SCHOOL ENTRY CUTOFF DATE AND THE TIMING OF BIRTHS

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ABSTRACT

Using birth records in Japan, where school entry rule is strictly enforced, this paper shows that more than 1,800 births a year are shifted from one week before the school entry cutoff date to one week following the cutoff date. Because older children perform better academically than their younger peers, parents who value potential long-term academic gains over the short-term gain of childcare cost savings do exploit birth timing as a means of early childhood investment. Heterogeneous responses by parents violate the assumption of regression discontinuity design that births around the school entry cutoff dates are random.

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1 Introduction

Many governments require children to be of a certain age by a specified date in the calendar year in order to start primary school. This school entry rule mechanically creates a one-year age gap within the school cohort. Parents who happen to give birth near the school entry cutoff dates face a tradeoff to time a birth *after* the cutoff date. On one hand, parents tend to think that older children perform better academically than their younger peers (e.g., Bedard and Dhuey, 2006).[1] On the other hand, parents must bear an additional year of childcare costs as parents need to look after their children longer (Dickert-Conlin and Elder, 2010).

Parents who value potential long-term academic gains of children over short-term gains from saving one year in childcare costs as well as those who can afford such costs may shift births after the cutoff dates as a form of childhood investment. To the extent that skills acquired in early childhood complement later learning (for a review, see Cunha et al., 2006), the timing of births may indeed have long-lasting consequences.[2]

This paper investigates whether parents react to such incentives and strategically alter the timing of births, and if so, which incentive dominates. Specifically, it examines the shifts of births around the school entry cutoff dates using birth certificate records in Japan from 1974–2010 that report exact dates of births. In addition, it exploits the characteristics of mothers and births to shed light on the heterogeneous responses of parents. Finally, it examines how much of the relative academic advantage of older students over younger students can be accounted for if birth timing is taken into account.

Japan is an interesting setting in which to examine such a tradeoff because the school entry cutoff date is strictly enforced. In fact, Kawaguchi (2011) documents that only 0.03 percent of primary school age children are exempted from the mandatory starting age. Therefore, the timing of births indeed determines when children start primary school later. This setting is in contrast to the case in the US, where a significant proportion of children defer school entry by a year (so-called "red-shirting"), in effect making them the oldest students in their year (Deming and Dynarski, 2008). However, such strict enforcement of the school entry rule is not unique to Japan. For example, Bedard and Dhuey (2006) list a few other countries for which there is little or no evidence of early/late starting or grade retention,

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[1] The evidence comes from a cross-country study by Bedard and Dhuey (2006), and country-level studies by Crawford et al. (2007) for the UK, Elder and Lubotsky (2009) for the US, Fredriksson and Öckert (2013) for Sweden, Kawaguchi (2011) for Japan, McEwan and Shapiro (2008) for Chile, Puhani and Weber (2007) for Germany, and Strom (2004) for Norway. However, the challenge is to understand such academic advantage for older children as due to either the *absolute* age at which they start school or their *relative* age to peers (e.g., Datar, 2006; Elder and Lubotsky, 2009). I refer to it as "relative academic advantage," which includes both absolute and relative age effects, throughout the paper. Furthermore, a few studies on the long-run impacts of delayed school entry (e.g., wages) find there are no impacts or even that children are harmed slightly. See, for example, Black et al. (2011), Cascio and Schanzenbach (2013), Dobkin and Ferreira (2010), and Fredriksson and Öckert (2013).

[2] Recent findings demonstrate the importance of early childhood intervention for long-term outcomes, such as health and human capital formation (Almond and Currie, 2011; Heckman 2006, 2007).

specifically, Iceland, Norway, and the United Kingdom.

My main finding is that more than 1,800 births per year are shifted roughly a week before the school entry cutoff date to a week following the cutoff date in Japan, where the mean daily number of births during this period is roughly 3,700. Some of the shifts are indeed real, rather than manipulation of birthdates, since I find an increase in birth weight and gestational length of mothers among births born just after the cutoff. This finding suggests that parents *do* exploit birth timing as a means of early childhood investment.[3]

This finding offers a new perspective into previous studies documenting that mothers shift the timing of births in response to incentives created by birth-related cutoff dates. Because the use of birth-related cutoff dates to determine eligibility for policy programs is quite common across the world—due to government resource constraints, the clearness of cutoff dates, and their easiness to implement—past studies have analyzed the timing of births in response to a variety of cutoff dates.[4] However, most of the incentives are immediate and *short-term* financial incentives, such as tax benefits (Dickert-Conlin and Chandra, 1999) and one-time monetary bonuses (Gans and Leigh, 2009). I show that some mothers are forward looking and take into account the *long-term* academic consequences of their children when they decide on birth timing.

In addition, there are some related findings. First, the overall shifts in births mask heterogeneous responses of mothers. Second-born births, and male births are more likely to be shifted than firstborn births, and female births, respectively. These results on birth parity are especially interesting because they may suggest that parents learn from prior experience that it is probably beneficial for children to be born after the cutoff date. This finding also has implications for the growing body of literature that use regression discontinuity (RD) design, assuming that births around the school entry cutoff date are random.[5] These heterogeneous responses create discontinuities in mother and child characteristics at the school entry cutoff dates, which violate the assumption of RD design. A few papers indeed examine the distribution of births around the school entry cutoff date in other countries, but none find evidence of sorting of births around the cutoff date.[6] While the findings of this paper in Japan may be country

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[3] While some mothers may value the additional year of time spent together with their children, this is unlikely to explain the delay in the timing of births observed given a steady increase in women's labor force participation as well as an increase in preschool enrollment during the period of the study.

[4] For example, shifts of birth timings are found in tax incentives in the US (Dickert-Conlin and Chandra, 1999; LaLumia et al., 2013; Schulkind and Shapiro, 2014), tax incentives in Japan (Kureishi and Wakabayashi, 2008), one-time pecuniary bonus payments in Australia (Gans and Leigh, 2009), and parental leave benefits reform in Germany (Neugart and Ohlsson, 2013; Tamm, 2012), while shifts are not found in expansion of job protection leave in Germany (Dustmann and Schönberg, 2012) and extension of leave duration in Austria (Lalive and Zweimüller, 2009).

[5] See, for example, Bedard and Dhuey (2006, 2012), Berlinski et al. (2011), Black et al. (2007, 2011), Cascio and Schanzenbach (2007), Crawford et al. (2007), Datar (2006), Dhuey and Lipscomb (2010), Dobkin and Ferreira (2010), Elder and Lubotsky (2009), Fertig and Kluve (2005), Fredriksson and Öckert (2013), Kawaguchi (2011), Leuven et al. (2010), McCrary and Royer (2011), McEwan and Shapiro (2008), Muhlenweg and Puhani (2010), Puhani and Weber (2007), Smith (2009), Stipek (2002), and Strom (2004).

[6] See, for example, Berlinski et al. (2011) in Argentina, Dickert-Conlin and Elder (2010) in the US, and McEwan and

specific, to the best of my knowledge, this is the first study that provides a cautionary note on applying such design in contexts in which the stakes of birth timing are high.[7]

Second, using another dataset that reports students' birth month (unfortunately *not* birthdate) and their test scores, I find that the fraction of low socioeconomic status (SES) parents is highest among students born just a month before the school entry cutoff date. This is because high SES parents—who care about their children's academic performance and can afford an additional year of childcare costs—may time births or conception after the school entry cutoff date, while low SES mothers may delay less to avoid an additional year of childcare costs. Interestingly, once I controls for these parental characteristics, the relative academic advantage of older students against younger students is lowered by 20–60 percent, suggesting that some of the observed academic disadvantages of the youngest children in a school year comes from the negative selection of parents.

This result has implications for school entry policies in other countries. Red-shirting—which is increasingly popular in the US, where the enforcement of the school entry rule is weak—can be socially problematic because socioeconomically advantaged parents tend to hold back their children. One proposed solution is to impose strict enforcement of school entry policy in which delayed entry is prohibited (Deming and Dynarski, 2008). However, to the extent that high SES parents evade the policy by manipulating either the timing of births or conception, the effect of such strict enforcement can be partially or even entirely offset. While the magnitude of the overall shifts in the timing documented is relatively small, the differential seasonal patterns of birth months by parental SES indicate that the timing of conception may be another way for high SES parents to avoid the strict school entry rule. However, this result should be viewed with considerable caution because there are many reasons other than the school entry rule that differentially affect the timing of conception by different SES parents (e.g., types of occupation and industry).

The remainder of this paper is organized as follows. Section 2 provides background information on the school system and birth registration in Japan. Section 3 describes the data and identification strategy used in this study. Section 4 reports the main results, and Section 5 presents supplemental analysis. Section 6 concludes.

Shapiro (2008) in Chile.

[7] In addition, Buckles and Hungerman (2013) question the validity of the instruments used by Angrist and Krueger (1991), who use yearly quarters of births as the instrument for years of schooling. However, note that they focus on the timing of conceptions rather than the timing of births, which is the main focus of this paper.

2 Background

2.1 School System

The school system in Japan is legally defined in the School Education Law (SEL) enacted in 1947. Since then, the school entry cutoff date has remained unchanged at April 2. Kindergartens follow the same academic year as primary schools. Article 22 of the SEL obliges parents to send their children to primary schools as soon as their children turn six years of age before the school starting day, which is April 1. However, according to Japanese law, people reach the additional age a day before their birthday. This means that the actual school entry cutoff date is April 2 instead of April 1; children born on April 1 enter primary schools on their 6th birthday, while those born on April 2 need to wait for another year, and enter primary school on the day before their 7th birthday. Thus, there is at most about a one year age difference among primary school students in the first grade. Importantly, the fact that April 2 instead of April 1 is the school entry cutoff date helps this study to isolate the effect of school from other potential mechanical confounders, such as first day of the month effects. To my knowledge, nothing other than the school entry cutoff date occurs on this specific day.[8]

This school entry rule is strictly enforced in Japan and, thus, students rarely delay or start primary school earlier than the scheduled date. Article 23 of the SEL allows a delay in school entry due to a child's illness or underdevelopment, but this exception is rarely applied. According to Kawaguchi (2011), the percentage of exemption is 0.03 percent.[9] This low exemption rate is not surprising as parents need to apply formally for an exemption and provide proof of underdevelopment or illness from physicians designated by the local educational advisory board (article 34 of the SEL).

The fact that almost all children start school without delay contrasts clearly with the situation in the US, where postponement of entry to kindergarten is becoming popular, especially among educated parents (Deming and Dynarski, 2008).[10] Also, the Japanese educational system is known for its social promotion system, in which automatic promotion occurs from one grade to the next. Article 23 of the SEL does not prohibit students from being fast-tracked to the grade above the scheduled grade, but this advancement is very rare.[11]

Furthermore, in Japan there is no systematic variation in years of schooling based on the timing of

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[8] For example, the tax year is January 1 to December 31 in Japan. See Kureishi and Wakabayashi (2008) on taxes and timing of births in Japan.

[9] In 2004, 7,200,933 children at primary school age (6–12 years) attended primary schools, while 2,261 did not, according to Kawaguchi (2011).

[10] In addition, the fact that there is only a single school entry cutoff date that applies to all children is in contrast to the US case; since each state has different school entry cutoff dates, and interstate migration is relatively common, parents may not know precisely which school entry cutoff date they should refer to. Furthermore, each state has repeatedly changed the school entry cutoff dates (Bedard and Dhuey, 2012). See Dickert-Conlin and Elder (2010) for school entry cutoff dates in the US, and Bedard and Dhuey (2006) for international school entry cutoff dates. Note that most countries have only one school entry cutoff date, unlike the case of the US.

[11] In addition, Japan is known for its high-stakes college entrance examinations.

births, unlike the US (Angrist and Krueger, 1991). Compulsory schooling in Japan is not defined by the age that students can leave, but by length of years: nine years of education (six years in primary school, and three years in junior high school) is mandated uniformly for all children. This means that parents in Japan do not face the well-known tradeoff in schooling in the US by which students who are the youngest in their school cohort typically have poorer academic performance, although, on average, they have slightly higher educational attainment (Dobkin and Ferreira, 2010).

Interestingly, some parents and schools recognize the relative academic advantages of older children. For example, a handful of elite kindergartens (such as *Keio*, and *Tsukuba*) specifically mention that they take into account the difference in maturity by birth months of children at the entrance exam but such differential treatment by birth month is still very uncommon.

2.2 Birth Registration

The birth certificate is written by physicians if births occur at either hospitals or clinics, while it is written by midwives in case of home deliveries. According to the birth data described in detail below, 99.4 percent of births occurred at medical institutions (either hospitals or clinics) during 1974–2010, and thus, it is very unlikely that this study's results are driven by home deliveries.

Parents are required to bring birth certificates signed by attending physicians (or midwifes) to register their children at their closest public health center (*Hokenjyo* in Japanese). The newborns need to be registered within 14 days after birth; parents must otherwise pay a fine. Since the birth certificate is signed by an attending physician, it is unlikely that manipulation of birthdates occurs at the reporting stage at public health centers. Thus, if manipulation does take place, it is more likely to occur at the stage of filling in birth certificates at medical institutions before being signed officially by physicians.

3 Data and Identification strategy

3.1 Data

The data used in this study come from four sources. The primary data are birth data, supplemented with death data to examine infant mortality, and insurance claim data to examine the timing of Cesarean-section (C-section) births. In addition, the Organisation for Economic Co-operation and Development's (OECD's) Programme for International Student Assessment (PISA) is used to examine parental socioeconomic status by children's birth months. To avoid confusion, this section focuses on my primary data source (birth data) and supplementary data sources (death data and insurance claim data). The secondary PISA data are described in Section 5.1.

The birth data are compiled by Japan's Ministry of Health, Labour and Welfare, and cover the universe of births in Japan during 1974–2010. The key variable in the birth data is the exact date of birth. Combining 1974–2010 birth data together provides information on more than 50 million births. The data are of high quality in that only 4,935 observations (less than 0.01 percent) are missing birthdate information, and these observations are excluded. Even if I restrict the sample to the last 7 days and the first 7 days around April 2, I still observe more than 1.8 million births. The birth data also contain information on exact hour of births, which is rare in the public versions of birth certificates available to researchers. Unless otherwise specified, the main outcome is the number of births at the daily level rather than hourly level because most past studies use daily observations; thus, the data are comparable across studies.

The birth data collect very limited characteristics of mothers, such as their ages at the time of births. Unfortunately, the data do not collect other key characteristics of mothers (e.g., education, income, and working status), delivery method (e.g., C-section and inducement), complications of births, and Apgar scores of newborns. In addition, the study examines a number of child characteristics collected in the birth certificates to investigate whether shifts in the timing of births are real rather than manipulated birthdate by analyzing the birth weight of newborns as well as the gestational length of mothers. Furthermore, it examines the heterogeneous responses of mothers by dividing the sample by gender of children, and parity of children (i.e., firstborn births vs. second-born births and above).

In addition to birth certificates, I use death certificates to examine infant mortality. The death certificates contain all death records that occurred in Japan during 1974–2010, which include information about the decedent's exact date of death, exact date of birth, gender, and cause of death (ICD8–10). Even though the birth and death certificates are not linked in Japan, it is nonetheless possible to calculate the infant mortality rate on each birthdate, where the numerator is the number of deaths for births on each birthdate from death certificates, and the denominator is the number of births for each birthdate from birth certificates. The summary statistics are reported in Appendix Table A.

I also complement the analysis on birth records with insurance claim data from roughly 500 hospitals for 2011–2012 because birth records lack information on delivery method. The unit of observation in this data is mother's deliveries instead of births. Thus, while exact dates of *admission* of mothers for delivery are available, exact dates of *birth* are not available. However, the data also include the exact dates of *surgery*. Thus, I assume that for C-section births, surgery dates are equivalent to birthdates, and test whether C-section births are shifted around April 2. I examine emergency C-section births and elective C-section births separately. Since C-sections involve physical risks for both mothers and children, I expect to see shifts of births, if any, only for elective C-section births.

3.2 Identification Strategy

The main specification uses the observations only around April 2 of each year. Note that days are organized in relation to April 2 for each year. The econometric model estimated is:

$$Y_{dy} = \alpha + \beta After_{dy} + \sum_{j=1}^{6} Dow(j)_{dy}\delta_j + \sum_{k=1}^{N} Holiday(k)_{dy}\lambda_k + \theta_y + \varepsilon_{dy} \qquad (1)$$

where Y_{dy} is the count of births for day d in year y. $After_{dy}$ takes one if the birthday d is after April 2 in each year y. $Dow(j)$ is one of six dummy variables for each day of the week, and $Holiday(k)$ is one of K dummy variables for each holiday. θ_y are year fixed effects to account for time trends in the overall number of births.[12] ε_{dy} is an idiosyncratic error term. The coefficient of interest is β. Replacing the counts of births by the log number of births in Equation (1) provides a measure of the proportion of births shifted. I also examine infant characteristics around the cutoff date, where Y_{dy} are the mean infant characteristics for day d in year y.[13]

Following Gans and Leigh (2009), I change the windows around April 2 from 7 days to 28 days. Widening the window has two purposes. First, it allows for births to have moved by more than one week, even though, as is shown later, birth shifting is concentrated within a week from the cutoff date. Second, it allows for the possibility of "attempted but unsuccessful moves," where some parents may have attempted to delay births until April 2, but instead could only move the births from mid-March to late-March (Gans and Leigh, 2009). In addition, if capacity constraints are binding, some births that would have taken place in early April may be shifted to mid-April. Both such moves attenuate the estimates from focusing on a narrow window.

Alternative specification uses not only observations around April 2 as the abovementioned specification, but also observations around the second day of the other months as well. Following Evans and Moore (2011, 2012) and Stephens (2003, 2006), I construct "synthetic" months and years: let Y_{dmy} be the birth counts for synthetic day d in month m and year y. Days are organized in relation to the second day of the month, so d is in the range of -14 to 14. Synthetic months do not follow the calendar; instead, synthetic months begin 14 days prior to the second day of the month and last until 14 days after the second day of the month. Month 1 contains data from December 19 to January 15 of the next year, Month 2 from January 19 to February 15, and so on. Similarly, synthetic years begin 14 days before January 2 of the next year.

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[12] In addition, I attempted to include the interactions of day of the week fixed effects and year fixed effects to allow each week day to have differential impact by each year. These results (not shown) are very similar.

[13] The individual birth as a unit of observation can be used instead of the mean at each birthdate; however, this study takes the former approach using the number of observations as weight to reduce the computational burden.

