	36.5%	34.8%
	(47.5%)	(47.1%)	(47.7%)	(48.2%)	(47.7%)
17	33.5%	33.8%	34.6%	32.4%	32.3%
	(47.2%)	(47.3%)	(47.6%)	(46.8%)	(46.8%)
18	14.5%	16.2%	18.8%	7.5%	12.0%
	(35.2%)	(36.8%)	(39.1%)	(26.3%)	(32.5%)
Proportion male	51.6%	51.1%	52.1%	49.3%	54.1%
	(50.0%)	(50.0%)	(50.0%)	(50.0%)	(49.8%)
Propotion farm house	6.8%	11.1%	6.3%	1.5%	2.8%
	(25.1%)	(31.4%)	(24.2%)	(12.0%)	(16.5%)
Parental education					
Mother≤high, Father≤high	67.6%	81.9%	68.9%	56.4%	44.8%
	(46.8%)	(38.5%)	(46.3%)	(49.6%)	(49.7%)
Mother≤high, Father>high	14.6%	11.0%	17.2%	19.4%	14.7%
	(35.3%)	(31.4%)	(37.8%)	(39.5%)	(35.4%)
Mother>high, Father≤high	4.9%	1.8%	3.5%	5.4%	13.3%
	(21.7%)	(13.3%)	(18.3%)	(22.6%)	(34.0%)
Mother>high, Father>high	12.9%	5.2%	10.4%	18.8%	27.2%
	(33.5%)	(22.3%)	(30.6%)	(39.1%)	(44.5%)
Observations	7096	2905	1648	1228	1315

Notes. KTUS 1999, 2004, 2009 and 2014 are used.

Appendix Table A.1.3 Progresiveness of Superintendents and Adoption of Liberal Policies

	Dependent variable: adoption of liberal policy (yes=1, no=0)									
	10PM curfew		11PM curfew		12AM curfew		Delayed school start time		Student right ordinance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Definition 1										
Progressive superintendent	0.110***	0.217***	-0.037**	0.005	0.015	-0.068**	0.143***	0.107***	0.353***	0.519***
	-0.027	-0.025	-0.016	-0.012	-0.027	-0.03	-0.016	-0.011	-0.019	-0.012
Panel B. Definition 2										
Progressive superintendent	0.065***	0.265***	-0.003	-0.011	0.043*	-0.083***	0.134***	0.070***	0.257***	0.433***
	-0.023	-0.019	-0.014	-0.009	-0.023	-0.023	-0.015	-0.008	-0.017	-0.01
Panel C. Definition 3										
Progressive superintendent	0.144***	0.174***	-0.013	-0.008	-0.034	0.001	0.133***	0.079***	0.347***	0.371***
	-0.024	-0.019	-0.014	-0.009	-0.024	-0.024	-0.015	-0.009	-0.017	-0.015
Panel D. Definition 4										
Progressive superintendent	0.102***	0.226***	0.016	-0.019**	-0.004	-0.028	0.129***	0.055***	0.265***	0.338***
	-0.021	-0.016	-0.013	-0.008	-0.021	-0.02	-0.014	-0.006	-0.015	-0.011
Control variables										
Observables; day, month fixed effects	√	√	√	√	√	√	√	√	√	√
Regional fixed effects	√	√	√	√	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√	√	√	√	√
Regional specific linear trends		√		√		√		√		√

Notes. Sample=7,096 individual-day observations in each panel. Superintendent of Gwanju in 1999 is regarded as progressive in Panel A and B and superintendent of Jeonnam in 1999 is regarded as progressive in Panel A and C. Year and regional fixed effects are included as control variables in each specifications. Unreported "Observables" include sex, age, parental education, farm household, single(or no)-parent. Column (2), (4), (6), (8) and (10) additionally controls for regional specific linear trends. Standard errors in parentheses, are clustered by individual.
***, **, and * Statstically significant at 1%, 5%, 10%.

