Patient Cost Sharing and Healthcare Utilization in Early Childhood: Evidence from a Regression Discontinuity Design

Hsing-Wen Han[*], Hsien-Ming Lien[†], Tzu-Ting Yang[‡]

February 16, 2019

Abstract

This paper estimates the price elasticity of healthcare utilization in early childhood. We employ regression discontinuity design by exploiting a subsidy that reduces patient cost-sharing for children aged under 3 in Taiwan. Using longitudinal medical claims of over 410,000 children, we find a modest price elasticity of outpatient expenditure (e.g. -0.12 for regular outpatient care). Furthermore, cost-sharing subsidy largely increases the chance of visiting expensive healthcare providers (e.g. teaching hospitals) for minor illnesses. In contrast, children's utilization of inpatient care is price insensitive. Finally, we find no evidence that subsidy-induced healthcare utilization improves children's health outcome.

[*]Department of Accounting, Tamkang University; Email: hwhan466@mail.tku.edu.tw

[†]Department of Public Finance, National Chengchi University; Email: hmlien@nccu.edu.tw

[‡]Corresponding author, Institute of Economics, Academia Sinica, Email: ttyang@econ.sinica.edu.tw.Yang would like to thank Joshua Gottlieb, Kevin Milligan, Thomas Lemieux and Marit Rehavi for their guidance and support. We are also grateful to Logan McLeod, Timothy J. Layton, Nicole Huang, Alexandre Corhay, Yi-Ling Lin, Xu Ting, Zhe Chen, Anirban Basu, Zih-Ting Peng, Yan-Yu Chiou, Rih-Cing Jhang, Fung-Mey Huang, Yi-Wen Tsai, Yiing-Jeng Chou, Bradley Chen, Wei-Der Tsai, Kamhon Kan, Stacey Chen, Chun-Fang Chiang, Elliott Fan, Joseph Tao-yi Wang, Yi-Ting Chen, Edward Norton, Ange Suziedelyte, Randall Ellis, Alix Duhaime-Ross, Timea Laura Molnar, Oscar Becerra, Daniel Shack as well as participants at the 2014 Canadian Health Economists' Study Group Meeting, the UBC Public Finance Reading Group and the 2014 Singapore Health Economics Association Conference, 2015 National Taxation Association meeting, 2015 Annual Health Econometrics Workshop, 2016 HSR annual meeting, seminars at Academia Sinica, NTU, and NCU for their valuable suggestions. National Health Insurance research data were provided and approved by the National Health Insurance Administration. This paper represents the views of the authors and does not reflect the views of the National Health Insurance Administration.

1 Introduction

Investment in health is considered one of the most valuable investments in a child's early stages of life (Almond et al., 2011; Bharadwaj et al., 2013; Currie, 2009).[1] In addition, young children are not only vulnerable to various diseases but also likely to incur large medical expenses for their families.[2] As such, countries all over the world have exempted—either partially or fully—the cost sharing of children's medical care in order to reduce barriers to necessary care. For instance, Children's Health Insurance Program, administered by the U.S. government, regulates the level of cost sharing to ensure children from middle- and low-income families can afford medical treatment. Similarly, nations with national health insurance, such as Japan and Korea, offer children under 6 years old a lower coinsurance rate. While the exemption for children's cost sharing is well received politically, the low level of cost sharing could incentivize some patients to overuse healthcare services with low marginal value; this potentially excessive use of healthcare might not actually improve children's health. Understanding how cost sharing affects children's healthcare use, as well as children's health in general, is essential to evaluating cost-sharing subsidy policies.[3] In spite of children—particularly young children—often being at the center of cost-sharing policies, surprisingly there is only scarce empirical evidence regarding cost sharing's effect on young children. Most existing studies have focused on more mature cohorts, for example, the elderly (Chandra et al., 2010a; Shigeoka, 2014; Fukushima et al., 2015), adults (Chandra et al., 2014, 2010b), and school-age children or adolescents (Iizuka and Shigeoka, 2018; Nilssona and Paul, 2018).

In this paper, we study the issue by exploiting a cost-sharing subsidy policy in Taiwan. Since

[1] Bharadwaj et al. (2013) and Almond et al. (2011) present convincing evidence that early-life medical treatments can reduce mortality and even result in better academic performance in school. Thus, health intervention in early childhood can be seen as an investment with high returns.

[2] In Taiwan, children under 4 years of age are the age group with the second-highest healthcare spending (the highest is the over-65s). The number of outpatient visits for children under the age of 4 is approximately 20 per year (see Online Appendix A). Compared with adults—with approximately 15 visits per year—this age group has an especially high need for healthcare services.

[3] Estimating the causal effect of cost sharing on healthcare utilization and health is a challenging task. The main reason for this is that the variation in cost sharing is not usually exogenous, and might depend on the outcome of interest. For example, people with high healthcare utilization could pay a larger share of medical costs due to the rules of their insurance plans, in that people in poor health might be forced to choose insurance plans with a high level of patient cost sharing.

March 2002, all children under the age of 3 have been completely *exempt*, in the case of both inpatient and outpatient services, from copayments (coinsurance) under the Taiwanese National Health Insurance (NHI) scheme.[4] Therefore, the expiration of the cost-sharing subsidy results in a drastic increase in patient cost sharing at the child's 3^{rd} birthday. By utilizing this sharp change in price and data on the longitudinal insurance claims of more than 0.41 million children, we follow the healthcare utilization of the same children over time and compare their healthcare use just before and just after their 3^{rd} birthdays using a regression discontinuity (RD) design. Moreover, by using mortality data from the death registry and tracking inpatient admissions of children with serious health problems at an older age, we also examine whether the additional use of healthcare induced by the cost-sharing subsidy produces any positive effect on children's health.

Our paper stands apart from previous literature on patient cost sharing in the following ways. First, our administrative data contain scrambled, but unique patient identifiers across years and utilize accurate age information. Therefore, we are not only able to follow the healthcare use of the same children but also to compare their healthcare utilization based on the unit of "days."[5] Since eligibility for the cost-sharing subsidy is based solely on a child's age (i.e., whether they have passed their 3^{rd}birthday), these features help us to plausibly isolate the effect of cost sharing from other confounding factors. Second, with the aid of our large sample size and the universal medical records of our insurance claims data, we can comprehensively investigate the price sensitivity of children's healthcare utilization by both service type and patient type in the same framework. Understanding the heterogeneity in the responsiveness to patient cost sharing is important for the design of optimal health insurance.

Third, the institutional setting in Taiwan makes our estimates of the cost-sharing effect immune from bias arising from either confounding demand-side or supply-side factors. Most previous studies estimating the price sensitivity of health demand faced two major challenges. First, the com-

[4]For an outpatient visit, a patient still needs to pay a registration fee, which is not covered by NHI.

[5]Prior studies using survey data have found there is substantial heaping in the reported birth dates of patients, which might reflect a measurement error in patients' ages. Shigeoka (2014) discussed the fact that respondents in the Japanese Patient Survey tended to report the first day of the month as their birthday if they could not remember their exact date of birth.

position of insurance enrollees might have been endogenously determined by the level of the cost sharing, an issue confronted by U.S. studies (Selby et al., 1996; Goldman et al., 2004; Trivedi et al., 2008; Chandra et al., 2010a, 2014). In addition, the estimates of a patient's demand could have been influenced by supply factors, such as the restrictions of a patient's medical care provider or the insurer's payments to health providers (Cutler, 1998; Wu, 2010; Clemens and Gottlieb, 2017), which is well discussed in Shigeoka (2014). To some extent, both of these concerns are mitigated under Taiwan's institutional setting. Since Taiwan's NHI is a compulsory single-payer system, everyone has to enroll in this health insurance plan. This feature ensures that the composition of children enrollees will not be influenced by the expiration of the cost-sharing subsidy or other confounding factors.[6] Furthermore, the single-payer scheme also prevents the provider from cost shifting among various health insurance plans.

Last but not least, we can examine the effect of cost sharing on the patients' provider choices, which, though an important behavioral response, has seldom been discussed in the literature. Unlike in the U.S. or European countries, many Asian countries—such as Japan, South Korea, Taiwan, and China—do not implement a gatekeeping system. That is, patients are free to visit any specialist at a hospital directly, without obtaining a referral from their primary care physician first. An important concern regarding free access to hospital outpatient services is that patients might use costly healthcare providers (e.g. teaching hospitals) to treat minor illnesses. Instead of using a gatekeeping system to control the patient flow, Taiwan's NHI has established a tiered copayment scheme for outpatient services, whereby the copayment differs according to the level of healthcare provider.[7] Since the cost-sharing subsidy essentially eliminates the tiered copayments for children under the age of 3, this gives us a unique opportunity to examine the impact of the tiered copayments on patients' provider choices, by comparing the choices made immediately before the 3^{rd}birthday (i.e., without the tiered copayments) to those made immediately after the 3^{rd}birthday (i.e., with the

[6] Besides changes in cost sharing, premium changes could also affect people's decision to enroll in health insurance (Dague, 2014).

[7] NHI implements a tiered copayment scheme based on the accreditations of healthcare providers. There are four types of healthcare providers: major teaching hospitals, minor teaching hospitals, community hospitals, and clinics. A major teaching hospital (clinic) visit requires the highest (lowest) copayment. In section 2.1, we will discuss this issue in details.

tiered copayments).

We obtain four key findings from our research. First, our estimate of the price elasticity of inpatient expenditure is almost zero.[8] A large increase in out-of-pocket (OOP) expenses at age 3 leads to little change in the utilization of children's inpatient care. Notice that this insignificant finding is not driven by the small sample size, as our sample consists of more than 0.41 million children. Such price elasticity for inpatient cases is substantially lower than found in previous studies examining this subject (Manning et al., 1987; Shigeoka, 2014; Chandra et al., 2014; Fukushima et al., 2015). For instance, the RAND Health Insurance Experiment (RAND HIE) found that the price elasticity of inpatient care was -0.17 for adults (Manning et al., 1987),[9] while Shigeoka (2014) and Fukushima et al. (2015) found the elasticity for the elderly—those above the age of 70—to be approximately -0.2 and -0.16, respectively.[10] As such, our results offer a rationale for providing full coverage to young children for inpatient care, since having free inpatient care does not result in excessive use but substantially lessens the financial risk faced by households.

Secondly, we find the higher cost sharing at age 3 significantly reduces children's use of outpatient care. However, our results are still distinct from those of previous studies in two regards. First, our study indicates that the implied price elasticity for outpatient expenditure is -0.12 for regular outpatient care and slightly less (in absolute value) for emergency room care (-0.07). This estimate is somewhat smaller than the figures obtained in previous studies, which focused on adults and the elderly (Manning et al., 1987; Shigeoka, 2014; Fukushima et al., 2015; Chandra et al., 2014).[11]

[8]Based on our estimates, we can rule out a price elasticity of inpatient expenditure larger than -0.05 (95% confidence interval, in absolute terms). For the number of inpatient admissions, we can even rule out a price elasticity larger than -0.03 (95% confidence interval, in absolute terms).

[9]The RAND HIE was conducted in the mid-1970s, and randomly assigned participating households to different levels of patient cost sharing (ranging from free care to 95% cost sharing).

[10]Shigeoka (2014) exploited the sharp reduction in patient cost sharing at age 70 in Japan and applied an RD design to estimate the price elasticity of healthcare utilization for the elderly. He found that inpatient care for the elderly was price sensitive and estimated the elasticity of inpatient admissions to be around -0.2. Fukushima et al. (2015) also exploited the sharp reduction in patient cost sharing at age 70 in Japan, but they used administrative claims data. They concluded that the price elasticity for inpatient expenditure was approximately -0.16 (i.e., statistically insignificant). Chandra et al. (2014) used a cost-sharing reform in Massachusetts as an exogenous variation in price, and obtained a price elasticity of total medical expenses of around -0.16 for low-income adults. Nonetheless, the point estimate of price elasticity for inpatient care was sizeable (-0.12), but statistically insignificant.

[11]For example, the RAND HIE found the price elasticity of outpatient care for adults to be -0.2, and Shigeoka (2014) and Fukushima et al. (2015) obtained similar estimates for the elderly in Japan.

The lack of price responses in healthcare for young children might reveal that the types of healthcare services used by adults are quite different from those used by children—the majority of outpatient visits for children are for acute diseases (e.g. asthma) rather than for chronic diseases (e.g. diabetes). Acute diseases usually produce noticeable symptoms (e.g. fever, cough, muscle pain, or difficulty breathing), even if some of them, such as the common cold, do not necessarily require medical intervention. Due to behavioral hazard (Baicker et al., 2015), parents without much experience of raising children could overweigh such symptoms, leading to a lack of adjustment of the healthcare utilization of their children in response to the price change. We examine this hypothesis by conducting subgroup analysis based on birth order. We find that the smaller estimates of price elasticity (in absolute terms) for young children in our main results could be driven by the first-born children. The estimated price elasticities of regular outpatient care and emergency room care for the first-born children are only -0.10 and -0.04, respectively. In contrast, the healthcare utilization of non-first-born children has larger price responses. Furthermore, our estimates suggest that beneficial or non-deferrable outpatient care is less price sensitive. Interestingly, we find that the utilization of preventive care and mental health services, which incur an immediate cost now but often have benefits only in the distant future, is quite price sensitive. The estimated price elasticities are much larger (in absolute value) for preventive care (-0.60) and mental health services (-0.26). Our results suggest parents could be somewhat present-biased (Baicker et al., 2015) when making healthcare decisions for their children.

Thirdly, we find that a patient's choice of provider of outpatient care is quite sensitive to the relative levels of copayment of different healthcare providers. The proportion of teaching hospital visits (i.e. high-intensity providers) decreases significantly, by around 40%, at age 3 when patients have to make tiered copayments. In addition, requiring patients to make tiered copayments can reduce the proportion of teaching hospital visits made for minor medical issues. Our findings shed some light on how relative levels of cost sharing could be used to influence a patient's provider choices, namely, how tiered copayments discourage patients with minor illnesses from using high-cost or high-complexity healthcare services at teaching hospitals.[12]

Lastly, in the online appendix, we provide suggestive evidence of the impact of patient cost sharing on children's health. Our results show that health status, as measured by the occurrence of serious pediatric health problems (i.e. pediatric complex chronic conditions) and by mortality, is not influenced by the expiration of the cost-sharing subsidy at age 3. More importantly, we find that the additional outpatient visits induced by the cost-sharing subsidy at ages 2-3 have little impact on children's long/medium-term health, which is measured by the rate of occurrence of serious pediatric health problems at ages 5-11.[13]

Our paper is relevant to the literature on the demand for healthcare among children. In fact, credible estimates of the price elasticity for children's healthcare utilization still rely on evidence from the RAND HIE. The RAND HIE found that a higher patient cost sharing could significantly reduce the outpatient care of children under the age of 14 (Leibowitz et al., 1985; Manning et al., 1981).[14] However, the experiment cannot conclude the effect of cost sharing on children's inpatient utilization due to the limited sample size.[15] Two recent papers using a quasi-experimental design (Iizuka and Shigeoka, 2018; Nilssona and Paul, 2018) obtained similar estimates of price elasticities for outpatient care found in this paper. However, our paper focuses on a relatively policy-relevant age group (i.e. young children), examines more comprehensive utilization behavior (i.e. choice of healthcare provider) and healthcare services (i.e. emergency room care and inpatient care), and

[12] In a recent paper, Brot-Goldberg et al. (2017) also investigated the effect of cost sharing on patients' choice of provider (i.e. price-shopping behavior). They exploited a large shift in employees' health insurance plans, from zero cost sharing to a high-deductible plan. Their results demonstrated that a high deductible/coinsurance amount had little impact on a patient's choice of provider. Nonetheless, in contrast to the situation covered in Brot-Goldberg et al. (2017), Taiwanese patients are free to choose their own healthcare providers, and they always know their OOP expenses in advance. For this reason, they are more likely to respond to the financial incentive embedded in the cost-sharing policy.

[13] Several recent papers (Wherry and Meyer, 2015; Wherry et al., 2018) have studied the effect of the U.S. Medicaid expansion on children's long-term health. They have found that increasing the health insurance coverage for children could reduce mortality rates and hospitalization rates in adulthood. However, their results stem from the mixed effects of the health insurance provision per se and changes in health insurance generosity. The policy change used in this paper is only related to a change in cost sharing (i.e., health insurance generosity), which is not confounded by large wealth effects coming from the provision of health insurance. In fact, our result is consistent with the findings in a recent paper (Iizuka and Shigeoka, 2018) using changes in patient cost sharing for school-aged children in Japan.

[14] On average, children assigned to the no-cost-sharing plan would make one fewer office visit per year than those assigned to the cost-sharing plan.

[15] As Leibowitz et al. (1985) comment, "Because hospitalizations for children are infrequent, our estimates of hospital use have wide confidence intervals, and we can be less certain than for outpatient care about the presence or absence of a cost sharing response."

uses a population-wide data.[16]

The remainder of this paper is organized as follows. Section 2 provides a brief overview of the institutional background. In Section 3, we discuss our data and sample selection. In Section 4, we discuss the results on healthcare utilization. Section 5 provides a general discussion of our results. Finally, in Section 6, we provide concluding remarks.

2 Policy Background

2.1 Taiwan's National Health Insurance

In March 1995, Taiwan implemented NHI, a government-run, single-payer health insurance plan. Prior to this, health insurance had been provided through three major social insurance plans: labor insurance for workers in the private sector, government-employee insurance for public employees, and farmers' insurance for farmers and fishermen. In total, these three social insurance plans covered approximately 57% of the Taiwanese population (Lien et al., 2008); the remainder of the population consisted of the elderly, children under 14, and the unemployed. The implementation of NHI sharply raised the coverage rate to 92% of the population by the end of 1995. Since 2000, the coverage rate of NHI has remained steady, at more than 99% of the population.

Three features of Taiwan's NHI are particularly relevant to our analysis. First, enrollees receive identical, generous benefits, which include outpatient and inpatient services, dental care, prescription drugs, and even traditional Chinese medicine services. Particularly for children under 3, almost all medical services are covered.[17]

Second, Taiwan does not employ a gatekeeping system; patients are able to access specialists directly, without first obtaining a referral from their primary care doctor.[18] To properly control

[16] Iizuka and Shigeoka (2018) exploited the various changes in patient cost sharing for school-aged children (7-14 years old) whose parents worked for large corporations and lived in the six largest prefectures in Japan. Nilssona and Paul (2018) utilized exemptions of copayment for outpatient care among children between 7 and 19 years old in one region in Sweden.In section 5.2, we compare the estimates in this paper with the ones in the above two papers.

[17] Some discretionary healthcare services, such as plastic surgery, sex reassignment surgery, and assisted reproductive technology, are not covered by NHI. Patients must pay the full cost of such services.

[18] The gatekeeping system is an important feature of many health systems found in North America and Europe. For instance, the National Health Service (NHS) in the United Kingdom requires a patient to obtain a referral from a primary care physician before they can see a specialist or other doctor.

patient flow and allocate medical resources efficiently, NHI includes a tiered copayment scheme for different accreditations of healthcare providers: major teaching hospitals, minor teaching hospitals, community hospitals, and clinics. In general, a higher copayment is charged for teaching hospitals and for the use of emergency room services. Therefore, patients suffering from minor medical issues are more likely to seek care at nearby clinics or community hospitals, leaving teaching hospitals available to help patients with more serious illnesses.

The teaching hospitals usually provide more intense and costly treatments for their patients than the clinics and community hospitals do. Table B2 of Online Appendix B shows that the average expenditure for a regular outpatient visit to a major teaching hospital is around 1,000 NT$, which is more than double that for a visit to a clinic. This is because physicians at teaching hospitals can carry out more complicated treatments and medical examinations. The average examination/treatment fee at a major teaching hospital is 465 NT$, but it is only 16 NT$ at a clinic. Thus, in the following analysis, we categorize teaching hospitals as high-intensity providers and clinics/community hospitals as low-intensity providers. In Online Appendix B, we offer more detailed information about healthcare providers in Taiwan.

Finally, in contrast with health plans in the U.S., NHI does not require patients to pay deductibles. For outpatient care, the OOP expenses are comprised of two parts: a fixed lump-sum copayment and a registration fee that covers the administrative costs of the healthcare provider.[19] Note that our data do not include information regarding the registration fees, so we propose a two-step procedure for "predicting" the registration fee of each regular outpatient and emergency room visit. We discuss the details of the estimation/imputation procedure in Online Appendix C. To illustrate the differences in OOP expenses among healthcare providers and health services, Panels A and B of Table 1 show the fee schedule for outpatient care during our sample period (2005–2008). As one can see from the first row, the copayment is 360 NT$ for a regular outpatient visit at a major

[19] In Taiwan, patients must pay 20% of the prescription drug costs but these are capped at 1,000 NT$. The maximum copayment is thus 200 NT$. Nonetheless, drugs costing under 100 NT$ do not require a copayment. Given that most visits by children under age 3 incur drug expenditure below 100 NT$, the average OOP expense for prescription drugs (under age 3) is quite small, at only 2.5 NT$ per visit. We have included this payment when calculating the OOP expense of an outpatient visit.

teaching hospital, 240 NT$ at a minor teaching hospital, 80 NT$ at a community hospital, and 50 NT$ at a clinic. Compared with a regular outpatient visit, the copayment for an emergency room visit at a community hospital nearly doubles (to 150 NT$). Clearly, the tiered copayment scheme provides an incentive for patients who are not seriously ill to get relatively simple treatments at clinics rather than utilize high-intensity medical services at teaching hospitals.

The OOP expense for an inpatient admission is a fixed proportion (known as the coinsurance rate) of the inpatient expenditure, depending on the length and type of admission (acute or chronic). For an acute admission, a patient pays for 10% of the inpatient expenditure for the first 30 days of their hospital stay, and a higher percentage thereafter (see Panel C of Table 1). In addition, during our sample period, there is an annual OOP maximum of roughly 47,000 NT$ (i.e. 10% of the GDP per capita in Taiwan) and an OOP maximum per admission of 28,000 NT$.[20] According to NHI statistics, very few patients (less than 1%) reach the OOP maximum.[21]

2.2 Taiwan Children's Medical Subsidy Program

To reduce the financial burden on parents and to ensure essential medical care was provided to young children, the Taiwan Children's Medical Subsidy Program (TCMSP) was launched in March 2002. This program, estimated to cost 1.8 billion NT$ annually, covers all copayments for outpatient care, prescription drugs, and inpatient care for children under the age of 3. Therefore, parents of children under 3 need only pay the registration fees for outpatient care, and almost nothing for inpatient care.

Figure ?? plots the age profiles of the OOP expenses per regular outpatient visit.[22] We have separate plots for each type of provider. Each dot in these figures represents the ten-day average OOP expense per visit at a given age, measured in days from the patient's 3^{rd} birthday. Due to the

[20]Note that the above information is based on the NHI rules in 2008. The OOP maximum rule does not apply for acute inpatient stays longer than 30 days or chronic inpatient stays longer than 180 days.

[21]This is because NHI waives the cost-sharing expense for patients with catastrophic illnesses (e.g., cancer), which generally have a higher probability of reaching the OOP maximum.

[22]We plot OOP expenses within the 180 days before and after the 3^{rd} birthday and group them into ten-day bins. For example, we group the first ten days after the 3^{rd} birthday to construct the first bin after the cutoff (i.e. the 19th bin in the graph). Thus, the bins of OOP expenses to the right of the 3^{rd} birthday do not include the observations exposed to the TCMSP (i.e. the cost-sharing subsidy). Therefore, we have 36 ten-day average OOP expense bins (i.e. 18 bins before and 18 bins after the 3^{rd} birthday).

expiration of the cost-sharing subsidy at age 3, one can see that the OOP expenses per visit are larger after that birthday than before it. Furthermore, the difference in OOP expenses between teaching hospitals and community hospitals/clinics becomes much larger after the child's 3^{rd} birthday. This same observation applies to the average OOP expenses for emergency room care, as shown in Figure ??.

Figure ?? presents the age profile of the OOP expenses per inpatient admission (180 days before and after the 3^{rd} birthday). Again, because of the expiration of the cost-sharing subsidy at age 3, one can see that the average OOP expense jumps from zero to approximately 1,300 NT$ after the child passes that birthday.

3 Data and Sample

3.1 Data

Our healthcare utilization data come from the National Health Insurance Research Database (NHIRD). The NHIRD data contain outpatient and inpatient claims that include information on patients' date of birth, dates of visits (admissions), diagnoses using codes from the International Classification of Diseases (ICD 9), and services provided, as well as the OOP expenses and total expenditure on outpatient visits (inpatient admissions).[23] We use a child's birthday and the date of the visit (admission) to precisely measure our key variable—a patient's age at the time of the visit. Moreover, these claim files contain two scrambled but unique identifiers: patient IDs and provider IDs. The first identifier, the patient ID, can be merged with the enrollment files to obtain the family's information, including a child's birth order, age, gender, and total number of siblings.[24] The second identifier, the provider ID, can be merged with the provider files to obtain a healthcare provider's ownership (i.e., public, private, or non-profit), accreditation level (i.e., major teaching hospital, minor teaching hospital, community hospital, or clinic), and the number of beds at their facility.

[23]Note that we add an imputed registration fee to construct OOP expenses for each outpatient visit.

[24]Because the NHI allows children to be enrolled through either the mother or the father, this offers some incentive for children to be enrolled through the parent with the lower salary in order to reduce the insurance premium, which is based on the parent's salary.

3.2 Sample

To mitigate the effect of a change in sample composition on our estimates, we focus on the same group of children over time. Specifically, our estimated sample comprises the children born between 2003 and 2004 for which complete demographic information is available (e.g. gender, birth date). We track their healthcare utilization from 180 days before their 3^{rd} birthday to 180 days after it using claims data from the NHIRD from July 2005 to June 2008. Since NHI covers almost the entire population, the analysis essentially uses all children born in Taiwan between 2003 and 2004. We plot outpatient and inpatient care, excluding services related to dental care, Chinese medicine, free health check-ups, chronic inpatient admissions, and acute inpatient admissions whose length of stay is more than 30 days, because these visits/admissions have quite different cost-sharing rules.[25]

We restrict our sample in a number of ways. First, we select only those children who were enrolled in NHI at both age 2 and age 3.[26] Then, we eliminate children suffering from catastrophic illnesses, as well as those from very low-income families, given that in both of these cases copayments are waived so there is no price increase when the child turns 3.[27] In total, these restrictions reduce the number of observations from 430,547 to 414,282, or by 3.8%. Table D1 of Online Appendix D provides summary statistics for the characteristics of the children at age 3, both before and after the sample selection criteria were applied. From Table D1, it is quite evident that the children's characteristics remain almost unchanged after the sample selection procedure.

[25] For example, the NHI copayment for outpatient visits for dental care and Chinese medicine is always 50 NT$, regardless of the type of healthcare provider. In addition, chronic inpatient admissions and acute inpatient admissions where there is a stay of more than 30 days have different rules for patient cost sharing. The coinsurance rate for chronic admissions is 5% for 1-30 days of stay, 10% for 31-90 days of stay, 20% for 91-180 days of stay, and 30% for more than 181 days of stay. The OOP maximum rule does not apply for acute inpatient stays longer than 30 days or chronic inpatient stays longer than 180 days. The chronic inpatient admissions and acute inpatient admissions involving stays of more than 30 days only account for 0.6% and 0.1% respectively of total inpatient admissions for children between ages 2 and 4.

[26] This selection reduces the number of children by 4,479. Since NHI is compulsory, those who did not continue to enroll may have either emigrated or died.

[27] During our sample period (July 2005 to June 2008), the eligibility rule for very low-income families required the monthly income per household member to be below a specific threshold, depending on the cost of living in the particular residential city/county. For example, the highest income cutoff was 14,152 NT$ in Taipei city and the lowest income cutoff was 9,829 NT$ in other cities/counties. In addition to the income test, eligible families also needed to pass an asset test. For example, the total wealth of the eligible families had to be lower than 3.5 million NT$ if they were living in Taipei.

Table 2 provides the descriptive statistics for regular outpatient care, emergency room care, and inpatient care. To illustrate the health utilization around the child's 3^{rd} birthday (i.e., the expiration of the subsidy), the upper panel shows the visit (admission) rate per 10,000 persons (on a daily basis), 90 days before the 3^{rd} birthday and 90 days after it, as well as the market share of the healthcare provider. From Table 2, it is clear that the average number of visits per 10,000 person-days for regular outpatient care is lower after than before the 3^{rd} birthday, dropping from 541.7 to 522.5 at age 3. Similarly, the number of emergency room visits person-days falls from 16.3 to 15.1. At the same time, we see almost no change in the number of inpatient admissions. The composition of healthcare providers also indicates an interesting change: the shares of regular outpatient visits to major and minor teaching hospitals after the 3^{rd} birthday change from 4% to 2% and from 6% to 4%, respectively. In other words, young children tend to visit large hospitals more frequently during the copayment-exemption period. A similar observation can be made about the emergency room care. In contrast, there is no change in provider choices for inpatient care.