Given this structure for the data, the econometric model is

$$\begin{aligned} Y_{dmy} &= \alpha + \beta(After2nd_{dmy} \cdot April_{dmy}) + \gamma After2nd_{dmy} \\ &\quad + \sum_{j=1}^{6} Dow(j)_{dmy}\delta_j + \sum_{k=1}^{N} Holiday(k)_{dmy}\lambda_k + \theta_y + \rho_m + \varepsilon_{dmy} \end{aligned} \tag{2}$$

where $After2nd_{dmy}$ takes one if the birthday d is after the second day of the synthetic month m in each year y, and $April_{dmy}$ takes one if the birthday is during synthetic months of April. ρ_m and θ_y capture synthetic month and year effects, and ε_{dmy} is an idiosyncratic error term.[14] The coefficient of interest is β, the coefficient on the interaction term between $After2nd$ and $April$. This specification allows for the isolation of the deviation of the number of births after April 2 from the second day of the other months. The coefficient on γ should capture whether days after the second day of each month is unusual compared to days before the second day of the month. I expect the coefficient on γ to be economically very small, since there is no reason to believe that the period around the second days of each month is unusual. Standard errors are estimated, allowing for arbitrary correlation in errors within each unique synthetic month. The advantage of this specification, Equation (2), over previous specification, Equation (1), is that any effects around the second day of the typical months can be isolated, while disadvantage is that the windows can be extended only up to 14 days around the cutoff because of the way the data are constructed. In fact, as shown in Section 4.1, both specifications yield very similar results, which provide reassurance that within monthly fluctuations do not drive the results.

4 Main Results

4.1 Shifts in the Timing of Births

Before running formal statistical analysis, a simple histogram-like plot reveals a striking pattern. Figure 1 displays the mean daily number of births throughout the year using the pooled 1974–2010 birth data. The markers with cross signs correspond to holidays. Note, once again, that the school entry cutoff date is April 2 instead of April 1.

Figure 1 depicts a clear heap on April 2, and relatively high frequency of births on subsequent days. In fact, April 2 is the day with the highest number of births throughout the year, and April 1, a day before the cutoff date, is the third lowest. Table 1 reports the top five and bottom five days of mean daily number of births, together with the ratio to average daily birth, computed as the average number of births on a given day divided by average births across all days. Thus, a value of 1.1 represents a 10

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[14] In addition, it is possible to replace $After2nd_{dmy}$ by dummies for each day within synthetic months (14 or 28 dummies, depending on the estimation window), but the results are very similar. The results are also very similar when I instead include the interaction of the synthetic month and synthetic year dummy variables instead of synthetic year and synthetic month dummies separately (not shown).

percent increase in daily births compared to the overall average. April 2, and April 3 have 20 and 10 percent more births than yearly average, respectively, while April 1—the day before the cutoff date—has 15 percent less births than average.[15] In addition, this graph highlights the importance of controlling for holidays in the estimation. Furthermore, there is variation in weekdays versus weekends, but the pooling of many years of data smooths out such an effect in the figure. In the regression, the day of the week fixed effects are included to control for within week fluctuations.

Figure 2A provides a closer look at births around the cutoff date by plotting the mean daily number of births around April 2. To provide symmetry, I report 28 days prior to April 2 (March 4–April 1), and 28 days after April 2 (April 2–April 29). Again, the markers with cross signs correspond to holidays. Starting about 10 days before April 2, daily number of births declines gradually and falls to roughly 2,800 per day on April 1, a day before the school entry cutoff date. The number of births then increases sharply to roughly 4,500 on April 2. Note that other dips around March 20 and April 29 are the result of holidays, Spring Equinox Day (either March 20 or 21) and Greenery day (April 29), respectively. Figure 2B accounts for holidays and weekends by plotting the residual of regressions of the daily number of births on holidays, days of the week, and year fixed effects. This graph shows a similar pattern to Figure 2A, without fluctuations due to holidays.

Table 2 summarizes the results from formal statistical tests of estimating Equation (1). The first column in Panel A restricts the sample to the last 7 days and the first 7 days around April 2, and shows that roughly 1,835 births are shifted within a week from April 2. Because the daily average of births during the sample period is 3,713, the size of shifts corresponds to roughly half of the mean daily number of births. In the remaining columns, the window of analysis is widened progressively. As the window is widened, the number of births shifted does not change much, which suggests that most of the shift is concentrated roughly within a week from the cutoff date. Panel B uses the natural log of the mean daily birth as an outcome. The first column shows that roughly 7 percent of births are shifted from one week before the school entry cutoff date to one week following the cutoff date.

Appendix Table B compares the estimates from Equations (1) and (2). To facilitate the comparison, columns with odd numbers replicate the results from the main Equation (1). Note that because of the way the data are constructed, the window around the cutoff date can be expanded only up to 14 days in Equation (2). Appendix Table B shows that the two equations yield very similar results. In addition, the estimates on $After2nd$ dummy in the columns with even numbers are very small economically, suggesting that the days after the second day of each month are not unusual compared to the days before the second day of the month.

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[15] February 29 is the lowest, not because it exists every four years, as the mean daily number of births on February 29 is calculated per existing years. The low frequency of births on February 29 indicates that shifting birth for a day or so is easily possible, either though manipulation of birthdate or actual shifts in birth timing. In addition, many clinics are closed around the New Year in Japan, which explains the huge dips before and after New Year in Figure 1.

Furthermore, I explore the patterns of shifts across periods. Appendix Figure A displays the mean daily number of births around April 2 by different time periods. While the magnitude of the shifts is largest in the earliest period (1974–1980), there are discernible delays of births in the most recent decade (2001–2010). To gauge the magnitude of the shifts across years, Equation (1) is estimated separately for each year with a seven day window from the cutoff. Because the equation is estimated for each year, the year fixed effects are not included in the estimation. Appendix Figure B plots the size of the shifts in each year.

There are two noteworthy points to mention. First, the estimates are positive across all years and statistically significant at the conventional level, indicating that delays of births are not limited to a certain period. For example, the proportion of births shifted is 5.2 percent in 2010—the last year available in the dataset—while the corresponding figure for the entire 1974–2010 period is 7 percent.

Second, the magnitude of the delays of births declines in recent years. It is not clear *a priori* whether more or fewer delays of births in recent years are expected to be observed. On one hand, it may be expected there will be more delays of births due to the development of medical technology to easily time births, rising competition in academic markets, and a quantity/quality tradeoff of children.[16] On the other hand, it may be expected there will be fewer delays of births if childcare costs increase and/or if the digitalization of medical records make it harder to manipulate birthdates.[17] Given the large secular changes in family structure and environment, it is difficult to isolate each channel over time. Nonetheless, the results at least indicate the latter story may be more dominant than the former story. In fact, as shown in Section 4.3.2, this result is in line with the finding that regions with higher availability of public daycare centers, and hence potentially lower costs of childcare, observe more delays in births.

4.2 Manipulation or Real Shifts?

Given the size of the magnitude of shifts, some of the birth shifts estimated are potentially due to the manipulation of reported birthdates. Figure 3 plots hourly numbers of births within 72 hours (3 days) before and after the school entry cutoff date using the pooled 1974–2010 birth data. A unique feature of Japan's birth certificates is that they report the exact hour of birth. The graph shows systematic patterns within a day, in which more births are observed during the daytime and fewer births late at

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[16] For example, the fraction of weekend births decreased from 25.7 percent in 1974 to 22.8 percent in 2010, which may reflect that fact that births can be more easily timed as medical technology advances to avoid weekend births. In addition, note that weekend births are always lower than the random distribution of 2/7 (=28.6 percent), which suggests that births can be shifted by at least a few days.

[17] In addition, as shown in Section 4.3.1, aging of mothers potentially accounts for the fewer delays in recent years because older mothers tend to delay births less than younger mothers. To examine how much of the recent decline in the magnitude of the shifts can be explained by the age of mothers, I perform a Blinder–Oaxaca decomposition to decompose the magnitude of the shifts into the fraction explained by the compositional change of mothers, and those remaining. Using 1974 as a baseline year, the age of mothers accounts for roughly 5–20 percent of the change in the magnitude (the results are available upon request).

night or early in the morning, possibly due to the preferences of physicians/hospitals to avoid deliveries when staffing levels are low.

Interestingly, bunching of reported births is observed at midnight of April 2, with a slight dip just a few hours before midnight. Such patterns around midnight of the other days are not observed. Because delaying birth by a few hours is much easier than delaying birth by a few days, this is consistent with the real shift of births. However, it is more likely to reflect the manipulation of reported birth hours because such bunching at midnight is rarely observed in recent data years, possibly because of the digitalization of medical records (not shown).

Nonetheless, there are a few reasons why it seems unlikely that manipulation of reported birthdates fully accounts for all the shifts. First, high frequency of births is observed not only on April 2 but even after April 2. Similarly, in the years when April 2 coincides with weekends, a peak of births on April 3 or later is observed (not shown). If manipulation is the main mechanism, there would be no need to shift births further after April 2. Additional evidence is documented in Sections 4.2.1 and 4.2.2.

4.2.1 Child Outcomes

Next, I show further evidence against pure manipulation by examining the birth weights of children and gestational length of mothers. Birth weight is of particular importance as there is ample evidence that initial health at birth has medium and long-term impacts on children.[18] I am aware of only three previous papers—Gans and Leigh (2009), Schulkind and Shapiro (2014), and Tamm (2013)—that analyze the impact of cutoff induced birth timing on infant health.

Figure 4A plots the mean birth weight around April 2.[19] The graph shows clearly that birth weights after the school entry cutoff date are heavier than those before April 2. Figure 4B plots the proportion of birth weights over 4000 grams (high birth weight) and shows similar patterns as mean birth weight. Table 3 presents the results of estimating Equation (1) in which the outcome is mean birth characteristics at each birthdate. Column (1) in Table 3 reports that children born after the cutoff date are roughly 2.3 grams heavier than those born before the cutoff date. Since 7 percent of births are delayed, this implies that delayed births are heavier by around 33 grams.[20] While delaying births seems more difficult

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[18] See, for example, Bharadwaj et al. (2012), Black et al. (2007), Johnson and Schoeni (2011), Oreopoulos et al. (2008), and Royer (2009).

[19] Birth weight is given in 100 gram intervals until 1995, and collected using single grams after 1995. Therefore, I divide birth weight collected after 1995 by 100. In addition, if the increase in birth weight is concentrated in recent years, it raises concern that some of the shifts in the early period are due to manipulation of reporting instead of real shifts. However, the increase in birth weight is clearly observed in the early periods as well. Furthermore, the coefficients on the probability of birth weights over 4000 grams estimated separately for each year are statistically significant for any single year during 1974–2010 (both results are available upon request).

[20] In Section 4.3, I show that babies born after the cutoff date are more likely to be boys and are more likely to be born to younger mothers; both of these factors are associated with higher birth weights. However, the birth weight estimates remain statistically significant ($P<0.05$) after controlling for gender of children and mothers' ages (coefficient= 1.636, SE= 0.799).

medically than hastening births, my result is consistent with that of Gans and Leigh (2009), who also find an increase in birth weight among *delayed* births so as to ensure parents are eligible for one-time pecuniary bonus payments given to children born after a certain date in Australia.[21] Column (2) reports that births after the school entry cutoff date are 0.05 percentage points more likely to be over 4000 grams (mean of 2.2 percent). Column (3) demonstrates that the proportion of deliveries after 42 weeks of gestation or more is higher after April 2, which is consistent with the increase in birth weight. Appendix Table C presents the results using different size of windows around the cutoff date.

Finally, as a part of child outcomes, I analyze infant mortality. On one hand, if the surge in the number of births right after the school entry cutoff date creates congestion or overcrowding in hospitals, it could potentially harm infant health. On the other hand, it may not affect infant health because hospitals can anticipate such a surge, and thus, they are well prepared. Consistent with the latter view, Figure 4C shows that while the mortality profile is noisy due to Japan's low mortality rate, there is no clear change in infant mortality around the cutoff date. Column (4) in Table 3 confirms that births right after the cutoff date do not show excess mortality.[22] Here it is important to note that mortality is just one health outcome and other health measures, such as readmission rate, are potentially affected because of the shifts of births. Unfortunately, due to lack of data, this study does not examine any other health outcomes.

4.2.2 C-section Births using Insurance Claim Data

I add further evidence against pure manipulation by examining whether C-section births are shifted in response to the school entry cutoff date. One disadvantage of birth data examined so far is that they do not report delivery procedures. To compensate, the insurance claim data are used below.

Figure 5 shows that for elective C-sections—the day of the operation can to some extent be chosen by mothers—are shifted after the cutoff date, although no shifts for emergency C-sections are observed.[23] The spike for elective C-sections does not occur exactly on April 2 in the graph because the insurance claim data is limited to two years (2011 and 2012), and thus if April 2 happen to coincide with weekends, the births are shifted to days after April 2.[24]

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[21] During casual conversations with physicians, some mention that an easy and simple way to delay birth for a few days is for pregnant mothers not to move around much near their due dates.

[22] Since this study is concerned with the effect of birth complications due to congestion on infant mortality, I also restricted infant deaths in the sample to those that occurred within 28 days from birth (neonatal death), and to those classified as "conditions originating in the perinatal period" (specifically, ICD-10 category P). These results are similar (they are available upon request).

[23] This result also provides some evidence for the power that parents exert on the timing of births. While there is ample evidence that a certain number of births can indeed be timed, it is generally not clear whether this timing is chosen by physicians/hospitals or parents. Because physicians/hospitals prefer to avoid congestion, this surge in the number of births right after the school entry cutoff date suggests that parents have some influence over physicians/hospitals on the timing of deliveries.

[24] April 2 fell on a Saturday in 2011 and on a Monday in 2012. As shown in Appendix Figure C, elective C-sections on

Table 4 separately shows the estimates of Equation (1) for any C-section, elective C-section, and emergency C-section. The outcome is the log of the mean daily number of births, and the sample is limited to a seven day window from the cutoff date. Column (2) shows that 26.3 percent of elective C-sections are shifted within a week around the cutoff date while Column (3) shows that estimate on emergency C-sections are economically small and statistically insignificant. These results are plausible since the C-sections involve physical risks for both mothers and children, and thus I expect to see the shifts of births only for elective C-sections. Also this result shows that while it may be medically more challenging to delay births than hasten births, shifting the timing of elective C-sections may be one way to ensure that births occur after the cutoff date. This result is consistent with Gans and Leigh (2009) who show that induction and C-section procedures account for most of the delays in births in response to bonus payments in Australia. Appendix Table D presents results from different size of windows around April 2.[25]

4.3 Heterogeneous Responses

4.3.1 By Mother and Child Characteristics

Thus far, there is evidence for sizeable shifts in births in response to the school entry cutoff date, and some of the shifts are indeed real instead of pure manipulation of birthdates. In this subsection, I exploit the characteristics of mothers and births to examine the heterogeneous responses of parents.

Figure 6–1, 6–2, and 6–3 plot the mean daily number of births of the subsample divided by a parity, mother's age, and gender of the child using the pooled 1974–2010 birth data. Table 5 summarizes the results from estimating Equation (1), where outcome is the log of the mean daily number of births separately for each subgroup. Because the shifts of births are concentrated within a week from the cutoff date, the sample is limited to within seven days of the cutoff date.

Figure 6–1A displays that births at higher parity are more likely to be delayed. This pattern is more apparent in Figure 6–1B, which plots the share of high parity births (second-born or later births) among all births. The figure shows that the share of high parity births increases discontinuously right after April 2. Columns (1) and (2) in Table 5 show that although 8.6 percent of births at higher parity are delayed, the corresponding estimate for firstborn births is 5.3 percent. The null hypothesis that coefficients of different parity are the same is rejected at the 1 percent significance level.

This result implies that mothers may learn from the experiences of their firstborn children that it is probably beneficial for later children to be born after the cutoff date. In addition, mothers have already gained experience through firstborn births, and thus, it may be easier for them to time second-born

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weekends and holidays are very rare

[25] Unfortunately, because the unit of observation is mothers instead of births in this dataset, I cannot examine the size of shifts in C-section births by gender of births.

births or later births by comparison. Note that the proportion of second-born or later births to all births seems to be increasing even after April 2 in Figure 6–1B, which implies that conception may also be timed. Section 5.2 reconsiders this point.

Next, the sample is divided by a mother's age at delivery (the mean is 29.8 years). Figure 6–2A shows that relatively younger mothers, that is, those less than 30 years of age at delivery, show a larger delay of births compared to mothers of more than 30 years.[26] Because of this differential pattern by mothers' age group, Figure 6–2B depicts a sharp decline in the mean mother's age at birth right after the school entry cutoff date.[27] Columns (3) and (4) in Table 5 report while 7.9 percent of births among mothers less than 30 years are delayed, the corresponding estimate for mothers older than 30 years is 5.6 percent. This enables rejection of the null hypothesis that coefficients on mothers less than 30 years and more than 30 years are the same at the conventional level. One possible but at best speculative explanation is that for older mothers, it is much more important to ensure the survival of their children and thus, mothers care less about the timing of births. In addition, since the delay of births is potentially harmful to a mother's health, the delays of births for older mothers may be physically difficult, and physicians may not allow such delays.

Finally, the sample is divided by the gender of newborns. Figure 6–3A clearly displays that the births of boys are more likely to be delayed than those of girls.[28] Figure 6–3B plots the fraction of male births and shows that the share of male births is substantially higher after the school entry cutoff date. Columns (5) and (6) in Table 5 report while 8 percent of male births are delayed, 6.1 percent of female births are delayed. Again, the coefficients on male and female births are statistically distinguishable. Appendix Table E presents the estimation results for each gender by parity. Consistent with the findings thus far, the table shows that male births at higher parity are most likely to be delayed. Unfortunately, because there is no mother identifier in the birth data, I cannot examine the shifts of second births conditional on the gender of the first birth.

There are a few possible explanations for this finding. First, the result may reflect parents' preferences for sons.[29] If so, this is an interesting finding because Japan is known to reveal little preference for sons, at least in the prenatal stage, and therefore, the country shows normal sex ratios of births, unlike many Asian countries with elevated sex ratios at births (Sen, 1990).[30] This result may imply a mild form of

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[26] Mothers' ages are further divided into finer intervals. Interestingly, the estimates monotonically decline as a mother's age increases. More specifically, the percentage shifts of births are 9.1, 8.1, 7.8, 6.1, 4.1, and 2.9 percent for mothers aged less than 19 years, 20–24 years, 25–29 years, 30–34 years, 35–39 years, and 40-plus years, respectively. All estimates are statistically significant at the 1 percent significance level.