Appendix Table A.1.4 Impact of the Curfew by Parental Education Level

	Parental education : low				Parental education : high			
	Private tutoring	Study-related traveling	Self-study session	Sleep	Private tutoring	Study-related traveling	Self-study session	Sleep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Average Effect-daily total								
β	5.120	1.281	-18.776**	9.745	20.854**	12.711***	-35.621***	5.439
	(5.141)	-(3.698)	(8.103)	(6.494)	-(8.723)	(4.548)	(11.788)	(7.722)
Panel B. Average Effect-before and after								
β_{before}	0.011**	0.004	-0.021***	0.006	0.032***	0.014***	-0.033***	-0.004
	(0.005)	-(0.003)	(0.007)	(0.004)	-(0.007)	(0.004)	(0.010)	(0.005)
β_{after}	-0.009***	-0.005	0.000	0.009	-0.016***	-0.001	-0.011	0.018*
	(0.003)	-(0.003)	(0.004)	(0.008)	-(0.006)	(0.004)	(0.006)	(0.009)
Panel C. Effect of each policy-daily total								
β_{10}	16.752**	5.802	-42.438***	19.871**	24.345**	18.411***	-62.045***	20.145*
	(8.535)	-(5.561)	(10.736)	(9.024)	-(11.926)	(6.442)	(15.639)	(11.159)
β_{11}	-2.668	9.627	-13.927	-5.233	40.338**	10.588	-26.966	-20.070
	(11.898)	-(8.103)	(19.603)	(15.383)	-(18.247)	(13.606)	(26.991)	(16.550)
β_{12}	-0.608	-3.052	-5.090	6.278	16.029*	10.542**	-25.365**	3.212
	(5.340)	-(3.864)	(9.405)	(7.183)	-(9.518)	(5.215)	(12.766)	(8.629)
Panel D. Effect of each policy--before and after								
$\beta_{10,before}$	0.020***	0.008*	-0.037***	0.011**	0.031***	0.018***	-0.050***	0.011
	(0.006)	-(0.004)	(0.008)	(0.005)	-(0.008)	(0.005)	(0.012)	(0.007)
$\beta_{10,after}$	-0.014**	-0.009*	-0.007	0.017	-0.026***	-0.002	-0.021**	0.022
	(0.007)	-(0.005)	(0.006)	(0.013)	-(0.010)	(0.006)	(0.010)	(0.014)
$\beta_{11,before}$	0.001	0.010	-0.014	0.012*	0.038***	0.012	-0.024	-0.023**
	(0.009)	-(0.006)	(0.015)	(0.007)	-(0.013)	(0.010)	(0.019)	(0.011)
$\beta_{11,after}$	-0.013*	-0.007	0.006	0.015	-0.009	-0.012	0.002	0.022
	(0.008)	-(0.006)	(0.012)	(0.021)	-(0.013)	(0.010)	(0.017)	(0.022)
$\beta_{12,before}$	0.000	-0.002	-0.003	0.003	0.016**	0.009**	-0.017*	0.000
	(0.004)	-(0.003)	(0.007)	(0.005)	-(0.007)	(0.004)	(0.009)	(0.005)
$\beta_{12,after}$	-0.003	0.000	-0.005	0.011	-0.013*	0.001	-0.023***	0.011
	(0.004)	-(0.003)	(0.004)	(0.013)	-(0.007)	(0.004)	(0.007)	(0.016)
Control variables								
Observables; day, month fixed effects	√	√	√	√	√	√	√	√
Province fixed effects	√	√	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√	√	√
Time x year fixed effects	√	√	√	√	√	√	√	√
Province specific linear Trends	√	√	√	√	√	√	√	√

Notes . Sample=4,797 individual-day observations for low parental education group and 2,297 individual-day observations for high parental education group. Student belongs to high parental group one of hir/her parents holds college degree or higher. Panel A reports average impact of policy on daily time use and Panel B shows average impact of policy on time allocation before and after the curfew times. Panel C shows impact of each policy on daily time usage and Panel D presents impact of each policy on time use before and after each curfew time. Column (1)-(4) corresponds to low parental education group and columns (5)-(8) corresponds to high income group. Year and regional fixed effects are included as control variables in each specifications. Interaction of time and year dummy is included. Unreported Observables" include sex, age, parental education, farm household, single(or no)-parent. Regional specific linear trends are included in all specifications. Standard errors in parentheses, are clustered by individual.

