School Entry Cutoff Date and the Timing of Births

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Abstract

This paper shows that mothers take into account the long-term academic consequences of their children when they make decisions on the birth timing. Many countries require children to reach a certain age by a specified date in the calendar year in order to start kindergarten/primary school. There is a clear trade-off for parents to time a birth *after* the school entry cutoff date; births just after cutoff date may benefit children from being older among the school cohort, which is shown to provide the children with academic advantage, while parents have to bear an additional year of child care costs. Using the universe of births during 1974–2010 in Japan, I find that more than 1,800 births per year are shifted roughly a week before the cutoff date to a week following the cutoff date. The overall shifts in births, however, may mask heterogeneous responses of mothers. I find that births by younger mothers, 2nd-born births, and male births are more shifted than births by older mothers, 1st-born births, and female births, respectively. I also find some suggestive evidence that families with high socioeconomic status are more likely to time births after the school entry cutoff date. This study may have implications for growing literature that assumes births around the school entrance cut-off dates are random.

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1. Introduction

Many studies have documented that mothers shift the timing of births in response to the incentives created by birth-related cutoff date such as tax benefits (Dickert‐Conlin and Chandra, 1999) and monetary bonuses (Gans and Leigh, 2009).[2] However, most of the incentives are immediate and short-term financial incentives. In this paper, I examine whether mothers also take into account the long-term academic consequences of their children when they make decision on the birth timing.

Many countries require children to reach a certain age by a specified date in the calendar year in order to start primary school. Parents who happen to give a birth near the school entry cutoff dates face a trade-off to time a birth *after* the cutoff date. The benefit of shifting births after the school entry cutoff date is accrued to children since academic performance, and even later labor outcome, are shown to be better for the older children within an academic cohort (relative age effects) including the case of Japan, a setting in this study (e.g., Bedard and Dhuey, 2006).[3] However, there is a cost for parents because parents need to retain their children longer before sending to school, and thus bear one additional year of child care costs and possibly lost wages from reduced labor force participation (Dickert-Conlin and Elder, 2010).[4] Thus, if mothers value the potential long-term academic gains of children over the short-term gain from saving of one-year child care cost, mothers may shift births after the cutoff dates.

Japan is an interesting setting to examine such a trade-off since the stake of the birth timing is particularly high for parents and hence their children because the school entry cutoff date is strictly enforced in Japan. In fact, the delay of the entry into primary school is very rare. For example, Kawaguchi (2012) documents that only 0.03 percent of primary school age children are exempted from the mandatory starting age.[5] Therefore the timing of births indeed determines when the

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[2] Since the use of birth-related cutoff to determine eligibility for policy programs due to governments' resource constraints is quite common across the world, past studies have analyzed the timing of births in response to a variety of cutoff date. Some papers find the evidence on shifts in the timing of births, while others do not. For example, shifts of birth timings are found in tax incentives in the US (Dickert-Conlin and Chandra, 1999; Schulkind and Shapiro, 2014; LaLumia et al., 2013); tax incentives in Japan (Kurenishi and Wakabayashi, 2008); bonus payment in Australia (Gans and Leigh, 2009); parental leave benefit reform in Germany (Tamm, 2012, Neugart and Ohlsson, 2013); while shifts are not found in expansion of job-protection leave in Germany (Dustmann and Schonberg, 2012); extending the leave duration in Austria (Lalive and Zweimuller, 2009).

[3] The evidence come from a cross-country study by Bedard and Dhuey (2006) and country-level studies by Kawaguchi (2011) for Japan, Elder and Lubotsky (2009) for the US, Fredriksson and Öckert (2013) for Sweden, Puhani and Weber (2007) for Germany, Strom (2004) for Norway, Crawford et al. (2007) for England, and McEwan and Shapiro (2008) for Chile.

[4] There is some convincing evidence that availability of kindergarten affects mother's labor supply (e.g., Berlinski and Galiani, 2007; Cascio, 2009; Gelbach, 2002; Schlosser, 2011). These findings suggest that kindergarten implicitly serve as a day care.

[5] Note, however, that this is not only unique to Japan. Bedard and Dhuey (2006) lists four countries for which

children start primary school later. This setting is in contrast to the case in the US where significant fraction of children defer school entry by a year (red-shirting), making them the oldest students (Deming and Dynarski, 2008).[6]

Since whether parents react to the incentives, and if so which incentive dominates is an empirical question, I first present the results on overall shifts of births. Using universe of birth certificate records 1974–2010 in Japan which reports exact date of births, I find 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.[7] This finding of delaying births suggests that parents indeed take into account the long-term academic consequences of their children when timing the births, and that on average parents care more about children's academic performance than additional cost of child care at least in Japanese setting.

Because I observe a gradual decline in the number of births before the cutoff date, this shift of births is more consistent with real shift instead of manipulation or misreporting of birthdates. Also I observe that the birth weight of children born after the cutoff date is slightly heavier, and the probability of overweight (>4000 grams) is also slightly higher. Further, I use the insurance claim data and find that elective C-sections, that the day of the operation can be to some extent chosen by mothers, are shifted after the cutoff date, while I do not observe any shifts for emergency C-sections. While some of the shifts may include the manipulation of birthdate, my finding supports the claim that part of the shifts is indeed real.

I also examine the health outcomes measured as infant mortality. If the surge in the number of births right after the school entry cutoff date creates the congestion or overcrowding in hospitals, it could potentially harm the health of infants. On the other hand, it may not affect the infant health since hospitals can anticipate such a surge, and thus they are well prepared. Consistent with the latter view, I do not find that births born right after the school entry cutoff date reveal an excess infant mortality. Here it is important to note that mortality is just one of the health outcomes I could examine here, and other measures such as readmission rate can be affected.

The overall shifts in births, however, may mask heterogeneous responses of mothers. I find

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there is little or no evidence of early/late starting or grade retention: England, Iceland, Japan, and Norway.

[6] Also, there is only one single school entry cutoff date that applies to all children in Japan. This is also in contrast to the case in the US; since each state has different school entry cutoff date, and inter-state migration is pretty common, parents may not know precisely which school entry cutoff date that they should refer to. For example, school entry cutoff date for California is December 1, and that for Texas is September 1. For school entry cutoff date in each state in the US, see Dickert-Conlin and Elder (2010). For international school entry cutoff date, see Bedard and Dhuey (2006). Note that most countries only have single school entry cutoff date unlike the case of the US.

[7] While delaying births is more medically difficult than hastening births, the results are consistent with Gans and Leigh (2009), which found that over 1,000 births were delayed so as to ensure that their parents were eligible for bonus payment in Australia.

that births by younger mothers, 2nd-born births, and male births are more shifted than births by older mothers, 1st-born births, and female births, respectively. The results on the birth parity are especially interesting since it may suggest that parents learn from the previous experience of first child that it is probably beneficial for forthcoming children to be born after the cutoff date. These differential responses by mothers suggest that births around the school entry cutoff date reflect the differences in mother's characteristics.

Since birth data in Japan has only limited parent characteristics (no income, no education), I turn to the data from Organisation for Economic Co-operation and Development (OECD) Programme for International Student Assessment (PISA), which collects information on 15-year-olds test scores, together with the parental socioeconomic status (SES) and birthdate. Unfortunately, birth date is reported in months, and not by day in this data, but I find that fraction of mothers with low-SES are highest among March born child. This result may imply that high-SES parents who care about their children's academic performance, and can afford additional year of child care cost, may time a birth after the school entry cutoff date, while low-SES mothers may delay less to avoid the additional year of child cost. In fact, interestingly, once I control for these parental characteristics, the relative age effects is lowered by 20–60 percent, suggesting that some of the observed academic disadvantage of youngest children come from the selection of mothers. However, it is important to note that these mechanisms are complement to the relative age effects, since even after controlling for these parental characteristics, older children's academic performance is better than that of younger children.

Finally, it is important to note that my results are just a part of the effect of the school entry cut-off dates on the timing of births because mothers can time conception so that children are born after the school entry cut-off dates. While the main focus in this paper is the timing of births instead of timing of conceptions, I also find that second or higher parity children are predominantly born in April–June, possibly due to learning from the births of first child to make sure that second child is born after the cutoff date. While there are many other reasons to time conceptions (and hence deliveries), it seems that school entry cutoff date affect both the timing of births, as well as conception of births. This result is consistent with a recent paper by Buckles and Hungerman (2013) that documents that winter births are disproportionally realized by teenagers and the unmarried in the US.[8]

This paper is related to several strands of literature in addition to a large literature on the timing of births. First, this paper may have an implication for growing body of literature that exploits the identification strategy that assumes that births around the school entry cutoff date are random.[9]

[8] Also, Dehejia and Lleras-Muney (2004) show that high-SES women are more likely to conceive when unemployment is higher.

[9] See e.g., Bedard and Dhuey(2006, 2012), Berlinski et al. (2011), Black et al. (2008, 2011), Cascio and

Researchers indeed examine the distribution of births or compare the characteristic of parents around the school entry cutoff date as outcomes or in the process of verifying the underlying assumption in their regression discontinuity (RD) setting, to make sure that these assumptions are satisfied.[10] While my results in Japan may be very country specific, to my knowledge, this is the first paper that documents the births around the school entry cutoff date may reflect the differences in mother's characteristics, and this paper provides a cautionary tale for assuming the randomness of birth timing in some settings. [11]

Second, this paper provides some evidence on the power that parents exert on the timing of births. While there is ample evidence that a certain number of births can be indeed timed, it is generally not clear whether this timing is chosen by doctors/hospitals or parents. [12] Since doctors/hospitals certainly prefer not to have congestions, this surge in the number of births right after the school entry cutoff date suggests that parents have some influence over doctors/hospitals on the timing of the deliveries.

Finally, this paper is related to a literature that investigates parents' differential treatment of children by gender of children.[13] I find that male births are more likely to be delayed than female births in response to school entry cutoff date. While I cannot completely separate "son preference" from "son weakness", this result *may* imply one form of son preference at postnatal stage instead of prenatal stage such as sex-selective abortion observed in many other Asian countries (Sen, 1990, 1992).

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

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), Leuven et al. (2010), McCrary and Royer (2011), McEwan and Shapiro (2008), Muhlenweg and Puhani (2010), Puhani and Weber (2007), Stipek (2002), and Strom (2004).

[10] Following papers specifically examined the distribution of births around the school entry cutoff date in each country, but none of them find the evidence of sorting of births around the cutoff date: Dickert-Conlin and Elder (2010) in the US, McEwan and Shapiro (2008) in Chile, and Berlinski et al. (2011) in Argentine.

[11] Buckles and Hungerman (2013) also question the validity of the instruments used by Angrist and Krueger (1991) that use the quarter of births as the instrument for years of schooling. For the instruments to be valid, instruments have to satisfy two conditions: exclusion restrictions and relevance. See also Bound et al. (1995).

[12] For instance, using my data from birth certificates I observe that the number of births that occurs on weekends or holidays is lower by around 25 percent than on weekdays. But it is not clear whether such shifts are driven by doctors/hospitals or parents.

[13]See e.g., Dahl and Moretti (2008), Lhila and Simon (2008), Baker and Milligan (2013), and Bharadwaj and Lakdawala (2013).

2. Background

2.1 School System

In this sub-section, I briefly describe the school system in Japan. The school system in Japan is legally defined in the School Education Law (SEL) enacted in 1947. The school entry cutoff date in Japan have been set April 2 since then, and it has not changed. SEL article 22 mandate parents to send their children to primary schools as soon as their children turn age six before the school starting day, which is April 1 in Japan. However, according to Japanese law, people reach the additional age a day before their birthday. This means that 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 schools on a day before their 7th birthday. So there is about a 1-year age difference at the maximum among primary school students in the first grade. Importantly, the fact that April 2 instead of April 1 is the school entry cutoff date help me isolate the effect of school from other potential mechanical confounders such as 1st day of the month effects. To my knowledge, nothing other than school entry cutoff date lies on this specific day.[14] Kindergartens follow the same academic year as primary schools.

This rule is strictly enforced in Japan and thus students rarely delay or start primary school earlier than scheduled date. Indeed, SEL Article 23 allows a delay in school entry due to a child's illness or underdevelopment, but this exception is rarely applied. According to Kawaguchi (2010), the percentage of exemption is 0.03 percent.[15] This is not surprising as parents need to formally apply for an exemption together with the proof of underdevelopment/illness from the doctors specified by the local educational advisory board (SEL article 34).

The fact that almost all children start attending school without delay contrasts with the situation in the US, where postponing entry to kindergarten (or referred to "redshirting") became popular especially among educated parents.[16] Also Japanese educational system is known for social promotion system, where automatic promotion occurs from one grade to the next. The SEL Article 23 also does not prohibit students from learning in the grade above the scheduled grade, but the advancement is also very rare.

Also there is no systematic variation in years of schooling based on the timing of births unlike the US (Angrist and Kruger, 1991); compulsory schooling in Japan is not defined by the age when students can leave, but by the length of the years; 9 years of education (6 years in primary school

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

[15] In 2004, 7,200,933 children at the primary school age (ages 6–12) attended primary schools, while 2,261 did not, according to Kawaguchi (2010).

[16] See e.g., Datar (2006), Elder and Lubotsky (2009), Cascio and Schanzenbach (2007), and Dobkin and Ferreira (2010).

and 3 years in junior high school) is uniformly required for all children.[17]

Interestingly, some parents and schools indeed recognize the relative academic advantage of the 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.

2.2 Birth Registration

The birth certificate is written by the physicians if births occur at either hospitals or clinics, while it is written by midwives in case of deliveries at home. In Japan, hospitals are defined as medical institutions with more than 20 beds, while clinics are defined as those with less than 20 beds or no bed. According to the birth data described in detail below, 99.4 percent of births occur at medical institutions (either at hospitals or clinics) during 1974–2010, and thus none of my results shown later can be driven by home deliveries.

Parents are then required to bring the birth certificate signed by the physician (or midwife) to register the birth at the near-by public health center (Hokenjyo). The newborns need to be registered within 14 days after births; otherwise parents need to pay a fine. Since the birth certificate is indeed signed by attending physician, it is unlikely that manipulation of birthdate occurs at the reporting stage at the public health center. Thus if the manipulation indeed takes place, it is more likely to happen at the stage of filling in the birth certificates at hospitals or clinics before signed by physicians.