[27] In addition, I find that fathers' ages (measured in years) increase discontinuously at the school entry cutoff date, possibly due to the associative matching of fathers and mothers in terms of age.

[28] Similarly, boys are more red-shirted than girls in the US (Deming and Dynarski, 2008).

[29] There is a growing body of literature that investigates parents' differential investment in children by gender. See, for example, Baker and Milligan (2013), Dahl and Moretti (2008), and Lhila and Simon (2008) for developed countries, and Barcellos et al. (2014), Bharadwaj and Lakdawala (2013), and Jayachandran and Kuziemko (2011) for developing countries.

[30] Having said so, Rohlfs et al. (2010) document that boys are predominately delivered in Japan in 1966, a year which girls

son preference in Japan, which differs from sex-selective abortion. Alternatively, the result may reflect the fact that boys are slower than girls in early childhood development and also socially less mature than girls; thus, parents may want to ensure that boys do not suffer from disadvantages of being the youngest. For example, Datar (2006) shows that boys' reading abilities benefit significantly more from delaying entry to kindergarten compared to girls' reading abilities in the US. In addition, larger body size of older cohorts may matter more for boys than girls when it comes to playing sports.[31] Unfortunately, this study cannot disentangle "son preference" from such "son weakness."

To summarize, the abovementioned heterogeneous responses by mothers suggest that births around the school entry cutoff date reflect the differences in mothers' characteristics, providing a cautionary note for a growing body of literature that assumes randomness of birth timing when the stakes of birth timing are high. This result provides one example of how endogenous sorting at discontinuities may invalidate RD design (Lee, 2008; McCrary, 2008, Urquiola and Verhoogen, 2009).

4.3.2 Availability of Public Day-care Centers

Unfortunately, birth data in Japan do not contain key maternal characteristics, such as income, working status, and education, which may be useful to understand the role of childcare costs as well as the opportunity cost of mothers in decisions about birth timing. This subsection, while far from being perfect, explores whether easier access to childcare, and hence, potentially lower costs of raising children, affects the timing of births. It assumes that greater availability of daycare in regions, the greater is the likelihood of observing delays of births because the additional year of childcare is less worrisome for a mother in these regions. I am aware that this is simply a correlation and not a causal estimate because there is no explicitly exogenous regional variation on daycare availability. Nonetheless, it is a relevant and interesting correlation and, therefore, this exercise should be viewed as complementary to the preceding analyses.

As a measure of availability of childcare, I exploit the year-to-year variation in prefectures of the availability of public daycare centers. More specifically, I compute the "capacity" measure at each prefecture for every year by dividing the total slots at public daycare centers by the total number of females between the ages of 20–39 years, the typical child-bearing age.[32] This measure captures the "potential" availability of childcare instead of the "actual" availability of childcare, in which the total slots of public daycare centers is often divided by the number of children before school entry age instead of the number of females of childbearing age. This measure is arguably better than actual daycare availability

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are regarded as less desirable astrologically (*Hinoeuma* in Japanese), suggesting that prenatal gender selection prevailed at least until 1966 in Japan.

[31] For example, Allen and Barnsley (1993) show that two and a half times as many boy players in Canada's Hockey League were born in January compared to December; the cutoff date for Canadian hockey is January 1.

[32] The female population is interpolated through the census, which is taken every five years (specifically, years ending with a 0 or 5).

because the number of children may be the result of mothers' fertility decisions, and hence, potentially endogenous to the timing of births (Unayama, 2012). There is considerable prefectural variation in the capacity variable, which ranges from 0.0355 (*Kanagawa* in 1974) to 0.293 (*Ishikawa* in 1979), with a mean of 0.144 (a standard deviation of 0.053) slots per females. There are 47 prefectures in Japan, and I utilize information on total slots of public daycare centers in each prefecture for 1974–2007.[33]

The relationship between the availability of public daycare centers and the magnitude of birth shifts is estimated in the following two steps. First, the following Equation (3) is estimated for each prefecture p and each birth year y cell separately using a seven day window from the cutoff:

$$\ln(birth_d^{yp}) = \alpha^{yp} + \beta^{yp} After_d^{yp} + \sum_{j=1}^{6} DOW(j)_d^{yp}\delta_j^{yp} + \sum_{k=1}^{N} Holiday(k)_d^{yp}\lambda_k^{yp} + \varepsilon_d^{yp} \tag{3}$$

This equation is simply the analogue of Equation (1), but β^{yp} is estimated at each prefecture/year-of-birth cell instead of using all pooled data at once, thus, generating a series of estimates across prefecture/year-of-birth (1,598 = 34 years × 47 prefecture/year-of-birth).[34] Note that, because Equation (3) is estimated for each year, the year of birth fixed effects is no longer included.[35]

In the second step, the following Equation (4) is estimated by regressing the magnitude of delays at prefecture/year-of-birth cell, $\hat{\beta}^{yp}$, on a capacity measures.

$$\hat{\beta}^{yp} = \theta + \pi \ln(capacity_{(y-1)p}) + \tau_p + \rho_y + X'_{yp}\psi + \mu_{yp} \tag{4}$$

The coefficient of interest is π. Note here that because the capacity variable is collected on October 1 in each year y, I use the capacity variable in $y-1$, a year prior to March/April in year y, when the shifts of births occur. X_{yp} are time-varying prefectural characteristics, and I specifically include real GDP per capita, which is deflated by the prefecture GDP deflator to Yen in 2000, and the job application-to-opening ratio at October of $y-1$, which roughly captures prefectural labor market conditions around the time of conception to partially control for selection in fertility.[36] The job application-to-opening ratio in March of the year y is included to account for the economic condition at the time of births.[37] These controls essentially have no impact on the estimates. The source of variables and years available are summarized in Appendix Table F. Equation (4) is estimated by weighted least squares where weight is the inverse of square of standard errors for each $\hat{\beta}^{yp}$ from estimating Equation (3).

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[33] I am grateful to Takashi Unayama for kindly sharing this data.

[34] This is conceptually the same as pooling the data for all years of births and including all the interactions of independent variables with a full set of prefecture/year-of-birth dummies.

[35] $\hat{\beta}^{yp}$ varies from -0.127 to 0.387 with a mean of 0.082 and standard deviation of 0.063.

[36] In fact, Dehejia and Lleras-Muney (2004) show that the business cycle affects the characteristics of mothers who conceived children in the US.

[37] While a more standard measure of labor market conditions, such as the unemployment rate at the prefectural level, is available only in the census years, the monthly job application-to-opening ratio at the prefectural level is available as early as 1963 in Japan.

Table 6 summarizes the results from estimating Equation (4). Column (1) reports that a 10 percent increase in the capacity of public daycare centers is associated with an increase of birth delays by 1.16 percent. This result is consistent with the view that better access to public daycare centers mitigates mothers' worries about childcare, and hence, they are more willing to delay births. While the result cannot be interpreted as causal, it may imply that an increase in the availability of public daycare potentially exacerbate the shifts of births. The addition of time-varying controls in Column (2) does not virtually affect the estimate. Finally, to check whether the results are driven by prefectures with large populations, which tend to have low availability of public daycare centers, Column (3) excludes Tokyo and Osaka, the two biggest prefectures. The estimate is very similar to the baseline estimate in Column (1). Finally, Column (4) limits the sample to the most recent years, 2000–2007. The underlying assumption in estimating Equation (4) is that mothers are aware of year-to-year variations in potential need for public daycare centers in their areas. It is plausible that mothers have good foresight about the availability of public daycare centers in their area, at least in recent years, because the shortage of slots in public daycare centers are covered in media very intensively. While the estimate in Column (4) is no longer statistically significant because of the small sample size, it is reassuring that the estimate in Column (4) is quantitatively similar to the baseline estimate in Column (1).

To summarize, these results are consistent with the hypothesis that childcare costs may be one of the driving forces of the birth shifts. However, these results should be viewed with considerable caution because the availability of public daycare is simply a crude proxy of the costs of childcare,[38] and also there is no exogenous regional variation on public daycare availability. Again, I stress that these results provide only correlations and not causal interpretation.

4.4 Magnitude of the Shifts

Next, the magnitude of the shifts is examined by simply comparing the results of this study to those of previous studies that analyzed the effect of birth-related cutoff dates on the timing of births in other contexts. The results are summarized in Table 7. Three things are noteworthy. First, the school entry cutoff date is known well in advance so that the timing of both conception as well as births could be affected by the school entry cutoff date. This is in contrast to the case of bonus payments in Australia in July 2004, which affected only the timing of births because mothers did not know the policy at the time of conception (Gans and Leigh, 2009). Second, the incentive of parents in this study is the long-term academic consequences for children, while other studies examine immediate financial incentives, such as tax incentives. Third, while the incentive structure of other studies moves in one direction (i.e., either delaying or hastening of births, but not both), there is a clear tradeoff in parents' incentives in this

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[38] While there are private daycare centers, public daycare centers tend to be cheaper and vary less in quality; thus public daycare centers are dominant in Japan.

study. Despite these differences, the 7 percent shift of births found in this study is within the range of other studies.

5 Supplemental Analysis and Discussion

5.1 Birth Timing, Parental SES, and Test Scores

The analysis on birth data demonstrates that parental characteristics are associated with the timing of births. However, the birth data in Japan contain very limited characteristics of parents, and in fact only mothers' ages at birth are examined. Therefore, I use other sources of data that report parental characteristics, as well as birthdates of children. Specifically, the data from PISA collected by the OECD are used and include information on the parental characteristics of 15-year-olds (normally 10th grade), birth months of students, and test scores on various subjects.[39]

The advantage of PISA is that it collects nearly complete information of parental education. PISA was first performed in 2000 and has been repeated every three years since. This study uses PISA 2003 because the data is much more complete than in other years.[40] In addition, this data is helpful for examining how much of the relative academic advantage of older students to younger students can be explained by parental background rather than relative age because the data collect test scores of children.

There are two drawbacks of this data that are noteworthy to mention. First, they reports only the birth months of students but not the birth day, and thus, I cannot precisely examine the distribution of births around April 2. This means I cannot distinguish timing of births and timing of conception in this data.[41] Second, the data are collected for one academic cohort (from April to March in the following year) and thus, does not contain data for the adjacent March and April of the same calendar year. Thus, I cannot examine the shifts of births from March to April. The summary statistics of PISA 2003 are shown in Appendix Table G.[42]

Figures 7A–C plot the birth months of students and the average of three different parental characteristics: proportion of fathers with white-collar jobs, fathers' years of schooling, and family economic,

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[39] The 10th grade corresponds to the first year of high school. The advancement rate to high schools was 97.3 percent in 2003.

[40] The missing rates of maternal and paternal educations are is only 0.34 percent and 0.63, respectively, in 2003, but vary between 4 and 11 percent in other years. Other similar sources of data, such as Trends in International Mathematics and Science Study (TIMSS), have much higher missing rates of parental education (roughly 25–40 percent) probably because students are still young (either in 4th or 8th grade) and may not be aware of their parents' education levels.

[41] Unfortunately, I am not aware of any dataset in Japan that contains both the exact date of birth and parental characteristics, except for birth data.

[42] There are 4,707 observations for Japan in PISA 2003. 10th graders in 2003 should have been born between April 1985 and March 1986, if students strictly follow the school entry cutoff rule. Indeed, out of 4,707 observations, there are only 7 born outside of this period. In fact, they are all born in April 1986 but it is not clear whether these observations fall outside of the required grade because the birthdates of these students can be April 1. To be conservative, I drop these seven observations. In any case, it is reassuring that only 0.15 percent of children (7/4707) at the maximum do not follow the assignment of the scheduled academic cohort in this data.

social, and cultural status (a variable called *ESCS*) constructed by the OECD based on parental education, parental occupation, and home possession, where higher values indicate higher SES (OECD, 2005, p. 316).

These figures show the obvious trends in parental characteristics by birth month, which may be driven by concerns about the relative advantage of older children. Children born right after the cutoff month (April) are more likely to have high SES parents, while those born right before April are less likely to have high SES parents. In particular, this is the case for March-born children, who are labeled in diamonds in the figure. Of all three variables that capture parental background, parents of children born in March are by far the most negatively selected.

Interestingly, Figure 8, which corresponds to Figure 7A, shows that the lower proportion of high SES parents in March is driven by fewer births by high SES parents rather than more births by low SES parents in March as the number of births by low SES mothers shows little seasonable variation.[43] This result implies that high SES parents tend to ensure that deliveries occur after the school entry cutoff date, while low SES parents do much less, probably because they cannot afford an additional year of childcare costs, or they simply do not recognize or value the relative academic advantage of older children.

Importantly, the negative selection of mothers may partly explain the relative academic disadvantages of younger children. In fact, Figure 7D shows that math test scores reported in PISA 2003 depict similar patterns to Figures 7A–C; namely, children born in March perform almost worst, suggesting that the relative academic advantage of older children may be driven in part by the negative selection of mothers.[44]

To investigate this point more formally, Equations (5) and (6) are estimated following a similar strategy to Buckles and Hungerman (2013):

$$Test\ score_i = \alpha + \beta_1 R_i + \varepsilon_i \tag{5}$$

$$Test\ score_i = \alpha + \beta_2 R_i + X_i^{'}\gamma + \varepsilon_i \tag{6}$$

where R_i is a linear measure of relative age for each individual student i. Following Bedard and Dhuey (2006), I construct R_i as follows: since April is the school entry cutoff month, $R_i = 0$ for students born in March, R_i= 1 for students born in February, and so on until $R_i = 11$ for students born in April.

The only difference between Equations (5) and (6) is that the latter includes controls for parental background characteristics X_i. X_i comprises the six categorical variables for education of mothers and fathers, *ESCS*, and a dummy that takes one if the father is a white-collar worker. While I replace missing

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[43] Similar patterns are observed when the sample is divided by education of fathers and mothers (not shown).

[44] PISA 2003 also reports test scores on reading, science, and problem solving, but all the subjects show similar patterns to Figure 7D (not shown).

values with 0 and include the indicator for the missing variable, because the missing rate is very low, the estimates are very similar even if these observations are dropped from the data (not shown).

To test whether parental background drives the relative academic advantage of older children, I compare the coefficients on R_i in Equations (5) and (6). If parental characteristics are orthogonal to relative age R_i or if they have no direct impact on test scores (i.e., $\gamma = 0$ in Equation (6)), adding parental controls would not change the estimates of the relative age coefficients from Equation (5). The null hypothesis that $\beta_1 = \beta_2$ is tested by estimating both Equations (5) and (6), using seemingly unrelated regression estimation.[45]

Table 8 demonstrates the results from this exercise. Columns (1) and (2) use the data for the whole year, and Columns (3) and (4) use the data only for children born in March and April, respectively. Column (1) shows that children born one month earlier score higher by 0.014–0.024 standard deviation. However, Column (2) shows that once these parental characteristics are controlled, the relative academic advantage of older children is lowered by 20–35 percent, suggesting that some of the observed academic disadvantages of younger children stems from the selection of mothers. More drastically, if the sample is limited to students born in March and April, as shown in Columns (3) and (4), the estimates are reduced by as much as 25–60 percent after controlling parental backgrounds.[46] In all cases, a Wald test rejects that the coefficients are the same at the 5 percent level. Appendix Table H presents the estimates from the same exercise separately for each gender and shows that relative age advantages of female students are much more attenuated after controlling parental backgrounds than those of male students.

These results suggest that the observed relative academic disadvantage of younger children is a combination of double deficits: children born right before the school entry cutoff dates are relatively younger within the school cohort and these children also come from low SES families. However, it is important to note that while the magnitude of the effect becomes smaller, the relative age effects remain even after controlling for parental characteristics. The persistence and magnitude of relative age effects may be driven partly by a parsimonious set of parental characteristics available in the data or there is, indeed, a relative age advantage.[47]

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[45] In addition, R_i is replaced by 11 birth month dummies, and a Wald estimate is computed in which the null hypothesis is that coefficients on each birth month are the same. The Wald test ($\chi(11)$) rejects this hypothesis at the ten percent significance level for science (the results are available upon request).

[46] This effect may be underestimated because births on April 1 are included in April instead of March due to observing only birth months.

[47] In fact, Bedard and Dhuey (2006) exploit the school entry cutoff date among OECD countries, which include Japan, and show that younger children within the academic cohort perform worse than older children. It is important to note that, in addition to estimating each country separately, Bedard and Dhuey (2006) pool the data from countries with different school entry cutoff dates, and therefore, include birth of month fixed effect to control for season of birth effects. They still find that older children perform significantly better than younger children. In addition, Kawaguchi (2011) finds that those born in March have worse test scores, less completed years of schooling, and lower wages than those born in April in Japan.

5.2 Timing of Conception

The main focus of this paper is the timing of births instead of timing of conception. However, shifts in the timing of births are only one limited margin of adjustment. Because the school entry cutoff date has been in place since 1947 and has not changed, it is plausible that risk-averse mothers who have a strong preference for their children to be the oldest in class are likely to time conception so that birth does not fall near April 2.

The effect of the school entry rule on the timing of conception is difficult to identify as there are many reasons other than the school entry rule that influence the timing of conception compared to the timing of births, which has a clear cutoff date of April 2. Thus, the results here are at best suggestive, and I essentially rely on the seasonable patterns of births using pooled 1984–2010 birth data to shed light on this possibility.

Figure 9A displays the mean daily number births by parity of birth throughout the year, extending essentially Figure 6–1A to a whole year. While the number of firstborn births is always higher than that of second-born births throughout the year, the gap almost disappears around May and June.[48] As a result, Figure 9B shows that the proportion of second-born births to all births peaks around May–June.[49] While we cannot conclude that this pattern is driven entirely by the school entry rule, the seasonal birth pattern is at least consistent with the view that parents become more aware of the importance of the birth months of children at second births, possibly through learning. This result is in line with Buckles and Hungerman (2013), who document that some types of mothers carefully time conception in the US.