Table 2 also displays the average medical expenditure per visit, the average OOP expense per visit, and the share of OOP expense within the 90 days before and after the 3^{rd} birthday. As seen in the lower part of this table, due to the expiration of the cost-sharing subsidy, the OOP expense is substantially higher immediately after the 3^{rd} birthday than immediately before it. Nonetheless, the average medical expenditure shows only a small difference. Thus, the patients' parents pay a much higher share of the medical expenses before the patients reach the age of 3.

Finally, in Table 3, we give a breakdown of the visits/admissions by showing the top five diagnoses in each healthcare service. Table 3 demonstrates that all of the top five diagnoses for regular outpatient care are related to upper respiratory infections. The top five diagnoses in emergency room care and inpatient care, including for example alteration of consciousness (e.g. comas), bronchopneumonia and pneumonia, are more severe than those in regular outpatient care.[28]

[28]In this paper, an emergency room visit represents a direct visit to the emergency department. While the emergency room is generally regarded as a department dealing with more servere conditions, such as comas, broken legs, head injuries, poisonings, heart attacks, strokes, or severe burns, this is not necessarily true in our case because some parents might consider a fever or allergic reaction as life-threatening for their young children. Thus, it is possible that emergency rooms, especially for children, are sometimes used for less serious illnesses. Overall, however, an emergency room visit is considered to be more severe than a regular outpatient visit. For example, comas (altered state of

4 Results on Healthcare Utilization

In this section, we estimate the causal effect of patients' cost sharing on children's utilization of outpatient and inpatient care by using an RD design that compares the utilization outcomes immediately before and after a patient's 3^{rd} birthday.

4.1 Identification Strategy

Our identification strategy is similar to that of other recent studies using an "age discontinuity" to identify the insurance coverage effect (Card et al., 2008, 2009; Anderson et al., 2012) and the patient cost-sharing effect (Shigeoka, 2014; Fukushima et al., 2015; Nilssona and Paul, 2018) on the medical utilization of more mature populations. The general form of our estimated regression is as follows:

$$Y_{ia} = \beta_0 + \beta_1 Age3_{ia} + f(a;\gamma) + \varepsilon_{ia} \tag{1}$$

where Y_{ia} is the outcome of healthcare utilization for child i at age a, including (1) total healthcare expenditure, (2) the number of visits (admissions), and (3) expenditure per visit (admission). The variable a is child i's age and is measured in days. The variable $Age3_{ia}$ is a treatment dummy that captures the higher level of the patient's cost sharing due to the expiration of the subsidy after the 3^{rd} birthday, being equal to 1 if child i's age at the time of their visit is greater than 3.[29] $f(a;\gamma)$ is a smooth function of age that controls the age profile of healthcare utilization. ε_{ia} is an error term that reflects all of the other factors that affect the outcome variables.

Our primary interest is in β_1, which measures any deviation from the continuous relation between the age and the outcomes Y_{ia} at child i's 3^{rd} birthday (i.e., when the treatment variable

consciousness) are the top cause of emergency room visits and account for 12.3% of them (see Table 3). Other severe diagnoses, such as gastroenteritis and colitis, also account for a significant share of emergency room visits. In contrast, the top five diagnoses (making up more than 70%) of regular outpatient visits are, as mentioned, related to acute upper respiratory infections, which are usually considered minor illnesses.

[29] Note that the 3^{rd} birthday is either the 1,096th or 1,095th day after birth. Since 2004 was a leap year, February 2004 had 29 days. Thus, for the children born before February 29, 2004, their 3^{rd} birthday would have been the 1,096th day after their birth (365 x 3 + 1 = 1096), while for those born after March 1, 2004, their 3^{rd} birthday would have been the 1,095th day after their birth.

switches from 0 to 1). The key identification assumption is that all factors except the patient's cost sharing vary continuously around the child's 3^{rd} birthday, so that β_1 can be interpreted as the causal effect of the increased cost sharing on the outcome variable.

For this age group, potential confounding factors could include vaccination and preschool attendance. The recommended immunization schedule could mechanically increase healthcare spending and use for young children at age 3. However, this concern is alleviated by the fact that most children in Taiwan do not need to have vaccines at age 3, as most are given before the child turns 2 years old (Center of Disease and Control, 2013).[30] Another factor is that the likelihood of going to preschool could affect the chance of a child picking up diseases (e.g., the flu), which would affect their healthcare use. Yet, this factor may not interfere with the cost-sharing change at age 3 because the age of entry for "public" preschools is 4 years of age and the government does not specify a statutory attendance age for "private" kindergartens. Note that the treatment variation in our analysis is based on days (i.e. age is measured in days). These two factors are unlikely to change on a daily basis, and are therefore unlikely to confound the effect of the change in patient cost sharing at age 3. As we will show in a later section, we examine our identification assumption—no other confounding factors change at age 3—by using pre-reform data. Specifically, we investigate whether was any discontinuity in healthcare utilization at the 3^{rd} birthday in the sample years before the introduction of the cost-sharing subsidy (1997—2001).

Because the policy variation occurs at the age level, following Card et al. (2009), Anderson et al. (2012) and Lemieux and Milligan (2008), we collapse the individual-level data into age cells (measured in days). According to Lee and Card (2008), the cell-level regression (weighting each cell by cell size) is equivalent to the individual-level regression using the clustered standard error (i.e. standard errors are clustered by age).[31] Since we follow the same birth cohort (i.e. 414,282

[30] http://www.cdc.gov.tw/professional/page.aspx?treeid=5B0231BEB94EDFFC&nowtreeid=1B4BACA0D1FDDB84

[31] See page 660 in Lee and Card (2008): "This shows that the clustered standard error formula in the micro-level regression is equivalent to using the conventional heteroskedasticity-consistent standard error in a 'cell-level' regression of Y_j on W_j , weighting each cell by the weight $\frac{n_j}{(N/J)}$. Consider the simplified case where $n_j = n_0$ for all cells, so the weight becomes 1..." Here, n_j is the sample size in cell j. N is the total sample size and J is the number of cells. Y_j and W_j represent a dependent variable and independent variables, respectively.

children born in 2003 and 2004) over time, the size of each cell's population is fixed.[32] Our baseline specification is the age-cell version of equation (1):

$$Y_a = \beta_0 + \beta_1 Age3_a + \gamma_1(a - 3bd) + \gamma_2 Age3_a(a - 3bd) + \varepsilon_a \tag{2}$$

Here, Y_a is the outcome of interest, aggregated at age a. In our main results, we estimate equation (2) locally within a bandwidth of 90 days before and 90 days after the 3^{rd} birthday (i.e., $3bd$) and specify $f(a;\gamma)$ as a linear function but allow the slope to be different on either side of the cutoff (i.e., we interact the age variable fully with the intercept and $Age3_a$). In Online Appendices E, F, and G of this paper, we examine whether our main results are sensitive to different bandwidth choices and specifications. Additionally, to ensure that β_1 can be interpreted as the percentage change in the dependent variable directly, in the estimation we take logs of Y_a and recenter the age variable on the 3^{rd} birthday.[33]

4.2 Outpatient Care

4.2.1 Change in Utilization of Outpatient Care at the 3^{rd} Birthday

We begin our analysis by examining the effect of the increased cost sharing on the utilization of outpatient care. Table 4 displays the RD estimates of the various outcomes and the estimated price elasticity for regular outpatient care (Panel A) and emergency room care (Panel B). The first row in column (1) suggests that the expiration of the cost-sharing subsidy results in a statistically significant increase of 63 NT$ in the OOP expense per regular outpatient visit. Relative to the baseline mean of 79 NT$ in Table 2 (i.e. average OOP expense per visit before the 3^{rd} birthday), this represents a 79% increase in the OOP expense. The expiration of the subsidy leads to a larger increase in the OOP expense for an emergency room visit, of 307 NT$ (i.e., a 151% increase). This is because emergency services require a higher copayment and are usually operated by hospitals

[32] Due to this fact, the estimated discontinuity in the aggregate-level outcomes at a given age can be interpreted as average estimates of discontinuity in the outcomes at a given age. In addition, using cell-level regression helps us to avoid the estimation problem of zero spending/visits when we take the log of our outcome variables, especially at the per person-day level.

[33] For those children born on or before February 29, 2004, the age variable is $a - 1096$. For those born on or after March 1, 2004, the age variable is $a - 1095$.

(see the third row in column (1)). The estimates in the second and fourth rows using the pre-reform data (1997–2001) suggest that the OOP expense is almost unchanged at the time of the 3^{rd} birthday. This implies that the variation in the OOP expense at the 3^{rd} birthday is driven exclusively by the expiration of the cost-sharing subsidy.

Figure 2 shows how the utilization of regular outpatient care varies with a patient's age at the time of their visit. Figure 2a presents the total expenditure per 10,000 person-days for regular outpatient care.[34] Corresponding to the higher level of cost sharing after the 3^{rd} birthday, the figure reveals that the total expenditure on regular outpatient visits decreases immediately after age 3. The change in total expenditure is a combination of the change in the number of visits and the expenditure per visit. Figures 2c and 2e reveal that both the visit rate and the expenditure per visit decline immediately after age 3.

The first row in columns (2)–(5) of Table 4 presents estimates of the change in utilization of regular outpatient visits at age 3. Column (2) shows that the increased cost-sharing at age 3 causes the total expenditure on regular outpatient visits to decrease significantly, by 6.6%. The estimated price elasticity of expenditure on a regular outpatient visit is approximately -0.12, which is close to the lower bound of price elasticity (in absolute value) produced by the RAND HIE for outpatient care: -0.17 to -0.31 (Keeler and Rolph, 1998).[35] The change in total expenditure can be decomposed into two margins: the number of visits (extensive margin) and the expenditure per visit (intensive margin). Column 3 reveals that the increased cost sharing at age 3 reduces the number of visits by 4.8%. Since several previous studies, such as Chandra et al. (2010a) and Shigeoka (2014), use the number of visits to represent healthcare utilization, here, we also report the implied price elasticity

[34] We computed these dots by dividing the total expenditure at a particular age by the number of enrollees born in 2003 and 2004, and then multiplying this figure by 10,000. This is a common way to present data in the health economics and public health literature, and it allows us to compare the estimated results across different sample periods and subgroups.

[35] Following previous research (Leibowitz et al., 1985; Manning et al., 1981; Chandra et al., 2010a), we compute the price elasticity using an arc-elasticity calculated as $((Q_2 - Q_1)/((Q_1 + Q_2)/2))/((P_2 - P_1)/((P_1 + P_2)/2))$, where Q_1 and P_1 denote, respectively, the baseline healthcare utilization and patient's OOP expense (i.e., the average Q and P within the 90 days before the 3^{rd} birthday), and Q_2 and P_2 are the healthcare utilization and patient's OOP expense affected by the cost-sharing subsidy (i.e., the average Q and P within the 90 days after the 3^{rd} birthday). This formula is especially suitable for empirical analysis in health economics. Since P_1 could be zero in some cases (e.g., the free plan in the RAND HIE, or the zero OOP expense for inpatient care discussed in this paper), the denominator of the price elasticity would be undefined.

based on the number of visits, -0.08, for comparison. Note that the change in the number of regular outpatient visits is smaller than the change in total expenditure because the increased cost sharing at age 3 also leads to a 1.8% decrease in the expenditure per visit (column (4)).

The change in the expenditure per visit is likely to be a mixture of two forces. First, the marginal patients who visit the doctor only because there is a subsidy in place are not as sick as those who would use the healthcare services regardless of the subsidy. In other words, patients who visit the doctor after their 3^{rd} birthday are more likely to have a serious illness than those who visit the doctor before age 3. Therefore, the expenditure per visit could be higher after age 3.[36] Second, the expiration of the subsidy causes a larger increase in cost sharing for high-intensity providers than for low-intensity providers due to the tiered copayments. This incentivizes patients to reduce their utilization of healthcare services at high-intensity providers (i.e., teaching hospitals) after age 3. Note that a visit to a high-intensity provider usually incurs greater expenditure than one to a low-intensity provider. Thus, the expiration of the cost-sharing subsidy could reduce the expenditure per visit after age 3. Our estimates imply that the latter force dominates the former. In a later section, we discuss this issue in more detail.

We replicate our RD design for the emergency room care. Figure 3 reveals that emergency room visits also see a salient change in utilization around the 3^{rd} birthday during the post-reform period (2005–2008). The third row in columns (2)–(5) of Table 4 shows that the increased cost-sharing at age 3 significantly reduces the total expenditure for an emergency room care, by 5.6%. The estimated price elasticity of total expenditure for an emergency room care is around -0.07. Again, this change can be decomposed into a 6.4% decrease in the number of visits (statistically significant) and a 0.8% increase in the medical expense per visit (statistically insignificant).

To examine any confounding factors affecting our estimates, we repeat the above analysis using pre-reform data (1997–2001) as a placebo test. Since children under the age of 3 were not eligible for the cost-sharing subsidy during this period, we should not observe any discontinuity in our outcomes if our main results are driven by the expiration of the cost-sharing subsidy. In sharp

[36] This assumes that healthcare providers spend more on treating sicker patients.

contrast to the graphs presented above, here, we find no visible discontinuity in utilization at the 3^{rd} birthday for either regular outpatient care (Figure 2) or emergency room care (Figure 3). Consistent with the graphical evidence, the second and fourth rows in columns (2)–(5) of Table 4 show that the estimated coefficients of $Age3$ are never significant and are much smaller in magnitude than the earlier results. These results confirm the validity of our RD design.

In Online Appendices E, F, and G, we present a series of robustness checks for our main results. Figures E1 and E2 systematically examine the sensitivity of our RD estimates to different bandwidths. Tables F1 and F2 examine the sensitivity of our RD estimates to various specifications (e.g. a quadratic specification) over different windows. In general, our main results are quite robust to the bandwidth choices and different empirical specifications. Yet, one caveat could threaten the validity of our RD design. Because every child eventually "ages out" of his/her cost-sharing subsidy, parents may anticipate the sharp increase in the price of healthcare services after the child's 3^{rd} birthday and strategically "stock up" on outpatient care.[37] This behavioral response would represent an inter-temporal substitution of healthcare (i.e., substituting future healthcare with current healthcare) rather than a "real" change (increase) in utilization induced by the cost-sharing subsidy, which is our main point of interest. Such a behavioral response would tend to upwardly bias our estimates of the change in healthcare utilization at age 3 (in absolute terms). Indeed, we see in Figures 2a and 2c that the total expenditure and the number of visits suddenly rise 20 days before the 3^{rd} birthday. In order to account for the possible anticipation effect, we decompose the effect of the age-3 cutoff into inter-temporal substitution and true demand-response. We estimate equation (2) but exclude from the sample those whose age is within 20 days before and after the 3^{rd} birthday. We then use the estimated regression (2) to predict counterfactual outcomes for those excluded ages as if there was no distorted response from the strategic stock-up behavior. Our decomposition result shows that only 9% of the change in total expenditure at the 3^{rd} birthday can be attributed to inter-temporal substitution.

[37] Since most visits of young children are for acute diseases (e.g., 74% of visits are for acute respiratory diseases), it is possible for parents to foresee the need for upcoming medical treatments, and then visit doctors one or two days earlier.

In addition, following previous studies (Barreca et al., 2011; Shigeoka, 2014), we conduct a "donut" RD by systematically excluding the utilization of outpatient care within 3 to 21 days of the 3^{rd} birthday. Although there is no consensus on the optimal size of a donut hole, and while eliminating the sample around the threshold seems to contrast with the spirit of RD design, this type of estimation can still provide us some sense of the "stocking up" effect's influence on our estimates. Tables G1 and G2 indicate that the estimates from different sizes of donut holes are very similar to our main estimates.

4.2.2 Subgroup Analysis: By Type of Visit

In this section, we investigate the heterogeneity in price responses by type of visit. Tables 5 and 6 present the results for regular outpatient care and emergency room care, respectively. Each row displays the RD estimates (coefficients of $Age3$) for the various subgroups.

In Panel A and Panel B, we use ICD 9 code to define beneficial or essential healthcare based on previous literature. The extent to which the utilization of beneficial or essential children's healthcare services can be affected by price has an important policy implication. If such utilization is sensitive to price, a cost-sharing subsidy might benefit children's health by increasing the use of this type of healthcare service. Panel A displays the estimates by beneficial or less beneficial treatment. Following Iizuka and Shigeoka (2018) and Gadomski et al. (1998), we use diagnoses listed as Ambulatory Care Sensitive Conditions (ACSCs) to represent beneficial treatments. ACSCs were developed by the Agency for Healthcare Research and Quality (AHRQ) to study the type of outpatient care that may reduce the need for inpatient admissions. Thus, these types of outpatient care are usually considered as beneficial treatments (i.e. having less moral hazard). For example, proper outpatient care for asthma, which is listed among the ACSCs, can substantially reduce children's utilization of inpatient care (Homer et al., 1996; Lieu et al., 1997). Table H1 of Online Appendix H lists the diagnoses (ICD 9 codes) defined as beneficial treatments. We find that the utilization of beneficial outpatient care is sensitive to price, which is similar to the finding in Iizuka and Shigeoka (2018). Moreover, our result suggests the increased cost sharing at age 3 leads to a smaller decline in the utilization of beneficial outpatient care than in that of less beneficial care. For example, Table

5 shows that expenditure on beneficial regular outpatient care decreases by 5% (i.e. price elasticity is -0.09) but expenditure on less beneficial regular outpatient care decreases by 6.9% (i.e. price elasticity is -0.12). A similar pattern can be found in Table 6 for emergency room care.

Furthermore, we examine the heterogeneity in price responses based on essential healthcare—patients' non-deferrable medical conditions (see Panel B). Inspired by Card et al. (2009), we identify the visits for non-deferrable conditions by using pre-reform (i.e. 2000–2001) data and a set of three-digit ICD 9 diagnosis codes that have similar visit rates on weekdays and weekends. For instance, if a given diagnosis code has similar emergency room visit rates on weekends and weekdays, then weekend visits should account for around 0.29 (2/7) of all visits for this specific diagnosis code. Therefore, we define the visits with diagnosis codes whose fraction of weekend visits is close to 0.29 as visits for non-deferrable conditions. Table I1 of Online Appendix I lists the top five diagnoses that are considered as non-deferrable conditions and their corresponding ICD 9 codes. For example, tracheostomy complications and concussion are very serious situations and should be treated immediately. They are the top diagnoses among non-deferrable regular outpatient visits and emergency room visits, respectively. The estimates in Tables 5 and 6 suggest that the effect of patient cost-sharing on the utilization of non-deferrable care is statistically insignificant. For example, the increased cost sharing at age 3 reduces the expenditure on non-deferrable regular outpatient care insignificantly, by 2.2% (i.e. price elasticity is -0.04).

Finally, we display the estimated price elasticities for preventive care and mental health services. We focus on preventive care because it could substantially reduce future medical costs. Likewise, early treatment for children's mental disorders (e.g., autism) could lead to better treatment outcomes. Yet, due to behavioral hazard (Baicker et al., 2015), patients (parents) might not fully understand the value of these healthcare services and underuse them. We find that the utilization of preventive care and that of mental health services have relatively larger price responses than do the overall estimates. Panel C in Table 5 shows that the increased cost sharing at age 3 reduced medical expenditure on mental illnesses by 24.7% and that on preventive care by 50.6%, respectively. The implied price elasticities for these types of healthcare services are quite large (in absolute values, -0.26 for mental health services and -0.60 for preventive care).[38]

To sum up the findings in Panel A to Panel C, our results suggest parents are less willing to adjust the utilization of beneficial or essential (non-deferrable) outpatient care for their children in response to the increased cost sharing at age 3. However, we also find that healthcare services that might not have immediate health benefits but could reduce future medical costs for young children, such as preventive care and mental health services, are somewhat price sensitive.

4.2.3 Subgroup Analysis: By Patient Type

In Tables 7 and 8, we utilize demographic information from the NHIRD to investigate the heterogeneity in price responses by patient type. Panel A displays the results by birth order. Previous studies (Price, 2008; Monfardini and See, 2011; Lehmann et al., 2018) have shown that parents are more cautious and make more parental investments (i.e. spend more time or money) when raising their first child. In addition, parents raising their first child could have limited experience and knowledge about making medical decisions for them. Especially acute diseases are major causes of outpatient visits for young children, and usually involve the appearance of salient symptoms (e.g. fever, cough, muscle pain, or difficulty breathing). Some of them, such as the common cold, might not necessarily require medical intervention. However, new parents could overweigh salient symptoms due to behavioral hazard (Baicker et al., 2015) so that they might not adjust the healthcare utilization of their children in response to the price change. The results show that first-born children's utilization of outpatient care is less price sensitive than non-first-born children's, especially for emergency room care.

Panel B presents the results by gender. We find the increased cost-sharing at age 3 significantly reduce the utilization of regular outpatient care for boys and girls. However, girls' utilization of emergency room care is more price sensitive than that of boys', suggesting that parents might think a daughter's emergency room visit is more discretionary than a son's. This result is consistent with

[38] NHI provides seven free health check-ups for children under the age of 7. These free health check-ups include a basic body check-up (e.g. height, weight, nutrition status, and vision test) and an early developmental assessment that covers basic preventive care. Since our sample excludes these free health check-ups, the preventive care in our analysis could be more discretionary. Besides behavioral hazard, this fact could help explain why we find large price elasticity for preventive care (in absolute terms).

Taiwanese parents' general preference for sons over daughters (Lin et al., 2014).

Panel C presents the results based on household income (per capita).[39] This subgroup analysis helps us understand whether the current levels of copayment create a situation in which some patients are unable to afford outpatient care. If affordability plays an important role in a patient's utilization decision, we would expect the utilization response to the increased cost sharing at age 3 to vary by household income. In particular, the use of outpatient care by low-income children should exhibit a larger decrease after age 3 because low-income children, who are more likely to be liquidity constrained, might not be able to afford care. For regular outpatient care, our results show that the increased cost sharing at age 3 leads to similar reductions in utilization across the different income groups. Thus, the estimated price elasticities are quite similar. This implies that healthcare affordability might play a limited role in the utilization of regular outpatient care. In contrast, we find that the increased cost sharing at age 3 causes a significant decrease in emergency room use for low-income children, but not for middle- or high-income children.[40] This finding implies that some parents of low-income children might not be able to afford emergency room services once they have to pay the NHI copayment.

Panel D examines the heterogeneity in price responses by patient's health status. Inspired by previous studies (Iizuka and Shigeoka, 2018; Dranove et al., 2003), we categorize children into two types of health status—sickly or healthy—using prior healthcare spending (i.e. median inpatient spending between ages 1 and 2). Specifically, the sickly children are defined as those with inpatient spending above the median. The definition of healthy children is the opposite. On average, the

[39]Note that the NHIRD does not include a direct measure of household income. However, it does have information on insured income for people who are working, and the non-working household members (e.g. children) must enroll in NHI through one of their household's working members. Thus, we use insured income as a proxy for household income. Since insured income is a better approximation of an employee's income than self-employed income, in this subgroup analysis we only use that portion of the sample whose parents are private-sector or public-sector employees. In this sense, we might underestimate the household income. A low-income household is defined as one ranked below the 25th percentile of the household income (per capita) distribution (i.e. the average monthly household income for this subgroup is around 27,000 NT$). A middle-income household is defined as one ranked between the 25th and 75th percentiles of the household income (per capita) distribution (i.e. the average monthly household income for this subgroup is around 51,000 NT$). A high-income household is defined as one ranked above the 75th percentile of the household income (per capita) distribution (i.e. the average monthly household income for this subgroup is around 98,000 NT$).

[40]Nilssona and Paul (2018) utilized Swedish data and obtained similar findings. They found that outpatient utilization by low-income children had a larger price response than that by high-income ones.

sickly children's parents spend more than 20,000 NT$ on their healthcare between ages 1 and 2. In contrast, healthy children do not have any inpatient admissions at all (i.e. zero inpatient spending) during this age range. Panel D displays RD estimates separately for sickly and healthy children. We find the increased cost sharing at age 3 significantly reduces both sickly and healthy children's utilization of outpatient care (i.e., regular outpatient care and emergency room care).[41]

In order to investigate the heterogeneity in price responses by accessibility of healthcare services, Panel E presents the results based on healthcare accessibility in children's birth counties. Supply-side factors, such as the supply capacity of healthcare services, could affect the price elasticities of healthcare demand. Panel E uses children born in counties with more than 14 pediatricians per 10,000 persons (i.e., the median value of this measure) to represent the subgroup with better access to healthcare services. Our results suggest that the increased cost-sharing at age 3 significantly reduces utilization of outpatient care regardless of living area with good or bad healthcare accessibility.

4.2.4 Change in Choice of Provider at the 3^{rd} Birthday

In this section, we examine the impact of cost sharing on patients' choice of provider of outpatient care. As mentioned before, NHI has a tiered copayment scheme (i.e., patients pay a higher copayment for teaching hospitals) to reduce the number of visits to teaching hospitals for minor ailments due to free access to healthcare services. In other words, the tiered copayments should incentivize patients not to choose teaching hospitals if their illness can be cured by a simple treatment at a clinic or community hospital. The cost-sharing subsidy essentially eliminate tiered copayments for the patients under age 3. Thus, we can investigate the effect of the tiered copayments on patients' provider choices by comparing the choices made immediately after the 3^{rd} birthday (i.e., under tiered copayments) to those made immediately before the 3^{rd} birthday (i.e., without tiered copayments). Note that, prior to the 3^{rd} birthday, patients have to pay a registration fee that varies

[41] The existing evidence is mixed. RAND HIE (Manning et al., 1987) found that the healthcare utilization of both healthier and sicker patients respond to the change in patient cost-sharing significantly. However, Brot-Goldberg et al. (2017) found that the sickest patients reduce their healthcare spending the most when faced with a high-deductible plan. Some other studies using quasi-experimental design have found smaller price reponsiveness among sicker adults (Chandra et al., 2014; Fukushima et al., 2015) and children (Iizuka and Shigeoka, 2018).

according to the type of healthcare provider.

To examine whether the tiered copayments discourage patients from visit teaching hospitals (i.e. high-intensity providers), Figures 4a to 4d present the age profiles of the share of regular outpatient visits by provider type. Figure 4a shows that the share of visits to major teaching hospitals declines immediately after the 3^{rd} birthday, by 1.8 percentage points (from 4.2% to 2.4%). Compared to the baseline mean (i.e., 4.2% of visits before the 3^{rd} birthday), this result suggests tiered copayments reduce the share of visits to major teaching hospitals by 43%. Similarly, the share of visits to minor teaching hospitals exhibits a substantial drop—of around 1.9 percentage points—at age 3 (from 5.6% to 3.7%, see Figure 4b). In contrast, the share of visits to community hospitals and to clinics exhibit the opposite pattern, showing increases of 0.9 and 2.7 percentage points respectively at age 3. In Online Appendix J, we show that the change in choice of healthcare providers is related to whether patients reside nearby major teaching hospitals.[42]

To further explore this issue, we utilize the panel structure of our dataset to calculate the conditional probability of a shift in provider, given the type of provider of the last visit. Conditional on a patient's last visit having been to a high-intensity provider (i.e., a teaching hospital) or a low-intensity provider (i.e. a clinic/community hospital), there are in total four types of shifting behaviors: (1) from high to high-intensity provider; (2) from high to low-intensity provider; (3) from low to low-intensity provider; (4) from low to high-intensity provider. The type (2) conditional probability, for instance, can be defined as follows:

$$\text{Prob}(visit_t = low|visit_{t-1} = high) = \frac{N_l^h}{N_h^h + N_l^h} \tag{3}$$

[42]As shown in Table B1 of Online Appendix B, most major teaching hospitals are located in cities (i.e., urban areas) but almost every city/county has at least one minor teaching hospital. Thus, Figures J1 and J2 in Online Appendix J display the change in the share of regular outpatient visits by provider type for the part of the sample born in cities/counties with and without a major teaching hospital, respectively. Figure J1a suggests that, for the children born in the cities/counties with major teaching hospitals, the increased cost sharing at age 3 reduces the share of major teaching hospital visits by 2.4 percentage points (i.e., from 5.4% to 3%). However, for the children born in the cities/counties without a major teaching hospital, the increased cost sharing at age 3 reduces the share of major teaching hospital visits by only 1 percentage point (i.e., from 2.4% to 1.4%). A similar pattern can be found for the emergency room visits (Figures L2 and L3 in Online Appendix L). In other words, it is indeed true that proximity to medical centers matters—children residing in locations without a major teaching hospital close by are less likely to visit a teaching hospital.

where N_h^h (N_l^h) represents the number of visits to high-intensity providers (low-intensity providers) given that the last visit was to a high-intensity provider.[43] Thus, equation (3) represents the conditional probability of the current visit being to a low-intensity provider given that the last visit was to a high-intensity provider. In Online Appendix K, we provide details of the construction of the conditional probability of a shift in healthcare provider.

