

参赛学生姓名: Jiayu Rong

中学: 上海中学国际部

省份: 上海

国家/地区: 中国

指导老师姓名: 刘志阔, 朱雅婷

指导老师单位: 复旦大学经济学院, 上海中学国际部

论文题目: Turning Sixty, Seeking Care? Evidence from
Hospital Outpatient Records in Shanghai

Turning Sixty, Seeking Care? Evidence from Hospital Outpatient Records in Shanghai

Jiayu Rong

Abstract

Population aging is placing increasing pressure on health insurance systems, as older adults use more healthcare services and have higher medical spending per person. Beyond aging itself, retirement is a major change in people's lives and their employment and insurance status. It may also affect healthcare demand by changing the time available for care and insurance-payment conditions. This study examines whether retirement increases outpatient healthcare utilization and investigates the mechanisms through which such changes may occur. First, a patient-choice model is developed in which individuals choose visit frequency and medical spending. The model predicts that both outpatient visits and medical expenditure increase when retirement lowers the time and inconvenience cost of each visit and reduces the patient's out-of-pocket share. Second, the empirical analysis uses 2016–2019 administrative records from a tertiary hospital in Shanghai to construct a monthly panel of 1,903 men whose observed health-insurance status changes from active employee to retiree around age 60. Because health typically changes gradually with age, monthly data help distinguish changes in healthcare use around the retirement transition from gradual age-related changes in health. The empirical analysis uses difference-in-differences and event-study methods. Further checks use matched DID, alternative definitions of the retirement month, group-time ATE estimates, and tests of whether extreme observations drive the results. Information on insurance payments, visit timing, departments, diagnoses, and the mix of services helps assess three possible explanations for changes in healthcare use. These are changes in the price patients pay, the time and inconvenience of seeking care, and attention to health. Across estimation approaches, outpatient healthcare utilization rises clearly after the observed transition to retiree health-insurance status. Using conservative full-window estimates, monthly medical expenditure increases by RMB 19.8 and monthly outpatient visits by 0.061, equivalent to 13.2% and 13.1% of the corresponding sample means. Overall, the post-retirement increase in utilization is reflected mainly in more frequent and broader use of outpatient care rather than in more expensive or more complex treatment within each visit. The evidence is strongest for lower out-of-pocket prices as an explanation for increased healthcare use. Evidence for lower time and inconvenience costs is weaker but points in the direction predicted by the model. In the context of population aging, retirement-related increases in healthcare utilization may place additional pressure on health insurance systems, while raising the retirement age may help postpone or smooth this short-run increase in utilization. Hospitals and health insurers should also pay greater attention to the rise in visit frequency and the broader range of care used after retirement.

Keywords: Retirement; health care utilization; health insurance; health care demand model; Staggered Difference in Difference; Matching

Contents

1	Introduction	3
2	Literature Review	6
3	A Model of Retirement and Outpatient Healthcare Utilization	8
3.1	Model Setup and Patient Optimization	8
3.2	Comparative Statics	10
4	Institutional Background	12
4.1	Statutory Retirement	12
4.2	Retirement, Employment-Linked Insurance Status, and Health Insurance Benefits in Shanghai	13
5	Data, Variables, and Descriptive Statistics	14
5.1	Data Source and Sample Construction	14
5.2	Retirement Identification and the Distribution of Retirement Age	15
5.3	Variable Definitions	17
5.4	Descriptive Statistics	19
6	Empirical Strategy and Models	19
6.1	Empirical Strategy	19
6.2	Staggered DID Model	21
6.3	Dynamic Effects	22
6.4	Matching and Stacked DID	23
6.5	Mechanism Tests	24
6.6	Robustness Analyses	25
7	Empirical Results	27
7.1	Main Results	27
7.2	Matched DID Results	29
7.3	Mechanism Tests	31
7.4	Robustness Analyses	38
8	Conclusion	41

1 Introduction

China is experiencing rapid population aging. By the end of 2025, 323.4 million people, or 23.0% of the population, were aged 60 or above ([National Bureau of Statistics of China, 2026](#)). As a growing share of the population leaves work and retires, pension and health insurance systems face increasing pressure. In response to demographic change and labor supply pressures, China began gradually raising its statutory retirement ages in 2025 ([Standing Committee of the National People’s Congress, 2024](#)). Understanding the consequences of retirement has therefore become increasingly important for evaluating both population aging and retirement-age reform.

Healthcare is especially important because older adults account for a larger share of healthcare use and spending than of the population. In China, the two-week medical consultation rate among older adults increased from 25.6% in 1993 to 40.1% in 2018 ([Wu et al., 2023a](#)). Similar patterns are observed elsewhere: in the United States, people aged 65 and above accounted for about 17% of the population but 37% of personal healthcare spending in 2020 ([Centers for Medicare & Medicaid Services, 2023](#)), while in Japan they represented about 29% of the population but 60.1% of national medical expenditure in fiscal year 2023 ([Ministry of Health, Labour and Welfare of Japan, 2025](#)). Beyond the effect of aging itself, retirement may further alter healthcare demand by changing how easily individuals can find time for care, their health insurance benefits, their income, and their health. Knowing how retirement affects healthcare use can therefore help us understand how retirement-age policies affect healthcare and government finances.

Previous studies report different results. Some find positive effects, some find negative effects, and others find no significant effect ([Eibich, 2015](#); [Lucifora and Vigani, 2018](#); [Nielsen, 2019](#); [Zhou et al., 2021](#)). This mixed evidence reflects the fact that retirement affects several determinants of healthcare demand, often in opposing directions. Leaving work may lower the opportunity cost of seeking care because patients no longer give up as much work time. More generous insurance after retirement may also lower the price patients pay for medical services. On the other hand, lower income after retirement may limit healthcare use. Less work stress and changes in lifestyle may also improve health and reduce the need for medical care ([Zhang et al., 2018](#); [Frimmel and Pruckner, 2020](#)). The overall effect therefore depends on the balance among these forces. It may differ across healthcare systems and types of medical services.

A growing number of studies have also examined this question in China. They generally find that retirement increases healthcare use, especially outpatient care ([Zhang et al., 2018](#); [Zhou et al., 2021](#); [Wu et al., 2023b](#)). Evidence for inpatient care, however, is less consistent.

Retirement may have little effect on the number or duration of hospitalizations and may even reduce expenditure per hospitalization (Fu and Xu, 2023). In addition, healthcare use around the statutory retirement age may fall before retirement and rise afterward (Yu et al., 2023). The question is therefore not only whether retirement increases healthcare use. The study also asks which kinds and aspects of care change and what might explain these changes.