***, **, and * Statstically significant at 1%, 5%, 10%.

Appendix Table A.2.1 Province-level Availability of Community Child Center and Subsidy

	Subsidy divided by the number of children (unit: Won)				Number of the centers relative to number of children (%)				Number of the center slots relative to number of children (%)			
	2008	2012	2017	2017-2008	2008	2012	2017	2017-2008	2008	2012	2017	2017-2008
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Variables divided by the number of children aged 6-12 in each province												
Seoul	7217	26127	47454	40237	3.9	6.4	8.0	4.2	1.2%	1.8%	2.4%	1.2%
Busan	11551	40020	63169	51618	5.7	9.3	11.3	5.7	1.6%	2.6%	2.9%	1.3%
Daegu	4910	33306	72241	67330	3.3	9.9	13.1	9.8	1.0%	2.6%	3.6%	2.6%
Incheon	13732	39180	52930	39198	6.4	9.2	9.5	3.2	2.1%	2.5%	2.6%	0.5%
Gwangju	17409	82520	161303	143893	10.8	22.4	29.1	18.3	3.2%	6.7%	8.3%	5.1%
Daejeon	17162	58442	83220	66058	9.2	12.2	14.2	5.0	3.5%	4.0%	4.4%	0.9%
Ulsan	11013	29258	37772	26759	4.6	6.6	6.7	2.2	1.3%	1.7%	1.7%	0.4%
Gyenggido	10253	33905	49917	39664	5.4	7.7	8.6	3.2	1.8%	2.4%	2.7%	0.9%
Gangwondo	20120	76510	117773	97653	10.5	15.2	18.3	7.8	3.1%	4.2%	5.2%	2.2%
North Chungbuk	21761	74807	106282	84521	11.2	17.7	18.3	7.1	3.3%	4.8%	5.3%	1.9%
South Chungbuk	15272	63965	96010	80738	8.4	14.5	17.1	8.7	2.5%	4.2%	5.1%	2.5%
North Jeolla	25671	91043	136834	111162	12.4	21.1	24.2	11.8	3.5%	5.8%	6.6%	3.1%
South Jeolla	37094	132840	189704	152609	18.3	30.0	33.5	15.3	5.4%	8.4%	9.3%	4.0%
North Gyeongsang	13487	59124	97119	83632	7.4	14.5	17.3	9.9	2.2%	4.0%	4.8%	2.6%
South Gyeonsang	11612	43088	63152	51540	6.3	10.5	11.6	5.3	1.7%	2.7%	3.2%	1.4%
Jeju	19034	68819	84953	65919	9.9	14.8	13.9	4.0	2.8%	4.2%	4.1%	1.3%
Panel B. Variables divided by the number of children aged 0-18 in each province												
Seoul	2685	8834	16350	13665	1.4	2.2	2.8	1.3	0.4%	0.6%	0.8%	0.4%
Busan	4354	13337	21524	17170	2.1	3.1	3.9	1.7	0.6%	0.9%	1.0%	0.4%
Daegu	1912	11478	24826	22914	1.3	3.4	4.5	3.2	0.4%	0.9%	1.2%	0.9%
Incheon	5240	13293	18722	13482	2.4	3.1	3.4	0.9	0.8%	0.9%	0.9%	0.1%
Gwangju	6992	29017	56657	49665	4.4	7.9	10.2	5.9	1.3%	2.4%	2.9%	1.6%
Daejeon	6696	20358	29219	22523	3.6	4.3	5.0	1.4	1.3%	1.4%	1.5%	0.2%
Ulsan	4285	9758	13056	8772	1.8	2.2	2.3	0.6	0.5%	0.6%	0.6%	0.1%
Gyenggido	4039	11955	17933	13894	2.1	2.7	3.1	1.0	0.7%	0.8%	1.0%	0.3%
Gangwondo	8023	27251	41450	33427	4.2	5.4	6.4	2.2	1.2%	1.5%	1.8%	0.6%
North Chungbuk	8588	25855	37295	28707	4.4	6.1	6.4	2.0	1.3%	1.7%	1.8%	0.5%
South Chungbuk	6040	22353	34378	28338	3.3	5.1	6.1	2.8	1.0%	1.5%	1.8%	0.8%
North Jeolla	10230	31877	48141	37911	4.9	7.4	8.5	3.6	1.4%	2.0%	2.3%	0.9%
South Jeolla	14884	45800	65371	50487	7.3	10.3	11.6	4.2	2.1%	2.9%	3.2%	1.1%
North Gyeongsang	5284	20286	33369	28085	2.9	5.0	5.9	3.1	0.9%	1.4%	1.6%	0.8%
South Gyeonsang	4585	14812	22338	17752	2.5	3.6	4.1	1.6	0.7%	0.9%	1.1%	0.4%
Jeju	7683	24840	30812	23130	4.0	5.3	5.0	1.0	1.1%	1.5%	1.5%	0.4%