Figures 5b and 5a show how the conditional probability of a shift in provider changes at age 3. From Figure 5a, it can be seen that under age 3 about 44% of children whose last visit was to a high-intensity provider switch to a low-intensity provider on the next visit.[44] However, this conditional probability jumps sharply to 58% once patients pass the age of 3. This result implies patients tend to switch to low-intensity providers when they face tiered copayments. In line with this finding, Figure 5b suggests that, for the patients whose last visit was to a low-intensity provider, the share of patients who shift to a high-intensity provider drops sharply, from 4.8% to 3.3% at age 3.[45] In sum, the above results suggest that tiered copayments play an important role in a patient's choice of provider. A patient's provider choice is quite sensitive to the differences in copayments between high- and low-intensity providers. Once patients have to pay tiered copayments, they are less likely to visit high-intensity providers.

So far, we have found that tiered copayments can substantially discourage patients to use outpatient care at teaching hospitals (i.e. high-intensity providers). However, it remains unclear what type of care at teaching hospitals are reduced. To answer this question, we estimate the change in the number of visits to teaching hospitals by the expenditure per visit, which serves as a proxy for the seriousness of the medical condition. Patients with more serious medical conditions usually incur more costly treatments, only available at teaching hospitals. In particular, the outcome of interest is number of visits (taking log) and we estimate equation (2) separately for four categories

[43] N denotes the number of visits to a specific type of provider given the provider type of the last visit. The superscript of N denotes the provider type of the last visit and the subscript of N denotes the provider type of the current visit. Therefore, $N^h = N_h^h + N_l^h$ represents the number of last visits to high-intensity providers.

[44] In other words, for the children under age 3, about 56% of patients whose previous visit was to a high-intensity provider again visit a high-intensity provider the next time.

[45] Again, this implies, for the children under age 3, that about 95.2% of patients whose previous visit was to a low-intensity provider again visit a low-intensity provider the next time.

of expenditure per visit: (1) 0–600 NT$, (2) 601–1,200 NT$, (3) 1,201–1,800 NT$, and (4) above 1,801 NT$. About 95% of visits that cost less than 600 NT$ are to clinics or community hospitals. The leading causes of such visits are all related to upper respiratory diseases, including common colds, which are considered minor conditions. In contrast, of the visits that cost more than 1,800 NT$, less than 25% are to clinics or community hospitals. Asthma, considered a serious condition for children, is the leading cause of such visits. The dotted lines in Figures 6a and 6b display the estimated coefficients on $Age3$ in equation (2) across the distribution of medical expenditure per visit (i.e., across the four categories). We find that increased cost sharing after age 3 can significantly reduce the number of regular outpatient visits to major teaching hospitals that cost less than 600 NT$, by 79%. By comparison, the number of visits that cost over 1,800 NT$ decreases by only 20%. Figure 6b suggests that a similar pattern emerges for minor teaching hospitals as well.

In sum, our results suggest that tiered copayments have a much larger effect on the utilization of outpatient care for minor illnesses at teaching hospitals. Consistent with this finding, Figure 7 shows that tiered copayments lead to a change in the case mix of regular outpatient visits to teaching hospitals. We find that the share of teaching hospital visits for minor illnesses (i.e. visits that cost less than 600 NT$) drops significantly, by 5.9 percentage points, from 74.8 to 68.9%, at age 3 (see Figure 7a). In addition, Figure 7b shows how the share of visits related to the common cold—a leading cause of minor illnesses for young children—changes before and after age 3. We find that it declines significantly at age 3, by 1.2 percentage points. In contrast, the shares of teaching hospital visits for two leading causes of serious illnesses for young children—asthma and delays in development—significantly increase, by 1 percentage points and 0.5 percentage points, respectively, immediately after age 3 (see Figure 7c and Figure 7d).

Regarding emergency room care, we replicate the above analysis in Online Appendix L and find similar results.[46] To sum up, for both regular outpatient care and emergency room care, we find that

[46]Similarly to the case of regular outpatient care, Figure L1 shows that the increased cost sharing (i.e. paying tiered copayments) at age 3 can discourage patients from using emergency room care at teaching hospitals. The shares of emergency room visits to major teaching hospitals and minor teaching hospitals decline by 2 percentage points and 3.3 percentage points, respectively, immediately after the 3^{rd} birthday. Corresponding to this result, the share of emergency room visits to community hospitals increases by 5.6 percentage points at age 3. Figure L4 reinforces the above findings, demonstrating that patients are less likely to switch from low-intensity providers to high-intensity

the tiered copayments substantially reduce the number of visits for relatively simple treatments (i.e., minor illnesses) at high-intensity providers. This indicates that there is a substantial moral hazard in terms of an increase in the use of high-intensity providers when patients are not exposed to the full cost.

4.3 Inpatient Care

For young children, inpatient admissions are less common than outpatient visits. Among our sample at age 2, the average annual number of outpatient visits is 19.8, but the average annual number of inpatient admissions is only 0.14.[47] Nevertheless, the expenditure for an inpatient admission is 27 times that for an outpatient visit, and 17% of healthcare spending for young children can be attributed to inpatient care. More importantly, the expiration of the cost-sharing subsidy at age 3 induces a much larger increase in OOP expenses for inpatient care than for outpatient care. Hence, inpatient care could have substantial impacts on both overall healthcare spending and individuals' OOP expenses. Understanding how young children's utilization of inpatient care responds to cost sharing could produce important policy and welfare implications.

The effect of the increased cost sharing on the utilization of inpatient care is intuitively ambiguous. On the one hand, higher cost sharing could discourage marginal patients from using inpatient care, which would decrease inpatient expenditure. On the other hand, the type of inpatient care that young children usually have might be price inelastic: the leading causes of inpatient admissions in early childhood (see Table 3) are bronchopneumonia, gastroenteritis (colitis) and pneumonia, which could result in serious symptoms for young children and can be treated with medication or bed rest.[48] Previous studies (Card et al., 2008; Shigeoka, 2014) have found that neither patient cost

providers for emergency room services after the 3^{rd} birthday (i.e., once they have to pay the tiered copayments). In addition, similarly to the situation with regular outpatient visits, Figure L5 suggests that the tiered copayments have a significantly negative effect on the utilization of emergency room services for minor illnesses (i.e. visits that cost less than 1,200 NT$) at teaching hospitals. The leading cause of such emergency room visits is acute upper respiratory infections. In contrast, the tiered copayments have little impact on the emergency room visits to teaching hospitals that cost more than 1,200 NT$. Open wounds on the head, which are considered a serious condition, are the number one cause of such emergency room visits. Finally, we find that the tiered copayments can also reduce the share of emergency room visits to teaching hospitals for minor illnesses; however, the estimates are not precise (see Figure L6).

[47] The number of outpatient visits is the sum of all regular outpatient visits and emergency room visits combined.

[48] In our estimated sample, about 95% of admissions do not require surgery.

sharing nor insurance coverage has a significant impact on this type of admission for the elderly. In addition, for young children, admissions requiring surgery are seldom selective (the examples of selective surgery: osteoarthritis or hip and knee replacements), but tend to be due to more life-threatening conditions (e.g., congenital heart disease) and therefore essential. Thus, we should expect the utilization of inpatient care for young children to be less sensitive to the price changes that occur at the time of the 3^{rd} birthday.

4.3.1 Changes in the Utilization of Inpatient Care at the 3^{rd} Birthday

The first row in column (1) of Table 9 shows that the expiration of the cost-sharing subsidy at age 3 significantly raises the OOP expense per admission by 1,271 NT$. The estimate shown in the second row, for the sample before the introduction of the cost-sharing subsidy, reveals that, for those children, there was almost no change in the average OOP expense at the 3^{rd} birthday.

Figure 8 displays the age profile for the utilization of inpatient care. Surprisingly, in contrast to the dramatic change in the utilization of outpatient care from immediately before to immediately after the 3^{rd} birthday, Figures 8a, 8c, and 8e show that there is little visual evidence of any discontinuity in inpatient expenditure, the number of inpatient admissions, or the expenditure per admission around patients' 3^{rd} birthdays. In fact, we find that the age profiles of these outcome variables are very similar to those obtained using pre-reform (1997–2001) data (see Figures 8b, 8d, and 8f).

As illustrated in the figures, the first row of columns (2)–(5) of Table 9 suggests that the increased cost sharing at age 3 has little impact on the utilization of inpatient care for young children. There is no significant change in the total expenditure, number of admissions, or expenditure per admission around the 3^{rd} birthday. The estimated price elasticity of expenditure is close to zero, suggesting that children's utilization of inpatient care is price insensitive. One possible explanation for this result could be that the majority of children's inpatient admissions are for serious respiratory diseases or gastroenteritis that can be treated with bed rest or medication. Previous studies have found this type of inpatient care not to be price sensitive. For example, in Japan, Shigeoka (2014) found that inpatient admissions treated with medication or bed rest, such as heart failure, bronchitis, and pneumonia, did not respond to a price change at age 70. Card et al. (2008) obtained similar findings for Medicare recipients in the U.S. Most admissions for young children involve these types of inpatient care (e.g., gastroenteritis, bronchitis, and pneumonia).[49] Therefore, we conclude that making inpatient care free should not result in an excessive use of inpatient services. In Online Appendices E and F, we examine the robustness of our results to different bandwidth choices and specifications. Figure E3 and Table F3 suggest that the RD estimates are quite stable across bandwidth choices and different empirical specifications.

5 Discussion

5.1 Own-Price Elasticity versus Cross-Price Elasticity

So far, we have estimated the price elasticities of regular outpatient care, emergency room care, and inpatient care separately. One potential concern regarding the above analysis is that our estimates might represent both own- and cross-price effects, since the OOP expenses for these healthcare services all increase substantially at age 3. To examine the impact of cross-price effects on our estimates, inspired by Shigeoka (2014), we group diagnoses into 56 groups based on the Basic Tabulations of Diagnoses (see a list of diagnosis groups in Table M1 of Online Appendix M) and compare the price elasticities of diagnosis groups for which the majority of healthcare expenditure occurs in regular outpatient care, emergency room care, or inpatient care, and the overall estimates for each healthcare service.[50] These subgroup estimates are more likely to represent own-price elasticity. If cross-price effects matter a lot, we should find that the above subgroup estimates are statistically different from our main estimates.

Specifically, we first select the diagnosis groups for which regular outpatient care accounts

[49] A patient could be treated by medication or bed rest in the following situations: (1) Their condition does not require surgical intervention, such as in the case of bronchopneumonia or pneumonia, which could still be quite serious diseases. (2) Their physical status prevents them from being suited to receiving an aggressive treatment (e.g. surgery). Therefore, the inpatient admissions treated by bed rest or medication might be less discretionary and less price responsive than those that require surgery. We think the above argument could also apply to young children. Especially, for young children, their physical status might make them unsuited to surgery.

[50] Unlike for the elderly (those around age 70) studied in Shigeoka (2014), the healthcare utilization of young children is predominated by regular outpatient care in terms of the number of visits. Thus, we use total expenditure to determine which diagnosis groups are mainly treated by regular outpatient care, emergency care, and inpatient care respectively.

for the highest fraction of expenditure among the three types of healthcare services, to represent own-price elasticity for regular outpatient care. These diagnosis groups include diseases of the upper respiratory tract, parasitic diseases, and others. For example, the fraction of expenditure on diseases of the upper respiratory tract (diagnosis group 31) is 92%. The first row in Table M2 of Online Appendix M shows that the RD estimate for regular outpatient expenditure for these diagnosis groups is -6.3%, which is not statistically different from the overall estimate of -6.6%. In addition, the estimated price elasticities for the diagnosis groups predominated by regular outpatient care are quite similar to the overall price elasticity.

We use the same criteria to select the diagnosis groups that are more likely to represent own-price elasticity of emergency care or inpatient care. For emergency care, only three diagnosis groups satisfy these criteria. For example, emergency care can account for 51% of total expenditure on intracranial and internal injuries (diagnosis group 49). The second row in Table M2 suggests that the RD estimate for emergency care expenditure for these diagnosis groups is -9.4%, which is somewhat higher than than the overall estimate of -5.6% (although not statistically significantly different).

For inpatient care, fifteen diagnosis groups, including diseases of the urinary system (diagnosis group 35), immunity disorders (diagnosis group 18) and fractures (diagnosis group 47), are included in the subgroup analysis. Inpatient care can account for at least 54% of the total expenditure in these diagnosis groups. The last row in Table M2 suggests that the RD estimate for inpatient expenditure for these diagnosis groups is 1.36%, which is not statistically significantly different from the overall estimate of 0.17%.

In sum, the above results suggest that, for diagnosis groups where cross-price effects are limited, the subgroup RD estimate is similar to the overall estimate, which includes both cross- and own-price effects. This suggests that cross-price effects have a limited impact on our main estimates.

5.2 Comparison to Previous Literature

Although young children are considered one of the big spenders on healthcare, empirical evidence regarding the cost-sharing effect for this age group is limited. Credible evidence still relies on subgroup results for children under age 14 in the Rand HIE. The results from the RAND HIE showed that higher cost sharing would reduce children's utilization of outpatient care but might not change inpatient use. Our results suggest that the price elasticities of outpatient expenditure for children around the age of 3 are -0.12 (for regular outpatient care) and -0.07 (for emergency room care). Furthermore, we find that the price elasticity of inpatient expenditure for this age group is close to zero. In general, the above results are consistent with findings in the RAND HIE. However, the RAND HIE did not report the estimated price elasticities for their children subgroup. Two recent papers (Iizuka and Shigeoka, 2018; Nilssona and Paul, 2018) provide estimated price elasticities of outpatient care for school-age children in Japan and Sweden, based on quasi-experimental designs. For example, the estimate in Iizuka and Shigeoka (2018) suggests that the arc price elasticity of outpatient expenditure is -0.11 for children aged 7.[51] Our estimated price elasticity of outpatient care is similar to their figures. To sum up, we have found that the estimated price elasticities for young children are considerably lower than previous estimates for adults and the elderly (in absolute term).

In spite of that, we would like to caution readers that many institutional differences exist between Taiwan and other countries (e.g. the United States). One important difference is that Taiwan, like Japan and Korea, does not have a primary physician system that helps direct patients' choice of health provider. It is common for patients in Taiwan to do doctor shopping and therefore have a high number of visits per year. This feature implies that some outpatient visits might be discretionary. As a result, our estimated price elasticity of outpatient care should be considered as an upper bound (in absolute terms) for young children in countries employing a gatekeeper system. In addition, our results represent particular estimates of price elasticity for young children, and might not generalize well to other cases (e.g. other age groups or other changes in cost sharing). Readers should be cautious when applying our estimates to other age groups and institutional settings.

[51] Both Iizuka and Shigeoka (2018) and Nilssona and Paul (2018) reported semi-arc price elasticities. We use a formula offered by Iizuka and Shigeoka (2018), which they used to calculate their arc price elasticities.

5.3 The Effect of Patient Cost-Sharing on Children's Health

In this section, we summarize the results of the cost-sharing effect on children's contemporaneous and later-life health outcomes. The details of the empirical specifications and results are discussed in Online Appendix N. In sum, our results suggest that the increased cost sharing at age 3 has little impact on children's short-term health status, as measured by mortality and by the occurrence of serious pediatric health problems (i.e. pediatric complex chronic conditions). Furthermore, we examine whether the lower level of patient cost sharing in early childhood has any effect on the health of children at older ages. We find that the additional outpatient utilization induced by the cost-sharing subsidy at age 2-3 does not affect the rate of occurrence of serious pediatric health problems at age 5-11. Here, we would like to remind readers to be cautious about interpreting our results on health effects. Since deaths and serious pediatric health problems are quite rare for this age group in Taiwan, we might not have sufficiently precise estimates to draw a strong conclusion on this issue.

5.4 Implications for Optimal Health Insurance

Finally, we discuss the implications of our estimates for cost-sharing policies (i.e., for determining the appropriate level of patient cost sharing). We first conduct a sufficient statistic approach for welfare analysis based on a simplified model without behavioral hazard from Baicker et al. (2015). In this model, we evaluate the cost-sharing policy from the view of a social planner who maximizes social welfare as the following expected utility $W(p)$:

$$W(p) \;=\; (1-\lambda)U(y-P) + \lambda \mathrm{E}[U(y-P-s+m(p)(b-p))|sick]$$

Consider an individual with wealth y who pays premium P so as to be eligible for national health insurance. He/she could get sick with probability λ and experience a negative health shock s, measured in monetary terms. In other words, with probability $1-\lambda$, an individual is healthy and receives utility $U(y-P)$. The magnitude of the health shock s is an individual's private information. In addition, the distribution of s follows $F(s)$, which has strictly positive density $f(s)$ and support with lower bound s_l and upper bound s_u. Medical treatment can alleviate the sickness by providing health benefits $b(s)$ but incurs the social cost π. The benefit of the treatment depends on the health shock s. Under NHI, an individual can receive medical treatment by paying only patient cost sharing p (i.e. part of the treatment cost π, $p < \pi$). Therefore, his/her healthcare demand $m(p)$ depends on whether the health benefit b is larger than the individual's cost sharing amount p:

$$m(p) = \begin{cases} 1, & \text{if } b(s) \geq p \\ 0, & \text{if } b(s) < p \end{cases}$$

If the health benefit of treatment, b, is larger than an individual's patient cost sharing amount, p, he/she will seek medical treatment, i.e., $m(p) = 1$, and will then receive utility $U(y-P-s+b-p)$. Otherwise, he/she will decide not to get medical treatment, $m(p) = 0$ and will receive utility $U(y - P - s)$. Finally, we assume that NHI must balance its budget: $P = M(p) \times (\pi - p)$, where $M(p) = E[m(p)]$ is the average healthcare demand (i.e. per capita aggregate healthcare demand) at a given cost-sharing. To understand how social welfare W changes when patient cost sharing p increases, in Online Appendix O, we first differentiate W with respect to p given the NHI budget constraint. Then, we divide $\frac{\partial W}{\partial p}$ by the welfare change that occurs when income increases by 1 dollar, $\frac{\partial W}{\partial y}$, to convert changes in social welfare into a money metric form:

$$\frac{\partial W}{\partial p} / \frac{\partial W}{\partial y} = -\frac{\partial M(p)}{\partial p} \times (\pi - p) - I(p) \times M(p) \tag{4}$$

where $I(p) = \frac{E[U^{'}(C)|m=1] - E[U^{'}(C)]}{E[U^{'}(C)]}$ and $C = y - P - s + m(p)(b(s) - p)$ so that $I(p)$ represents the value of health insurance for those getting treatment. This formula suggests that the impact of an increase in patient cost sharing on social welfare is driven by two key terms. The first term, $-\frac{\partial M(p)}{\partial p} \times (\pi - p)$, represents the welfare gain from raising patient cost sharing that occurs due to a reduction in the inefficient utilization of healthcare services (i.e., moral hazard), since the social cost of healthcare services is always higher than the patient's cost-sharing amount: $\pi > p$. Thus, we can measure this welfare gain by estimating the sensitivity of healthcare demand to the patient cost-sharing amount, $\frac{\partial M(p)}{\partial p}$. The second term (i.e., $-I(p) \times M(p)$) represents the welfare loss due to raising patient cost sharing, since a higher cost-sharing amount can reduce all patients' insurance value by decreasing their consumption when they get sick.

Combining the above formula with our estimates can provide some insights into the design of a cost-sharing policy for young children. Our results suggest that young children's demand for inpatient care is price insensitive, namely, $\frac{\partial M(p)}{\partial p} = 0$. Therefore, increasing patient cost-sharing for inpatient care will only result in a welfare loss due to a reduction in the insurance value. This result implies that full insurance coverage for young children's inpatient care could be efficient because having free inpatient care will not raise the total amount of healthcare expenditure, but could increase the insurance value for sick individuals by lessening their financial risk. On the other hand, we find that young children's utilization of outpatient care is moderately sensitive to the change in patient cost sharing. Our results imply that a certain level of patient cost sharing is necessary for outpatient care: since OOP expenses for outpatient care are quite low in Taiwan, keeping it constant or increasing it should produce only a limited welfare loss in terms of risk protection (i.e., insurance value), but could substantially reduce excessive use of outpatient care (i.e., moral hazard), especially for low-value care at high-intensity providers (i.e., teaching hospitals). Note that the above model does not include behavioral hazard (Baicker et al., 2015). In fact, we find that the utilization of healthcare services that could involve behavioral hazard, such as preventive care and mental health services, have much larger price elasticities (in absolute terms) than the overall estimates. If we consider behavioral hazard, reducing patient cost sharing for such types of healthcare could be efficient. People might overweigh the current medical cost and undervalue future health benefits, so that they myopically utilize healthcare too little unless encouraged to do so through a cost-sharing reduction. Investigating health response to patient cost-sharing can help us infer the degree of behavioral hazard. Our results indicate that the subsidy-induced outpatient utilization has little impact on children's health. However, it is possible that health benefits, though small on average, concentrate on a subgroup of children (e.g. children with psychiatric problems). Due to data limitation, we are unable to explore this issue so that cannot quantify the magnitude of behavioral hazard for preventive care and mental health services.

6 Conclusion

In this paper, we estimate the causal effect of patient cost sharing on healthcare utilization in early childhood. Since 2002, Taiwan implements a cost-sharing subsidy policy that exempted copayments of healthcare utilization for children under the age of 3. This medical subsidy policy has resulted in variations in out-of-pocket expenses based only on patient's age, allowing us to employ regression discontinuity design to estimate the price elasticity of various health services. Using longitudinal medical claims of over 410,000 children covered by universal health insurances in Taiwan, we find a modest price elasticities of health expenditure for outpatient care (-0.12 for regular outpatient care and -0.07 for emergency room care). In addition, we find that the expiration of cost-sharing subsidy at age 3 significantly decreases the chance to visit specialists at teaching hospitals for minor illnesses. In contrast, the sharp increase in the OOP expenses for inpatient care does not reduce the use of inpatient care. Finally, additional healthcare utilization induced by this cost-sharing subsidy seem to produce negligent impact on children's health outcomes.

Our findings sheds some lights of future research. To start with, our study appears to be the first analysis that shows a credible estimate—almost zero—price elasticity of children's inpatient care. Notice that our sample consist of medical claims of over 410,000 children. Therefore, the insignificant result is not driven by a small sample size or infrequent hospital admissions for young children as in other studies (e.g. RAND HIE). The price insensitivity implies the extent of overuse in healthcare, even present, is very limited, and therefore suggest the full coverage of inpatient care for young children. In light of its importance in policy implications, we encourage additional empirical evidence to confirm our finding on price elasticity of children's inpatient care.

Second, our findings indicate that patient cost-sharing not only affects the quantity of doctor visits, but also change a patient's choice of healthcare provider, especially for one with a minor illness. This finding is perhaps related to one important feature in Taiwanese healthcare system: a patient can visit any healthcare provider freely without a primary doctor's referral. Given that this feature is common among Asian countries (e.g. China, Japan, and South Korea), it is interesting to examine if similar phenomena occur in other countries adopting no gatekeeper system.

Finally, we find additional health utilization induced by this cost-sharing subsidy produces little impact on children's health. Nonetheless, our analysis for health outcomes are subject to data limitations. Most problematic is that our data sample is not long enough to secure valid measures of health outcomes. Future research would seek to employ better health measures to help understand the full impact of induced healthcare use on children's long-run health.

References

Almond, D. (2006). Is the 1918 influenza pandemic over? Long-term effects of in utero influenza exposure in the post-1940 U.S. population. *Journal of Political Economy 114*(4), 672–712.

Almond, D., J. Doyle, A. Kowalski, and H. Williams (2011). Estimating marginal returns to medical care: Evidence from at-risk newborns. *Quarterly Journal of Economics 125*(2), 591–634.

Anderson, M., C. Dobkin, and T. Gross (2012). The effect of health insurance coverage on the use of medical services. *American Economic Journal: Economic Policy 4*(1), 1–27.

Aron-Dine, A., L. Einav, , and A. Finkelstein (2013). The RAND health insurance experiment, three decades later. *Journal of Economic Perspectives 27*(1), 197—222.

Baicker, K., S. Mullainathan, and J. Schwartzstein (2013). Behavioral hazard in health insurance. *Harvard Working Paper*.

Baicker, K., S. Mullainathan, and J. Schwartzstein (2015). Behavioral hazard in health insurance. *The Quarterly Journal of Economics 130*(4), 1623–1667.

Barreca, A. I., M. Guldi, J. M. Lindo, and G. R. Waddell (2011). Robust nonparametric confidence intervals for Regression-Discontinuity designs. *The Quarterly Journal of Economics 126*(4), 2117–2123.

Bharadwaj, P., K. V. Løken, and C. Neilson (2013). Early life health interventions and academic achievement. *American Economic Review 103*(5), 1862–1891.

Brot-Goldberg, Z., A. Chandra, B. Handel, and J. Kolstad (2017). What does a deductible do? the impact of cost-sharing on health care prices, quantities, and spending dynamics. *Quarterly Journal of Economics 132*(3), 1261–1318.

Card, D., C. Dobkin, and N. Maestas (2008). The impact of nearly universal insurance coverage on health care utilization: Evidence from medicare. *American Economic Review 98*(5), 2242–2258.

Card, D., C. Dobkin, and N. Maestas (2009). Does medicare save lives? *The Quarterly Journal of Economics 124*(2), 597–636.

Carneiro, P., K. V. Løken, and K. G. Salvanes (2015). A flying start? maternity leave benefits and long-run outcomes of children. *Journal of Political Economy 123*(2), 365–412.

Case, A., A. Fertig, and C. Paxson (2005). The lasting impact of childhood health and circumstance. *Journal of Health Economics 24*(2), 365–389.

Cattaneo, M. D., S. Calonico, and R. Titiunik (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica 82*(6), 2295–2326.

Center of Disease and Control (2013). *Vaccination Schedule in Taiwan*. Center of Disease and Control.

Chandra, A., J. Gruber, and R. McKnight (2010a). Patient cost-sharing and hospitalization offsets in the elderly. *American Economic Review 100*(1), 193–213.

Chandra, A., J. Gruber, and R. McKnight (2010b). Patient cost sharing in low income populations. *American Economic Review 100*(2), 303–308.

Chandra, A., J. Gruber, and R. McKnight (2014). The impact of patient cost-sharing on low-income populations: Evidence from Massachusetts. *Journal of Health Economics 33*(1), 57–66.

Cherkin, D., L. Grothaus, and E. Wagner (1989). The effect of office visit copayments on utilization in a health maintenance organization. *Medical Care 27*, 1036–1045.

Clemens, J. and J. D. Gottlieb (2017). In the shadow of a giant: Medicare's influence on private payment systems. *Journal of Political Economy 125*(1), 1–39.

Currie, J. (2009). Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development. *Journal of Economic Literature 47*(1), 87–122.

Currie, J. and B. Madrian (1999). Health, health insurance, and the labor market. *Handbook of Labor Economics 3*(2), 365–389.

Cutler, D. M. (1998). Cost shifting or cost cutting?: The incidence of reductions in medicare payments. In Tax Policy and the Economy, Volume 12, edited by James M. Poterba, chap. 1. Cambridge, Mass.: MIT Press.

Dague, L. (2014). The effect of medicaid premiums on enrollment: a regression discontinuity approach. *Journal of Health Economics 37*, 1–12.

Dranove, D., D. Kessler, M. McClellan, and M. Satterthwaite (2003). Is more information better? the effects of 'report cards' on health care providers. *Journal of Political Economy 111*(3), 555–588.

Einav, L., A. Finkelstein, and M. Polyakova (2018). Private provision of social insurance: Drug-specific price elasticities and cost sharing in medicare part d. *Journal of Health Economics 10*(3), 122–153.

Feudtner, C., D. A. Christakis, and F. A. Connell (2000). Pediatric deaths attributable to complex chronic conditions: A population-based study of washington state, 1980–1997. *Pediatrics 106*(1), 205–209.

Fukushima, K., S. Mizuoka, S. Yamamoto, and T. Iizuka (2015). Patient cost sharing and medical expenditures for the elderly. *Journal of Health Economics 45*(1), 115—130.

Gadomski, A., P. Jenkins, and M. Nichols (1998). Impact of a medicaid primary care provider and preventive care on pediatric hospitalization. *Pediatrics 101*(3), 1–10.

Goldman, D. P., G. F. Joyce, J. J. Escarce, J. E. Pace, M. D. Solomon, M. Laouri, P. B. Landsman, and S. M. Teutsch (2004). Pharmacy benefits and the use of drugs by the chronically ill. *Journal of the American Medical Association 291*(19), 2344–2350.

Grossman, M. (1972). The demand for health: A theoretical and empirical investigation. Columbia University Press.

Han, H.-W. and H.-M. Lien (2008). Do children visit doctors more when the fee is lower? evidence from the medical care subsidy program in taipei. *Taiwan Economic Review 36*(4), 589–623.

Heckman, J., R. Pinto, and P. Savelyev (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review 103*(6), 2052–2086.

Heckman, J. J., S. H. Moon, R. Pinto, P. A. Savelyev, and A. Yavitz (2010). The rate of return to the highscope perry preschool program. *Journal of Public Economics 94*(1), 114–128.