Answering these questions requires detailed data recorded at a high frequency to show how patients use care, how they pay, when they visit, and what services they receive. This study uses high-frequency outpatient administrative records from a tertiary hospital in Shanghai between 2016 and 2019 to examine changes in healthcare utilization around patients' observed transition from active-employee to retiree health-insurance status. Monthly records give us a clearer view of changes around one transition month than annual or less frequent survey data. Gradual changes in health due to aging are less likely to explain a change concentrated around particular transition month. At the same time, the hospital records contain detailed information on medical expenditures, insurance payments, registration and treatment times, departments, diagnoses, and service items, allowing us to examine changes in those factors. Shanghai's population began aging relatively early, and the city has a well-developed employee health-insurance system. Its experience may therefore be useful for regions that face similar demographic and retirement changes later.

The study first develops a model of patient choices. It considers how retirement may affect outpatient use by changing the time and inconvenience cost of seeking care and the price paid by the patient. The model predicts how these changes affect visit frequency and medical spending. For the empirical analysis, a patient-month panel is constructed for 1,903 men. A difference-in-differences model is used to estimate the overall effect of the observed transition to retiree health-insurance status, while an event-study design shows how this effect changes over time. Robustness is assessed using matched DID, alternative definitions of the retirement month, group-time ATT estimates, and checks for the influence of extreme observations. The analysis then uses information on insurance payments, visit timing, departments, diagnoses, and the mix of services to examine the roles of price and time costs described in the model, as well as other possible explanations.

The empirical results show a clear increase in outpatient healthcare utilization after patients' transition to retiree health-insurance status. Different estimation approaches yield consistently positive effects. Using conservative estimates, monthly outpatient expenditure increases by approximately 13.2%, while monthly outpatient visits rise by about 13.1%. These findings indicate an economically meaningful increase in healthcare utilization around the retirement transition, and the pattern is robust across alternative methods and speci-

cations.

The mechanism analysis suggests that this increase is broadly consistent with the model's predictions about lower out-of-pocket prices and lower time and inconvenience costs. However, the evidence supports the price explanation more strongly than the time-cost explanation. The clearest evidence supports lower out-of-pocket prices as an explanation for increased healthcare use. After retirement, patients are more likely to enter the coinsurance segment and have higher reimbursement rates calculated from their bills. Controlling for coinsurance-segment status in the same month substantially reduces the estimated retirement effects on both visits and medical expenditure. This pattern indicates a close association between more favorable insurance-payment conditions and higher healthcare utilization. By contrast, direct evidence for the time-and-inconvenience-cost channel is weaker. There is little systematic reallocation of visits between weekdays and weekends or across times of day, but patients visit more departments and receive diagnoses spanning more disease groups after retirement. This pattern is consistent with patients seeking a broader range of care when they have more time available. At the same time, the shares of spending on different services, mean registration fees, and diagnosis complexity within departments remain largely unchanged. This provides little evidence that the increase in healthcare use is mainly driven by worsening health or a sharp increase in attention to health. Overall, the evidence is most consistent with the view that retirement lowers the combined time, inconvenience, and out-of-pocket costs patients face, leading them to seek outpatient care more often and use a broader range of services.

This study makes two main contributions to the literature. First, it uses high-frequency data on the same patients to provide evidence on short-run changes in healthcare use around the retirement transition. Compared with studies based on annual data, the monthly patient panel helps distinguish changes in healthcare use around the retirement transition from gradual age-related changes in health. It therefore gives a more precise picture of how healthcare demand changes before and after retirement. Second, the study examines which aspects of healthcare use change after retirement and what might explain these changes. These questions have received less attention in the literature. Using detailed hospital administrative records, the analysis examines visit frequency, medical expenditure, insurance payment terms, visit timing, the range of departments visited, diagnoses, and the mix of services used. The study thus goes beyond identifying retirement's overall effects to describe in more detail how healthcare use changes and which economic mechanisms may explain those changes.

2 Literature Review

This study draws on two areas of research: healthcare use and retirement. Research on healthcare use asks what affects medical demand, while research on retirement asks how leaving work changes economic behavior, time use, and health. This study brings these areas together by asking how retirement affects healthcare use.

Research on healthcare use shows that medical need is not the only factor that shapes demand. Financial conditions and healthcare-system rules also matter. Many health-economics studies find that insurance coverage and patient cost sharing can strongly affect how much care people use. [Card et al. \(2008\)](#) use the start of Medicare eligibility at age 65 in the United States and find that expanded insurance coverage increases medical-service use. [Finkelstein et al. \(2012\)](#), using the randomized Oregon Medicaid lottery, similarly find that gaining insurance increases primary care, preventive care, and hospital utilization. For older people, [Shigeoka \(2014\)](#) uses a sharp reduction in patient cost sharing at age 70 in Japan and finds that both outpatient and inpatient use respond to the price patients pay themselves. [Brot-Goldberg et al. \(2017\)](#) also find that healthcare spending changes substantially when deductibles change the price patients face. Together, these studies show that medical need and economic incentives both shape healthcare use at older ages. Changes in insurance coverage and cost sharing around retirement may therefore be important for medical demand ([Card et al., 2008](#); [Finkelstein et al., 2012](#); [Shigeoka, 2014](#); [Brot-Goldberg et al., 2017](#)).

Labor and public economists have long studied retirement as an important economic transition. Some of these studies ask how pension rules and statutory retirement ages affect older people. For example, [Staubli and Zweimüller \(2013\)](#) use increases in Austria’s early retirement age to show that retirement-age rules have substantial effects on employment among older workers. [Lalive et al. \(2023\)](#) find that an increase in the full retirement age delays both pension claiming and retirement, while [Rabaté et al. \(2024\)](#) document large employment responses to an increase in the statutory retirement age in the Netherlands. Retirement can also have consequences beyond labor supply. [Hallberg et al. \(2015\)](#) find that an early-retirement offer to Swedish military officers reduces inpatient care and mortality, whereas [Fitzpatrick and Moore \(2018\)](#) document an increase in male mortality at the U.S. Social Security eligibility age of 62 that is closely associated with retirement from the labor force. Together, these studies show that retirement is not simply the end of a person’s career. It is a major life change that can affect employment, public finances, and health ([Staubli and Zweimüller, 2013](#); [Hallberg et al., 2015](#); [Fitzpatrick and Moore, 2018](#); [Lalive et al., 2023](#); [Rabaté et al., 2024](#)).

The studies most closely related to ours ask how retirement itself affects healthcare use.

They reach different conclusions, which is consistent with retirement changing demand for care in several ways. Using SHARE data from ten European countries, [Lucifora and Vigani \(2018\)](#) find that doctor visits increase after retirement. The increase differs according to how people used their time before retirement. They interpret this pattern as consistent with a lower opportunity cost of time. In contrast, [Nielsen \(2019\)](#) uses Danish population registers and finds that early retirement reduces GP visits and hospitalizations by approximately 8–10 percent in the short run, while statutory retirement has no detectable effect on healthcare utilization. [Hallberg et al. \(2015\)](#) also find lower inpatient utilization following an early-retirement offer. These different results suggest that the effect of retirement on healthcare use depends on the type of retirement being studied, such as early or statutory retirement, and the rules that shape healthcare access and the time cost of seeking care ([Hallberg et al., 2015](#); [Lucifora and Vigani, 2018](#); [Nielsen, 2019](#)).

