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ABSTRACT

This dissertation studies the short-term infant health effects of manipulation of birth timing, the short-term elderly health effects of retirement and long-run associations between childhood socioeconomic status and health outcomes later in life.

In the first chapter, I assess the impact of the small change of birth timing on infant health at birth, by exploiting a phenomenon in which some parents avoid holiday babies, especially during the holiday season at the end of the year. I focus on all full-term singleton births delivered by mothers without medical problems during pregnancy because newborns' health outcomes are believed to be similar in the traditional full term pregnant period (37 weeks to 41 weeks). Using New Jersey birth certificate data with a baby's exact date of birth and the exact date of the mother's last menstrual period during the years 1989 to 2011, it was estimated that about 207 singleton births per year are moved to an early time from the Christmas break and the New Year's break in the holiday season at the end of the year. Among different delivery methods, I find that induced vaginal and induced C-section deliveries are the two main methods used for the birth timing manipulation. I also find the group of mothers whose babies were born shortly before the holiday break appear to be slightly older, more educated, more likely to be white, more likely to be married, having more prenatal visits and fewer risky behaviors during pregnancy than mothers whose babies born during the holiday break. In addition, birth timing manipulation causes babies to be born before their expected delivery dates, which carries greater health risks, including lower Apgar scores, a lower probability of getting normal Apgar scores (i.e., scores > 7), and a higher probability of having respiratory problems.

In the second chapter, I investigate the short-term effects of retirement on health related outcomes and the mechanisms behind the effects by using a comprehensive, nationally

representative sample from the China Health and Retirement Longitudinal Study (CHARLS). The mandatory retirement policy in China provides a quasi-experimental setting for the identification of the effects of retirement. By focusing on a sharp change in retirement status among males just below and just above the mandatory retirement age 60, and using regression discontinuity models, I show that retirement improves the mental health and well-beings of retirees. Although the effects are not statistically significant, I find retirement still improve the subjective health status and objective physical health of retirees. I further find that paying more attention to one's own health, increased social activities as well as more frequent physical exercises might be the key mechanisms through which retirement improve health and well-beings.

In the third chapter, I also use the CHARLS to estimate the long-term effect of childhood social-economics status (CSES) on several health outcomes of the elderly (people aged 45 to 80) in China. I find that for both men and women, unfavorable childhood life situation is associated with adverse health status in later life. Although those effects are partially mediated through education and adult income status, those effects remain statistically significant when I control for the education and income. I also find long-term CSES effects are stronger for women than for men.

Chapter 1: Manipulation of Birth Timing and its Impact on Health at Birth

1.1 Introduction

Since the 1990s, there have been some notable changes in approaching labor and delivery by physicians and parents. Physician financial incentives, parents' preference, physicians' convenience, unique cultures and educational benefits relative to school entry cutoff date drive the increase of scheduling birth at a time before the natural arrival of the baby, and this increase may be an important reason triggering the increase of induction, simulation and Cesarean section (C-section).

C-section (both elective and non-elective) has become the most common operation for women in American hospitals (Hall, et al., 2010). The overall C-section delivery rates have increased 60 percent from the most recent low of 20.7 percent in 1996 to the high of 32.9 percent in 2009 (Martin et al., 2012), and declined slightly to 32.7 percent in 2013 (Hamilton et al., 2013). These rates have also exceeded the maximum C-section delivery rate of 15 percent, recommended by World Health Organization (WHO) more than one decade ago. At the same time, the rate of induction of labor has more than doubled from 9.6 percent in 1990 to 23.8 percent in 2010 (Osterman and Martin 2014). However, the C-section rates are much lower in other developed countries, such as in 2008 French 18.8 percent, Japan 17.4 percent, Norway 16.6 percent and Netherlands 13.52 percent.[1]

[1] Gibbons, L., Belizán, J. M., Lauer, J. A., Betrán, A. P., Merialdi, M., & Althabe, F. (2010). The global numbers and costs of additionally needed and unnecessary cesarean sections performed per year: overuse as a barrier to universal coverage. World

Because of the dramatic increase of induction and C-section, the average gestational age for singleton births in the United States slightly decreased (Davidoff et al., 2006; Bettegowda et al., 2008). The number of Birth with 40 or more weeks' gestation significantly decreased, and deliveries at 34 to 39 weeks' gestation increased (Davidoff et al., 2006).

What are the consequences of small change in the timing of birth on the neonatal health outcomes? In the past, the period from 3 weeks before until 2 weeks after the estimated date of delivery was considered "term", with the expectation that neonatal outcomes from deliveries in this interval were uniform and good.[2] Some researchers believe there is an insignificant difference in health outcomes between newborns whose birth dates were changed by elective induction or C-section and those whose birth dates are determined naturally. As a result, they support the use of scheduled delivery without a compelling medical reason through elective induction and elective C-section to satisfy physicians' convenience and parents' preference. Some research has shown that among "term" deliveries average neonatal outcomes still can vary by the timing of delivery even with this 5-week gestational age window: likelihood of adverse outcomes can be U-shaped, with the nadir around 39 weeks through 40 weeks of gestation (Tita et al., 2009; Reddy et al., 2011),[3] which suggests that induction and C-section without a compelling medical reason could be associated with greater risk of neonatal respiratory morbidity and mortality. Because physicians' conducting randomized experiments on pregnant

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health report, 30, 1-31.

[2] Gestation in singleton pregnancies lasts an average of 40 weeks (280 days) from the first day of the last menstrual period to the estimated date of delivery. In the past, the period from 3 weeks before until 2 weeks after the estimated date of delivery was considered "term". The new definitions for term deliveries published in the Journal Obstetrics & Gynecology and endorsed in 2013 by the American College of Obstetricians and Gynecologists and the Society for Maternal-Fetal Medicine are: Early term: 37 0/7 weeks through 38 6/7 weeks; Full term: 39 0/7 weeks through 40 6/7 weeks; Late term: 41 0/7 weeks through 41 6/7 weeks; Post term: 42 0/7 weeks and beyond.

[3] In this paper, 37 weeks of gestation means 37 0/7 – 37 6/7 weeks of gestation, 38weeks of gestation means 38 0/7 – 38 6/7 weeks of gestation, 39 weeks of gestation means 39 0/7 – 39 6/7 weeks of gestation, 40 weeks of gestation means 40 0/7 – 40 6/7 weeks of gestation, 41 weeks of gestation means 41 0/7 – 41 6/7 weeks of gestation, and 42 weeks of gestation means 42 0/7 – 42 6/7 weeks of gestation.

women are impossible assessing the risks of small change in the timing of birth, without exogenous variation in this small change.[4]

However, holiday season at the end of each year could induce a “natural experiment” for a pregnant woman whose expected date of delivery is around Christmas and New Year’s Day.[5] On the one hand, she may deliver her baby slightly before holiday through elective induction and elective C-section for several reasons.[6] For example, she does not want her baby to have a “holiday birthday”; she wants her baby to meet other family members before the holiday break; she wants a long post-natal break; she wants to get more tax refund if she can deliver her baby before the last day of a year; she may fear that her physician will not be available on a holiday, and so on. Lisa and Teny (1999) find that increasing the tax benefits by $500 raises the likelihood of delivering a baby in the last week of December rather than the first week of January by 26.9 percent. Furthermore, some other special dates may also affect parents’ decision on when they want their babies to arrive. Lo (2003), Gans and Leigh (2006), Lin et.al (2006) show that parents schedule baby's delivery on auspicious dates and avoid inauspicious birth dates. On the other hand, physicians may also like to shift the timing of birth early to satisfy their time arrangement. Gans et al. (2007) find that deliveries decreased by 1 to 4 percent during the days of the annual obstetricians and gynecologists’ conference in Australia and the United States, accompanied by an increase of those before the conference day.

In this study, using New Jersey birth certificate data with baby’s exact date of birth and exact date of mother’s last menstrual period (LMP) during the years 1989 to 2011, I assess the impact

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[4] It is almost impossible for physicians to randomly choose some pregnant mothers as treatment group and execute elective induction or C-section to them around their estimated timing of delivery.

[5] Although some parents may plan ahead about getting pregnant to delivery their babies on their favorite date or to avoid their unfavorable date, it is very hard to fortunately conceive on specific date.

[6] Few physicians want to be pacing the halls on Thanksgiving or Christmas, waiting for a mother to deliver," said Marilyn Curl, CNM, MSN, LCCE, FACCE and president of Lamaze International. Families often can feel stressed about the uncertainty of the baby's arrival and feel it may compromise the celebration of holidays. Some women also fear that their preferred healthcare provider won't be available and will agree to a scheduled early delivery to guarantee that their provider will be there for the birth. http://www.pregnancy.org/article/holidays-put-pressure-women-schedule-early-delivery.

of small change of birth timing on infant health at birth, by exploiting a phenomenon that some parents avoid holiday babies, especially in the holiday season at the end of each year. I focus on all full-term singleton birth delivered by mothers without medical problems during pregnancy. The reason why I only choose full term births is that newborns' health outcomes are believed to be similar in the traditional full term pregnant period (i.e., 37 to 41 weeks), and the reason why I choose singleton births is that multiple pregnancies may increase the risk of certain pregnancy complications.

My results indicate that in New Jersey during the holiday season, about 207 singleton births per year are moved to an early time from the Christmas break and the New Year's break in the holiday season at the end of each year from 1989 to 2011. The average daily number of singleton births during this period is about 295. Here, I define the Christmas break as the period from the day before Christmas Eve to the day after Christmas Day (i.e., December 23rd to December 26th). New Year break is defined as the period from the day before the New Year's Day to the day after the New Year's Day (i.e., December 31st to January 2nd). And holiday season is defined as the period from December 16th to January 5th. I find that induced vaginal and induced C-section delivery are two main methods used for the birth timing manipulation. In addition, I find a slight decrease in birth weight and gestational age among births in days just before the holiday break. This finding suggests that parents manipulate their baby's birth timing during a holiday season probably in response to tax refund benefits, or the convenience for physicians and parents.

I also find that mothers whose babies were born shortly before the holiday break appear to be slightly older, more educated, more likely to be white, married, have more prenatal visits and fewer risky behaviors during pregnancy than mothers whose babies born during the holiday break were. I also find that birth timing manipulation that lets babies be born a little earlier than their expected delivery dates could increase health risks of having lower Apgar scores, a lower probability of getting normal Apgar scores (Apgar scores > 7) and a higher probability of having respiratory problems.[7] Because those negative short-term health consequences are usually associated with higher health care costs, breastfeeding difficulties, learning and behavioral problems, as well as long-term health outcomes, parents and physicians should carefully evaluate whether scheduling delivery without compelling medical reasons through elective induction and elective C-section is indeed necessary. Policymakers also should pay more attention to the potential negative impact on infant health of scheduling delivery through elective induction and elective C-section.

The rest of the paper is organized as follows. I will discuss previous studies in Section 2, and describe the data in Section 3. Section 4 presents my empirical analysis and results. Section 5 performs robustness checks, and Section 6 concludes.

1.2 Previous studies

When the natural arrivial of the baby would put the baby's or mother's life or health at risk, parents and physicians always change the timing of birth through induction and C-section to lower health risk of newborns and pregnant women. However, even mothers and babies do not have a compelling medical problem to do so, the birth timing manipulation is still performed for a variety of other reasons.

First of all, the birth timing represents some unique pattern. Mathers (1983) analyzes births occurring in Australia and finds birth numbers per day have “seven-day birth cycle”. The most births are concentrated on Tuesdays to Fridays and least births on Sundays, which had 26 percent

[7] Apgar score is a measure of the physical condition of a newborn infant. It is obtained by adding points (2, 1, or 0) for heart rate, respiratory effort, muscle tone, response to stimulation, and skin coloration; a score of ten represents the best possible condition.

fewer births than expected. Gans and Leigh (2008) also find that in U.S. and Australia, about one-third births who would have been delivered on a weekend were delivered on a weekday.

Parents who believe the possible long-term academic gains is more important than the short-term savings of childcare cost may manipulate the birth timing as a way of early childhood investment. The reason is that older children perform better academically than their younger peers (McEwan & Shapiro 2008, McEwan & Shapiro 2008). Using birth records in Japan, where school entry rule is strictly enforced, Hitoshi (2015) finds that more than 1,800 births a year who would have been delivered in the week before the school entry cutoff date were delivered to the week following the school cutoff date.

Parents and physicians may alter the birth timing because of their preference, convenience, and unique cultures. Using C-section rates from home countries of immigrant mothers in Norway as the measurement of patient preference of delivery, Grytten et al. (2013) find that a substantial share of C-section is due to delivery preferences and the high elective C-sections rate. Gans and Leigh (2012) exploit the particular conflict parents and physicians meet when they bargain over the timing of birth. Parents may not like inauspicious dates like February 29th and April 1st. If these inauspicious dates occur on a Monday or Friday, patients may have a strong preference to give birth on weekend, but the physicians may not want to work on the weekend. Their results show that parents' preference defeats those of physicians in about one-quarter cases, suggesting parents could successfully manipulate the birth timing. Gans and Leigh (2009) find the number of births rose by 12 percent on 1 January 2000, the Millennium. Levy et al. (2011) find that in U.S. on Valentine's Day the spontaneous births increased by 3.6 percent and C-section births increased by 12.1 percent. On Halloween, the spontaneous births decreased by 5.3 percent and C-section births increased by 16.9 percent. Almond et al. (2015) find that increased Chinese-

American births on the dates with the lucky number 8 in Chinese culture, such as 8th, 18th, or 28th days of the month, and decreased Chinese-American births on the 4th, 14th and 24thof the month, those dates are considered unlucky in Chinese culture.

Parents and physicians may also manipulate the birth timing due to financial incentives. For physicians, Gruber et al. (1999) find that higher reimbursement fee triggers more C-section deliveries, the C-section procedure is one of the main mechanism of changing the timing of birth. A similar result was found by Grant (2009), his finding indicates that the one percentage point increase in C-section rate from about one-quarter of the original rate is attributed to an additional $1000 reimbursement for C-section procedure. For parents, Dickert-Conlin and Chandra (1999) find the increased tax benefit rise the probability of having the child in the last week of December rather than the first week of next year. Gans and Leigh (2009) find that in 2004 over 1000 births were moved from June to July to get the $3000 baby bonus, which is eligible for children born on or after July 1st, 2004 in Australian. This shifting constituting 6 percent of the babies who would have been born in June. They also find the drop in the birth of June was mainly due to fewer C-section and induction procedures in June. And of the rise in births of July, half were C-section births, three-tenths were non-induced vaginal births, and two-tenths were induced vaginal births. All of these studies suggest that parents and physicians manipulate the birth timing because of monetary incentive, personal preference, unique cultures and so on.

Regarding the health concerns, elective induction has been shown to increase the risk of C-section for pregnant women who has never given birth either by choice or for any other reason, to increase in-hospital pre-delivery time and costs (Seyb et al. 1999; Maslow & Sweeny 2000), and in turn C-section increases the probability of maternal mortality and morbidity, the risk of babies' respiratory morbidity, the rate of complications, and the probability of neonatal intensive care unit admissions (Shearer 1993; Levine et al. 2001).

However, there is limited correlational evidence in the medical and economics literature on the relationship between gestational length and health outcomes beyond birth. In addition, for pregnant women without medical reasons, the consequences of a small change in birth timing through elective induction and elective C-section on health have not been clearly assessed. Recent work in economics suggest that the small change of birth timing induced by tax benefits at the end of the year leads to a lower birth weight, a lower Apgar score, and an increase in the probability of being born with a low birth weight (Schulkind and Shapiro. 2014), and children born close to the 2,500-euro universal child benefit cancellation date in Spain suffered significantly higher hospitalization rates in the weeks following birth (Borra et al. 2016).

The first reason why I have limited literature in this area is no randomized trial data comparing infant health outcomes among births from elective induction and elective C-section versus vaginal delivery. It has been difficult to identify and report election induction and elective C-section because those procedures may not be included in hospital coding system or among payer's reimbursable insurance claims is the second reason (Signore and Klebanoff 2008).

This study makes three important contributions to current literature. First, studying data from the 1990s and 2000s, the period in which notes of induction and C-section rates increased dramatically, makes me able to understand how parents' and physicians' react to the incentives of altering birth time. Second, with baby's exact date of birth and exact date of mother's last menstrual period (LMP), I am able to calculate the gestational weeks and then distinguish mothers who have strong incentive to manipulate their baby's birth time from who do not have this behavior. Finally, I am able to access the possible impacts of small birth timing manipulation on infant health at birth. The investigation will have strong implications for making health policies and making birth timing manipulation decision with regard to elective induction and elective C-section.

1.3 Data

My analysis relies on the restricted-access data: Vital Statistics Natality records (birth certificates) for the years 1989 to 2011. The Vital Statistics Natality records are compiled by New Jersey Department of Health and Human Services and cover the universe of birth in New Jersey. These data include records for every birth and each record has information about family demographic characteristics including parents age, education, and marital status; about mother's health and behavior during pregnancy (such as medical risk factors for this pregnancy, prenatal visit information, and behavior of smoking, taking drugs and drinking); about procedures and problems during labor and delivery (delivery method, obstetric procedures, and complications of births), as well as many newborns' health measures including birth weight, congenital malformations, the 1-minute Apgar score, the 5-minute Apgar score, and information on assisted ventilation usage. The two key variables in the confidential version of the data I obtained are the exact date of birth and the first day of Mother's Last Menstrual Period (also called LMP).

I only focus on singleton lower risk term births.[8] The reason why I focus on the singleton births is that the health risk caused by multiple birth pregnancy will contaminate the health consequences caused by birth timing manipulation through elective induction and elective C-section. The reason why I focus on the lower risk births is that I need to investigate the consequences of elective induction and C-section. I drop all the birth whose mothers have any

[8] When I analyzed the birth data, I tried to include all births. The results (not shown) are very similar with the results I got from singleton births analysis.

medical risk factors during pregnancy from the sample of my singleton term birth, because the induction and C-section used by those pregnancies are to reduce natural childbirth risk caused by medical risk factors (Cardiac Disease, Diabetes, Renal Disease, Rh sensitization, Genital herpes and so on) on pregnancy. In addition, the reason why I focus on term births is that the expected neonatal health outcomes from deliveries in the term interval are believed uniform and good. So after the pregnancy passes 37 weeks, parents and physicians may manipulate the birth timing for their own reasons. To analyze delivery procedure through which parents manipulate the birth timing, the characteristics of those parents, and health consequences of their babies, I do impose additional restrictions on the sample. First, I limit the sample to mothers between the ages of 20 and 45, because the teen and older mother's delivery decision are potentially complicated by other factors. Second, I limit the sample to families with five or fewer children in order to avoid the idiosyncrasies of especially large families. Finally, I combine 1989 – 2011 (23 years) of birth data provides information on 2.3 million singletons lower risk term births.

Table 1.1 presents descriptive statistics for births of four groups occurring in the holiday season, the period from December 16th to January 5th. Holiday breaks are the Christmas break and New Year break. Here the Christmas break is the period from the day before Christmas Eve to the day after Christmas Day, December 23rd – December 26th. New Year break is the period from the day before New Year's Day to the day after New Year's Day, December 31st – January 2nd. Four groups are singleton term birth, singleton term, and low-risk birth, singleton low-risk birth with gestational ages between 38 weeks to 40 weeks, and singleton low-risk birth with gestational ages between 39 weeks to 40 weeks. For every group, column (1) provides the summary statistics of births on the rest of days except holiday break in the holiday season, column (2) shows the statistics of births on holiday break, while column (3) reports the difference. For example, the average mother's age who give birth in others days of the holiday season is 0.32 years older than those who give birth in holiday break. A comparison of the sample on the column (3) shows that on average, mothers who do not give birth in holiday break are more likely to be white, older, educated, and have more prenatal visits than mothers who give birth in holiday break. In addition, C-section and induction are more popular in holiday break than in other days of the holiday season. Babies born in others days of holiday appear to be healthier than births in holiday break.[9]

When I estimate the effects of birth timing manipulation on newborns health outcomes, I expand the sample to include a set of comparison period, which is 15 days before Holiday season (December 1st to December 15th) and 15 days after Holiday season (January 6th to January 20th). Table 1.2 provides a summary statistic for births in Holiday Season and in the comparison period. For every panel, column (1) provides the summary statistics of comparison period, column (2) shows the summary statistics of the holiday season, and column (3) reports the difference. Although many differences between Holiday Season and comparison period are smaller than the differences between holiday break and other days of the holiday season, the births in holiday season still appear to be in poor health relative to the births in the comparison period. These health outcome differences may be due to manipulation of birth timing in the holiday season.

[9] There is the issue of selection in the decision to manipulate birth time. Only low-risk mothers will manipulate the birth timing because of their preference or monetary incentive.

1.4 Empirical analysis [10]

1.4.1 Manipulation of the birth timing

Figure 1.1, Figure 1.2, Figure 1.3 and Table 1.3, was made from New Jersey pooled 1989-2011 birth data. Figure 1.1 shows the number of singleton births in December of 2000, 2003, 2007 and 2010 and their following January (I randomly chose these four years from 1989-2011). I observe a trough around Charismas day, a trough around the New Year day, a peak before Charismas day and a peak before the New Year's Day. In addition, it shows strong weekly cycle in the number of birth. More babies are delivered on weekdays and less on weekend.

Using pooled data from 1989 to 2011, I draw Figure 1.2. Every cell represents the average daily number of singleton births in NJ between 1989 and 2011, along with a ranking represented by the intensity of the color. Dark color represents this birthday is more common and vice versa. It indicates a large proportion of babies are born in fall and fewer babies are born in spring and winter. I can find that September clearly has many of the top days, but July and August aren't far behind. It looks like people conceive during all of those Thanksgiving, Christmas, and New Year's parties. The 13th seems to be least common on average. Perhaps that's because many people see that as an unlucky day. In addition, it is clearly shown that around major holidays (July 4th, Thanksgiving, Christmas, New year's day) there fewer babies born. At the end of the year, not only Christmas day but also the day around Christmas day, few singleton births were delivered. The Same situation happens around the New Year's Day. Manipulation of birth timing may be the reason of this difference.

Table 1.3 shows top 30 and bottom 30 days of the mean daily number of singleton births throughout the year. The third least popular birthday falls on Christmas Eve, December 24th,

[10] All my empirical analysis is based on singleton birth. The number of births means the number of singleton birth.

followed by December 25th and January 1st. It's obvious that the least common birthdays fall at the beginning of January, at the end of November, and around Christmas time.

On day's level, to test whether or not different days at the end of and the beginning of the year do have different effects on the number of birth per each day. Using all days in December and January (23 years * 62 days = 1426 days), I design the econometric model as blow:

$$Y_{dy} = \alpha + \beta_j Day(\mathrm{j})_{dy} + \delta_k \sum_{k=1}^{6} Dow(\mathrm{k})_{dy} + Year_y + \varepsilon_{dy} \quad (1)$$

The dependent variable Y_{dy} takes two forms, the daily number of singleton birth for day d in year y and the log transformation of daily number of singleton birth to correct left-skewed distribution. $Day(j)$ is the dummy variable for each day in December and January, and $Dow(k)$ is one of six dummy variables for each day the week. $Year_y$ indicates the series of year trend.[11] ε_{dy} is the error term. My interested coefficient is the series of β_j, so I run 1426 (23 years * 62 days = 1426 days) equations to get a group if β_j. Every β_j represent each day's effect on daily number of singleton birth comparing with the average of all other days.

Results of the model (1) are shown in Table 1.4. Panel A and B represent similar results. The coefficients of column December 23th, 24th, 25th, 26th, 31th, January 1st and 2nd are negative and statistically significant at the 1 percent level. However, the coefficients of column December 16th -22nd and 27th - 30th are positive and statistically significant at the 1 percent level, showing more singleton births on these days. For example, the coefficient on column December 25th is negative 101. Since a birth that is moved from this day will increase the number of other days. I calculate the total number of births moved from December 25th by dividing the coefficient of this day by 2. So I estimate that about 50 (=101/2) births were moved from December 25th. In addition, the

[11] I allowed the interaction term between the day of week fixed effects and year fixed effects to capture the different day of week effect of each year. These results are very similar.

dependent variable of panel B is the log of the number of births on every day, so about 20 percent births on December 25th were shifted to the earlier time.[12] In general, fewer babies are born in days around Christmas day and in days around the New Year's Day, and more babies are born before these days around Christmas day and before these days around the New Year's Day. This pattern is consistent with what shown in Figure 1.3 (the line shows the mean daily number of births over the mean number of birth in the holiday season by different delivery methods.)