Homer, C. J., P. Szilagyi, L. Rodewald, S. R. Bloom, P. Greenspan, S. Yazdgerdi, J. M. Leventhal, D. Finkelstein, and J. M. Perrin (1996). Does quality of care affect rates of hospitalization for childhood asthma? *Pediatrics 98*(1), 1–24.

Iizuka, T. and H. Shigeoka (2018). Free for children? patient cost-sharing and health care utilization. NBER Working Paper No. 25306.

Imbens, G. and K. Kalyanaraman (2012). Optimal bandwidth choice for the Regression Discontinuity estimator. *The Review of Economic Studies 79*(3), 933–959.

Keeler, E. B. and J. E. Rolph (1998). The demand for episodes of treatment in the health insurance experiment. *Journal of Health Economics 7*(4), 337–367.

Lee, D. S. and D. Card (2008). Regression discontinuity inference with specification error. *Journal of Econometrics 142*(1), 655–674.

Lee, D. S. and T. Lemieux (2010). Regression Discontinuity designs in economics. *Journal of Economic Literature 48*(2), 281–355.

Lehmann, J.-Y. K., A. Nuevo-Chiquero, and M. Vidal-Fernandez (2018). Explaining the birth order effect:the role of prenatal and early childhood investments. *Journal of Human Resources 53*(1), 123–156.

Leibowitz, Manning, Keeler, Duan, Lohr, and Newhouse (1985). Effect of cost-sharing on the use of medical services by children: Interim results from a randomized controlled trial. *Pediatrics 75*(5), 942–951.

Lemieux, T. and K. Milligan (2008). Incentive effects of social assistance: A Regression Discontinuity approach. *Journal of Econometrics 142*(2), 807–828.

Lien, H.-M., S.-Y. Chou, and J.-T. Liu (2008). Hospital ownership and performance: Evidence from stroke and cardiac treatment in Taiwan. *Journal of Health Economics 27*(5), 1208–1223.

Lieu, T. A., C. P. Quesenberry, A. M. C. Jr, M. E. Sorel, K. E. Martin, and G. R. Mendoza (1997). Outpatient management practices associated with reduced risk of pediatric asthma hospitalization and emergency department visits. *Pediatrics 100*(3), 334–341.

Lin, M.-J., J.-T. Liu, and N. Qian (2014). More missing women, fewer dying girls: The impact of sex-selective abortion on sex at birth and relative female mortality in taiwan. *Journal of the European Economic Association 12*(4), 899–926.

Ludwig, J. and D. Miller (2007). Does head start improve children's life chances? Evidence from a Regression Discontinuity design. *Quarterly Journal of Economics 122*(2), 159–208.

Manning, W. G. and M. Marquis (1996). Health insurance: the tradeoff between risk pooling and moral hazard. *Journal of Health Economics 15*, 609–640.

Manning, W. G., J. P. Newhouse, N. Duan, E. B. Keeler, and A. Leibowitz (1981). Some interim results from a controlled trial of cost sharing in health insurance. *New England Journal of Medicine 305*(1), 1501—1507.

Manning, W. G., J. P. Newhouse, N. Duan, E. B. Keeler, and A. Leibowitz (1987). Health insurance and the demand for medical care: Evidence from a randomized experiment. *American Economic Review 77*(3), 251—277.

Monfardini, C. and S. G. See (2011). Birth order and child outcomes: Does maternal quality time matter? Working Paper.

National Health Insurance Administration (2012). *National Health Insurance Research Database codebook*. National Health Insurance Administration.

Nilsson, A. and A. Paul (2015). The effect of copayments on children's and adolescents' use of medical care. *Working Paper*.

Nilssona, A. and A. Paul (2018). Patient cost-sharing, socioeconomic status, and children's health careutilization. *Journal of Health Economics 59*(1), 109–124.

Price, J. (2008). Parent-child quality time. *Journal of Human Resources 43*(1), 240—265.

Rice, T. and K. Y. Matsuoka (2004). The impact of cost-sharing on appropriate utilization and health status: A review of the literature on seniors. *Medical Care Research and Review 61*(4), 415—452.

Selby, J. V., B. H. Fireman, and B. E. Swain (1996). Effect of a copayment on use of the emergency department in a health maintenance organization. *New England Journalof Medicine 334*(10), 635–642.

Selden, T. M., G. M. Kenney, M. S. Pantell, and J. Ruhter (2009). Cost sharing in Medicaid and CHIP: How does it affect out-of-pocket spending? *Health Affairs 28*(4), 607–619.

Sen, Blackburn, Morrisey, Kilgore, Becker, Caldwell, and Menachemi (2012). Did copayment changes reduce health service utilization among CHIP enrollees? Evidence from Alabama. *Health Services Research 47*(4), 1603—1620.

Shigeoka, H. (2014). The effect of patient cost-sharing on utilization, health and risk protection. *American Economic Review 104*(7), 2152–2184.

Trivedi, A. N., W. Rakowski, and J. Z. Ayanian (2008). Effect of cost sharing on screening mammography in medicare health plans. *New England Journal of Medicine 358*(4), 375–383.

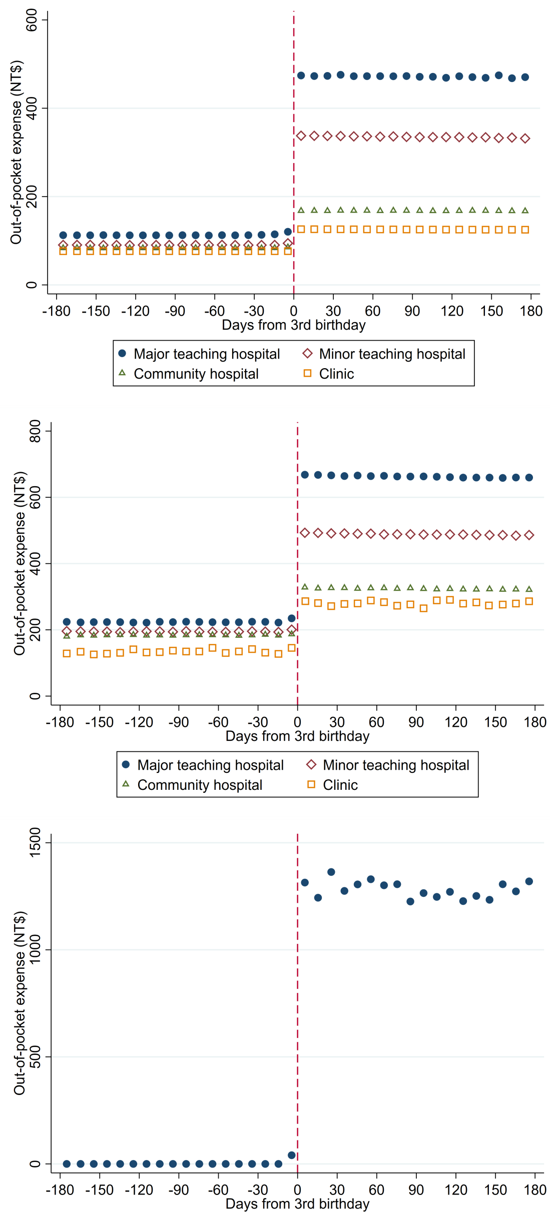
Uddin, S. G., K. S. O'Connor, and J. J. Ashman (2016). Physician office visits by children for well and problem-focused care: United states, 2012. *NCHS Data Brief 248*, 1–8.

Wherry, L. R. and B. D. Meyer (2015). Saving teens: Using a policy discontinuity to estimate the effects of medicaid eligibility. *Journal of Human Resources 51*(3), 556–588.

Wherry, L. R., S. Miller, R. Kaestner, and B. D. Meyer (2018). The long-term health effects of early life medicaid coverage. *Journal of Human Resources forthcoming*.

Wu, V. (2010). Hospital cost shifting revisited: New evidence from the balanced budget act of 1997. *International Journal of Health Care Finance and Economics 10*, 61–83.

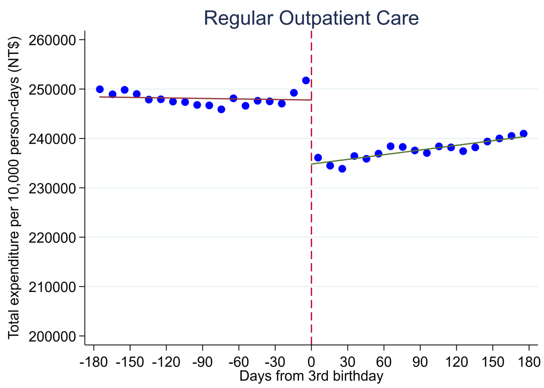
Figures



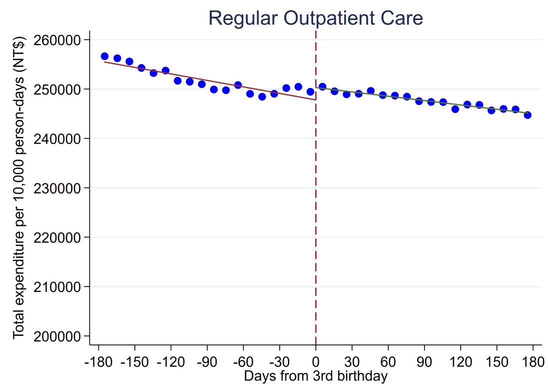
Notes: We pool NHI claims of regular outpatient care for 2003-2004 birth cohort using 2005-2008 NHIRD data, which records patient's NHI copayment (coinsurance) of each outpatient visit (inpatient admission). For regular outpatient visits and emergency room visits, we impute registration fee using the method described in the Online Appendix C. The dependent variable is the average OOP expense by patient's age at visit (admission). The average OOP expense is measured in New Taiwanese Dollar (NT$). 1 US$ is equal to 32.5 NT$ in 2006. All expenses in our sample period are inflation-adjusted (in 2006 NT$). The age at visit is measured in days. We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable.

Figure 2: Utilization of Regular Outpatient Care Before and After the 3^{rd} Birthday

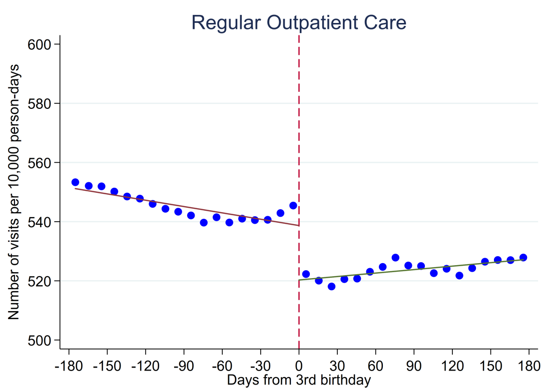
(a) Total Expenditure per 10,000 Person-Days: 2005–2008



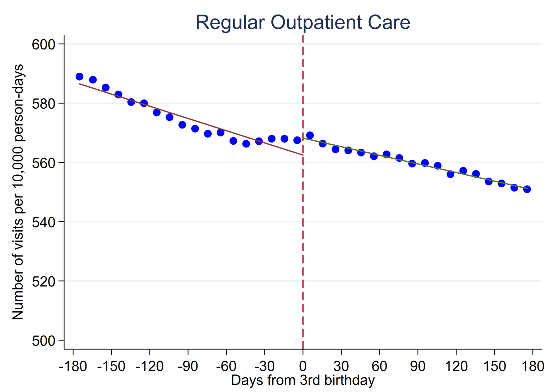
(b) Total Expenditure per 10,000 Person-Days: 1997–2001



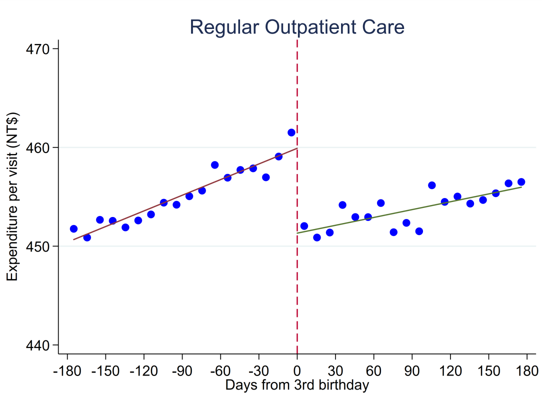
(c) Number of Visits per 10,000 Person-Days: 2005–2008



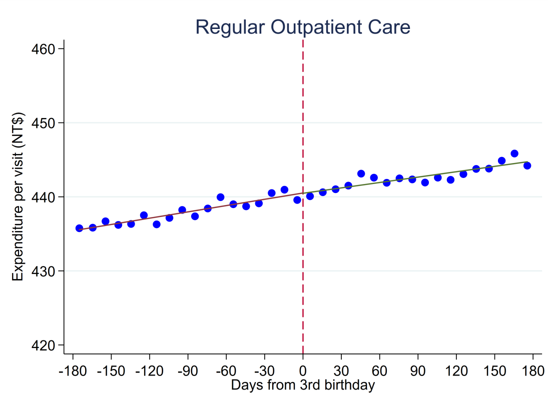
(d) Number of Visits per 10,000 Person-Days: 1997–2001



(e) Expenditure per visit: 2005–2008



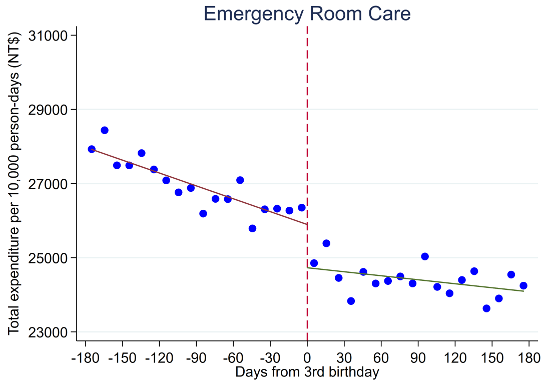
(f) Expenditure per visit: 1997–2001



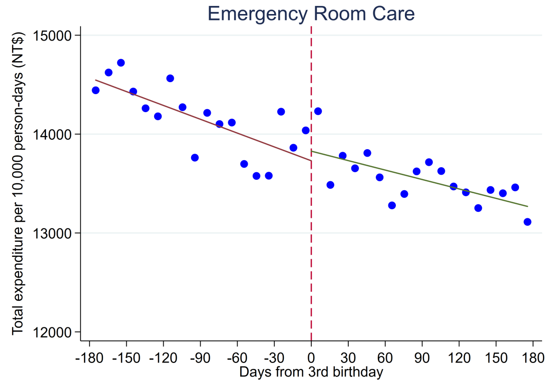
Notes: We pool NHI claims of regular outpatient care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variables are total expenditure (NT$) per 10,000 person-days, number of visits per 10,000 person-days, and expenditure (NT$) per visit by patient's age at visit. 1 US$ is equal to 32.5 NT$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT$). The age at visit is measured in days. We plot the dependent variables within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variables. The line is from fitting a linear regression on age variables fully interacted with $Age3$.

Figure 3: Utilization of Emergency Room Care Before and After the 3^{rd} Birthday

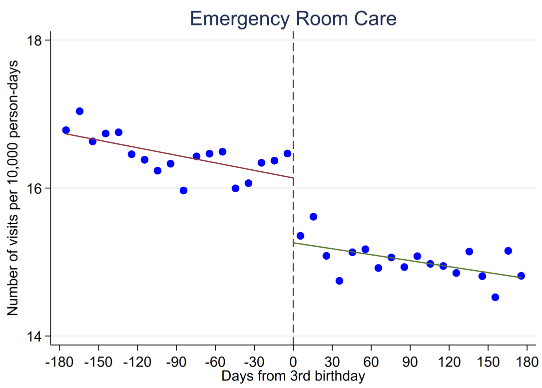
(a) Total Expenditure per 10,000 Person-Days: 2005–2008



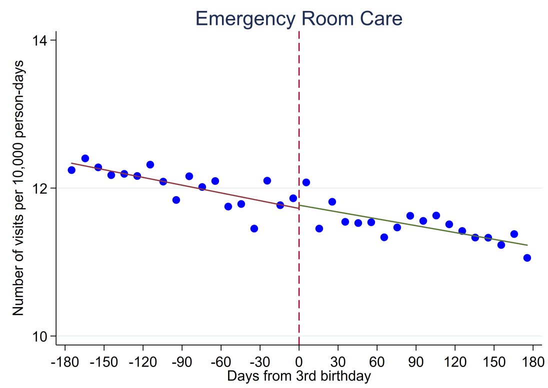
(b) Total Expenditure per 10,000 Person-Days: 1997–2001



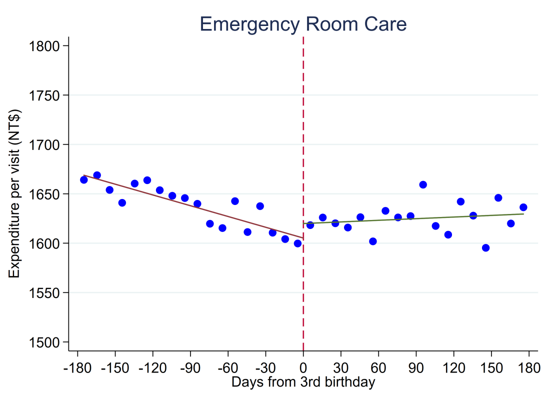
(c) Number of visits per 10,000 Person-Days: 2005–2008



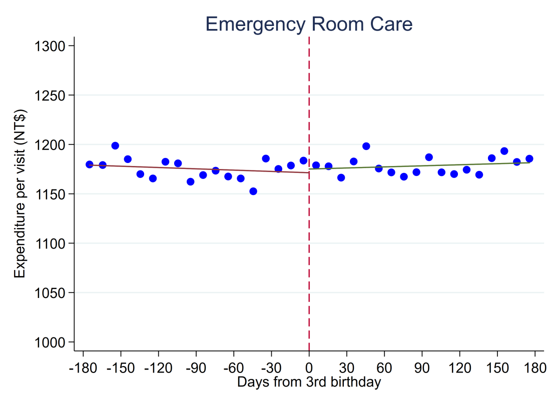
(d) Number of visits per 10,000 Person-Days: 1997–2001



(e) Expenditure per Visit: 2005–2008



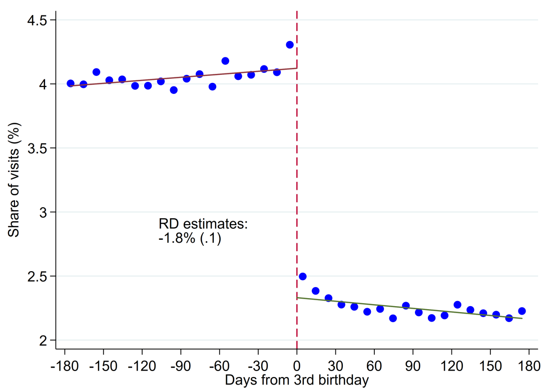
(f) Expenditure per Visit: 1997–2001



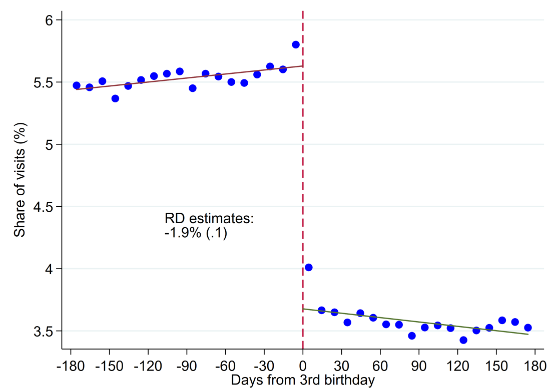
Notes: We pool NHI claims of emergency room care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variables are total expenditure (NT$) per 10,000 person-days, number of visits per 10,000 person-days, and expenditure (NT$) per visit by patient's age at visit. 1 US$ is equal to 32.5 NT$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT$). The age at visit is measured in days. We plot the dependent variables within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variables. The line is from fitting a linear regression on age variables fully interacted with $Age3$.

Figure 4: Provider Choice Before and After the 3^{rd} Birthday:
Regular Outpatient Care

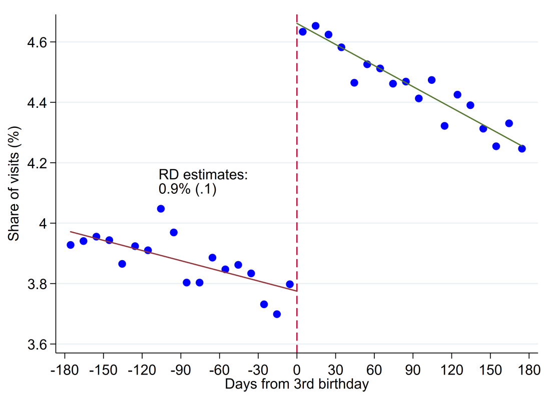
(a) Major Teaching Hospital



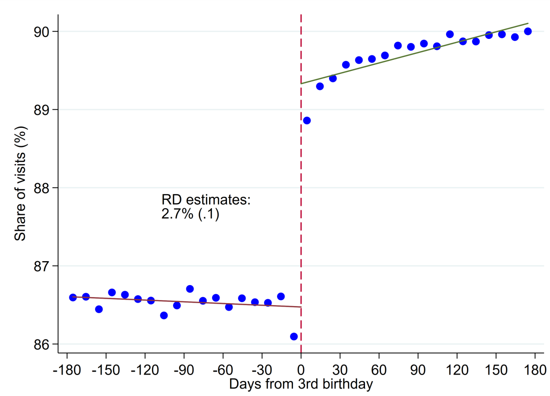
(b) Minor Teaching Hospital



(c) Community Hospital



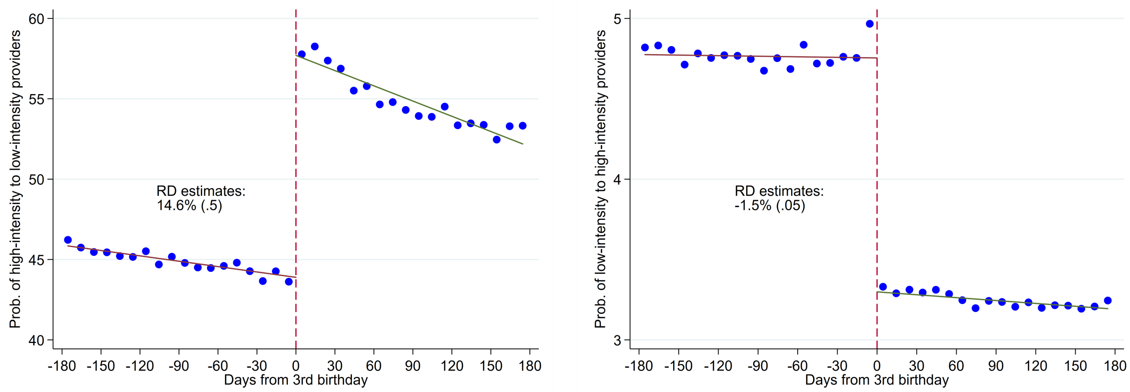
(d) Clinic



Notes: We pool NHI claims of regular outpatient care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variable is share of visits for each type of healthcare provider. The age at visit is measured in days. We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable. The line is from fitting a linear regression on age variables fully interacted with $Age3$. The RD estimates are based on estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth. The standard error of the RD estimates are presented in parentheses.

Figure 5: Providers Switching Before and After the 3^{rd} Birthday: Regular Outpatient Care

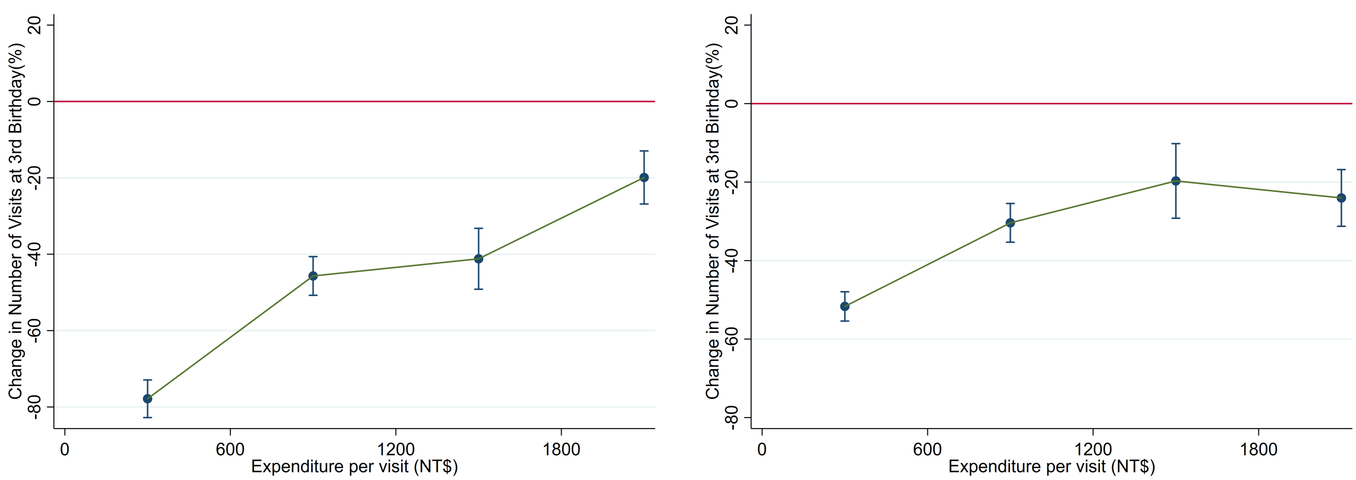
(a) Prob. of high-intensity to low-intensity providers (b) Prob. of low-intensity to high-intensity providers



Notes: We pool NHI claims of regular outpatient care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variables in Figure 5a is conditional probability of current visit is low-intensity provider (i.e. community hospitals/clinics) given the last visit is high-intensity provider (i.e. teaching hospitals). The dependent variables in Figure 5b is conditional probability of current visit is high-intensity provider (i.e. teaching hospitals) given the last visit is low-intensity provider (i.e. community hospitals/clinics). We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable. The line is from fitting a linear regression on age variables fully interacted with $Age3$.

Figure 6: Utilization Responses at the 3^{rd} birthday By Expenditure per Regular Outpatient Visit

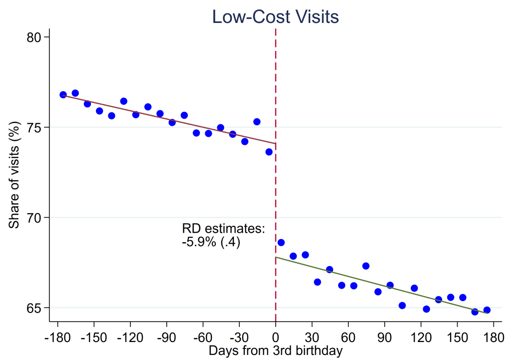
(a) Major Teaching Hospital (b) Minor Teaching Hospital



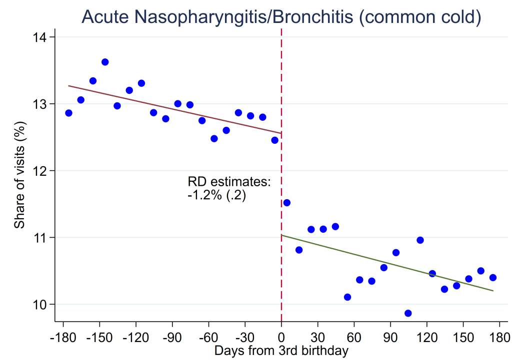
Notes: We pool NHI claims of regular outpatient care for 2003-2004 birth cohort using 2005-2008 NHIRD data. We estimate equation (2) separately by expenditure per regular outpatient visit: (1) 0-600 NT\$; (2) 601-1,200 NT\$; (3) 1,201-1,800 NT\$; (4) above 1,801 NT\$ for major teaching hospital visits (see Figures 6a) and minor teaching hospital visits (see Figures 6b). The dotted line in Figures 6a and 6b displays the estimated coefficients on $Age3$ from equation (2) and the corresponding 95% confidence intervals. 1 US\$ is equal to 32.5 NT\$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT\$).