Interestingly, I find that this conception pattern can be inter-generational, especially for mothers who are themselves born in March and April, both of which are adjacent to the school entry cutoff date. Since 1992, mothers' exact birthdates have been reported in the birth data.[50] Table 9 shows the relation between mothers' birth months and their children's birth months. Row (1) shows the distribution of children's birth months by mothers born in January. Row (2) shows the case of mothers born in February, and so on. All figures in this table are in percentages. For example, cell (4)–(v) shows that mothers born in April give birth in May with a probability of 8.46 percent. The sum of each row should be equal to 100 percent. The cells with shadows show cases in which the birth month of a mother and that of her child are the same (i.e., diagonal cells (1)–(i), (2)–(ii), and so forth).[51]

Table 9 shows that mothers indeed seem to prefer to deliver in their own birth months. However, it

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[48] It is not clear why I observe another peak of firstborn births in the fall.

[49] Assuming the uniform distribution of births throughout a year as a counterfactual, I can calculate a very rough estimate of excess second-born births in May and June. This back-of-envelope calculation suggests that 6,094 births per year are "manipulated" by timing of conception because of the school entry rule. This figure is more than three times as large as births shifted by timing (1,835 births per year, as documented in Section 4.1). Note that this is an extremely rough estimate because I ignore other reasons to time deliveries in May and June, and thus, considerable caution should be employed in interpreting the result.

[50] I also confirm that the number of mothers' exact date of births peaks on April 2 (the results are available upon request).

[51] Note that April 1, the day before the school entry cutoff date, is included in March.

is interesting to note that mothers born in March and April have a much stronger tendency to do so: mothers born in March (April) are much more likely to give birth in March (April). To illustrate this, at the second to last row, for each column (i.e., for each child's birth month), I report the highest fraction of births in bold text excluding that of same birth month mothers (the cells with shadows). For example, for children born in January, the highest proportion of births excluding mothers born in January is mothers born in February at 8.65 percent (cell (2)–(i)). Then, the last row shows the difference between the proportion of their own cell (the cells with shadows) and the highest proportion presented in the second to last row. Using the same example, because the proportion of January births by mothers born in January is 8.63 percent (cell (1)–(i)), the difference is -0.02. The last row clearly shows that mothers born in March and April have by far a stronger preference to give birth in the same months as their own birth months (0.33 and 0.30 for mothers born in March and April, respectively) compared to mothers born in other months.

This result implies that mothers born in April may be aware of the relative academic advantage of older children due to their own experience, and thus, prefer to time births in April. On the other hand, it is quite surprising that mothers born in March do not avoid delivering births in March, even if they themselves may have suffered from this relative disadvantage while they were young. It is possible that mothers born in March are not aware of such disadvantages and/or they cannot simply afford an additional year of childcare costs. While the precise reasons for strong preference of mothers born in March and April to time births in their own birth month are unknown, the result possibly implies that, even though the magnitude is small, the persistence of mothers' preferences regarding birth months may partially contribute to the persistence of inter-generational immobility.

5.3 Hard or Soft Cutoff Date?

An important policy question is whether stricter enforcement of the school entry rule is socially beneficial. Red-shirting, the practice of delaying school entry of children to give them an edge, has become increasingly popular in the US and elsewhere where the enforcement of school entry rules is not strictly binding. In fact, one out of six children born in 1999 in the US delayed entering first grade by a year (Deming and Dynarski, 2008). Red-shirting can be socially problematic because it may exacerbate inequality as socioeconomically advantaged parents tend to hold back their children.

One proposed solution is strict enforcement of school entry policy that prohibits delayed entry (Deming and Dynarski, 2008). However, to the extent that high SES parents avoid early entry by manipulating either timing of births or timing of conception, the effect of such strict enforcement can be partially or even entirely offset.

From this perspective, Japan is an interesting case due to its hard cutoff date. The magnitude of the overall shifts documented in this paper is relatively small (half of the mean daily number of births), implying that an education system with stricter enforcement may possibly be effective in lessening delayed school entry. However, I cannot examine the magnitude of the shifts by parental SES due to the lack of such information in the birth data, and thus, this study may underestimate the magnitude of shifts by high SES parents. Furthermore, different seasonal patterns of birth months by parental SES using PISA indicate that timing of conception may be another way for high SES parents to evade the strict school entry rule. Because there are many reasons other than the school entry rule that differentially affect the timing of conception by different SES parents (e.g., types of occupation and industry), the argument here is at best speculative.

6 Conclusion

Many governments impose a school entry cutoff date, which mechanically creates a one year age gap within a school cohort. Parents—who value the potential long-term academic gains of children over the short-term gain of saving one year in childcare costs—have incentives to time births after the cutoff dates as a form of early childhood investment. Indeed, this paper found that in Japan, where the school entry rule is strictly enforced, more than 1,800 births per year are shifted roughly a week before the cutoff date to a week following the cutoff date. This finding suggests that parents exploit birth timing as a means of early childhood investment.

Previous studies, which investigated the distribution of births around the school entry cutoff date in the US, Chile, and Argentina, did not find such behavioral responses of parents, probably because of weak enforcement of the school entry rule. However, the strict enforcement of the school entry rule is not unique to Japan. Whether a similar shift in the timing of births is observable in other countries with strict enforcement is potentially interesting. In particular, given the lack of key parental variables such as education and income in Japan's birth data, an investigation of whether strict enforcement is socially beneficial using data from these countries is an avenue for future research.

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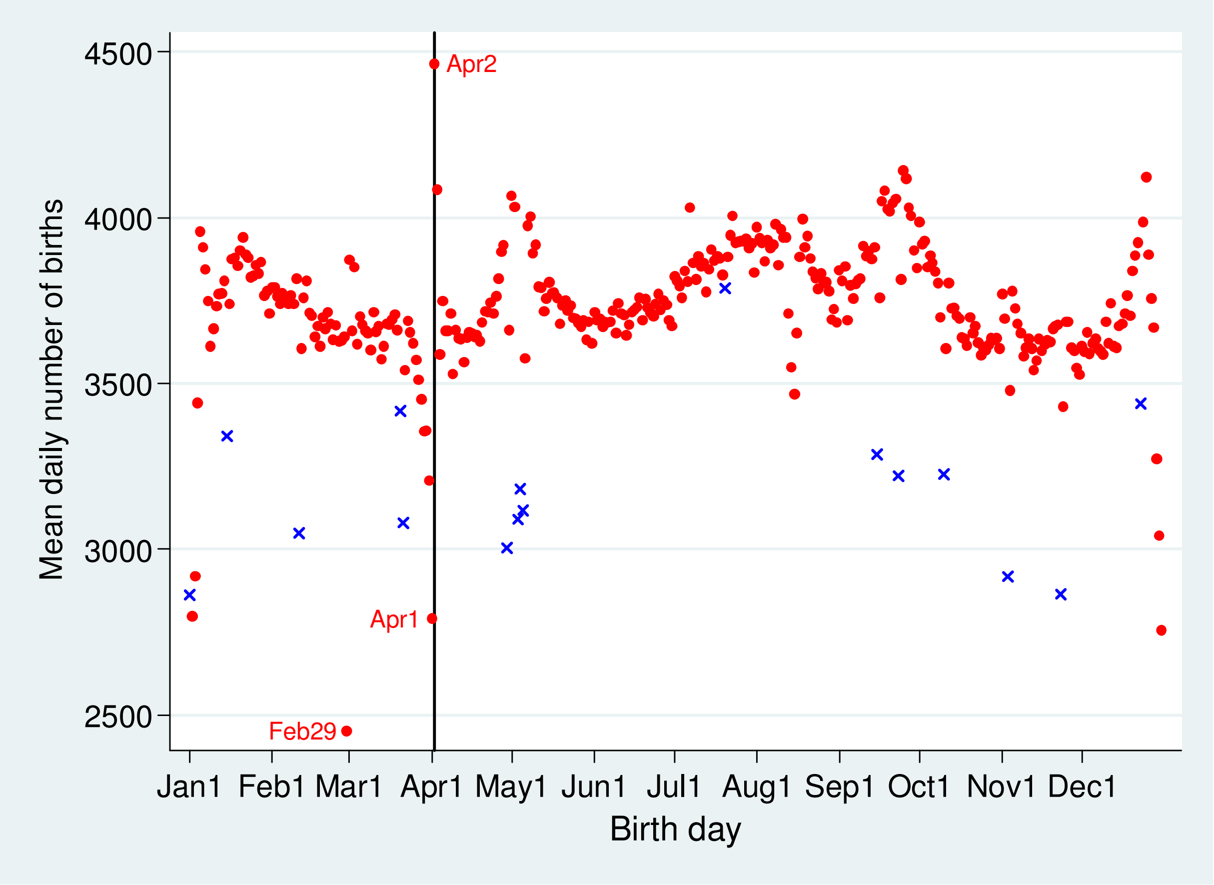
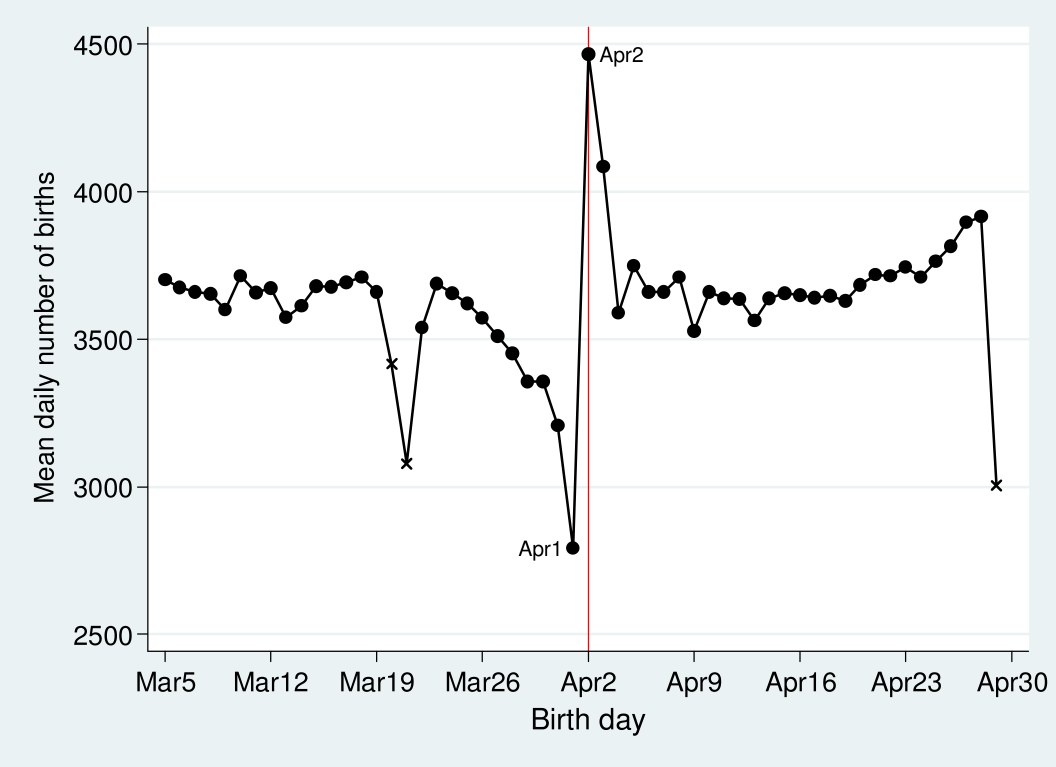
Figure 1: Mean daily number of births throughout the year



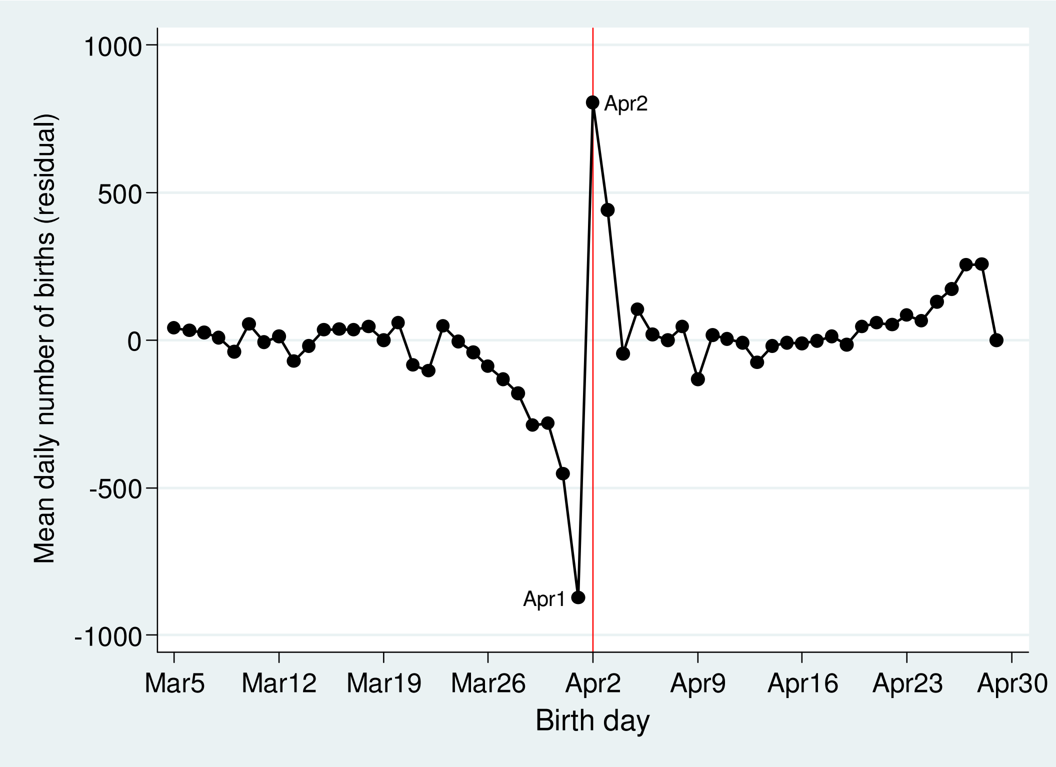
Note: Each plot is the mean daily number of births. The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The markers with cross signs are holidays. The data come from pooled 1974–2010 birth data.

Figure 2: Mean daily number of births around April 2

A. Raw data

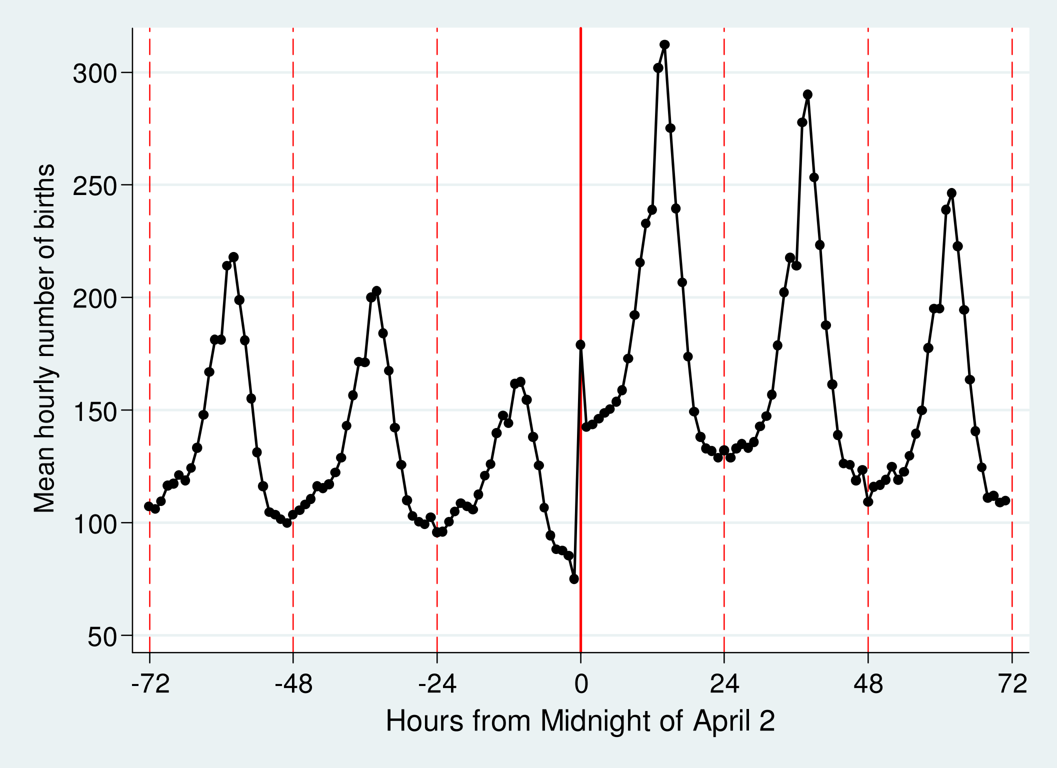


B. Adjusted



Note: Each plot is the mean daily number of births. The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The markers with cross signs in Panel A are holidays (March 20 or March 21 depending on the year, and April 29). Panel B adjusts for holidays, day of week, and year fixed effects. The data come from pooled 1974–2010 birth data.