Notes. The Table presents province-level availability of Community Child Center and Subsidy. Panel A shows the availability and subsidy relative to the number of children aged 6-12 and panel B shows the availability and subsidy relative to the number of children aged 0-18.

Appendix Table A.2.2 Reduced Form Regression: Impact of the Lagged Community Child Center Subsidy on Employment Rate of Married Women Aged 35-44

	Dependent variable: cell-mean employment rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total subsidy in province in year t-1 divided by number of children aged 6 to 12 years in the province in year t-1 (unit: 10,000 Won)	0.809***	1.377***	0.164**	0.171**	0.207***	0.186***	0.161**
	(0.085)	(0.129)	(0.067)	(0.069)	(0.068)	(0.068)	(0.068)
Divorced				20.995***	21.026***	19.256***	7.920***
				(0.813)	(0.793)	(0.782)	(0.696)
Bereaved				18.677***	18.645***	17.590***	7.109***
				(0.769)	(0.727)	(0.715)	(0.575)
Elemantary					18.653***	18.518***	17.532***
					(2.710)	(2.747)	(2.704)
Middle					23.309***	23.072***	21.739***
					(2.593)	(2.644)	(2.589)
High					19.086***	20.372***	19.020***
					(2.721)	(2.749)	(2.703)
College					17.800***	20.692***	19.315***
					(2.683)	(2.714)	(2.678)
University					17.758***	20.175***	18.676***
					(2.776)	(2.818)	(2.776)
Master					31.567***	34.142***	32.445***
					(2.725)	(2.772)	(2.739)
PhD					46.369***	48.679***	46.669***
					(2.981)	(3.023)	(2.958)
Age 40-44						10.301***	9.959***
						(0.293)	(0.299)
Head of household							13.597***
							(0.571)
Constant	53.360***	55.418***	52.653***	51.288***	31.776***	24.894***	25.377***
	(0.770)	(1.415)	(0.580)	(0.591)	(2.690)	(2.707)	(2.661)
Year fixed effects		√	√	√	√	√	√
Province fixed effects			√	√	√	√	√
Obervations	8,365	8,365	8,365	8,365	8,365	8,365	8,365
R-squared	0.059	0.105	0.195	0.343	0.402	0.569	0.663