Figure 7: Composition Change in Teaching Hospital Visits at the 3^{rd} birthday: Regular Outpatient Care

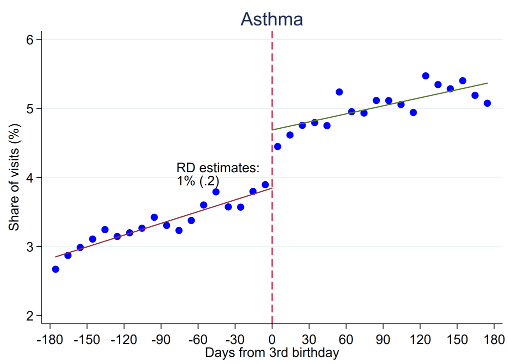
(a) Low-Cost Visits



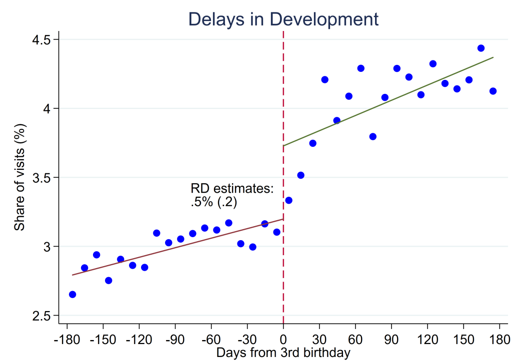
(b) Acute Nasopharyngitis/Bronchitis (Common Cold)



(c) Asthma



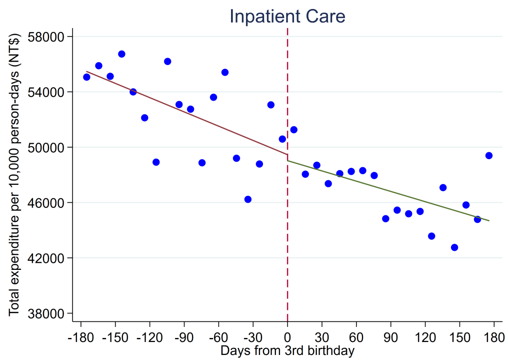
(d) Delays in Development



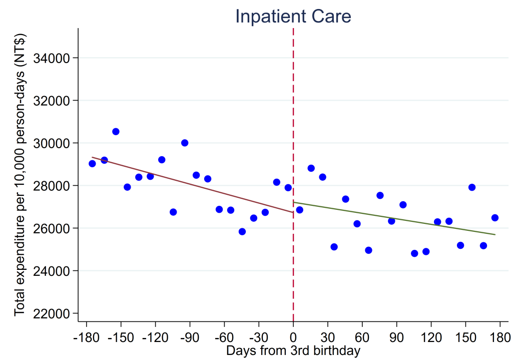
Notes: We pool NHI claims of regular outpatient care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variable is share of visits for selected diagnosis. 3-digit ICD 9 code for Acute Nasopharyngitis/Bronchitis (Common Cold): 460 and 466, for Asthma: 493, and for Delays in Development: 315. The age at visit is measured in days. We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable. The line is from fitting a linear regression on age variables fully interacted with $Age3$. The RD estimates are based on estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth. The standard error of the RD estimates are presented in parentheses.

Figure 8: Utilization of Inpatient Care Before and After the 3^{rd} Birthday

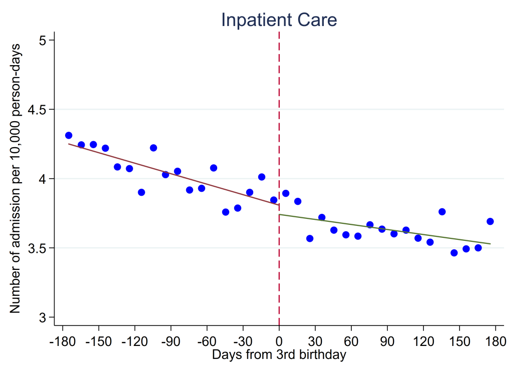
(a) Total Expenditure per 10,000 Person-Days: 2005–2008



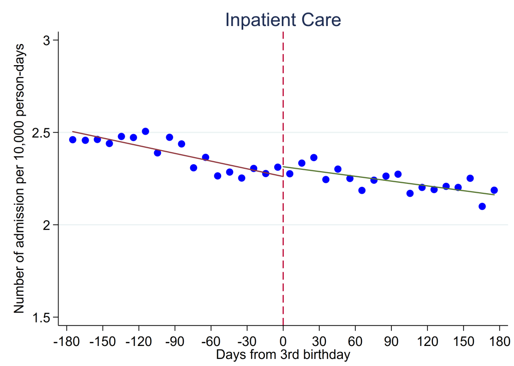
(b) Total Expenditure per 10,000 Person-Days: 1997–2001



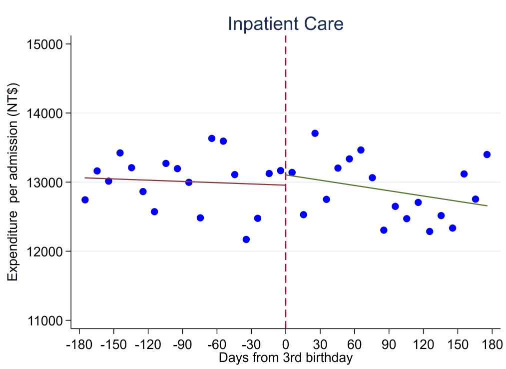
(c) Number of Admissions per 10,000 Person-Days: 2005–2008



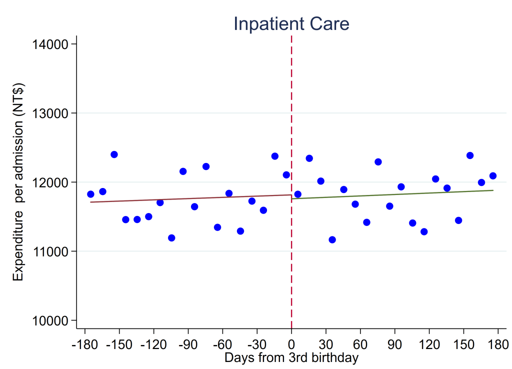
(d) Number of Admissions per 10,000 Person-Days: 1997–2001



(e) Expenditure per Admission: 2005–2008



(f) Expenditure per Admission: 1997–2001



Notes: We pool NHI claims of inpatient care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variables are total expenditure (NT$) per 10,000 person-days, number of visits per 10,000 person-days, and expenditure (NT$) per visit by patient's age at visit. 1 US$ is equal to 32.5 NT$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT$). The age at visit is measured in days. We plot the dependent variables within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variables. The line is from fitting a linear regression on age variables fully interacted with $Age3$.

Tables

Table 1: Patient Cost-Sharing in Taiwan NHI

	Patient Cost-Sharing			
	Major Teaching Hospital	Minor Teaching Hospital	Community Hospital	Clinic
Panel A: Regular Visit				
Copayment	360	240	80	50
Average Registration Fee	111	91	82	76
Panel B: Emergency Visit				
Copayment	450	300	150	150
Average Registration Fee	221	194	178	132
Panel C: Inpatient care				
1-30 days		10%		
31-60 days		20%		
after 61 days		30%		

Notes: 1 US$ is 32.5 NT$ in 2006. For outpatient care, patient cost-sharing is through copayment. A patient pays copayment plus registration fee for each visit. Information about copayment is from NHIRD codebook (2012 version). NHI implemented this fee schedule since July 2005. Since our sample period is from July 1st 2005 to June 30th 2008, all outpatient visits in our sample are based on the above fee schedule. Before July 1st 2005, copayment for a regular outpatient (emergency room) visit is according to the following fee scheme: 210 (420) NT$ for major teaching hospital, 140 (300) NT$ for minor teaching hospital, 50 (200) NT$ for community hospital, and 50 (150) NT$ for clinic. In addition, for regular outpatient care, people who get a referral at the lower-rank providers only pay 210 NT$ for a major teaching hospital visit, 140 NT$ for a minor teaching hospital visit, and 50 NT$ for a community hospital visit. However, very few patients get a referral at the lower-rank providers (i.e. less than 0.5% of total teaching hospital visits). We calculate average registration fee based on the method described in the Online Appendix C. For inpatient care, patient cost-sharing takes place through coinsurance. Depending on the days of stay and the type of admission (acute or chronic admission), a patient is required to pay 10% to 30% of the expenditure per admission. The above fee schedule is only for acute inpatient admissions since we only focus on the acute inpatient admissions with less than 30 days. The chronic inpatient admissions and acute inpatient admissions with more than 30 days of stay only account for 0.6% and 0.1% of total inpatient admissions for the children between age 2 and 4.

Table 2: Summary Statistics: Estimated Sample Before and After 3^{rd} Birthday

	Regular outpatient care		Emergency room care		Inpatient care	
	Before 3^{rd} birthday	After 3^{rd} birthday	Before 3^{rd} birthday	After 3^{rd} birthday	Before 3^{rd} birthday	After 3^{rd} birthday
Visit rate	541.74	522.52	16.30	15.12	3.92	3.68
Number of visits per person per year	19.77	19.07	0.59	0.55	0.14	0.13
Share of major teaching hospital	0.04	0.02	0.35	0.34	0.29	0.30
Share of minor teaching hospital	0.06	0.04	0.52	0.47	0.59	0.58
Share of Community hospital	0.04	0.05	0.12	0.18	0.13	0.12
Share of Clinic	0.87	0.90	0.01	0.01	0.00	0.00
Avg. expenditure (per visit)	457.75	452.57	1620.39	1621.72	12776.43	13001.53
	(0.43)	(0.42)	(4.83)	(4.88)	(110.91)	(123.73)
Avg. OOP expense (per visit)	78.92	142.67	203.02	515.82	0.00	1292.48
	(0.01)	(0.05)	(0.20)	(0.55)	(.)	(12.61)
Share of OOP expense	0.20	0.36	0.16	0.40	0.00	0.10
Number of children	364,966	359,055	48,358	46,307	13,417	12,677
Number of children-visit	2,019,904	1,948,220	60,775	56,391	14,604	13,737

Notes: Data are from 2005–2008 NHIRD. The summary statistics are based on healthcare utilization happened within 90 days before the 3^{rd} birthday and 90 days after the 3^{rd} birthday. Visit rate is the number of visit per 10,000 person-days. Average expenditure and average OOP expense are reported in New Taiwan Dollar (NT$). 1 US$ is 32.5 NT$ in 2006. All expenditures/expenses in our sample period are inflation-adjusted (in 2006 NT$).

Table 3: List of Top 5 Diagnosis in Each Healthcare Services

Diagnosis	ICD 9 Code	Share
Panel A: Regular Outpatient Care		
Acute upper respiratory infections	465	25.7%
Acute bronchitis and bronchiolitis	466	12.2%
Acute sinusitis	461	10.6%
Acute tonsillitis	463	5.8%
Acute nasopharyngitis	460	5.1%
Panel B: Emergency Room Care		
Alteration of consciousness (e.g. coma)	780	12.3%
Acute upper respiratory infections	465	9.2%
Gastroenteritis and colitis	558	7.2%
Acute pharyngitis	462	6.6%
Acute tonsillitis	463	6.2%
Panel C: Impatient Care		
Bronchopneumonia	485	17.1%
Gastroenteritis and colitis	558	10.5%
Pneumonia	486	8.1%
Herpangina	074	7.9%
Acute tonsillitis	463	6.5%

Notes: This table lists of top 5 diagnosis and their corresponding ICD 9 code in regular outpatient care, emergency room care, and inpatient care. We calculate share of visits for each diagnosis using claim data from 2005–2008 NHIRD.

Table 4: The Effect of Patient Cost-Sharing on Utilization of Outpatient Care at Age 3

Variables	(1) OOP expense	(2) log(total expenditure)	(3) log(# of visits)	(4) log(expenditure/visit)	(5) elasticity
Panel A: Regular outpatient care					
Sample: 2005–2008					
Age3	62.86***	-6.63***	-4.82***	-1.81***	-0.12
	(2.62)	(0.47)	(0.32)	(0.27)	
Sample: 1997-2001					
Age3	3.73	0.19	0.25	-0.06	
	(2.56)	(0.23)	(0.17)	(0.12)	
Panel B: Emergency Room Care					
Sample: 2005-2008					
Age3	306.89***	-5.59***	-6.38***	0.78	-0.07
	(10.83)	(1.53)	(1.15)	(0.78)	
Sample: 1997-2001					
Age3	0.45	1.35	0.72	0.63	
	(1.20)	(1.18)	(1.02)	(0.83)	

Notes: The estimated sample in the first and third row are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. The estimated sample in the second and fourth row are 866,383 children born in 1995 to 1997. We use 1997-2001 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. Column (1)-(4) present the estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth (i.e. 180 observations). The dependent variables in all the regressions above are average OOP expense (NT$), the log of total expenditure, the log of number of visits, and the log of expenditure per visit, at each age in days. For column (2) - (4), the estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Column (5) displays estimated price elasticity of total expenditure using the information from Column (1) and (2). 1 US$ is equal to 32.5 NT$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT$). Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

Table 5: The Effect of Patient Cost-Sharing on Utilization of Regular Outpatient Care at Age 3: By Types of Visit

Variables	(1) OOP expense	(2) log(total expenditure)	(3) log(# of visits)	(4) log(expenditure/visit)	(5) elasticity
Panel A: By beneficial care					
More beneficial care	65.53***	-5.03***	-4.11***	-0.91***	-0.09
	(2.73)	(0.69)	(0.60)	(0.27)	
Less beneficial care	62.45***	-6.85***	-4.93***	-1.92***	-0.12
	(2.60)	(0.50)	(0.35)	(0.30)	
Panel B: By essential healthcare					
More essential healthcare	54.94***	-2.23	-4.10	1.87	-0.04
	(2.54)	(4.44)	(3.75)	(2.51)	
Less essential healthcare	62.88***	-6.65***	-4.83***	-1.82***	-0.12
	(2.62)	(0.47)	(0.32)	(0.27)	
Panel C: By preventive care					
Mental illness	166.54***	-24.71***	-25.49***	0.78	-0.26
	(6.39)	(2.95)	(2.56)	(1.56)	
Preventive care	119.90***	-50.64***	-54.57***	3.93	-0.60
	(9.16)	(8.28)	(6.49)	(6.37)	

*Notes:*The estimated sample are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. In Panel A, we define beneficial care as diagnosis list (3-digit ICD 9 code) in the Table Online Appendix H. In Panel B, we define essential care as diagnosis list (3-digit ICD 9 code) in the Online Appendix I. In Panel C, we define preventive care using the following 3-digit ICD 9 code: V70,V72,V20, V03-V06 and define mental health service using ICD 9 code: 290-319. Column (1)-(4) present the estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth (i.e. 180 observations). The dependent variables in all the regressions above are average OOP expense (NT$), the log of total expenditure, the log of number of visits, and the log of expenditure per visit, at each age in days. For column (2) - (4), the estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Column (5) displays estimated price elasticity of total expenditure using the information from Column (1) and (2). 1 US$ is equal to 32.5 NT$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT$). Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

Table 6: The Effect of Patient Cost-Sharing on Utilization of Emergency Room Care at Age 3: By Types of Visit

Variables	(1) OOP expense	(2) log(total expenditure)	(3) log(# of visits)	(4) log(expenditure/visit)	(5) elasticity
Panel A: By beneficial care					
More beneficial care	323.78***	-4.45*	-5.73**	1.28	-0.05
	(12.50)	(2.60)	(2.33)	(1.43)	
Less beneficial care	301.41***	-5.86***	-6.56***	0.70	-0.07
	(10.33)	(1.78)	(1.25)	(0.94)	
Panel B: By essential healthcare					
More essential healthcare	289.58***	5.00	3.31	1.69	0.06
	(10.73)	(8.31)	(6.55)	(5.53)	
Less essential healthcare	307.56***	-6.08***	-6.68***	0.61	-0.07
	(10.91)	(1.53)	(1.18)	(0.77)	

Notes: The estimated sample are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. In Panel A, we define beneficial care as diagnosis list (3-digit ICD 9 code) in the Online Appendix H. In Panel B, we define essential care (i.e. non-deferrable visits) as diagnosis list (3-digit ICD 9 code) in the Online Appendix I. Column (1)-(4) present the estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth (i.e. 180 observations). The dependent variables in all the regressions above are average OOP expense (NT$), the log of total expenditure, the log of number of visits, and the log of expenditure per visit, at each age in days. For column (2) - (4), the estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Column (5) displays estimated price elasticity of total expenditure using the information from Column (1) and (2). 1 US$ is equal to 32.5 NT$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT$). Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

Table 7: The Effect of Patient Cost-Sharing on Utilization of Regular Outpatient Care at Age 3: By Patient Types

Variables	(1) OOP expense	(2) log(total expenditure)	(3) log(# of visits)	(4) log(expenditure/visit)	(5) elasticity
Panel A: By birth order					
1st child	64.89***	-5.96***	-4.69***	-1.27***	-0.10
	(2.70)	(0.53)	(0.33)	(0.38)	
2nd child	60.90***	-7.25***	-4.88***	-2.38***	-0.13
	(2.55)	(0.65)	(0.44)	(0.39)	
3rd child (above)	59.06***	-8.08***	-5.01***	-3.08***	-0.15
	(2.46)	(1.33)	(0.76)	(1.04)	
Panel B: By gender					
Male	63.96***	-7.24***	-4.89***	-2.36***	-0.13
	(2.65)	(0.59)	(0.37)	(0.40)	
Female	61.53***	-5.84***	-4.74***	-1.10***	-0.10
	(2.59)	(0.57)	(0.38)	(0.33)	
Panel C: By income					
Low-income	60.89***	-6.80***	-4.85***	-1.95***	-0.12
	(2.56)	(0.77)	(0.55)	(0.61)	
Middle-income	62.75***	-6.78***	-4.16***	-2.62***	-0.12
	(2.67)	(0.67)	(0.44)	(0.46)	
High-income	66.54***	-6.35***	-4.59***	-1.77***	-0.11
	(2.70)	(0.85)	(0.49)	(0.62)	
Panel D: By health status					
Sicky children	72.51***	-8.46***	-5.95***	-2.51***	-0.13
	(3.00)	(0.96)	(0.57)	(0.71)	
Healthy children	60.61***	-6.16***	-4.56***	-1.61***	-0.11
	(2.53)	(0.48)	(0.31)	(0.28)	
Panel E: By healthcare accessibility					
Greater access to healthcare	66.39***	-5.51***	-4.09***	-1.41***	-0.09
	(2.65)	(0.72)	(0.47)	(0.47)	
Less access to healthcare	61.52***	-6.96***	-5.02***	-1.95***	-0.12
	(2.61)	(0.47)	(0.34)	(0.28)	

Notes: The estimated sample are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. In Panel C, a low-income household is defined as one ranked below 25th percentile of the household income (per capita) distribution (i.e. the average monthly household income for this subgroup is around 27,000 NT$). A middle-income household is defined as one ranked between 25th percentile to 75th percentile of the household income (per capita) distribution (i.e. the average monthly household income for this subgroup is around 51,000 NT$). A high-income household is defined as one ranked above 75th percentile of the household income (per capita) distribution (i.e. the average monthly household income for this subgroup is around 98,000 NT$). In Panel D, the sicker children are defined as those with inpatient spendings during age 1-2 above median. The definition of healthier children is opposite. On average, the sicker children spend more than 20,000 NT$ during their age 1-2. In contrast, healthier children do not even have any inpatient admission (i.e. zero inpatient spending) during this age range. In Panel E, we use the children born in the counties with more than 14 pediatricians per 10,000 persons to indicate the subgroup that have greater access to healthcare services. Column (1)-(4) present the estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth (i.e. 180 observations). The dependent variables in all the regressions above are average OOP expense (NT$), the log of total expenditure, the log of number of visits, and the log of expenditure per visit, at each age in days. For column (2) - (4), the estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Column (5) displays estimated price elasticity of total expenditure using the information from Column (1) and (2). 1 US$ is equal to 32.5 NT$ in 2006. All expenditures/incomes in our sample period are inflation-adjusted (in 2006 NT$). Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

Table 8: The Effect of Patient Cost-Sharing on Utilization of Emergency Room Care at Age 3: By Patient Types

Variables	(1) OOP expense	(2) log(total expenditure)	(3) log(# of visits)	(4) log(expenditure/visit)	(5) elasticity
Panel A: By birth order					
1st child	312.30***	-3.29*	-5.76***	2.47**	-0.04
	(11.01)	(1.87)	(1.59)	(0.96)	
2nd child	299.99***	-8.27***	-6.56***	-1.71	-0.10
	(10.72)	(2.82)	(2.20)	(1.59)	
3rd child (above)	287.45***	-14.59**	-11.76**	-2.83	-0.18
	(11.64)	(5.80)	(4.58)	(3.46)	
Panel B: By gender					
Male	307.79***	-2.86	-5.58***	2.72***	-0.03
	(11.00)	(2.03)	(1.50)	(0.98)	
Female	305.74***	-9.27***	-7.43***	-1.84	-0.11
	(10.71)	(2.24)	(1.53)	(1.32)	
Panel C: By household income					
Low-income	301.82***	-11.87***	-14.81***	2.95*	-0.14
	(11.04)	(3.53)	(3.05)	(1.73)	
Middle-income	308.79***	-1.73	-2.10	0.36	-0.02
	(11.23)	(2.37)	(2.05)	(1.33)	
High-income	325.92***	-4.71	-4.94*	0.22	-0.05
	(10.67)	(3.41)	(2.97)	(1.75)	
Panel D: By health status					
Sicky children	301.41***	-7.46***	-8.50***	1.04	-0.09
	(11.00)	(2.80)	(2.49)	(1.53)	
Healthy children	308.67***	-4.90***	-5.61***	0.71	-0.06
	(10.84)	(1.68)	(1.25)	(0.84)	
Panel E: By healthcare accessibility					
Greater access to healthcare	336.03***	-6.85**	-6.61***	-0.23	-0.08
	(11.58)	(2.67)	(2.16)	(1.47)	
Less access to healthcare	293.95***	-5.34***	-6.33***	0.99	-0.06
	(10.59)	(1.93)	(1.49)	(0.90)	

Notes: The estimated sample are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. In Panel C, a low-income household is defined as one ranked below 25th percentile of the household income (per capita) distribution (i.e. the average monthly household income for this subgroup is around 27,000 NT$). A middle-income household is defined as one ranked between 25th percentile to 75th percentile of the household income (per capita) distribution (i.e. the average monthly household income for this subgroup is around 51,000 NT$). A high-income household is defined as one ranked above 75th percentile of the household income (per capita) distribution (i.e. the average monthly household income for this subgroup is around 98,000 NT$). In Panel D, the sicker children are defined as those with inpatient spendings during age 1-2 above median. The definition of healthier children is opposite. On average, the sicker children spend more than 20,000 NT$ during their age 1-2. In contrast, healthier children do not even have any inpatient admission (i.e. zero inpatient spending) during this age range. In Panel E, we use the children born in the counties with more than 14 pediatricians per 10,000 persons to indicate the subgroup that have greater access to healthcare services. Column (1)-(4) present the estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth (i.e. 180 observations). The dependent variables in all the regressions above are average OOP expense (NT$), the log of total expenditure, the log of number of visits, and the log of expenditure per visit, at each age in days. For column (2) - (4), the estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Column (5) displays estimated price elasticity of total expenditure using the information from Column (1) and (2). 1 US$ is equal to 32.5 NT$ in 2006. All expenditures/incomes in our sample period are inflation-adjusted (in 2006 NT$). Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

Table 9: The Effect of Patient Cost-Sharing on Utilization of Inpatient Care at Age 3

Variables	(1) OOP expense	(2) log(total expenditure)	(3) log(# of admissions)	(4) log(expenditure/admission)	(5) elasticity
Sample: 2005–2008					
Age3	1271.07***	0.17	-1.36	1.52	0.001
	(46.71)	(4.35)	(2.62)	(3.17)	
Sample: 1997-2001					
Age3	23.63	4.20	2.99	1.21	
	(35.51)	(3.64)	(2.07)	(3.16)	

Notes: The estimated sample in the first and third row are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. The estimated sample in the second and fourth row are 866,383 children born in 1995 to 1997. We use 1997-2001 NHIRD data to get their healthcare utilization around age 3. Column (1)-(4) present the estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth (i.e. 180 observations). The dependent variables in all the regressions above are average OOP expense (NT$), the log of total expenditure, the log of number of admissions, and the log of expenditure per admission, at each age in days. For column (2) - (4), the estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Column (5) displays estimated price elasticity of total expenditure using the information from Column (1) and (2). 1 US$ is equal to 32.5 NT$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT$). Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

Online Appendix: For Online Publication

Section A	Healthcare Utilization for Children under Age 4 in Taiwan
Section B	Healthcare Providers in Taiwan
Section C	Imputation of Registration Fee
Section D	Sample Selection Process
Section E	Robustness Check for Bandwidth Choices
Section F	Robustness Check for Empirical Specifications
Section G	Donut RDD Analysis
Section H	List of Ambulatory Care Sensitive Conditions (ACSC)
Section I	List of Top 5 Diagnosis in Non-Deferrable Visits
Section J	Additional Results on Regular Outpatient Care
Section K	Details of the Construction of the Conditional Probability of a Shift in Healthcare Provider
Section L	Additional Results on Emergency Room Care
Section M	Examine Own-Price Elasticity
Section N	Results for Children's Health
Section O	A Sufficient Statistics Model for Evaluating Patient Cost-Sharing Policy

A Healthcare Utilization for Children under Age 4 in Taiwan

Table A1: Healthcare Utilization for Children under Age 4 in Taiwan

	Age 0 to 1	Age 1 to 2	Age 2 to 3	Age 3 to 4
Total expenditure (NT$)	16,830	16,288	13,998	12,128
Outpatient expenditure (NT$)	9,187	12,120	11,303	10,159
Inpatient expenditure (NT$)	7,643	4,167	2,695	1,968
Number of outpatient visits	18.35	24.55	22.64	20.85
Number of inpatient admission	0.27	0.26	0.18	0.14

Notes: This table displays the healthcare utilization for children under age 4 in Taiwan using 2007-2008 claim data from NHIRD. The number of outpatient visits include both regular outpatient visit and emergency room visit. 1 US$ is equal to 32.5 NT$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT$).

B Healthcare Providers in Taiwan

In this section, we provide some general information about the major teaching hospitals, minor teaching hospitals, community hospitals, and clinics in Taiwan. Based on criteria from the Ministry of Health and Welfare, a major teaching hospital needs to have at least 500 acute-care beds, 22 departments, and to have passed various teaching hospital accreditations. In addition, doctors in major teaching hospitals need to conduct medical research. Likewise, a minor teaching hospital needs to have at least 300 beds, 7 departments, and to have passed the teaching hospital accreditation. Both major and minor teaching hospitals take responsibility for training interns. A community hospital needs to have at least 20 beds. It also needs to provide general outpatient care, emergency care, and inpatient care. A clinic will usually only provide regular outpatient care (primary care) and cannot provide inpatient care.

As shown in Table B1, in 2008, the numbers of major teaching hospitals, minor teaching hospitals, community hospitals, and clinics were 23, 87, 440, and 22,053, respectively. In general, most of the major teaching hospitals are located in cities (urban areas) but almost every city and county has at least one minor teaching hospital. It is generally believed that major and minor teaching hospitals provide better care than community hospitals and clinics. For instance, in 2003, the percentages of doctors working in hospitals that were specialists (i.e., had received certificates in various specialties) were 78% for major teaching hospitals, 75% for minor teaching hospitals, and 54% for community hospitals. In addition, the average medical expenditure in teaching hospitals is much higher than in community hospitals and clinics.

Finally, like the NHI copayments, the reimbursements to hospitals are based on the NHI Fee Schedule. According to this schedule, all hospitals receive the same reimbursement for certain procedures and treatments, such as health checks. However, for some procedures and treatments, teaching hospitals receive higher reimbursements than community hospitals and clinics. On average, teaching hospitals receive slightly higher reimbursement rates than community hospitals and clinics since they usually accept patients with more serious conditions and provide a better quality of care. For example, in treating acute upper respiratory infections (ICD 9 code 465), the average reimbursement is 299 NT$ for teaching hospitals but just 278 NT$ for clinics and community hospitals.

Table B1: Distribution of Healthcare Providers in Taiwan

City/Counties	Major Teaching Hospital	Minor Teaching Hospital	Community Hospital	Clinic
Taipei City	7	7	22	2,970
Kaohsiung City	2	7	47	1,686
Taipei County	1	9	49	2,756
Ilan County	0	3	8	302
Taoyuan County	1	7	22	1,325
Hsinchu County	0	1	7	315
Miaoli County	0	2	14	353
Taichung County	0	7	27	1,284
Changhua County	1	4	29	991
Nantou County	0	2	8	412
Yunlin County	0	5	10	502
Chiayi County	0	2	2	261
Tainan County	1	3	17	764
Kaohsiung County	1	2	29	882
Pingtung County	0	5	20	626
Taitung County	0	1	5	152
Hualien County	1	2	6	273
Penghu County	0	0	3	82
Keelung City	0	2	5	275
Hsinchu City	0	2	6	380
Taichung City	3	3	23	1,736
Chiayi City	0	3	7	376
Tainan City	2	4	8	918
Kinmen County	0	0	1	32
Lienkiang County	0	0	1	6
Total	20	83	376	19,659

Notes: This table displays the spatial distribution of healthcare providers in Taiwan using 2008 Health and Welfare statistics.