Two reasons may explain why holiday effects at the end of the year and beginning of the following year on the number of births extend beyond just two days (Christmas and the New Year's Day). First, many companies and federal department adjust their Christmas holiday and the holiday of New Year's Day when these two days fall on weekends. It means that a day off usually is observed on Monday (if the holiday falls on Sunday) or Friday (if the holiday falls on Saturday). Second, some people including pregnant women take annual leave during the Christmas and New Year Period.

Based on the results of the model (1), I choose the related windows shown in Table 1.5 to do the following analysis. Here holiday break is consisting of the Christmas break and New Year break. the Christmas break is the period from the day before Christmas Eve to the day after Christmas Day, December 23rd – 26th. New Year break is the period from the day before New Year's Day to the day after New Year's Day, December 31st – January 2nd. Holiday season is the holiday period at the end of the year and the beginning of the following year, December 16th – January 5th. The comparison period is 15 days before the holiday season and 15 days after the holiday season, December 1st – December 15th and January 6th – January 20th.

[12] I suppose that the majority way of this movement is moving forward, because moving delivery date afterward is difficult to execute for pregnant mothers.

On day's level, to test the entire holiday break effect on the birth number, I use below econometric model (2). *HB* is the dummy variable indicating all days on holiday break.

$$Y_{dy} = \alpha + \beta * HB + \delta_k \sum_{k=1}^{6} Dow(\mathrm{k})_{dy} + Year_y + \varepsilon_{dy} \quad (2)$$

Table 1.6 shows the results of the model (2). Column 1 represents the results of all singleton low-risk term births, and other columns show the results of subgroups by different delivery procedures. Comparing the number of births in holiday break and the number of births in other days of the holiday season (Panel 1), the coefficient of holiday break is negative 59 for all births. This indicates that the total number of births moved from the holiday break to early days in the holiday season is about 207 (7*59/2 = 207). The dependent variable of Panel B in table 1.6 is log number of birth. The coefficient of holiday break is negative 0.214. I divide it by two and then convert it from log points to percentage points. I find that about 11.29 percent babies who would have been born in the holiday break were manipulated to delivery on others days before the holiday break.

1.4.2 Nature of manipulation

Figure 1.2 (part 1 and part 2) decomposes the ratio of the daily number of birth to an average birth number by different birth procedures in December and January. The jump up and down patterns, which are similar to part 2 of Figure 1.2, clearly shows that births delivered by each procedure are less in holiday break and more in days before holiday break (Christmas and the New Year break), with the most significant decrease in induced vaginal births and on induced C-section births.

To understand the determinants of the manipulation of birth timing occurred at the end of the year, I try to figure out two different types of manipulation: "shifting" and "switching" on individuals' level, which is originally presented by Schulkind and Shapiro (2014). Shifting is defined as a movement of birth timing but keeping the method of delivery unchanged. For example, having a birth before the the Christmas break than it would have, but the type of delivery is unchanged. Switching is defined as a change in the method of delivery. For instance, changing the delivery method from vaginal to C-section to have a baby a little early to avoid Christmas day. The birthing timing can only be shifted, be switched, or both shifted and switched. The regressions take two forms:

$$BP_i = \alpha + \beta * HB + \delta_k \sum_{k=1}^{6} Dow(\mathrm{k})_{dy} + Year_y + \varepsilon X_i + County_i + \varepsilon_i \quad (3)$$

$$BP_i = \alpha + \beta * HS + \delta_k \sum_{k=1}^{6} Dow(\mathrm{k})_{dy} + Year_y + \varepsilon X_i + County_i + \varepsilon_i \quad (4)$$

First, limiting all births between December 16th and January 5th (holiday season), I use model (3) to determine the manipulation of "shifting". Then, limiting all births between December 1st and January 20th (holiday season and comparison period), I use model (4) to determine the manipulation of "switching".

The dependent variable, BP_i, is the set of indicator variables for different delivery procedures, such as C-section, vaginal, induced C-section, non-induced C-section, induced vaginal and non-induced vaginal delivery. For example, BP_i equals to one if the birth procedure is C-section and zero otherwise. *HB* of equation (3) is the dummy variable indicating all days on holiday break. *HS* of equation (4) is the dummy variable indicating all days on holiday season. X_i is a vector of parents and child characteristics includes indicators for whether this mother is black or white; four mother education categories (<12, high school, some college, and college or more); mother age categories (20-24, 25-34, 35+); indicators for smoking, drug, alcohol, and prenatal visits during pregnancy; indicators for birth order; indicators for the number of children in this family; and an indicator for male child. $County_i$ captures county fixed effects. The interested coefficient is β, which measures the likelihood of having a certain type of delivery in holiday break relative to this type in other days in holiday season.

Table 1.7 and 1.8 separately shows the estimates of the model (3) and (4) for different delivery procedures. Panel A shows the results of the babies who are all full term (37 weeks - 41 weeks) singleton low-risk births, whose mothers are between the ages of 20 and 45, whose families with five or fewer children, and whose mothers have any medical risk factors for this pregnancy. To get panel B, I only keep the gestation of 38 weeks - 40 weeks from panel A, and keep the gestation of 39 weeks - 40 weeks to get panel C. The coefficient on HB, displayed in column (1) of Table 1.7, can be interpreted as the effect of HB on the likelihood of a holiday break C-section in holiday season. For Panel A, HB is associated with approximately a 2.1 percentage point decrease in the probability of C-section births in holiday break. An analogous estimate for vaginal and induction are displayed in Column (3) and Column (4). HB is associated with a 2.11 percentage point increase in the probability of vaginal births in holiday break, and with a 4.75 percentage point decrease in the probability of induced births in holiday break.

Then, I estimate the regression (3) by four mutually exclusive delivery procedures: inducted C-section, non-induced C-section, induced vaginal, and non-induced vaginal. Results are shown in column (4)-(7) of Panel A of table 1.7, I estimate that HB is associated with about a 4.75 percentage point, 0.743 percentage point, 1.36 percentage point, 3.99 percentage point decrease in the probability of induction, induced C-section, non-induced C-section, and induced vaginal births in holiday break. Correspondingly, HB is associated with about a 6.1 percentage point increase in the probability of a non-induced vaginal in holiday break, which is the closest proxy I have for a spontaneous, non-scheduled birth. This finding confirms the possibility that pregnant women may be able to control the timing of spontaneous births in somehow.[13] Even though I restrict the sample to Panel B, and C, the magnitude of these effects does not change significantly. So, these results suggest that scheduling C-section and induction are two most possible channels through which parents manipulate the birth timing to deliver babies earlier.

To examine whether any of the changes in the timing of birth can be attributed to the manipulation of "switching", I investigate whether holiday season is correlated with the likelihood of having a certain type of delivery in holiday season relative to a comparison period. The regression takes the model (4), where I extend the sample to include the births on comparison period. It is important to note that those parents who have babies on comparison period have less incentive of avoiding holiday babies. So ε_k is our coefficient of interest; it measures whether specific delivery births are more likely in holiday season compared to in comparison period. The results are showed in table 1.8. For all delivery methods, the coefficients in each Panel are small and statistically insignificant. This imply that parents manipulate the timing of birth to avoid holidays at the end of the year not by changing the delivery methods, but by schedule C-section and induction earlier. This scheduled induction result in the increase induced vaginal births and induced C-section births. Thus, the effects on newborns' health outcome in the following analysis are considered to be primarily the results of changing the timing of the births and not changing the type of delivery.

[13] Gans & Leigh (2009) find that the non-induced vaginal births rose after the introduction of baby bonus. Levy et al. (2011) find that for spontaneous births, there were a 5.3 percent decrease on Halloween and a 3.6 percent increase on Valentine's Day.

1.4.3 Parental characteristics

In this part, I want to figure out the relationship between higher or lower socioeconomic status (SES) that parents belong to and the behavior of the birth timing manipulation, and also the relationship between health-related behavior and the behavior of the birth timing manipulation. There are two concerns about this relationship. The first one is that higher-SES parents are more likely to have private health insurance than lower-SES parents, so they are more able to affect the birth timing. Second, since many health insurance companies do not cover elective induction and elective C-section, higher-SES parents might afford those higher bills. Third, parents who are more likely to move their baby's birth date to earlier days before holiday break might also have better prenatal care and better health-related behaviors during pregnancy. I regress parent's characteristics, the situation of prenatal care, and health-related behaviors on *HB* (holiday break), controlling day of week, year and county fixed effects. The model (5) is:

$$Parents_i = \alpha + \beta * HB + \delta_k \sum_{k=1}^{6} Dow(\mathrm{k})_{dy} + Year_y + County_i + \varepsilon_i \quad (5)$$

Table 1.9 represents the results of the model (5). It appears that parents whose children were born shortly before the holiday break are slightly older; more likely to be educated, be white, be married; and less likely to be Hispanic. In addition, they have a higher probability of having prenatal visits, have a higher number of total prenatal visits, and have less risk behavior (smoking and taking drugs) during pregnancy. These results are consistent with my hypothesis that parent who manipulates their baby's birth date to days shortly before holiday breaks at the end of the year are more likely to be higher SES.

1.4.4 Health outcomes

I pay attention to some health consequences of birth time manipulations, such as gestational age at birth, birth weight, Apgar score and the usage of the ventilator. Gestation is an important outcome I need to investigate because it presents how long the fetus growing in utero. Gestation is the duration of the children's birth date and the mother's last menstrual period (LMP).[14] If parents manipulate baby's birth timing to a little bit early time before the expected due date, I can forecast that the average gestation weeks will be slightly decreased. Apgar is a quick test on baby's Appearance, Pulse, Grimace, Activity and Respiration at 1 and 5 minutes after birth. For each category, the infant is given a score of 0, 1 or 2. The scores are added up and the total sum is their Apgar score, and the score between 7 and 10 is generally considered normal. Apgar is also an important indicator of infant's overall health situation. Of course, birth weight can even reflect the future health situation. Furthermore, birth timing manipulation may increase the probability of having immature lung and respiratory problem, and then increase the probability of using ventilation.

To assess how a small and elective change of birth timing affect infant health outcomes in short term, I use regression model (4) with infant health outcomes as the dependent variable. I compare health outcomes of birth in the holiday season with health outcomes of birth in the comparison period (15 days before the holiday season and 15 days after the holiday season). The reason why I do not compare health outcomes of births in holiday break and those in other days of the holiday season is that I want to avoid sample selection problem. For example, two babies are all due on December 25th. Baby one would weight 3200g on December 25, but baby two would only weight 2600g on December 25. Suppose the birth time of baby one may be

[14] Last menstrual period (LMP) is an important variable helping us to calculate gestation. And gestation is related to birth time manipulation behavior and many other health outcomes. However, getting confidential information of LMP and birth date from public data or survey date is very difficult.

manipulated by elective C-section to December 20 and baby one's birth weight will become to 3000g (5 days forward). If I compare the birth weight of baby one, who was shifted, with the birth weight of baby two who was not shifted. I may conclude that manipulation of birth timing makes baby bigger (3200 g is greater than 2600g). However, the fact is that baby one is smaller because of manipulation of birth timing (baby one's birth weight changed from 3200g to 3000g). So I compare health outcomes in the holiday season and in comparison period to eliminate selection bias.

Panel A of Table 1.10 displays the health results for all full-term singleton birth. It shows that babies born in holiday season are associated with shorter gestation, lower birth weight, and lower Apgar 5 score. On average, babies born in holiday season have a 0.0195-week decrease in gestation weeks relative to the comparison period. This effect, on average, is about 0.14 day (3.28 hour) reduction in gestation per child born in the holiday season (not just those who are shifted), and this reduction is corresponding to the 4.97-gram birth weight drop. Babies gain approximately 225 grams per week in the final trimester of pregnancy. 4.97-gram drop in birth weight is about 0.15 percent of the mean birthweight 3351 gram. In addition, 5 minutes Apgar score and the likelihood of getting normal 1 minute Apgar score are less for those babies who born slightly before the holiday break. As I narrow down my sample to babies whose mother is a low-risk mother, and to births whose gestation is between 39 weeks to 40 weeks, the effect on birthweight become statistically insignificant, but the probability of using ventilation greater than 30 minutes increased. Although the magnitude of these statistically significant effects is small, I should know that they are driven by a small number of births whose birth dates are successfully shifted. The related health cost and medical cost may be very large.

1.5 Robustness check

In this part, using a great deal of information about pregnancy and delivery methods in New Jersey Vital Statistics records, I try to figure out which mother is highly likely to manipulate her baby's birth time. Then I directly test the relationship between birth timing manipulation and parents' characteristics and estimate the health effects of birth timing manipulation on newborns.

First of all, I choose the group of all low-risk term birth, because only parents who believe their babies are healthy in the uterus and will be healthy when delivered may consider manipulating their baby's birth timing to slightly early days by reason of holidays at the end of the year. In other words, to exclude the effects of concerns about medical problems on decision making of delivery methods, I only keep term birth whose mothers have fewer health problems during pregnancy. To get this group, from entry sample I drop all births whose mothers have any medical risk factors, such as diabetes, renal disease, cardiac disease, genital herpes, incompetent cervix, for this pregnancy. I drop some birth with some complications of labor and/or delivery, such as prolonged labor (>20 hrs.), seizures during labor, breech, cephalopelvic disproportion, anesthetic complications fetal distress and etc. Then I keep birth whose mother may have the incentive to manipulate the birth timing. Incentive means if any day of holiday break is in expectant mother's expected term delivery period (37 weeks to 41 weeks), this expectant mother may love to avoid holiday babies.

From above restricted sample, I choose all non-induced vaginal births as my control group based on the delivery procedure, because the non-induced vaginal birth is the closest proxy for spontaneous and non-scheduled birth without any manipulation of birth timing. From remaining birth (non-induced C-section, induced C-section, and induced vaginal birth), I drop repeat C-section birth, because in many cases vaginal delivery is not recommended after C-section.

Furthermore, I drop those whose birth date is later than their expected due date, because passing the due date (the 280th day after last menstrual period or the day at fully 40 weeks) is an important reason for physicians to suggest induction and/or C-section. Then the remaining births are my treatment group. Their timing of birth is highly likely to be manipulated to avoid holiday breaks at the end of the year. I need to clarify that mothers on my treatment group are not sure to change their baby's birth timing, but they are higher likelihood to alert their baby's birth timing due to holiday breaks at the end of the year.

Table 1.11 presents the summary statistics for the control group, in which babies are all non-induced vaginal birth, and for treatment group, which includes all birth whose birth timing are highly likely to be manipulated. Panel A are all birth satisfying the setting of my treatment and control group. Panel B and Panel C are under the restriction of birth date. Panel B restricts the birth date to December 1st – January 20th, which are combined period of the holiday season and comparison period. Similarly, Panel C restricts the birth date to December 16th – January 5th (Holiday season period). It shows that parents on treatment group are slightly older, higher educated, having more prenatal visits, and having fewer risk behaviors on pregnancy. It also presents that babies on control group have slightly higher Apgar scores, and have a lower likelihood of getting the aid of ventilation. Even I narrow down the window of birth date to Panel B and C, those differences between two groups present the similar pattern.

To investigate the relationship between parents' characteristics and parents' manipulation behavior, and the relationship between babies' health outcomes and parents' manipulation behavior. I use below two models. The $HL\_manipulate$ indicates the treatment group in which baby's birth timing are highly likely to be manipulated.

$$Parents_i = \alpha + \beta * HL\_manipulate + \delta_k \sum_{k=1}^{6} Dow(\text{k})_{dy} + Year_y + County_i + \varepsilon_i \quad (6)$$

$$Health\_Outcomes_i = \alpha + \beta * HL\_manipulate + \delta_k \sum_{k=1}^{6} Dow(\mathrm{k})_{dy} + Year_y + \lambda_i X_i + County_i + \varepsilon_i \quad (7)$$

Table 1.12 represents the results of the model (6). In the treatment group, mothers are about one year older than mothers in control group; fathers are about 0.63 years older; mothers have about 0.4 more years of education, and fathers have about 0.3 more years of education. In addition, parents are less likely to be Hispanic, to have risk behaviors on pregnancy, and more likely to have prenatal visits. Again, all panels (narrow down the window of birth date to Panel B and C) with different birth date restrictions show a similar pattern.

Table 1.13 displays the results of the model (7). Apgar and ventilation usage are my interested health outcomes of newborns. Columns (1) and (2) show that the behavior of highly likely to manipulate birth timing is associated with a decreased 1 minute Apgar score and a decrease in the likelihood of getting a normal minute Apgar score. Converting the results of Column (1) to the point estimate suggesting that babies whose birth timing are highly likely to be manipulated have 0.31 percent, 0.35 percent, 0.53 percent decrease in average 1 minute Apgar score for Panel A, B, and C. In addition, Columns (3) shows that the 5 minute Apgar scores of the newborn is also negatively affected by the behavior of manipulation birth timing. Although the likelihood of getting normal 5 minute Apgar score is a little bit higher for babies on treatment group, they are statistically insignificant. In addition, Column (5), (6), and (7) suggests that the probability of getting the aid of ventilation is higher for births on treatment group, in which babies' birth timing are highly likely to be manipulated. Evaluating the point estimate of Column (5) shows that 0.088 and 0.097-point increase of the probability of using any ventilation for panel A and B at 90 percent significant level. Because ventilation usage is very rare, converting the point change showed on Column (5) to percentage change, the corresponding effects are 54.8 percent and 60.43 percent increase. Although the effect of "highly likely to manipulate" on ventilation usage greater than 30 minutes and on ventilation usage less than 30 minutes are statistically insignificant, the positive point estimates suggest an increased probability of using ventilation.

These results again confirm my conclusion drawn from the previous main analysis, under which I compare the newborns' average health outcomes in the holiday season and in the comparison period. The higher-SES parents might be more able to affect their children's birth time, and manipulation of birth timing without any medical problems will negatively affect the infant's health consequences.

1.6 Conclusion and future directions

Scheduling births without any medical reasons has become more and more common all over the world. To satisfy parents and physicians' preference and convenience, some parents and physicians schedule to let them happen before the natural determined dates, using elective induction or elective C-section. However, the effects of a small reduction on gestational length on newborns' health outcomes have not been fully examined. Holiday season at the end of the year could be thought as a "natural experiment" for pregnant women whose expected due dates are around Christmas day or New Year's Day. Analysis on the effects of the holiday season helps me assess the infants' health costs if mothers without any medical problems during pregnancy alter their babies' birth timing in the holiday season.

Using restricted-access New Jersey birth data from 1989 to 2011, I estimate that in New Jersey about 207 singleton births per year are shifted from the Christmas break and the New Year's break to a slightly early time. This shift is mainly driven by the change in delivery procedures, that is the increased use of elective C-section and elective induction. Among the reduction in singleton low-risk births during the holiday break, 44 percent were C-section births, and 34 percent were induced births. Further dividing the drop by four mutually exclusive delivery methods, I estimate that about 11.5 percent induced C-section, 5.6 percent non-induced C-section, 16.7 percent induced vaginal, and 4.4 percent non-induced vaginal births are shifted to an early time from the holiday breaks at the end of a year. The results suggest that induced C-section and induced vaginal delivery are two main methods used for manipulating the birth timing.

The individual-level analysis indicates that mothers whose babies were born shortly before the holiday break appear to be slightly older, more educated, more likely to be white, married, and having more prenatal visits than mothers whose babies were born during the holiday break. My findings show that the average gestation age and birth weight are lower for births in the holiday season than births in the comparison period. In addition, Apgar scores, the likelihood of getting normal Apgar scores, and the probability of getting the aid of ventilation are also affected by the small change of birth timing.

As the induction and C-section rate continues to rise, parents and physicians should carefully compare the costs and benefits of birth timing manipulation even when mothers and fetus do not have medical problems. Policymakers should take into account the health costs of elective induction and elective C-section. More empirical studies on the long-term health effects of birth timing manipulation by elective induction and elective C-section are also needed.