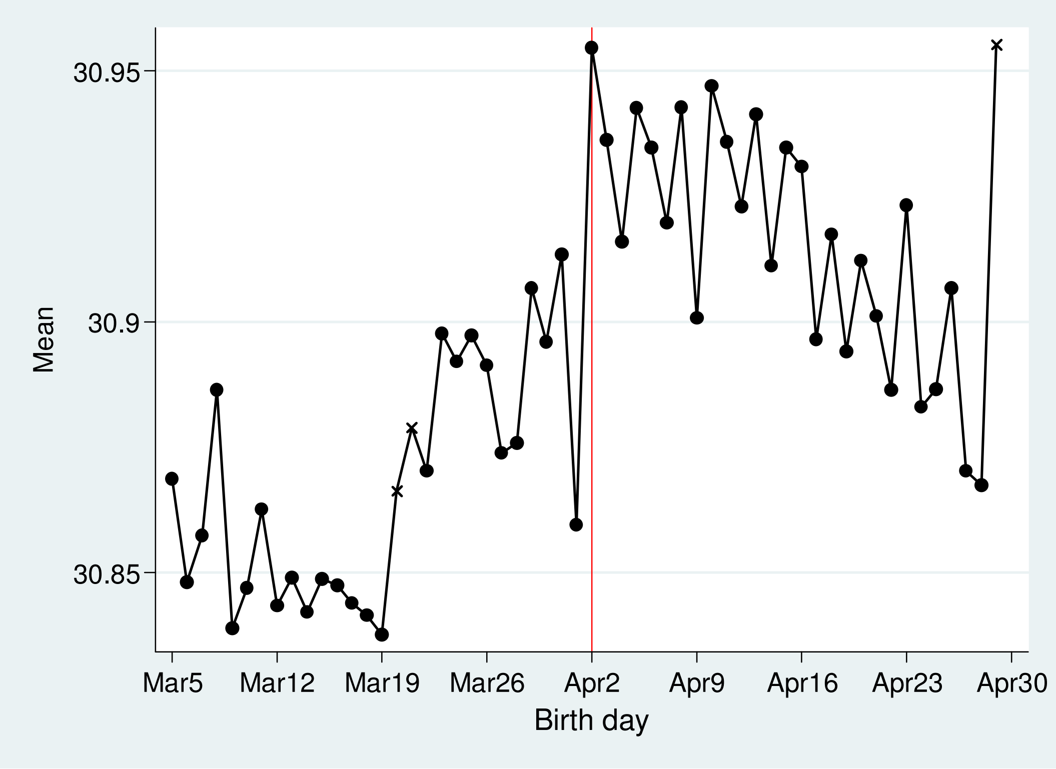
Figure 3: Reported birth hours within 72 hours from midnight of April 2



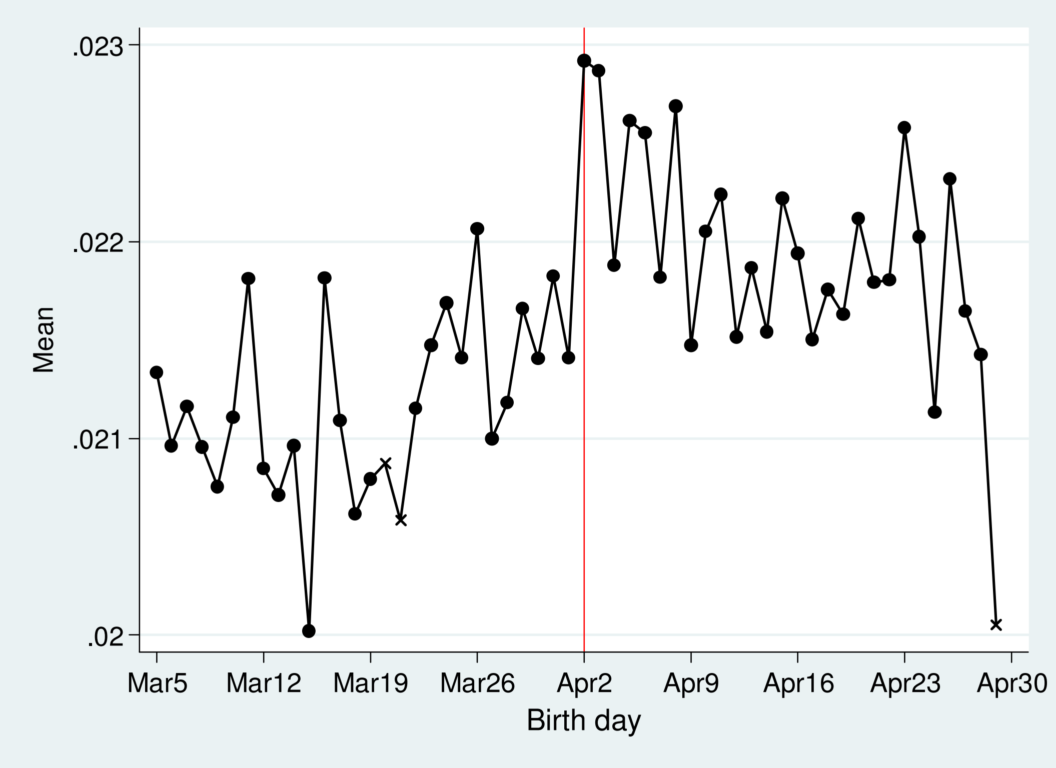
Note: Each plot is the mean hourly number of births. The vertical solid line corresponds to the midnight of April 2, which is the exact school entry cutoff time in Japan. Every vertical dashed line corresponds to the midnight of other days. The data come from 1974–2010 pooled birth data.

Figure 4: Child Outcomes

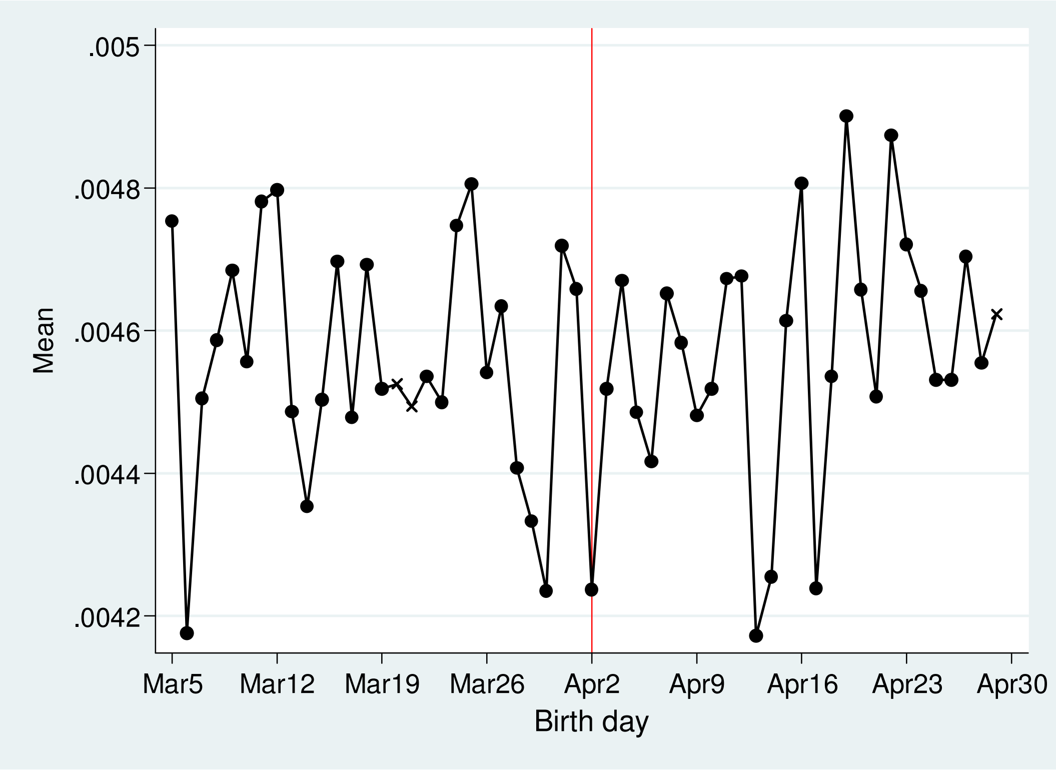
A. Birth weight (100 grams)



B. Proportion of birth weights over 4000 grams

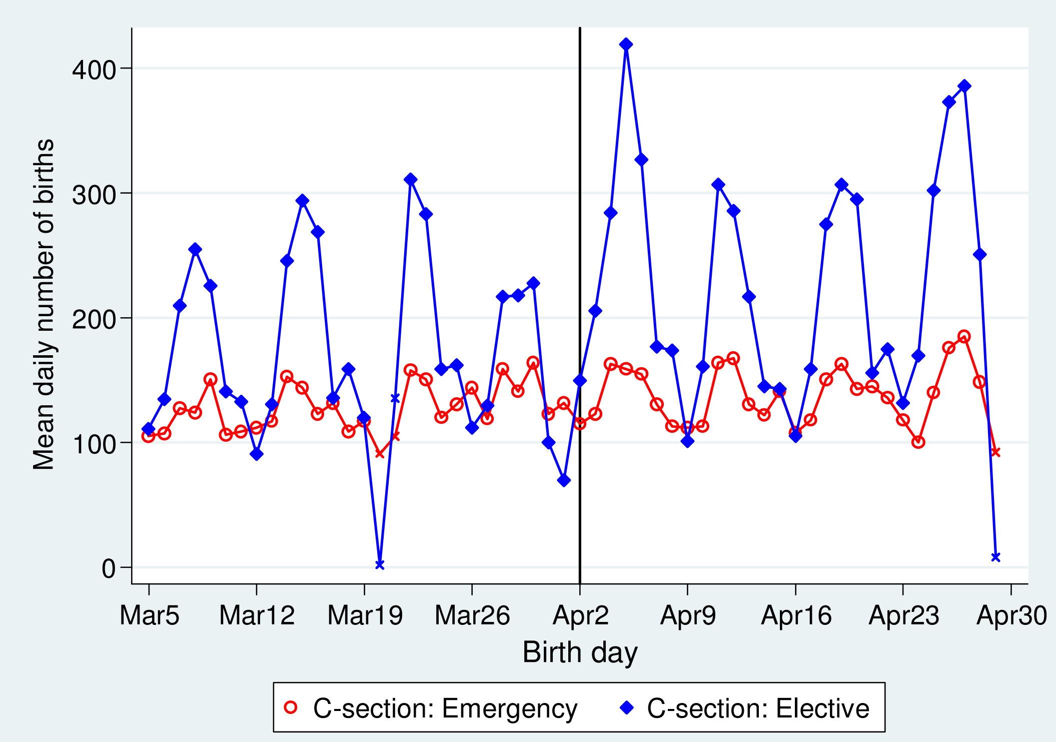


C. Infant mortality



Note: Each plot is the mean outcome in each day. The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The markers with cross signs are holidays. The data for Panels A and B come from pooled 1974–2010 birth data. The data for Panel C come from pooled 1974–2010 birth and death data.

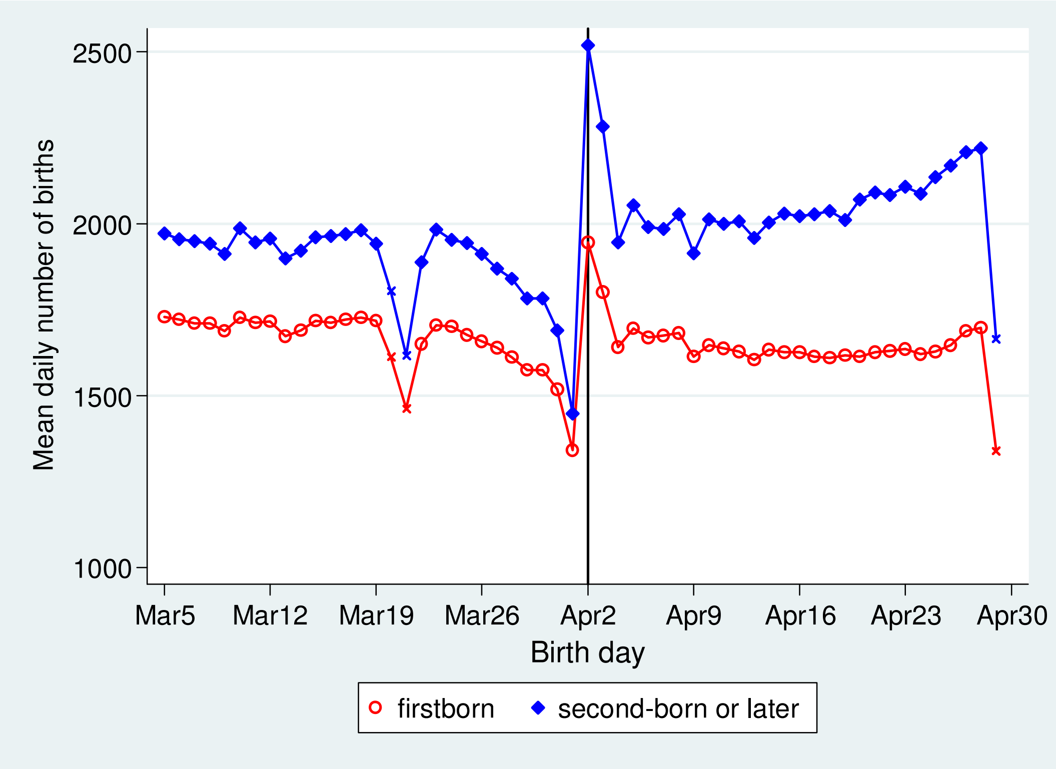
Figure 5: C-section (raw data)



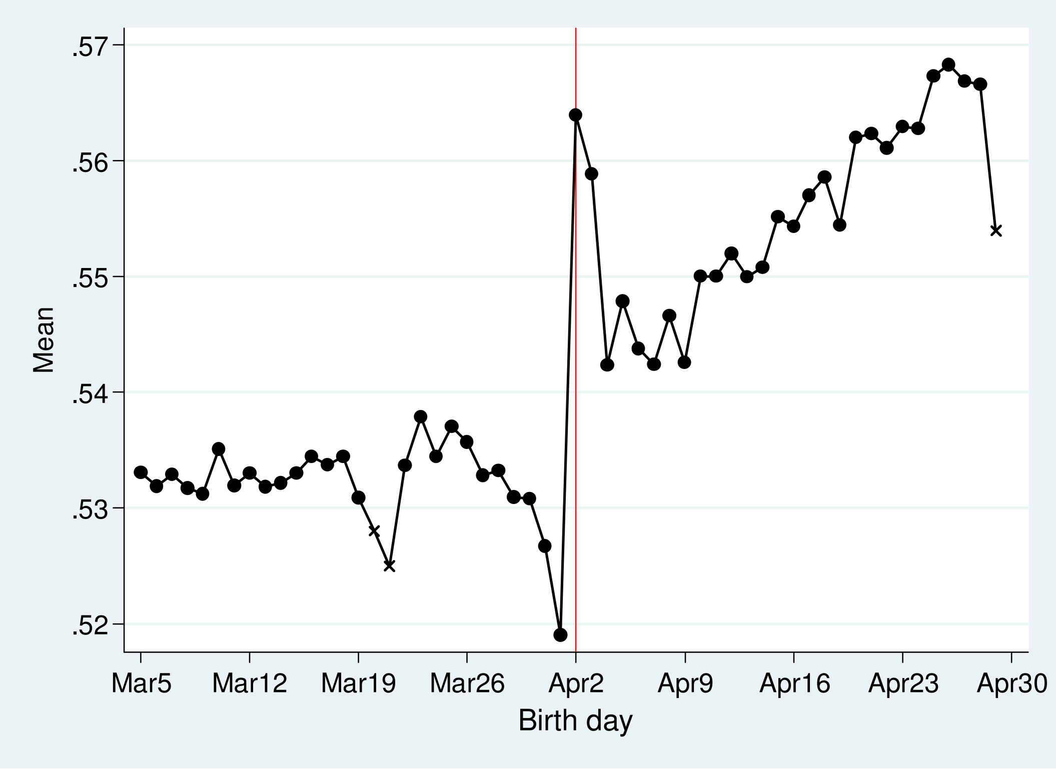
Note: Each plot is the mean daily number of births. The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from pooled 2011–2012 insurance claim data.

Figure 6-1: Heterogeneous responses, by parity

A. Number of births by parity (raw data)



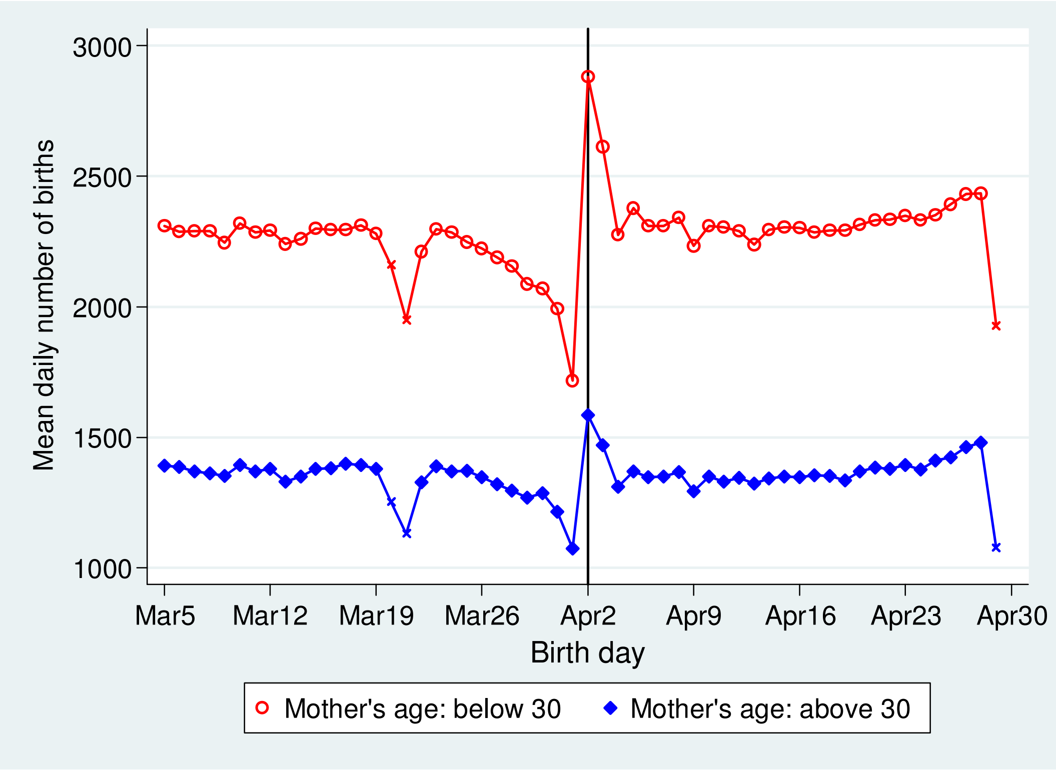
B. Proportion of second-born births among all births



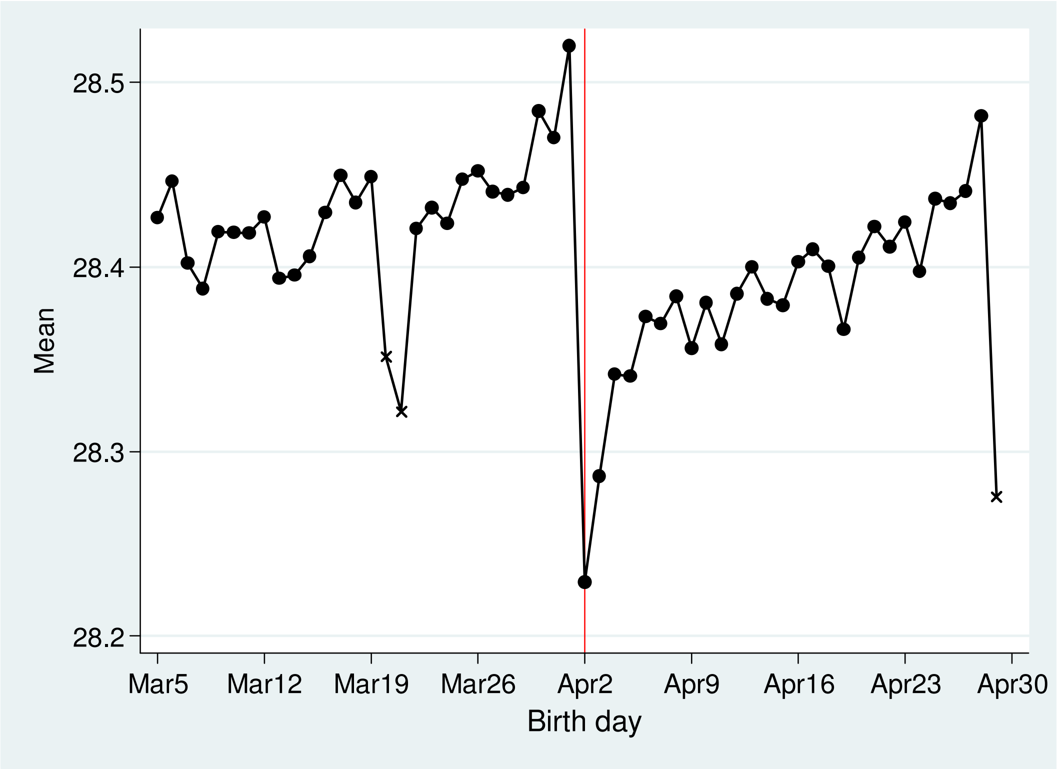
Note: Each plot in Panel A is the mean daily number of births. Each plot in Panel B is the mean outcome in each day. The markers with cross signs in Panels A and B are holidays. The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from pooled 1974–2010 birth data.