3. Data and Identification Strategy

3.1 Data

The data used in this study come from four sources. The primary data for this analysis are birth data, and I supplement it with death data to examine the infant mortality, and insurance claim data to examine the timing of C-section births. In addition, I use OECD Programme for International Student Assessment (PISA) to examine the parental socioeconomic status by children's birth months. To avoid confusion, this section focuses on my primary (birth data) and supplementary (death data and insurance claim data) data sources. The secondary data (PISA) is described in Section 5.

The birth data is compiled by Ministry of Health, Labour and Welfare, and it cover the universe of births occurred in Japan during 1974–2010. The key variable in the birth data is the

[17] This also means that parent in Japan do not face a well-known tradeoff in schooling in the US where though students who are the youngest in their school cohort typically have poorer academic performance, on average, they have slightly higher educational attainment (Dobkin and Ferreira, 2010).

exact date of births. Combining 1974–2010 birth data together provides me with information on over 50 million births. The data are of high quality in that only 4,935 observations (less than 0.01 %) are missing birthdate information, and I drop these observations. The birth data also contains information on exact hour of births, which is rare in the public-version of birth certificates available to researchers. Otherwise specified, the main outcome is the number of births at daily level rather than hourly level since most of past studies uses the daily observations, and thus comparable across these studies.

The birth data also collect very limited mother's characteristics such as mothers' age at the time of births. Unfortunately, they do not collect key mother's characteristics (e.g., education of mothers), delivery method (e.g., C-section and inducement), complications of births, and Apgar scores of infants. I also examine a number of child characteristics collected in the birth certificates to investigate whether the shifts in the timing of births are indeed real rather than pure manipulation of birthdate by looking at the birth weight of newborns as well as gestational length of mothers. I also examine the gender of a child, and the parity of a child (1^{st}-born birth or 2^{nd}-born births and above).

In addition to birth certificates, I use the death certificates to examine the infant mortality. The death certificates contain all death records occurred in Japan, which include information about the decedent's exact date of death, exact date of birth, gender, and cause of death (ICD8–10). While the birth and death certificates are not linked in Japan, I can still calculate the infant mortality rate on each birthdate, where the number of deaths for births born each birthdate from death certificates is the numerator, and the number of births for each birthdate from birth certificates is the denominator. Summary statistics is reported in Appendix Table B.

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

3.2 Identification Strategy

The main identification strategy uses the data only around April 2 of each year. Days are organized in relation to the April 2 for each year. The econometric model I estimate is:

$$Y_{dy} = \alpha + \beta After_{dy} + \sum_{j=1}^{6} DOW(j)_{dy}\gamma_j + \sum_{k=1}^{N} Holiday(k)_{dy}\delta_k + \theta_y + \varepsilon_{dy} \quad (1)$$

where Y_{dy} is the counts 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 weekday, and $Holiday(k)$ is one of K dummy variables for each holiday. θ_y captures year effects, and ε_{dy} is an idiosyncratic error term. The year indicators are included to account for time trends in the overall number of births.[18] 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} is the mean infant characteristics for day d in year y.[19]

I change the windows around April 2, from 7 days to 28 days following Gans and Leigh (2008). Widening the window has two purposes. First, it allows for births to have been moved by more than one week even though as I show 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 their births until April 2, but instead only could move the birthdate from mid-March to late-March (Gans and Leigh, 2008). Also, if capacity constraints are binding, some births that would have taken place in the early-April may be shifted to mid-April. Both of such moves attenuate the estimates from focusing on a narrow window.

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

Given this structure for the data, the econometric model is

$$Y_{dmy} = \alpha + \beta(After2nd_{dmy}XApril_{dmy}) + \gamma After2nd_{dmy} + \sum_{j=1}^{6} DOW(j)_{dmy}\gamma_j + \sum_{k=1}^{N} Holiday(k)_{dmy}\delta_k + \theta_y + \rho_m + \varepsilon_{dmy} \quad (2)$$

[18] I also tried to include day of week*year fixed effect to allow each week day to have differential impact by each year. The results are very similar.

[19] I can alternatively use the individual birth as a unit of observation instead of mean at each birthdate but I take former approach to reduce the computational burden.

$After2nd_{dmy}$ takes one if the birthday d is after 2nd of the 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.[20] My coefficient of interest is β, the coefficient on the interaction term between $After2nd_{dmy}$ and $April_{dmy}$. This specification allows me to isolate the deviation of the number of births after 2nd of April from 2nd of the other months. The coefficient on γ should capture whether days after 2nd of each month is unusual compared to days before 2nd of the month. I expect the coefficient on γ to be economically very small, since there is no reason to believe that period around 2nd of the months is unusual. I estimate standard errors, allowing for arbitrary correlation in errors within each unique synthetic month. The advantage of this specification (2) over previous specification (1) is that I can isolate any effects around the 2nd of the typical months, while disadvantage is that I can only extend the windows up to 14 days around the cut-off because of the way the data is constructed. In fact, as shown later, both specifications yield very similar results, reassuring that within monthly fluctuations are not driving my results.

4. Basic Results

4.1 Shifts in the Timing of Births

Before running formal statistical analysis, a simple histogram reveals the 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 sign correspond to holidays. Note once again that school entry cutoff date is April 2 instead of April 1.

Figure 1 depicts that there is clearly a 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 5 and bottom 5 days of mean daily number of births, together with the relative number of births, computed as the average number of births on a given day divided by the average births across all days. Thus, a value of 1.1 represents a 10 percent increase in the daily births compared to the overall average. April 2, and April 3 see 20 and 10 percent more births than average, while April 1, a day before the cutoff date, sees 15 percent less births than average. This graph also shows the importance of controlling for holidays in the estimation. There is also variation in the weekdays vs. weekends, but pooling many years of data smooth out such an effect in the figure. In the

[20] I can also replace $After_{dmy}$ 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 (all results available from the author upon request).

regression, I include the day of the week fixed effects to control for the within week fluctuations.

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

Table 2 summarizes the results from formal statistical test of estimating equation (1). First column in Panel A restricts the sample to the last 7 days and first 7 days around April 2, and it shows that roughly 1,835 births are shifted within a week from April 2 where daily average of births throughout the year is 3,713. In the remaining columns, I progressively widen the window of analysis. As I widen the window, the number of births shifted does not change much, suggesting that most of the shift is concentrated roughly within a week from the cutoff date. Panel B uses natural log of the mean daily birth as an outcome. First column shows that roughly 7.0 percent of births are shifted from a week before April 2 to a week after.

Appendix Table B compares the estimates from main specification (1) and specification (2), where I also use the observations from months other than those around April 2. To facilitate the comparison, columns with odd numbers replicate the results from the main specification (1). Note that because of the construction of the data for specification (2), I can only expand the window around the cutoff date up to 14 days to compare with specification (1). Table B show that two specifications yield very similar results. Also the estimates on *After* dummy in the columns with even numbers are economically very small, suggesting that days after 2nd of each month is not unusual compared to days before 2nd of the month in other months.

Given the size of the magnitude, some of the birth shifts can be potentially due to the manipulation of reported birthdate. However, there are a couple reasons why it seems unlikely that manipulation of reported birthdate can account for all the shifts. First, I observe high frequency of births not only on April 2 but also even after April 2.[21] Similarly, in the years when April 2

[21] The shifts cannot be driven by the home deliveries where manipulation seems easier since only 0.6 percent of births occur at home during 1974–2010. The fraction of births at home shows the declining trend, but even in 1974, the first year of data available, the fraction of home deliveries is only 1.07 percent. It is 0.18 percent in 2010, the last year of data available.

coincides with weekends, I tend to observe the peak of births on April 3 or later (results available upon request). These observation strengthens the claim that there is a real shift because if manipulation is the main mechanism, there is no need to shift births after April 2. Finally, further evidence against pure manipulation comes from the fact that the birth weight of infants, and gestational length of mothers also increase at the cutoff date as shown later.

I also explore the patterns of shifts across periods. Appendix Figure A displays the mean daily number of birth around April 2 by different time periods. While the magnitude of the shifts is largest in the earliest period (1974–1980), I also see the discernible delays of births in the most recent decade (2001–2010). To gauge the magnitude of the shifts across years, I run the regression equation (1) separately for each year with 7 days window from the cutoff. Note that since the equation is estimated for each year, I do not include the year fixed effect in the estimation. Appendix Figure B plots the size of the shifts in each year. There are two things worthwhile to mention. First, across all years, the estimates are all positive 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 entire 1974–2010 is 7.0 percent.

Second, I observe that magnitude of the delays of births is declining in the recent years. It is not clear *in a prior* whether I expect to observe more or fewer delays of births in recent years. On one hand, one may expect to observe more delays of births due to the development of medical technology to easily time births, more familiarity of the mothers with information on academic advantage of older children, rising competition in academic market, and quantity/quality trade-off of children.[22] On the other hand, one may expect to observe fewer delays of births if the digitalization of the medical record may make it harder to manipulate the birthdate in the recent years and/or if child care cost increases.[23]

A unique feature of the birth certificates in Japan is that they also report exact hour of birth. Figure 3 plots hourly number of births within 72 hours (3 days) before and after the school entry cutoff date using the pooled 1974–2010 birth data. The graph shows systematic patterns within a day, where more births are observed during the daytime and fewer births on late at night and early

[22] For example, the fraction of weekend births has been decreasing 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. Note also that weekend births are always lower than the random distribution of 2/7 (=28.6 percent), suggesting that births can be shifted at least a few days.

[23] Also as I show later, aging of mothers may potentially account for the fewer delays in recent years since 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 aging of mothers, I did a Blinder–Oaxaca decomposition to decompose the magnitude of the shifts into the fraction explained by the compositional change of mothers, and that of remaining. Using 1974 as a baseline year, mother' age can account for roughly 5–20 percent of the change in the magnitude depending on the choice of baseline year (results available upon request).

in the morning.[24] Interestingly, I observe bunching of reported births on the midnight of April 2, and a slight dip just a few hours before the midnight. Obviously, I do not observe such a pattern around the midnights of other days. Since delaying births a few hours is much easier than delaying births a few days, it can be consistent with the real shift of births. However, this is more likely to reflect the manipulation of the reported birth hours, since such bunching at the midnights are hardly observed in the most recent years of data (not shown).

4.2 Child Outcomes

Since I observe the increase in the number of births even after April 2, it seems unlikely that manipulation of reported birthdate accounts for the entire shift of births. Here I show further evidence against pure manipulation by examining the birth weight 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.[25] I am aware of only three previous papers by Gans and Leigh (2009), Tamm (2012), and Maghakian and Schulkind (2013) that analyze the impact of cutoff induced birth timing on infant health.[26]

Figure 4A plots the mean birth weight around April 2.[27] The graph clearly shows that births after the school entry cutoff date are heavier than those before April 2. Figure 4B plots the probability of births over 4,000 grams, and shows similar patterns as mean birth weight. Table 3 presents the results of estimating equation (1) where outcome is mean birth characteristics at each birthdate. Column (1) in Table 3 reports that children born after cutoff date is roughly 2.3 gram heavier than those born before the cutoff date. Since 7.0 percent of births are delayed, this would imply that births that are actually delayed are heavier by around 33 grams.[28] This result is consistent with Gans and Leigh (2009), which also found the increase in birth weight among births delayed so as to ensure that their parents were eligible for bonus payment in Australia.[29] Column (2) reports that births born after school entry cutoff date is 0.05 percentage points more likely to

[24] This observation may be driven by the preferences of physicians/hospitals to avoid deliveries when staffing is low.

[25] See e.g. Black et al. (2007), Oreopoulos et al. (2008), Royer (2009), Johnson and Schoeni (2011), Bharadwaj et al. (2012).

[26] Unfortunately, I cannot examine the effect of shifts of births on mother's health due to the lack of the data.

[27] The birth weight is collected with 100 grams interval till 1995, and collected with a single gram after 1995. Therefore I divide the birth weight collected after 1995 by 100. Also if increase in the birth weight is concentrated in recent years, it raises the concern that some of the shifts in the early period are due to the manipulation of reporting instead of real shifts. However, increase in birth weight can be clearly observed in the early periods as well. Also the coefficients on the probability of over 4000 gram estimated separately for each year are statistically significant for any single year during 1974–2010 (results available upon request).

[28] This result is also consistent with the fact that boys tend to be heavier than girls at the time of births shown in Section 4.2. However the estimates on birth weight change very little even if I control for gender of child.

be over 4,000 grams (mean of 2.2 percent). I also find that fraction of births delivered after over 42 weeks of gestation is higher after April 2 in Column (3), which is consistent with the increases in birth weight. Appendix Table C presents results from different size of windows around the cutoff date.

Finally, I analyze infant mortality. One the one hand, if the surge in the number of births right after the school entry cutoff date creates the congestion or overcrowding in hospitals, it could potentially harm the health of infants. On the other hand, it may not affect the infant health since 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 the low mortality rate in Japan, there is no clear change in infant mortality. Column (4) in Table 3 confirms that births born right after the cutoff date do not show the excess mortality.[30] Here it is important to note that mortality is just one of the health outcomes, and other measures such as readmission rate can be affected. Unfortunately, due to the lack of the data, I cannot examine any other health outcomes.

4.3 C-sections Births Using Insurance Claim Data

The disadvantage of birth data is that they do not report the delivery procedures. To compensate for it, I use the insurance claim data to examine whether C-sections births are shifted in response to the school entry cutoff date. Figure 5 shows that elective C-sections, that the day of the operation can be to some extent chosen by mothers, are shifted after the cutoff date, while I do not observe any shifts for emergency C-sections. The spike 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 first half of the week after April 2.[31] As shown in Appendix Figure C, elective C-sections on weekends and holidays are very rare.

Table 4 shows the estimates of equation (1) for any C-sections, elective C-sections, and emergency C-sections separately with different windows where the outcome is log of the mean daily number of births. 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 some 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 is medically more challenging to delay births than hasten births, shifting the timing of elective C-sections may be

[30] Since I am interested in the effect of birth complications due to congestion on infant mortality, I also restricted infant deaths in the sample to those occurred within 28 days from births (neonatal death), and in which the death is classified as "conditions originating in the perinatal period" (specifically, ICD-10 category P). The results are similar (results available upon request).

[31] April 2 is Saturday in 2011, and Monday in 2012.

one way to ensure that births occur after the cutoff date.[32] Appendix Table D presents results from different size of windows around the April 2.