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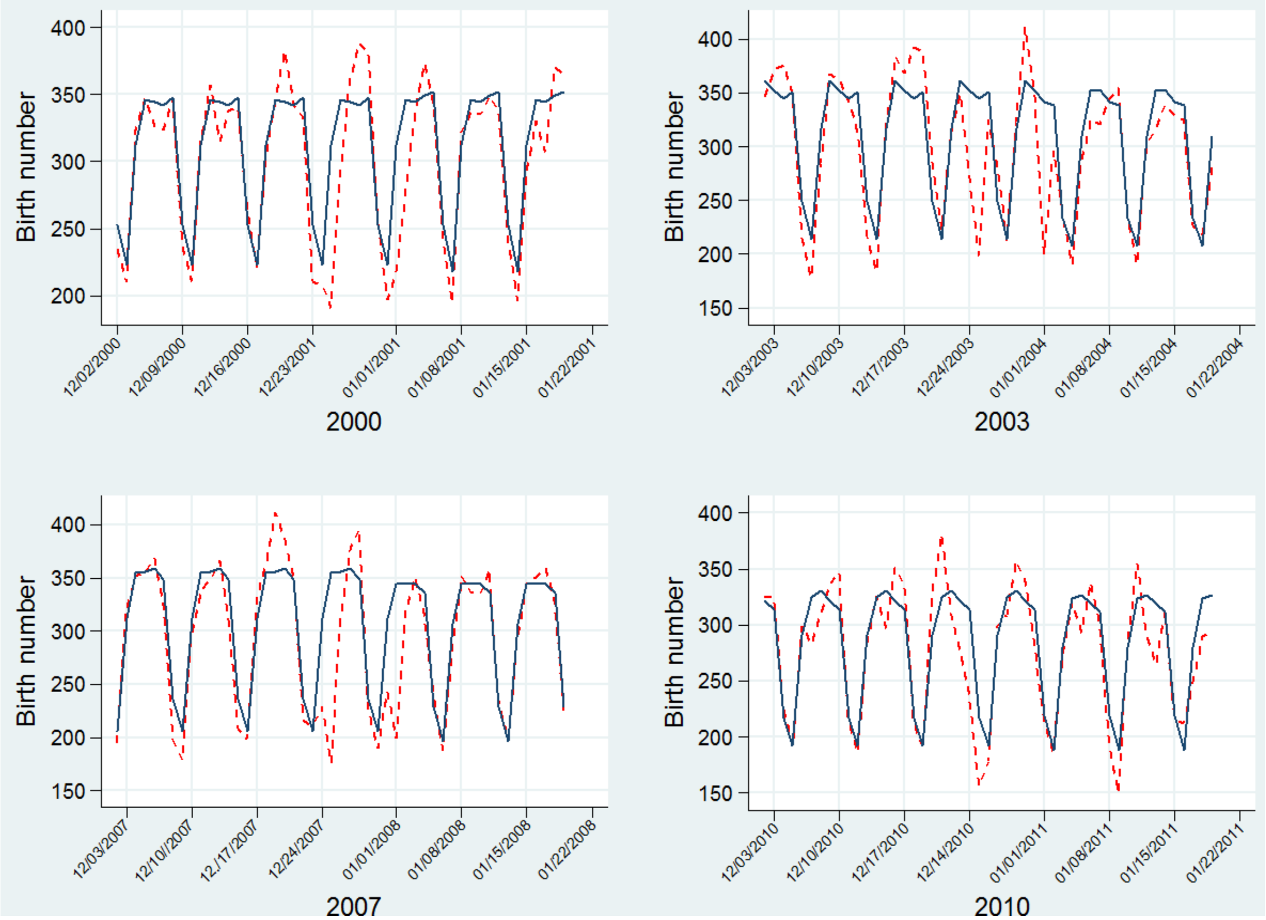
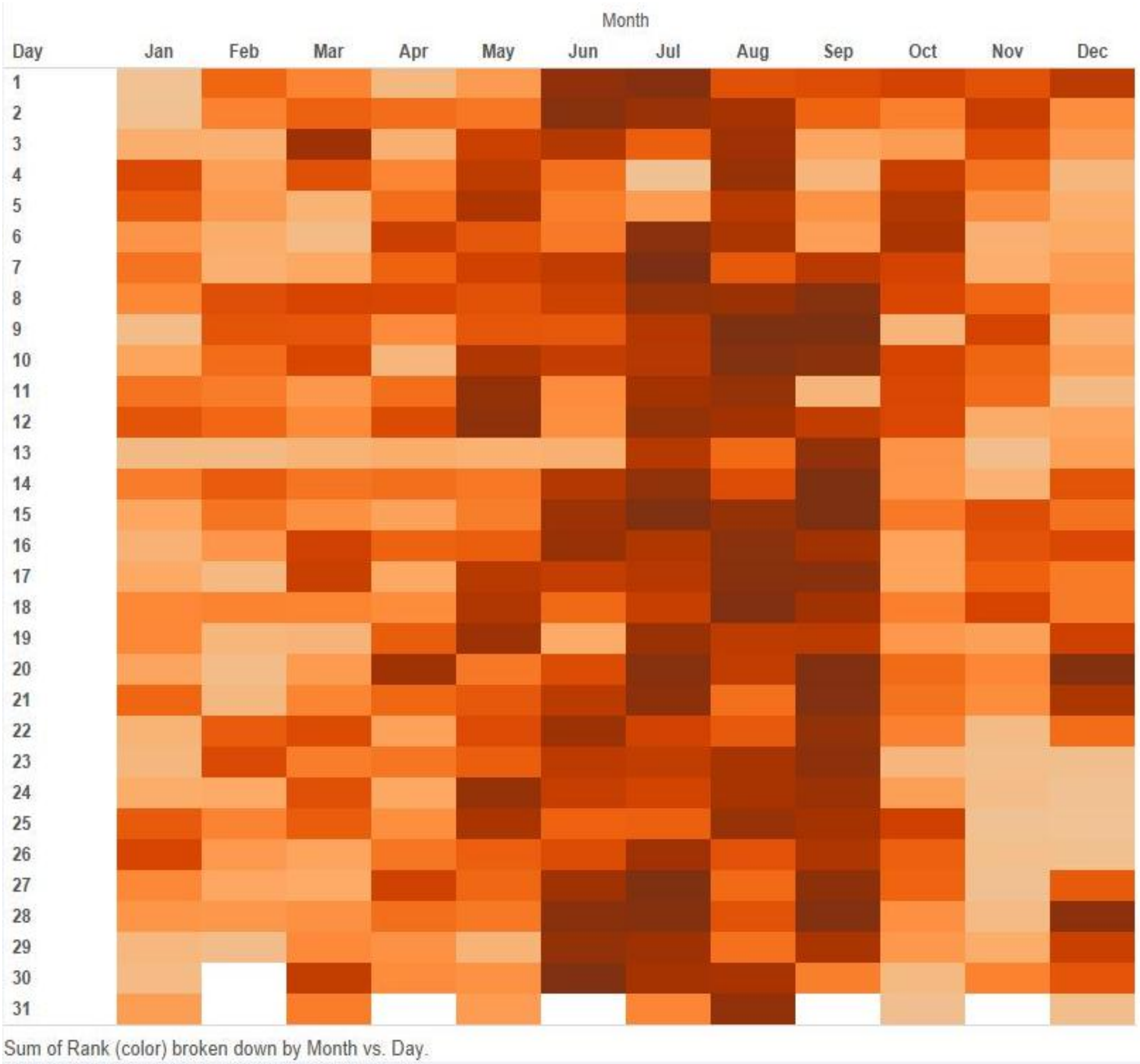
1.8 Tables and Figures

Figure 1.1 The number of singleton births in December of 2000, 2003, 2007 and 2010 and their following January



The dotted line represents the singleton birth number. The solid line shows the average birth number on Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday using pooled data from 1989 to 2011.

Figure 1.2 Rank of the singleton birth in one year



Every cell represents the average number of babies born in NJ between 1989 and 2011. The darker, the more common days. And the lighter, the less common days.

Figure 1.3 Singleton birth by different procedures

The line shows the mean daily number of births over the mean number of birth in the holiday season by different delivery methods. The data come from polled 1989 – 2011 birth data.

Table 1.1 Summary statistics - Comparison of Holiday Break and others days in Holiday Season

Variables	Term + Low risk + [37, 42]			Term + Low risk + [38, 40]			Term + Low risk + [39, 40]		
	Other days	Holiday Break	Diff.	Other days	Holiday Break	Diff.	Other days	Holiday Break	Diff.
mother_age	29.80	29.58	0.22 ***	29.90	29.64	0.26 ***	29.84	29.55	0.29 ***
mother_edu	13.79	13.68	0.11 ***	13.83	13.71	0.12 ***	13.84	13.71	0.13 ***
% mother_married	77.03	76.24	0.79	77.75	76.24	1.51 **	78.08	76.78	1.30 *
% mother_black	13.26	14.28	-1.03 **	13.13	14.64	-1.52 ***	12.66	14.32	-1.65 ***
% mother_white	75.87	74.52	1.35 **	75.52	73.80	1.73 ***	76.42	74.63	1.79 ***
% mother_hispanic	19.22	20.19	-0.97 *	19.33	20.20	-0.87 *	19.09	19.66	-0.57
% mother_asian	8.36	8.48	-0.13	8.74	8.87	-0.13	8.36	8.40	-0.04
% mother_alcohol	1.37	1.22	0.15	1.22	1.19	0.03	1.28	1.21	0.07
% mother_tobacco	7.30	7.95	-0.65	7.11	7.72	-0.61 *	7.02	7.72	-0.70 *
% prenatal_visits	99.56	99.46	0.10	99.62	99.50	0.12	99.66	99.52	0.14
prenatal_visits_number	10.98	10.89	0.09 **	10.94	10.88	0.06	11.03	10.95	0.08 *
father_age	32.62	32.41	0.20 ***	32.71	32.52	0.19 **	32.68	32.43	0.25 **
father_edu	13.85	13.77	0.08 **	13.89	13.80	0.09 **	13.89	13.79	0.10 **
% boy	50.52	50.30	0.22	50.48	50.40	0.08	49.90	49.70	0.20
number of children	1.78	1.77	0.01	1.79	1.78	0.02	1.78	1.76	0.02
						0.00			
% c section	17.14	15.51	1.63 ***	16.76	14.96	1.80 ***	16.62	15.08	1.54 ***
% vaginal	81.90	83.47	-1.57 ***	82.32	84.13	-1.81 ***	82.42	83.99	-1.58 ***
% induction	17.47	12.40	5.07 ***	16.17	11.27	4.90 ***	16.57	11.62	4.95 ***
% induced c section	3.54	2.82	0.72 ***	3.01	2.37	0.64 ***	3.24	2.59	0.65 **
% non induced c section	13.59	12.67	0.92 **	13.75	12.57	1.17 **	13.38	12.48	0.89 *
% induced vaginal	13.78	9.46	4.32 ***	13.03	8.81	4.21 ***	13.21	8.93	4.28 ***
% non induced vaginal	68.03	73.88	-5.85 ***	69.22	75.18	-5.97 ***	69.13	74.92	-5.79 ***
Gestational age	39.30	39.26	0.04 ***	39.15	39.16	-0.01	39.49	39.50	-0.01 *
Birth weight	3409.49	3395.77	13.72 **	3407.81	3397.54	10.28 *	3445.20	3438.67	6.53
apgar1	8.52	8.52	0.00	8.53	8.54	0.00	8.52	8.53	-0.01
% apgar1 >= 7	96.39	96.42	-0.03	96.60	96.66	-0.06	96.41	96.60	-0.19
apgar5	9.05	9.05	0.00	9.05	9.06	-0.01	9.05	9.06	-0.01
% apgar5 >= 7	99.69	99.69	0.01	99.71	99.72	0.00	99.70	99.69	0.01
% ventilation < 30	0.12	0.12	-0.01	0.11	0.07	0.04	0.13	0.05	0.09 *
% ventilation >= 30	0.11	0.11	0.00	0.11	0.10	0.01	0.12	0.09	0.03
% Any ventilation	0.22	0.23	-0.01	0.22	0.17	0.05	0.25	0.14	0.11
% RDS	0.07	0.07	-0.01	0.06	0.07	-0.01	0.06	0.06	0.00
N	37,948	15,385	53,333	28,467	11,743	40,210	21,916	9,049	30,965

Holiday Season (**HS**) is the period of [12/16, 1/5].

Holiday Break (**HB**) consists of period of [12/23, 12/26] and period of [12/31,01/02].

*** p<0.01, ** p<0.05, * p<0.1

Table 1.2 Summary statistics - comparison of holiday season and comparison period

Variables	Term + Low risk				Term + Low risk + [38, 40]				Term + Low risk + [39, 40]			
	Comparison Period	Holiday season	Diff.		Comparison Period	Holiday season	Diff.		Comparison Period	Holiday season	Diff.	
mother_age	29.81	29.74	0.07	*	29.92	29.82	0.09	**	29.89	29.76	0.13	***
mother_edu	13.77	13.76	0.01		13.80	13.80	0.00		13.82	13.80	0.02	
% mother_married	77.52	76.80	0.72	**	77.74	77.31	0.43		78.20	77.70	0.50	
% mother_black	13.33	13.56	-0.22		13.43	13.57	-0.14		12.86	13.14	-0.29	
% mother_white	75.72	75.48	0.24		75.22	75.02	0.20		76.19	75.90	0.30	
% mother_hispanic	18.95	19.50	-0.56	*	19.05	19.58	-0.54	*	18.65	19.25	-0.60	*
% mother_asian	8.35	8.39	-0.04		8.69	8.78	-0.09		8.43	8.37	0.06	
% mother_alcohol	1.30	1.33	-0.02		1.25	1.21	0.04		1.28	1.26	0.02	
% mother_tobacco	7.31	7.48	-0.17		7.10	7.29	-0.19		6.96	7.23	-0.27	
% prenatal_visits	99.58	99.54	0.05		99.62	99.58	0.04		99.63	99.62	0.01	
prenatal_visits_numbe	10.99	10.95	0.04	*	10.96	10.92	0.04		11.05	11.01	0.05	
father_age	32.63	32.56	0.07	*	32.73	32.66	0.07		32.70	32.61	0.09	*
father_edu	13.84	13.83	0.01		13.86	13.86	0.00		13.88	13.86	0.02	
% boy	50.79	50.46	0.33		50.99	50.46	0.53		50.09	49.84	0.25	
number of children	1.79	1.78	0.01	*	1.80	1.79	0.02	**	1.79	1.77	0.01	*
% c section	16.94	16.67	0.27		16.23	16.24	0.00		16.39	16.17	0.22	
% vaginal	81.99	82.36	-0.37		82.74	82.85	-0.11		82.49	82.88	-0.39	
% induction	15.84	16.01	-0.17		14.58	14.74	-0.16		15.11	15.12	-0.01	
% induced c section	3.47	3.33	0.13		2.90	2.83	0.07		3.15	3.05	0.10	
% non induced c sectio	13.46	13.32	0.14		13.33	13.41	-0.08		13.23	13.12	0.12	
% induced vaginal	12.24	12.54	-0.29		11.58	11.80	-0.21		11.85	11.96	-0.11	
% non induced vaginal	69.65	69.72	-0.07		71.06	70.96	0.10		70.55	70.82	-0.27	
Gestational age	39.29	39.29	0.00		39.16	39.15	0.01	*	39.50	39.50	0.01	*
Birth weight	3410.53	3405.54	4.99	*	3407.24	3404.81	2.43		3444.15	3443.29	0.86	
apgar1	8.52	8.52	0.01		8.54	8.53	0.01		8.53	8.52	0.01	
% apgar1 >= 7	96.63	96.40	0.23	*	96.82	96.62	0.20		96.65	96.47	0.18	
apgar5	9.06	9.05	0.00		9.06	9.05	0.01	*	9.06	9.05	0.01	*
% apgar5 >= 7	99.69	99.69	0.00		99.72	99.71	0.01		99.73	99.70	0.03	
% ventalation < 30	0.13	0.12	0.01		0.13	0.10	0.03		0.15	0.11	0.04	
% ventalation >= 30	0.08	0.11	-0.02		0.06	0.10	-0.04	*	0.06	0.11	-0.06	**
% Any ventalation	0.21	0.23	-0.01		0.19	0.20	-0.01		0.20	0.22	-0.02	
% RDS	0.08	0.07	0.01		0.07	0.07	0.00		0.07	0.06	0.01	
N	53,333	79,928	133,261		40,210	61,157	101,367		30,965	40,279	71,244	

Holiday Season (**HS**) is the period of [12/16 , 01/05].
Comparison Period of Holiday Season (**CHS**) consists of the period of [12/01, 12/15] and the period of [01/06, 01/20].
They are fifteen days before and fifteen days after Holiday Season (**HS**).
*** p<0.01, ** p<0.05, * p<0.1

Table 1.3 Top 30 and bottom 30 days of mean daily number of singleton births throughout the year

Top 30 days

Birth date		Mean daily number of births	Ratio to average daily birth	Rank
Month	Day			
7	7	350	1.13	1
9	15	340	1.10	2
7	15	338	1.09	3
9	9	336	1.08	4
9	28	336	1.08	5
8	10	336	1.08	6
9	27	335	1.08	7
7	10	334	1.08	8
9	18	334	1.08	9
9	17	333	1.07	10
9	22	333	1.07	11
7	8	333	1.07	12
9	21	333	1.07	13
9	14	333	1.07	14
6	30	333	1.07	15
9	23	333	1.07	16
7	28	333	1.07	17
6	28	333	1.07	18
7	20	332	1.07	19
9	10	332	1.07	20
7	1	332	1.07	21
8	18	332	1.07	22
9	29	332	1.07	23
7	14	331	1.07	24
8	9	331	1.07	25
9	20	331	1.07	26
7	6	330	1.06	27
8	12	330	1.06	28
9	13	330	1.06	29
7	27	330	1.06	30

Bottom 30 days

Birth date		Mean daily number of births	Ratio to average daily birth	Rank
Month	Day			
4	13	294	0.95	30
1	3	294	0.95	29
12	10	292	0.94	28
2	13	292	0.94	27
12	6	292	0.94	26
1	30	292	0.94	25
2	19	291	0.94	24
4	1	290	0.94	23
1	13	290	0.94	22
1	9	288	0.93	21
10	30	288	0.93	20
11	29	288	0.93	19
11	22	286	0.92	18
11	24	285	0.92	17
11	13	285	0.92	16
2	29	283	0.91	15
11	23	279	0.90	14
12	**31**	**279**	**0.90**	**13**
11	28	277	0.89	12
10	31	277	0.89	11
11	26	275	0.89	10
11	27	271	0.87	9
12	**23**	**271**	**0.87**	**8**
12	**26**	**266**	**0.86**	**7**
11	25	264	0.85	6
1	**2**	**259**	**0.84**	**5**
7	4	255	0.82	4
12	**24**	**239**	**0.77**	**3**
1	**1**	**224**	**0.72**	**2**
12	**25**	**194**	**0.63**	**1**

Notes: The ratio to the average is the average number of singlton births on a given day divided by average singleton births across all days. Therefore, a value of 1.10 presents a 10 percent increase in daily births compared to the yearly average. Mean daily singleton birhs during 1989 - 2011 are 316. The days relative to our Holiday Season are indicated by boldface. The data comes from pooled 1989 - 2011 birth data.

Table 1.4 Days effects on number of singleton births

Table 1.4
Days effects on number of singleton births

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dec	Dec	Dec	Dec	Dec	Dec	Dec	Dec	Dec	Dec
	16th	17th	18th	19th	20th	21st	22nd	23rd	24th	25th
Panel A: Dependent Variable is the number of birth										
Number of birth	18.64***	14.73***	19.13***	20.63***	25.40***	19.04***	3.958	-23.93***	-56.17***	-101.0***
	-4.24	-4.199	-4.539	-4.427	-5.602	-4.686	-2.753	-5.201	-7.487	-9.23
Observations	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426
R-squared	0.705	0.704	0.705	0.705	0.706	0.705	0.703	0.706	0.719	0.756
Panel B: Dependent Variable is ln(number of birth)										
ln(Number of birth)	0.0644***	0.0502***	0.0578***	0.0662***	0.0799***	0.0627***	0.0211**	-0.0785***	-0.201***	-0.411***
	-0.0151	-0.0148	-0.0159	-0.0139	-0.0192	-0.0162	-0.0106	-0.0195	-0.0282	-0.0347
Observations	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426
R-squared	0.705	0.704	0.705	0.705	0.706	0.705	0.704	0.706	0.719	0.769

Variable	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	Dec	Dec	Dec	Dec	Dec	Dec	Jan	Jan	Jan	Jan	Jan
	26th	27th	28th	29th	30th	31st	1st	2nd	3rd	4th	5th
Panel A: Dependent Variable is the number of birth											
Number of birth	-28.09***	10.42**	20.10***	15.19***	20.28***	-14.93***	-71.35***	-35.96***	-3.421	10.42**	4.975
	-5.657	-4.097	-5.404	-4.26	-5.138	-5.141	-9.734	-5.64	-4.878	-4.977	-4.168
Observations	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426
R-squared	0.707	0.703	0.705	0.704	0.705	0.704	0.73	0.71	0.703	0.703	0.703
Panel B: Dependent Variable is ln(number of birth)											
ln(Number of birth)	-0.0966***	0.0349**	0.0657***	0.0537***	0.0678***	-0.0484***	-0.265***	-0.128***	-0.00577	0.0296*	0.0259*
	-0.0208	-0.0156	-0.017	-0.0145	-0.0164	-0.0177	-0.0371	-0.0227	-0.0173	-0.0169	-0.0145
Observations	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426
R-squared	0.707	0.704	0.705	0.705	0.705	0.704	0.731	0.71	0.703	0.704	0.704

Notes: Reuslts of equation (1). This regression is on day's level.
Sample includes all full term with low risk singleton births. Day of week dummies and year dummies are controlled in the regression.
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.5 Holiday break, holiday season, and comparison period

Table 1.5
Holiday break, holiday season, and comparison period

Terms		December																January					
Holiday Break (HB)									23	24	25	26					31	1	2				
Holiday Season (HS)		16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	1	2	3	4	5	
Comparison Period (CHS)	12/1-12/15																						1/6 - 1/20

Table 1.6 Effects of Holiday Break (HB) on birth numbers in Holiday Season (HS)

Table 1.6
Effects of Holiday Break (HB) on birth numbers in Holiday Season (HS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All Birth	C-section	Vaginal	Induction	Induced C-section	Non-induced C-section	Induced Vaginal	Non-induced Vaginal
Panel A: Reuslts of equation (2) Dependent Variable is the number of birth								
HB	-59.40***	-26.47***	-29.96***	-20.20***	-4.227***	-22.29***	-15.95***	-14.02***
	(4.479)	(2.436)	(2.508)	(1.614)	(0.594)	(2.283)	(1.288)	(1.776)
Number of birth moved	207	93	105	71	15	79	56	50
R-squared	0.823	0.828	0.824	0.831	0.743	0.800	0.812	0.865
Panel B: Reuslts of equation (2) Dependent Variable is ln(Number of birth)								
HB	-0.214***	-0.355***	-0.160***	-0.530***	-0.422***	-0.349***	-0.563***	-0.0890***
	(0.0167)	(0.0322)	(0.0138)	(0.0430)	(0.0567)	(0.0346)	(0.0482)	(0.0114)
Shared of birth moved	11.29%	19.42%	8.33%	30.34%	23.49%	19.07%	32.51%	4.55%
R-squared	0.823	0.821	0.827	0.816	0.738	0.798	0.792	0.865
Observations	483	483	483	483	483	483	483	483

Notes: This regression is on days level.

Robust standard errors in parentheses. Day of week dummies and year dummies are controlled in the regression.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.7 Shifting Births: Effects of Holiday Break (HB) on different delivery methods in Holiday Season (HS)

Table 1.7
Shifting Births: Effects of Holiday Break (HB) on different delivery methods in Holiday Season (HS)

VARIABLES	(1) C-section	(2) Vaginal	(3) Induction	(4) Induced C-section	(5) Non-induced C-section	(6) Induced Vaginal	(7) Non-induced Vaginal
Panel A: Term + LR							
HB	-2.107***	2.114***	-4.750***	-0.743***	-1.359***	-3.989***	6.099***
	(0.00479)	(0.00486)	(0.00486)	(0.00242)	(0.00444)	(0.00440)	(0.00592)
Mean	16.67%	82.36%	16.01%	3.34%	13.33%	12.53%	69.72%
N	42,475	42,475	42,475	42,475	42,475	42,475	42,475
Panel B: Term + LR + [38, 40]							
HB	-2.479***	2.471***	-4.791***	-0.792***	-1.687***	-3.977***	6.446***
	(0.00549)	(0.00556)	(0.00544)	(0.00261)	(0.00514)	(0.00495)	(0.00676)
Mean	16.24%	82.85%	14.74%	2.83%	13.41%	11.80%	70.96%
N	32,290	32,290	32,290	32,290	32,290	32,290	32,290
Panel C: Term + LR + [39, 40]							
HB	-2.165***	2.276***	-4.698***	-0.699**	-1.466**	-3.992***	6.260***
	(0.00626)	(0.00634)	(0.00629)	(0.00313)	(0.00582)	(0.00569)	(0.00771)
Mean	16.17%	82.88%	15.12%	3.05%	13.12%	11.96%	70.82%
N	24,706	24,706	24,706	24,706	24,706	24,706	24,706

Notes: Reuslts of equation (3). This regression is on individual level. All regressions include county, birth order, interaction term between the day of week and the year, and parents demographic variables. Robust standard errors in parentheses. I report percentage point effects for binary dependent variables.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 1.8 Switching Births: Effects of Holiday Season (HS) on different delivery methods in the combined period of Holiday Season (HS) period and Comparison Period (CHS)

Table 1.8
Switching Births: Effects of Holiday Season (HS) on different delivery methods in the combined period of Holiday Season (HS) period and Comparison Period (CHS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	C-section	Vaginal	Induction	Induced C-section	Non-induced C-section	Induced Vaginal	Non-induced Vaginal
Panel A: Term + LR							
HS	-0.286	0.355	0.295	-0.166	-0.116	0.409	-0.107
	(0.00230)	(0.00233)	(0.00239)	(0.00120)	(0.00212)	(0.00217)	(0.00285)
Mean	16.83%	82.13%	15.91%	3.41%	13.41%	12.36%	69.68%
N	105,420	105,420	105,420	105,420	105,420	105,420	105,420
Panel B: Term + LR + [38, 40]							
HS	-0.0217	0.0841	0.216	-0.0861	0.0692	0.305	-0.228
	(0.00259)	(0.00263)	(0.00265)	(0.00127)	(0.00242)	(0.00241)	(0.00323)
Mean	16.68%	82.35%	14.64%	2.87%	13.36%	11.67%	71.02%
N	80,716	80,716	80,716	80,716	80,716	80,716	80,716
Panel C: Term + LR + [39, 40]							
HS	-0.123	0.245	0.174	-0.0805	-0.0395	0.264	-0.0241
	(0.00296)	(0.00300)	(0.00306)	(0.00150)	(0.00275)	(0.00279)	(0.00370)
Mean	16.30%	82.64%	15.12%	3.11%	13.19%	11.89%	70.66%
N	62,002	62,002	62,002	62,002	62,002	62,002	62,002

Notes: Reuslts of equation (4).This regression is on individual level. All regressions include county, birth order, interaction term between the day of week and the year, and parents demographic variables. Robust standard errors in parentheses. I report percentage point effects for binary dependent variables.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.9 Parental characteristics: Correlation between Holiday Break (HB) and Parental characteristics in Holiday Season (HS)

Table 1.9

Parental characteristics : Correlation between Holiday Break (HB) and Parental characteristics in Holiday Season (HS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	Mother's edu	Father's edu	Mother's age	Father's age	Black	White	Hispanic	Married	Prenatal visit	# of Prenatal visits	Drug	Tobacco	Alcohol
Panel A: Term + LR													
Other days in HS	-0.116***	-0.106***	-0.238***	-0.183**	0.977**	-1.477***	1.397***	-1.011**	-0.0722	-0.0745*	0.247**	0.621*	-0.0857
	(0.0314)	(0.0332)	(0.0608)	(0.0748)	(0.00403)	(0.00503)	(0.00460)	(0.00500)	(0.000865)	(0.0415)	(0.00109)	(0.00319)	(0.00139)
Mean	13.76	13.83	29.74	32.56	13.56%	75.48%	19.50%	76.80%	99.54%	10.95	0.60%	7.48%	1.33%
N	50,673	47,297	52,010	49,122	51,871	51,871	51,655	51,744	50,542	50,542	43,446	51,307	51,275
Panel B: Term + LR + [38, 40]													
Other days in HS	-0.134***	-0.132***	-0.274***	-0.180**	1.375***	-1.484**	1.251**	-1.920***	-0.103	-0.0453	0.327***	0.677*	-0.0361
	(0.0358)	(0.0380)	(0.0698)	(0.0854)	(0.00466)	(0.00585)	(0.00529)	(0.00572)	(0.000937)	(0.0467)	(0.00125)	(0.00362)	(0.00158)
Mean	13.80	32.66	29.82	13.86	13.57%	75.02%	19.58%	77.31%	99.60%	10.92	0.61%	7.30%	1.21%
N	38,213	35,776	39,209	37,128	39,103	39,103	38,954	39,000	38,097	38,097	33,020	38,704	38,674
Panel C: Term + LR + [39, 40]													
Other days in HS	-0.177***	-0.161***	-0.353***	-0.288***	1.591***	-1.707***	1.373**	-2.123***	-0.0605	-0.0801	0.220	0.834**	-0.0879
	(0.0408)	(0.0433)	(0.0790)	(0.0967)	(0.00524)	(0.00658)	(0.00597)	(0.00651)	(0.00101)	(0.0529)	(0.00135)	(0.00409)	(0.00182)
Mean	13.80	13.86	29.76	32.61	13.14%	75.90%	19.25%	77.70%	99.62%	11.01	0.54%	7.23%	1.26%
N	29,432	27,597	30,199	28,625	30,115	30,115	30,006	30,037	29,370	29,370	25,245	29,791	29,769

Notes: Reuslts of equation (5). Robust standard errors in parentheses.