A main challenge in this literature is that retirement may be endogenous. In other words, health can affect when a person retires, while retirement may later affect health and healthcare use. [French \(2005\)](#), for example, models retirement jointly with health, wages, wealth, and pension incentives, illustrating the close connection between health and late-life labor supply decisions. A direct comparison of workers and retirees may therefore confuse the effect of retirement with the fact that health can influence who retires. To address this problem, causal studies often use institutional rules or reforms that change pension eligibility or statutory retirement ages. In the broader retirement-and-health literature, studies most often use instrumental-variable (IV) or regression-discontinuity (RD) designs. Difference-in-differences (DID) is used mainly when a policy reform creates treated and comparison groups ([Filomena and Picchio, 2023](#)). [Nielsen \(2019\)](#) combines an IV design based on a reform with an RD design based on age. [Barschkett et al. \(2022\)](#) use a DID design with a retirement-age reform affecting specific cohorts and detailed administrative diagnosis records.

This study adds to this literature by using monthly outpatient claims to follow short-run changes in healthcare use around a recorded transition from employed to retired health-insurance status. The patient-month panel helps distinguish an abrupt change around the transition from longer-run trends in healthcare use that may accompany aging or evolving health. The records include insurance and out-of-pocket payments, visit timing, departments, and diagnoses. The analysis uses this information to examine whether changes in healthcare use are accompanied by changes in financial incentives, when patients seek care, or the mix of services they receive. We use event-study, matched DID, and group-time estimates to study when the response occurs and whether the results change with different comparison groups or averaging methods. Together, the monthly records and detailed claims information make it possible to examine how healthcare use changes and what might explain

those changes.

3 A Model of Retirement and Outpatient Healthcare Utilization

This section presents a simple economic model of two ways retirement may change outpatient healthcare use. First, the model assumes that retirement lowers the time and inconvenience cost of a hospital visit by removing conflicts between work and seeking care. Second, retirement may reduce the share of each additional yuan of medical spending paid by the patient. The model is used to study how these changes affect the number of visits and total medical spending.

3.1 Model Setup and Patient Optimization

Let $R \in \{0, 1\}$ denote retirement status, where $R = 0$ indicates pre-retirement and $R = 1$ indicates post-retirement. The model describes the patient's outpatient care using two variables. n is the number of visits, and p is total medical spending on those visits. When $n > 0$, average spending per visit is p/n . Although the number of visits takes integer values, the model treats n as continuous to make the problem easier to solve. Total medical spending includes payments made by both the patient and the insurer:

$$p = \underbrace{\theta_R p}_{\text{patient payment}} + \underbrace{(1 - \theta_R)p}_{\text{insurance payment}} ,$$

where $\theta_R \in (0, 1]$ denotes the patient's marginal out-of-pocket share under retirement status R . The optimization problem treats p as a choice variable, but this is a modeling simplification. In practice, both physician recommendations and the patient's decisions to seek and accept care affect total spending. Thus, p represents spending on the care the patient ultimately receives, and the model does not separately describe the physician-patient interaction.

When $n > 0$, p/n is average spending per visit. We use it as a simple proxy for treatment intensity and define effective care per visit as $Q\left(\frac{p}{n}\right) = q\left(\frac{p}{n}\right)^\alpha$ with $q > 0$ and $0 < \alpha < 1$. The parameter q measures how productively the resources used during a visit generate effective care. The parameter α is the elasticity of effective care with respect to spending per visit. It means that a 1 percent increase in spending per visit raises effective care by approximately α percent. Because $0 < \alpha < 1$, greater spending per visit increases effective care, but at a

diminishing rate.

The model assumes that effective care adds up across visits. Total effective outpatient care therefore equals the number of visits multiplied by effective care per visit. Thus, total effective outpatient care is

$$H(n, p) = nQ\left(\frac{p}{n}\right) = qn^{1-\alpha}p^\alpha.$$

The term $H(n, p)$ represents effective care, or expected treatment benefit, rather than a directly observed clinical health outcome. This formulation distinguishes how often patients visit the hospital, measured by n , from how much is spent per visit, measured by p/n .

The patient faces two types of private cost. The first is the time and inconvenience associated with each visit. We express this burden in monetary units as $\tau_R > 0$. So the total cost of n visits is $\tau_R n$. Before retirement, τ_R may include travel and waiting time, scheduling inconvenience, lost wages or bonuses, difficulty obtaining leave, and other employment-related consequences. Retirement is assumed to remove the employment-related components, although travel, waiting, and other inconveniences remain.

The second cost is the patient's out-of-pocket payment. Because the patient pays the share θ_R , this payment equals $\theta_R p$. The patient's total private cost is therefore

$$G_R(n, p) = \tau_R n + \theta_R p.$$

This cost is measured from the patient's perspective. It excludes the insurer's payment $(1 - \theta_R)p$ and does not represent the hospital's production cost.

The patient values effective care according to

$$V(H(n, p)) = \omega \ln(1 + H(n, p)), \quad \omega > 0,$$

where ω measures how strongly the patient values effective care and may reflect underlying medical need.¹ The logarithm means that each additional unit of effective care adds less value than the previous one. In the baseline model, ω is held fixed across retirement states so that retirement affects utilization only through τ_R and θ_R .

The patient chooses n and p to maximize the value of effective care minus the private

¹The parameter ω can also capture attention to health. If retirement makes patients more attentive to health, a higher ω would increase both visits and spending. We therefore examine registration fees and the shares of examination and laboratory-test spending as indirect indicators of greater attention to health.

cost of obtaining it. Thus, the optimization problem for a patient is following

$$\max_{n,p \geq 0} \{ \omega \ln(1 + qn^{1-\alpha}p^\alpha) - \tau_R n - \theta_R p \}. \quad (1)$$

3.2 Comparative Statics

The patient's problem is solved in two steps. The first step finds the lowest-cost combination of visits and medical spending for any target level of effective care H . The second step uses this minimum cost to find the patient's optimal level of effective care.

For a given $H > 0$, the first-stage problem is

$$\begin{aligned} G_R^*(H) &= \min_{n,p \geq 0} \tau_R n + \theta_R p \\ \text{s.t.} \quad & qn^{1-\alpha}p^\alpha \geq H. \end{aligned}$$

Because $H > 0$ requires both $n > 0$ and $p > 0$, and both inputs are costly, the lowest-cost choice produces exactly H , not more than H . The care requirement is therefore met exactly. Let $n_R(H)$ and $p_R(H)$ denote the lowest-cost choices for a given H . The first-order conditions imply

$$\frac{p_R(H)}{n_R(H)} = \frac{\alpha}{1-\alpha} \frac{\tau_R}{\theta_R}.$$

This equation gives the lowest-cost balance between visits and medical spending needed to produce H . The minimum private cost of obtaining H units of effective care is

$$G_R^*(H) = \kappa_R H,$$

where

$$\kappa_R = \frac{1}{q} \left(\frac{\tau_R}{1-\alpha} \right)^{1-\alpha} \left(\frac{\theta_R}{\alpha} \right)^\alpha.$$

Thus, κ_R is the minimum private cost of one unit of effective outpatient care under retirement status R . It combines the time and inconvenience cost of visits, τ_R , with the patient's share of medical spending, θ_R , while also accounting for how visits and spending produce effective care.