4.4 Heterogeneous Responses by Mothers' and Child Characteristics

So far I show that there are sizeable shifts in births in response to the school entry cutoff date, and that some of the shifts are indeed real instead of pure manipulation of the birth date. In this subsection, I exploit the characteristics of mother and birth to shed a light on the incentives of parents behind the shift of births. Figure 6A, 6B, and 6C plot the mean daily number of births by a parity, mother's age, gender of child using the pooled 1974–2010 birth data. Table 5 summarizes the results from estimating equation (1) where outcome is log of the mean daily number of births separately for each sub-group. Since the shifts of births are concentrated within a week from cutoff date, I estimate the equation within 7 days from the cutoff date.

Figure 6A-1 displays that births at higher parity are more likely to be delayed. This pattern is more apparent in Figure 6A-2 which plots the share of high parity birth (2^{nd} and above births) among all births. The figure shows that share of high parity births discontinuously increases right after April 2. Panel C in Table 5 reports while 8.6 percent of birth at higher parity is delayed, the corresponding estimate for 1^{st}-born birth is 5.3 percent. The null hypothesis that coefficients on different parity are the same is rejected at 1 percent level. This result implies that mothers may learn from the previous experience of first child that it is probably beneficial for forthcoming children to be born after the cutoff date. Also mothers already gained experience, and thus it may be easier for them to time 2^{nd} births than 1^{st} births. Note that the fraction of 2^{nd} or above births among all births seems to be increasing even after April 2 in the Figure 6B, implying that the conception may be also timed. I will come back to this point in Section 5.

Figure 6B-1 displays that relatively younger mothers less than 30 years old show a larger delay of births, compared to mothers more than 30 years old.[33] Because of this differential pattern by mother's age group, Figure 6B-2 depicts a sharp decline in mean mother's age at birth right after the school entry cutoff date. One possible explanation is that for older mothers it is much more important to make sure that they are going to have a kid and thus care less about the timing of births. Also since the delay of births can be potentially harmful to the mother's health, the delays of births for older mothers may be physically difficult, and doctors/hospitals may not admit requests from mothers to delay births.

Next, I examine the mother's differential responses by the gender of births. Figure 6C-1 clearly displays that boys are more likely to be delayed than girls. Figure 6C-2 plots the fraction

[32] This result is consistent with Gans and Leigh (2009) which showed that induction and cesarean section procedures accounted for most of the delays in births in response to bonus payment in Australia.
[33] Note that mean age of birth is 29.81 years old.

of male births, and the figure shows that the share of male birth is substantially higher after the school entry cutoff date. Panel C in Table 5 reports while 8.0 percent of male births are delayed, 6.1 percent of female births are delayed.[34] I can reject the null hypothesis that coefficients on male and female births are the same at the conventional level. Appendix Table E presents results of estimation for each gender by parity. Consistent with the finding so far, the table shows that male births at higher parity are most likely to be delayed.[35]

There are a couple of possible explanations for this finding. First, this result may reflect son preference of the parents. If so, it is interesting since Japan is known to reveal little son preference in the prenatal stage, and therefore shows normal sex ratio at births unlike many of Asian countries with elevated sex ratio at births (Sen, 1990, 1992).[36] This result may imply a different form of son preference at postnatal stage instead of prenatal stage such as sex-selective abortion. Alternatively, the result may reflect the fact that boys are slower in the development in early childhood and also socially less mature than girls so that parents want to ensure that male births do not suffer from disadvantage of being the youngest within the academic cohort.[37] Also the size of the body may matter more for boys than girls for example for sports.[38] Unfortunately, I cannot disentangle "son-preference" from such "son-weakness" here.

In sum, these differential responses documented so far suggest that births around the school entry cutoff date reflect the differences in mother's characteristics.

4.5 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 help me understand the role of child care cost and opportunity cost of mothers in the decision of birth timing. In this sub-section while far from perfect, I explore whether the easier access to child care, and hence the lower cost of raising child, affects the timing of births. The idea behind is that the more available the day-care is at the region, the more I may observe the delays of births, since additional year of child care is less a concern for mothers in these regions. I am certainly aware that this is simply a correlation and not causal

[34] Instead, I can simply regress male birth dummy as an outcome in equation (1). The coefficient on *After* is 0.009 (SE 0.001), and statistically significant at 1 percent level.
[35] I cannot examine the shifts of births for second child by gender conditional on the gender of first child since birth data do not include a mother identifier.
[36] Rohlfs et al. (2010) document that boys are predominately delivered than girls in Japan in 1966, a year which girls are regarded as astrologically less desirable (Hinoeuma), suggesting that prenatal gender selection were prevailing at least until 1966 in Japan.
[37] Datar (2006) shows that boys benefit significantly more in reading from delaying entry to kindergarten compared to girls.
[38] Allen and Barnsley (1993) show that two and a half times as many boy players in the Hockey League in Canada were born in January as in December where the cutoff date for Canadian hockey is January 1. See also Dudink (1994).

estimates since there is no explicitly exogenous regional variation on day-care availability. Nonetheless this is a relevant and interesting correlation and therefore this exercise should be viewed as a complement to the analysis in the preceding sections.

As a measure of availability of child care, I exploit the year-to-year prefecture variation of availability of public day-care centers. More specifically, I compute the "capacity" measure at each prefecture for every year by dividing the total slots of public day-care centers by the total number of females between ages 20–39, the child-bearing age.[39] This measure captures the "potential" availability of child care instead of the "actual" availability of child care, where the total slots of the public day-care centers is often divided by the number of children before school entry age instead of the number of females in childbearing age as I do here. This measure is arguably better than actual day-care availability, since the number of children may be the result of mother's fertility decisions, and hence potentially endogenous to the timing of birth shifts (Unayama, 2012). There is considerable prefectural variations in capacity variable – ranging from 0.0355 (Kanagawa in 1974) to 0.293 (Ishikawa in 1979) with mean of 0.144 (SD of 0.053) slot per females. There are 47 prefectures in Japan, and I have information on total slots of public day-care centers at each prefecture for period of 1974–2007.[40]

I estimate the relationship between the availability of public day-care centers and the magnitude of the birth shifts in the following two steps. First, I estimate the following equation (3) for each prefecture p and each birth year y cell separately using 7 days window from the cutoff:

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

This equation is simply the analogue of the 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=47 prefecture/year-of-birth×34 years).[41] Note that since the equation is estimated for each year, I no longer include the year of birth fixed effects.[42]

In the second step, I estimate the following equation (4) where I regress this magnitude of delays at prefecture/year-of-birth cell, $\hat{\beta}^{yp}$, on a capacity measures as I mentioned above.

$$\hat{\beta}^{yp} = \alpha + \beta \ln(capacity_{(y-1)p}) + \gamma_p + \theta_y + \delta X_{yp} + \mu_{yp} \quad (4)$$

Note here that since capacity variable is collected as of October 1 in each year y, I use the capacity variable in y-1, a year prior to March/April when the shifts of births occur in year y. X_{yp} is time-

[39] The number of female population is interpolated through the Census which is collected every five years ending with 0 or 5.
[40] I am grateful to Takashi Unayama for kindly sharing this data.
[41] Note that this is conceptually the same as pooling the data for all years of births, and including all the interaction of independent variables with a full set of prefecture/year-of-birth dummies.
[42] $\hat{\beta}^{yp}$ vary from -0.127 to 0.387 with mean of 0.082 and standard deviation of 0.063.

varying prefectural characteristics, and I specifically include the real GDP per capita which is deflated by prefecture GDP deflator to Yen in 2000, and 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 into fertility. In fact, Dehejia and Lleras-Muney (2004) highlighted the effect of the business cycle on the characteristics of mothers who conceived children in the US. I also include job application-to-opening ratio in March of the year y, to account for the economic condition at the time of births as well.[43] These controls essentially have no impacts on the estimates. The mean daily number of births at each prefecture/year-of-birth is used as weights. The source of variable and years available are summarized in Appendix Table F.

Table 6 summarizes the results from estimating equation (4). Column (1) reports that the 10 percent increase in the capacity of public day-care centers is associated with the increase of delays by 1.1 percent. This result is consistent with the view that better access to public day-care centers reduces the cost of child care, and hence mothers are more willing to delay the births. While I cannot interpret the result as causal, it may imply that increase in the availability of public day-care may potentially exacerbate the shifts of the births. Adding time-varying controls in Column (2) does not virtually affect the estimate. Finally, to check whether my results are driven by prefectures with large populations which tend to have low availability of public day-care centers, Column (3) excludes Tokyo and Osaka, two biggest prefectures. The result is essentially the same as Column (1).

In sum, I find that the results are consistent with the hypothesis that child care cost may be one of the driving forces of the birth shifts. However, I need to view this result with a considerable caution since the availability of public day-care is just a crude proxy of the cost of child care.[44] Also again, I stress that I can only provide correlations and not causal interpretation here.

4.6 Magnitude of the Shifts

Here I examine the magnitude of the shifts by comparing this study to the previous studies that also look at the effect of birth-related cutoff on the timing of births in other contexts. The results are summarized in Table 7. Three things are noteworthy to mention before comparison. First, the school entry cutoff date is known well in advance like tax benefits so that the timing of both conceptions as well as births could be potentially affected by the school entry cutoff date. It is in contrast to the case of bonus payment in July 2004 in Australia which only affects the timing

[43] While more standard measure of labor market conditions such as unemployment rate at the prefecture level is only available in the Census years, the monthly job application-to-opening ratio at the prefecture level is available since as early as 1963 in Japan.
[44] While there are private day-care centers, public day-care centers tend to be cheaper than private day-care centers.

of births because mothers did not know the policy at the time of conceptions (Gans and Leigh, 2009). Second the incentives created by the school entry cutoff date potentially affect the later outcome of children, while other studies examine the immediate financial incentives such as tax incentives. Third, while incentive structure in the other studies goes in one direction in all studies (i.e., either delaying or hastening of births and not both), there is a clear trade-off in parents' incentives in my case. Despite these differences, 7 percent shifts of births found in this study are within the range of other studies.

5. Supplemental analysis

5.1 Birth timing, parental SES, and test scores

The analysis on birth data implies that parental characteristics is associated with the timing of births. However, the birth data in Japan have very limited characteristics of parents, and in fact I can only examine mother's age.[45] Therefore I use the other source of the data that report the parental characteristics, as well as birthdate of children. I use the data from PISA, which collects information on 15-year-olds (normally 10th grade) test scores on a various subjects, together with the parental characteristics and birth month of the students.

The advantage of PISA is that it collects nearly complete information of parental education. PISA was first performed in 2000 and then repeated every three years since then. I use PISA 2003 because the data is much more complete than other years. While missing rate of maternal and paternal educations are 4–11 percent in other years, the missing rate is only 0.34 percent and 0.63 percent for maternal and paternal educations respectively in 2003. The other similar source of data such as Trends in International Mathematics and Science Study (TIMSS) have much higher missing rate of parental education (roughly 25–40 percent) probably because students are still young (either 4th or 8th grade) and may not be aware of their parents' education level.

This data is also helpful to examine how much of the relative academic advantage can be explained by parental background rather than relative age since it collects test score of children. There are two drawbacks of this data that are noteworthy to mention. First, it reports only birth month of student but not birth day, and thus I cannot precisely examine the distribution of births around April 2. This means that I cannot distinguish timing of births and timing of conception in this data.[46] Second, it collects the data for one academic cohort (from April to March in the following year) and thus does not have data for adjacent March and April in the same calendar year. Thus I cannot examine the shifts of births from March to April. The summary statistics of

[45] I also find that father's age discontinuously increase at the school entry cutoff date, possibly due to the associative matching of fathers and mothers in terms of age.

[46] Unfortunately, to my knowledge, I am not aware of any dataset in Japan which contain both the exact date of birth, and parental characteristics except for birth data.

PISA 2003 is shown in Appendix Table G.[47]

Figures 7A–C plots the birth month of the children and the average of three different parental characteristics: father's years of schooling, fraction of fathers with white-collar job, and family economic, social and cultural status (a variable called *escs*) constructed based on parental education, parental occupation, and home possession, where higher value indicates higher SES (Organisation for Economic Co-operation and Development, 2005).[48]

These figures clearly show that children who are born right after "cutoff month" (April) are more likely to have high-SES parents, while those born right before cutoff month are less likely to have high-SES parents. This is particularly the case for children who are born in March labeled in diamonds in the figure; for all these three variables that capture parental background, parents of children born in March are by far negatively selected. Since I do not observe births in March and April in the same calendar year, it is not clear whether this is the result of the shift of the timing of births around the school entry cutoff date as I observed in the birth data or result of timing of conception. But the observation reveals that high-SES parents tend to ensure that births are delivered after the school entry cutoff date, while low-SES parents may do so less probably because they cannot afford additional year of child care cost, or simply they lack knowledge as to the relative academic advantage of older children.

These figures also indicate that some of the relative academic advantage of older children may be partly driven by the negative selection of mothers at least in Japanese setting. In fact, Figure 7D shows that math test score reported in PISA 2003 depicts the similar patterns as Figure 7A-C; children born in March perform worst, where test score is standardized to mean zero and standard deviation of one. PISA 2003 also reports test scores on reading, science, and problem solving, but all the subjects show similar pattern as Figure 7D (not shown).

To investigate this point more formally, I estimate two equations as below, following a similar strategy as Buckles and Hungerman (2013),

$$Test\ score_i = \alpha + \beta_1 R_i + \varepsilon_i \quad (5)$$

$$Test\ score_i = \alpha + \beta_2 R_i + X_i' \gamma + \varepsilon_i \quad (6)$$

[47] There are 4,707 observations for Japan in PISA 2003. The grade 10 in 2003 should be born during April 1985 and March 1986 if students strictly follow the rule. Indeed, out of 4,707 observations, there are only 7 observations born outside of this period. In fact, they are all born in April 1986 but it is not clear whether this observation is out of the supposed-to-be grade since birthdates of these students can be April 1 so that they are included in this academic cohort. To be conservative, I drop these 7 observations but all the subsequent analysis hold if I include these observations. In any case, it is reassuring that at the maximum only 0.15 percent of children (7/4707) are not following the assignment of scheduled academic cohort in this data.

[48] "The ESCS index for PISA 2003 was derived from three variables related to family background: highest level of parental education (in number of years of education according to the ISCED classification), highest parental occupation (HISEI score) and number of home possessions (WLEs)." (Page 316, Organisation for Economic Co-operation and Development, 2005).

Following Bedard and Dhuey (2006), I construct a linear measure of relative age R_i for each individual student i as follows. Since April is the school entry cutoff months, R_i = 0 for students born in March, and R_i =11 for students born in April.