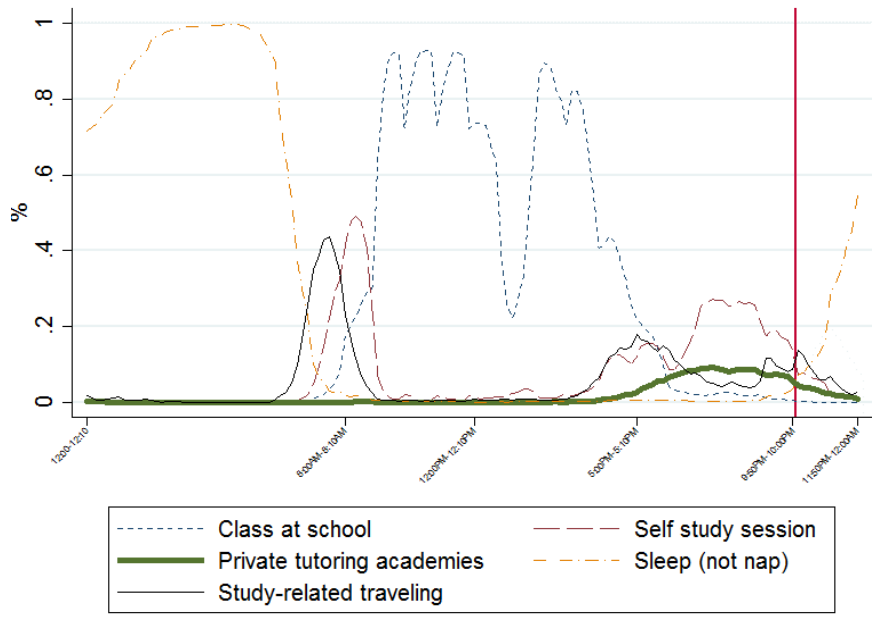
Notes. The table shows the impact of lagged Community Child Center Subsidy on cell-mean employment rate of women aged 35-44. Each cell represents combination of year (10), province (16), marital status (3), education (8), 5-year age bin (9) and head of household (2). For the regressions presented in the table, we confine our attention to non-single women aged between 35 and 44. This gives us 15,360 cells. However, due to the missing cells, total number of cells is 8,365. Moreover, we lose additional observations as we use lagged subsidy. Final number of cells is 7,165. The variable of interest is subsidy divided by the lagged number of children aged 6 to 12 years in the province. Column (1) shows bivariate relationship between subsidy and employment rate and colum (2) additionally controls for year fixed effects. Column (3) to (7) present the difference in differences estimates as we control for both year and province fixed effects. Standard errors in parentheses, are clustered at year-province level.
*, ** and *** significant at 1%, 5%, 10% level.

Appendix Table A.3.1 Childbirth Probability Conditional on Work Environment

Flexibility at t-1	Proportion	Gave birth between t-1 and t	
		Conditional Mean	Conditional SD
Average workers stay at work more than 12 hours at t-1	65.0%	5.0%	21.7%
Average workers stay at work less than 12 hours at t-1	35.1%	8.3%	27.6%

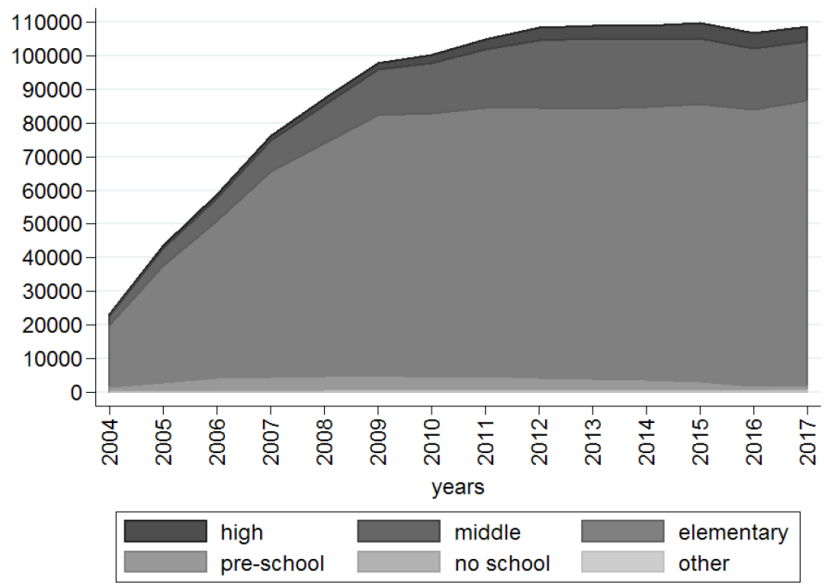
Notes. KWMP 2007, 2008, 2010, 2012, 2014 and 2016 are used in calculation. Total 19,401 individual-year observations are used.