Given the unit cost κ_R , the second-stage problem becomes

$$\max_{H \geq 0} \{ \omega \ln(1 + H) - \kappa_R H \}.$$

A strictly positive solution requires $\omega > \kappa_R$. The first-order condition is

$$\frac{\omega}{1 + H_R^*} = \kappa_R.$$

Solving this condition gives the optimal level of effective care. Substituting it into the first-stage choices yields

$$\begin{aligned} H_R^* &= \frac{\omega}{\kappa_R} - 1, \\ n_R^* &= \frac{1 - \alpha}{\tau_R}(\omega - \kappa_R), \\ p_R^* &= \frac{\alpha}{\theta_R}(\omega - \kappa_R). \end{aligned}$$

The following theorem summarizes how retirement affects the patient's optimal number of visits and total medical spending.

Theorem 1 (Retirement comparative statics). *Suppose that the pre-retirement solution is interior, so that $n_0^* > 0$ and $p_0^* > 0$. Also assume that retirement lowers the time and inconvenience cost of a visit and does not increase the patient's marginal out-of-pocket share, such that $\tau_1 < \tau_0$ and $\theta_1 \leq \theta_0$. Then the post-retirement solution is also interior, and*

$$n_1^* > n_0^*, \quad p_1^* > p_0^*.$$

Moreover, for each $R \in \{0, 1\}$, the interior optimal choices satisfy

$$\frac{\partial n_R^*}{\partial \tau_R} = -\frac{(1 - \alpha)(\omega - \alpha\kappa_R)}{\tau_R^2} < 0 \tag{2}$$

$$\frac{\partial n_R^*}{\partial \theta_R} = -\frac{\alpha(1 - \alpha)\kappa_R}{\tau_R\theta_R} < 0, \tag{3}$$

$$\frac{\partial p_R^*}{\partial \tau_R} = -\frac{\alpha(1 - \alpha)\kappa_R}{\tau_R\theta_R} < 0, \tag{4}$$

$$\frac{\partial p_R^*}{\partial \theta_R} = -\frac{\alpha[\omega - (1 - \alpha)\kappa_R]}{\theta_R^2} < 0. \tag{5}$$

Proof. From the definition of κ_R ,

$$\frac{\kappa_1}{\kappa_0} = \left(\frac{\tau_1}{\tau_0}\right)^{1-\alpha} \left(\frac{\theta_1}{\theta_0}\right)^\alpha < 1.$$

Hence, $\kappa_1 < \kappa_0$. Since the pre-retirement solution is interior, $\omega > \kappa_0 > \kappa_1$. Therefore,

$$n_1^* = \frac{1 - \alpha}{\tau_1}(\omega - \kappa_1) > \frac{1 - \alpha}{\tau_0}(\omega - \kappa_0) = n_0^*,$$

and

$$p_1^* = \frac{\alpha}{\theta_1}(\omega - \kappa_1) > \frac{\alpha}{\theta_0}(\omega - \kappa_0) = p_0^*.$$

Moreover,

$$\frac{\partial \kappa_R}{\partial \tau_R} = \frac{(1 - \alpha)\kappa_R}{\tau_R}, \quad \frac{\partial \kappa_R}{\partial \theta_R} = \frac{\alpha\kappa_R}{\theta_R}.$$

Differentiating the closed-form solutions gives

$$\begin{aligned} \frac{\partial n_R^*}{\partial \tau_R} &= -\frac{(1 - \alpha)(\omega - \alpha\kappa_R)}{\tau_R^2} < 0, \\ \frac{\partial n_R^*}{\partial \theta_R} &= -\frac{\alpha(1 - \alpha)\kappa_R}{\tau_R\theta_R} < 0, \\ \frac{\partial p_R^*}{\partial \tau_R} &= -\frac{\alpha(1 - \alpha)\kappa_R}{\tau_R\theta_R} < 0, \\ \frac{\partial p_R^*}{\partial \theta_R} &= -\frac{\alpha[\omega - (1 - \alpha)\kappa_R]}{\theta_R^2} < 0. \end{aligned}$$

The signs follow from $\omega > \kappa_R$, $0 < \alpha < 1$, $\tau_R > 0$, and $\theta_R > 0$. □

To summarize, the model holds underlying medical need, represented by ω fixed. Retirement lowers the time and inconvenience cost of a visit τ_R , and may also lower the patient's marginal out-of-pocket share, θ_R . These changes lower the unit cost of effective care, κ_R , and increase both the optimal number of visits and total medical spending.

4 Institutional Background

4.1 Statutory Retirement

The sample period, 2016-2019, predates China's gradual increase in statutory retirement ages that took effect in 2025. During the period studied in this paper, the standard statutory retirement age was generally 60 for male employees, 50 for women in worker positions, and 55 for female cadres or women in managerial and technical positions. For workers on the normal retirement track, retirement age was mainly set by rules based on gender and job category rather than freely chosen in response to current health. However, there were several exceptions. Workers engaged in hazardous or physically demanding occupations could retire

earlier, and individuals certified as having completely lost their capacity to work could also qualify for early retirement. Special arrangements also allowed some groups to retire later.

These exceptions are important for our sample construction. People in poor health may retire early through disability or another special rule, while healthier people or those with stronger ties to their jobs may retire later. We focus on men rather than both men and women because the standard retirement age for men was clearly defined at age 60, whereas the applicable retirement age for women could be either 50 or 55 depending on their job classification. The hospital records do not contain the employment information needed to determine which threshold applies to each woman. We therefore restrict the analysis to men whose observed transition from active-employee to retiree insurance status occurs between the month in which they turn 60 and the month immediately preceding their 61st birthday. This restriction focuses the analysis on transitions around the standard male retirement age and excludes transitions clearly outside that range.

4.2 Retirement, Employment-Linked Insurance Status, and Health Insurance Benefits in Shanghai

Shanghai's Urban Employee Basic Medical Insurance (UEBMI) program is tied to employment and uses different benefit rules for active employees and retirees. During the sample period, employees who reached the relevant statutory age and completed the retirement procedure became eligible for retiree benefits. Each outpatient record identifies the employee or retiree insurance status used for that visit. We use the first month in which retiree status appears as the patient's observed retirement month.