Table B2: Summary Statistics of Regular Outpatient Care: By providers

Providers	Major Teaching Hospital	Minor Teaching Hospital	Community Hospital	Clinic
Visit rate	22.23	30.19	20.62	468.70
Share of respiratory diseases	0.47	0.60	0.62	0.75
Share of digestive diseases	0.08	0.07	0.05	0.06
Share of skin diseases	0.04	0.04	0.03	0.04
Share of injury and poisoning	0.04	0.05	0.11	0.01
Share of mental disorders	0.06	0.04	0.03	0.00
Avg. expenditure (per visit)	999.56	744.80	594.73	407.54
	(7.51)	(4.04)	(3.10)	(0.14)
Avg. OOP expense	113.07	90.45	83.61	76.35
	(0.09)	(0.06)	(0.07)	(0.01)
Share of OOP expense	0.21	0.18	0.19	0.20
Avg. drug fee	180.24	127.08	80.12	49.80
Avg. treatment/examination fee	465.53	278.78	180.52	16.50
Avg. diagnosis fee	198.71	202.74	209.24	250.62
Avg. dispensing fee	43.17	45.93	41.45	14.29
Avg. drug days	6.67	5.09	3.70	3.10
Number of children-visit	82,871	112,552	76,901	1,747,580

Notes: Data are from 2005–2008 NHIRD. The summary statistics are based on healthcare utilization happened within 90 days before the 3^{rd} birthday. Visit rate is number of visit per 10,000 person-days. Average expenditure and average OOP expense are reported in New Taiwan Dollar (NT$). 1 US$ is equal to 32.5 NT$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT$).

Table B3: Summary Statistics of Emergency Room Care: By providers

Providers	Major Teaching Hospital	Minor Teaching Hospital	Community Hospital	Clinic
Visit rate	5.76	8.44	1.95	0.15
Share of respiratory diseases	0.40	0.36	0.25	0.34
Share of digestive diseases	0.14	0.13	0.08	0.04
Share of skin diseases	0.02	0.02	0.02	0.03
Share of injury and poisoning	0.14	0.17	0.43	0.38
Avg. expenditure (per visit)	1788.66	1512.78	1616.23	1273.46
	(9.33)	(6.02)	(12.67)	(38.34)
Avg. OOP expense (per visit)	223.55	194.66	183.96	134.73
	(0.31)	(0.26)	(0.51)	(1.56)
Share of OOP expense	0.16	0.16	0.15	0.14
Avg. drug fee	120.41	83.57	51.36	16.41
Avg. treatment/examination fee	739.12	536.45	720.61	553.12
Avg. diagnosis fee	654.38	647.33	618.10	556.27
Avg. dispensing fee	52.74	51.43	44.58	15.25
Avg. drug day	3.51	2.67	2.25	2.47
Number of children-visit	21,480	31,451	7,268	576

Notes: Data are from 2005–2008 NHIRD. The summary statistics are based on healthcare utilization happened within 90 days before the 3^{rd} birthday. Visit rate is number of visit per 10,000 person-days. Average expenditure and average OOP expense are reported in New Taiwan Dollar (NT$). 1 US$ is 32.5 NT$ in 2006. All expenditures/expenses in our sample period are inflation-adjusted (in 2006 NT$).

C Imputation of Registration Fee

We propose the following two-step procedure to "predict" the registration fees for each regular outpatient and emergency room visit. First, we use the "patient's self-reported answer" on the registration fee, from the 2005 Taiwan National Health Interview Survey (TNHIS) and combine the TNHIS's rich individual information to obtain the determinants of the registration fee.[52] In practice, we estimate the following regression:

$$RegFee_{ij} = \theta_0 + \theta_1 Age_i + \theta_2 Age_i^2 + \sum_{s=1}^{3} \theta_{4j} Level_{sj} + \sum_{k=1}^{24} \theta_{5k} County_{kj} + \upsilon_i$$

$RegFee_i$ is the registration fee that an individual i paid for his/her last visit j. Age_i is individual i's age. $Level_s$ is a set of dummies for the level of healthcare provider, using clinics as the reference group.[53] $County_k$ is a set of dummies for the county in which an individual lives.[54] Second, we utilize the above estimates and combine the corresponding variables in the NHIRD data to obtain a predicted value for the registration fee for each visit. By doing so, we allow much richer variation in registration fees, instead of a fixed-fee amount within each level of healthcare provider. Figure C1 displays the distribution of imputed registration fee for each type of healthcare provider. We also show the (predicted) average registration fees for the four types of healthcare provider in Table 1.

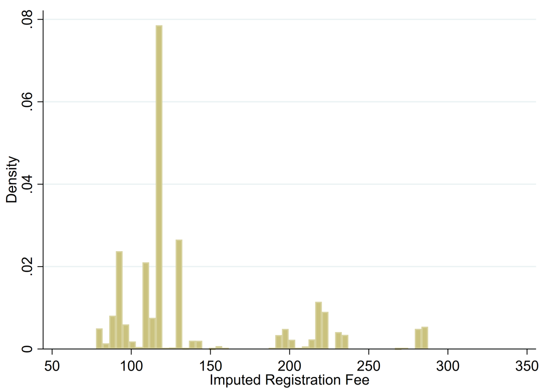
[52] The sample size for estimating the following regression is 4,419 (regular outpatient care) and 577 (emergency room care).

[53] There are 4 types of healthcare provider in Taiwan.

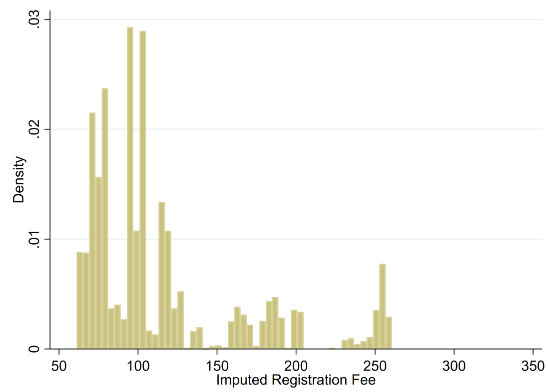
[54] There are 25 counties/cities in Taiwan. We use Taipei county as a reference group.

Figure C1: The Distribution of Imputed Registration Fee:
Outpatient Care

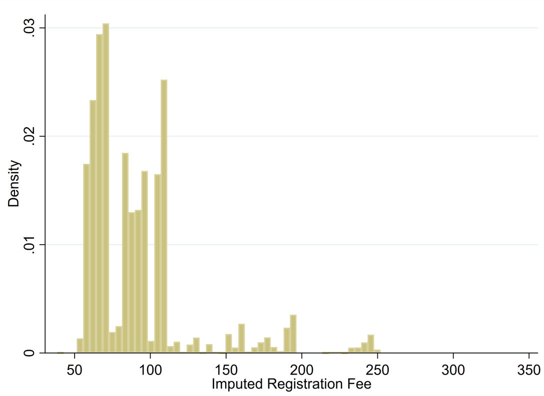
(a) Major Teaching Hospital



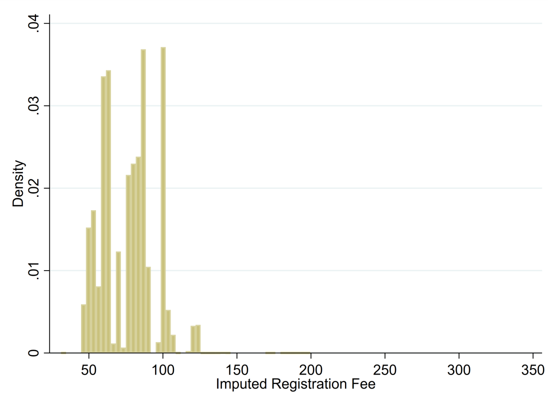
(b) Minor Teaching Hospital



(c) Community Hospital



(d) Clinic



Notes: We pool NHI claims of outpatient care for 2003-2004 birth cohort using 2005-2008 NHIRD data. This figure displays the density of imputed registration fee for each type of healthcare provider. 1 US$ is 32.5 NT$ in 2006. The imputed registration fee in our sample period is inflation-adjusted (in 2006 NT$).

D Sample Selection Process

Table D1: Summary Statistics: Sample Selection

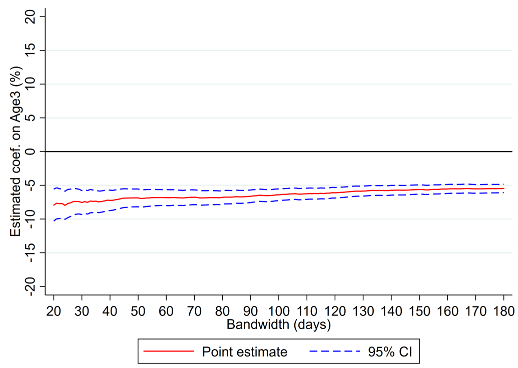
Variables	(1) Original Sample	(2) Continuous enrollment at age two and three	(3) Eliminating cost-sharing waiver
Male	0.52	0.52	0.52
Birth year:2003	0.51	0.51	0.51
Birth year:2004	0.49	0.49	0.49
1st birth	0.53	0.53	0.53
2nd birth	0.36	0.36	0.36
3rd birth	0.09	0.09	0.09
Number of siblings	1.88	1.88	1.87
Number of children	430,547	426,068	414,282

Notes: Column (1) presents the characteristics for original sample: all NHI enrollees who were born in 2003 and 2004 and had with complete demographic information. Column (2) restricts the sample to enrollees who continuously register in NHI at age 2 and 3. Column (3) eliminates observations with cost-sharing waiver, such as children with catastrophic illness (e.g. cancer) or children from very low income families since these children do not experience any price change when turning three.

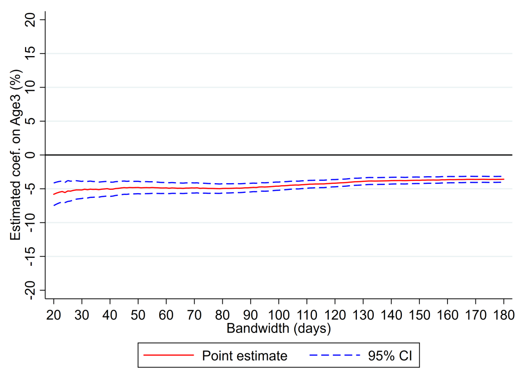
E Robustness Check for Bandwidth Choices

Figure E1: Robustness Check for Bandwidth Choices: Regular Outpatient Care

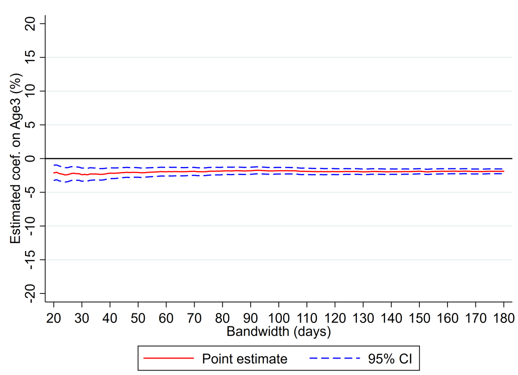
(a) Total expenditure



(b) Number of visit



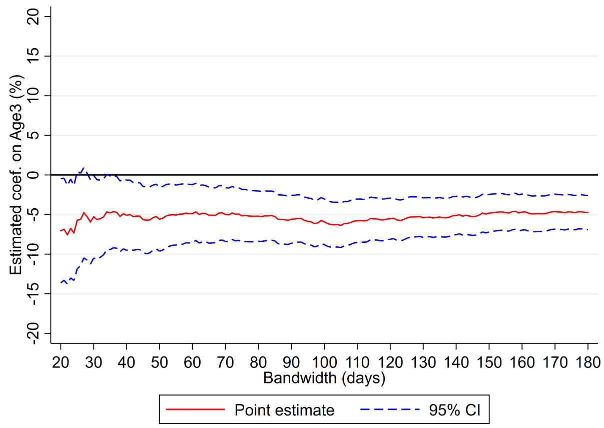
(c) Expenditure per visit



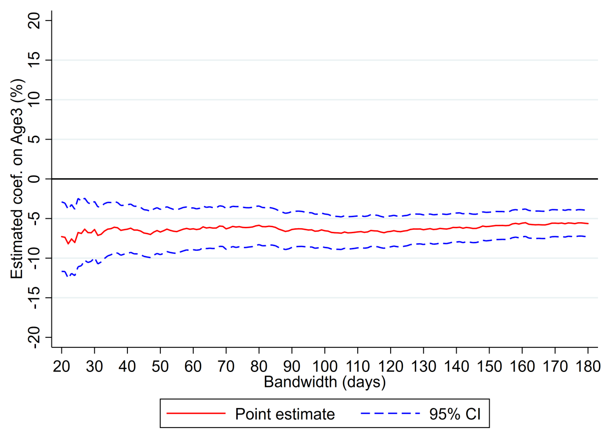
Notes: These figures display the estimated coefficients on $Age3$ (red line) in equation (2) and the corresponding 95% confidence interval (blue dash line) by different bandwidths. The dependent variables in these figures above are the log of total expenditure, the log of number of visits, and the log of expenditure per visit for regular outpatient care.

Figure E2: Robustness Check for Bandwidth Choices: Emergency Room Care

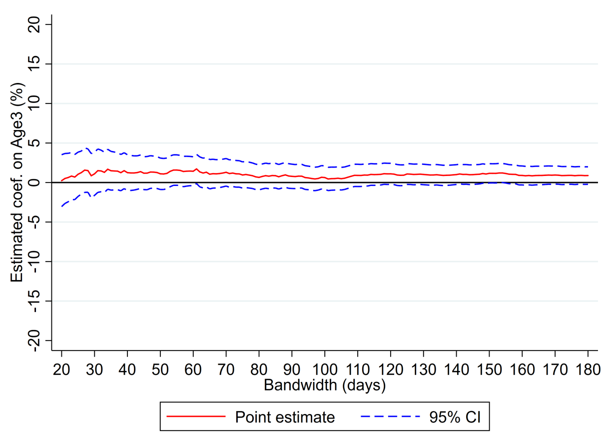
(a) Total expenditure



(b) Number of visit



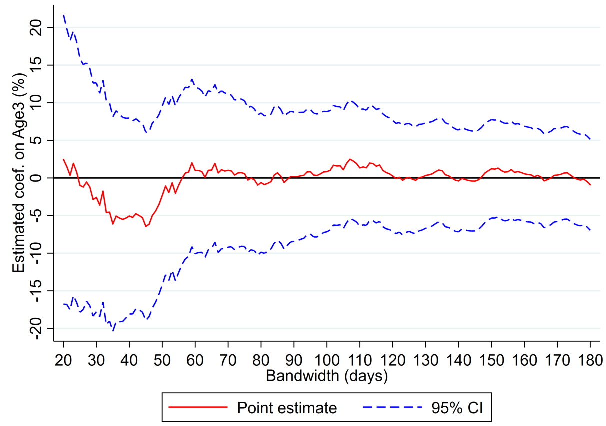
(c) Expenditure per visit



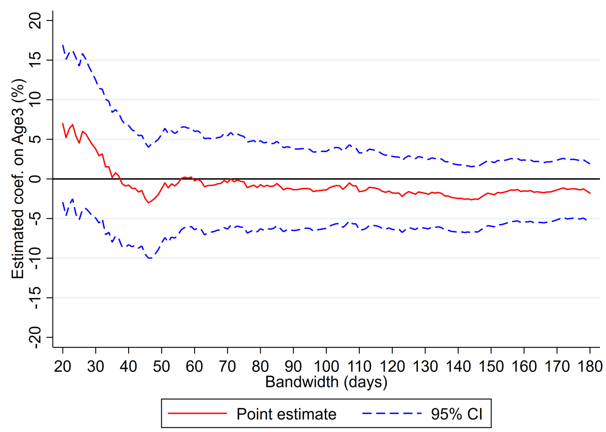
Notes: These figures display the estimated coefficients on $Age3$ (red line) in equation (2) and the corresponding 95% confidence interval (blue dash line) by different bandwidths. The dependent variables in these figures above are the log of total expenditure, the log of number of visits, and the log of expenditure per visit for emergency room care.

Figure E3: Robustness Check for Bandwidth Choices: Inpatient Care

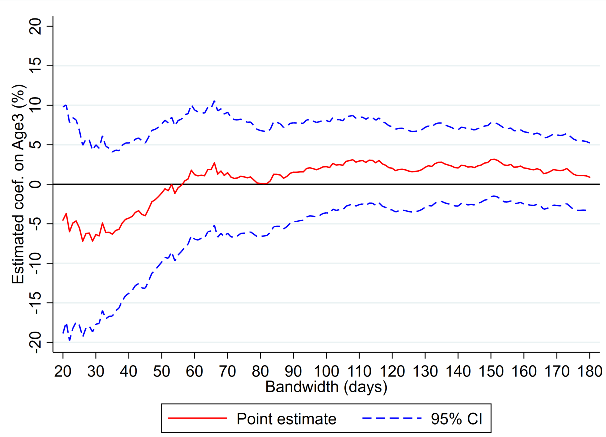
(a) Total expenditure



(b) Number of admission



(c) Expenditure per admission



Notes: These figures display the estimated coefficients on $Age3$ (red line) in equation (2) and the corresponding 95% confidence interval (blue dash line) by different bandwidths. The dependent variables in these figures above are the log of total expenditure, the log of number of admissions, and the log of expenditure per admission for inpatient care.

F Robustness Check for Empirical Specifications

Table F1: Robustness Check for Empirical Specifications: Regular Outpatient Care

	log(total expenditure)					
Bandwidth(days)	60	90	120	150	180	CCT bandwidth
Polynominal						
1	-6.83***	-6.63***	-6.11***	-5.63***	-5.46***	-7.06***
	(0.60)	(0.47)	(0.40)	(0.35)	(0.31)	(0.69)
2	-7.52***	-7.25***	-7.22***	-7.03***	-6.59***	
	(0.95)	(0.74)	(0.63)	(0.55)	(0.49)	
3	-8.44***	-7.55***	-7.42***	-7.49***	-7.52***	
	(1.37)	(1.05)	(0.89)	(0.77)	(0.70)	
	log(# of visits)					
Bandwidth(days)	60	90	120	150	180	CCT bandwidth
Polynominal						
1	-4.87***	-4.82***	-4.17***	-3.75***	-3.58***	-6.32***
	(0.41)	(0.32)	(0.27)	(0.24)	(0.22)	(1.15)
2	-5.19***	-5.11***	-5.38***	-5.06***	-4.64***	
	(0.68)	(0.52)	(0.44)	(0.39)	(0.34)	
3	-6.16***	-5.19***	-5.13***	-5.59***	-5.61***	
	(0.94)	(0.76)	(0.63)	(0.54)	(0.49)	
	log(expenditure/visit)					
Bandwidth(days)	60	90	120	150	180	CCT bandwidth
Polynominal						
1	-1.96***	-1.81***	-1.94***	-1.88***	-1.88***	-1.89***
	(0.33)	(0.27)	(0.22)	(0.19)	(0.18)	(0.27)
2	-2.33***	-2.13***	-1.83***	-1.96***	-1.95***	
	(0.49)	(0.40)	(0.34)	(0.31)	(0.28)	
3	-2.28***	-2.36***	-2.29***	-1.90***	-1.91***	
	(0.66)	(0.54)	(0.47)	(0.41)	(0.37)	

Notes: The estimated sample are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. Row 1 to 3 present the estimated coefficient on $Age3$ using different polynomial models within a given bandwidth. We use the following polynomial models. Row 1: see equation (2); Row 2: quadratic control for age, interacted with dummy for age 3 and older; Row 3: cubic control for age, interacted with dummy for age 3 and older. The last column displays the estimate based on a local linear regression using a triangular kernel. We use the algorithm proposed by (Cattaneo et al., 2014) to select the corresponding bandwidth. The dependent variables are the log of total expenditure, the log of number of visits, and the log of expenditure per visit, at each age in days. The estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

Table F2: Robustness Check for Empirical Specifications: Emergency Room Care

	log(total expenditure)					
Bandwidth(days)	60	90	120	150	180	CCT bandwidth
Polynominal						
1	-4.86***	-5.59***	-5.53***	-4.83***	-4.75***	-5.55***
	(1.84)	(1.53)	(1.32)	(1.21)	(1.09)	(1.51)
2	-6.08**	-4.66**	-5.67***	-6.34***	-5.72***	
	(2.68)	(2.24)	(1.92)	(1.77)	(1.61)	
3	-6.49*	-6.41**	-4.33*	-4.58**	-5.95***	
	(3.85)	(2.94)	(2.54)	(2.30)	(2.09)	
	log(# of visit)					
Bandwidth(days)	60	90	120	150	180	CCT bandwidth
Polynominal						
1	-6.29***	-6.38***	-6.62***	-5.99***	-5.63***	-6.32***
	(1.33)	(1.15)	(0.99)	(0.91)	(0.84)	(1.15)
2	-7.18***	-6.18***	-6.29***	-6.99***	-6.79***	
	(1.87)	(1.59)	(1.43)	(1.29)	(1.20)	
3	-7.26***	-7.72***	-6.33***	-5.99***	-6.84***	
	(2.56)	(2.12)	(1.76)	(1.63)	(1.53)	
	log(expenditure/visit)					
Bandwidth(days)	60	90	120	150	180	CCT bandwidth
Polynominal						
1	1.43	0.78	1.10	1.16*	0.88	0.95
	(0.92)	(0.78)	(0.68)	(0.62)	(0.56)	(0.68)
2	1.09	1.52	0.62	0.65	1.07	
	(1.37)	(1.15)	(0.99)	(0.89)	(0.81)	
3	0.76	1.31	2.00	1.41	0.90	
	(1.85)	(1.52)	(1.31)	(1.17)	(1.07)	

Notes: The estimated sample are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. Row 1 to 3 present the estimated coefficient on $Age3$ using different polynomial models within a given bandwidth. We use the following polynomial models. Row 1: see equation (2); Row 2: quadratic control for age, interacted with dummy for age 3 and older; Row 3: cubic control for age, interacted with dummy for age 3 and older. The last column displays the estimate based on a local linear regression using a triangular kernel. We use the algorithm proposed by (Cattaneo et al., 2014) to select the corresponding bandwidth. The dependent variables are the log of total expenditure, the log of number of visits, and the log of expenditure per visit, at each age in days. The estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

Table F3: Robustness Check for Empirical Specifications: Inpatient Care

	log(total expenditure)					
Bandwidth(days)	60	90	120	150	180	CCT bandwidth
Polynominal						
1	1.01	0.17	0.26	1.22	-0.91	2.11
	(5.60)	(4.35)	(3.74)	(3.32)	(3.07)	(3.73)
2	-7.82	-1.66	0.81	-1.06	2.16	
	(7.96)	(6.66)	(5.78)	(5.05)	(4.62)	
3	-0.88	-5.23	-6.21	0.30	-2.88	
	(10.57)	(8.48)	(7.41)	(6.84)	(6.25)	
	log(# of admissions)					
Bandwidth(days)	60	90	120	150	180	CCT bandwidth
Polynominal						
1	-0.21	-1.36	-1.77	-1.89	-1.80	-0.75
	(3.13)	(2.62)	(2.34)	(2.07)	(1.88)	(2.79)
2	0.43	0.72	0.29	-0.92	-1.07	
	(4.61)	(3.71)	(3.28)	(2.98)	(2.77)	
3	7.95	1.51	0.16	1.46	-0.35	
	(6.12)	(5.03)	(4.30)	(3.84)	(3.53)	
	log(expenditure/admission)					
Bandwidth(days)	60	90	120	150	180	CCT bandwidth
Polynominal						
1	1.22	1.52	2.03	3.12	0.89	2.27
	(4.13)	(3.17)	(2.67)	(2.38)	(2.20)	(2.60)
2	-8.25	-2.37	0.52	-0.13	3.23	
	(5.76)	(5.02)	(4.34)	(3.72)	(3.40)	
3	-8.83	-6.74	-6.37	-1.16	-2.53	
	(7.27)	(6.18)	(5.52)	(5.20)	(4.68)	

Notes: The estimated sample are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. Row 1 to 3 present the estimated coefficient on $Age3$ using different polynomial models within a given bandwidth. We use the following polynomial models. Row 1: see equation (2); Row 2: quadratic control for age, interacted with dummy for age 3 and older; Row 3: cubic control for age, interacted with dummy for age 3 and older. The last column displays the estimate based on a local linear regression using a triangular kernel. We use the algorithm proposed by (Cattaneo et al., 2014) to select the corresponding bandwidth. The dependent variables are the log of total expenditure, the log of number of admissions, and the log of expenditure per admission, at each age in days. The estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

G Donut RDD Analysis

Table G1: Donut RD for Utilization of Regular Patient Care

	log(total expenditure)							
Size of Donut around 3^{rd} birthday	0	3	6	9	12	15	18	21
Age3	-6.63***	-6.42***	-6.45***	-6.30***	-6.08***	-6.11***	-6.21***	-6.06***
	(0.47)	(0.41)	(0.43)	(0.45)	(0.47)	(0.49)	(0.54)	(0.61)
	log(# of visits)							
Size of Donut around 3^{rd} birthday	0	3	6	9	12	15	18	21
Age3	-4.82***	-4.62***	-4.62***	-4.65***	-4.62***	-4.71***	-4.78***	-4.85***
	(0.32)	(0.25)	(0.25)	(0.26)	(0.27)	(0.31)	(0.34)	(0.37)

Notes: The estimated sample are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. We conduct a "donut" RD (Barreca et al., 2011; Shigeoka, 2014) by systematically excluding outpatient expenditure and visits within 3–21 days before and after the 3^{rd} birthday. This table presents the estimated coefficient on $Age3$ in equation (2). The estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

Table G2: Donut RD for Utilization of Emergency Room Care

	log(total expenditure)							
Size of Donut around 3^{rd} birthday	0	3	6	9	12	15	18	21
Age3	-5.59***	-5.17***	-5.24***	-5.24***	-5.03**	-5.13**	-6.78***	-7.47***
	(1.53)	(1.67)	(1.74)	(1.94)	(2.15)	(2.43)	(2.53)	(2.73)
	log(# of visits)							
Size of Donut around 3^{rd} birthday	0	3	6	9	12	15	18	21
Age3	-6.38***	-6.04***	-6.09***	-6.04***	-5.81***	-5.80***	-6.95***	-7.02***
	(1.15)	(1.25)	(1.35)	(1.49)	(1.65)	(1.89)	(1.92)	(2.06)

Notes: The estimated sample are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. We conduct a "donut" RD (Barreca et al., 2011; Shigeoka, 2014) by systematically excluding outpatient expenditure and visits within 3–21 days before and after the 3^{rd} birthday. This table presents the estimated coefficient on $Age3$ in equation (2). The estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

H List of Ambulatory Care Sensitive Conditions (ACSC)

Table H1: List of Ambulatory Care Sensitive Conditions (ACSC)

Diagnosis	ICD 9 Code
Immunization preventable conditions	033, 037, 045, 320.0, 390, 391
Grand mal status	345
Convulsions “A”	780.3
Severe ENT infections	382, 462, 463, 465, 472.1
Bacterial pneumonia	481, 482.2, 482.3, 482.9, 483, 485, 486
Asthma	493
Tuberculosis	011–018
Cellulitis	681, 682, 683, 686
Diabetes “A”	250.1, 250.2, 250.3
Diabetes “B”	250.8, 250.9
Diabetes “C”	250.0
Hypoglycemia	251.2
Gastroenteritis	558.9
Kidney/urinary infection	590, 599.0, 599.9
Dehydration-volume depletion	276.5
Iron deficiency anemia	280.1, 280.8, 280.9
Nutritional deficiencies	260, 261, 262, 268.0, 268.1

Notes: This table displays the diagnosis and the corresponding ICD 9 code for Ambulatory Care Sensitive Conditions (ACSCs). ACSCs are developed by the Agency for Healthcare Research and Quality (AHRQ) to study the type of outpatient care that may reduce the need for inpatient admissions. Thus, these outpatient care are usually considered as beneficial treatment (i.e. less moral hazard).