Appendix Figure A.1.1 Distribution of the Activities in 1999



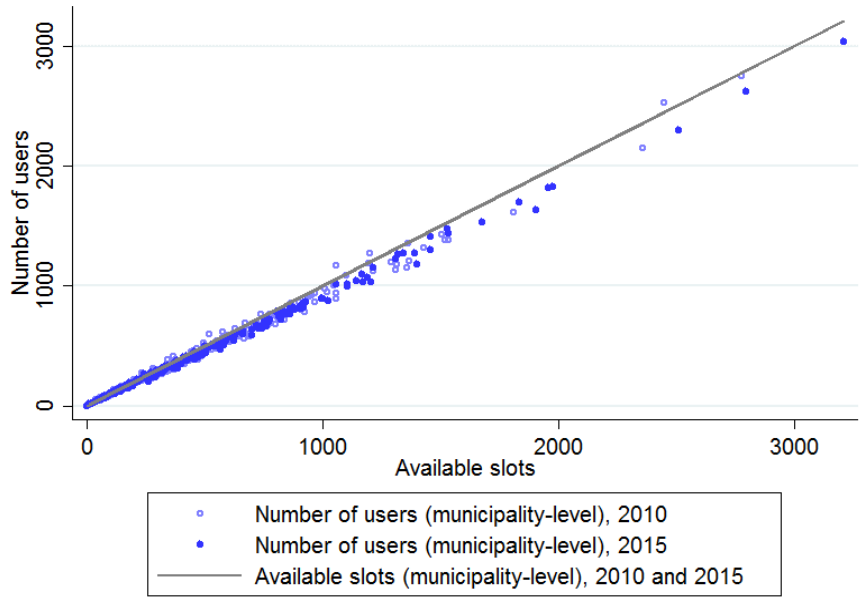
Notes. The figure depicts distribution of the activities. KTUS 1999 is used to draw the figure.

Appendix Figure A.2.1 Proportion of the Children using the Center by their Grades



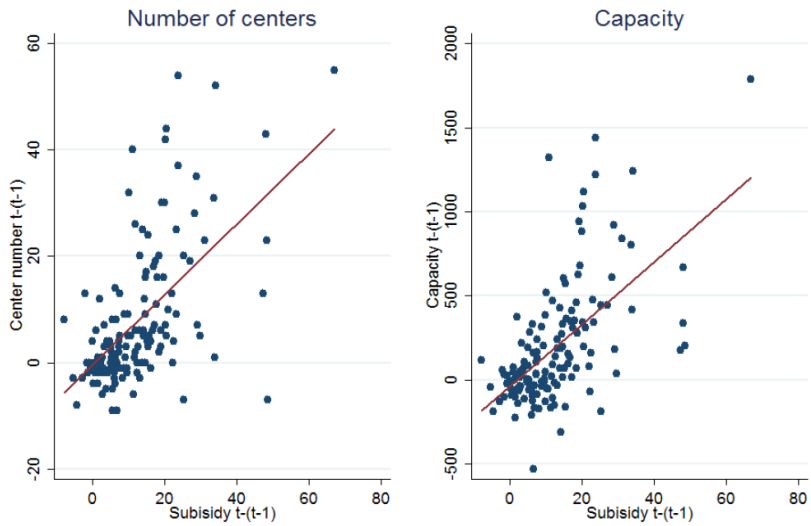
Notes. The table shows the proportion of children using the center by their grades.

Appendix Figure A.2.2 Number of Users and Available Slots in each Municipality



Notes. The figure shows the number of users in each municipality. Blue circles represent the number of users in each municipality in 2015 and blue-hollow circles represent the number of users in each municipality in 2010. There are 231 municipalities in each year. We matched the municipalites in different years using the municipality definitions in 2015. 45 degree line depicts the available slots in each municipality.