The transition to retirement changes outpatient cost sharing. Under the Shanghai's UEBMI system during the study period, outpatient expenses were first paid from the individual's current-year medical savings account. Once these funds were exhausted, active employees faced an annual outpatient deductible of RMB 1,500, whereas the corresponding deductible for retirees was RMB 700. For individuals in the age groups studied in this paper, expenses above the deductible at tertiary hospitals were generally reimbursed at 60 percent for active employees and 70 percent for retirees. Thus, retirees faced both a lower deductible and a smaller out-of-pocket share above the deductible.

The observed transition combines two changes that may lower the patient's cost of outpatient care. More generous retiree insurance may reduce the amount paid by the patient. Leaving regular employment or working less may also make it easier to find time for care.

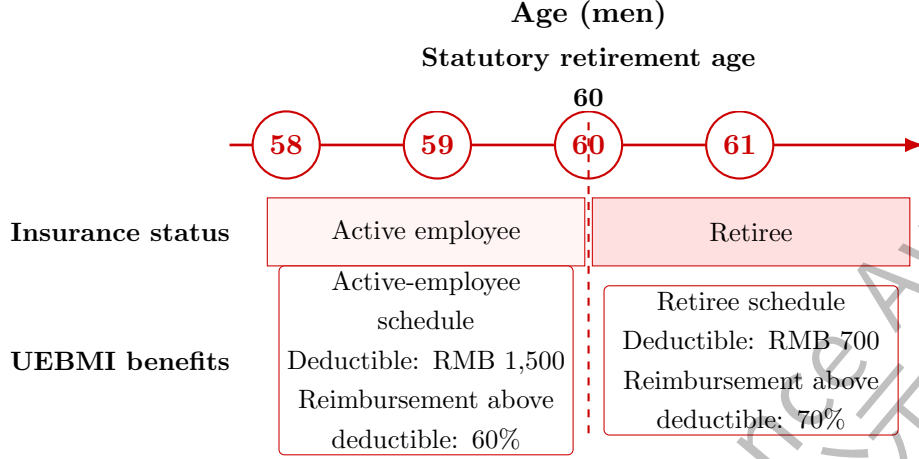


Figure 1: Age, insurance status, and outpatient benefits around the standard retirement age for men

Notes: The figure summarizes the rules relevant to male patients during 2016–2019. The reimbursement rates are the applicable rates at tertiary hospitals after the annual deductible is reached.

Figure 1 gives a visual summary of the institutional setting. At age 60, men move from the active-employee to the retiree UEBMI schedule. The deductible falls from RMB 1,500 to RMB 700 and the reimbursement rate above the deductible rises from 60% to 70%. Retirement may also make it easier to schedule outpatient care by reducing work-related time constraints.

5 Data, Variables, and Descriptive Statistics

5.1 Data Source and Sample Construction

This study uses outpatient visit records for patients enrolled in Shanghai’s UEBMI program who received care at a tertiary hospital between 2016 and 2019. The data cover outpatient care delivered at this hospital and do not contain healthcare utilization at other providers.

Each row in the raw data represents one outpatient visit. For each visit, the data record total expenditure, insurance payment, out-of-pocket payment, expenditure outside the insurance benefit package, and registration fees². They also record registration and treatment

²Total expenditure is the amount charged for all services and items in a visit before payment is divided between the patient and UEBMI. Insurance payment is the amount paid or reimbursed by UEBMI. Out-of-pocket payment is the amount paid by the patient, including required cost sharing and spending on items not covered by UEBMI. Expenditure outside the insurance benefit package is spending on services, drugs, tests, or other items that are not eligible for UEBMI reimbursement. It is part of the patient’s out-of-pocket payment. A registration fee is charged for the outpatient consultation, not for later drugs, tests, or treatments. Registration records may belong to different service categories, such as ordinary outpatient,

times, clinical department, Chinese- and Western-medicine diagnoses, and billed service items. Patient information includes an anonymized identifier, date of birth, sex, and the employment-related insurance status under which each visit was settled.

We combine all visits for the same patient in the same calendar month to create a patient-month panel. For each expenditure measure, the monthly value is the sum across those visits, and monthly visits equal the number of visit records. For each included patient, we construct an observation for every calendar month in the study period. When a patient has no outpatient record at this hospital in a given month, monthly visits and expenditures are set to zero. These zero values therefore indicate no recorded outpatient use at the study hospital.

5.2 Retirement Identification and the Distribution of Retirement Age

Each outpatient record states whether the patient used the UEBMI status for an active employee or a retiree. We retain patients who are observed first as active employees and later as retirees. For patient i , G_i is the first calendar month in which retiree status appears in the hospital records. We call G_i the observed retirement month.

Figure 2 reports the distribution of G_i separately for men and women. For men, transitions are concentrated at age 60 and in the following months. For women, there are two clear concentrations, around ages 50 and 55. These patterns correspond to the statutory retirement ages that applied during the study period.

Figure 3 reports the corresponding cumulative distributions. Unlike the main regression sample, this figure uses all patients with an observed transition and does not restrict men to the age-60–61 window. The male curve rises sharply at and just after age 60, but continues to increase well beyond age 61. The female curve has separate jumps at ages 50 and 55. The cumulative distributions therefore confirm the concentration around statutory ages while also showing the spread in the month when retiree status is first observed at this hospital.

specialist or expert outpatient, and special-service outpatient registration. The applicable fee can therefore vary with the type of clinic, the physician's professional rank or seniority, and the service arrangement. Registration fees are part of total expenditure and may be paid by the patient, UEBMI, or both.

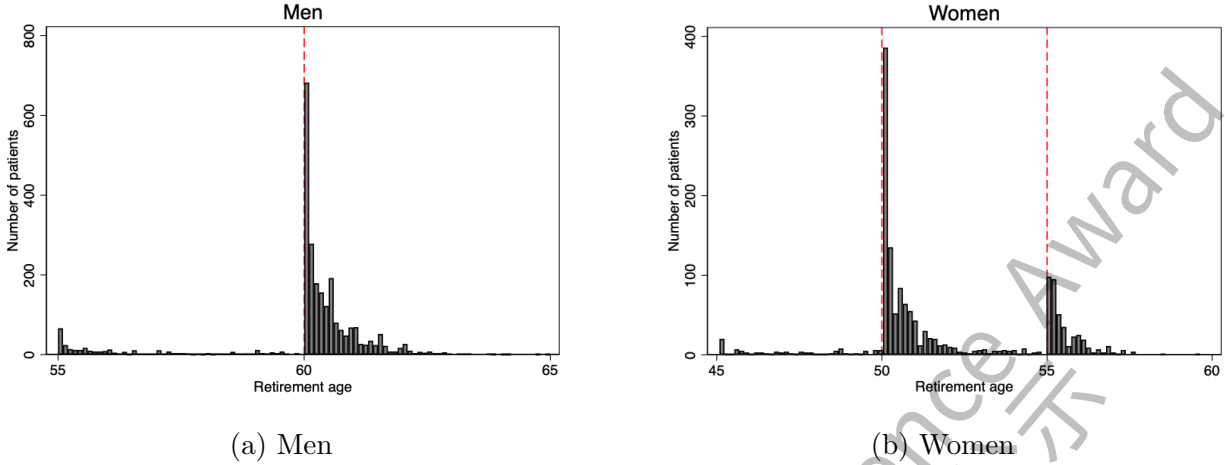


Figure 2: Age Distribution at the Observed Retirement Month for Men and Women
Notes: For each patient, age at the observed retirement transition is calculated as the number of months elapsed between the patient's birth month and G_i , expressed in years. The vertical dashed line in the male panel indicates the statutory retirement age of 60. The vertical dashed lines in the female panel indicate the statutory retirement ages of 50 and 55 applicable to different categories of female employees.