The only difference between equations (5) and (6) is that latter includes controls for parental background characteristics X_i. The parental characteristics X_i are the six categorical variables for education of mother and father, *escs*, and a dummy that takes one if the father is white-collar worker. For the variables that miss the information, I replace it with zero and include the indicator for missing variable. Since the missing rate is very low, the estimates are very similar even if I drop these observations from the data (not shown).

I test whether parental background drive the relative age effects by comparing 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. γ =0 in equation (6)), adding parental controls would not change the estimates of the relative age coefficients. I test the null hypothesis that β_1 = β_2 by estimating both equations (5) and (6) using seemingly unrelated regression estimation.[49]

Table 8 shows the results from this exercise. Columns (1) and (2) use the data for whole year, and the columns (3) and (4) use the data only for March, and April born children, which is my main focus. Column (1) shows that children born one month earlier score higher by 0.014–0.024 standard deviation. However, Column (2) shows that once I control for these parental characteristics, the relative age effects is lowered by 20–35 percent, suggesting that some of the observed academic disadvantage of younger children stems from the selection of mothers. More drastically, if I only limit the sample to March and April born students as shown in Column (3) and (4), the estimates are reduced by as much as 25–60 percent when I control parental backgrounds.[50] In all cases, a Wald test rejects that the coefficients are the same at the five percent level. Appendix Table H shows the estimates from the same exercise separately for each gender.

These results suggest that the observed relative age effects are the combination of "double deficits": children born right before the school entry cutoff dates are relatively younger within the school cohort and also these children have low-SES parents. Put differently, these results imply that the school entry cutoff dates, a very common government rule everywhere, have unintendedly exacerbated academic disadvantage of children from low-SES families. However, it is important to note that while the magnitude of the effect becomes smaller, the relative age effects still remain even after controlling for parental characteristics. The persistence and magnitude of relative age

[49] I also replaced R_i by 11 birth month dummies, and compute a Wald estimates where null hypothesis is that coefficients on each birth month are the same. For a science, a Wald test ($\chi(11)$) rejects that each coefficient on birth month dummy is the same at the ten percent level (results are available upon request).
[50] This effect may be underestimated since births on April 1 are included in April instead of March since I only observe birth months.

effects may be partly driven by parsimonious set of parental characteristics available in the data or there is indeed the relative age advantage.[51]

5.2 Timing of conception of births

So far, I focus on the timing of births instead of timing of conceptions. However, since the school entry cutoff date have been in place since 1947, it is plausible that sensible mothers time conception to ensure that children are older and thus more mature within the school cohort. Compared to the timing of the shifts which has a clear cutoff date of April 2, the effect of school entry date on timing of conception is hard to identify. Therefore I rely on the seasonable patterns of births to shed light on this possibility. In fact, Buckles and Hungerman (2013) show that some types of mothers carefully time the conception in the US.

Using pooled 1984–2010 birth data, Figure 8A shows that the number of 2nd births peaks early May, and thus fraction of 2nd births among all births in Figure 8B show a peak around April–June. While there are many other reasons to time conception, the seasonal birth pattern is consistent with the view that parents become more aware of the importance of the birth months of children at the second births.

Interestingly, I find that this conception patterns can be intergenerational especially for mothers who are born in March and April, both of which are near the school entry cutoff date. Since 1992 on, the mothers' exact birthdates are also reported in the birth data.[52] Table 9 shows the relation between mother's own birth months and children's birth months. First row shows the birth month distribution by January-born mothers. Second row is the case of February–born mothers and so on. All figures in this table are in percentage. For example, January-born mothers give a birth in January with the probability of 8.63 percent. The sum of each row should be equal to 100 percent. Note that April 1, a day before the school entry cutoff date, is included in March.

The cells with shadow are the cases where birth month of mother and a child are the same. Table 9 shows that mothers indeed seem to prefer to give a delivery on their own birth months. However, interestingly, mothers born in March and April have much stronger tendency to do so: mothers who are born in March (April) are much more likely to give births in March (April). To illustrate this, at the second to last row, for each child's birth month, I report the highest fraction

[51] 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 do perform worse than older children. It is important to note that in addition to estimating each country separately, Bedard and Dhuey (2006) also pooled the data from countries with different school entry cutoff date, and therefore include birth of month fixed effect to control for season of birth effects, and still find that older children perform significantly better than younger children. Kawaguchi (2010) also finds that those born in March have worse test scores, less completed years of schooling and lower wages than those born in April within the school cohort in Japan.

[52] I also confirm that number of mothers' exact date of birth also peaks April 2 (results available upon request).

of births excluding the mothers with the same birth months (the cells with shadow). For example, for January-born child, the highest fraction of births excluding January-born mother is February-born mothers (8.65 percent). The last row shows the difference between the fraction of their own cell (the cells with shadow) and the highest fraction presented in the second to last row. Using the same example, since the fraction of January births by January-born mothers is 8.63 percent, the difference is -0.02. The last row clearly shows that mothers born in March and April have much stronger preference to give births in the same months as their own birth months (0.32 and 0.30 for 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 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 they themselves may suffer from the relative disadvantage while they are young. While the exact reason for strong preference of March and April born mothers to time birth in their own birth month, the result may imply that while the magnitude is small, the persistence of mother's reference on birth months by mother may partially contribute to the persistence of the intergenerational immobility.

6. Conclusion

Parents are known to time birth in response to various incentives. Previous studies have already documented that parents do react to incentives if the financial reward is immediate such as tax benefits and monetary bonuses. This paper examines whether parents also react to less immediate outcomes: future academic advantage of children. Since children born after school entry cutoff date are academically benefited due to their relative age within the school cohort, some mothers may time births to make sure that they are born after the cutoff date.

Examining the universe of births in Japan, I find that mothers in Japan indeed shift the timing of births in response to school entry cutoff date. This result indicates that mothers are forward looking, and thus time the births by taking into account of future outcomes of children. I also show the suggestive evidence that low-SES parents are *less* likely to deliver births after the school entry cutoff date than high-SES parents. These results imply that the school entry cutoff dates, a very common government rule everywhere, have unintendedly exacerbated academic disadvantage of children from low-SES families.

One remaining question is as to why I find the shifts of births in response to school entry cutoff date in Japan, while other studies in US, Chile and Argentine do not find such behavioral responses of mothers. The strict enforcement of school entry age in Japan, and social promotion education system without delays, and advancement, suggests that the stake of birth timing is much higher in Japan. Whether a similar shift in the timing of births can be observed in other countries for which there is little or one avenue for the future research.

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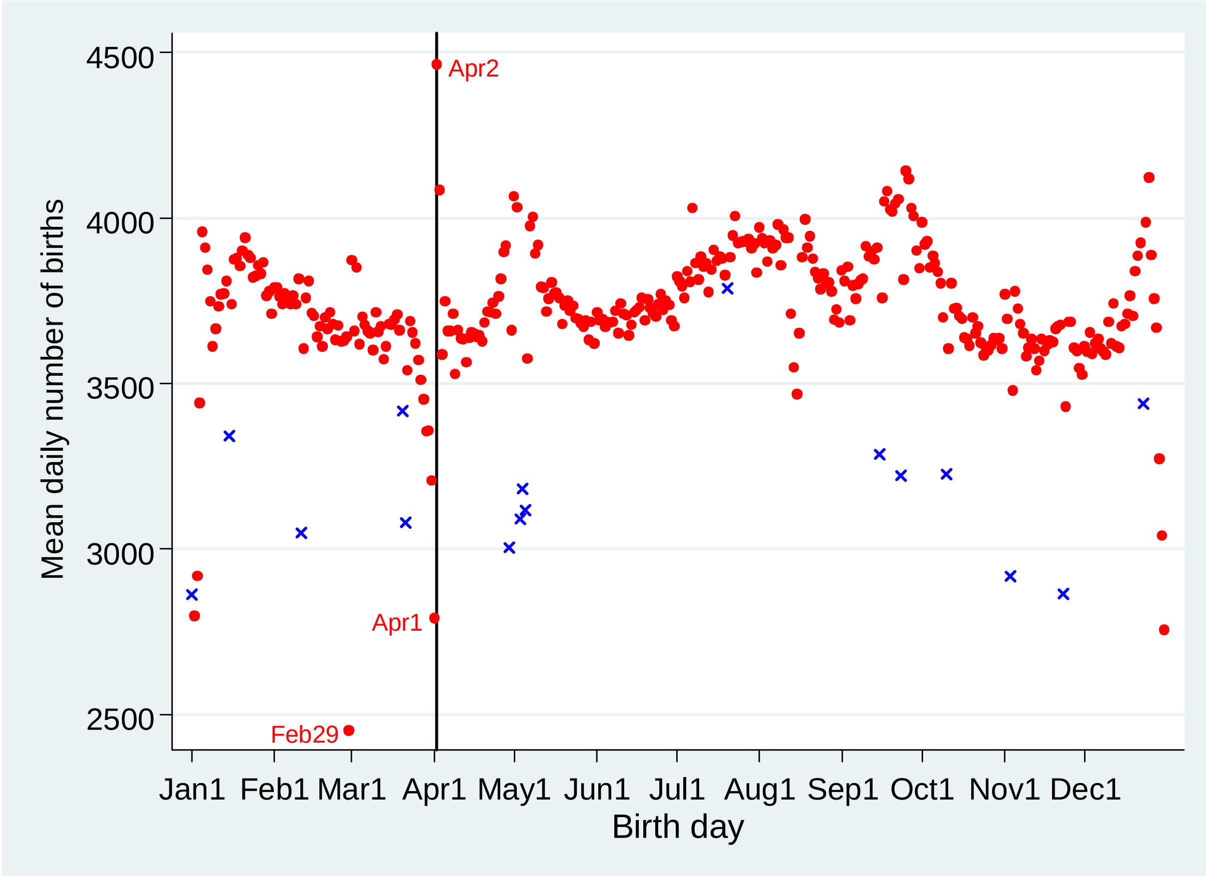
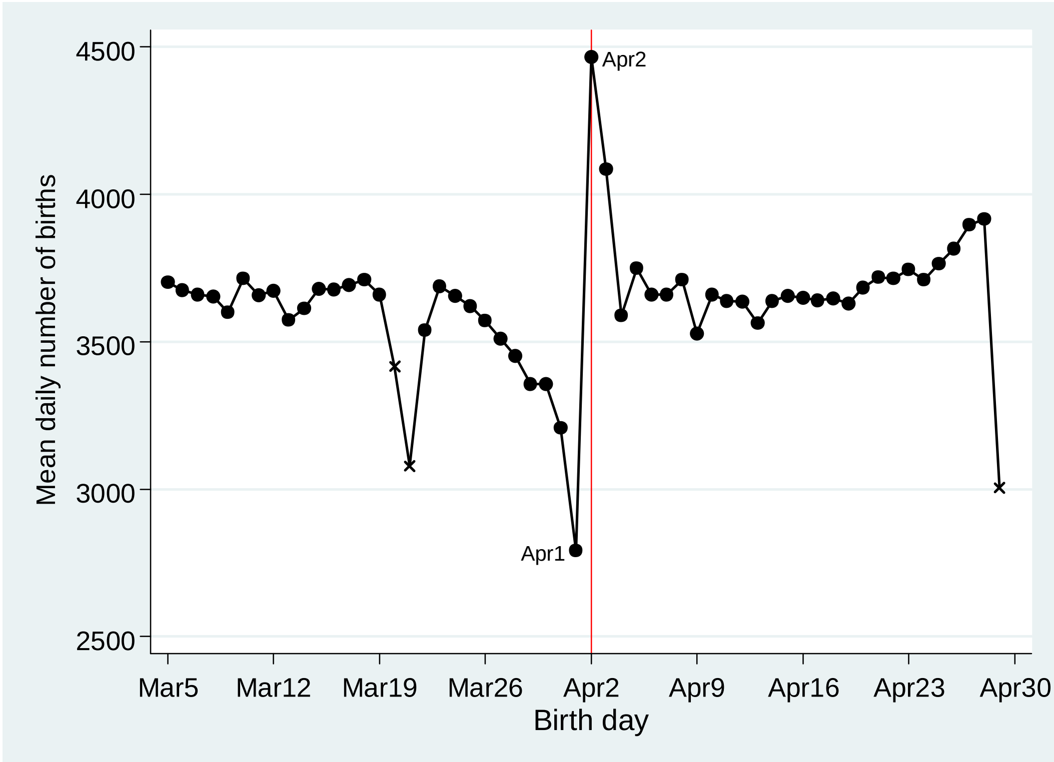
Figure 1: Mean daily number of births throughout the year



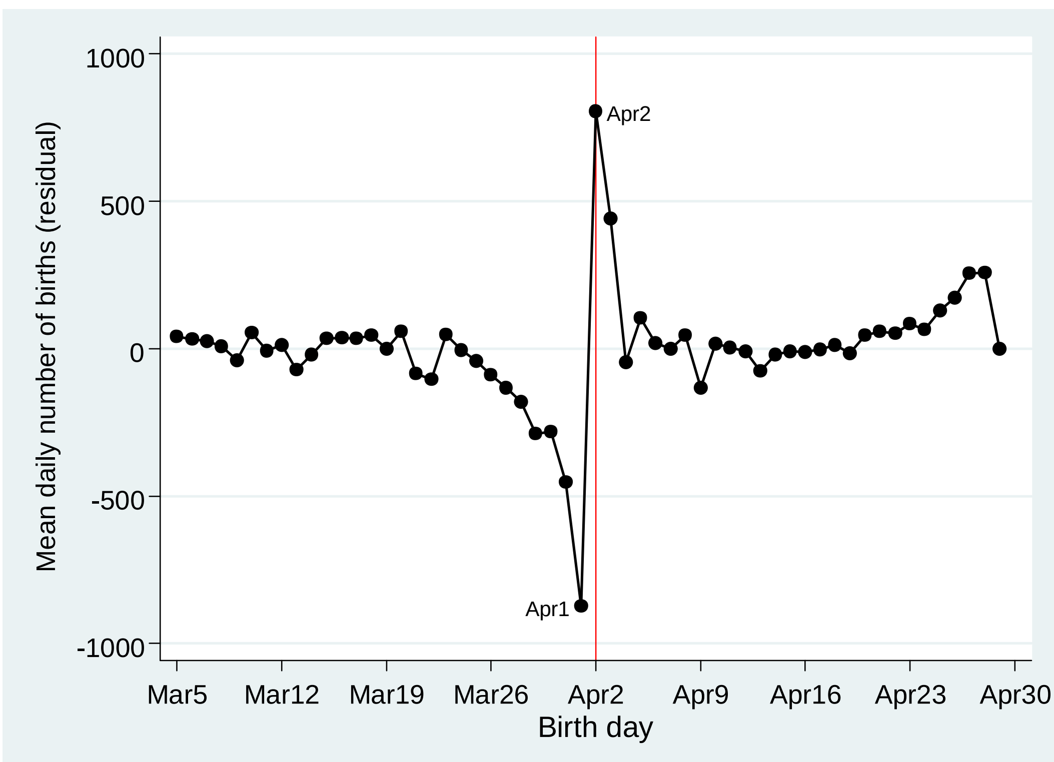
Note: The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from pooled 1974–2010 birth data. The markers with cross sign are holidays.