Figure 6-2: Heterogeneous responses, by mothers’ age

A. Number of births by mother’s age (raw data)



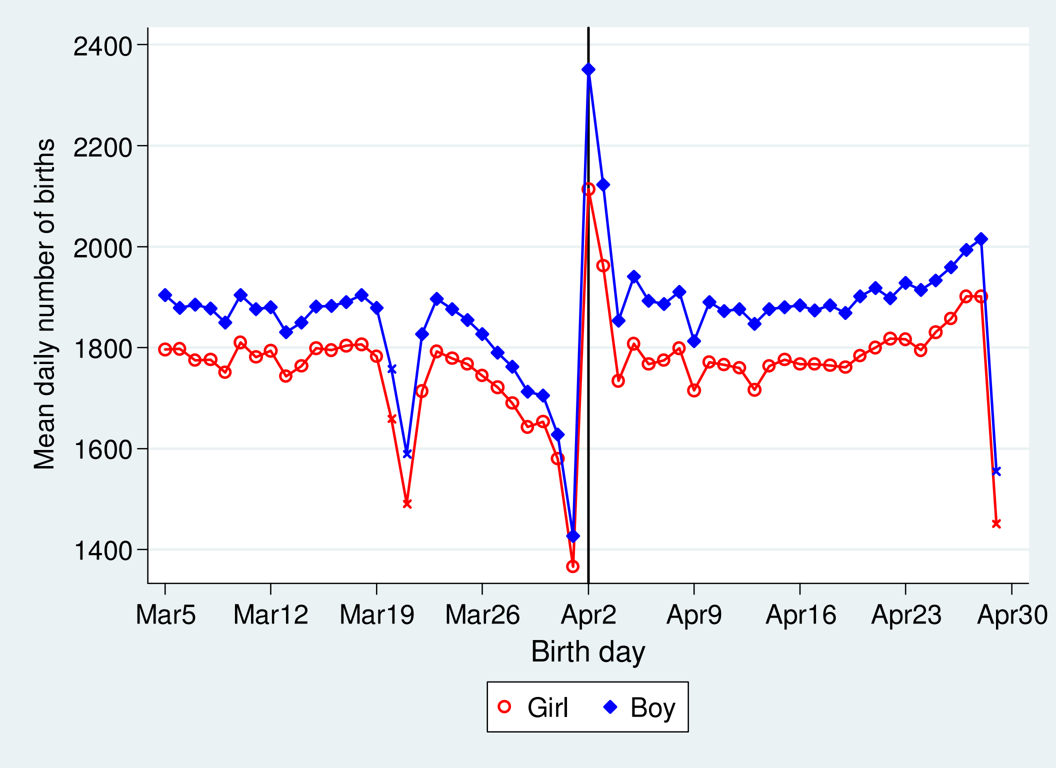
B. Mothers’ age



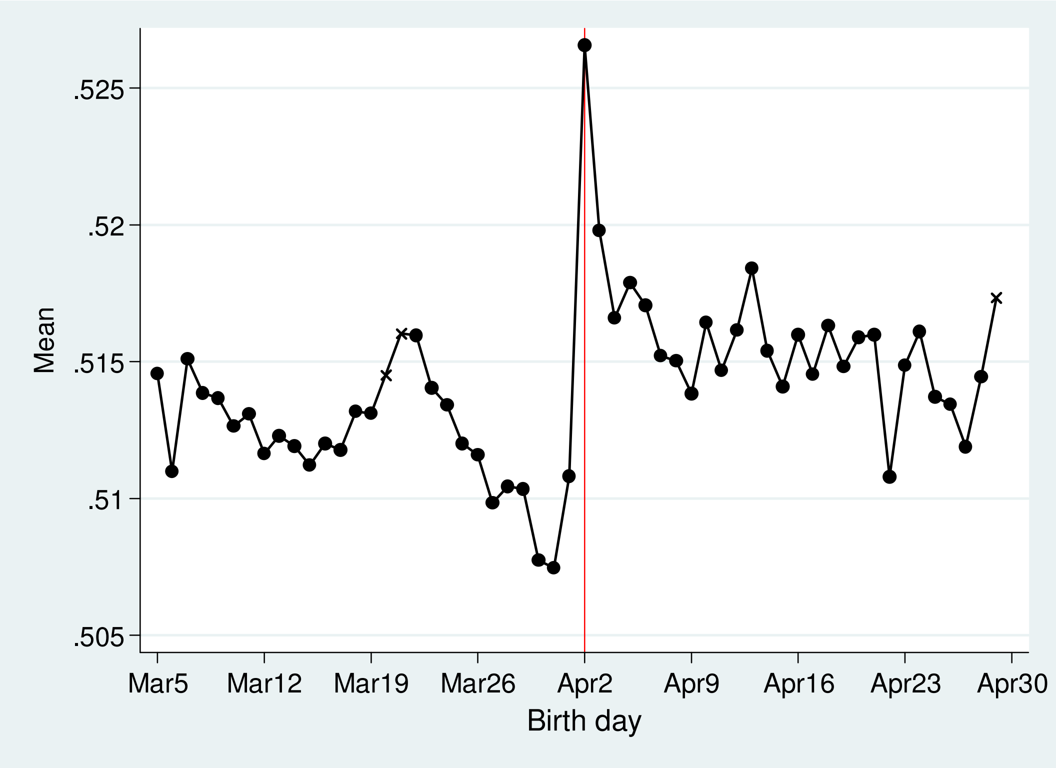
Note: Each plot in Panel A is the mean daily number of births. Each plot in Panel B is the mean outcome in each day. The markers with cross signs in Panels A and B are holidays. The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from pooled 1974–2010 birth data.

Figure 6-3: Heterogeneous responses, by gender

A. Number of births by gender (raw data)



B. Proportion of male births

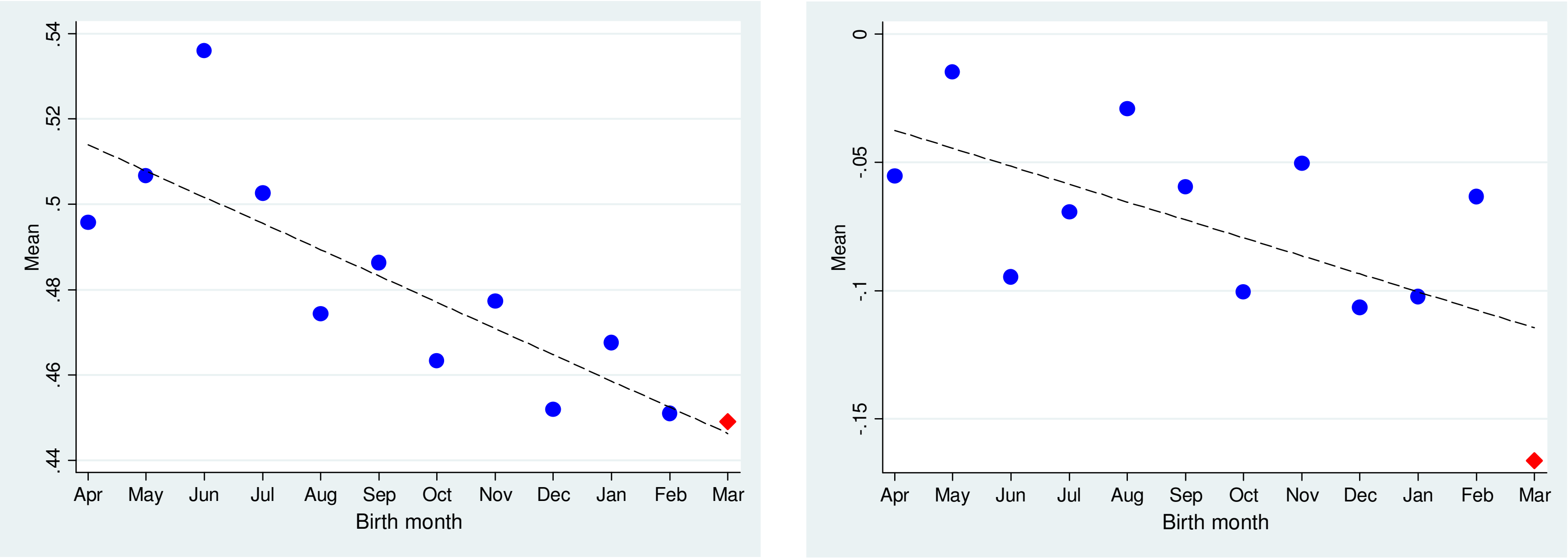


Note: Each plot in Panel A is the mean daily number of births. Each plot in Panel B is the mean outcome in each day. The markers with cross signs in Panels A and B are holidays. The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from pooled 1974–2010 birth data.

Figure 7: Birth months and outcomes

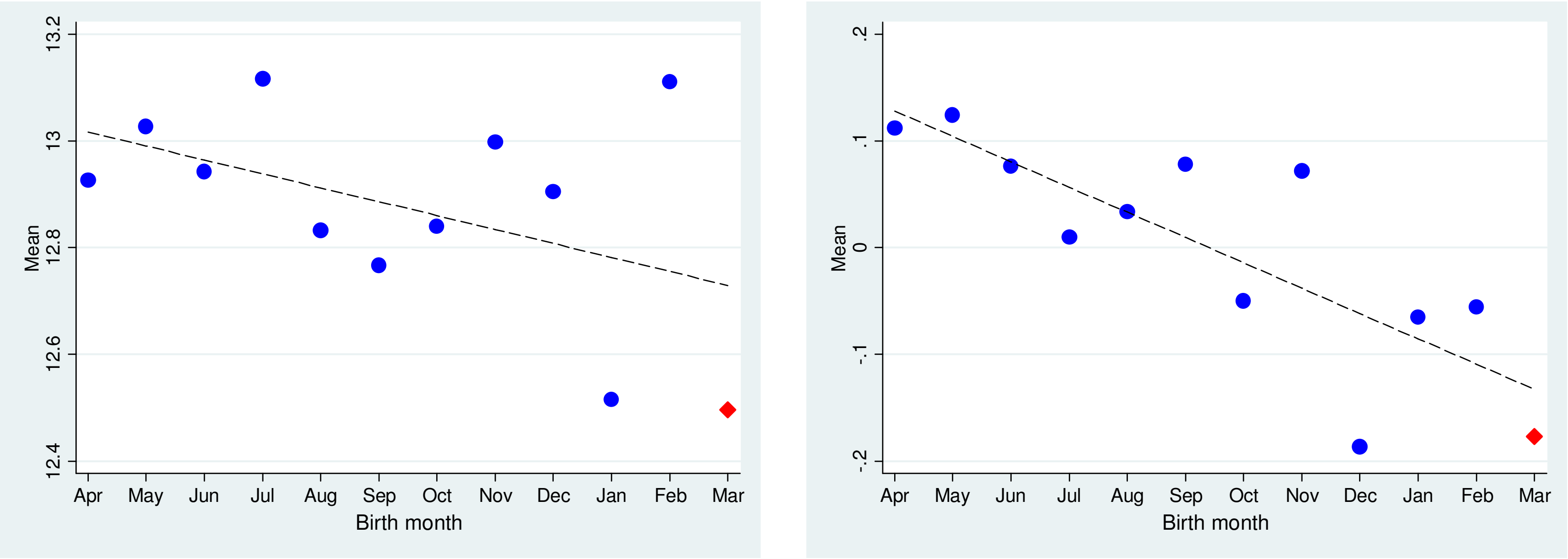
A. Father is white-collar

C. Family socioeconomic status



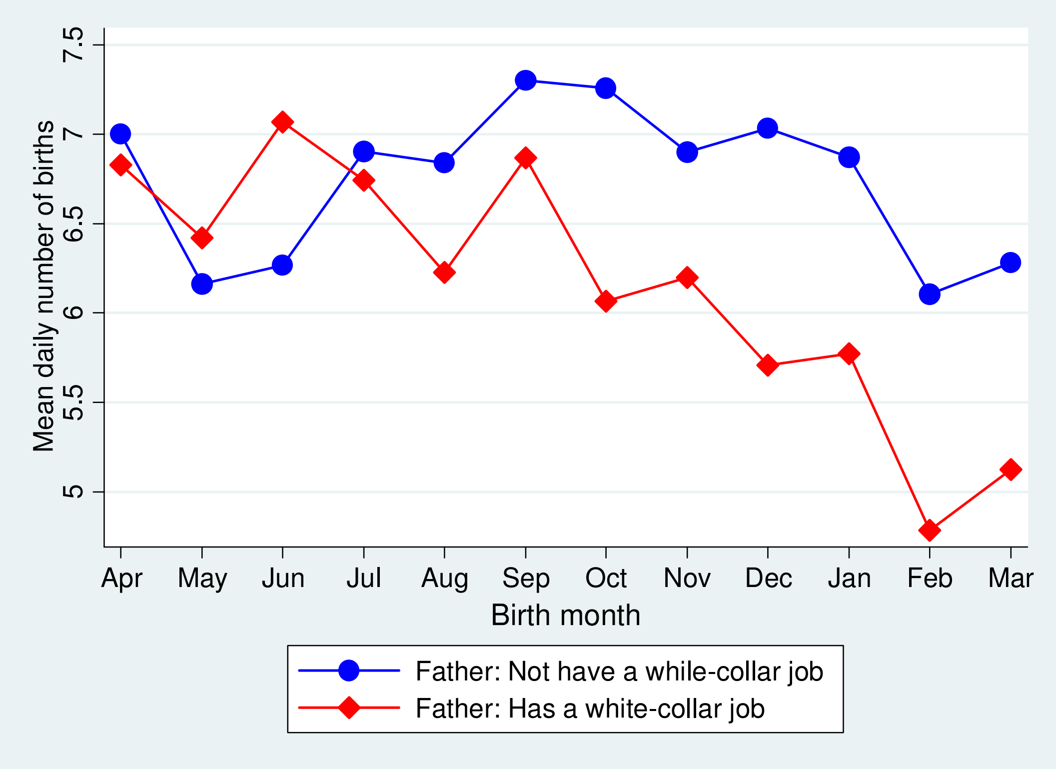
B. Fathers' years of schooling

D. Math score



Note: Each plot is the mean of each outcome at birth month of students. The markers with diamonds correspond to March-born students. Math score is standardized to mean 0 with standard deviation of 1. Family socioeconomic status is economic, social and cultural status (a variable called *ESCS*) constructed by the OECD based on parental education, parental occupation, and home possession, where a higher value indicates higher SES (OECD, 2003).The dotted line is the linear projection. The data come from PISA 2003 data for Japan.