I List of Top 5 Diagnosis in Non-Deferrable Visits

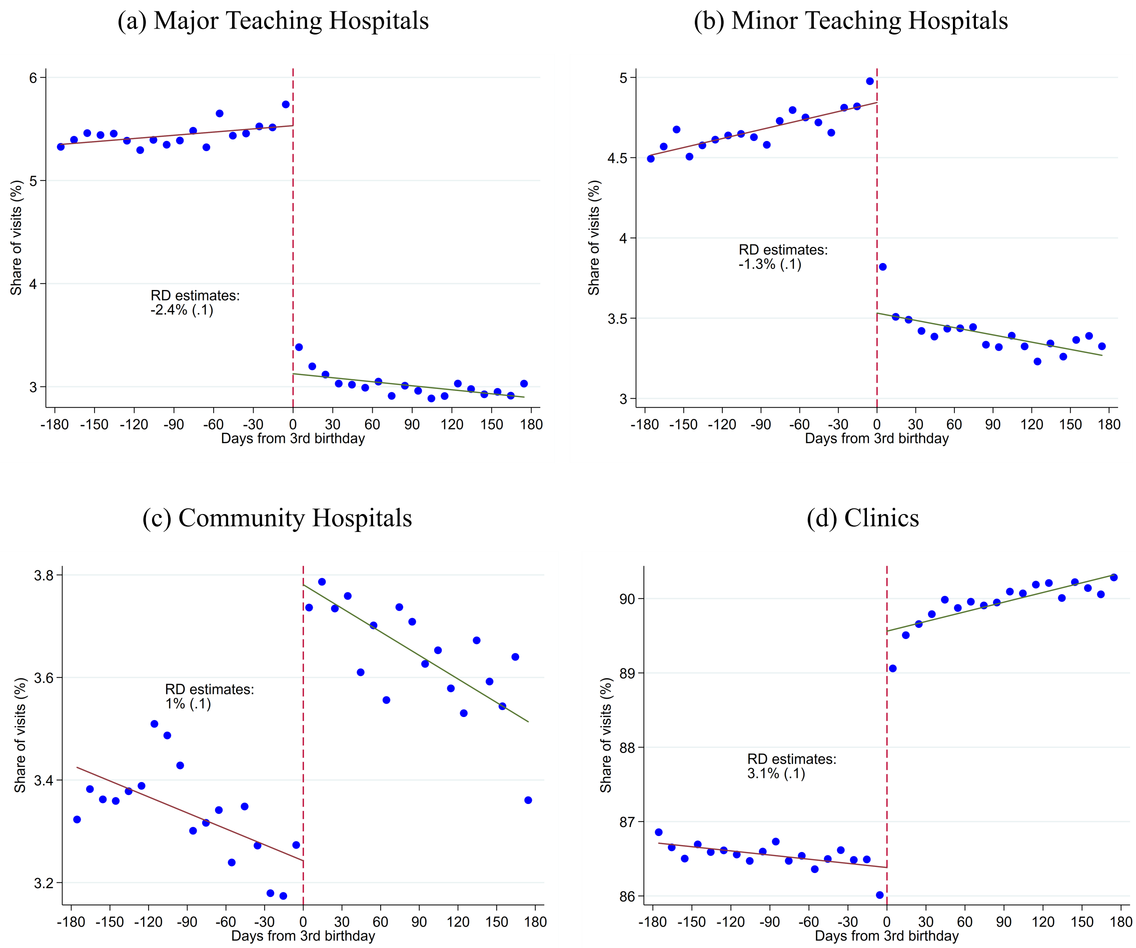
Table I1: List of Top 5 Diagnosis in Non-Deferrable Visits

Diagnosis	ICD 9 Code	Share
Panel A: Regular Outpatient Care		
Tracheostomy complications	519	54.1%
Peritonsillar abscess	475	17.0%
Pneumonia And Influenza	480	12.7%
Relapsing fever	087	7.9%
Nasal polyps	471	3.7%
Panel B: Emergency Room Care		
Concussion	850	21.2%
Open wound of finger(s)	883	15.8%
Open wound of ocular adnexa	870	5.4%
Foreign body in mouth esophagus and stomach	935	5.1%
Open wound of hand except finger(s) alone	882	4.6%

Notes: This table lists the top 5 diagnosis that are considered as non-deferrable conditions and their corresponding ICD 9 codes. Inspired by Card et al. (2009), we identify the visits for non-deferrable conditions by using pre-reform (i.e. 2001) data and a set of 3-digit ICD 9 diagnosis codes that have similar visit rates on weekdays and weekends. For instance, if a given diagnosis code has similar emergency room visit rate on a weekend and on a weekday, then weekend visits should account for around 0.29 (2/7) of total visits for this specific diagnosis code. Therefore, we define the visits with diagnosis codes whose fraction of weekend visits is close to 0.29 as visits for non-deferrable conditions.

J Additional Results on Regular Outpatient Care

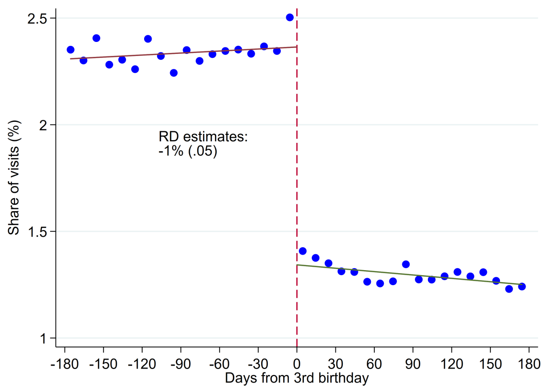
Figure J1: Provider Choice for Regular Outpatient Care Before and After the 3^{rd} Birthday: Birthplace with Major Teaching Hospitals



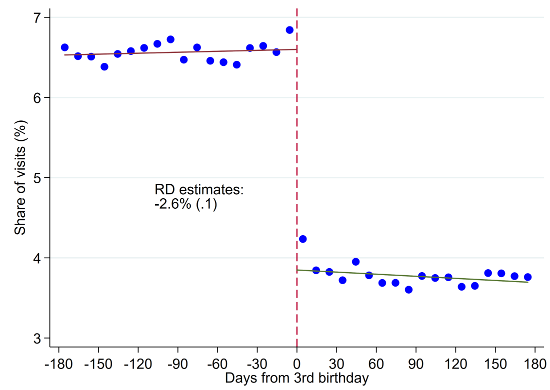
Notes: We pool NHI claims of regular outpatient care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variable is share of visits for each type of healthcare provider. We restrict sample to the children born in a city/county with at least one major teaching hospitals. The age at visit is measured in days. We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable. The line is from fitting a linear regression on age variables fully interacted with $Age3$. The RD estimates are based on estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth. The standard error of the RD estimates are presented in parentheses.

Figure J2: Provider Choice for Regular Outpatient Care Before and After the 3^{rd} Birthday: Birthplace without Major Teaching Hospitals

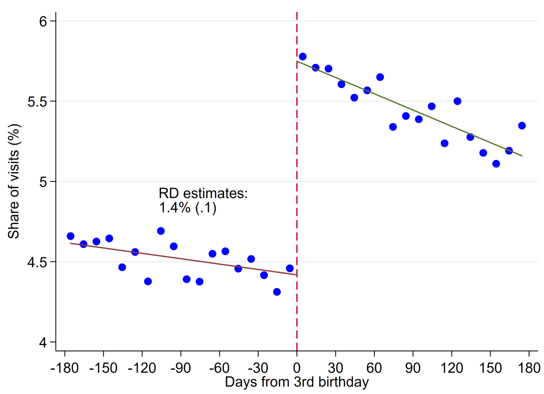
(a) Major Teaching Hospitals



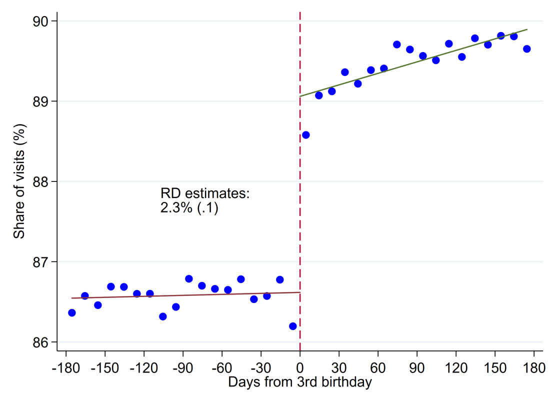
(b) Minor Teaching Hospitals



(c) Community Hospitals



(d) Clinics



Notes: We pool NHI claims of regular outpatient care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variable is share of visits for each type of healthcare provider. We restrict sample to the children born in a city/county without any major teaching hospital. The age at visit is measured in days. We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable. The line is from fitting a linear regression on age variables fully interacted with $Age3$. The RD estimates are based on estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth. The standard error of the RD estimates are presented in parentheses.

K Details of the Construction of the Conditional Probability of a Shift in Healthcare Provider

Given the provider type of the last visit, we carry out the following steps to calculate the conditional transition probability of a shift in provider:

- Step 1: we order the outpatient visits by visit date to determine the provider type of both the last visit and the current visit.

- Step 2: based on the provider type of the last visit, we define the type of shift in provider for each visit. In our case, the last visit could be to either a high-intensity provider or a low-intensity provider. If the last visit was to a high-intensity provider, we have the following types of shift in provider: (1) from high- to high-intensity provider; (2) from high- to low-intensity provider. Similarly, if the previous visit was to a low-intensity provider, we can define the following types of shift in provider: (1) from low- to low-intensity provider; (2) from low- to high-intensity provider.

- Step 3: using the above definition, we calculate the number of visits for each type of shift at a given age (i.e., the age at the time of the current visit). N_h^h (N_l^h): the number of visits to high-intensity providers (low-intensity providers) when the last visit was to a high-intensity provider. N_l^l (N_h^l): the number of visits to low-intensity providers (high-intensity providers) when the last visit was to a low-intensity provider.

- Step 4: we also need to calculate the number of times the last visit was to a high-intensity provider (N^h) or a low-intensity provider (N^l) at a given age, respectively:

$$N^h = N_h^h + N_l^h$$

$$N^l = N_l^l + N_h^l$$

These numbers serve as the denominator of the conditional probability for each type of shift.

- Step 5: we combine the above information to get the conditional probability of each type of shift at a given age. For example, to obtain the conditional probability for moving from a high- to a low-intensity provider, we divide the number of visits where the patient has moved from a high- to a low-intensity provider (steps 2 & 3) by the number of previous visits to high-intensity providers (step 4):

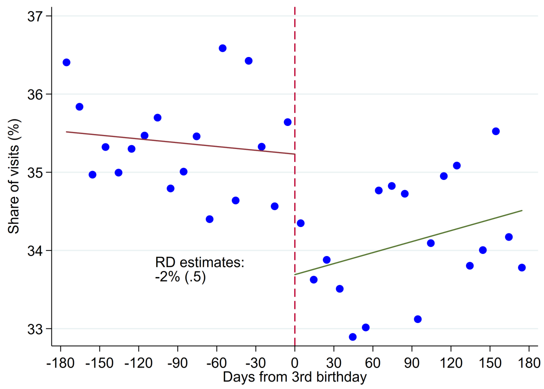
$$\text{Prob}(visit_t = low|visit_{t-1} = high) = \frac{N_l^h}{N_l^h + N_h^h}$$

For other types of shift, we use a similar logic to calculate the conditional probabilities.

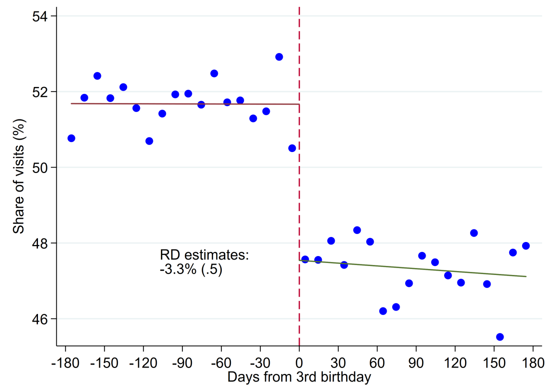
L Additional Results on Emergency Room Care

Figure L1: Provider Choice Before and After the 3^{rd} Birthday:
Emergency Room Care

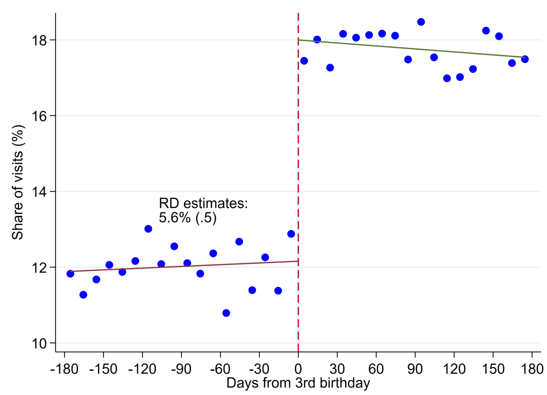
(a) Major Teaching Hospital



(b) Minor Teaching Hospital



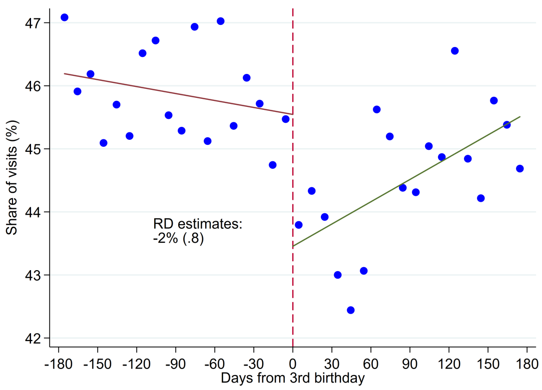
(c) Community Hospital



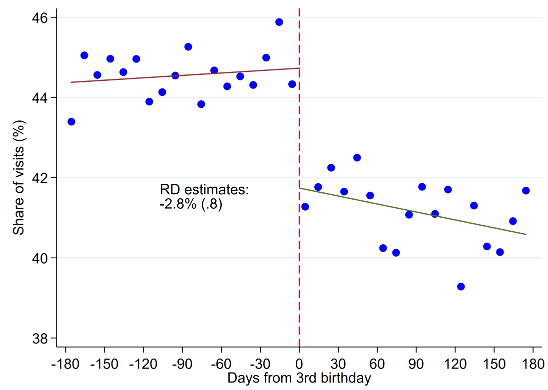
Notes: We pool NHI claims of emergency room care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variable is share of visits for each type of healthcare provider. The age at visit is measured in days. We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable. The line is from fitting a linear regression on age variables fully interacted with $Age3$. The RD estimates are based on estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth. The standard error of the RD estimates are presented in parentheses.

Figure L2: Provider Choice for Emergency Room Care Before and After the 3^{rd} Birthday: Birthplace with Major Teaching Hospitals

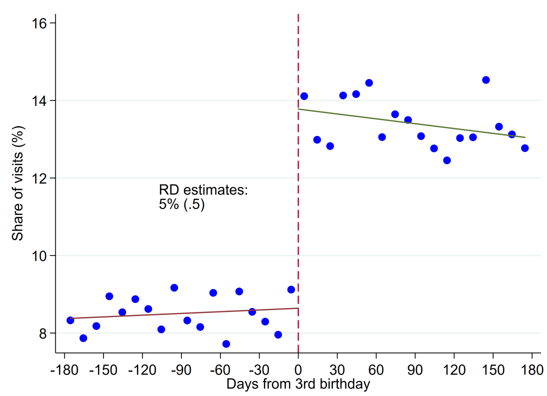
(a) Major Teaching Hospitals



(b) Minor Teaching Hospitals



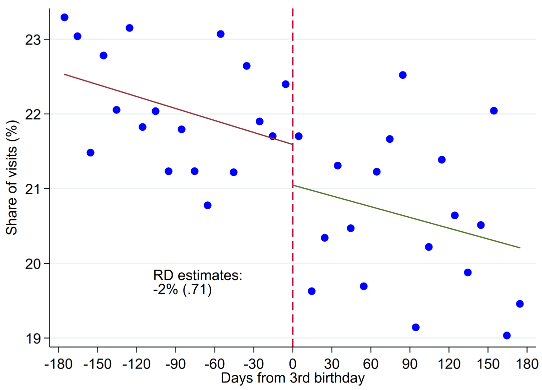
(c) Community Hospitals



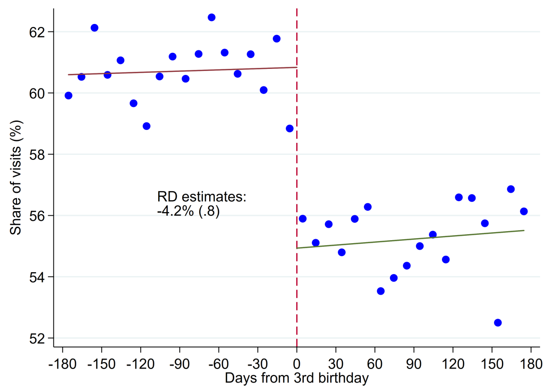
Notes: We pool NHI claims of emergency room care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variable is share of visits for each type of healthcare provider. We restrict sample to the children born in a city/county with at least one major teaching hospitals. The age at visit is measured in days. We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable. The line is from fitting a linear regression on age variables fully interacted with $Age3$. The RD estimates are based on estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth. The standard error of the RD estimates are presented in parentheses.

Figure L3: Provider Choice for Emergency Room Care Before and After the 3^{rd} Birthday: Birthplace without Major Teaching Hospitals

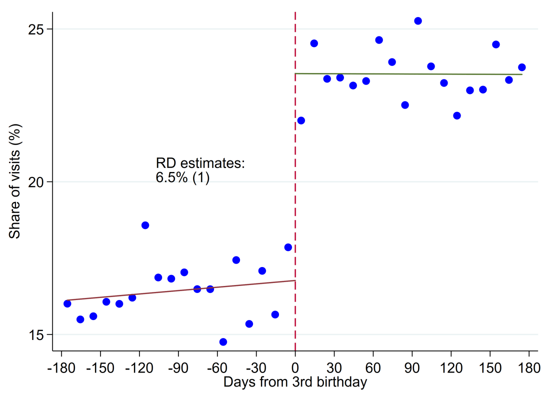
(a) Major Teaching Hospitals



(b) Minor Teaching Hospitals



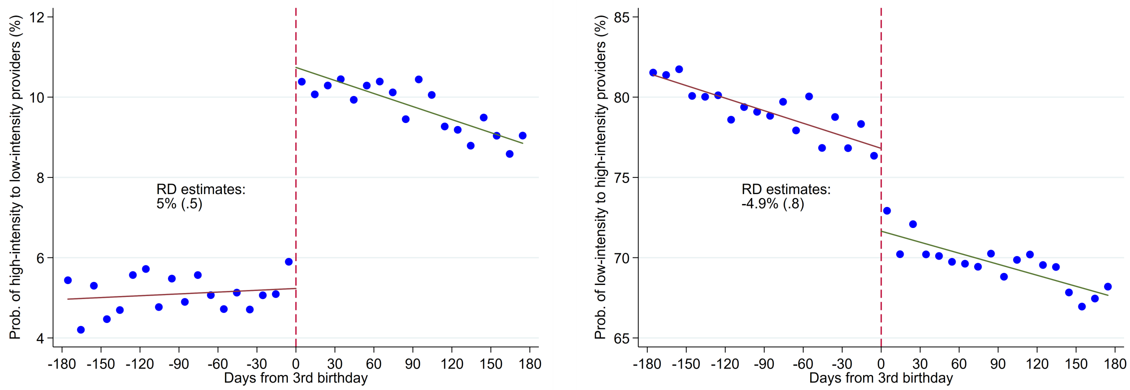
(c) Community Hospitals



Notes: We pool NHI claims of emergency room care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variable is share of visits for each type of healthcare provider. We restrict sample to the children born in a city/county without any major teaching hospital. The age at visit is measured in days. We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable. The line is from fitting a linear regression on age variables fully interacted with $Age3$. The RD estimates are based on estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth. The standard error of the RD estimates are presented in parentheses.

Figure L4: Providers Switching Before and After the 3^{rd} Birthday:
Emergency Room Care

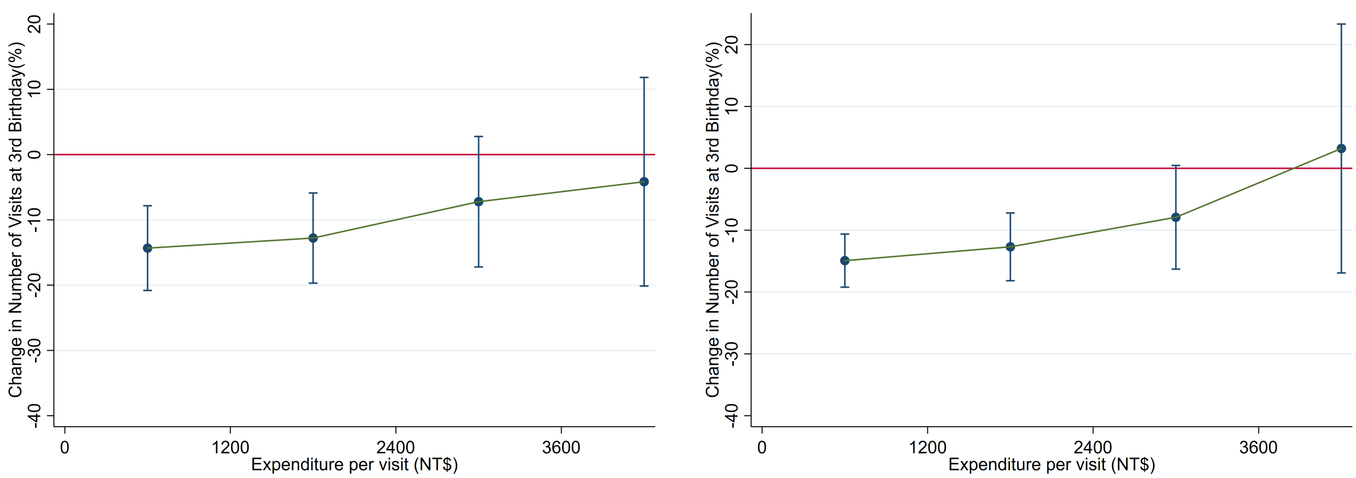
(a) Prob. of high-intensity to low-intensity providers (b) Prob. of low-intensity to high-intensity providers



Notes: We pool NHI claims of emergency room care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variables in Figure L4a is conditional probability of current visit is low-intensity provider (i.e. community hospitals/clinics) given the last visit is high-intensity provider (i.e. teaching hospitals). The dependent variables in Figure L4b is conditional probability of current visit is high-intensity provider (i.e. teaching hospitals) given the last visit is low-intensity provider (i.e. community hospitals/clinics). We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable. The line is from fitting a linear regression on age variables fully interacted with $Age3$.

Figure L5: Utilization Responses at the 3^{rd} birthday
By Expenditure per Emergency Room Visit

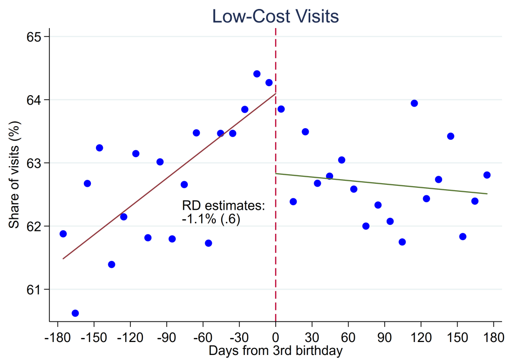
(a) Percent Change in Visits to Major Teaching Hospital (b) Percent Change in Visits to Minor Teaching Hospital



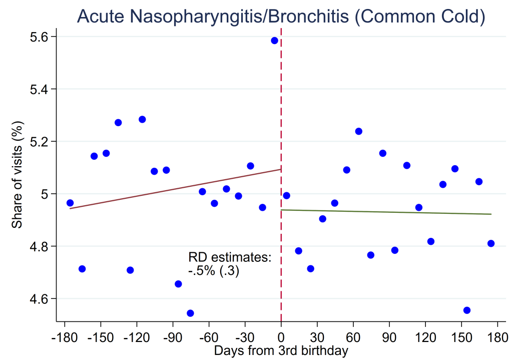
Notes: We pool NHI claims of emergency room care for 2003-2004 birth cohort using 2005-2008 NHIRD data. We estimate equation (2) separately by expenditure per regular outpatient visit: (1) 0-1,200 NT$; (2) 1,201-2,400 NT$; (3) 2,401-3,600 NT$; (4) above 3,601 NT$ for major teaching hospital visits (see Figures L5a) and minor teaching hospital visits (see Figures L5b). 1 US$ is 32.5 NT$ in 2006. All expenditures in our sample period are inflation-adjusted (in 2006 NT$). The dotted line in Figures L5a and L5b displays the estimated coefficients on $Age3$ in equation (2) using a 90-days bandwidth and the corresponding 95% confidence intervals.

Figure L6: Composition Change in Teaching Hospital Visits at the 3^{rd} birthday: Emergency Room Care

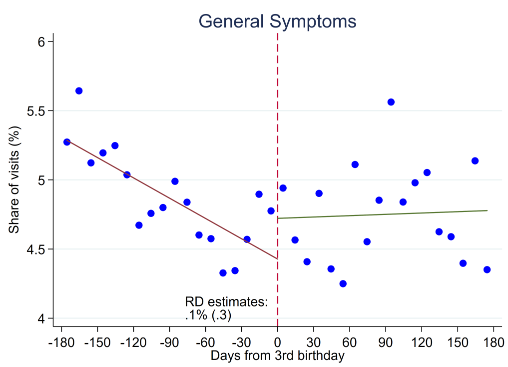
(a) Low-Cost Visits



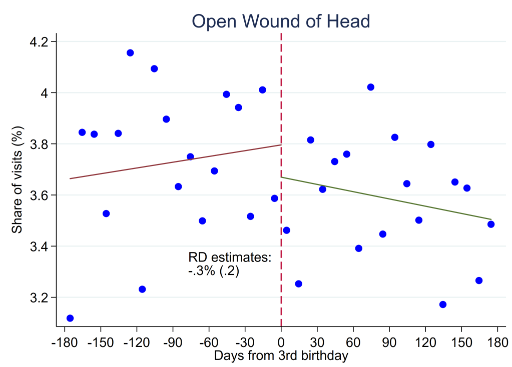
(b) Acute Nasopharyngitis/Bronchitis (Common Cold)



(c) General Symptoms



(d) Open Wound of Head



Notes: We pool NHI claims of emergency room care for 2003-2004 birth cohort using 2005-2008 NHIRD data. The dependent variable is share of visits for selected diagnosis. The age at visit is measured in days. We plot the dependent variable within 180 days before and after the 3^{rd} birthday and group up it every ten days as a bin from the 3^{rd} birthday. Thus, each dot represents the 10-day average of the dependent variable. The line is from fitting a linear regression on age variables fully interacted with $Age3$. The RD estimates are based on estimated coefficient on $Age3$ in equation (2) using a 90-days bandwidth. The standard error of the RD estimates are presented in parentheses.

M Examine Own-Price Elasticity

Table M1: List of Diagnosis Group

No.	Diagnosis Group	ICD 9
1	Intestinal Infectious Diseases	001-009
2	Tuberculosis	010-018
3	Other Bacterial Diseases	020-041
4	Viral Diseases	045-079
5	Rickettsiosis and Other Arthropod-borne Diseases	080-088
6	Venereal Diseases	090-099
7	Other Infectious and Parasitic Diseases and Late Effects of Infectious and Parasitic Diseases	100-139
8	Malignant Neoplasm of Lip, Oral Cavity, and Pharynx	140-149
9	Malignant Neoplasm of Digestive Organs and Peritoneum	150-159
10	Malignant Neoplasm of Respiratory and Intrathoracic Organs	160-165
11	Malignant Neoplasm of Bone, Connective Tissue, Skin, and Breast	170-175
12	Malignant Neoplasm of Genitourinary Organs	179-189
13	Malignant Neoplasm of Other and Unspecified Sites	190-199
14	Malignant Neoplasm of Lymphatic and Hematopoietic Tissue	200-208
15	Benign Neoplasm	210-229
16	Carcinoma in Situ	230-234
17	Other and Unspecified Neoplasm	235-239
18	Endocrine and Metabolic Diseases, Immunity Disorders	240-259 270-279
19	Nutritional Deficiencies	260-269
20	Diseases of Blood and Blood-forming Organs	280-289
21	Mental Disorders	290-319
22	Diseases of the Nervous System	320-359
23	Disorders of the Eye and Adnexa	360-379
24	Diseases of the Ear and Mastoid Process	380-389
25	Rheumatic Fever and Heart Disease	390-398
26	Hypertensive Disease	401-405
27	Ischemic Heart Disease	410-414
28	Diseases of Pulmonary Circulation and Other Forms of Heart Disease	415-429
29	Cerebrovascular Disease	430-438
30	Other Diseases of the Circulatory System	440-459
31	Diseases of the Upper Respiratory Tract	460-465, 470-478
32	Other Diseases of the Respiratory System	466, 480-519
33	Diseases of Oral Cavity, Salivary Glands, and Jaws	520-529
34	Diseases of Other Parts of the Digestive System	530-579
35	Diseases of Urinary System	580-599
36	Diseases of Male Genital Organs	600-608
37	Diseases of Female Genital Organs	610-629
38	Abortion	630-639
39	Direct Obstetric Causes	640-646
40	Indirect Obstetric Causes	647-648
41	Normal Delivery	650
42	Diseases of Skin and Subcutaneous Tissue	680-709
43	Diseases of the Musculoskeletal System and Connective Tissue	710-739
44	Congenital Anomalies	740-759
45	Certain Conditions Originating in the Perinatal Period	760-779
46	Signs, Symptoms, and Ill-defined Conditions	780-799
47	Fractures	800-829
48	Dislocations, Sprains, and Strains	830-848
49	Intracranial and Internal Injuries, Including Nerves	850-869 950-957
50	Open Wounds and Injury to Blood Vessels	870-904

Table M1: List of Diagnosis Group (Continued)

No.	Diagnosis Group	ICD 9
51	Effects of Foreign Body Entering through Orifice	930-939
52	Burns	940-949
53	Poisonings and Toxic Effects	960-989
54	Complications of Medical and Surgical Care	996-999
55	Other Injuries, Early Complications of Trauma	910-929, 958-959, 990-995
56	Late Effects of Injuries, of Poisonings, of Toxic Effects, and of Other External Causes	905-909

Note: This table display 56 groups of diagnosis and their corresponding ICD 9 code based on the Basic Tabulations of Diagnoses.