Figure 2: Mean daily number of births around April 2

A. Raw data

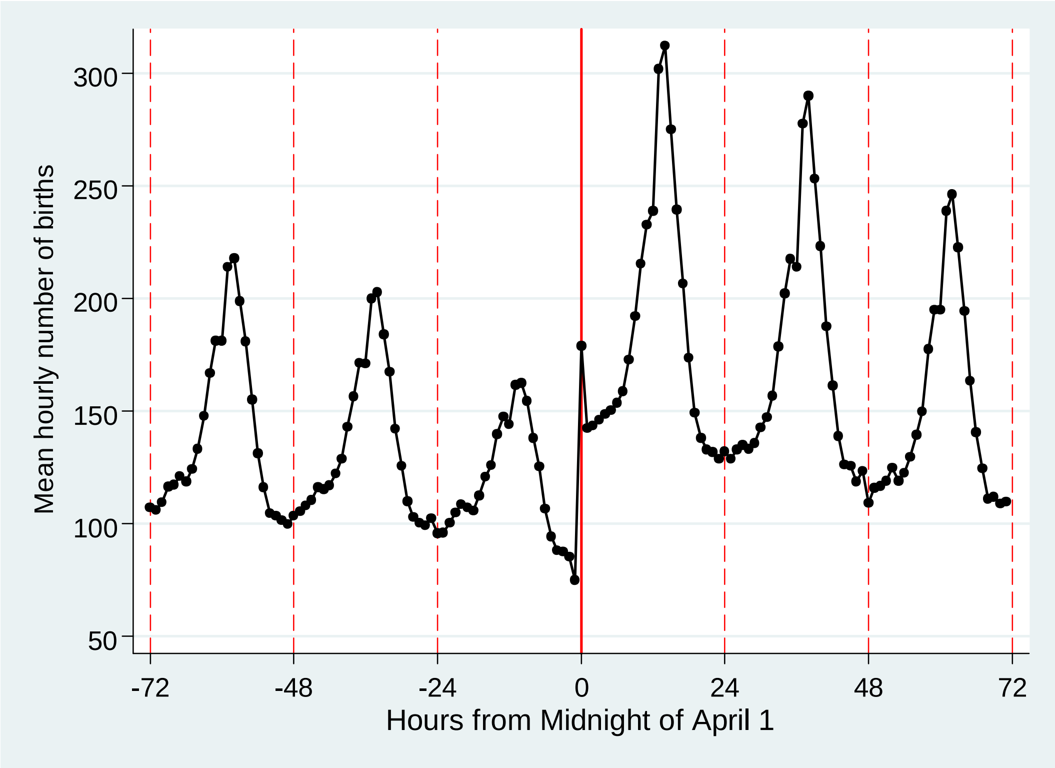


B. Adjusted



Note: 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. Each plot is the mean daily number of birth. The markers with cross sign in Panel A are holidays (either March 20 or March 21 depending on the year, and April 29). Panel B adjusts for holidays, year and day of week fixed effects.

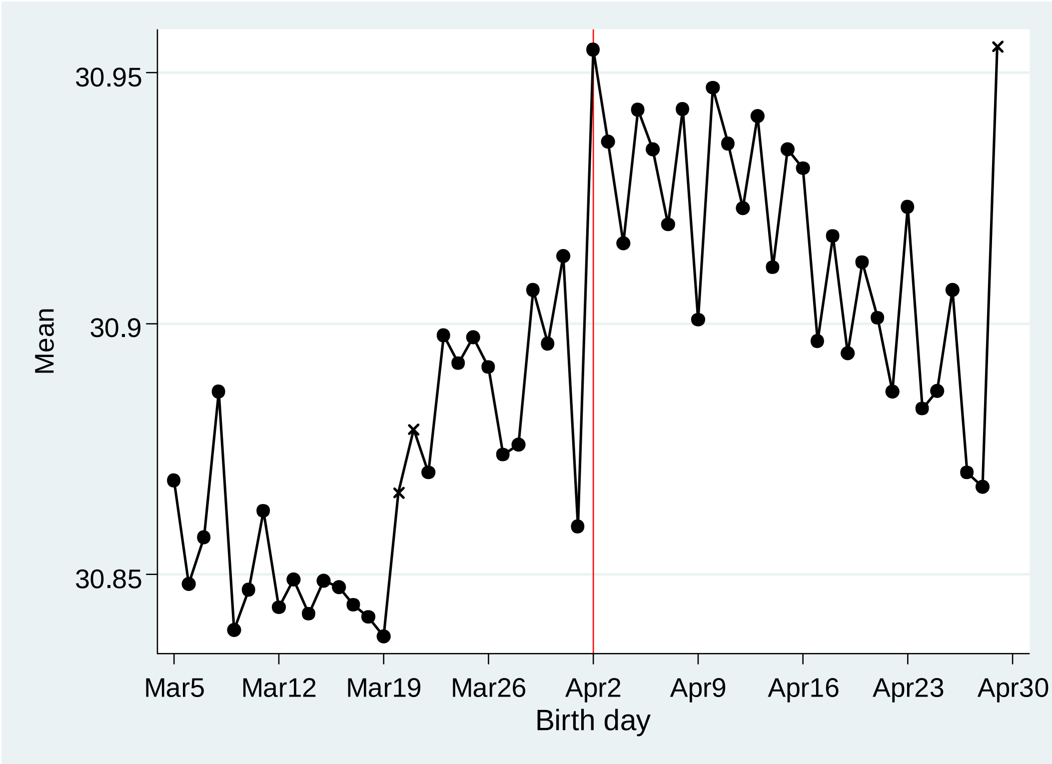
Figure 3: Reported birth hours within 72 hours from midnight of April a



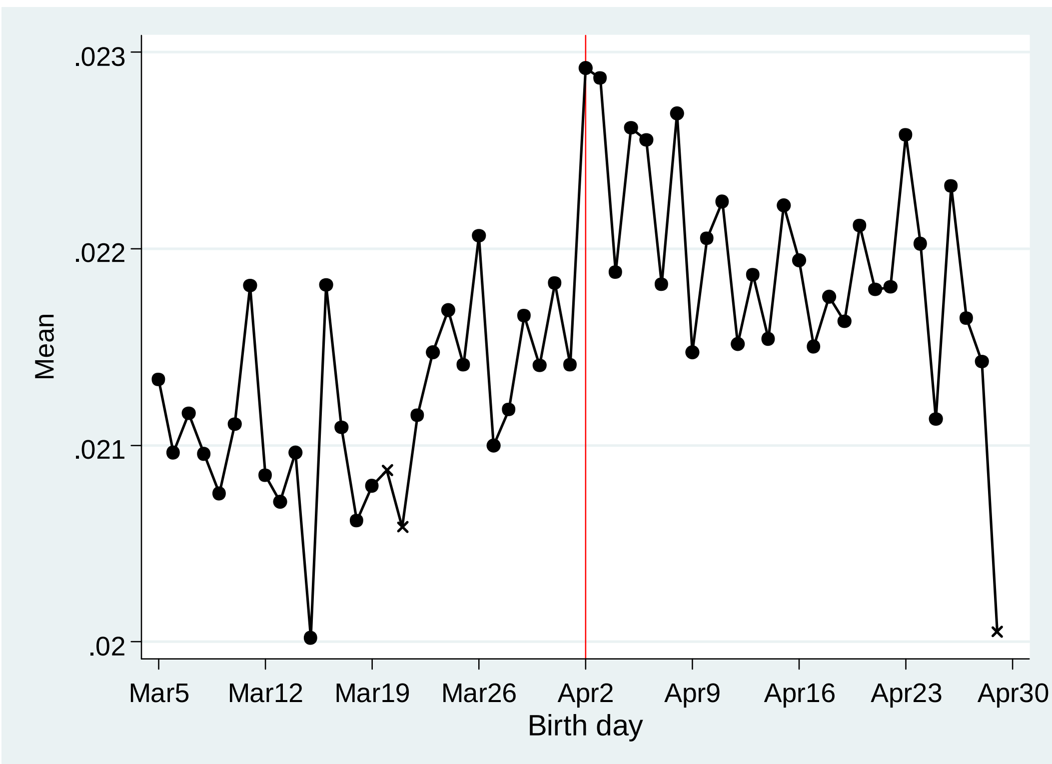
Note: The data come from 1974–2010 pooled birth data. The sold vertical line corresponds the midnight of April 1, which is the exact school entry cutoff time in Japan. Every vertical dashed line corresponds to the midnight of other days. Each plot is the mean hourly number of births.

Figure 4: Child Outcomes

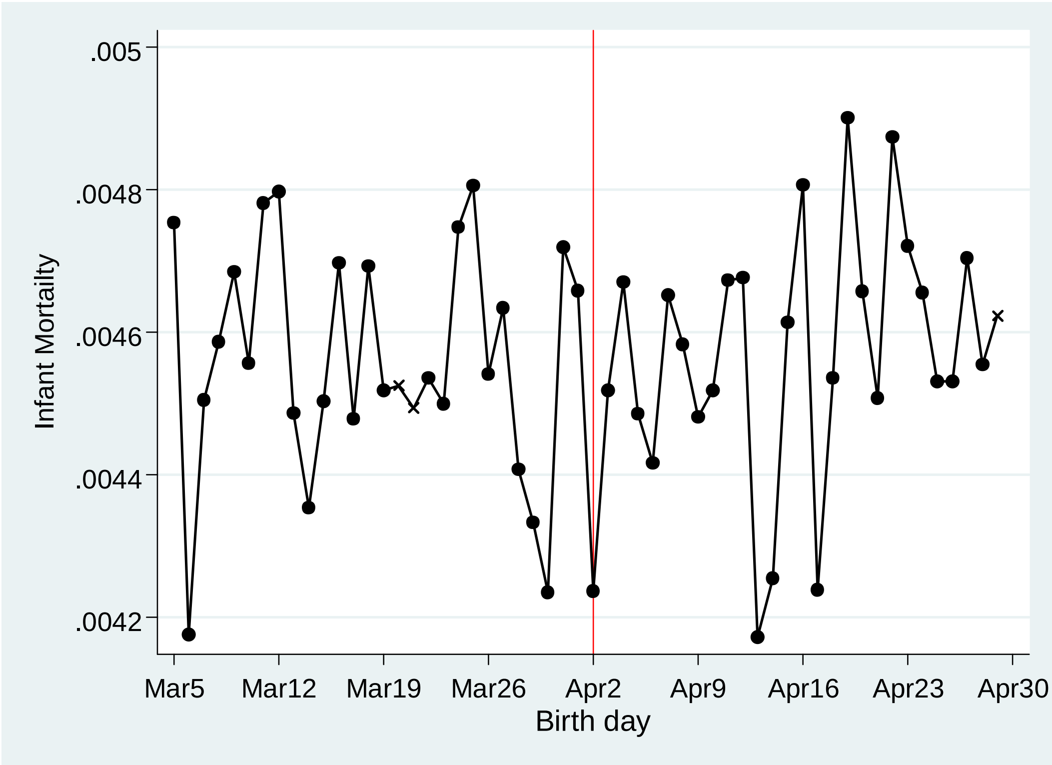
A. Mean Birth weight (100 grams)



B. Fraction of births over 4,000 grams

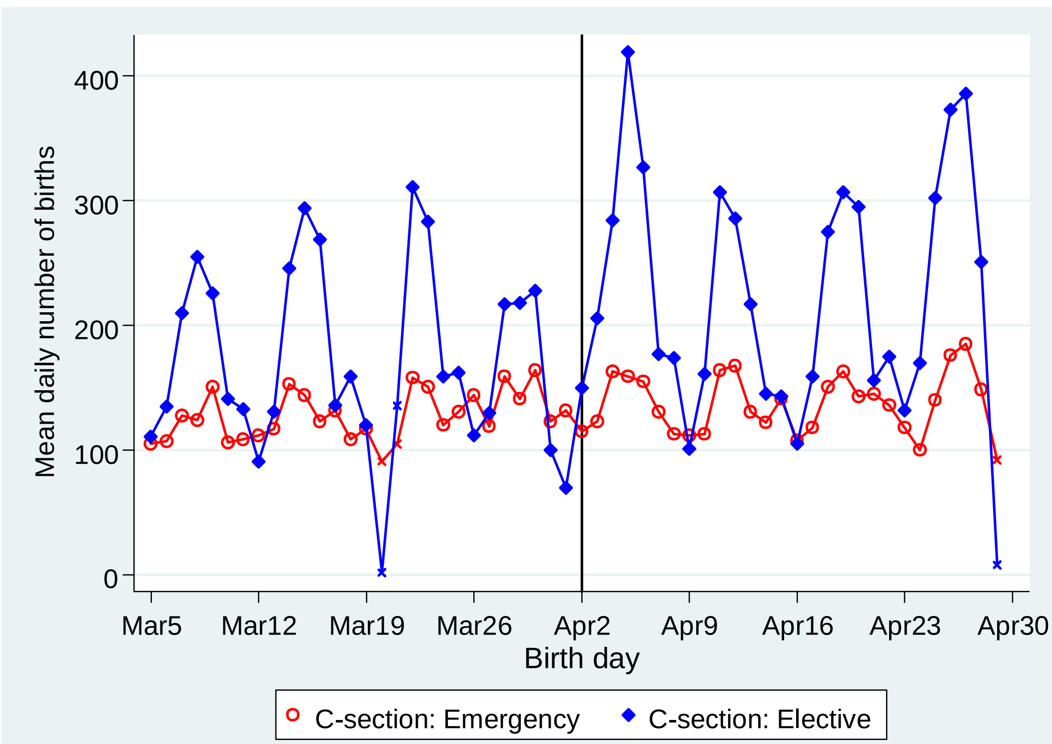


C. Infant mortality



Note: 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. Each plot is the mean of outcome in each day. The markers with cross sign are holidays.