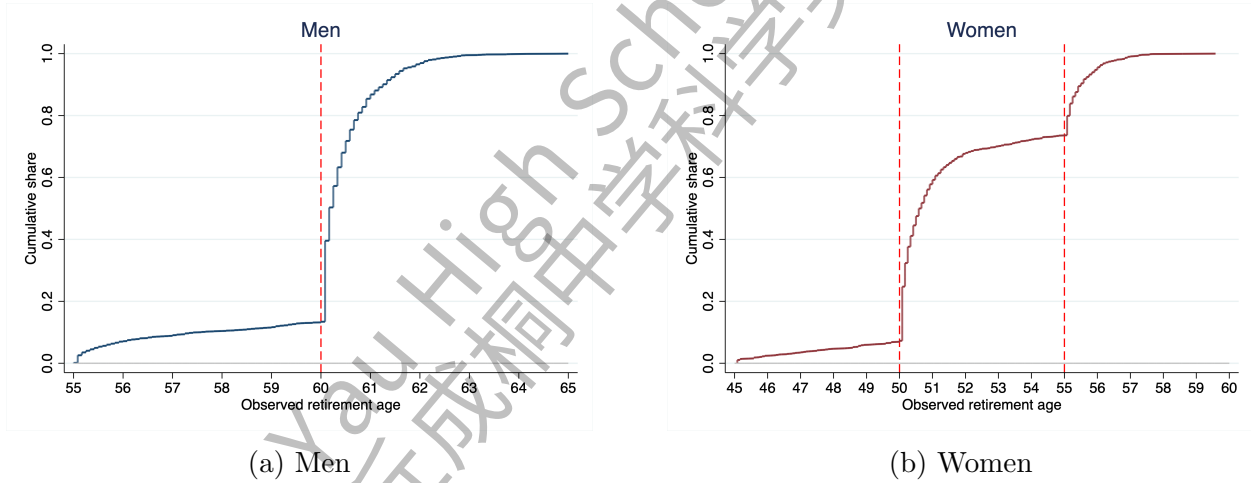


Figure 3: Cumulative Distribution of Age at the Observed Retirement Month
Notes: The figure uses one observation for every patient with an observed active-employee-to-retiree transition in the full 2016–2019 visit-level data. It is not restricted to the male age-60–61 main regression sample. The vertical dashed line marks age 60 for men and ages 50 and 55 for women.

For women, the applicable statutory retirement age depends on employment classification, but the hospital records do not indicate whether age 50 or 55 applies to a given woman. The main analysis therefore focuses on men, for whom the standard statutory retirement age was 60. We retain men whose observed retirement month falls from their 60th birthday month through the month before their 61st birthday.

5.3 Variable Definitions

Outpatient utilization and spending. The main outcomes are monthly total outpatient expenditure and the number of outpatient visits at the study hospital. Total expenditure is the sum of all charges in a patient-month, and visits are the number of outpatient records in that month. Both are set to zero when the patient has no recorded visit at this hospital. We also examine an indicator for any visit and total expenditure in months with at least one visit. These measures help distinguish a change in the probability of using care from a change in spending when care is used.

Insurance-use information. The insurance variables describe the payment terms actually observed in the hospital bill. The coinsurance segment is the part of the UEBMI payment rules under which expenses are reimbursed after the relevant deductible or account threshold is reached. The indicator equals one if at least one claim in a patient-month enters this segment. It equals zero otherwise, including months without a visit. The reimbursement rate is UEBMI payment divided by total expenditure and is defined for months with positive expenditure. We also use monthly out-of-pocket payment, monthly expenditure outside the UEBMI benefit package, and the patient-payment share (out-of-pocket payment divided by total expenditure).

Care process and service composition. We extract the calendar date and clock time separately from registration and actual-visit records. For months with the relevant records, we calculate the shares occurring on weekends (Saturday or Sunday), in the morning (08:00–11:59), in the afternoon (12:00–16:59), and outside regular daytime hours (before 08:00 or at or after 17:00), as well as the mean registration and visit hours. We also calculate the mean registration fee, defined as total registration fees divided by the number of registration records in that month. Finally, in months with positive total expenditure, we calculate the share of spending on each of six service groups: Western-medicine drugs, Chinese patent drugs, Chinese herbal drugs, examinations, laboratory tests, and treatment.

Departments and diagnosis text. We measure the range of recorded care in three ways. First, we count distinct raw department names and distinct Chinese–Western diagnosis-text combinations in each patient-month. Second, we use manually reviewed keyword rules to place the records into broad department categories and disease groups, reducing differences caused only by wording. Third, we divide the raw text into tokens, or text units, and count the distinct tokens.³ All of these current-month counts are zero when there is no recorded outpatient visit.

To assess whether a patient returns to a familiar department with similar diagnosis text,

³For example, “General Cardiology Clinic” and “Cardiology Expert Clinic” can be classified as cardiology, while tokenization separately identifies words such as “general,” “cardiology,” and “expert.”

we use patient–department–month observations. A department is defined by its raw name after spaces are removed. For each patient–department pair, valid diagnosis text from months $k = -12$ through $k = -7$ is combined into a fixed reference text. This reference is compared with diagnosis text recorded when the patient returns to the same department in months $k = -6$ through $k = -1$ and $k = 1$ through $k = 6$.