I report percentage point effects for binary dependent variables.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.10 Infant Health outcomes: Effects of Holiday Season (HS) on different delivery methods in the combined period of Holiday Season (HS) period and Comparison Period (CHS)

Table 1.10

Infant Health outcomes: Effects of Holiday Season (HS) on different delivery methods in the combined period of Holiday Season (HS) period and Comparison Period (CHS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABL	Gestational Weeks	h_bwt	Apgar1	Apgar1 >= 7	Apgar5	Apgar5 >= 7	Any Ventilation	Vent >= 30 minutes	Vent < 30 minutes
Panel A: Term+LR									
HS	-0.0122*	-3.584	-0.00686	-0.207*	-0.596**	0.0106	0.0103	0.0193	-0.0108
	(0.00730)	(2.620)	(0.00580)	(0.00115)	(0.00268)	(0.000348)	(0.000297)	(0.000206)	(0.000215)
Mean	39.29	3410.53	8.52	96.63%	9.06	99.70%	0.21%	0.08%	0.13%
N	105,420	105,420	105,214	105,214	105,222	105,222	100,719	100,719	100,719
Panel B: Term+LR + [38, 40]									
HS	-0.0177***	-0.389	-0.00876	-0.217*	-0.834***	-0.0112	0.03	0.0391*	-0.0115
	(0.00557)	(2.928)	(0.00644)	(0.00128)	(0.00298)	(0.000377)	(0.000329)	(0.000224)	(0.000243)
Mean	39.16	3406.28	8.54	96.74%	9.06	99.72%	0.20%	0.08%	0.12%
N	80,716	80,716	80,569	80,569	80,574	80,574	77,223	77,223	77,223
Panel C: Term+LR + [39, 40]									
HS	-0.0112***	1.645	-0.00655	-0.150	-0.953***	-0.0342	0.0456	0.0654**	-0.0199
	(0.00414)	(3.294)	(0.00748)	(0.00151)	(0.00341)	(0.000440)	(0.000390)	(0.000260)	(0.000292)
Mean	39.5	3443.81	8.26	96.58%	9.06	99.71%	0.21%	0.08%	0.13%
N	62,002	62,002	61,895	61,895	61,900	61,900	59,315	59,315	59,315

Notes: Robust standard errors in parentheses. All regressions include county, birth order, interaction term between the day of week and the year, and parents demographic variables. I report percentage point effects for binary dependent variables.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.11 Summary statistics - Comparison of two groups (highly likely to manipulate and highly unlikely to manipulate babies' birth date)

Variables	Panel A			Panel B			Panel C		
	All births			[12/1 - 1/20]			[12/16 - 1/5]		
	No birth time restriction			Holiday season + Comparison period			Holiday season		
	All	Control group	Treatment group	All	Control group	Treatment group	All	Control group	Treatment group
		HUL	HL		HUL	HL		HUL	HL
number of birth	88,425	76,324	12,101	80,055	68,436	11,619	39,373	33,703	5,670
mother_age	29.70	29.54	30.68	29.73	29.57	30.67	29.69	29.54	30.59
mother_edu	13.70	13.63	14.15	13.71	13.64	14.15	13.71	13.63	14.16
% mother_married	77.20	76.93	78.89	77.20	76.92	78.86	76.86	76.59	78.50
% mother_black	13.51	13.52	13.45	13.65	13.68	13.49	13.66	13.73	13.23
% mother_white	75.72	75.92	74.47	75.43	75.59	74.50	75.47	75.59	74.76
% mother_hispanic	19.57	19.82	17.94	19.64	19.91	18.04	19.90	20.14	18.51
% mother_asian	8.13	7.87	9.77	8.27	8.02	9.72	8.24	7.99	9.71
% mother_alcohol	1.27	1.31	1.01	1.26	1.30	1.02	1.28	1.30	1.19
% mother_tobacco	7.43	7.56	6.59	7.37	7.50	6.58	7.42	7.58	6.49
% prenatal_visits	99.54	99.49	99.86	99.53	99.48	99.86	99.50	99.45	99.84
prenatal_visits_numbe	10.89	10.87	11.02	10.88	10.85	11.04	10.87	10.85	10.98
father_age	32.54	32.43	33.28	32.58	32.45	33.29	32.56	32.44	33.23
father_edu	13.80	13.75	14.08	13.80	13.75	14.08	13.80	13.75	14.09
% boy	50.18	49.83	52.34	50.35	50.02	52.32	50.09	49.69	52.45
number of children	1.88	1.90	1.75	1.88	1.90	1.76	1.87	1.89	1.74
apgar1	8.57	8.57	8.55	8.58	8.58	8.56	8.57	8.58	8.55
% apgar1 >= 7	97.27	97.35	96.77	97.33	97.42	96.80	97.25	97.35	96.61
apgar5	9.07	9.08	9.03	9.07	9.08	9.03	9.07	9.08	9.03
% apgar5 >= 7	99.79	99.79	99.80	99.79	99.79	99.81	99.80	99.79	99.81
% ventilation < 30	0.09	0.09	0.09	0.08	0.08	0.09	0.08	0.08	0.09
% ventilation >= 30	0.07	0.07	0.10	0.08	0.07	0.11	0.09	0.08	0.15
% Any ventilation	0.16	0.16	0.20	0.16	0.15	0.20	0.17	0.16	0.24

*** p<0.01, ** p<0.05, * p<0.1

HL: Highly likely to manipulate babies' birth date

HUL: Highly unlikely to manipulate babies' birth date

Table 1.12 Parental characteristics: Correlation between parental characteristics and the behavior of highly likely to manipulate (HL) babies' birth date.

Table 1.12
Parental characteristics: Corrleation between parental characteristics and the behavior of highly likely to manipulate (HL) babies' birth date.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Varibale	Mother's edu	Father's edu	Mother's age	Father's age	Black	White	Hispanic	Married	Prenatal visit	# of Prenatal visits	Drug	Tobacco	Alcohol
Panel A: All births whose parents may have incentive to manipulate their birth date													
HL	0.397***	0.283***	0.991***	0.642***	0.47	0.335	-4.33***	4.00***	0.389***	0.372***	-0.199***	0.156	-0.01
	(0.0251)	(0.0264)	(0.0513)	(0.0626)	(0.00333)	(0.00424)	(0.00378)	(0.00405)	(0.000479)	(0.0330)	(0.000723)	(0.00251)	(0.00102)
Mean	13.70	13.81	29.7	32.54	13.51%	75.72%	19.57%	77.20%	99.54%	10.89	0.61%	7.47%	1.27%
N	84,317	78,812	86,265	81,476	86,022	86,022	85,637	86,022	84,273	84,273	71,179	85,529	85,454
Panel B: Restrict the birth dates of Panel A to [12/1 -1/20], which is the holiday season and comparison period.													
HL	0.390***	0.277***	0.957***	0.626***	0.346	0.65	-4.27***	3.89***	0.411***	0.399***	-0.190**	0.19	0.0257
	(0.0257)	(0.0271)	(0.0526)	(0.0643)	(0.00343)	(0.00435)	(0.00389)	(0.00416)	(0.000496)	(0.0339)	(0.000739)	(0.00258)	(0.00105)
Mean	13.71	13.80	29.73	32.58	13.65%	75.43%	19.64%	77.20%	99.53%	10.88	0.60%	7.37%	1.26%
N	76,346	71,357	78,105	73,779	77,883	77,883	77,541	77,883	76,325	76,325	64,829	77,465	77,398
Panel C: Restrict the birth dates of Panel A to [12/16 -1/5], which is the holiday season.													
HL	0.427***	0.312***	0.944***	0.601***	-0.154	1.04*	-4.20***	4.18***	0.440***	0.357***	-0.202*	-0.0474	0.255
	(0.0373)	(0.0389)	(0.0754)	(0.0917)	(0.00490)	(0.00626)	(0.00563)	(0.00598)	(0.000756)	(0.0482)	(0.00104)	(0.00366)	(0.00160)
Mean	13.71	13.80	29.69	32.56	13.66%	75.47%	19.90%	76.86%	99.50%	10.87	0.60%	7.42%	1.28%
N	37,587	35,066	38,413	36,253	38,319	38,319	38,170	38,412	37,488	37,488	32,172	38,126	38,102

Notes: Reuslts of equation (6). Robust standard errors in parentheses.
I report percentage point effects for binary dependent variables.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.13 Infant health outcomes: Correlation between infant health outcome and the behavior of highly likely to manipulate (HL) babies' birth date

Table 1.13

Infant health outcomes: Correlation between infant health outcome and the behavior of Highly likely to manipulate (HL) babies' birth date

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
/ARIABLE	Apgar1	Apgar1 >= 7	Apgar5	Apgar5 >= 7	Any Ventilation	Vent >= 30 minutes	Vent < 30 minutes
Panel A: All births whose parents may have incentive to manipulate their birth date							
HL	-0.0271***	-0.264	-0.0044	0.0587	0.0877*	0.0395	0.0472
	(0.00959)	(0.00191)	(0.00411)	(0.000468)	(0.000536)	(0.000386)	(0.000373)
Mean	8.57	97.27%	9.07	99.79%	0.16%	0.07%	0.09%
N	69,294	69,294	69,303	69,303	66,653	66,653	66,653
Panel B: Restrict the birth dates of Panel A to [12/1 -1/20], which is the holiday season and comparison period.							
HL	-0.0300***	-0.322*	-0.0051	0.0576	0.0967*	0.0489	0.0468
	(0.00974)	(0.00195)	(0.00423)	(0.000488)	(0.000546)	(0.000402)	(0.000370)
Mean	8.58	97.33%	9.07	99.79%	0.16%	0.08%	0.08%
N	63,119	63,119	63,127	63,127	60,684	60,684	60,684
Panel C: Restrict the birth dates of Panel A to [12/16 -1/5], which is the holiday season.							
HL	-0.0452***	-0.596**	-0.0110*	0.0018	0.125	0.0762	0.0492
	(0.0146)	(0.00291)	(0.00637)	(0.000778)	(0.000796)	(0.000645)	(0.000469)
Mean	8.57	97.25%	9.07	99.90%	0.17%	0.09%	0.08%
N	31,350	31,350	31,352	31,352	30,038	30,038	30,038

Notes: Reuslts of equation (7). Robust standard errors in parentheses.
All regressions include county, birth order, interaction term between the day of week and the year, and parents demographic variables. I report percentage point effects for binary dependent variables.
*** p<0.01, ** p<0.05, * p<0.1

Chapter 2: How Does Retirement Affect Health? Evidence from Urban People in China

2.1 Introduction

With the population aging rapidly and life expectancy improving dramatically, public health care for the elderly and social security systems in developed and developing countries are more and more stressed. Very low birth rates in developed countries, coupled with birth rate declining in most developing countries, yield that the global share of older people (aged 60 years or over) increased from 9.2 percent in 1990 to 11.7 percent in 2013 and is expected to reach 21.1 percent by 2050 (World Population Aging 2013, United Nations). Average life expectancy at birth has increased globally over the past half century from 46.5 years in 1950--1955 to 65.2 years in 2002, and it increased to 71.4 years in 2015.[15] The above two striking worldwide changes of population structure generate an extended retirement period, and then impose several challenges, such as limited pension pool and shortfall of public health care for the elderly, to the financial sustainability of public health and social security systems.

In response, policymakers in many countries have encouraged aging people to work longer and postpone retirement. In some developed countries, they have decided to increase the normal retirement age, and adjust the early retirement age too. For example, the UK Pension Commission in 2006 published the law to extend the state pension age for both women and men

[15] On average, the gain in life expectancy was 9 years in developed countries (including Australia, European countries, Japan, New Zealand and North America), 17 years in the high-mortality developing countries (with high child and adult mortality levels), including most African countries and poorer countries in Asia, the Eastern Mediterranean Region and Latin America; and 26 years in the low-mortality developing countries. (The world health report 2003, WHO) The details are available at http://www.who.int/whr/2003/en/whr03_en.pdf

from 65 to 68 in three stages between 2024 and 2046.[16] In Germany, the retirement age is to be increased gradually and reaches 67 years in 2029.[17] Similar policy changes happened in the U.S., Australia, Belgium, Denmark, France, Ireland, Japan etc. Even in developing countries, they are planning to raise the retirement age also. China has set the timeline for the gradual, multiyear process to increase the retirement age to 65 until 2045.

However, whether such policies can successfully reduce government expenditure has been long debated by economists. For the elderly, the better health, the less government expenditure. On the one hand, if retirees have less pressure after they leave their work environment, and would like to spend more spare time doing physical exercises and attending social activities, then increasing the retirement age will likely result in better health outcomes and eventually decrease expenditure. On the other hand, if retirees feel lonely and have worse health behaviors than the working people, extended retirement may lead to additional costs for individuals and the entire society besides increased expenditure on health care and pension. Therefore, to fully assess the well-being of the elderly and the welfare of society of the consequence of extending retirement age, it is very important to understand the relationship between retirement and health.

Although a number of studies have investigated the relationship between retirement and health, these studies focus on developed countries. In addition, few studies attempt to estimate the causal effects and existing results are mixed. Some find retirement has no or negative effects on health (Dave et al., 2008; Lindeboom, et al., 2002). Some find retirement improves self-reported overall health, reducing depression, increasing life satisfaction, and even making memory better (Johnston et al., 2009; Bonsang et al., 2012; Coe et al., 2012; Eibich 2015). The

[16] The Pensions Act 2007 (c22), Security in retirement: towards a new pension system, Department for Work and Pensions, the United Kingdom. The details are available at https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/272299/6841.pdf
[17] European Commission. "2009 ageing report: economic and budgetary projections for the EU-27 Member States (2008-2060). The details are available at http://ec.europa.eu/economy_finance/publications/publication14992_en.pdf

main empirical complication in estimating the effect of retirement on health is the endogeneity problem caused by the effect of health on retirement. Recent studies exploit the discontinuous retirement behavior around pension eligibility age to overcome the endogeneity problem. However, this discontinuity is may not exist due to voluntary retirement in many western countries.

Studying China helps to exam this issue for the following reasons. First, contrary to most western counties, China has the mandatory retirement policy imposing uniform retirement age for urban workers: 55 for the male blue-collar; 60 for all other male workers; 50 for the female blue-collar; 55 for all female workers. These age cutoffs have not been changed since the implementation of the retirement system in 1951. It means that as soon as workers reach the retirement age, urban workers in China have no choice but to leave their current jobs, although they have the right to find other jobs. In this case, the change of retirement probability around the mandatory retirement age will be sharp. In addition, the relatively young retirement age makes the decision of retirement less likely to be caused by bad health. Therefore, the endogeneity problems could be mitigated. Furthermore, another important feature of China's retirement system is that access to public health insurance does not change dramatically around the official retirement age, which is quite different from the system of the U.S. with the Medicare eligibility age 65. Therefore, it is unclear whether the conclusion about the effects of retirement on health drawn from the developed countries can be applied to developing counties, such as China. So investigating the case of China will be important and valuable to current literature.

In this study, I focus on the male urban workers in China. Using data from the China Health and Retirement Longitudinal Study (CHARLS) and a fuzzy regression discontinuity design, I investigate the retirement effects on individual's physical, mental health, well-being and the potential mechanisms driving these effects. My results show that retirement has significant and positive effect on mental health, well-being, life satisfaction, and cognitive functioning. Most importantly, the results suggest that attending more social activities, having more physical activities, and paying more attention to health care could be the main mechanisms through which retirement improves health.

The rest of the paper is organized as follows. Section 2 presents a review of the literature. Section 3 details the institutional background. Section 4 discusses the data. Section 5 shows the identification strategy and the empirical specification. Section 6 dicussess the results and robustness checks. Finally, Section 7 concludes.

2.2 Previous studies

Although evaluating the relationship between retirement and health is an old topic, there is little conclusive empirical evidence thus far. The culturally dependent retirement policy might be the first reason. In addition, many of the early studies compare individuals' health before and after retire. since they may not address the endogeneity problem of retirement, researchers following this methodology can only infer correlations, not causality. Some of the studies find retirement has no correlation with health (Adams and Lefebvre, 1981), some find a positive correlation with health (Thompson and Streib, 1958; Mein et al., 2003), and some others find a negative correlation with health (Casscells et al., 1980; Gonzales, 1980; Dave et al., 2006).

Some existing studies try to solve the endogeneity of retirement decision in examining the future health. The first group of literature uses the panel data to control for endogeneity. For example, Using the panel data from two waves of a survey of Dutch elderly and applying fixed effects method, Kerkhofs and Lindeboom (1997) account for the time-invariant factors that may confound the results, and find that health deteriorates with increased working effects and that increasing retirement age may negatively influence late-life health outcomes. However, they do not control the time-varying factors, such as income and socioeconomic conditions. Dave et al., (2008) explore seven waves (spanning from 1992 through 2005) of longitudinal study in the U.S. (the Health and Retirement Study), to estimate the effects of retirement on health status such as indicators of physical and functional limitations, illness conditions, and depression. The conclusion shows that complete retirement may have unfavorable effects on mobility, illness conditions, and mental health. However, these estimates may also be biased if some unobservable time-varying factors can influence both retirement decision and health.

Another group of studies use instrumental variables (IV), using instruments based on social security eligibility ages or other exogenous variation in retirement regulations. For example. using a group of binary variables indicating early and normal retirement age, as well as retirement policy changes in the 1980s as instrumental variables, Charles (2004) shows that retirement improves the psychological well-being of males in the U.S. Similarly, Neuman (2008) uses extended set of age dummies and categorical age variables as instruments showing that health impact of retirement may be positive. Using European 11 countries-specific early and full time retirement ages as instruments to exam the effects on retirement on self-reported health, mental health and cognitive ability, Coe and Gema (2011) find that retirement affects general health significantly. However, using HRS data and eligibility age for social security as an instrument, Bonsang et al, (2012) highlight a significant unfavorable effect of retirement on cognitive functioning measures. Interestingly, using same data set HRS, but using offers of early retirement windows as instruments, Coe et al, (2012) find a favorable effect of retirement duration on later-life cognition for blue-collar workers.

Other studies exploit the discontinuity of retirement status around the official retirement age set by governments. If this discontinuity of retirement is significant, and all factors but retirement are smooth around the official retirement, RDD (regression discontinuity design) may have the potential to identify the short-term causal effects of retirement on health. For example, Johnston and Lee (2009) uses a RDD based on the discontinuity at age 65 in the probability of retirement in England to estimate the impact of retirement on subjective and objective health. Their results indicate that retirement increases an individual's sense of well-being and their mental health. In German pension system, 60 is the pension eligibility age for women, for unemployment and partial retirement, and for severely disabled people; age 65 is the standard pension age. Using a RDD and two pension ages as cutoffs, Eibich (2015) identifies the causal effects of retirement on health and the mechanisms behind the effects, and finds that retirement improves subjective health status and mental health, while reduces outpatient care utilization. Relieving from work-related stress, increased sleep duration, as well as frequent physical activities seem to be key mechanisms through which retirement affects health. However, since the retirement behavior is voluntary in developed counties relative to developing countries, sometimes the discontinuity of retirement status of developed countries is not sharp enough to apply RDD approach. In addition, there may have other significant changes around retirement age for elderly. For example, age 65 is also the Medicare eligibility cutoff in the U.S. This health insurance availability may confound, or cause impact of the retirement to be biased upward.

A recent small group of studies has begun estimating the impact of retirement on health-related behaviors, such as social activities, smoking and drinking status, preventive health behaviors and so on. Zhao et al, (2013) indicate that individuals increase participation into regular exercising and drinking, yet reduce smoking intensity significantly after retirement.

Insler (2014) shows that a reduction in smoking and an increase in physical activity as potential incentive to invest in their health.

There are few relevant empirical studies in China. Using one percent population survey, Lei et al, (2010) identified a short-term causal effect of retirement on health by exploring China's mandatory retirement policy with a RDD. They find that retirement has an immediate negative effect on self-reported health status. However, limited by less information, they could not exam other objective health outcomes, mental health, and potential channels deriving these effects.

2.3 Retirement Policy in China

There are two public pension systems in China: a formal system, under which urban employees receive generous pensions and face mandatory retirement by age 60, and an informal system, under which rural residents and urban residents in the informal sector rely on family support when they retire and always have much longer working lives.

2.3.1 History

China's first retirement system was established in the 1951 under the State Council's Regulations on Labor Insurance. Since then, China's pension system has gone through several stage of reform as the dramatically change of economics and social environment.

In the beginning, the system only covered government employees and urban workers in state-owned enterprises (SOEs) on a pay-as-you-go basis. During the Cultural Revolution (1966-1976), management of enterprise pensions became the responsibility of individual firms: each enterprise paid the pensions of its own retirees out of its current revenue, while government employees continued to obtain their pension from central government. Because there was almost no private businesses and self-employment at that time, the retirement system covered all urban workers. Any urban workers who started working at least ten years (the minimum number of to qualify for a pension) before the retirement age would qualify for the pension (in the state sector, the retirement age was strictly enforced: anyone who reaches retirement age must apply for the process of retirement and end their current employment).