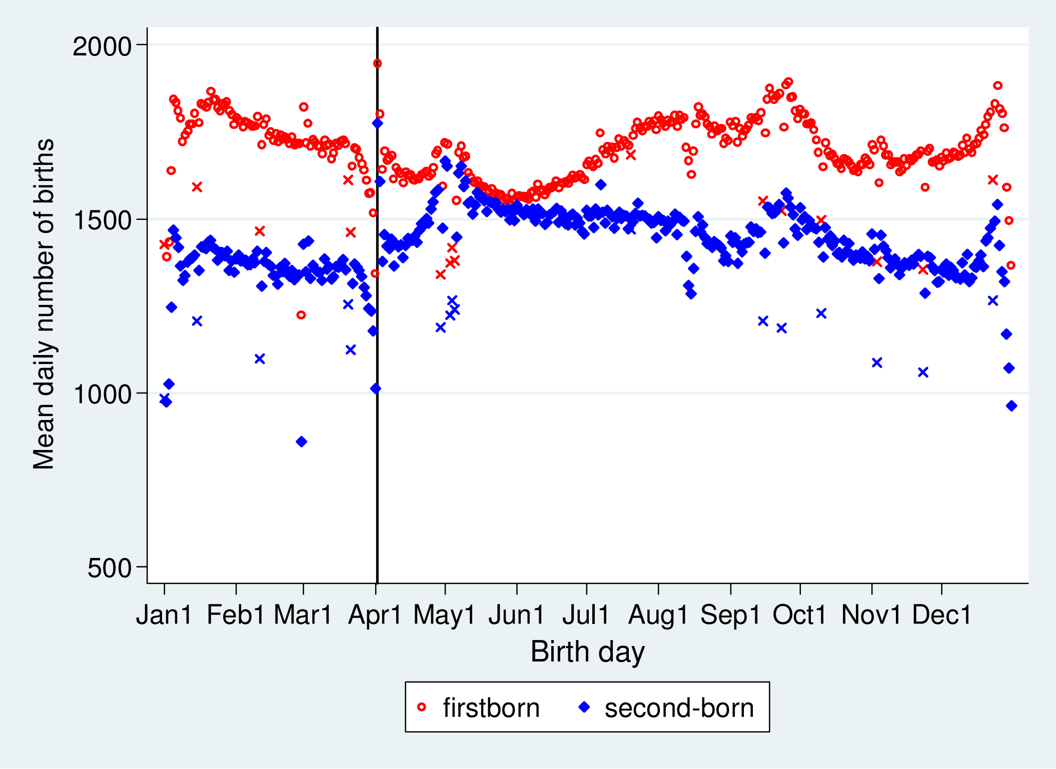
Figure 8: Mean daily number of births by fathers' job types



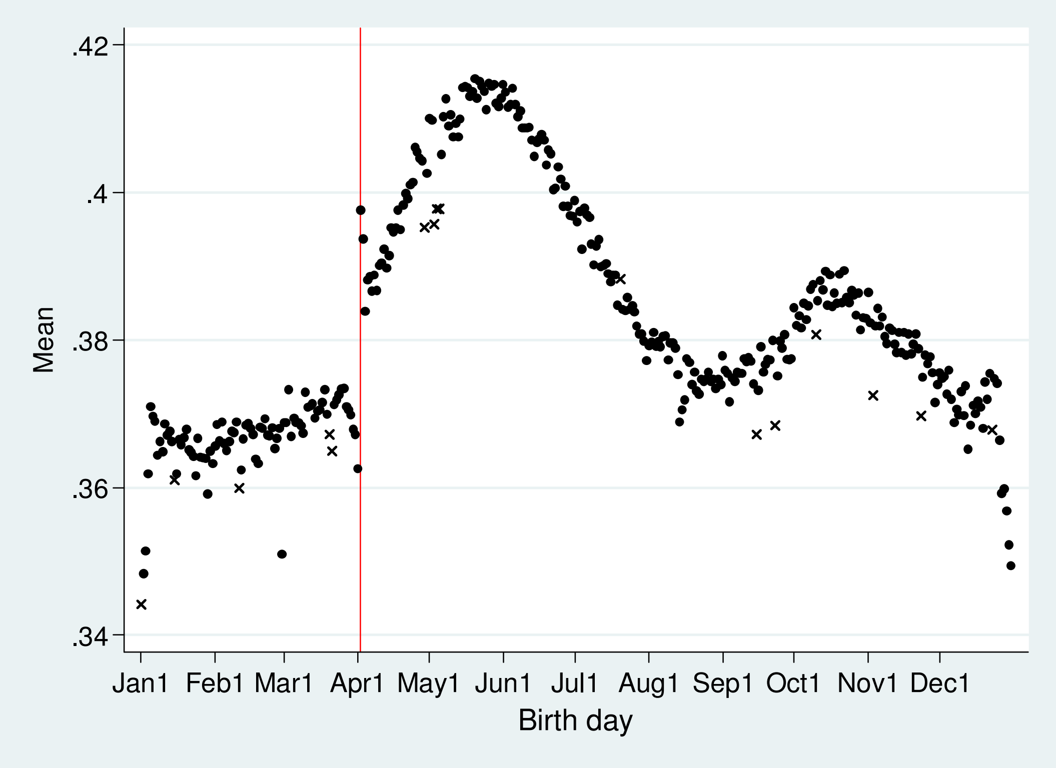
Note: Each plot is the mean daily number of births, which is the number of students born each month divided by the number of days in each month. The data come from PISA 2003 data for Japan.

Figure 9: Mean daily number of births through the year, by parity

A. Firstborn and second-born births



B. Proportion of second-born births among all births



Note: Each plot in Panel A is the mean daily number of births. Each plot in Panel B is the mean outcome in each day. The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The markers with cross signs are holidays. The data come from pooled 1974–2010 birth data.

Table 1: Top five and bottom five days of mean daily number of births within a year

	Date	Mean daily number of births	Ratio to average daily birth
Top 5			
	April 2	**4,465**	**1.20**
	Sep 25	4,143	1.12
	Dec 25	4,122	1.11
	Sep 26	4,119	1.11
	April 3	**4,085**	**1.10**
Bottom 5			
	Feb 29	2,452	0.66
	Dec 31	2,757	0.74
	April 1	**2,791**	**0.75**
	Jan 2	2,798	0.75
	Jan 1	2,862	0.77

Notes: The ratio to the average is the average number of births on a given day divided by average births across all days. Therefore, a value of 1.1 represents a 10 percent increase in daily births compared to the yearly average. Mean daily births during 1974–2010 are 3,713. The days included within a week of April 2 are indicated by boldface. April 2 is the school entry cutoff date in Japan. The data come from pooled 1974–2010 birth data.

Table 2: Shift of births

Windows	(1) ±7 days	(2) ±14 days	(3) ±21 days	(4) ±28 days
A: Number of births				
After	524.2***	268.6***	178.9***	166.2***
	(34.3)	(20.6)	(14.4)	(11.5)
Number of births moved	*1,835*	*1,880*	*1,879*	*2,327*
R2	0.83	0.86	0.89	0.90
B: ln(number of births)				
After	0.136***	0.070***	0.047***	0.043***
	(0.008)	(0.005)	(0.004)	(0.003)
Share of births moved	*7.0%*	*3.6%*	*2.4%*	*2.2%*
R2	0.86	0.88	0.90	0.91
N	518	1,036	1,554	2,072

Notes: * p<0.10, ** p<0.05, *** p<0.01. Coefficients on *After* are reported. *After* is a dummy that takes 1 if the birthday is after April 2 in each year and 0 otherwise. April 2 is the school entry cutoff date in Japan. Robust standard errors are reported in parentheses. The data come from pooled 1974–2010 birth data. The sample is the number of daily births within the relevant window from the school entry cutoff date. The window denotes the number of days before and after April 2. For example, the ±7 day window covers the 7 days prior to April 2, and the 7 days after April 2. All specifications include holiday, year, and day of week fixed effects. Number of births moved is $W\beta/2$, where W is the number of days in the window, and β is the coefficient on *After*. The share of births moved is $\exp(\beta/2)-1$. Note that mean daily births during 1974–2010 is 3,713.

Table 3: Children's characteristics

	Birth weight	Birth weight >4000 g	Gestation >42 wks	Infant mortality (per 1000 births)
	(1)	(2)	(3)	(4)
After	2.198***	0.0005**	0.0007***	-0.090
	(0.762)	(0.0002)	(0.0003)	(0.090)
R2	0.988	0.967	0.987	0.883
Mean	3,090.42	0.022	0.022	4.155
N	518	518	518	518

Notes: * p<0.10, ** p<0.05, *** p<0.01. Coefficients on *After* are reported. *After* is a dummy that takes 1 if the birthday is after April 2 in each year and 0 otherwise. April 2 is the school entry cutoff date in Japan. Robust standard errors are reported in parentheses. The data for Columns (1)–(3) come from pooled 1974–2010 birth data. The data for Column (4) come from pooled 1974–2010 birth and death data. The window is restricted to the 7 days prior to April 2, and the 7 days after April 2. All specifications include holiday, year, and day of week fixed effects.

Table 4: Shift of C-section births from insurance claim data

	Any C-section	Elective C-section	Emergency C-section
	(1)	(2)	(3)
After	0.198***	0.467***	-0.040
	(0.061)	(0.085)	(0.043)
Share of births moved	*10.4%*	*26.3%*	*-2.0%*
R2	0.961	0.985	0.910
Mean daily births	170	100	69

Notes: * p<0.10, ** p<0.05, *** p<0.01. Outcome is log number of births. Coefficients on *After* are reported. *After* is a dummy that takes 1 if the birthday is after April 2 in each year and 0 otherwise. April 2 is the school entry cutoff date in Japan. Robust standard errors are reported in parentheses. The data come from pooled 2011–2012 insurance claim data. The window is restricted to the 7 days prior to April 2, and the 7 days after April 2. All specifications include holiday, year, and day of week fixed effects. The share of births moved is $\exp(\beta/2)-1$, where β is the coefficient on *After*.

Table 5: Heterogeneous responses, by mothers' and children's characteristics

	Parity		Mother's age		Gender	
	Firstborn	Second-born or above	Less than 30	More than 30	Girl	Boy
	(1)	(2)	(3)	(4)	(5)	(6)
After	0.101***	0.164***	0.151***	0.109***	0.118***	0.153***
	(0.007)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Share of births moved	*5.2%*	*8.6%*	*7.9%*	*5.6%*	*6.1%*	8.0%
R2	0.851	0.871	0.949	0.847	0.863	0.855
Mean of daily births	1,645	1,938	2,253	1,330	1,740	1,843
N	518	518	518	518	518	518

Notes: * p<0.10, ** p<0.05, *** p<0.01. Outcome is log number of births. Coefficients on *After* are reported. *After* is a dummy that takes 1 if the birthday is after April 2 in each year and 0 otherwise. April 2 is the school entry cutoff date in Japan. Robust standard errors are reported in parentheses. The data come from pooled 1974–2010 birth data. The window is restricted to the 7 days prior to April 2, and the 7 days after April 2. All specifications include holiday, year, and day of week fixed effects. The share of births moved is exp(β/2)−1, where β is the coefficient on *After*.

Table 6: Magnitude of shifts and capacity of child care centers

	(1)	(2)	(3)	(4)
	Basic	With Controls	Exclude Tokyo and Osaka	Limit sample to 2000–2007
Capacity	0.116***	0.118***	0.125***	0.107
	(0.026)	(0.027)	(0.036)	(0.107)
N	1,598	1,597	1,529	376
R2	0.495	0.495	0.481	0.339
Weight	X	X	X	X
Year fixed effects	X	X	X	X
Prefecture fixed effects	X	X	X	X
Controls		X	X	X
Without Tokyo and Osaka			X	

Notes: * p<0.10, ** p<0.05, *** p<0.01. Coefficients on *capacity* are reported. *Capacity* is defined as total slots of the daycare centers (i.e., total capacity of daycare centers) divided by the total number of females between the ages of 20–39 years, the child-bearing age at prefecture-year level. There are 47 prefectures in Japan. Other controls include real GDP per capita, which is deflated by a prefectural GDP deflator to Yen in 2000, job application-to-opening ratio at October of year *y*-1 (a year prior to March/April when the shifts of births occur in year *y*), and application-to-opening ratio in March of the year *y*. All specifications include prefecture and year fixed effects. The weight is the inverse of square of standard errors from first-stage estimation described in detail in the text. Tokyo and Osaka are the two largest prefectures in Japan. Standard errors clustered at prefectural level are reported in parentheses.

Table 7: Magnitude of the timing of shifts from other studies

Authors	Policy	Country	Incentives	Could policy also affect conceptions?	Share of births moved
Dickert-Conlin and Chandra (1999)	Tax changes from 1979–1993	US	Hasten	Yes	13.6%
Gans and Leigh (2009)	Baby Bonus introduction in 2004	Australia	Delay	No	16.2%
Gans and Leigh (2009)	Baby Bonus increase in 2006	Australia	Delay	Yes	9.2%
Tamm (2012)	Parental leave benefit reform in 2006/2007	Germany	Delay	Yes	7.8%
Neugart and Ohlsson (2013)	Parental leave benefit reform in 2006/2007	Germany	Delay	Yes	5.4%
Shigeoka (2014)	School entry cutoff dates from 1974–2010	Japan	*Both*	Yes	7.0%

Notes: The share of births moved in the last column is based on estimates from a seven-day window from the cutoff dates.

Table 8: Estimates of relative age on test scores (PISA 2003)

Sample	All months				March vs. April			
	(1)	(2)	*Reduction*	χ 2(1) [p-value]	(3)	(4)	*Reduction*	χ 2(1) [p-value]
<u>A: Math</u>								
Relative age	0.0239***	0.0192***	*19.6%*	6.03	0.0262***	0.0180***	*31.6%*	6.27
	(0.0050)	(0.0043)		[0.014]	(0.0066)	(0.0061)		[0.012]
R2	0.008	0.158			0.021	0.201		
<u>B: Reading</u>								
Relative age	0.0224***	0.0178***	*19.9%*	6.39	0.0254***	0.0183***	*25.8%*	5.55
	(0.0047)	(0.0041)		[0.012]	(0.0062)	(0.0059)		[0.018]
R2	0.019	0.166			0.040	0.214		
<u>C: Science</u>								
Relative age	0.0136***	0.0089**	*34.6%*	6.70	0.0122*	0.0052	*57.0%*	6.45
	(0.0048)	(0.0042)		[0.010]	(0.0064)	(0.0062)		[0.011]
R2	0.003	0.147			0.004	0.169		
<u>D: Problem solving</u>								
Relative age	0.0237***	0.0194***	*18.1%*	5.53	0.0280***	0.0203***	*26.9%*	5.29
	(0.0050)	(0.0042)		[0.019]	(0.0067)	(0.0064)		[0.022]
R2	0.007	0.151			0.024	0.184		
Sample size	4,700	4,700			759	759		
Gender	X	X			X	X		
Fathers’ education		X				X		
Mothers’ education		X				X		
Family socioeconomic status		X				X		
Father is white-collar		X				X		

Notes: * p<0.10, ** p<0.05, *** p<0.01. Coefficients on *relative age* are reported. Since April is the school entry cutoff month, relative age takes 0 for students born in March, and it takes 11 for students born in April. Each test score is standardized to mean 0 with standard deviation of 1. Family socioeconomic status is economic, social and cultural status (a variable called *ESCS*) constructed by the OECD based on parental education, parental occupation, and home possession, where a higher value indicates higher SES (OECD, 2003). Robust standard errors are reported in parentheses. P-values are reported in the brackets. The data come from PISA 2003 data for Japan.

Table 9: Mothers' birth months and children's birth months

		Children's birth month											
		(i) Jan	(ii) Feb	(iii) Mar	(iv) Apr	(v) May	(vi) Jun	(vii) Jul	(viii) Aug	(ix) Sep	(x) Oct	(xi) Nov	(xii) Dec	*Sum*
Mothers' birth month	(1) Jan	8.63	7.71	8.56	7.75	8.39	8.13	8.69	8.63	8.58	8.52	8.00	8.41	*100*
	(2) Feb	**8.65**	7.83	**8.58**	7.77	8.32	8.13	8.67	8.57	8.53	8.46	8.06	8.43	*100*
	(3) Mar	8.59	**7.81**	8.91	7.61	8.37	8.12	8.67	8.62	8.48	8.36	8.01	**8.45**	*100*
	(4) Apr	8.48	7.65	8.33	8.19	8.46	8.22	8.74	8.65	8.50	8.44	8.00	8.34	*100*
	(5) May	8.34	7.63	8.51	**7.89**	8.62	8.31	8.83	8.64	8.56	8.42	7.96	8.29	*100*
	(6) Jun	8.32	7.57	8.54	7.86	8.53	8.30	8.83	8.72	8.60	8.47	7.96	8.29	*100*
	(7) Jul	8.31	7.51	8.44	**7.89**	8.50	8.31	8.89	8.77	8.61	8.48	7.96	8.33	*100*
	(8) Aug	8.33	7.48	8.42	7.80	**8.54**	**8.32**	**8.93**	8.79	8.61	8.47	7.99	8.33	*100*
	(9) Sep	8.37	7.52	8.36	7.75	8.47	8.31	8.83	**8.78**	8.71	8.54	8.01	8.35	*100*
	(10) Oct	8.34	7.48	8.41	7.78	8.37	8.24	8.85	8.73	**8.74**	8.69	8.08	8.31	*100*
	(11) Nov	8.40	7.50	8.42	7.77	8.40	8.18	8.84	8.76	8.63	**8.60**	8.15	8.37	*100*
	(12) Dec	8.46	7.54	8.41	7.81	8.37	8.13	8.71	8.73	8.66	8.56	**8.10**	8.52	*100*
	Highest of (1)-(12) excluding Own	8.65	7.81	8.58	7.89	8.54	8.32	8.93	8.78	8.74	8.60	8.10	8.45	
	Own-Highest	-0.02	0.02	0.33	0.30	0.08	-0.02	-0.04	0.01	-0.03	0.09	0.05	0.07	

Notes: All figures in this table are in percentages. The cells with shadow are the cases where the birth month of a mother and that of her child are the same (i.e., diagonal cells (1)–(i), (2)–(ii), and so forth). For each column (i.e., for each child's birth month), the second to last row reports the highest fraction of births in bold text, excluding that of same birth month mothers (the cells with shadows). The last row shows the difference between own cell (i.e., mothers' birth months are the same as children's birth months) and the highest proportion presented in the second to last row. April 1, a day before the school entry cutoff date, is included in March. The data come from pooled 1992–2010 birth data.