The TF–IDF method assigns greater weight to tokens that appear frequently in a particular reference text but appear in relatively few reference texts across the sample. Tokens that occur in many reference texts receive lower weights because they are less informative for distinguishing records. For patient–department pair d , the TF–IDF weight of token v in the fixed reference text is

$$w_{vd} = c_{vd} \log \left(\frac{N}{df_v} \right), \quad (6)$$

where c_{vd} is the number of times token v appears in the reference text for pair d , N is the total number of reference pairs, and df_v is the number of reference pairs containing token v . Collecting these token-level weights gives the TF–IDF vector for the reference text,

$$\mathbf{w}_d = (w_{1d}, \dots, w_{Vd})'.$$

For the current-month diagnosis text, an analogous TF–IDF vector $\mathbf{x}_{it}$ is constructed using the same IDF weights, $\log(N/df_v)$, calculated from the fixed reference texts. TF–IDF cosine similarity then compares the current-month diagnosis text with the fixed reference text for pair d :

$$\text{Cosine}(\mathbf{x}_{it}, \mathbf{w}_d) = \frac{\mathbf{x}_{it}' \mathbf{w}_d}{\|\mathbf{x}_{it}\| \|\mathbf{w}_d\|}. \quad (7)$$

Two additional measures compare the sets of distinct diagnosis tokens. Let S_{it} be the current-month token set and S_{id}^0 the fixed reference token set for the patient and department being compared. Jaccard similarity is $|S_{it} \cap S_{id}^0| / |S_{it} \cup S_{id}^0|$. It measures the proportion of distinct tokens appearing in either set that appear in both. The share of new tokens is $|S_{it} \setminus S_{id}^0| / |S_{it}|$. It measures the proportion of distinct current-month tokens that do not appear in the reference set.

Higher cosine or Jaccard similarity indicates that the current diagnosis text more closely resembles the earlier text. A higher share of new tokens indicates more wording absent from the reference. These measures describe changes in recorded diagnosis text, not disease severity.

5.4 Descriptive Statistics

Table 1 reports descriptive statistics for outpatient utilization recorded at the study hospital between 2016 and 2019. The sample comprises 1,903 male patients whose observed retirement-transition month, G_i , occurs between the calendar month in which they turn 60 and the month immediately preceding their 61st birthday. The patient-month panel contains all 48 calendar months from 2016 through 2019. After excluding each patient’s observed transition month, each patient contributes 47 months, yielding $1,903 \times 47 = 89,441$ patient-month observations. These descriptive statistics use the full 2016–2019 panel rather than the shorter event window used in the main regressions.

Patients average 0.465 recorded outpatient visits and RMB 149.96 in total outpatient expenditure per month. The standard deviations and maximum values indicate that expenditure is strongly right-skewed, while 75.3% of patient-months contain no recorded visit. Timing measures, payment ratios, and within-department text measures are available only in the relevant smaller samples. The main expenditure and visit outcomes include all patient-months, including months with no recorded use.

6 Empirical Strategy and Models

The preceding section defined the observed retirement transition and the monthly measures of outpatient utilization. We now use differences in the timing of this transition to compare outpatient use before and after it. We first define the event month, analysis window, and comparison groups. We then present the pooled DID, event-study, and matched DID. Finally, we describe the robustness checks and the measures used to study possible mechanisms.

6.1 Empirical Strategy

Using the observed retirement month defined in Section 5.2, the main sample includes men whose transition occurs from their 60th birthday month through the month before their 61st birthday. We require the available data to cover the 11 months before the observed retirement month and the interval through the month before the patient’s 61st birthday. Because the panel includes zero-use months, this requirement does not require a hospital visit in every month.

The hospital records do not report the date on which a patient completed the retirement procedure or left work. The observed retirement month may therefore be later than the underlying administrative transition. We interpret it as the month in which retirement first

Table 1: Descriptive Statistics of Outcomes and Mechanism Variables among Male Patients Retiring at the Statutory Age, 2016–2019

Variable	Observations	Mean	Std. Dev.	Min.	Max.
<i>Panel A: Outpatient utilization</i>					
Monthly total expenditure	89,441	149.961	412.943	0.000	21,636.000
Monthly outpatient visits	89,441	0.465	1.046	0.000	19.000
Any outpatient visit	89,441	0.247	0.431	0.000	1.000
<i>Panel B: Insurance-use information</i>					
Monthly out-of-pocket payment	89,441	97.700	273.828	0.000	21,532.401
Monthly expenditure outside insurance	89,441	14.140	118.960	0.000	21,488.000
Observed in coinsurance segment	89,441	0.110	0.313	0.000	1.000
Average reimbursement rate	19,600	0.283	0.298	0.000	0.735
Patient payment share	19,600	0.717	0.298	0.265	1.000
<i>Panel C: Timing of recorded care</i>					
Registration weekend share	22,053	0.148	0.334	0.000	1.000
Registration morning share	22,053	0.473	0.465	0.000	1.000
Registration afternoon share	22,053	0.385	0.458	0.000	1.000
Registration off-hour share	22,053	0.143	0.329	0.000	1.000
Visit weekend share	21,843	0.149	0.336	0.000	1.000
Visit morning share	21,843	0.541	0.465	0.000	1.000
Visit afternoon share	21,843	0.416	0.462	0.000	1.000
Visit off-hour share	21,843	0.043	0.185	0.000	1.000
Average registration hour	22,053	11.307	2.849	0.266	23.825
Average visit hour	21,843	11.976	2.750	0.143	23.974
Mean registration fee	22,053	29.167	21.432	0.000	266.000
<i>Panel D: Department and diagnosis measures</i>					
Raw department types	89,441	0.321	0.643	0.000	9.000
Broad department categories	89,441	0.179	0.502	0.000	6.000
Diagnosis-text combinations	89,441	0.308	0.617	0.000	9.000
Broad disease groups	89,441	0.307	0.723	0.000	6.000
Distinct department tokens	89,441	0.409	0.898	0.000	13.000
Distinct diagnosis tokens	89,441	0.772	1.642	0.000	16.000
Diagnosis-text combinations per department	22,053	1.063	0.274	0.000	5.000
<i>Panel E: Conditional expenditure composition</i>					
Western-medicine drug share	22,053	0.323	0.353	0.000	0.988
Chinese patent drug share	22,053	0.170	0.268	0.000	0.984
Chinese herbal drug share	22,053	0.227	0.342	0.000	0.989
Examination share	22,053	0.022	0.104	0.000	1.000
Laboratory-test share	22,053	0.026	0.109	0.000	0.987
Treatment share	22,053	0.054	0.176	0.000	0.987

Notes: The sample includes men whose observed retirement month falls from their 60th birthday month through the month before their 61st birthday. The observed retirement month is omitted. Months without a recorded outpatient visit at this hospital have zero visits and expenditure. Payment ratios, timing measures, registration fees, and expenditure shares are reported only when their denominator is observed; expenditure shares are conditional on positive spending. Amounts are in RMB.

becomes visible in this hospital's records, and study outpatient use around that observed change.

The observed retirement month necessarily contains a hospital visit: it is the visit at which retiree status first appears. We remove this month so that the visit required to observe the transition is not counted as a post-retirement outcome. For the remaining observations, relative event time is $k = t - G_i$, where t is the calendar month. Thus $k = -1$ is the month immediately before the observed retirement month and $k = 1$ is the following month. All main specifications retain $-11 \leq k \leq 11$ and exclude $k = 0$. Patients need not contribute all 22 retained event months.