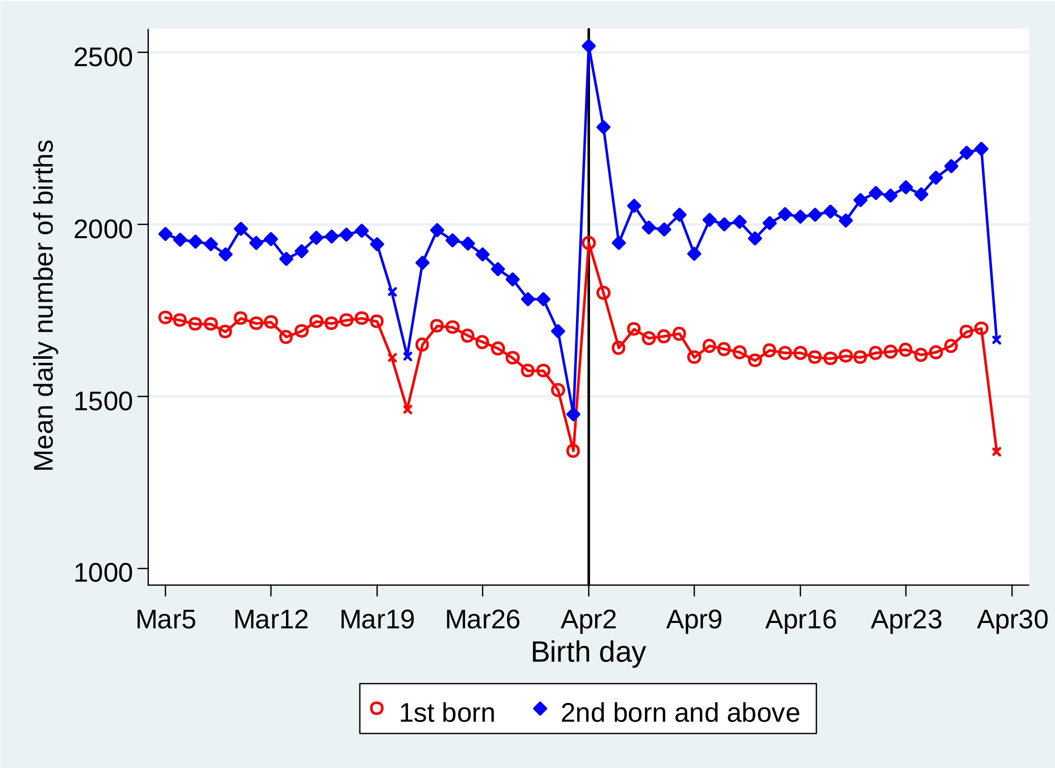
Figure 5: C-section (raw data)



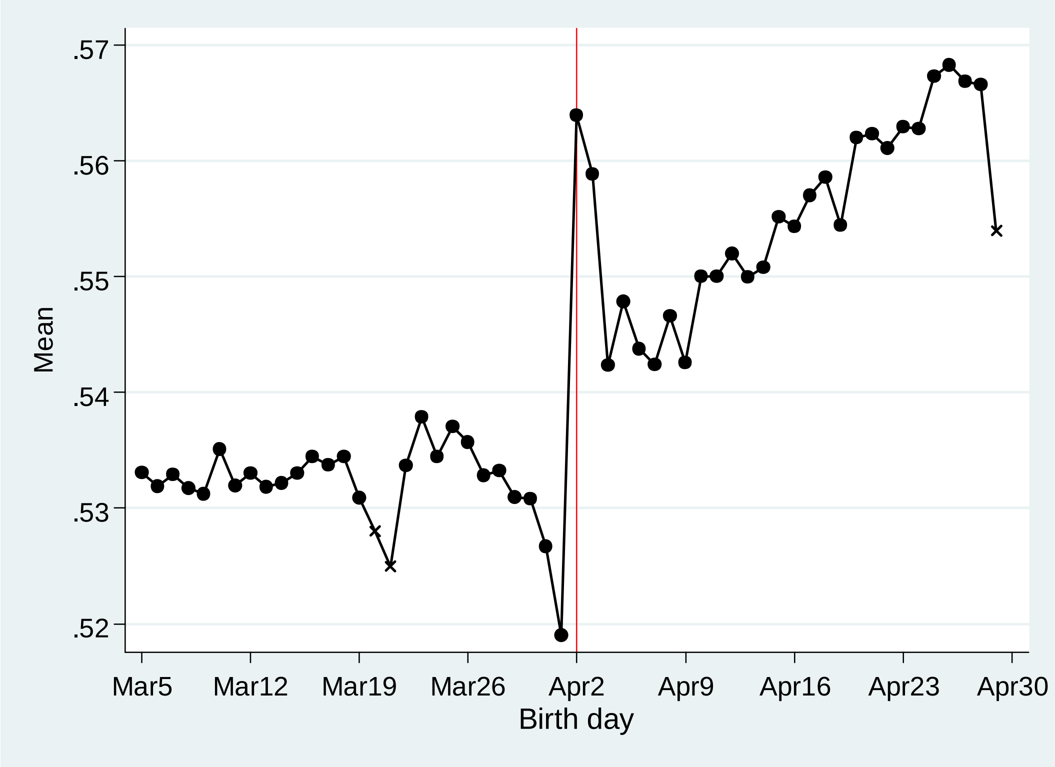
Note: The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from pooled 2011–2012 DPC data. The graph plots the mean daily number of birth.

Figure 6A: Heterogeneous responses, by parity

1. Number of births by parity (raw data)



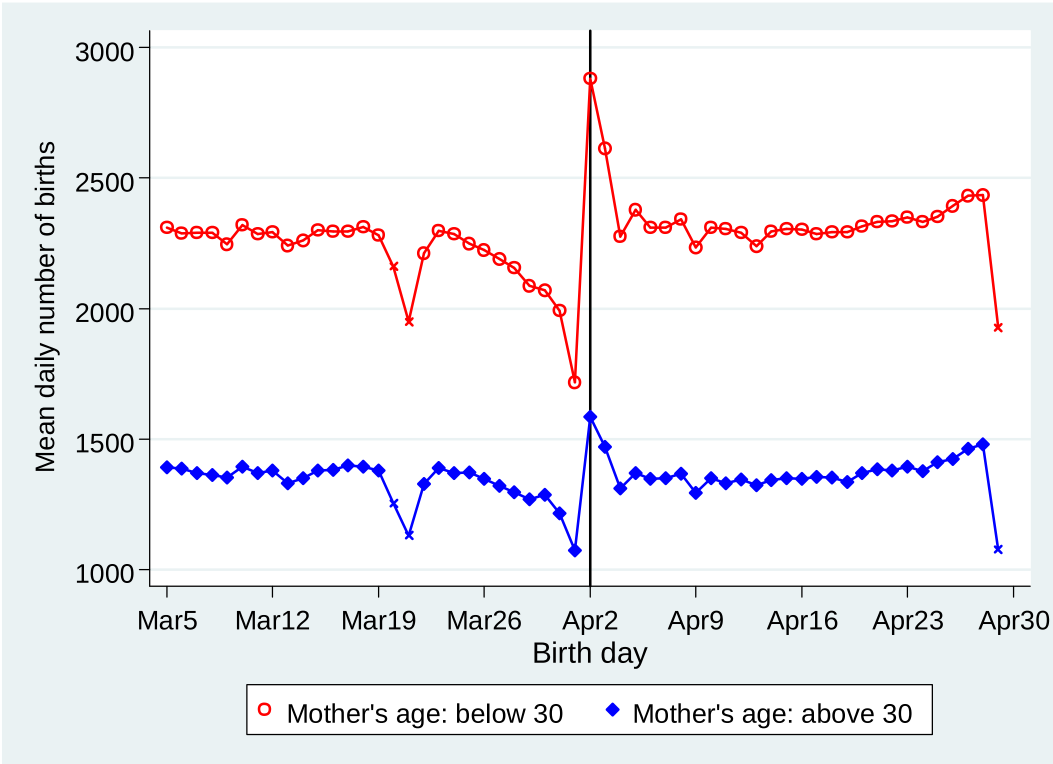
2. Fraction of 2^{nd}+ births among all births



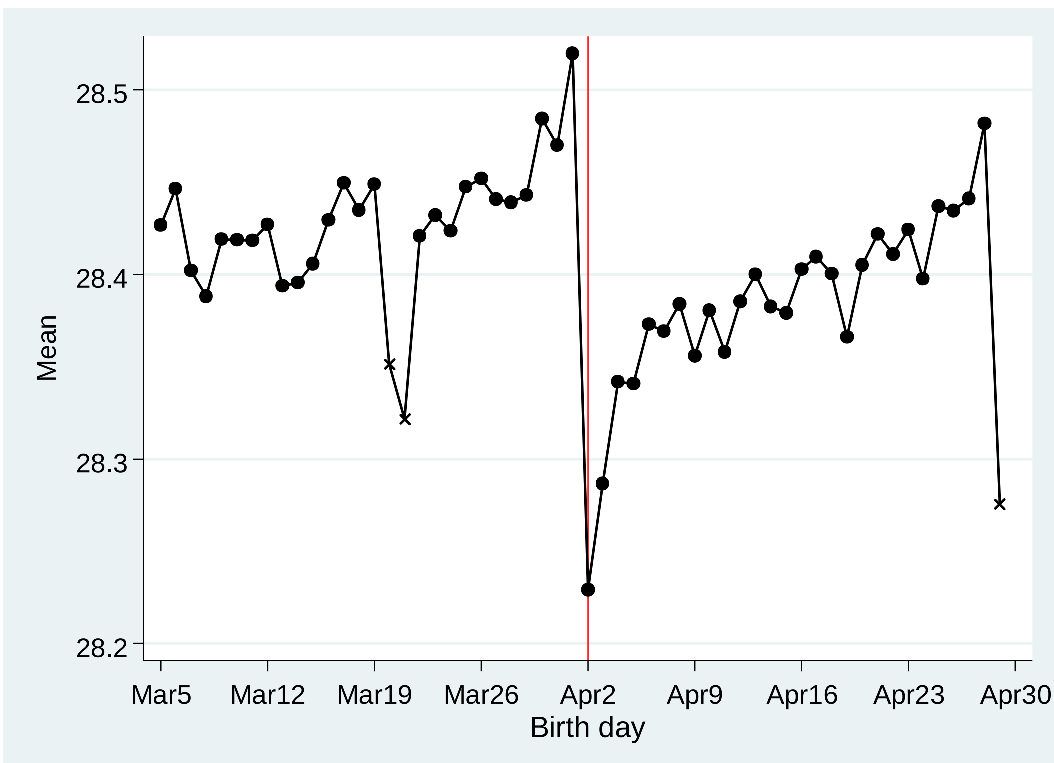
Note: The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from pooled 1974–2010 birth data. Each plot in Panel A is the number of births in each day. Each plot in Panel B is the mean of outcome in each day. The markers with cross sign in Panel A and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

Figure 6B: Heterogeneous responses, by mother's age

1. Number of births by mother's age (raw data)



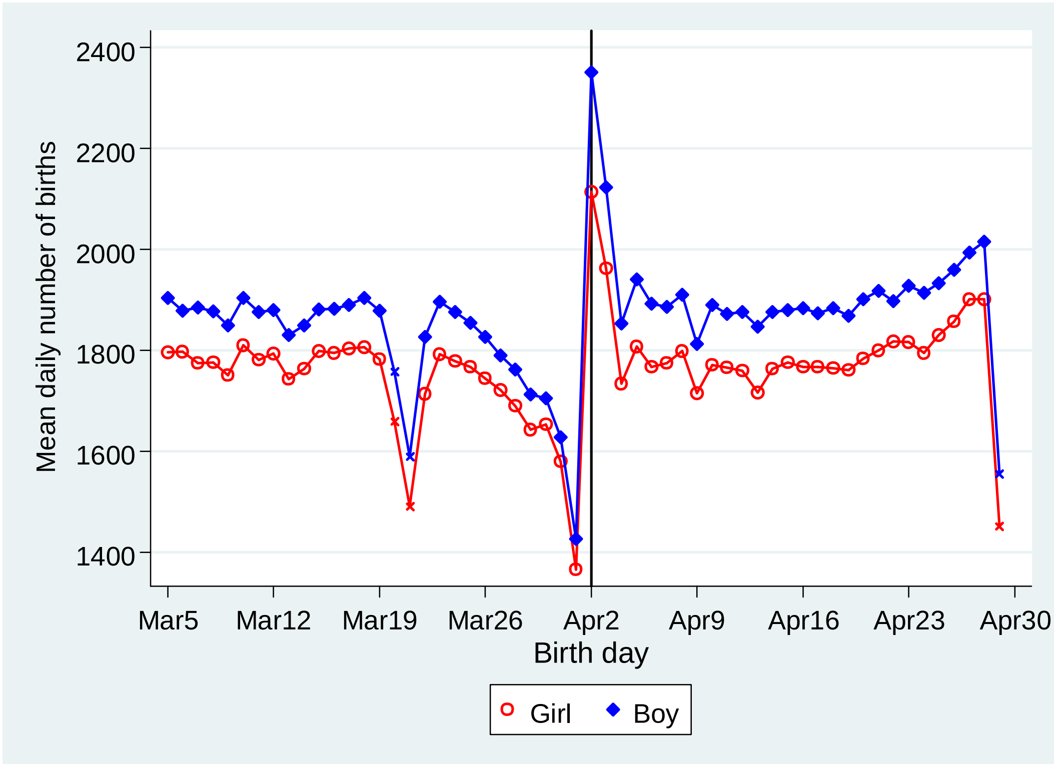
2. Mother's age



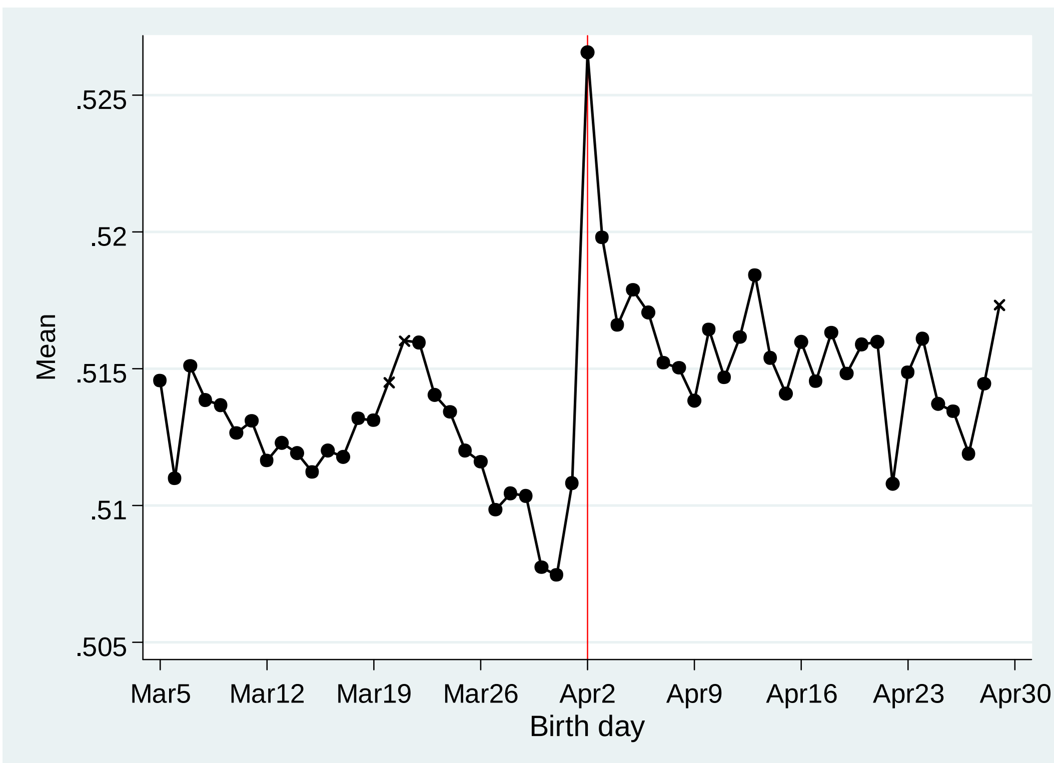
Note: The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from pooled 1974–2010 birth data. Each plot in Panel A is the number of births in each day. Each plot in Panel B is the mean of outcome in each day. The markers with cross sign in Panel A and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