Soon after Deng Xiaoping in 1978 opened China to foreign businesses that wanted to invest in the country, the government began to redevelop the social security system, including reintroducing a unified pension pooling system in 1986. However, increasingly intense market competition during the transition from a planned economy to a market economy made the revenue of state-owned enterprises (SOEs) fall below their expenditure. In addition, the government also realized it would have difficulty attaining the pension burden of public employees. At the same time, more and more private business and self-employed sprouted over. Therefore, the government began to lay the foundations of the "basic pension system" for urban workers in the early 1990s. In 1997, government initiated a transition from the old pay-as-you-go plan to a two-tiered system consisting of a scaled-back pay-as-you-go benefit and a personal retirement account, and still in this year all urban enterprise (private and self-employed) employees were required to participate the retirement pension system. At present, with a small part of contributions are in individual accounts, county- or city- level governments administer the pension pools. For rural resident and urban resident without jobs, the new rural pension system has been implemented since 2009, the participation is voluntary, and operational matters are left to local governments.[18]

[18] Staring from 2009, each rural resident pays 55 RMB (China currency) a month (equivalent to $8.50 USD) to participate, and after age 60 (for all female and male), residents receive 100 RMB ($15.00 USD) to 500 ($80.00) RMB a month. These residents do not require exiting from their work (agricultural activities) to claim it. Government officials have indicated that they expect the scheme to cover 10 percent of rural regions by the end of 2009, about 50 percent by 2012, and 100 percent by 2020 (China News, 2009).

2.3.2 Modern System for urban employees

For formal sector employees (Public service employee and Urban employee), China has some of world's youngest official retirement ages, and these ages have not changed since the starting of the retirement system in 1951. Table 2.1 shows detailed information.

Even with China's low official retirement age, substantial retirement happens even earlier. First, policy allows early retirement due to health reasons and hazardous work conditions. For example, blue-collar women can be retired at 45 if they work underground for 10 years. Second, some evidences show that a part of local government grant early retirement liberally to get available positions to hire young workers or to promote current employees.[19] Another special circumstance leading to early exit from work is known as internal retirement, especially for enterprise employee. This is the special practice during 1990s when many firm experienced financial difficulties. Firms let redundant workers exit from workplace before the normal retirement age with a tiny living wage or without any wage, but the firm continues to support workers payment of pensions to maintain workers eligibility for social insurance after they reach the formal retirement age. Many employees would like to accept the internal retirement since their total income would increase if they get another job.[20] In addition, rural migrant workers are not generally covered by the urban pension system.[21]

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[19] For instance, some local governments set local retirement policy for public service (government and institution) employee that they can "leave then retire". It means they can leave the workplace before the normal retirement age with guaranteed same or even better salary and benefits, and then process the retirement after they reach the formal retirement age.

[20] Since if they get a new job after they internal retire, the new employer do not need to pay 20% employer contribution to social retirement pool, and they do not need to pay 8% of individual salary to social retirement pool either.

[21] Migrant works are approximately 150 million in China. Participation of pension is allowed, but not compulsory. Both employers and rural migrant workers are reluctant to join, because joining entails higher labor costs for employers and migrant workers are more interested in immediate wages than in pensions. What's more, their high mobility across regions impedes participation.

2.4 Data

2.4.1 Data source

This paper uses the China Health and Retirement Longitudinal Study (CHARLS) national baseline survey wave1 and wave2 to analyze the effect of retirement on health measurements and lifestyle habits. The China Health and Retirement Longitudinal Study (CHARLS) is a nationally representative longitudinal survey of the middle-aged and elderly of China, that is, of persons 45 years of age or older.[22] Wave 1 was fielded in 2011 and includes about 10,000 households and 17,500 individuals in 150 counties/districts and 450 villages/resident committees. Wave 2 is the following up survey after 2 years.

The CHARLS baseline data shows three major advantages over other existing Chinese datasets.[23] First, the CHARLS is nationally representative, which many other related surveys in China are not. Second, it is publicly available and harmonized with many international surveys, making cross-study results comparable. Last, the CHARLS questionnaire covers an extensive set of topics: demographics, family structure/transfer, health status and functioning, biomarkers, health care and insurance, work, retirement and pension, income and consumption, assets (individual and household), and community level information. These rich data allow us to study the connection between retirement and the related health outcomes.

[22] CHARLS is designed after the Health and Retirement Study (HRS) in the United States, and is also harmonized with many leading international surveys of elderly people in other countries, such as the English Longitudinal Survey on Aging (ELSA), the Korean Longitudinal Study of Aging (KLoSA), the Longitudinal Aging Study in India (LASI), the Survey on Health, Aging, and Retirement in Europe (SHARE) and the Japanese Study of Aging and Retirement (JSTAR). All data in CHARLS are maintained at the National School of Development of Peking University and will be requested accessible to researchers around the world at the study website: http://charls.ccer.edu.cn/en /.

[23] The Chinese Longitudinal Healthy Longevity Survey (CLHLS) conducted by Duck University is publicly available, but it is not nationally representative and has the different survey design compared to the HRS in the U.S. In addition, it has less economic variables such as asset, debts and consumptions. Study on Global Ageing and Adult Health (SAGE) is a series of global surveys on the aged by World Health Organization. China part has less observations, and lack variables related to income, wealth, and working status. The most famous household survey of the China Health and Nutrition Survey (CHNS) does not focus on elders, and only collected data from nine provinces.

I then construct data as below. First, I eliminate those individuals who have never worked at least three months in his/her life and those who have not worked since age 50, either because of personal choice or physical or mental problems. Second, I restrict my analysis to the sample with urban "hukou" (household registration status) status because of two distinct retirement patterns (one for urban people and another one for rural people) in China. Third, I continue to limit my analysis to male respondents to avoid potential confounding of female labor force participation, which presents very different pattern from male caused by different retirement policy. Fourth, I keep individuals who are between 55 and 65 years. This short age restriction around male formal retirement age 60 enable us to estimate the short run retirement effects on health outcomes and lifestyles. To make the sample size larger, I pooled the CHARLS national baseline wave1 and wave 2. The final sample include 1083 individuals and 1588 observations.

2.4.2 Variables

In order to obtain a rich picture, I estimate effects of retirement on various outcomes: physical and mental health, well-being, cognitive functioning, and the potential mechanisms for these conditions, such as change in health-related behavior and life style. The sample is restricted to urban man aged 55 to 65 years who were born between 1946 and 1958 and who were in job market or retired. Table 2.2 provides the descriptive statistics for all the variables discussed below. Column 1 and 2 show the overall mean and standard deviation of the variable. Column 3 to 5 give the overall minimum, maximum and the number of observations. Column 6 provides the mean for retirees (treatment group). The means for non-retirees (control group) are given in column 7. Column 8 indicates the t-statistic for the equality of means of both groups.

Definition of retirement: In general, retirement implies that an individual leaves his/her job and ceases working. There are three main definitions used in the literature. First is self-reported retirement status, the second is that person is not in the paid labor market, and the third is that the person is not in the labor market. However, I define individuals as "retired" if they report not to work or work less than 3 hours per month in the last year. Although in China some retirees officially leave their main occupation, they may continue to work either full or part time in other occupations with pay or without pay. This group of people should not be considered as "retired" in this paper since they meet co-workers, may have less leisure time, and should have different life style with the group of people who totally leave the labor market. To estimate the effect of working status on health related outcomes, I set this group of people as not retired.

Physical health: Self-rated health status is derived from a question asking the individual to rate their health on a five-point scale: very good, good, fair, bad and very bad.[24] I then condense these responses to a two-point scale: one is bad health (bad and very bad categories), zero is good health (very good, good and fair categories).[25] Activities of daily living (ADLs) and Instrumental activities of daily living (IADLs) measure limitations in some daily skills.[26] The number of chronic diseases is a count of diseases an individual might have.[27] Mobility limitation measures whether the response is able to run or jogging about 1 km; to get up from a chair after sitting for a long period; to climb several flights of stairs without resting; to stoop, kneel, or crouch; to reach or extend the arms above shoulder level; and to pick up a small coin from a table. Number of doctor visit in last month measures outpatient health utilization.

[24]The CHARLS also records the second version of the five-point scale (excellent, very good, good, fair, and poor). We do not use this second version in the paper.

[25] In Chinese language, "fair" always means good

[26] ADLs measure skills of dressing, bathing, eating, transferring (get into or out of bed), toilet use (including getting up and down), and controlling urination and defecation. IADLs measure skills of doing housework; preparing meals; groceries shopping; making phone calls; taking medications (preparing and taking correct dose); and managing money (paying bills, keeping track of expenses, or managing assets).

[27] 14 diseases: high blood pressure; high cholesterol; diabetes; cancer; chronic lung diseases; liver disease; heart problems; stroke; kidney disease; stomach disease; psychiatric problems; memory-related disease, arthritis; asthma.

Mental health: A depression index shows the score of the 10-item Center for the Epidemiological Studies of Depression Short Form (CES-D-10) that ask interviewees to rate how often over the past week they experienced symptoms associated with depression, such as restless sleep, feeling fearful, and feeling lonely. Response options range from zero to three for each item (zero = Rarely or None of the Time, one = Some or Little of the Time, two = Moderately or Much of the time, three = Most or Almost All the Time). Scores range from 0 to 30, with high scores indicating greater depressive symptoms. A score of 10 or greater is considered depressed.

Well-being: HWB12, a newly developed well-being measure (Jacqui Smith and Arthur Stone, 2011) is a set of the 12 overall experiences of hedonic well-being occurring during the previous day. It asks interviewee to rate how often over the last day they experienced symptoms associated with positive feelings (happy, enthusiastic and content); negative feeling (frustrated, sad, angry, stressed, worried, depressed) and fatigue feelings (tired, lonely, bored, and pain). Response options range from zero to four for each item (0 = Not at all, 1 = A little, 2 = Somewhat, 3 = Quite a bit, 4 = Very).[28] Satisfactory life is measured using responses to a question asking the individual to rate on their life on a five-point scale: completely satisfied, very, somewhat satisfied, not very satisfied and not at all satisfied. I then condense these responses to an indicator: 1 is satisfied (completely satisfied, very, somewhat satisfied), 0 is not satisfied (not very satisfied and not at all satisfied).

Cognitive functioning: For cognitive functioning, I consider measures of, immediate, delayed and total word recall, date recall, working memory, short-term memory and self-rated memory.[29] I also combined the scores from both immediate and delayed word recall to obtain an

[28] For positive feelings, scores runs from 0 to 12 with high scores indicating grater positive feeling. For negative feelings, scores runs from 0 to 20 with low scores indicating greater depressive symptoms. In addition, for fatigu feelings, scores runs from 0 to 16 with low scores indicating greater depressive symptoms.

[29] Immediate and delayed word recall aim at assessing memory performance based on words recall test. The score for immediate word recall counts the number of correct responses, leading to a test score between 0 and 10. Roughly 5 min later (after the

overall summary measure for recall (total word recall), whose score ranges from 0 to 20. Date recall aim at assessing memory performance based on the number of correct answers about the date today (year, month, day), the day of the week, the current season, leasing to a score between 0 and 5. Working memory is the ability to process and store information simultaneously.[30] Short-term memory is the capacity for holding, but not manipulating, a small amount of information in mind in an active, readily available state for a short period.[31] I translated verbal responses to Self-rated memory to an indicator 1 is poor (poor category) and 0 is good (including excellent, very good, good, fair categories).

Health behavior and lifestyle measures: The CHARLS data contains several measures of health behavior. My analysis exploits a series of measures like the attitude to their health, smoking, alcohol consumption, the sleeping duration, as well as the status of social activities participation.[32] For social activities, the data shows the status of attending some specific activities. In this paper, I focus on the activities such as took care of grandchildren, interacted with friends, engaged in leisure activities (Ma-jong, played chess, played cards, or went to community club), suffered internet and did voluntary or charity work. These activities can enhance mental health. Furthermore, sports activities definitely improve physical health.

Covariates: To check the heterogeneous effect, I include major socioeconomic status (SES) variables, such as education, number of children and income.[33] I use per capita expenditure as the

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administration of some additional survey instruments), the respondent is again asked to recall as many words from the previously read list of nouns. Again, corresponding test score is obtained as the sum of each correct answer (delayed word recall, range 0–10).

[30] It is assessed based on a serial 7s subtraction test. In the serial 7s test, respondents are asked to subtract 7 from 100 and continue subtracting 7 from each subsequent number for a total of five trials. This test thus requires respondents to perform a basic arithmetic operation (subtracting 7) while memorizing the result from the previous subtraction that is required as an input in this process. The serial 7s subtraction test score counts each correct subtraction, leading to scores between 0 and 5.

[31] It is assessed based on whether the respondent can draw the picture or failed to draw after you show the picture of two pentagons overlapped, leading to scores 1 (success) or 0 (failure).

[32] Attitude to their health is captured by a dummy variable that takes on the value "1" if an individual took physical exam in the past two years. Smoking and alcohol consumption are captured by two indicators individually. Respondents also answer how long they typically sleep on a regular weekday.

[33] Three groups measure education attainment: individuals who did not finished middle school, finished middle school but did not

proxy of income because income is measured with much more error and per capita expenditure is a better measure of long-run resources.

2.5 Empirical Strategy

The sharp change in retirement probability generated by mandatory retirement policy provides us an excellent opportunity to use a fuzzy RDD (Imbens and Lemieux 2008; Lee and Lemieux 2010) to analyze the health effects of retirement. My identification strategy is similar with studies using an RD design to examine the effect of turning pension eligible age 65 in the U.S. (Card, Dobkin, and Maestas 2004, 2009; Chay, Kim, and Swaminathan 2010). In China, the change at age 60 only reflects retirement status rather than the combined effects of change in any insurance coverage and benefit generosity (Medicare). Figure 2.1 shows the share of retirees at every age between 55 and 75 for all urban male in China. The dots indicate bins of 3 months. It presents a sharp discontinuity around age 60, the probability of retirement increases by about 20-23% points from 38% just below the age 60 to about 61% just above the age 60. It also presents that there are already a few retirees before 50, the probability of retirement increases by 27 % from 50 to 60, but the retirement status does not change dramatically around the early retirement age 55.[34]

Before I move to the RDD results, I present two main RDD validity check (Imbens and Lemieux 2008). The first is whether the forcing variable, age, is smooth around the cutoff age 60. It means whether the individual manipulate their age. Although the actual age cannot be manipulated, and the age I are using is calculated from their reported birth date, the measurement

finished college degree and got at least a college degree.

[34] Appendix Figure 1 and Figure 2 show the share of retirees at every age between 55 and 75 for male and rural male in China separately. Figure 1 presents that the retirement rate slightly increase as age increased from 45 and 60, and there is 6% jump just below and just above 60, then the retirement rate continue increase, and finally increase dramatically after around 68. Urban male's retirement status mainly drives this 6% discontinuity in retirement status.

error caused by misreporting will threaten my identification strategy. Panel (a) of Figure 2.1 shows a histogram of age for the entire range in bins of 2 years. Panel (b) of Figure 1 shows the McCrary (2008) density test of the jump at cutoff. Neither graph shows the density of age just above and just below the cutoff is significant. They support the validity of my method.

The second test is whether the observed characteristics are continuous around the cutoff. If there is no significant discontinuity around age 60 on these characteristics that may confound the effect from retirement, the RDD method will be valid. Figure 2.3 panel (a) and (b) show the continuity of various characterizes I check for. The dots in the scatter plot depict the average over 3 months bin. Panel (a) of Figure 2.3 show the number of children, whether only one child, marital status and educational categories, none of the graph shows significant jumps at the cutoff age 60. However, I do find a small discontinuity in total expenditure per household member at age 60, showed on panel (b) of Figure 2.3. This may reflect that retirees change the life style in China, they spend more on food, traveling, and even utilities after retired. Change of expenditure may be a channel through which change health-related behaviors to affect the health-related outcomes. Therefore, I do include the expenditure per household member in the robustness check model, but the results do not change dramatically. Therefore, the results from McCrary test and the continuity of covariates strongly suggest that the assumptions of the RDD are valid in this setting.

My research design exploits the fact that retirement status is discontinuous function of a person's age. Consider the following model of the relationship between outcomes (Y_{it}) and retirement status (R_{it}):

$$Y_{it} = \beta_0 + \beta_1 R_{it} + \varepsilon_{it} \qquad (1)$$

Specifically, I estimate the following model:

$$Y_{it} = \beta_0 + \beta_1 R_{it} + f(\text{age}) + L_{it} + \nu_{it} \qquad (2)$$

Where Y_{it} is the outcome variable of interest for observation i in time t, such as self-reported health, number of chronic diseases, sleeping time and so on. R_{it} is an indicator of retirement. $f(age)$ is a smooth function of age. L_{it} are location and survey years fixed effect, and v_{it} is an unobserved error component. My parameter of interest is the coefficient β_1. Other controls include the interviews survey year and region variables. By choosing the suitable bandwidth with a linear control function (a linear in age, fully interacted with post dummy as the baseline specification), I estimate a local linear regression. I follow the algorithm proposed by (Imbens and Kalyanaraman 2012) to calculate an optimal bandwidth for each regression. As robustness checks, I change the sample to different age window (a bandwidth of 1 year to 3 years), and include quadratic terms in age, fully interacted with the post dummies in the model.

2.6 Results and Robustness Check

Table 2.3, 2.4 and 2.5 show the estimated effects of retirement on physical health, well-being and mental health, and cognitive functioning, separately. Column (5) of table 2.3 show that retirement makes the number of physical mobility problems decreased by 1.545, which is about 22.07% of the total seven physical mobility problems. The estimated coefficients for self-assessed health status, problems of ADL, problems of IADL, the number of chronic diseases and the number of doctor visit last month are not significant. As I change the bandwidth from 1 year to 3 years, the magnitude of coefficient of the number of physical mobility problems do not change significantly.

Table 2.4 indicates the coefficients of well-being and mental health variables. Column (1) represents the retirement significantly increased individual's self-reported life satisfaction.

Column (4) represents the retirement significantly relieved the feeling of fatigue. Column (5) shows the retirement decrease depression index by 5.246 points, which is about 17.48% of full depression index, or about 1.2 standard deviations. Column (6) shows the corresponding probability of being depressed decreased by 59 percentage points. Those coefficients are still significant as I adjust the bandwidth.

Table 2.5 shows the effects of the retirement on various cognitive functioning outcomes. Column (1) represents that the retirement makes the number of immediate word recall increased by 1.838, which is about 18.38% of the total number of words (10 words) responders need to recall. In addition, this effect is consistent and significant when I choose different bandwidths. The estimated coefficients of other cognitive functioning such as delayed word recall, date recall, serial 7 substation, draw assigned picture and self-rated memory are not significant. The corresponding discontinuity showed by Figure 3 is presented in Appendix.

Overall, the results indicate that the retirement improve ability of physical mobility, the mental health, and cognitive functioning of immediate word recall. These findings are consistent with the results of Johnston and Lee (2009) and Blake and Garrouste (2012).

Table 2.6 presents the effects of retirement on people's attitude to health, health related behaviors and other social activities, through which the physical health, mental health and cognitive functioning be changed. I do not find significant effects on the probability of smoking, the sleeping duration, and the alcohol consumption. Column (6) shows the probability of attending any social activities increases by 39.3 percentage points, which is about 0.84 standard deviation. In particular, column (9), (10), (12) and (13) shows that people are more likely to participate in physical activities, leisure activities, and surfing internet, even stock investment. After the retirement, they spend increased free time to attend leisure activities and to participate in physical exercise, which potentially contribute back to their mental and physical health. The corresponding discontinuity showed by Figure 4 is presented in Appendix.

I take robustness check by adding quadratic age trend to age smooth function, and by adding a set of individual covariates, including education, marriage status, number of children, and average expenditure per year per household member. Table 2.7, 2.8 and 2.9 show the effects of retirement on physical health, well-being and mental health and cognitive functioning, and potential mechanisms separately. The effect on number of physical mobility problems and mental health are still exist, but less significant. Column (1) of table 2.9 shows the effects of retirement on immediate word recall become less significant. The effects of retirement on delayed word recall presented on column (2) of table 2.9 become significant in 10% level. The effects of retirement on total recall presented on column (3) of table 2.9 become significant in 10% level. The effects of retirement on potential mechanisms showed on table 2.10 are very robust. It supports that people change their life style after the retirement: engage more leisure activities and participating physical exercises, which potentially contribute back to their mental and physical health.

2.7 Conclusion

This paper exploits China's mandatory retirement policy to investigate the short-term effects of retirement on health related outcomes and the mechanisms behind these effects, using a comprehensive, nationally representative sample from the China Health and Retirement Longitudinal Study (CHARLS). The results indicate that retirement could have positive effects on mental health, improving self-reported life satisfaction, reducing depression and feeling of fatigue in short run. However, I do not find statistically significant effects of retirement on several physical health measurements and many memory-related health outcomes such as the number of physical mobility problems and the number of immediate word recall.

Furthermore, the investigation on health behaviors and participation of social activities suggests the important mechanisms through which retirement affects health: retirees use their additional spare time to have a more active lifestyle by having more daily activities, attending more leisure activities and exercising more frequently.

Because the change of health behaviors and participation of social activities may take time to affect retirees' physical health and cognitive functioning, estimating these effects in a long timeframe should be more appropriate, but not considered in this study due to data limitation.

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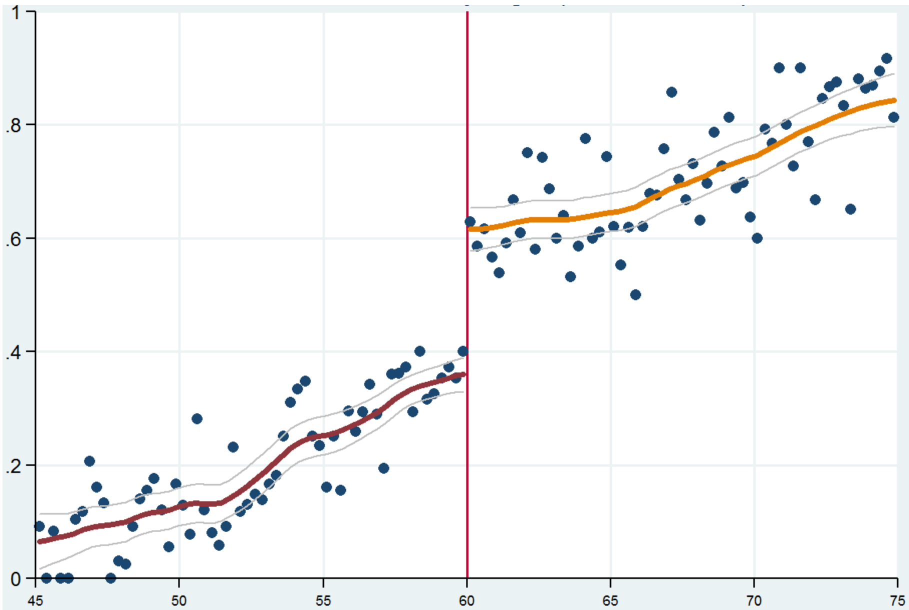
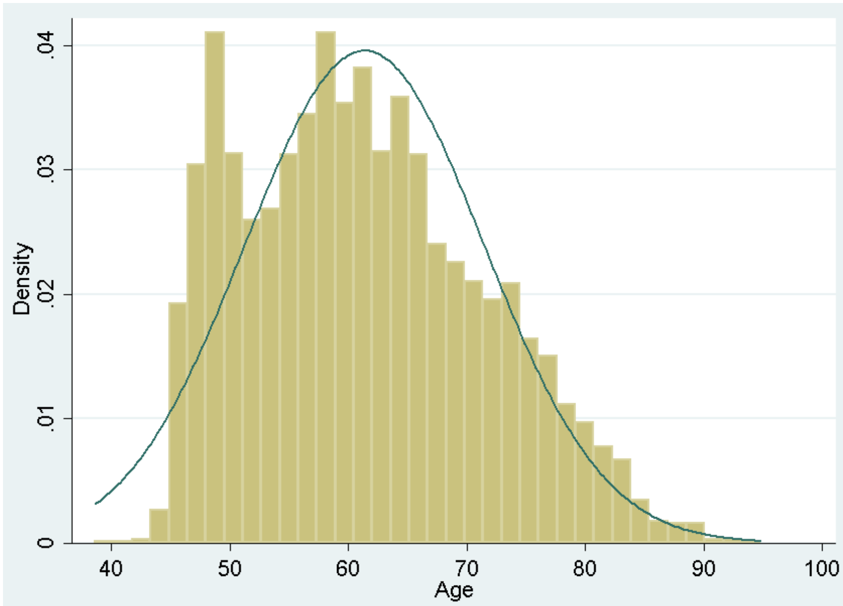
2.9 Tables and Figures

Figure 2.1 Share of Retirees of all urban male in China

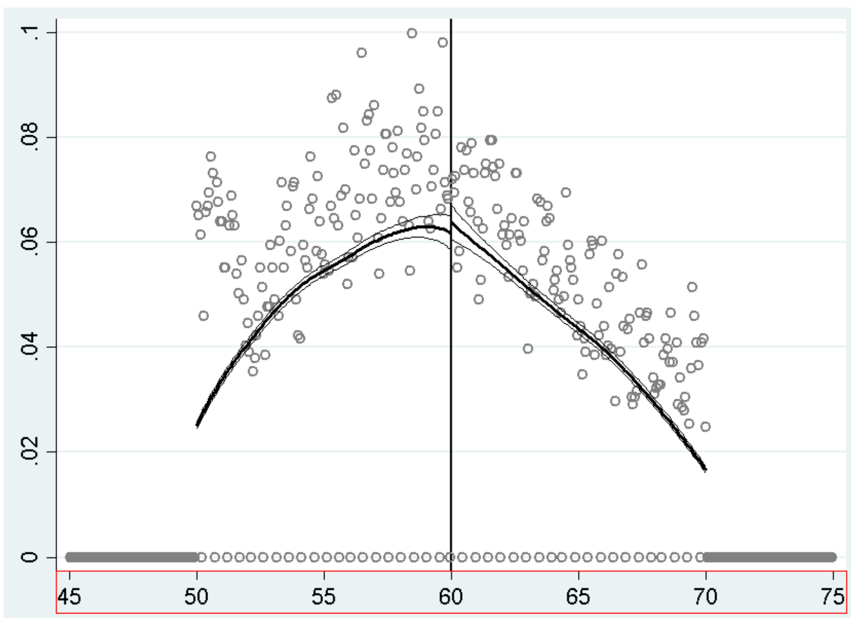


Notes: The markers represent the share of retirees in the window of three month. The solid line represents the predicted values of a local linear smoother estimated using raw data on each side of the threshold at age 60. Outer gray lines indicate 95 percent confidence intervals.