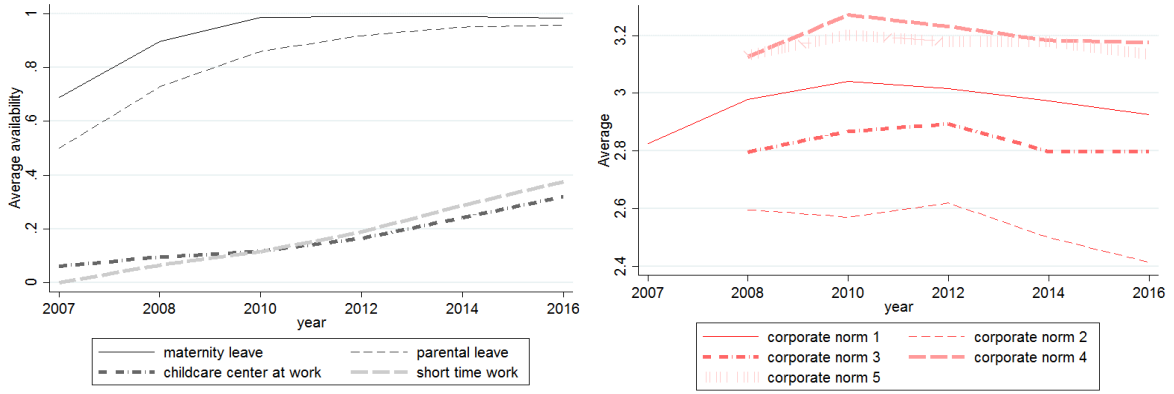
Appendix Figure A.2.3 Changes in Subsidy and Changes in Community Child Center Availability



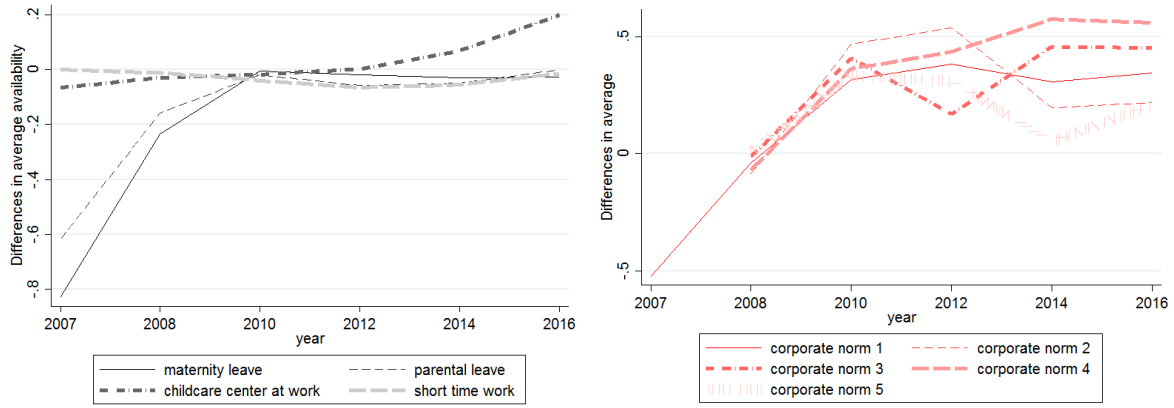
Notes. The figure depicts relationshp between changes in Community Child Center availability and changes in subsidy. Panel A shows the relationship between subsidy and number of the centers and panel B presents the relationship between subsidy and number of the center slots.

Appendix Figure A.3.1 Differential Time Trends in Family-friendly Policies and Family-unfriendly Corporate Norms

Panel A. Overall time trends in family-friendly policies and family-unfriendly corporate cultures



Panel B. Differences in time trends in family-friendly policies and family-unfriendly corporate cultures between firms with long working hours and relativey short working hours



Notes. The figure depicts time trends in family-friendly policies and family-unfriendly corporates norms. Panel A shows the average time trends and Panel B shows differences in time trends between firms with long workhours and firms with relatively short working hours. For each panel, left figure presents the time trends for family-friendly policies and right figure depicts the time trends for inflexible corporate culture. KWMP 2007, 2008, 2010, 2012, 2014 and 2016 is used.

국문초록

시간 사용의 경제학에 대한 세 가지 소고

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본 박사학위논문은 시간 사용에 중점을 두고 개인의 의사결정을 연구한다. 첫째로, 학원 강습 시간대를 직접 규제하는 교육 정책이 고등학생의 시간사용에 미친 효과를 분석한다. 둘째로, 비시장 시간(non-market time)의 가치에 영향을 미치는 지역아동센터의 확대가 기혼 여성의 노동공급에 미친 효과를 분석한다. 셋째로, 출산 전 장시간 근로가 여성 관리자의 출산 후 고용 확률을 낮추는지 검증한다.