Figure 6C: Heterogeneous responses, by gender

1. Number of births by gender (raw data)

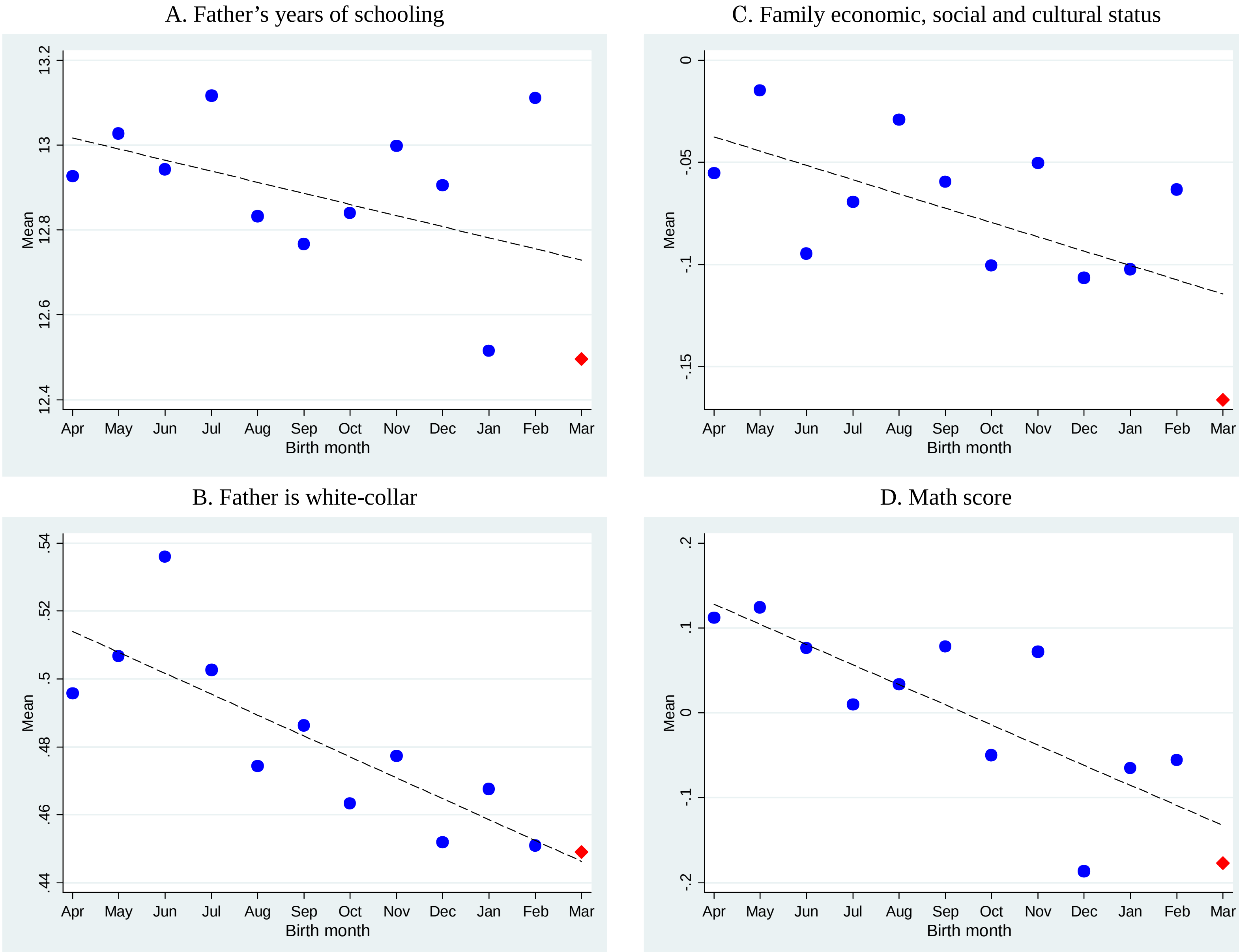


2. Fraction of male births



Note: 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. Each plot in Panel A is the number of births in each day. Each plot in Panel B is the mean of outcome in each day. The markers with cross sign in Panel A and B are holidays.

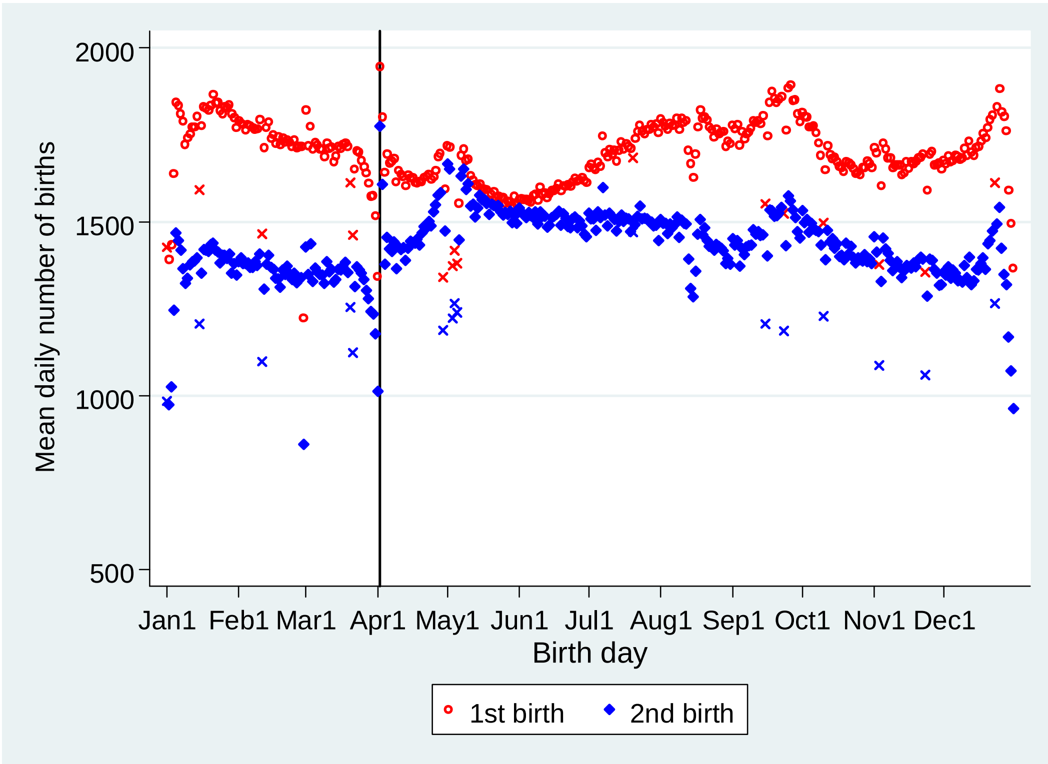
Figure 7: Birth months and outcomes



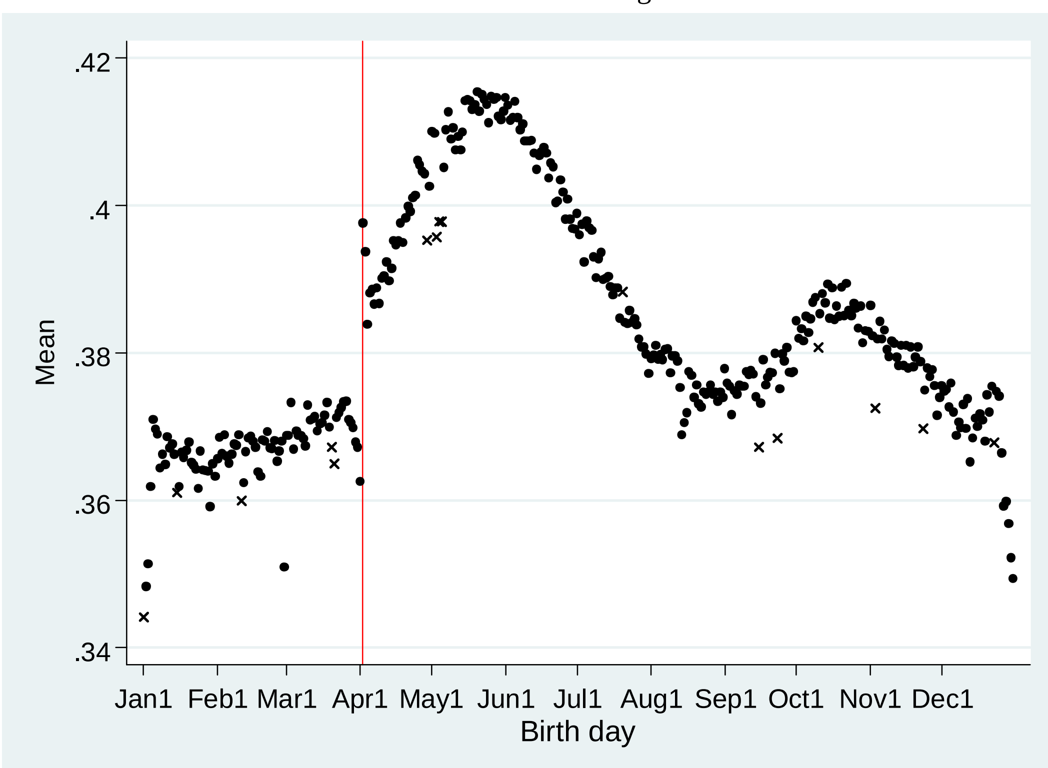
Note: Sample is PISA 2003 data for Japan. Each plot is the average of each outcome at birth month of students. The mark with diamond corresponds to March born students. Math score is standardized to mean zero with standard deviation of one. Family socioeconomic status is economic, social and cultural status (a variable called *escs*) is constructed by the parental education, parental occupation, and home possession, where higher value indicates higher SES (OECD, 2003).The dotted line is the linear projection.

Figure 8: Mean daily number of births through the year, by parity

A. 1st and 2nd or above



B. Fraction of 2nd birth among all births



Note: 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. The markers with cross sign are holidays.

Table 1: Top 5 and bottom 5 of mean daily birth within a year

	Date	Mean daily 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 daily births divided by the mean daily births. Therefore a value of 1.1 represents a 10 percent increase in the daily births compared to the average in the year. Sample is daily births from pooled 1974–2010 birth data. Mean daily births during 1974–2010 are 3,713. Solid ones are within a week from April 2, a school entry cutoff date in Japan.

Table 2: Shift of births

Windows	(1) ±7 days	(2) ±14 days	(3) ±21 days	(4) ±28 days
Panel 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
Panel 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: Coefficient on *After* is reported. *After* is a dummy that takes one if the birthday is after April 2 in each year and zero otherwise. April 2 is a school entry cutoff date in Japan. Robust standard errors are reported in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Sample is daily births within the relevant window from pooled 1974–2010 birth data. Window denotes the number of days before and after April 2. For example, the ±7 day window covers the seven days prior to April 2, and the first seven days after April 2. All specifications include public 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*. Share of births moved is $\exp(\beta/2)-1$. Note that mean daily births during 1974–2010 are 3,713.

Table 3: Child's characteristics

	A. Birth weight	B. Birth weight>4000 g	C. Gestation>42 wks	D. 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: Coefficient on *After* is reported. *After* is a dummy that takes one if the birthday is after April 2 in each year and zero otherwise. April 2 is a school entry cutoff date in Japan. Robust standard errors are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01 significant at 1%. Sample for column (1)–(3) is daily mean from pooled 1974–2010 birth data. Sample for column (4) come from pooled 1974–2010 birth data, and pooled 1974–2010 death data. All specifications include public holiday, year, and day of week fixed effects. The window is restricted to the seven days prior to April 2, and the first seven days after April 2.

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

Note: Outcome is log number of births. Coefficient on *After* is reported. *After* is a dummy that takes one if the birthday is after April 2 in each year and zero otherwise. April 2 is a school entry cutoff date in Japan. Robust standard errors are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01 significant at 1%. Sample is individual birth from pooled 2011–2012 insurance claim data. The window is restricted to the seven days prior to April 2, and the first seven days after April 2. All specifications include public holiday, and year and day of week fixed effects. Share of births moved is $\exp(\beta/2)-1$, where β is the coefficient on *After*.