Figure 2.2 Density test



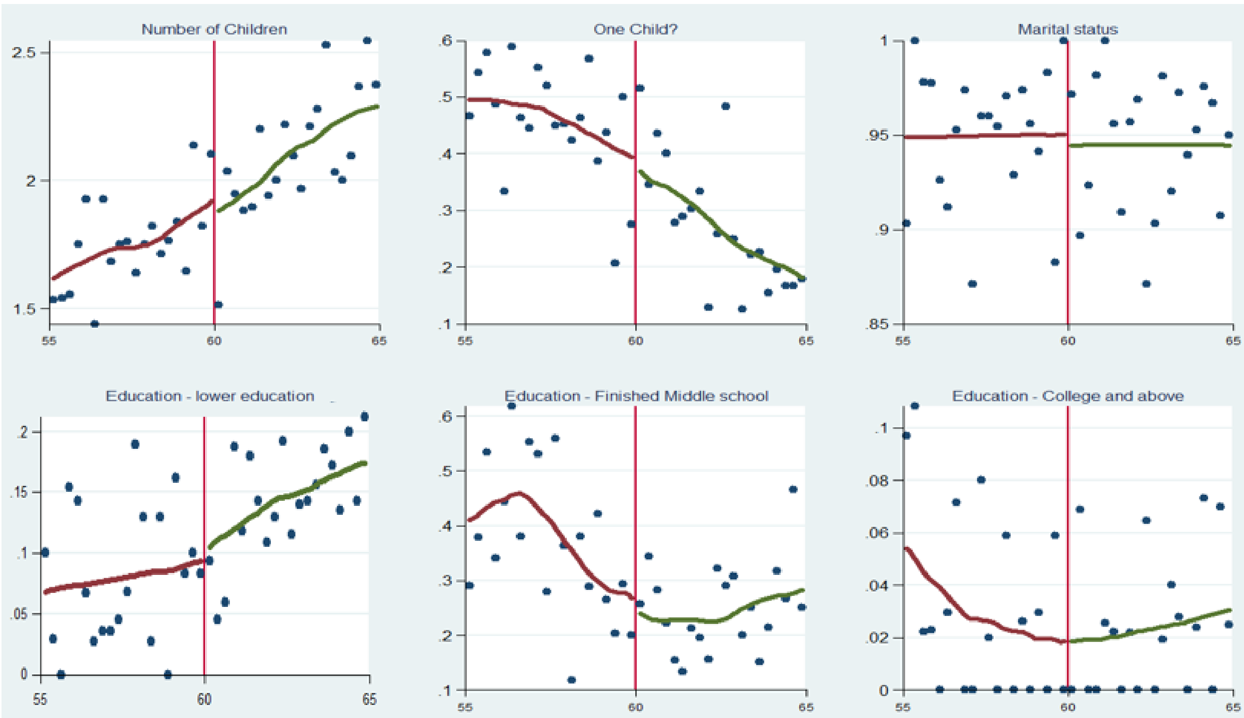
(a) Global Histogram



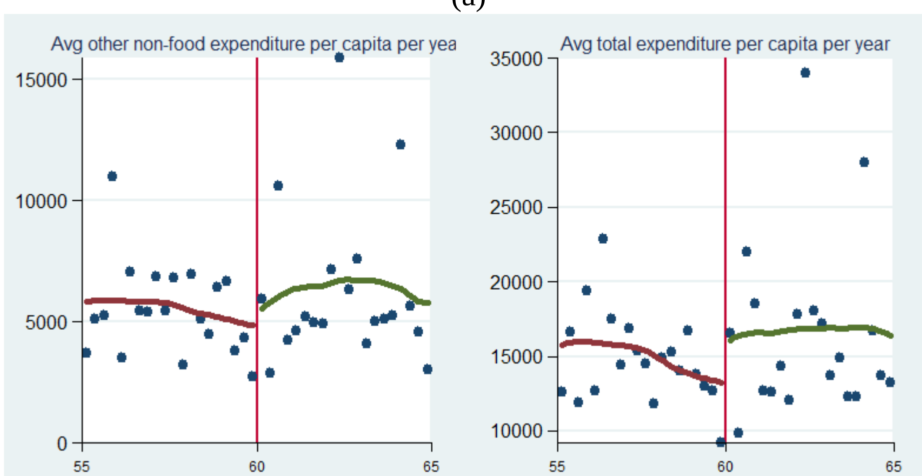
(b) McCray Test

Notes: Is the density of age continues at 60? Panel (a) shows histogram of age for the full range age in current data in 2 years bin. The graph in Panel (b) shows the McCrary (2008) test of whether there is a discontinuity in the density of age around 60.

Figure 2.3 Discontinuity checks for other observed characteristics



(a)



(b)

Notes: Ppanel (a) and (b) show the continuity of various characterizes I check for. The dots in the scatter plot depict the average over 3 months bin.

Table 2.1 Brief summary of China retirement policy and pension system

Type of pension	Gender	Type of work	Eligibility Criteria	Pension	Retirement age: Disable people: Work-caused disability	Retirement age: Disable people: Network-caused disability	Retirement age: People who worked in hazards associated environment: Early	Retirement age: Normal People: Official
Public service employee	Male	White-collar	Mandatory	More generous	Any age	50	-	60
		Blue-collar				50	55	60
	Female	White-collar				45	-	55
		Blue-collar				45	45	50
Urban employee social insurance pension system	Male	White-collar				50	-	60
		Blue-collar				50	55	60
	Female	White-collar				45	-	55
		Blue-collar				45	45	50
Rural and urban resident system	Male	Self-employed / Peasant	Voluntary	Less generous	-	-	-	60
	Female				-	-	-	60

Source:
Labour Insurance Regulations of the People's Republic of China
State Council Temporary Measures on Providing for Old, Weak, Sick, and Handicapped Cadres
State Council Temporary Measures on Workers' Retirement, Resignation
Regulations of social endowment insurance system for non-working urban residents
Regulations of social endowment insurance system for the urban working group
Regulations of new social endowment insurance system for rural residents

Table 2.1 Brief summary of China retirement policy and pension system

Table 2.2 Summary Statistics

	Variable	Mean	SD	Min.	Max.	N	Mean of non-retirees	Mean of retirees	t-Statistic
A.	**Physical health**								
	Self-reported health	0.157	0.364	0	1	1295	0.095	0.216	(-6.04)
	ADL Activities of daily living	0.166	0.704	0	6	1545	0.086	0.256	(-4.73)
	IADL Instrumental activities of daily living	0.212	0.754	0	5	1544	0.130	0.303	(-4.53)
	Number of Chronic diseases	1.482	1.487	0	11	1495	1.313	1.686	(-4.86)
	Number of morbidity problems	0.743	1.272	0	7	1328	0.595	0.886	(-4.19)
	Doctor visits in last month	0.339	1.558	0	30	1320	0.280	0.398	(-1.37)
B.	**Mental health**								
	Mental health	4.915	4.358	0	23	1390	4.879	4.965	(-0.37)
	Depression	0.147	0.354	0	1	1390	0.149	0.145	(0.17)
C.	**Well-being**								
	Satisfactory life	0.909	0.287	0	1	1359	0.914	0.903	(0.67)
	Somewhat satisfied life	0.690	0.463	0	1	1359	0.678	0.702	(-0.95)
	Not very satisfied life	0.079	0.269	0	1	1359	0.073	0.086	(-0.84)
	Not at all satisfied	0.012	0.108	0	1	1359	0.013	0.011	(0.30)
	Positive feeling HWB-12	2.708	2.723	0	12	719	2.681	2.754	(-0.35)
	Negative feeling HWB-12	0.972	2.241	0	17	725	0.877	1.094	(-1.29)
	Fatigue feeling HWB-12	1.134	1.746	0	12	723	1.170	1.076	(0.72)
D.	**Cognitive functioning**								
	Immediate word recall	4.719	1.606	0	10	1351	4.614	4.834	(-2.51)
	Delayed word recall	3.747	1.895	0	9	1358	3.706	3.792	(-0.83)
	Total word recall	8.492	3.164	0	18	1349	8.344	8.655	(-1.80)
	Date recall	4.172	1.496	0	5	1514	4.035	4.330	(-3.83)
	Serial 7 subtraction	3.928	1.586	0	5	1313	3.952	3.913	(0.45)
	Draw assign picture	0.874	0.332	0	1	1382	0.881	0.870	(0.61)
	Self-reported memory	0.149	0.356	0	1	1397	0.156	0.144	(0.64)
E.	**Health related behaviors**								
	Physical exam in past 2 years	0.585	0.493	0	1	1522	0.559	0.613	(-2.13)
	Alcohol consumption	0.590	0.492	0	1	1544	0.603	0.578	(1.00)
	Smoking	0.460	0.499	0	1	1218	0.464	0.457	(0.25)
	Sleeping duration	7.042	1.760	1	15	1410	7.030	7.044	(-0.15)
F.	**Social activities**								
	Take care grandchildren	0.647	0.478	0	1	1109	0.634	0.664	(-1.04)
	Attending some activities	0.676	0.468	0	1	1418	0.639	0.717	(-3.12)
	Number of activities	1.306	1.309	0	8	1418	1.212	1.409	(-2.83)
	Interacted with friends	0.362	0.481	0	1	1558	0.342	0.390	(-1.97)
	Leisure activities	0.297	0.457	0	1	1558	0.271	0.329	(-2.50)
	sports, social club	0.177	0.382	0	1	1558	0.130	0.236	(-5.46)
	Voluntary or charity work	0.022	0.146	0	1	1558	0.021	0.024	(-0.37)
	Stock investment	0.022	0.148	0	1	1558	0.012	0.033	(-2.81)
	Used the internet	0.112	0.315	0	1	1558	0.102	0.125	(-1.44)

G.	**Covariates**							
	Age	59.954	2.879	55	65	1558	59.103	60.906	(-12.91)
	Number of children	2	1.002	0	8	1332	1.900	1.792	(1.94)
	Only one child	0.412	0.492	0	1	1306	0.402	0.422	(-0.72)
	Marriage	0.954	0.209	0	1	1337	0.963	0.944	(1.61)
	Middle school	0.294	0.456	0	1	1338	0.298	0.287	(0.47)
	High school	0.516	0.500	0	1	1338	0.511	0.520	(-0.32)
	Some collage	0.158	0.365	0	1	1338	0.148	0.173	(-1.23)
	Graduate	0.031	0.174	0	1	1338	0.043	0.021	(2.28)
	Own house	0.967	0.178	0	1	1257	0.976	0.960	(1.54)
	Log of yearly average expenditure per household member	9.173	0.909	3.549	12.479	1270	9.047	9.302	(-5.03)

Notes: Descriptive statistics for CHARLS waves 2012 and 2014. The sample is restricted to urban man aged 55 to 65 years who were born between 1946 and 1958 and who were in job market or retired. Column 1 and 2 show the overall mean and standard deviation of the variable. Column 3 to 5 gives the overall minimum, maximum and the number of observations. Column 6 provides the mean for retirees (treatment group). The means for non-retirees (control group) are given in column 7. Column 8 indicated the t-statistic for the equality of means of both groups.

Table 2.3 The effect of retirement on physical health

VARIABLES	Physical Health					
	(1)	(2)	(3)	(4)	(5)	(6)
	Self-Assessed Health Status	# of Difficulties of ADL (Activities of daily living)	# of Difficulties of IADL (Instrumental activities of daily living)	# of Chronic diseases	# of physical mobility problems	# of doctor visit last month
	dummy 1 is good; 0 is bad	0-6	0-5	0-11	0 - 7	0 - 30
Optimal Bandwidth	-0.116	-0.0421	-0.0959	-0.294	-1.545**	-0.889
	(0.289)	(0.563)	(0.484)	(0.597)	(0.601)	(0.835)
	2.566	3.01	3.18	3.63	3.519	3.681
Bandwidth size 1 year	-0.431	0.321	0.735*	-2.133***	-1.334***	-1.862**
	(0.278)	(0.521)	(0.412)	(0.756)	(0.494)	(0.756)
	274	308	309	302	277	276
Bandwidth size 2 years	-0.217	0.141	0.409	-0.472	-1.920***	-1.139
	(0.319)	(0.558)	(0.387)	(0.720)	(0.636)	(1.003)
	538	647	648	600	551	548
Bandwidth size 3 years	-0.101	-0.0408	-0.0399	-0.0742	-1.545**	-0.980
	(0.277)	(0.563)	(0.478)	(0.639)	(0.602)	(0.899)
	805	916	919	896	824	820

Note: Separate regressions by different dependent variables using polled sample of the China Health and Retirement Longitudinal Study (CHARLS) wave 1 and wave 2 in 2011 and 2013. Robust standard errors in parentheses all clustered at age in month level. All models include a piecewise linear trends, individual – fixed effects and separate dummy variables for month and year of the interview.

*   p < .01.

** p < .001

***p < .000

Table 2.4 The effect of retirement on Well-being and Mental Health

Variables	Well-being				Mental Health	
	(1)	(2)	(3)	(4)	(5)	(6)
	Satisfactory life	Positive feeling index of HWB-12	Negative feeling index of HWB-13	Fatigue index of HWB-12	Depression index	Depressed?
	dummy	0 - 12	0 - 20	0 - 16	0 - 30	dummy
	1 is satisfied; 0 is unsatisfied	Larger, more positive feeling	Smaller, less negative feeling	Smaller, less fatigue feeling	Smaller, less pressure	1 is yes; 0 is no
Optimal Bandwidth	0.710***	1.562	-1.908	-2.514*	-5.246*	-0.590**
	(0.204)	(2.279)	(2.011)	(1.410)	(2.766)	(0.243)
	1.874	4.896	3.857	4.329	3.89	2.338
Bandwidth size 1 year	0.740***	4.465	-6.552**	-6.971***	-5.720**	-0.255
	(0.237)	(3.231)	(2.775)	(2.541)	(2.817)	(0.183)
	251	120	120	119	254	254
Bandwidth size 2 years	0.706***	5.549*	-4.805**	-4.943***	-7.793***	-0.636**
	(0.200)	(2.923)	(2.446)	(1.310)	(2.840)	(0.254)
	491	254	255	254	501	501
Bandwidth size 3 years	0.528***	3.556	-2.989	-2.805**	-5.758**	-0.483**
	(0.134)	(2.463)	(2.176)	(1.391)	(2.802)	(0.214)
	720	384	387	386	736	736

Note: Separate regressions by different dependent variables using polled sample of the China Health and Retirement Longitudinal Study (CHARLS) wave 1 and wave 2 in 2011 and 2013. Robust standard errors in parentheses all clustered at age in month level. All models include a piecewise linear trends, individual – fixed effects and separate dummy variables for month and year of the interview.

* p < .01.

** p < .001

***p < .000

Table 2.5 The effect of retirement on cognitive functioning

VARIABLES	Cognitive functioning						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Immediate word recall	Delayed word recall	Total word recall	Date recall	Serial 7 subtraction	Draw assign picture	Self-rated Memory
						dummy	dummy
	0 -10	1 -10	0-20	0-5	0-5	1 is yes; 0 is no	1 is poor; 0 is good
Optimal Bandwidth	1.838**	-0.199	1.084	0.592	0.474	0.206	-0.106
	(0.933)	(1.235)	(1.461)	(1.026)	(0.934)	(0.275)	(0.364)
	3.527	3.547	4.492	3.384	3.627	2.062	2.464
Bandwidth size 1 year	2.702***	4.176**	6.190***	0.357	0.225	0.467	0.187
	(0.922)	(2.060)	(1.505)	(1.546)	(1.311)	(0.368)	(0.252)
	249	251	249	272	239	253	255
Bandwidth size 2 years	3.470***	2.223*	5.285***	1.412	1.427	0.277	-0.0819
	(1.242)	(1.324)	(0.862)	(1.509)	(1.582)	(0.305)	(0.400)
	487	489	486	542	472	500	502
Bandwidth size 3 years	2.208**	0.246	2.409*	0.754	0.454	0.151	-0.103
	(0.970)	(1.285)	(1.324)	(1.042)	(0.936)	(0.228)	(0.337)
	711	716	710	806	697	735	741

Note: Separate regressions by different dependent variables using polled sample of the China Health and Retirement Longitudinal Study (CHARLS) wave 1 and wave 2 in 2011 and 2013. Robust standard errors in parentheses, all clustered at age in month level. All models include a piecewise linear trends, individual – fixed effects and separate dummy variables for month and year of the interview.

* p < .01.

** p < .001

***p < .000

Table 2.6 Mechanisms

Table 2.6 Mechanisms

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Attitude to health	**Health related behaviors**			**Social Activities**								
	Did physical exam in past 2 years?	Alcohol Consumption	Smoking	Sleeping Duration	Take care of grandson	has any activity in last month	# of activities last month	Interacted with friends	Leisure activities	Sports, social, or other kind of club	Voluntary or charity work	Stock investment	Used the internet
	dummy	dummy	dummy	0 - 15 hours	dummy	dummy	0 - 12	dummy	dummy	dummy	dummy	dummy	dummy
	1 is Yes; 0 is No.	1is Yes; 0 is No.	1is Yes; 0 is No.		1is Yes; 0 is No.	1is Yes; 0 is No.		1is Yes; 0 is No.	1is Yes; 0 is No.	1is Yes; 0 is No.	1is Yes; 0 is No.	1is Yes; 0 is No.	1is Yes; 0 is No.
Optimal Bandwidth	0.292	0.0565	-0.447	0.150	0.391	0.393*	0.691	0.0887	0.481**	0.638***	0.0336	0.177**	0.388**
	(0.190)	(0.402)	(0.404)	(1.227)	(0.477)	(0.205)	(0.630)	(0.213)	(0.214)	(0.193)	(0.0649)	(0.0697)	(0.168)
	2.728	2.665	2.131	3.877	2.653	2.199	3.163	2.498	2.125	1.82	1.92	1.937	1.798
Bandwidth size 1 year	0.222	0.489	-0.340	0.538	0.0802	0.487***	2.299***	0.0642	0.201	1.037***	0.105**	0.275***	0.626***
	(0.241)	(0.597)	(0.457)	(1.342)	(0.423)	(0.102)	(0.510)	(0.236)	(0.132)	(0.338)	(0.0508)	(0.0850)	(0.0706)
	270	277	226	259	261	261	277	277	277	277	277	277	277
Bandwidth size 3 years	0.314	0.0252	-0.439	0.172	0.246	0.238	0.594	0.0594	0.347**	0.293	0.0374	0.145**	0.108
	(0.192)	(0.388)	(0.332)	(1.345)	(0.438)	(0.211)	(0.658)	(0.209)	(0.175)	(0.243)	(0.0628)	(0.0656)	(0.195)
	809	820	650	749	753	753	824	824	824	824	824	824	824

Note: Separate regressions by different dependent variables using polled sample of the China Health and Retirement Longitudinal Study (CHARLS) wave 1 and wave 2 in 2011 and 2013. Robust standard errors in parentheses, all clustered at age in month level. All models include a piecewise linear trends, individual – fixed effects and separate dummy variables for month and year of the interview.

Table 2.7 Robustness Check - Piecewise quadratic age trends and Add control variables The effect of retirement on physical health

	Physical Health					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Self-Assessed Health Status	# of Difficulties of ADL (Activities of daily living)	# of Difficulties of IADL (Instrumental activities of daily living)	# of Chronic diseases	# of physical mobility problems	# of doctor visit last month
	dummy 1 is good; 0 is bad	0-6	0-5	0-11	0 - 7	0 - 30
Bandwidth size 1 year	-2.932	-0.988	0.0500	-4.864	-3.958	-3.375
	(1.944)	(1.316)	(1.275)	(3.265)	(2.751)	(2.186)
	274	308	309	302	277	276
Bandwidth size 2 years	-0.233	-0.0619	0.824	-3.639	-2.007***	0.918
	(0.656)	(1.083)	(0.843)	(2.411)	(0.621)	(1.732)
	538	647	648	600	551	548
Bandwidth size 3 years	-0.0495	0.0231	0.326	0.356	-1.215**	-0.533
	(0.490)	(0.626)	(0.508)	(1.147)	(0.572)	(1.381)
	805	916	919	896	824	820

Note: Separate regressions by different dependent variables using polled sample of the China Health and Retirement Longitudinal Study (CHARLS) wave 1 and wave 2 in 2011 and 2013. Robust standard errors in parentheses, all clustered at age in month level. All models include a piecewise linear trends, piecewise quadratic age trends, education in three categories, marital status, number of students, average expenditure per household member per year, individual – fixed effects and separate dummy variables for month and year of the interview.

* $p < .01$.
** $p < .001$
***$p < .000$

Table 2.8 Robustness Check - Piecewise quadratic age trends and Add control variables (The effect of retirement on Well-being and Mental Health)

Variables	Well-being				Mental Health	
	(1)	(2)	(3)	(4)	(5)	(6)
	Satisfactory life	Positive feeling index of HWB-12	Negative feeling index of HWB-13	Fatigue index of HWB-12	Depression index	Depressed?
	dummy	0 - 12	0 - 20	0 - 16	0 - 30	dummy
	1 is satisfied; 0 is unsatisfied	Larger, more positive feeling	Smaller, less negative feeling	Smaller, less fatigue feeling	Smaller, less pressure	1 is yes; 0 is no
Bandwidth size 1 year	0.901	7.959	-8.628	-11.39*	-12.11*	-0.487
	(1.139)	(7.317)	(5.625)	(6.526)	(6.815)	(0.504)
	251	120	120	119	254	254
Bandwidth size 2 years	0.610**	6.195	-3.546	-4.809	-10.61**	-0.958**
	(0.294)	(5.342)	(4.274)	(3.004)	(5.204)	(0.414)
	491	254	255	254	501	501
Bandwidth size 3 years	0.347	2.366	-1.610	-2.525	-7.547	-0.691
	(0.222)	(3.495)	(3.074)	(2.114)	(5.601)	(0.457)
	720	384	387	386	736	736

Note: Separate regressions by different dependent variables using polled sample of the China Health and Retirement Longitudinal Study (CHARLS) wave 1 and wave 2 in 2011 and 2013. Robust standard errors in parentheses, all clustered at age in month level. All models include a piecewise linear trends, piecewise quadratic age trends, education in three categories, marital status, number of students, average expenditure per household member per year, individual – fixed effects and separate dummy variables for month and year of the interview.