Table M2: Examine Own-Price Elasticity

Variables	(1) OOP expense	(2) log(total expenditure)	(3) log(# of visits)	(4) log(expenditure/visit)	(5) elasticity
Dominated by Regular Outpatient Care					
Age3	61.46***	-6.32***	-4.51***	-1.81***	-0.11
	(2.57)	(0.40)	(0.32)	(0.19)	
Dominated by Emergency Room Care					
Age3	261.24***	-9.43***	-9.13***	-0.30	-0.12
	(10.21)	(3.38)	(2.64)	(1.99)	
Dominated by Inpatient Care					
Age3	1360.95***	1.36	0.19	1.16	0.01
	(68.57)	(6.55)	(3.60)	(5.59)	

Notes: The estimated sample in the first and third row are 414,282 children born in 2003 to 2004. We use 2005-2008 NHIRD data to get their healthcare utilization around age 3. We collapse the individual-level data into age cells and measure age in days. We select the diagnosis groups where regular outpatient care (emergency room care, inpatient care) accounts for the highest fraction of expenditure among the three types of healthcare services to represent own-price elasticity for regular outpatient care (emergency room care, inpatient care). Column (1)-(4) present the estimated coefficient on Age3 in equation (2) using a 90-days bandwidth (i.e. 180 observations). The dependent variables in all the regressions above are average OOP expense (NT$), the log of total expenditure, the log of number of visits (admissions), and the log of expenditure per visit (admission), at each age in days. For column (2) - (4), the estimated coefficients are multiplied by 100 to show the percentage change in the outcome. Column (5) displays estimated price elasticity of total expenditure using the information from Column (1) and (2). 1 US$ is 32.5 NT$ in 2006. All expenditures/expenses in our sample period are inflation-adjusted (in 2006 NT$). Robust standard errors are in parentheses. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

N Results for Children's Health

Thus far, our results imply that the cost-sharing subsidy significantly increases the utilization of outpatient care and causes patients to switch from low-intensity to high-intensity providers. Receiving more treatments could result in better health. However, we also find that the subsidy induces patients to visit high-intensity providers when they have minor illnesses. In addition, the subsidy has little impact on the utilization of inpatient care. Therefore, based on the results on utilization, it is unclear whether the cost-sharing subsidy really benefits children's health.

N.1 Impact on Contemporaneous Health

In this section, we examine the effect of the increase in the amount of cost sharing at age 3 on contemporaneous (short-term) health outcomes. We first use mortality to measure children's health and utilize a RD design by comparing the mortality of children immediately before and after age 3.

Figure N1a displays the age profiles of the mortality rate per 10,000 person-months among children born in 2003-2004 and aged between 2 and 4 using 2005–2008 Cause of Death Registry data.[55] Since Cause of Death Registry data only provide information on people's birth month and death month, we measure the children's age at death in months. Thus, each dot represents the number of death per 10,000 person-months. We find that mortality does not exhibit a significant discontinuity at age 3.[56] Our result suggests that increased cost sharing at age 3 does not lead to higher mortality for the children just over 3 years old than for those just under 3 years old.[57]

In addition to the mortality rate, we examine the impact of cost sharing on a less severe health outcome measure—the presence of complex health problems. Specifically, following Iizuka and Shigeoka (2018), we use the occurrence of pediatric complex chronic conditions (CCCs), developed by Feudtner et al. (2000) to measure children's health status.[58] Notice that the presence of

[55] The Cause of Death Registry covers all deaths in Taiwan and uses ICD 9 codes to record causes of death. We computed the mortality rate by dividing the total number of deaths at a particular age by the number of children born in 2003 and 2004, and then multiplying this figure by 10,000.

[56] The point estimate is -0.037, which is based on equation (2) using a 12-months bandwidth.

[57] Our estimates can rule out that the expiration of cost-sharing subsidy at age 3 increases mortality rate by more than 0.047 per 10,000 person-months.

[58] The definition of a CCC is "Any medical condition that can be reasonably expected to last at least 12 months (unless death intervenes) and to involve either several different organ systems or 1 organ system severely enough to

pediatric CCCs substantially increases children's one-year mortality rate. The diagnoses of CCCs and corresponding ICD 9 codes are listed in Table N1. For comparison with the mortality results in Figure N1a, Figure N1b displays the age profiles of the morbidity rate of pediatric CCCs (per 10,000 person-months) from 12 months before the 3^{rd} birthday to 12 months after it.[59] There is little evidence of any discontinuity in the morbidity rate of pediatric CCCs at age 3.[60] The above results might not be surprising since our utilization results imply marginal patients may only reduce low-value visits in response to higher cost sharing after the 3^{rd} birthday, which might not affect their health status. More importantly, the health effect (if any) is probably hard to detect in the short term, since it will only gradually deteriorate the stock of health (Grossman, 1972).

N.2 Impact on Later-Life Health

In this section, we investigate whether the cost-sharing subsidy in early childhood has any effect on the health of children at older ages. Our identification strategy exploits the fact that the length of the period for which a child is eligible for the cost-sharing subsidy is determined by his or her birth date. For example, individuals born before March 1, 1999 were ineligible for the subsidy (i.e., the control group). Thus, Figure N2a indicates that the number of days on which children in this group were eligible for the cost-sharing subsidy is zero. For those born between March 2, 1999 and March 1, 2002, however, the number of days on which they were eligible ranges between 1 and 1,096 days (i.e., the treatment group). Therefore, the number of eligible days is an increasing function of birth date for this group, as shown in Figure N2a.

Consistent with this observation, as seen in Figure N2b, the average OOP expense per visit and the birth date exhibit a negative relationship for those born after March 1, 1999. Not surprisingly, the healthcare expenditure and the number of outpatient visits for this cohort increase as their birth date becomes more recent, due to the cost-sharing subsidy. Figures N2c and N2d show the relationship between the birth date and outpatient expenditure, at all providers and at teaching

require specialty pediatric care and probably some period of hospitalization in a tertiary care center."

[59]Similarly, we computed the morbidity rate by dividing the total number of inpatient admissions with pediatric CCCs at a particular age by the number of enrollees born in 2003 and 2004, and then multiplying this figure by 10,000.

[60]The point estimate based on equation (2) and a 12-months bandwidth is -0.128, which is insignificantly different from zero.

hospitals, respectively. From these two figures, it is obvious that the outpatient expenditure, either at all providers or just at teaching hospitals, becomes more positively correlated with the birth date for the children born after March 1, 1999, implying that the cost-sharing subsidy induces the use of more healthcare for these children in their early life. In spite of that, there is no systematic relationship between the birth date and the morbidity rate of pediatric CCCs when children are older. Figure N3 shows that there is almost no change in the slope of the relationship between children's later-life health and their birth date after March 1, 1999, as measured for various age groups (age 5-11, age 5-7, age 7-9, and age 9-11). Table N2 provides the summary statistics of the sample (i.e. treatment/control groups) used to estimate the long/medium-term health effects.

To understand the statistical significance of the above findings, we estimate the following regression:

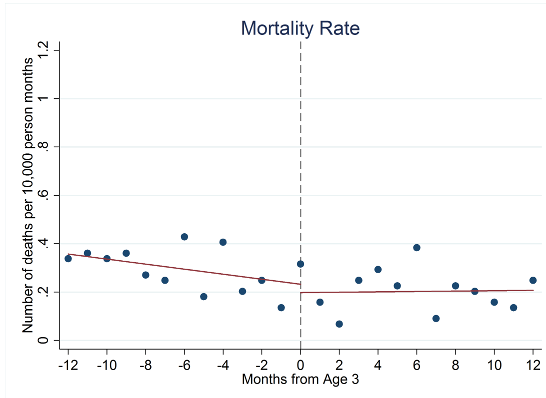
$$H_i = \kappa_0 + \kappa_1 After99_i + \kappa_2 Distance1999_i + \kappa_3 After99_i * Distance1999_i + \kappa_4 X_i + \varsigma_i \tag{N.1}$$

The H_i are the outcome variables, which can represent (1) the average OOP expense per visit for individual i aged 2-3; (2) the outpatient expenditure across all providers for individual i aged 2-3; (3) the outpatient expenditure at teaching hospitals for individual i aged 2-3; (4) the presence of pediatric CCCs, a dummy indicating that an individual i has at least one inpatient admission for a pediatric CCC, over various age groups (age 5-11, age 5-7, age 7-9, and age 9-11). $Distance1999_i$ denotes the number of days between individual i's birth date and March 1, 1999. $After99_i$ is a dummy indicating that individual i's birth date is later than March 1, 1999. The key variable is the interaction term between $After99_i$ and $Distance1999_i$. Its coefficient, κ_3, measures the changes in the slopes of the relationships between the outcome variables and the child's birth date, for individuals born just before and those born just after March 1, 1999. As mentioned before, the length of eligibility for the cost-sharing subsidy and the child's birth date have a positive relationship for the children born after March 1, 1999. If there are no other confounding factors that might affect the healthcare utilization or health of children born around March 1, 1999, κ_3 will represent the causal effect of the cost-sharing subsidy on the outcome variables.

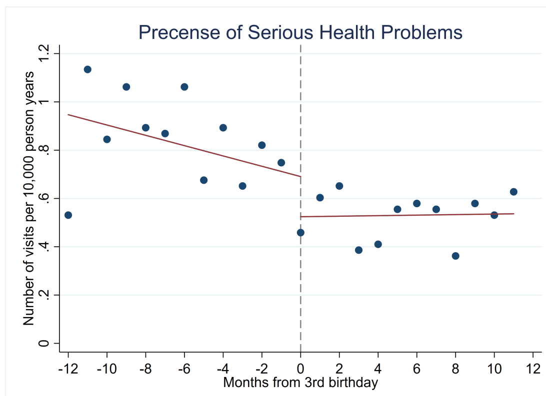
Table N3 reports the effect of the cost-sharing subsidy on healthcare utilization for children aged 2-3. The coefficients of $After99 * Distance1999$ (i.e. κ_3) suggest that the cost-sharing subsidy significantly reduces the average OOP cost per visit, by 67.1 NT$. In addition, a one-year cost-sharing subsidy can increase outpatient expenditure during the ages 2-3 by 303.4 NT$ (i.e., by around 3%). Most increases in outpatient expenditure occur at teaching hospitals. A one-year cost-sharing subsidy can increase outpatient expenditure at teaching hospitals during the ages 2-3 by 322.4 NT$ (i.e., by around 17%). Nonetheless, the increase in healthcare use does not seem to contribute to children's health. Table N4 displays the effect of the cost-sharing subsidy on the occurrence of pediatric CCCs during the ages 5-11. In contrast to the results in Table N3, none of the estimated coefficients on $After99 * Distance1999$ (i.e. κ_3) is statistically significant. In sum, our findings imply that the cost-sharing subsidy has little impact on children's health later in life.

Figure N1: Mortality and Morbidity Rate Before and After the 3^{rd} Birthday

(a) Mortality Rate

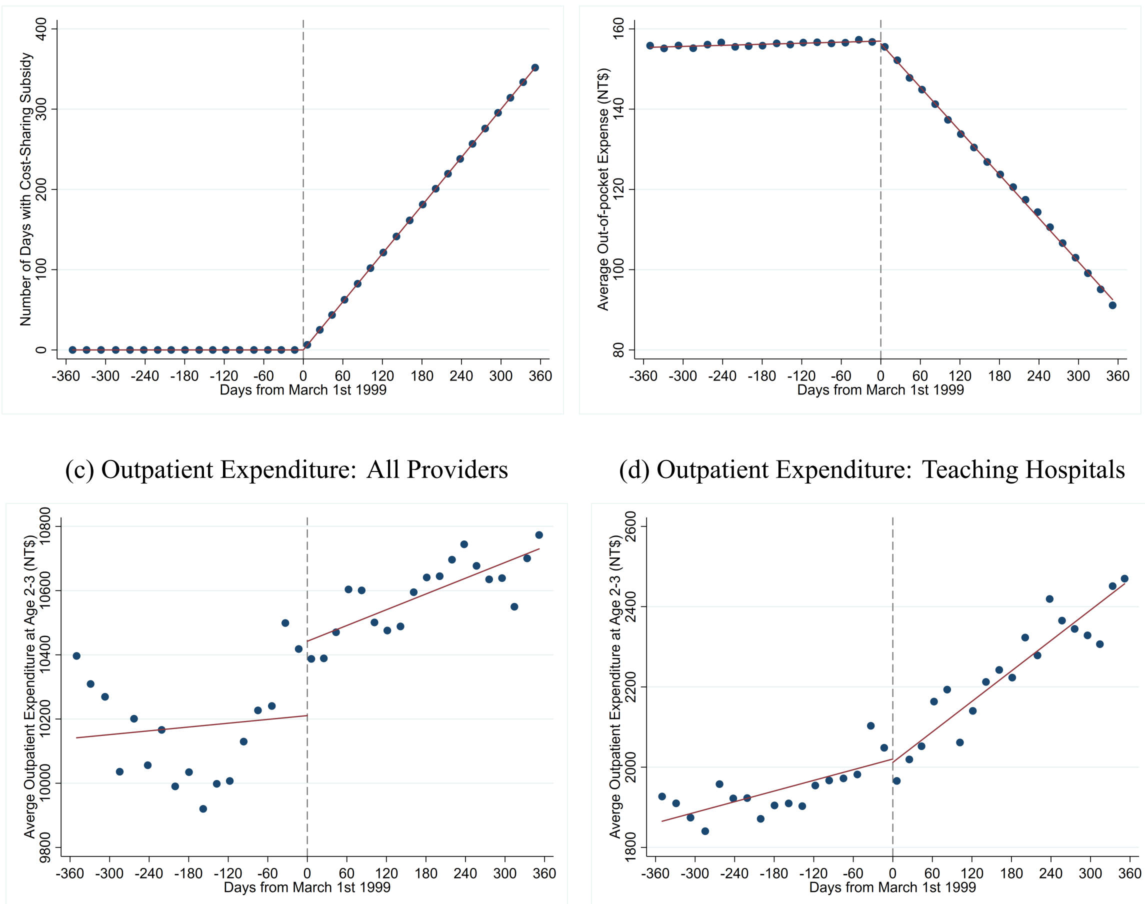


(b) Morbidity Rate of Pediatric Complex Chronic Conditions



Notes: Figure N1a displays the age profiles of the mortality rate per 10,000 person-months among children born in 2003-2004 and aged between 2 to 4 using 2005-2008 death registry data. The age at death is measured in months. Figure N1b displays the age profiles of morbidity rate per 10,000 persons-months for pediatric complex chronic conditions (CCCs) from 12 months before 3^{rd} birthday to 12 months after it. The diagnosis of CCCs and corresponding ICD 9 codes are listed in Table N1.

Figure N2: The Effect of Cost-Sharing Subsidy on Healthcare Utilization During Age 2-3



(a) Number of Days with Cost-Sharing Subsidy

(b) Average Out-of-Pocket Expense

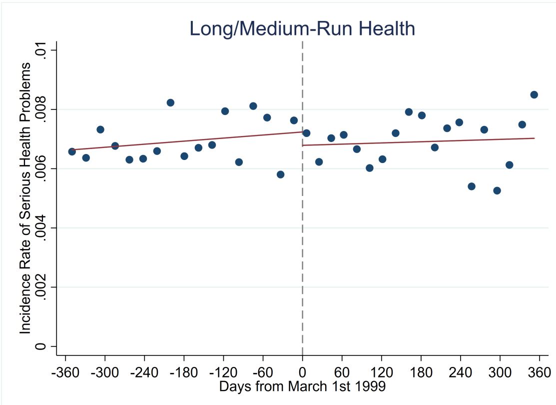
(c) Outpatient Expenditure: All Providers

(d) Outpatient Expenditure: Teaching Hospitals

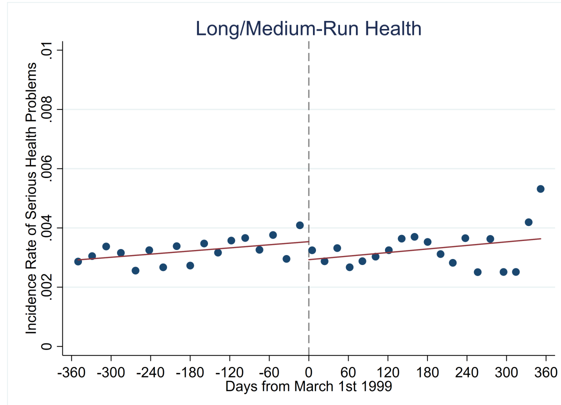
Notes: Figure N2a illustrates the relationship between the length of eligibility for the cost-sharing subsidy during age 0 to 3 and the birth date. Figure N2b displays the relationship between average OOP expense per visit during children's age 2-3 and birth date. Figure N2c displays the relationship between outpatient expenditure during children's age 2-3 and their birth date. Figure N2d displays the relationship between outpatient expenditure for teaching hospitals during children's age 2-3 and their birth date. Figure N2b to N2d are based on data from 2002-2004 NHIRD. 1 US$ is 32.5 NT$ in 2006. All expenditures/expenses in our sample period are inflation-adjusted (in 2006 NT$). Note that the horizon axis is the days from March 1st 1999 so zero means March 1st 1999. We plot the dependent variables within 360 days before and after March 1st 1999 and group up it every twenty days as a bin from March 1st 1999. Thus, each dot represents the 20-day average of the dependent variables.

Figure N3: The Effect of Cost-Sharing Subsidy on Morbidity Rate During Age 5-11

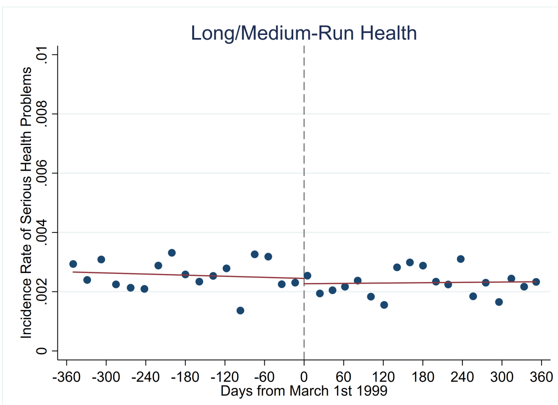
(a) Age 5-11



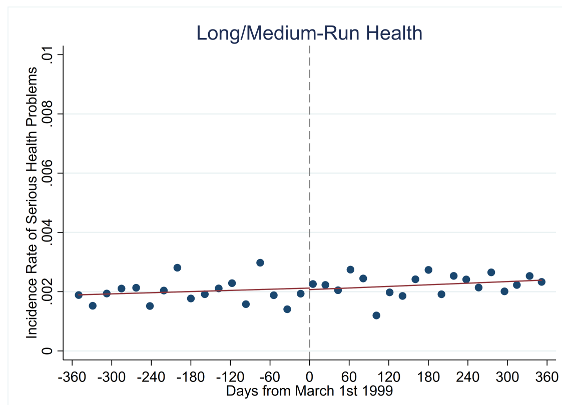
(b) Age 5-7



(c) Age 7-9



(d) Age 9-11



Notes: Figure N3 displays the relationship between the morbidity rate of pediatric CCCs over various age groups (age 5-11, age 5-7, age 7-9, and age 9-11) and the birth date using claim data of inpatient care from NHIRD. Note that the horizon axis is the days from March 1st 1999 so zero means March 1st 1999. We plot the dependent variables within 360 days before and after March 1st 1999 and group up it every twenty days as a bin from March 1st 1999. Thus, each dot represents the 20-day average of the dependent variables.

Table N1: List of CCCs

Diagnosis	ICD 9 Code
Brain and spinal cord malformations	740.0–742.9
Mental retardation	318.0–318.2
Central nervous system degeneration and disease	330.0–330.9, 334.0–334.2,335.0–335.9
Infantile cerebral palsy	343.0–343.9
Muscular dystrophies and myopathies	359.0–359.3
Heart and great vessel malformations	745.0–747.4
Cardiomyopathies	425.0–425.4, 429.1
Conduction disorders	426.0–427.4
Dysrhythmias	427.6–427.9
Respiratory malformations	748.0–748.9
Chronic respiratory disease	770.7
Cystic fibrosis	277.0
Congenital anomalies	753.0-753.9
Chronic renal failure	585
Congenital anomalies	750.3, 751.1–751.3,751.6–751.9
Chronic liver disease and cirrhosis	571.4–571.9
Inflammatory bowel disease	555.0–556.9
Sickle cell disease	282.5–282.6
Hereditary anemias	282.0–282.4
Hereditary immunodeficiency	279.00–279.9, 288.1–288.2, 446.1
Acquired immunodeficiency	0420–0421
Amino acid metabolism	270.0–270.9
Carbohydrate metabolism	271.0–271.9
Lipid metabolism	272.0–272.9
Storage disorders	277.3, 277.5
Other metabolic disorders	275.0–275.3, 277.2, 277.4, 277.6, 277.8–277.9
Chromosomal anomalies	758.0–758.9
Bone and joint anomalies	259.4, 737.3, 756.0–756.5
Diaphragm and abdominal wall	553.3, 756.6–756.7
Other congenital anomalies	759.7–759.9
Malignant neoplasms	140.0–208.9, 235.0–239.9

Notes: This table displays the diagnosis and the corresponding ICD 9 code for pediatric complex chronic conditions (CCCs) developed by Feudtner et al. (2000) to measure children's health status. The definition of CCCs is "Any medical condition that can be reasonably expected to last at least 12 months (unless death intervenes) and to involve either several different organ systems or 1 organ system severely enough to require specialty pediatric care and probably some period of hospitalization in a tertiary care center"

Table N2: Summary Statistics of Estimated Sample for Health Effects

	Impact on Later Life Health	
	Born before March 1999	Born after March 1999
Panel A: Variables at Age 5-11		
Share of CCCs at age 5-11(%)	0.69	0.69
Panel B: Variables at Age 2-3		
Average OOP expense per visit at 2-3	156.2	123.5
	(41.9)	(39.4)
Average outpatient expenditure at 2-3 (all providers)	10,175.5	10,590.9
	(7,290.2)	(7546.1)
Average outpatient expenditure at 2-3 (teaching hospitals)	1,941.4	2,241.42
	(4,609.5)	(5,018.9)
Number of children	236,689	257,578

Notes: We use enrollee data and claim data of outpatient care and inpatient care from NHIRD when targeted cohort are age 2-3 or 5-11 and restrict our sample to those born 360 days before and after March 1st 1999. Average expenditure and average OOP expense are reported in New Taiwan Dollar (NT$). 1 US$ is 32.5 NT$ in 2006.

Table N3: The Effect of Cost-Sharing Subsidy on Outpatient Utilization During Age 2-3

Dependent Variable:	Outpatient Utilization During Age 2-3					
	OOP Expense		Outpatient Expenditure All Providers		Outpatient Expenditure Teaching Hospitals	
	(1)	(2)	(3)	(4)	(5)	(6)
After1999 $\times Distance1999$	-67.81***	-67.12***	226.5***	303.4***	300.2***	322.4***
	(0.380)	(0.333)	(74.26)	(73.55)	(48.64)	(48.28)
Covariates		√		√		√
Sample Size	494,267	494,267	494,267	494,267	494,267	494,267

Notes: This table reports the estimated coefficients on $After1999 \times Distance1999$ in the regression (N.1). The dependent variables are OOP expense per visit during age 2-3, total outpatient expenditure during age 2-3, outpatient expenditure of teaching hospital visits during age 2-3. Covariates include gender, birth county, birth order, and household income during age 2-3. 1 US$ is 32.5 NT$ in 2006. All expenditures/expenses in our sample period are inflation-adjusted (in 2006 NT$). Standard errors are reported in parentheses and clustered at birth date. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

Table N4: The Effect of Cost-Sharing Subsidy on Morbidity Rate During age 5-11

Dependent Variable:	Morbidity Rate During age 5-11							
	Age 5-11		Age 5-7		Age 7-9		Age 9-11	
	(1)	(2)	(3)	(4)	(5)	(6)	(5)	(6)
After1999 $\times Distance1999$	-0.0004	-0.0004	-0.0001	-0.0001	0.0002	0.0002	0.0001	0.0001
	(0.0008)	(0.0008)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Covariates		√		√		√		√
Sample Size	494,267	494,267	494,267	494,267	494,267	494,267	494,267	494,267

Notes: This table reports the estimated coefficients on $After1999 \times Distance1999$ in the regression (N.1). The dependent variables are the occurrence of serious health problem (CCCs) during age 5-11, 5-7, 7-9, and 9-11, respectively. Covariates include gender, birth county, birth order, and household income during age 2-3. Standard errors are reported in parentheses and clustered at birth date. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

O A Sufficient Statistics Model for Evaluating Patient Cost-Sharing Policy

Note that all notation has been defined in Section 5.4. The social planner chooses the level of patient cost sharing p to maximize social welfare given the budget constraint $P = M(p) \times (\pi - p)$.

$$\begin{aligned} W(p) &= (1-\lambda)U(y-P) + \lambda \mathrm{E}[U(y-P-s+m(p)(b(s)-p))|sick] \\ &= (1-\lambda)U(y-P) + \lambda\left[\int_{s_l}^{s} U(y-P-s)dF(s)\right] \\ &\quad +\lambda\left[\int_{s}^{s_u}(U(y-P-s+m(p)(b(s)-p)))dF(s)\right] \end{aligned}$$

Differentiating $W(p)$ with respect to p subject to the budget constraint $P = M(p) \times (\pi - p)$ gives the following expression:

$$\begin{aligned} \frac{\partial W}{\partial p} &= -(1-\lambda)U^{'}(y-P)\frac{\partial P}{\partial p} - \lambda \mathrm{E}[\frac{\partial U(y-P-s+m(p)(b(s)-p))}{\partial P}\frac{\partial P}{\partial p}] \\ &\quad +\lambda \mathrm{E}[\frac{\partial U(y-P-s+m(p)(b(s)-p))}{\partial \delta}\frac{\partial \delta(p)}{\partial p}] \\ &\quad +\lambda \mathrm{E}[\frac{\partial U(y-P-s+m(p)(b(s)-p))}{\partial s}\frac{\partial s}{\partial p}] \end{aligned} \tag{O.1}$$

where $\delta(p) = m(p)(b(s) - p)$ and $C = y - P - s + m(p)(b(s) - p)$. We can express equation (O.1) as follows:

$$\begin{aligned} \frac{\partial W}{\partial p} &= -(1-\lambda)U^{'}(y-P)\frac{\partial P}{\partial p} - \lambda \mathrm{E}[U^{'}(C)\frac{\partial P}{\partial p}] \\ &\quad +\lambda \mathrm{E}[U^{'}(C)\frac{\partial \delta(p)}{\partial p}] \\ &\quad +\lambda\left\{f(s)[U(y-P-s) - U(y-P-s+b(s)-p)]\frac{\partial s}{\partial p}\right\} \\ &= -\mathrm{E}[U^{'}(C)]\frac{\partial P}{\partial p} - \mathrm{E}[U^{'}(C)|m=1]M(p) \\ &\quad +\lambda\left\{[U(y-P-s) - U(y-P-s+b(s)-p)]f(s)\frac{\partial s}{\partial p}\right\} \end{aligned} \tag{O.2}$$

We can substitute $\frac{\partial P}{\partial p}$ and $-\lambda f(s)\frac{\partial s}{\partial p}$ in equation (O.2) with the following terms:

$$\begin{aligned} \frac{\partial P}{\partial p} &= \frac{\partial M(p)}{\partial p} \times (\pi - p) - M(p) \\ -\lambda f(s)\frac{\partial s}{\partial p} &= \frac{\partial M(p)}{\partial p} \end{aligned}$$

After rearranging equation (O.2), we can derive the following expression:

$$\begin{aligned}
\frac{\partial W}{\partial p} &= -\mathrm{E}[U^{'}(C)][\frac{\partial M(p)}{\partial p}(\pi - p) - M(p)] - E[U^{'}(C)|m = 1]M(p) \\
&= -\mathrm{E}[U^{'}(C)][\frac{\partial M(p)}{\partial p}(\pi - p)] - \left\{E[U^{'}(C)|m = 1] - \mathrm{E}[U^{'}(C)]\right\} M(p) \qquad \text{(O.3)}
\end{aligned}$$

Finally, we convert the change in social welfare into a money metric by normalizing the increase in welfare by the welfare gain from increasing income by 1, which yields

$$\begin{aligned}
\partial W / \partial y &= (1 - \lambda)U^{'}(y - P) + \lambda \mathrm{E}[U^{'}(C)] \\
&= \mathrm{E}[U^{'}(C)] \qquad \text{(O.4)}
\end{aligned}$$

Then, we combine equations (O.3) and (O.4) and get the formula in Section 5.4:

$$\frac{\partial W}{\partial p} / \frac{\partial W}{\partial y} = -\frac{\partial M(p)}{\partial p} \times (\pi - p) - I(p) \times M(p)$$