Table 5: Heterogeneous response, by mother's and children's characteristics
(Outcome: *ln(number of births)*)

	A. Parity		B. Mother's age		C. Gender	
	1st born	2nd 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: Coefficient on *After* is reported. *After* is a dummy that takes one if the birthday is after April 2 in each year and zero otherwise. April 2 is a school entry cutoff date in Japan. Robust standard errors are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Sample is daily births from pooled 1974–2010 birth data. The window is restricted to the seven days prior to April 2, and the first seven days after April 2. All specifications include public holiday, and year*day of week fixed effects. 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)
	Basic	Controls	Exclude Tokyo and Osaka
Capacity	0.110***	0.112***	0.111***
	(0.019)	(0.020)	(0.032)
N	1,598	1,597	1,529
R2	0.538	0.538	0.523
Weight	X	X	X
Year fixed effects	X	X	X
Prefecture fixed effects	X	X	X
Controls		X	X
Without Tokyo and Osaka			X

Notes: Coefficient on *capacity* is reported. *Capacity* is defined as the total slots of the day-care centers (i.e. total capacity of day-care centers) divided by the total number of females between ages 20–39, the child-bearing age. Other controls include the real GDP per capita which is deflated by prefecture 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)*, application-to-opening ratio in March of the year *y*. Weight uses the mean daily number of births at each prefecture/year cell. Tokyo and Osaka are two largest prefectures in Japan. Standard errors are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

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 (2013)	School entrance cutoff dates from 1974–2010	Japan	*Both*	Yes	7.0%

Note: The share of birth moved in the last column is based on the estimates from a 7-days window from the cutoff dates.

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

	All months				March vs. April			
	(1)	(2)	*reduction*	χ 2(1) [p-value]	(3)	(4)	*reduction*	χ 2(1) [p-value]
A: Math								
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		
B: Reading								
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		
C: Science								
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		
D: Problem solving								
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				759			
Gender	Yes	Yes			Yes	Yes		
Father's education	No	Yes			No	Yes		
Mother's education	No	Yes			No	Yes		
Socioeconomics variable	No	Yes			No	Yes		
Father is white-collars	No	Yes			No	Yes		

Note: Sample is PISA 2003 data for Japan. Coefficient on *relative age* is reported. See the text for the construction of relative age. Robust standard errors are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. P-value is reported in the bracket.

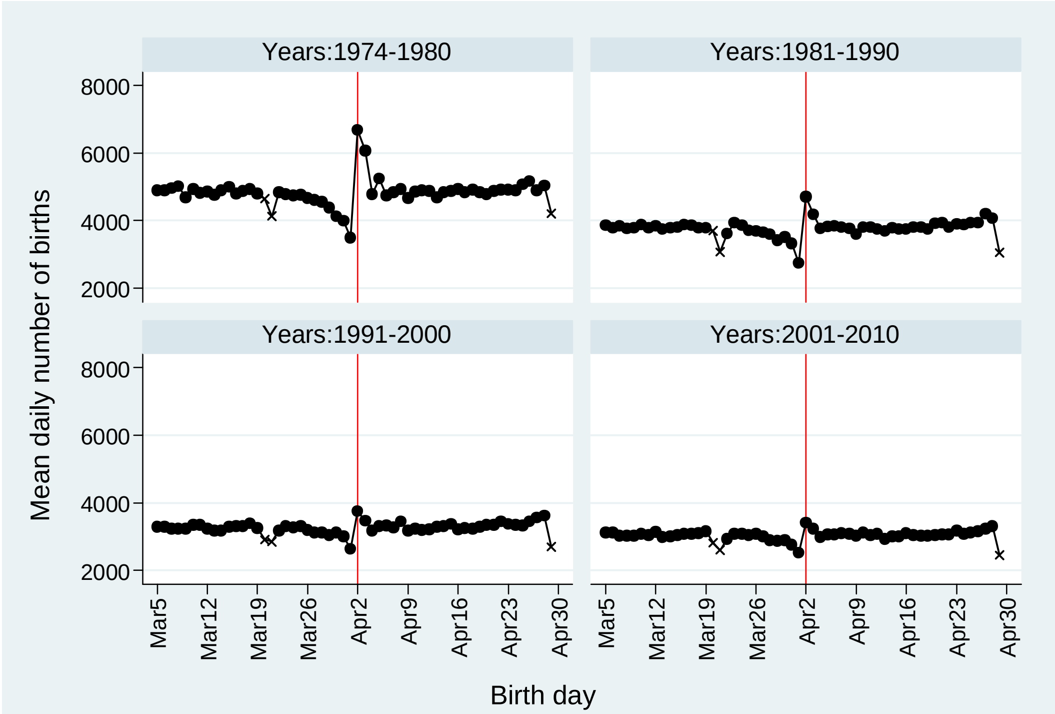
Table 9: Mothers' birth months and children's birth months

Mother's birth month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	*Sum*
(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	**0.32**	**0.30**	0.08	-0.01	-0.03	0.01	-0.03	0.09	0.05	0.07	

Notes: All figures in this table are in percentages. The cell with shadow is the fraction of births where children's birth months are the same as that of mothers. April 1, a day before the school entry cutoff date, is included in March. The second to the last row report the highest fraction of births among each birth month of mothers excluding their own child's birth month. The last row shows the difference from the highest fraction and that of their own cell (i.e. mothers birth months are the same as children's birth months).

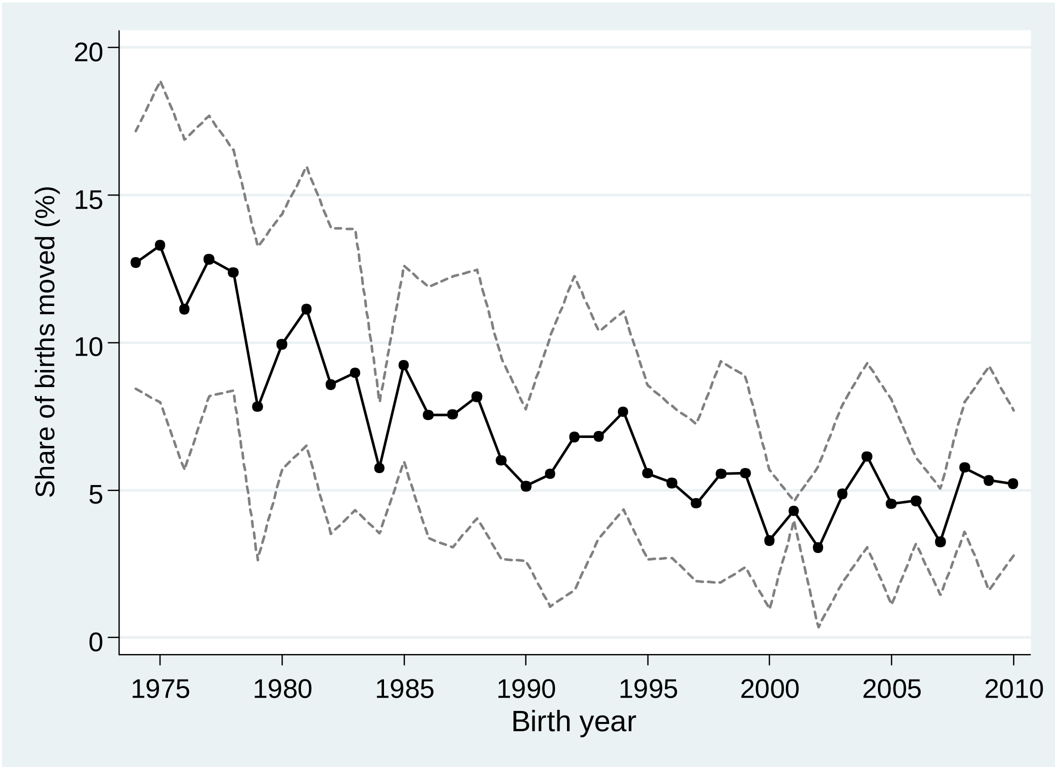
Appendix Figures and Tables

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



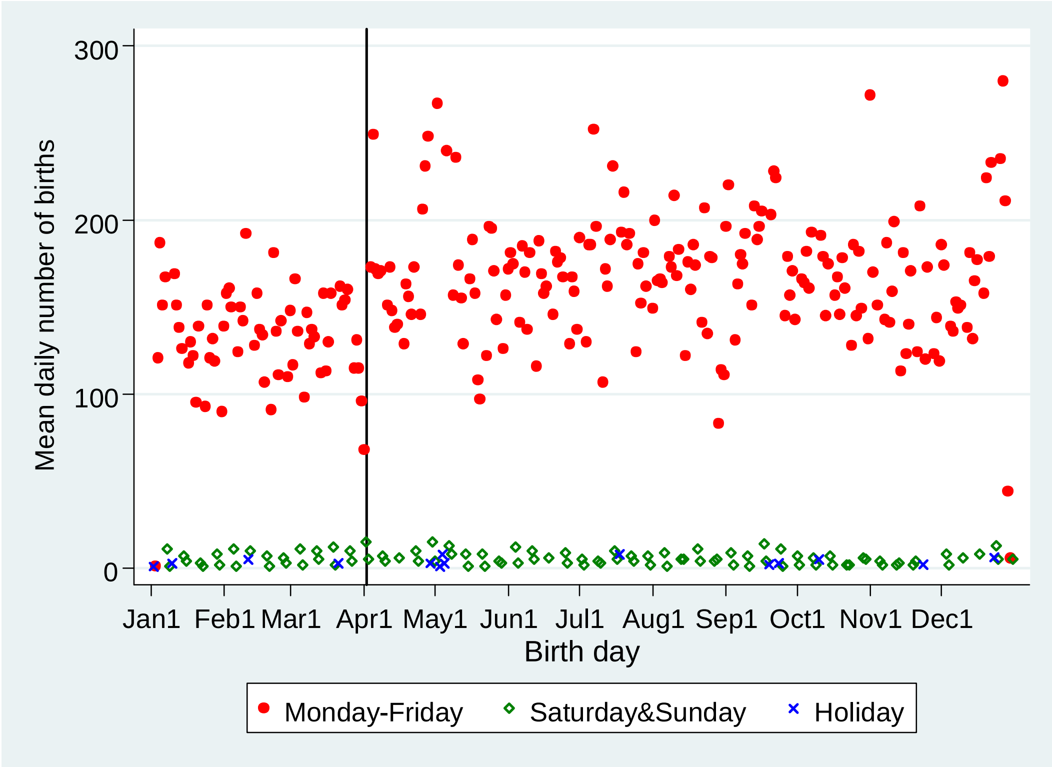
Note: The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from pooled 1974–2010 birth data. The markers with cross sign are holidays. Each plot is the mean daily number of births.

Figure B: Share of births moved by each birth year



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

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



Note: The vertical line corresponds to April 2, which is the school entry cutoff date in Japan. The data come from 2011 DPC data. Each plots the daily number of birth.

Table A: Summary statistics of birth and death data

	7 days before cutoff date	7 days after cutoff date	Dif (2)-(1)	Entire year
	(1)	(2)	(3)	(4)
Mother's age (in years)	29.84	29.75	-0.091***	29.81
1st-born birth child	0.47	0.45	-0.020***	0.46
2nd-born birth child	0.37	0.39	0.021***	0.38
Birth weight (in 1000 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
Delivered at hospital	0.54	0.52	-0.021***	0.53
Delivered at clinic	0.43	0.45	0.016***	0.44
Delivered at home	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. The data come from pooled 1974-2010 birth data. Colum (1) is mean from the sample in seven days prior to April 2, and Column (2) is mean from sample in the first seven days after April 2, and Colum (3) is difference between (2) and (1). Column (4) is the mean from data that cover entire year.

Table B: Robustness checks

Windows	±7 days		±14 days	
	(1)	(2)	(3)	(4)
Panel 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
Panel 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, Column (1) and (3) report the estimates from specification (1), while Column (2) and (4) report estimation from the specification (2), which use the observations from other months as well.

Table C: Child's characteristics

Windows	Mean	(1) ±7 days	(2) ±14 days	(3) ±21 days	(4) ±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: Coefficient on *After* is reported. *After* is a dummy that takes one if the birthday is after April 2 in each year and zero otherwise. April 2 is a school entry cutoff date in Japan. * p<0.10, ** p<0.05, *** p<0.01. Sample is daily average from pooled 1974–2010 birth data. Window denotes the number of days before and after the April 2. For example, the ±7 day window covers the seven days prior to April 2, and the first seven days after April 2. All specifications include public holiday, year, and day of week fixed effects. Share of births moved is $\exp(\beta/2)-1$, where β is the coefficient on *After*.

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

	Mean daily births	(1) ±7 days	(2) ±14 days	(3) ±21days	(4) ±28 days
Panel 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
Panel 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
Panel 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: Outcome is log number of births. Coefficient on *After* is reported. *After* is a dummy that takes one if the birthday is after April 2 in each year and zero otherwise. April 2 is a school entry cutoff date in Japan. Robust standard errors are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01 significant at 1%. Sample is individual birth from pooled 2011–2012 insurance claim data. Window denotes the number of days before and after the April 2. For example, the ±7 day window covers the seven days prior to April 2, and the first seven days after April 2. All specifications include public holiday, year, and day of week fixed effects. Share of births moved is exp(β/2)−1, where β is the coefficient on *After*.

Table E: Heterogeneous response, by gender/parity of child

	A: Girl			B: Boy		
	All births	1st born	2nd born or above	All births	1st born	2nd 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
Mean of daily births	1,740	799	940	1,843	846	998
N	518	518	518	518	518	518

Coefficient on *After* is reported. *After* is a dummy that takes one if the birthday is after April 2 in each year and zero otherwise. April 2 is a school entry cutoff date in Japan. Standard errors clustered at the birth day are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Sample is daily births from pooled 1974–2010 birth data. The window is restricted to the seven days prior to April 2, and the first seven days after April 2. All specifications include public holiday, and year*day of week fixed effects. Share of births moved is $\exp(\beta/2)-1$, where β is the coefficient on *After*.

Table F: 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 (Oct)	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)

Table G: Summary statistics of PISA 2003

	(1)	(2)	(3)	(4)
	All	March	April	Dif
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: years of education	12.84	12.50	12.89	0.391*
	(3.15)	(3.26)	(3.09)	(0.23)
Mother: years of education	12.84	12.83	12.85	0.02
	(2.44)	(2.39)	(2.48)	(0.18)
Father: white-collar job	0.477	0.447	0.494	0.047
	(0.500)	(0.498)	(0.501)	(0.036)
N	4,700	358	401	

Table H: 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*	χ 2(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				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				403		
Gender	Yes	Yes			Yes	Yes		
Socioeconomics variable	No	Yes			No	Yes		
Mother's education	No	Yes			No	Yes		
Father's education	No	Yes			No	Yes		
Father is white-collar	No	Yes			No	Yes		

Note: Sample is PISA 2003 data for Japan. Coefficient on *relative age* is reported. See the text for the construction of relative age. Robust standard errors are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. P-value is reported in the bracket.