* p < .01.
** p < .001
***p < .000

Table 2.9 Robustness Check - Piecewise quadratic age trends and Add control variables (The effect of retirement on cognitive functioning)

VARIABLES	Cognitive functioning						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Immediate word recall	Delayed word recall	Total word recall	Date recall	Serial 7 subtraction	Draw assign picture	Self-rated Memory
						dummy	dummy
	0 -10	1 -10	0-20	0-5	0-5	1 is yes; 0 is no	1 is poor; 0 is good
Bandwidth size 1 year	3.291*	10.35*	12.37**	0.802	1.199	0.645	-0.386
	(1.874)	(5.669)	(5.427)	(2.604)	(3.049)	(0.790)	(0.672)
	249	251	249	272	239	253	255
Bandwidth size 2 years	5.820*	5.964*	10.44**	2.413	5.427	0.921	0.0301
	(3.095)	(3.624)	(4.363)	(2.024)	(3.824)	(0.796)	(0.458)
	487	489	486	542	472	500	502
Bandwidth size 3 years	4.419*	1.763	5.916*	1.109	1.874	0.0655	-0.185
	(2.435)	(2.065)	(3.473)	(1.068)	(1.463)	(0.449)	(0.463)
	711	716	710	806	697	735	741

Note: Separate regressions by different dependent variables using polled sample of the China Health and Retirement Longitudinal Study (CHARLS) wave 1 and wave 2 in 2011 and 2013. Robust standard errors in parentheses all clustered at age in month level. All models include a piecewise linear trends, piecewise quadratic age trends, education in three categories, marital status, number of students, average expenditure per household member per year, individual – fixed effects and separate dummy variables for month and year of the interview.

*   p < .01.
** p < .001
***p < .000

Table 2.10 Robustness Check on Mechanisms: Adding Piecewise quadratic age trends and control variables

Table 2.10 Robustness Check on Mechanisms: Adding Piecewise quadratic age trends and control variables

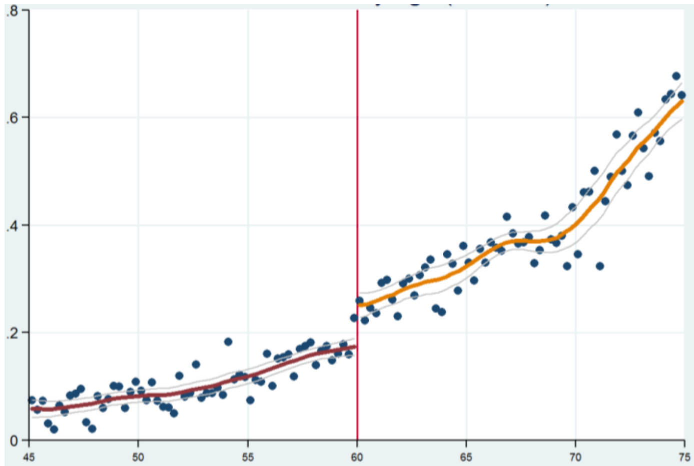
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Attitude to health	**Health related behaviors**			**Social Activities**								
	Did physical exam in past 2 years?	Alcohol Consumption	Smoking	Sleeping Duration	Take care of grandson	Has any activity in last month	# of activities last month	Interacted with friends	Leisure activities	Sports, social, or other kind of club	Voluntary or charity work	Stock investment	Used the internet
	dummy	dummy	dummy	0 - 15 hours	dummy	dummy	0 - 12	dummy	dummy	dummy	dummy	dummy	dummy
	1 is Yes; 0 is No.	1is Yes; 0 is No.	1is Yes; 0 is No.		1is Yes; 0 is No.	1is Yes; 0 is No.		1is Yes; 0 is No.	1is Yes; 0 is No.	1is Yes; 0 is No.	1is Yes; 0 is No.	1is Yes; 0 is No.	1is Yes; 0 is No.
Bandwidth size 1	1.479	0.210	-3.850	-2.849	-0.748	2.581*	8.838	0.330	1.359**	3.404	0.426	0.505**	1.544***
	(1.662)	(1.425)	(3.562)	(3.217)	(0.519)	(1.495)	(5.714)	(0.629)	(0.586)	(2.104)	(0.332)	(0.226)	(0.491)
No. of observations	270	277	226	259	261	261	277	277	277	277	277	277	277
Bandwidth size 2	0.686**	0.108	-0.215	2.269	0.250	0.784***	2.420**	-0.0775	0.960***	0.783**	0.0439	0.227**	0.691***
	(0.344)	(0.616)	(0.489)	(2.846)	(0.707)	(0.247)	(1.036)	(0.271)	(0.357)	(0.319)	(0.0927)	(0.111)	(0.227)
No. of observations	540	550	448	506	510	510	551	551	551	551	551	551	551
Bandwidth size 3	0.286	-0.0744	-0.905*	-0.166	0.462	0.704***	2.139**	0.141	0.800**	0.768***	0.0574	0.214**	0.439**
	(0.197)	(0.506)	(0.471)	(2.183)	(0.702)	(0.245)	(0.937)	(0.307)	(0.345)	(0.258)	(0.0792)	(0.0879)	(0.215)
No. of observations	809	820	650	749	753	753	824	824	824	824	824	824	824

Note: Separate regressions by different dependent variables using polled sample of the China Health and Retirement Longitudinal Study (CHARLS) wave 1 and wave 2 in 2011 and 2013. Robust standard errors in parentheses, all clustered at age in month level. All models include a piecewise linear trends, piecewise quadratic age trends, education in three categories, marital status, number of students, average expenditure per household member per year, individual – fixed effects and separate dummy variables for month and year of the interview.

* p < .01.
** p < .001
***p < .000

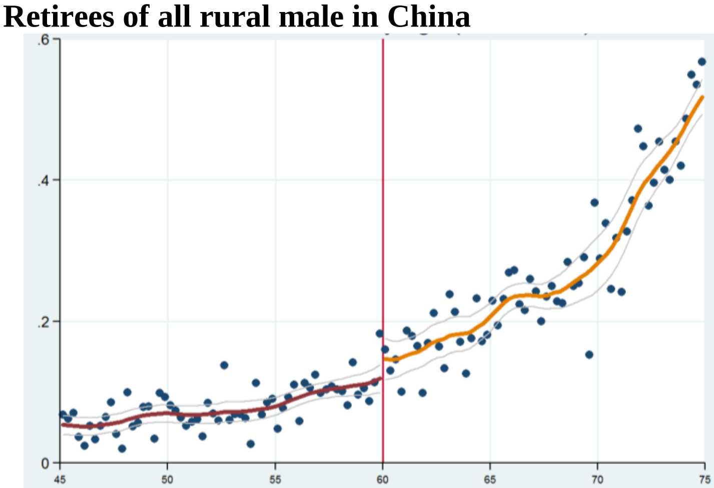
Appendix 1:

Figure 1: Share of Retirees of male in China



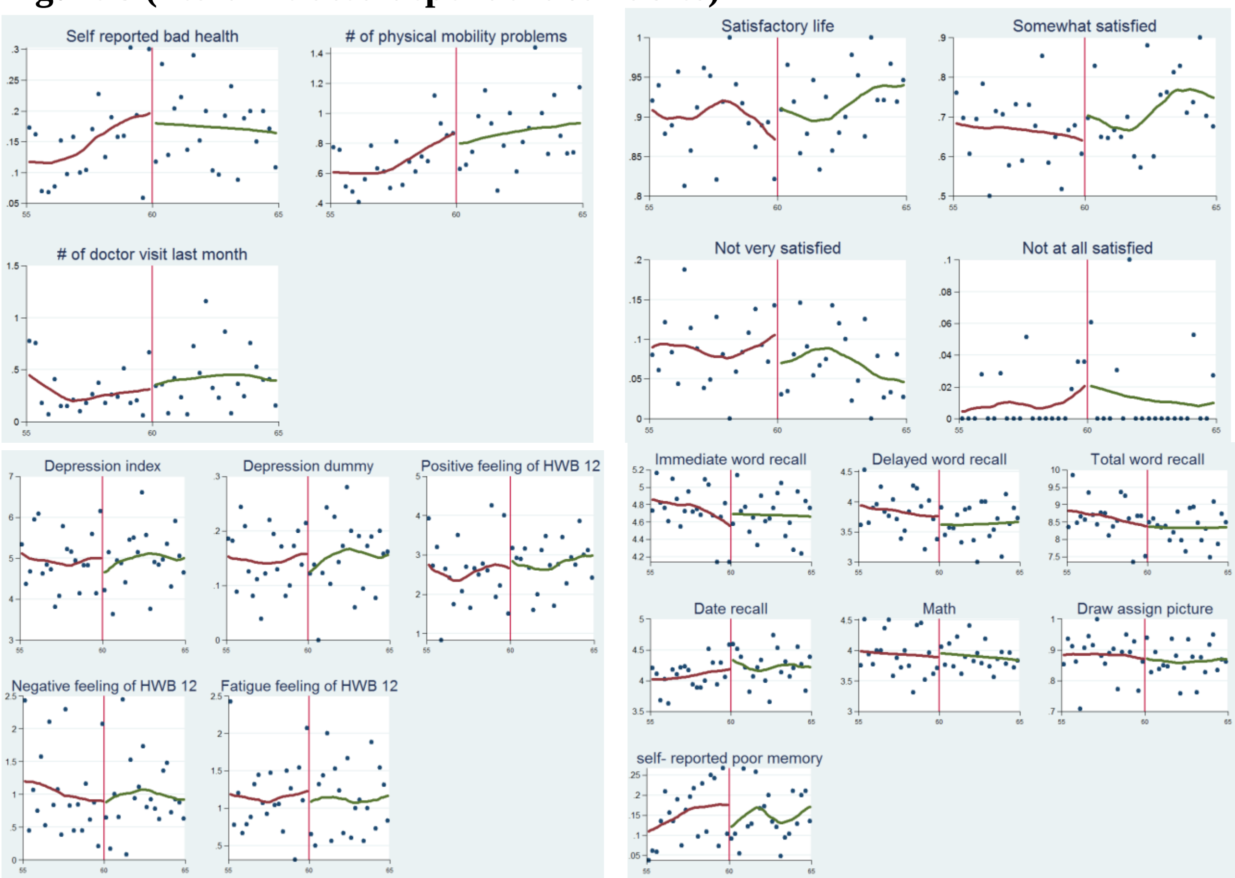
Notes: The markers represent the share of retirees in the window of three month. The solid line represents the predicted values of a local linear smoother estimated using raw data on each side of the threshold at age 60. Outer gray lines indicate 95 percent confidence intervals.

Figure 2: Share of Retirees of all rural male in China



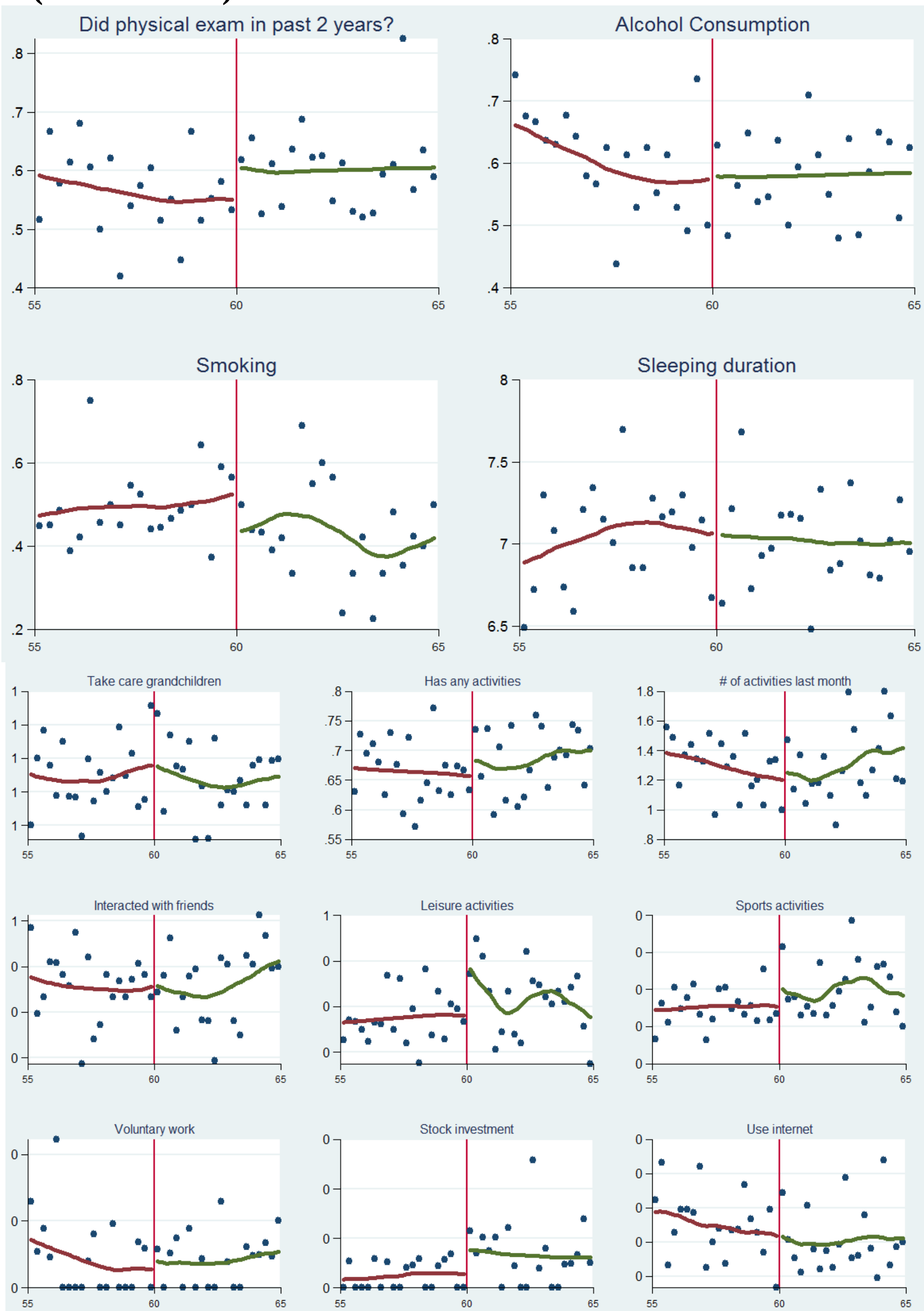
Notes: The markers represent the share of retirees in the window of three month. The solid line represents the predicted values of a local linear smoother estimated using raw data on each side of the threshold at age 60. Outer gray lines indicate 95 percent confidence intervals.

Figure 3 (health related dependent variables)



Notes: Figure 3 shows the continuity of various health related dependent variables I check for. The dots in the scatter plot depict the average over 3 months bin.

Figure 4 (Mechanisms)



Notes: Figure 4 shows the discontinuity of various mechanisms variables I check for. The dots in the scatter plot depict the average over 3 months bin.

Chapter 3: The Effects of Childhood Socioeconomic Status on Health Outcomes of Mid-Aged and the Elderly in China: Evidence from the CHARLS National Baseline Survey and Health History Survey

3.1 Introduction

Several types of research across economic, epidemiological, and sociological fields document that early life circumstances, such as in-uterus exposures, socio-economics, childhood shocks and health are powerful predictors of health, economic socioeconomic status and well-being in later life. Some link birth situation to adult health (Barker, 1995; Godfrey and David JP Barker 2001; Roseboom et al., 2006; Currie and Moretti, 2007; Oreopoulos et al., 2008; Maccini and Yang, 2009). Some investigate the effects of the childhood socioeconomic status or health on disease in adulthood (Lynch et al., 1994; Gunnel et al., 1998; Dietz, 1998; Marmot et al., 2001; Galobardes et al., 2006; Biro et al., 2010; Cohen et al., 2010). Other papers root in income, education and working status (Case et al., 2002; Luo and Linda, 2005; Currie, 2009), conclusing that situation in early life generates long-run impacts on the well-being of later life. Also, from a public policy standpoint, such long-lasting consequences may make potential policy intervention particularly important.

With the population aging rapidlly and life expectancy improving dramatically, developing countries are facing several tough challenges from the aging population.[35] Health of aging people and the related government spending on healthcare are two critical issues. The elderly have a higher risk of experiencing chronic diseases, having difficulties in activities of daily living (ADLs) or instrumental activities of daily living (IADLs). If governments have to transfer public spending from education and infrastructure investment to health care utilization for the elderly, economic growth and overall quality of life can be affected. However, the majority of those analyses examine many Western and developed countries and focus on the children's health or adults' health. Only a few papers explore the long-run effects of childhood condition on the elderly in developing countries (Grimard et al., 2010; Smith et al., 2012).

In this paper, I examine the health outcomes of mid-aged and the elderly in China, and investigate the effects of early life conditions on difference dimensions of health status in adulthood and elderhood. I also focus on the difference between men and women. To do so, I use recently collected data from the China Health and Retirement Longitudinal Study (CHARLS) 2011 national baseline wave and the 2016 history wave to document health conditions of those aged 45 to 80. I use the health measurements provided by the CHARLS including self-reported health, chronic disease indication, the number of chronic diseases, disable indicator, the number of difficulties of ADLs and IADLs, sleeping time and biomarker of height. I also control for the potential channel of health effects because early life conditions may have indirect effects through education, health, occupation, wealth, and other conditions, on the health in late life. I find that

[35] World report on ageing and health (2015) shows that two thirds of the world's older persons live in the developing regions now and their numbers are growing faster there than in the developed regions. The number of older persons in the less developed regions grew from 376 million in 2000 to 602 million in 2015 (an increase of 60 percent) and it is projected to grow by 71 percent between 2015 and 2030, when a projected 1 billion people aged 60 years or over will reside in the less developed regions. Projections indicate that 1.7 billion people aged 60 years or over nearly 80 per cent of the world's older population—will live in the less developed regions in 2050.

the effects are strong and statistically significant even when I control for an individual's education and wealth. This finding suggests that the childhood situations have the impact on socio-economic conditions beyond adulthood and into elderhood. Also, the results indicate that policies aimed at improving children's health, living conditions and SES may have long-lasting benefits for the individual and also for the society as a whole.

The remaining part of the paper is structured as follows. Section 2 reviews the literature, Section 3 discusses conceptual issues and the empirical models, followed by section 4 describing the CHARLS national baseline data, health history data, and variables I use. Section 5 discusses the results and robustness checks. Section 6 concludes.

3.2 Literature review

The literature presenting several mechanisms, through which the childhood socioeconomic status (CSES) affects health in elderhood, can be summarized in two groups. Critical-period programming and life course models.

First, critical-period programing is the concept that environmental conditions in a certain sensitive period of life may have long-lasting and permanent effects. The term "fetal-origins hypothesis" has been used to represent the programing induced by circumstances experienced in the fetal period (Barker, 1997), and it also include the period of infancy and early childhood. It suggests a direct link of the conditions in utero, at birth or in early infancy to health later that may be independent of social class in adult life. Specifically, there is growing evidence that conditions during such a critical period can change an individual's physiology causing a permanent and downward shift in her health much later. Elo and Preston (1992) suggest that adult height is essentially determined by events in the first three years of life, and height can have long-lasting negative impacts on health status (Strauss and Thomas, 2008). Using a 1958 British birth cohort who were followed prospectively into their adult years. Case et al., (2005) explore the long-lasting associations between childhood health on adult health, exam performance, employment, and measures of socioeconomic status (SES). They show that people who experienced low birth weight or chronic disease when they were children had worse health, poor exam performance, and lower working statuses, even after controlling for parental background, such as education and income. Almond (2006) use 1918 Influenza Pandemic, which was unexpected and short, to identify the in-uterus conditions effects on late health. Using roughly one-third of those born in early 1919 whose mothers contracted influenza while pregnant as treatment group, and those born in early 1918, who had essentially zero prenatal exposure to the 1918 pandemic as control group, he find that children of infected mothers were more likely to be disabled and experienced lower, as well as less educational attainment. Currie and Walker (2011) investigate the introduction of E-ZPass (electronic toll collection) greatly decrease traffic congestion and vehicle emissions near highway toll plazas. Their results suggest that traffic congestion contributes significantly to adverse health conditions among infants.

Second is life course models, which is broader than the critical-period programing (fetal-origins hypothesis). [36] It assumes that the physical and social hazards during gestation, childhood, adolescence, young adulthood and midlife may have long-term consequences for health during adulthood, either directly through the illness itself or indirectly by restricting educational achievement and life opportunities (Kuh and Wadsworth 1993; Kuh and Ben-

[36] A life course is defined as "a sequence of socially defined events and roles that the individual enacts over time". In particular, the approach focuses on the connection between individuals and the historical and socioeconomic context in which these individuals lived. The origins of this approach can be traced back to pioneering studies of the 1920s such as Thomas' and Znaniecki's "The Polish Peasant in Europe and America" and Mannheim's essay on the "Problem of generations".

Shlomo 1997). The life course models operate in two ways. The pathway models suggest that early experiences place an individual onto a certain "life trajectory," eventually indirectly impacting later life health (Kuh et al. 1997; Marmot et al. 2001; Hertzman et al. 2001).The cumulative model suggests the psychosocial and physiological experiences and environments during early, and later life accumulate to influence the late life health (Davey-Smith et al, 2002). Case and Paxson (2008) shows that having good health during childhood and growing up in a more comfortable environment result in a higher level of education, and good health and higher economic status later in life.