본 논문의 첫 번째 장은 10 시 이후 학원 운영을 금지하는 법적 제한이 예상과 달리 학원에서 보내는 시간을 오히려 증가시켰음을 보인다. 지역별로 정책의 도입 시점이 다른 사실을 활용하여 이중차분법을 이용하여 법적 제한이 학생들의 시간 사용에 미친 효과를 추정한다. 추정 결과는 제한 정책의 도입이 학생들의 수면 시간을 유의하게 증가시켰지만, 동시에 학원에서 보내는 시간 역시 증가시켰음을 나타낸다. 선뜻 이해하기 어려운 결과를 이해하기 위하여 시간 일지 자료의 장점을 활용하여 제한 정책이 규제 시각 전과 후에 미친 효과를 개별적으로 추정한다. 변형된 삼중차분법 및 군집추정법을 통한 추정결과는 제한 정책이 효과적으로 도입되어 10 시

이후 학원에서 보내는 시간을 유의하게 낮췄음을 제시한다. 하지만 동시에, 학생들은 제한 정책 이후 10 시 이전에 학원에서 보내는 시간을 유의하게 늘린 것으로 나타난다. 또한 이러한 10 시 이전의 학원 시간 증가는 야간자율학습의 대폭적인 감소를 동반한다. 10 시 이후의 학원 시간의 감소분보다 10 시 이전의 학원 시간의 증가분이 컸기 때문에 전체적인 학원 시간은 증가하였다. 이러한 결과는 개인의 시간 사용을 제한하는 정책의 경우 하루 내 시간 대체를 고려해야 함을 제시한다.

본 논문의 두 번째 장은 지역아동센터의 공급이 기혼 여성의 노동공급에 미친 효과를 연구한다. 지역아동센터는 18 세 이하의 아동에게 교육과 보호를 제공하기 때문에 어머니들의 일과 가정 양립에 도움을 줄 것으로 기대한다. 지역아동센터는 저소득 가정의 경우 무료로 이용할 수 있기 때문에 저소득 가정의 어머니들의 보육 비용을 낮춘다. 본 연구는 지역아동센터에 대한 보조금을 지급하는 정책의 도입 이후 지역아동센터가 빠르게 늘어났다는 사실을 이용한다. 정책 도입 이후 지역아동센터의 확장 속도가 지역별로 상이하였기 때문에, 식별을 위하여 지역별 공급률의 변동을 활용한다. 이중차분법을 통한 추정결과는 지역아동센터 공급률의 증가가 기혼 여성의 노동시장참여를 유의하게 높였음을 제시한다. 이러한 노동공급에 대한 긍정적인 효과는 초등학생 자녀를 가졌을 확률이 높은 어머니에게서 발견되었는데 이는 지역아동센터의 주 이용자가 초등학생이기 때문이다. 추정결과의 잠재적인 편의를 덜기 위하여 공급률에 대한 도구변수로 보조금률을 이용한다. 도구변수를 이용한 추정결과 역시 이중차분 분석결과를 확인해준다. 본 장의 발견은 저소득층을 겨냥한 보육시설의 확대가 초등학생 자녀를 가진 저소득 여성의 노동공급을 증가시킴을 제시한다.

본 논문의 세 번째 장은 장시간 근로가 어머니들의 노동공급에 미치는 효과를 분석한다. 본 연구는 출산 이전의 근로 환경과 출산 이후의 고용 확률을 연결한다. 두 조사 시점 사이에 출산을 경험한 여성관리자 표본을 이용하여, 출산 이전에 근로자들이 평균 12 시간 이상 일터에 머무는 회사에 근무했을 경우 출산 이후 근로할 확률이 낮은지 검증한다. 분석 결과는 출산을 경험한 새로운 어머니들은 출산 전 근로시간이 매우 긴 회사에 근무했을 경우 출산 후 일할 확률이 유의하게 낮음을 제시한다. 본 장은 어린 자녀를 가진 여성관리자들이 장시간 근로의 비용에 민감함을 제시한다.

주요어: 시간 사용, 심야교습 제한정책, 하루 내 시간 분배, 지역아동센터, 기혼 여성 노동공급, 장시간 근로, 여성 관리자
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