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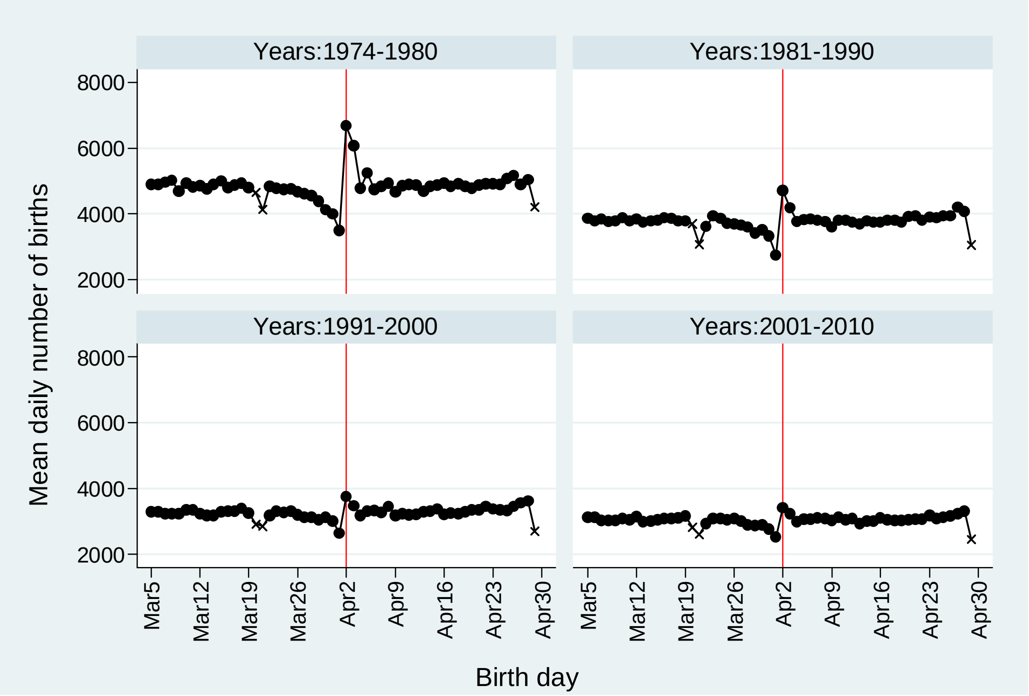
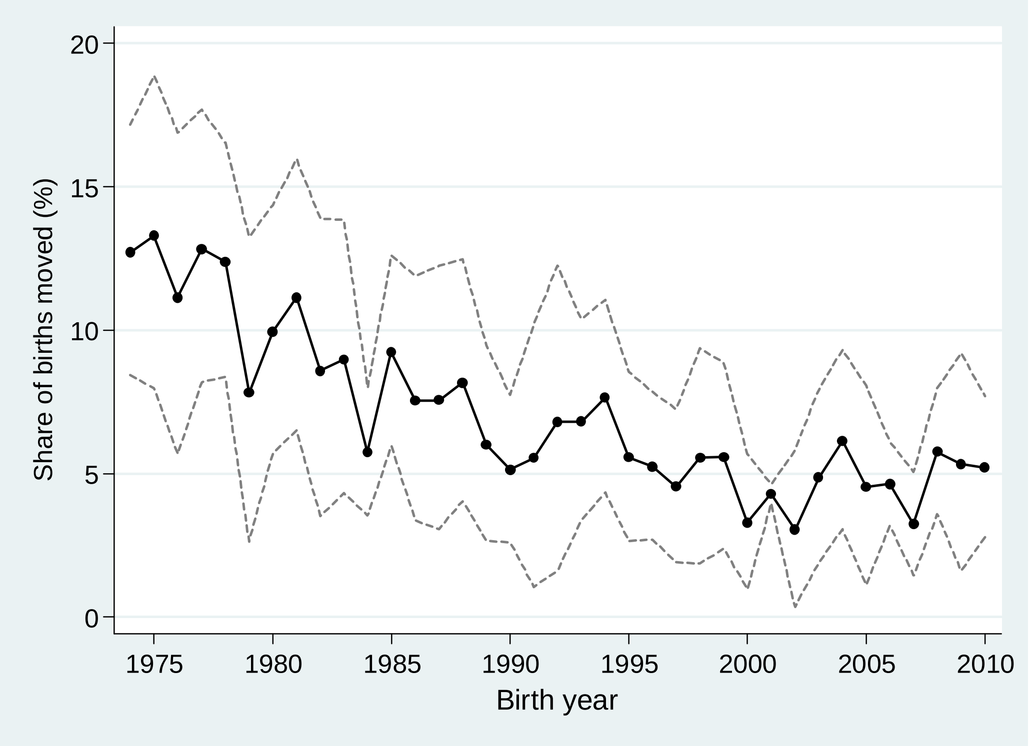
Appendix Figures and Tables

Figure A: Mean daily number of births around April 2, by period



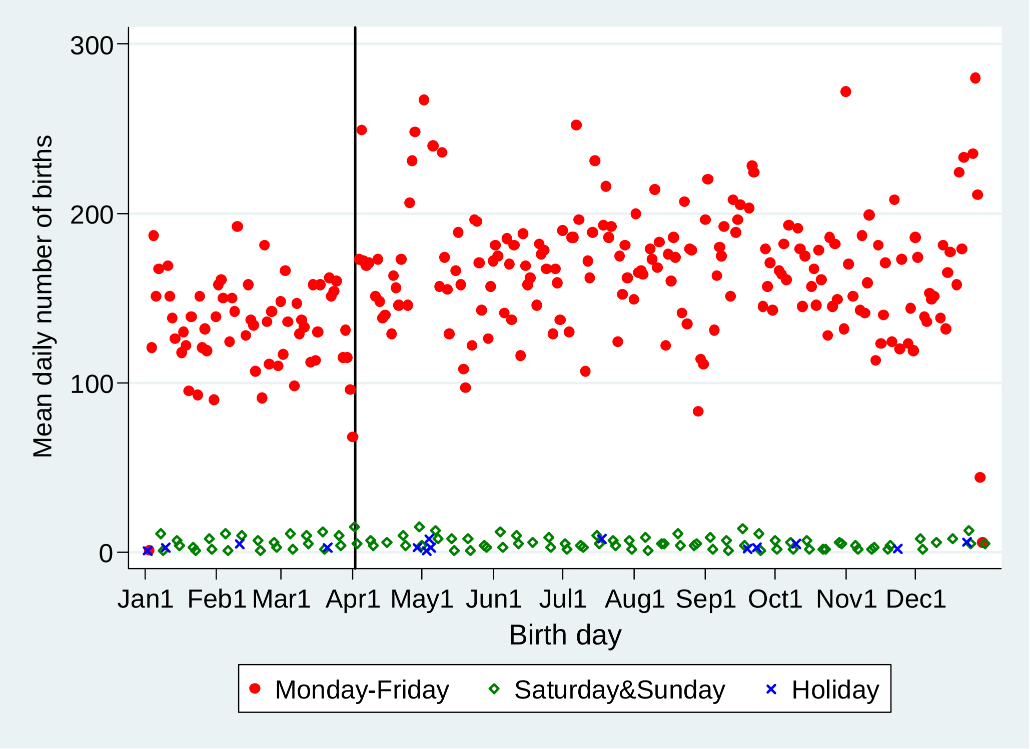
Note: Each plot is the mean daily number of births. The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The markers with cross signs are holidays. The data come from 1974–2010 birth data.

Figure B: Share of births moved by each birth year



Note: The dotted line represents 95 % confidence interval. The data come from 1974–2010 birth data.

Figure C: Seasonality of elective C-sections (Year 2011)



Note: Eachplot is the mean daily number of births. The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from 2011insurance claim data.

TableA: Summary statistics of birth and death data

	7 days before cutoff date (1)	7 days after cutoff date (2)	Dif (2)-(1) (3)	Entire year (4)
Mother’s age (in years)	29.84	29.75	-0.091***	29.81
Firstborn birth	0.47	0.45	-0.020***	0.46
Second-born birth	0.37	0.39	0.021***	0.38
Birth weight (in grams)	3,089	3,094	4.7***	3,089
Birth weight (>3500 grams)	0.1783	0.1819	0.0037***	0.1785
Birth weight (>4000 grams)	0.0215	0.0225	0.0010***	0.0216
Birth weight (>4500 grams)	0.0017	0.0018	0.0001*	0.0017
Gestational length (weeks)	39.21	39.23	0.017*	39.20
Home deliveries	0.003	0.004	0.0005**	0.003
Infant mortality	0.0042	0.0041	-0.0001	0.0042
Mean daily number of births	3,321	3,845	524***	3,713

Note: * p<0.10, ** p<0.05, *** p<0.01. Colum (1) is mean from the sample in 7 days prior to April 2, and Column (2) is mean from sample in the 7 days after April 2, and Column (3) is difference between Columns (2) and (1). Column (4) is the mean from data that cover entire year.The data come from pooled 1974–2010 birth data.

TableB: Robustness checks

Windows	±7 days		±14 days	
	(1)	(2)	(3)	(4)
A: Number of births				
After2nd× April	524.2***	540.0***	268.6***	305.1***
	(34.3)	(34.3)	(20.6)	(21.2)
After2nd		-15.9**		-36.5***
		(7.0)		(4.9)
Number of births moved	*1,835*	*1,890*	*1,880*	*2,136*
N	518	6,202	1,036	12,404
R2	0.83	0.89	0.86	0.89
B: ln(number of births)				
After2nd× April	0.136***	0.140***	0.070***	0.079***
	(0.008)	(0.008)	(0.005)	(0.005)
After2nd		-0.004**		-0.009***
		(0.002)		(0.001)
Share of births moved	*7.0%*	*7.3%*	*3.6%*	*4.0%*
N	518	6,202	1,036	12,404
R2	0.86	0.88	0.88	0.88

Note: * p<0.10, ** p<0.05, *** p<0.01. To facilitate the comparison between different specifications, Columns (1) and (3) report the estimates from Equation (1), while Columns (2) and (4) report estimates from the Equation (2), which use the observations from other months as well.The data come from pooled 1974–2010 birth data.

Table C: Children’s characteristics

		(1)	(2)	(3)	(4)
Windows	Mean	±7 days	±14 days	±21 days	±28 days
A: Birth weight (100 g)					
After	3,090.4	2.198***	3.785***	4.667***	4.436***
		(0.762)	(0.534)	(0.443)	(0.407)
R2		0.988	0.981	0.979	0.975
B: Birth weight>4000 g					
After	0.022	0.0005**	0.0006***	0.0007***	0.0007***
		(0.0002)	(0.0002)	(0.0001)	(0.0001)
R2		0.940	0.942	0.940	0.937
C: Gestation>42 wks					
After	0.023	0.0007***	0.0001	0.0003*	0.0005***
		(0.0003)	(0.0002)	(0.0002)	(0.0002)
R2		0.969	0.961	0.954	0.948
D: Mortality per 1000 births					
After	4.155	-0.090	-0.100	-0.030	-0.010
		(0.090)	(0.060)	(0.050)	(0.050)
R2		0.883	0.844	0.826	0.817
N		518	1,036	1,554	2,072

Notes: * p<0.10, ** p<0.05, *** p<0.01. Coefficients on *After*are reported. *After* is a dummy that takes 1 if the birthday is after April 2 in each year and 0 otherwise. April 2 is the school entry cutoff date in Japan. Robust standard errors are reported in parentheses. The window denotes the number of days before and after the April 2. For example, the ±7 day window covers the 7 days prior to April 2, and the 7 days after April 2. All specifications include holiday, year, and day of week fixed effects. The share of births moved is exp(β/2)−1, where β is the coefficient on *After*.The datafor Panels A, B, and Ccome from pooled 1974–2010 birth data. The data for Panel Dcome from pooled1974–2010 birth anddeath data.

Table D:Shift of C-section births from insurance claim data

	Mean daily births	(1)	(2)	(3)	(4)
		±7 days	±14 days	±21days	±28 days
A: Any					
After	170	0.198***	0.086**	0.094***	0.137***
		(0.061)	(0.042)	(0.031)	(0.034)
Share of births moved		*10.4%*	*4.4%*	*4.8%*	*7.1%*
R2		0.961	0.959	0.963	0.945
B: Elective					
After	100	0.467***	0.241***	0.199***	0.227***
		(0.085)	(0.070)	(0.059)	(0.080)
Share of births moved		*26.3%*	*12.8%*	*10.4%*	*12.0%*
R2		0.985	0.979	0.976	0.941
C: Emergency					
After	69	-0.040	-0.018	0.017	0.057**
		(0.043)	(0.035)	(0.027)	(0.028)
Share of births moved		*-2.0%*	*-0.9%*	*0.9%*	*2.9%*
R2		0.910	0.854	0.850	0.799
N		28	56	84	112

Notes: * p<0.10, ** p<0.05, *** p<0.01. Outcome is log number of births. Coefficients on *After* are reported. *After* is a dummy that takes 1 if the birthday is after April 2 in each year and 0 otherwise. April 2 is the school entry cutoff date in Japan. Robust standard errors are reported in parentheses. The window denotes the number of days before and after the April 2. For example, the ±7 day window covers the 7 days prior to April 2, and the 7 days after April 2. All specifications include holiday, year, and day of week fixed effects. The share of births moved is exp(β/2)−1, where β is the coefficient on *After*.The data come from pooled 2011–2012insurance claim data.

Table E: Heterogeneous responses, by gender/parity of children

	Girl			Boy		
	All births	Firstborn	Second-bornor above	All births	Firstborn	Second-born or above
	(1)	(2)	(3)	(4)	(5)	(6)
After	0.118***	0.084***	0.145***	0.153***	0.117***	0.183***
	(0.029)	(0.024)	(0.033)	(0.029)	(0.024)	(0.034)
Share of births moved	*6.1%*	*4.3%*	*7.5%*	*8.0%*	*6.0%*	*9.6%*
R2	0.948	0.944	0.946	0.952	0.944	0.950
Meandaily births	1,740	799	940	1,843	846	998
N	518	518	518	518	518	518

Note: * p<0.10, ** p<0.05, *** p<0.01. Coefficients on *After* are reported. *After* is a dummy that takes 1 if the birthday is after April 2 in each year and 0 otherwise. April 2 is the school entry cutoff date in Japan. Robust standard errors are reported in parentheses. The window is restricted to the 7 days prior to April 2, and the 7 days after April 2. All specifications include holiday, year, and day of week fixed effects. The share of births moved is exp(β/2)−1, where β is the coefficient on *After*.The datacome from pooled 1974–2010 birth data.

TableF: Source of variables

Variable name	Years available	Mean	SD	Source
Total slots of day-care centers	1974–2007: yearly level	42,199	30,829	Survey of Social Welfare Institutions
Number of female population between ages 20-39	1970–2010: every five years	371,624	378,970	Census
GDP per capita	1974–2009: yearly level	2,269	730	Prefecture SNA, available at http://www.esri.cao.go.jp/jp/sna/data/data_list/kenmin/files/files_kenmin.html (last accessed March 11, 2013)
Prefecture specific deflator	1974–2009: yearly level	91	12	Prefecture SNA, available at http://www.esri.cao.go.jp/jp/sna/data/data_list/kenmin/files/files_kenmin.html (last accessed March 11, 2013)
Job application-to-opening ratio (October)	1974–2009: monthly level	0.863	0.561	Job/employment placement services statistics, available at http://www.e-stat.go.jp/SG1/estat/List.do?lid=000001108017 (last accessed March 11, 2013)
Job application-to-opening ratio (March)	1974–2009: monthly level	0.839	0.475	Job/employment placement services statistics, available at http://www.e-stat.go.jp/SG1/estat/List.do?lid=000001108017 (last accessed March 11, 2013)

TableG: Summary statistics of PISA 2003

	(1)	(2)	(3)	(4)
	All	March-born	April-born	Dif (3)-(2)
A. Test Score				
Math	-0.006	-0.173	0.101	0.274***
	(0.998)	(1.035)	(0.957)	(0.072)
Reading	-0.007	-0.196	0.081	0.277***
	(1.000)	(1.036)	(0.959)	(0.072)
Science	-0.006	-0.124	0.007	0.130*
	(0.998)	(1.033)	(0.984)	(0.073)
Problem solving	-0.007	-0.203	0.095	0.298***
	(0.997)	(1.045)	(0.963)	(0.073)
B. Family controls				
Family socioeconomic status	-0.084	-0.167	-0.068	0.099*
	(0.732)	(0.702)	(0.740)	(0.053)
Father’s years of education	12.84	12.50	12.89	0.391*
	(3.15)	(3.26)	(3.09)	(0.23)
Mother’s years of education	12.84	12.83	12.85	0.02
	(2.44)	(2.39)	(2.48)	(0.18)
Father has a white-collar job	0.477	0.447	0.494	0.047
	(0.500)	(0.498)	(0.501)	(0.036)
N	4,700	358	401	

Note: * p<0.10, ** p<0.05, *** p<0.01. Column (1) is mean from the entire sample. Column (2) is mean ofMarch-born students, and column (3) is mean ofApril-born students. Column (4) is difference between Columns (3) and (2). Each test score is standardized to mean 0 with standard deviation of 1. Family socioeconomic status is economic, social and cultural status (a variable called *ESCS*) constructed by the OECD based on parental education, parental occupation, and home possession, where a higher value indicates higher SES (OECD, 2003).The data come from PISA 2003 data for Japan.

TableH: Estimates of relative age on test scores, by gender (PISA 2003)

	All months				March vs. April			
	No controls (1)	Controls (2)	*Reduction*	χ2(1) [p-value]	No controls (3)	Controls (4)	*Reduction*	χ2(1) [p-value]
Male								
A: Math								
Relative age	0.0273***	0.0237***	*13.1%*	1.17	0.0221**	0.0192**	*13.3%*	0.31
	(0.0079)	(0.0066)		[0.278]	(0.0103)	(0.0097)		[0.577]
R2	0.007	0.184			0.012	0.232		
B: Reading								
Relative age	0.0252***	0.0219***	*13.0%*	1.03	0.0249**	0.0223**	*10.3%*	0.21
	(0.0074)	(0.0062)		[0.310]	(0.0099)	(0.0093)		[0.650]
R2	0.006	0.185			0.016	0.256		
C: Science								
Relative age	0.0150**	0.0114*	*23.6%*	1.21	0.0102	0.0080	*21.6%*	0.18
	(0.0073)	(0.0063)		[0.272]	(0.0097)	(0.0094)		[0.674]
R2	0.002	0.174			0.003	0.214		
D: Problem solving								
Relative age	0.0301***	0.0266***	*11.5%*	1.20	0.0321***	0.0288***	*10.3%*	0.44
	(0.0078)	(0.0065)		[0.273]	(0.0105)	(0.0101)		[0.505]
R2	0.009	0.173			0.025	0.209		
Sample size	2,301	2,301			356	356		
Female								
A: Math								
Relative age	0.0208***	0.0160***	*23.0%*	3.88	0.0297***	0.0174**	*41.4%*	7.68
	(0.0061)	(0.0053)		[0.049]	(0.0093)	(0.0078)		[0.0056]
R2	0.006	0.137			0.032	0.227		
B: Reading								
Relative age	0.0198***	0.0144***	*27.2%*	5.05	0.0257***	0.0146*	*43.3%*	6.76
	(0.0062)	(0.0055)		[0.025]	(0.0089)	(0.0079)		[0.0093]
R2	0.005	0.136			0.025	0.204		
C: Science								
Relative age	0.0123*	0.0073	*40.4%*	4.57	0.0139	0.0041	*70.5%*	5.21
	(0.0065)	(0.0058)		[0.033]	(0.0091)	(0.0080)		[0.022]
R2	0.002	0.129			0.007	0.167		
D: Problem solving								
Relative age	0.0179***	0.0134**	*25.1%*	3.48	0.0244***	0.0127*	*47.9%*	7.25
	(0.0062)	(0.0054)		[0.062]	(0.0091)	(0.0077)		[0.0071]
R2	0.004	0.136			0.021	0.216		
Sample size	2,399	2,399			403	403		
Gender	X	X			X	X		
Father's education		X				X		
Mother's education		X				X		
Family socioeconomic status		X				X		
Father is white-collar		X				X		

Note: * p<0.10, ** p<0.05, *** p<0.01. Coefficients on *relative age* are reported. Since April is the school entry cutoff month, relative age takes 0 for students born in March, and it takes 11 for students born in April. Each test score is standardized to mean 0 with standard deviation of 1. Robust standard errors are reported in parentheses. P-values are reported in the brackets. The data come from PISA 2003 data for Japan.