3.3 Conceptual issues and empirical models

3.3.1 Conceptual issues

Michael Grossman's 1972 model of health production treats every individual as both a producer and a consumer of health.[37] Health is treated as a stock which degrades over time in the absence of "investments" in health. Following his model, and especially the model of Grimard et al., (2010), I generate the conceptual framework. I consider that individual health at time t (H_t) should be a function of an individual's history health from initial health to the most recent health $(H_0, H_1, \ldots, H_{t-2}, H_{t-1})$; the health investment of the past periods $(I_1, \ldots, I_{t-2}, I_{t-1})$; the time histories of community characteristics $(C_0, C_1, \ldots, C_t)$, which include the community infrastructure and disease environment; and important time-invariant demographic variables (X) such as gender and age. I summarize those important health determinants below:

[37] The model acknowledges that health is both a consumption good that yields direct satisfaction and utility, and an investment good, which yields satisfaction to consumers indirectly through fewer sick days. Investment in health is costly as consumers must trade off time and resources devoted to health, such as exercising at a local gym, against other goals. These factors are used to determine the optimal level of health that an individual will demand. The model makes predictions over the effects of changes in prices of healthcare and other goods, labor market outcomes such as employment and wages, and technological changes.

$$H_t = h(H_0, H_1, \ldots, H_{t-2}, H_{t-1};\ I_1, \ldots, I_{t-2}, I_{t-1}; C_0, \ldots, C_t; X) \qquad (3.1)$$

Since health stock is treated as a recursive process, I consequently replace health at any time (H_m) with above expression for each period t = 0 to t = m-1 induces the following reduced equation of health:

$$H_t = h(H_0;\ I_1, \ldots, I_{t-2}, I_{t-1}; C_0, \ldots, C_t; X) \qquad (3.2)$$

The initial health endowment H_0 is partly determined by genetic characteristics (G) determined at pregnancy. Both critical-period programming model and life-course model support that early-life socio-economic status (SES) directly and indirectly affects the health of later life. So I treat childhood socioeconomic status (CSES) as another initial health determinate. Also, the original location characteristic is also a determinate of the original health endowment.

$$H_0 = k(CSES; C_0; G) \qquad (3.3)$$

3.3.2 Empirical models

In examining the relationship between individual's childhood socioeconomic status (CSES) and health in mid-age and the elderly, I begin with the below-reduced equation, setting health in old age (H_i) is the function of an individual's childhood socioeconomic status (CSES), demographic characteristics and current location.

$$H_{ijt} = \beta * CSES + \gamma * X_i + \delta * L_{it} + t_i + \varepsilon_{ijt} \qquad (3.4)$$

H_{ijt} is the health of individual *i* living in district *l* in period *t*. I are interested in the coefficient of β, the impact of CSES on the elderly health outcome. X_i presents demographic controls such as age, marital status, the number of children, and current hukou status.[38] L_{it} is the group of location dummies. I also include the interview month fixed effect. ε_{ijt} is the mean-zero error

[38] A hukou is a record in a government system of household registration required by law in mainland China, and determines where citizens are allowed to live. The system itself is more properly called "huji", and has origins in ancient China.

term. Because in this equation 3.5 I assume that the effects captured by β is very strong, it might be driven upwards by omitted variable bias. I except the magnitude of β will decrease if I control the education E_i and the log of per capita expenditure W_i. All equations are estimated for men and women separately.

$$H_{ijt} = \beta * CSES + \theta E_i + \gamma * X_i + \delta * L_{it} + t_i + \varepsilon_{ijt} \quad (3.5)$$

$$H_{ijt} = \beta * CSES + \theta E_i + \lambda W_i + \gamma * X_i + \delta * L_{it} + t_i + \varepsilon_{ijt} \quad (3.6)$$

3.4 Data and Sample

China Health and Retirement Longitudinal Study (CHARLS) is a multidisciplinary longitudinal survey of middle-aged and the elderly population in China on health, socioeconomic status, and social and family network.[39]

The formal survey years of CHARLS are 2011, 2013 and 2014. The baseline national wave1 was fielded in 2011 and includes about 10,000 households and 17,500 individuals in 150 counties/districts and 450 villages/resident committees. The respondents are followed every 2 years, using a face-to-face computer-assisted personal interview (CAPI). The baseline national wave 2 finished in 2013. CHARLS wave 3, conducted in 2014 and released in June 2016, collected detailed retrospective life histories. I use wave 1 national baseline data and wave 3 life history data. The survey includes measurements on health, such as self-reported health condition and individual's functional status; demographics of both individuals and families, educational background, childhood living conditions, and several economic measures, such as incomes,

[39] CHARLS is designed after the Health and Retirement Study (HRS) in the United States, and is also harmonized with many leading international surveys of the elderly people in other countries, such as the English Longitudinal Survey on Aging (ELSA), the Korean Longitudinal Study of Aging (KLoSA), the Longitudinal Aging Study in India (LASI), the Survey on Health, Aging, and Retirement in Europe (SHARE) and the Japanese Study of Aging and Retirement (JSTAR).
See http://charls.pku.edu.cn/en.

savings and expenditures. I keep the observations with age 45 to 80, which represents mid-age and the elderly group of people. Table 3.1 shows the definition of variables and he sample size and statistics for each variable are shown in Table 3.2.

I construct a group of dependent variables including good health, disable, chronic disease, and difficulty of ADLs / IADLs indicators, the number of chronic diseases, sleeping time and adult height.[40] For self-rated health status is derived from a question asking the individual to rate their health on the five-point scale: very good, good, fair, bad and very bad.[41] I then condense these responses to a two-point scale: 0 is bad health (bad and very bad categories), 1 is good health (very good, good and fair categories).[42] There are about 80% of men report they have good health status, and 73% for women.

To generate the CSES measure, I use the survey question about hunger, family's financial situation, neighborhood cleanliness, access clean water, and energization whey they were before 17 years old. There are many channels through which those situation affect health. For example, not accessing clean water may cause bacterial infections, cholera, dysentery, hepatitis A, typhoid and polio.[43] Hunger in childhood can lead to insufficient nutrition and, finally linked to adverse health outcomes in later life. Using similar strategy with Grimard (2010), I give each condition the same weight and combine them together. So the CSES index decreasing with good childhood social-economics condition. A CSES index value ranges 0 to 1. Value 1 indicates that the

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[40] Activities of daily living (ADLs) measure limitations in the following six skills: dressing, bathing, eating, transferring (get into or out of bed), toilet use (including getting up and down), and controlling urination and defecation. Instrumental activities of daily living (IADLs) measure the five skills including doing housework; preparing meals; groceries shopping; making phone calls; taking medications (preparing and taking correct dose); and managing money (paying bills, keeping track of expenses, or managing assets).

[41] The CHARLS also records the second version of the five-point scale (excellent, very good, good, fair, and poor). I do not use the second version in the paper.

[42] In Chinese language, "fair" always means good

[43] http://www.who.int/mediacentre/factsheets/fs391/en/

individual had worse family's financial condition, experienced hunger, lived in unclean neighborhood, did not access clean water and no energized in childhood.

Education is measured by a dummy variable for individuals who finished primary school. Since dataset has more missing values on income questions and it might be measured with much more error. I use per capita expenditure, a better measure of long-run resources, to substitute the income.

3.5 Results and robustness check

Table 3.3 shows the results of equation 3.4, 3.5 and 3.6. Panel A shows the effects of CSES on respondents' self-reported health status, which groups "fair", "good", "very good" as "good health". It shows the effects are significant and the magnitudes become lower as I control for adult education and expenditure (the proxy of income). In addition, the effects of CSES on other health indicators such chronic disease, disease, without ADL problems, and without IADL problem are significant and also showing that bad CSES leads to adverse health measurements in the late time. Another important finding is the different effects across gender: effects on women is stronger than effects on men. Differential mortality between women and men may explain this difference partly (Kishor, 1995). Since females have a mortality advantage during infancy and low-health-men might be dead at young age, comparing "good-health-men" with both "good-health-women" and "low-health-women" generates the gender bias effects in the long-term.

Considering the possible endogeneity problem occurs on CSES (the intergenerational effects of parents' SES on children's SES), I control for SES of the individual's parents. On life history survey, every interviewee was asked questions about parents' education and occupation circumstance when they were children. Table 3.4 shows the results of equation 3.6, controlling for parents background. For women, doing so does not change the significant and magnitude of the CSES effects a lot on health outcomes in later life. However, for men, doing so make the coefficients of CSES less significant. Also, for bother men and women the parental SES variables are jointly insignificant for the dependent variables. This exam confirms my conclusion that lower CESC is significantly associated with negative health indicators later. However, for respondents who are age 45 to 80 in 2011 (survey year), their parents were born at the end of the 19th century and grown at the beginning of the 20th century. China was in a state of radical upheaval in this period. The majority of people experienced very low living conditions and attained less education. For instance, in my sample, the percentage of literate mothers is only 1% and 4% for literate fathers. Therefore, the variables of parents' background may not be enough to extract parents' SES. I should re-investigate this problem after getting data with more information in the future.

Taking the possible bias of self-reported health status consideration, I generate a more restricted indicator of respondents' self-reported health status grouping "good" and "very good" as "good health." The results showed on Table 3.5 is robust to this concern. The magnitude of effects decreases and is significant for both women and men. In addition, the effects of CSES on other health indicators such as the number of chronic diseases, the number of ADL problems, the number of IADL problem, and sleeping time are significant and also showing that the bad CSES leads to adverse health measurements in the late time. For variable "height" measured by centimeter, I do not find the significant effect on men. Although the effect for women is significant, the significance is disappeared after I control for adult education and expenditure (a proxy for income).

3.6 Conclusion

Using the Chinese Health and Retirement Longitudinal Study, I estimate the long-term effects of childhood social-economics status (CSES) on several health outcomes of the elderly (people who are aged 45 to 80) in China. I find that for both men and women, unfavorable childhood life situation is associated with adverse health status in later life. Although those effects could be partially mediated through education of attainment and income during adulthood, those effects remain statistically significant when I control for the education of attainment and income during adulthood. I also find the long-term CSES effects are stronger for women than for men.

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3.8 **Tables and Figures**

Table 3.1 Variable Definitions

Variable Name	**Definition**
Background information	
Age	Age in 2016
Marital Status	Dummy = 1 if Married or living with a partner
Number of children	Number of living children
Hukou status	Dummy = 1 for Urban
City	City categories
Childhood social economics status	
Family's financial situation	Dummy = 1 if respondent's family financial situation was somewhat/ a lot worse off compared to the situation of the average family in the same community when the respondent was a child.
Hungary	Dummy = 1 if respondent had ever suffered hunger when he/she was a child.
Neighborhood Safety	Dummy = 1 if respondent's neighborhood where he/she lived as a child was not safe at all or not very safe.
Neighborhood Cleanliness	Dummy = 1 if respondent's neighborhood where he/she lived as a child was not clean at all/ not very clean.
Clean water	Dummy = 1 if respondent started using clean water when he/she was a child.
Water closet	Dummy = 1 if respondent started using water closet when he/she was a child.
Energization	Dummy = 1 if respondent started energized when he/she was a child.
CSES index	0 = best CSES, 1 = Worst CSES. Combined above seven conditions and giving them same weight.
Adult social economics status	
Completed primary school	Dummy = I if respondent had completed primary school
Log of per capita expenditure	Log of per capita expenditure
Outcome Measures	
Good health in 2011	Dummy = 1 if respondent reports
Alternative Good health in 2011	Dummy = 1 if the respondent is disabled.
Disable	Dummy = 1 if the respondent is disabled.
Chronic disease	Dummy = 1 if the respondent has any chronic disease.
ADLs	Dummy = 1 if respondent has no any difficulty in Activities of Daily Living
IADLs	Dummy = 1 if respondent has no any difficulty in Instrumental Activities of Daily Living
# of chronic disease	Number of chronic diseases (Hypertension, Dyslipidemia, Diabetes, Cancer, Stroke, Arthritis, Asthma, Chronic Lung/ Liver/ Hear/ Kidney/ Stomach/ Memory-related / Psychiatric disease.)
# of difficulties of ADLs	Number of difficulties on Activities of Daily Living (Bathing, dressing, going to the toilet, Transfer, Continence, and feeding.)
# of difficulties of IADLs	Number of difficulties on Instrumental Activities of Daily Living (Housekeeping, food preparation, shopping, financial management, and medication.)
Sleeping time	Average sleeping time for one night during the past month.
Height	Biomarker of height (cm) in 2011
Parental background information	
Mother is literate	Dummy = 1 if biological mother is literate
Father is literate	Dummy = 1 if biological father is literate
Mother's main work	Dummy = 1 if mother's main occupation is farming
Father's main work	Dummy = 1 if father's main occupation is farming

Table 3.2 Descriptive statistics

Variables	Men			Women		
	Mean	Standard deviation	Obs.	Mean	Standard deviation	Obs.
Age	59.882	8.673	6618	58.643	8.945	7343
Marital Status	0.920	0.271	6618	0.869	0.338	7340
Number of children	2.544	1.339	6606	2.700	1.394	7330
Hukou status	0.203	0.402	6617	0.173	0.378	7340
Family's financial situation	0.413	0.492	6580	0.387	0.487	7292
Hungary	0.746	0.435	6563	0.684	0.465	7269
Neighborhood Cleanliness	0.403	0.491	6471	0.322	0.467	7195
Clean water	0.069	0.253	6618	0.068	0.252	7343
Energization	0.088	0.283	6618	0.095	0.293	7343
CSES index	0.682	0.219	6426	0.646	0.223	7121
Completed primary school	0.423	0.494	6611	0.234	0.423	7336
Log of per capita expenditure	8.480	0.893	6492	8.444	0.909	7161
Good health in 2011	0.809	0.393	6592	0.730	0.444	7300
Alternative Good health in 2011	0.300	0.458	6592	0.212	0.409	7300
Disable	0.187	0.390	6601	0.155	0.362	7310
Chronic disease	0.656	0.475	6601	0.689	0.463	7309
ADLs	0.894	0.308	6536	0.847	0.360	7221
IADLs	0.842	0.365	6567	0.768	0.422	7258
# of chronic disease	1.282	1.346	6601	1.424	1.412	7309
# of difficulties of ADLs	0.228	0.821	6536	0.318	0.924	7221
# of difficulties of IADLs	0.314	0.885	6567	0.481	1.058	7258
Sleeping time	7.121	2.011	6080	6.720	2.121	6927
Height	163.664	6.743	4639	152.656	6.425	5300
Mother is literate	0.100	0.300	6295	0.106	0.308	7025
Father is literate	0.405	0.491	6204	0.402	0.490	6611
Mother's main work	0.940	0.238	5839	0.940	0.238	6455
Father's main work	0.826	0.379	6205	0.813	0.390	6859

Table 3.3 Effects of CSES on Middle and aged people's health

	Men			Women		
	Eq. (3)	Eq. (4)	Eq. (5)	Eq. (3)	Eq. (4)	Eq. (5)
Panel A: dependent variable (measure of good health)						
CSES Index	-0.118***	-0.103***	-0.0980***	-0.208***	-0.188***	-0.186***
	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)
Completed primary school		0.0535***	0.0529***		0.0631***	0.0656***
		(0.011)	(0.011)		(0.014)	(0.015)
Log of per capita expenditure			0.0058			-0.00762
			(0.006)			(0.006)
Regression Wald chi_squared	366.16	381.2	379.22	557.04	577.12	571.68
Pseudo R-squared	0.067	0.0707	0.0713	0.0722	0.0752	0.0757
Observations	6203	6198	6118	6914	6911	6781
Panel B: dependent variable: (disable)						
CSES Index	0.0744***	0.0549**	0.0499**	0.0716***	0.0543***	0.0509**
	(0.023)	(0.023)	(0.024)	(0.020)	(0.020)	(0.020)
Completed primary school		-0.0683***	-0.0653***		-0.0572***	-0.0492***
		(0.011)	(0.011)		(0.012)	(0.012)
Log of per capita expenditure			-0.0139**			-0.0188***
			(0.006)			(0.005)
Regression Wald chi_squared	456.13	489.76	494.64	570.73	583.74	582.57
Pseudo R-squared	0.0895	0.0966	0.0978	0.1119	0.1157	0.1165
Observations	6157	6152	6079	6915	6911	6772
Panel C: dependent variable: (chronic disease)						
CSES Index	0.0601**	0.0548**	0.0587**	0.103***	0.102***	0.116***
	(0.028)	(0.028)	(0.028)	(0.025)	(0.026)	(0.026)
Completed primary school		-0.0139	-0.021		-0.00148	-0.007
		(0.013)	(0.013)		(0.014)	(0.014)
Log of per capita expenditure			0.0339***			0.0292***
			(0.007)			(0.007)
Regression Wald chi_squared	505.97	508.52	502.52	590.87	589.71	594.32
Pseudo R-squared	0.0665	0.0669	0.0678	0.0783	0.0782	0.0814
Observations	6267	6262	6179	6967	6963	6824
Panel D: dependent variable (without problem of ADL)						
CSES Index	-0.0545***	-0.0462**	-0.0469**	-0.117***	-0.106***	-0.106***
	(0.019)	(0.019)	(0.019)	(0.020)	(0.021)	(0.021)
Completed primary school		0.0348***	0.0352***		0.0393***	0.0386***
		(0.009)	(0.009)		(0.012)	(0.012)
Log of per capita expenditure			0.00344			0.00364
			(0.005)			(0.005)
Regression Wald chi_squared	431.13	444.97	448.31	690.61	701.42	695.54
Pseudo R-squared	0.1184	0.1247	0.1226	0.1438	0.1463	0.1471
Observations	5886	5881	5818	6813	6809	6678
Panel E: dependent variable (without problem of IADL)						
CSES Index	-0.0832***	-0.0655***	-0.0633***	-0.135***	-0.106***	-0.108***
	(0.021)	(0.022)	(0.022)	(0.023)	(0.024)	(0.024)
Completed primary school		0.0642***	0.0610***		0.0948***	0.0923***
		(0.010)	(0.010)		(0.014)	(0.014)
Log of per capita expenditure			0.0113**			0.0107*
			(0.005)			(0.006)
Regression Wald chi_squared	562.63	603.32	598.96	762.15	802.99	774.13
Pseudo R-squared	0.126	0.1337	0.135	0.1202	0.1275	0.1243
Observations	6,181	6,176	0.135	6,901	6,897	6,708

Notes: All regressions include controls for age, number of living children, marital status, hukou status and location dummies, survey month. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.4 Effects of CSES on Middle and aged people's health, controlling for parental background

Variables	Male (Probit marginal effect)				
	Measure of good health	Disable	With at one Chronic Disease	Without any difficulty of ADL	Without any difficulty of IADL
CSES index	-0.0925***	0.0576**	0.0649*	-0.0448**	-0.0667**
	(0.028)	(0.028)	(0.033)	(0.022)	(0.026)
Completed primary school	0.0671***	-0.0708***	-0.0208	0.0346***	0.0577***
	(0.013)	(0.012)	(0.015)	(0.010)	(0.011)
Log of per capita expenditure	0.00428	-0.0168**	0.0293***	0.00638	0.0143**
	(0.007)	(0.007)	(0.008)	(0.005)	(0.006)
Mother is literate	0.00934	0.0263	0.0087	0.000281	0.022
	(0.021)	(0.020)	(0.024)	(0.017)	(0.021)
Father is literate	0.0173	0.00481	-0.0123	0.00764	0.00637
	(0.012)	(0.012)	(0.015)	(0.010)	(0.011)
Mother's main work is farming	0.032	-0.0374	0.0224	-0.0211	-0.0316
	(0.033)	(0.033)	(0.038)	(0.029)	(0.032)
Father's main work is farming	0.00839	0.0238	-0.0101	-0.00695	-0.00185
	(0.019)	(0.019)	(0.023)	(0.015)	(0.018)
Regression Wald chi squared	335.91	401.1	412.61	391.1	462
Pseudo R-squared	0.832	0.0998	0.072	0.1359	0.1345
Joint F-test of parental background variables	3.8	4.28	0.96	2.78	3.97
Observations	4,691	4,645	4,778	4,381	4,619

Variables	Female (Probit marginal effect)				
CSES index	-0.179***	0.0567**	0.116***	-0.0900***	-0.0908***
	(0.030)	(0.025)	(0.031)	(0.025)	(0.029)
Completed primary school	0.0652***	-0.0384***	-0.00706	0.0212	0.0820***
	(0.017)	(0.015)	(0.017)	(0.014)	(0.017)
Log of per capita expenditure	-0.00968	-0.0234***	0.0223***	0.00307	0.00627
	(0.007)	(0.006)	(0.008)	(0.006)	(0.007)
Mother is literate	0.00771	-0.00262	-0.0331	0.0153	0.00356
	(0.022)	(0.018)	(0.021)	(0.019)	(0.021)
Father is literate	0.00413	0.00592	-0.0129	-0.0014	0.011
	(0.013)	(0.010)	(0.014)	(0.010)	(0.012)
Mother's main work is farming	-0.0426	-0.0522**	-0.0573*	-0.0355	0.0323
	(0.035)	(0.027)	(0.034)	(0.031)	(0.033)
Father's main work is farming	0.0218	0.0263	-0.00448	0.000168	-0.0502***
	(0.020)	(0.017)	(0.020)	(0.016)	(0.019)
Regression Wald chi squared	5,112	4,882	5,141	4,918	5,003
Pseudo R-squared	0.0868	0.1256	0.083	0.1469	0.1311
Joint F-test of parental background variables	2.35	5.28	8.05*	1.77	8.89*
Observations	5017	4794	5046	4772	4890

Notes: All regressions include controls for age, the number of living children, marital status, Hukou status and location dummies, survey month. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.5 Robustness checks (Changed dependent variables)

	Men			Women		
	Eq. (3)	Eq. (4)	Eq. (5)	Eq. (3)	Eq. (4)	Eq. (5)
Panel A: dependent variable (alternative measure of good health status)						
CSES INDEX	-0.0944***	-0.0790***	-0.0746***	-0.174***	-0.157***	-0.152***
	(0.027)	(0.027)	(0.027)	(0.022)	(0.023)	(0.023)
Completed primary school		0.0574***	0.0537***		0.0457***	0.0439***
		(0.012)	(0.013)		(0.012)	(0.013)
Log of per capita expenditure			0.0199***			0.00215
			(0.007)			(0.006)
Regression Wald chi_squared	491.98	512.78	508.74	517.22	534.08	528.52
Pseudo R-squared	0.0704	0.0736	0.0738	0.0797	0.0814	0.0822
Observations	6,258	6,253	6,173	6,958	6,955	6818
Panel B: dependent variable (number of chronic diseases)						
CSES INDEX	0.238***	0.223***	0.250***	0.511***	0.497***	0.522***
	(0.0788)	(0.0799)	(0.0807)	(0.0765)	(0.0779)	(0.0787)
Completed primary school		-0.0417	-0.0683*		-0.0428	-0.0790*
		(0.0370)	(0.0376)		(0.0428)	(0.0437)
Log of per capita expenditure			0.117***			0.119***
			(0.0211)			(0.0199)
Regression F-test	7.05	7.01	7.06	9.70***	9.62***	9.50***
R-squared	0.1085	0.109	0.112	0.140	0.140	0.143
Observations	6,222	6,217	6,135	6,808	6,804	6,673
Panel C: dependent variable (number of ADL problems)						
CSES INDEX	0.112***	0.0905**	0.0905**	0.152***	0.148***	0.149***
	(0.0433)	(0.0436)	(0.0441)	(0.0470)	(0.0479)	(0.0485)
Completed primary school		-0.0793***	-0.0791***		-0.0124	-0.0148
		(0.0202)	(0.0209)		(0.0242)	(0.0254)
Log of per capita expenditure			-0.00654			0.00683
			(0.0146)			(0.0133)
Regression F-test	3.17	3.12	3.06	4.68***	9.69***	9.64***
R-squared	0.067	0.069	0.069	0.100	0.100	0.101
Observations	6,204	6,199	6,122	6,884	6,880	6,746
Panel D: dependent variable (number of IADL problems)						
CSES INDEX	0.120***	0.0873*	0.0774*	0.277***	0.237***	0.231***
	(0.0461)	(0.0463)	(0.0466)	(0.0526)	(0.0535)	(0.0542)
Completed primary school		-0.117***	-0.116***		-0.112***	-0.109***
		(0.0209)	(0.0211)		(0.0273)	(0.0281)
Log of per capita expenditure			-0.0184			-0.0112
			(0.0147)			(0.0153)
Regression F-test	3.98	4.1	4.04	6.50***	6.61***	6.32***
R-squared	0.083	0.087	0.089	0.114	0.116	0.118
Observations	6,241	6,236	6,158	6,924	6,920	6,787

Panel E: dependent variable (sleeping time)						
CSES INDEX	-0.433***	-0.407***	-0.391***	-0.504***	-0.438***	-0.458***
	(0.121)	(0.123)	(0.124)	(0.117)	(0.120)	(0.122)
Completed primary school		0.0887	0.0937		0.184***	0.203***
		(0.0568)	(0.0578)		(0.0638)	(0.0656)
Log of per capita expenditure			-0.00258			-0.0549*
			(0.0339)			(0.0329)
Regression F-test	3.62	3.64	3.63	4.70***	4.79**	4.77***
R-squared	0.070	0.070	0.071	0.086	0.087	0.088
Observations	5,792	5,791	5,718	6,634	6,632	6,503
Panel F: dependent variable (height)						
CSES INDEX	-2.192	-1.912	-1.907	-0.961**	-0.570	-0.450
	(1.660)	(1.672)	(1.715)	(0.436)	(0.444)	(0.447)
Completed primary school		1.018	1.047		1.182***	0.982***
		(0.981)	(1.030)		(0.227)	(0.228)
Log of per capita expenditure			0.0231			0.626***
			(0.431)			(0.110)
Regression F-test	1.16			10.99***	11.31***	11.73***
R-squared	0.040	0.040	0.040	0.167	0.170	0.177
Observations	4,435	4,432	4,377	5,071	5,070	4,971

Notes: All regressions include controls for age, the number of living children, marital status, Hukou status and location dummies, survey month. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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