The analysis uses differences across patients in the calendar month of the observed retirement transition. For any calendar month g , patients with $G_i = g$ constitute transition cohort g , while t denotes the calendar month in which the outcome is measured. For patients in cohort g , observations with $t < g$ occur before the observed transition, the observation with $t = g$ is excluded, and observations with $t > g$ occur after the transition. Their relative event time is therefore $k = t - g$.

Consider cohort g in a retained post-transition month t , such that $1 \leq t - g \leq 11$. In the same calendar month, we intend to compare this cohort with patients j whose observed transitions occur later, so $G_j > t$. Month t must also be within the comparison patient's 11-month pre-transition window, so $1 \leq G_j - t \leq 11$. Thus, the outcome of cohort g after its transition is compared with the outcomes of later transition cohorts observed in the same calendar month but before their own transitions.

To interpret the estimates causally, we assume that, without the observed retirement transition, outcomes for cohort g and the eligible later-transitioning cohorts would have changed in the same way over these calendar months. The following model specifications state how patient and calendar-month differences are accounted for.

We begin in Section 6.2 by estimating the average post-retirement change over the full event window. The later specifications examine when the response occurs and whether it changes when we use different comparison groups.

6.2 Staggered DID Model

For each retained patient month, define $D_{it} = \mathbf{1}(t > G_i)$. Thus, $D_{it} = 0$ during months $k = -11, \dots, -1$ and $D_{it} = 1$ during months $k = 1, \dots, 11$, where $k = t - G_i$. The transition month, $k = 0$, is excluded from the estimation sample. The following two way fixed effects model is estimated:

$$Y_{it} = \alpha_i + \lambda_t + \beta D_{it} + \varepsilon_{it}, \quad (8)$$

where Y_{it} is the outcome for patient i in calendar month t , α_i denotes patient fixed effects, and λ_t denotes calendar month fixed effects. Patient fixed effects account for additive differences across patients that do not change over time. Calendar-month fixed effects account for seasonality, hospital-wide shocks, and other changes shared by all patients in month t . Standard errors are clustered at the patient level.

Patients reach their observed retirement transitions in different calendar months. In any retained month t , patient i is classified as pre-transition if $t < G_i$, so that $D_{it} = 0$, and as post-transition if $t > G_i$, so that $D_{it} = 1$. The transition month $t = G_i$ is excluded. Because patients transition in different months, the model can distinguish changes around G_i from changes shared by patients in a particular calendar month. Patient fixed effects compare each patient's post-transition outcomes with that patient's own pre-transition outcomes, while calendar month fixed effects remove changes common to all patients in month t . The coefficient β therefore summarizes the regression difference between outcomes during months 1–11 after G_i and outcomes during months 1–11 before G_i , after accounting for the fixed effects. This pooled two-way fixed-effects model uses the basic comparison logic of difference-in-differences designs ([Abadie, 2005](#)).

6.3 Dynamic Effects

To show how outcomes change around the observed transition and whether they were already changing beforehand, we estimate the following event-study model:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k=-11}^{-2} \beta_k \mathbf{1}(t - G_i = k) + \sum_{k=1}^{10} \beta_k \mathbf{1}(t - G_i = k) + \varepsilon_{it}. \quad (9)$$

Month $k = -1$ is the omitted reference period, and the transition month $k = 0$ is excluded from the sample. The estimation sample is restricted to $-11 \leq k \leq 11$. The $k = 11$ indicator is omitted because, in this specification, it can be written as an exact linear combination of the patient fixed effects, calendar-month fixed effects, and other event-time indicators. The identified coefficients are $k = -11, \dots, -2$ and $k = 1, \dots, 10$. Each coefficient β_k measures the difference in the outcome at event month k relative to month $k = -1$, after accounting for patient and calendar-month fixed effects.

The coefficients for $k = -11, \dots, -2$ compare the outcome in each earlier pre-transition month with the outcome in the reference month, $k = -1$. A systematic pattern in these coefficients would indicate that utilization was already changing as patients approached G_i , rather than changing only after the observed transition. These coefficients therefore help us check for pre-transition trends. The coefficients for $k = 1, \dots, 10$ show how outcomes evolve

after the observed transition relative to $k = -1$.

6.4 Matching and Stacked DID

Matching sharpens the comparison by pairing each treated patient with later-transitioning patients who have similar observed characteristics before the treated patient’s transition. For a given month g , treated patients are those with $G_i = g$. Eligible controls satisfy $G_j > g+11$, ensuring that their observed transitions occur after the entire outcome window centered on g . Each eligible control is assigned g as the index month for that set, while the control’s actual transition month G_j remains unchanged. The control’s analysis window is therefore centered on the treated cohort’s transition month rather than on the control’s own transition.

Matching variables are measured during calendar months $g - 11, \dots, g - 1$. They include average monthly outpatient visits, average monthly total expenditure, the share of expenditure outside the insurance benefit package, the number of months with a visit, the number of months in which the patient is observed in the coinsurance segment, and the average monthly numbers of department and diagnosis types. Patients must have at least three usable observations during this matching period.

We first place patients into broad groups based on the number of pretransition months with a visit and whether they are observed in the coinsurance segment during the matching period. We then put the continuous variables on the standardized scale and, within each group, match treated patients to eligible controls using Euclidean distance. Matching is conducted with replacement, so the same later transitioning patient may serve as a control more than once.

We report three matching specifications: one nearest neighbor, five nearest neighbors with equal weights, and five nearest neighbors with inverse distance weights. The first specification uses the single closest control. The five-neighbor specifications use more controls to improve precision. Inverse distance weighting assigns less weight to controls that are less similar to the treated patient. Results from all three specifications are reported rather than selecting among them based on statistical significance. This procedure combines covariate matching and difference in differences estimation, drawing on the related matching literature (Li et al., 2001; Heckman et al., 1997; Stuart et al., 2014).

After fixing the matches and their weights, the analysis assesses covariate balance separately for each of the three specifications by checking how similar the treated and control groups are on the observed matching variables. For every matching variable, we report the weighted mean in the treated and control observations and the standardized mean difference, defined as the difference in weighted means divided by the square root of the average of the

two weighted variances. An absolute standardized mean difference below 0.10 is commonly taken to show balance on that observed pre-transition characteristic. The balance diagnostic reflects the comparability of observed pre-transition characteristics.

After matching, the records from all matched sets are combined into one estimation sample. This step is called stacking. Let s index a matched set and let g_s denote its index month, which is the observed transition month of the treated patient in that set. Define $Treat_{is}$ as an indicator equal to one if patient i is the treated patient in set s and zero if patient i is a matched control. Define $Post_{st} = \mathbf{1}(t > g_s)$ for observations with $t \neq g_s$. Thus, $Post_{st} = 0$ during months $g_s - 11, \dots, g_s - 1$ and $Post_{st} = 1$ during months $g_s + 1, \dots, g_s + 11$. The index month $t = g_s$ is omitted for every patient in the matched set.

The stacked matched sample is used to estimate

$$Y_{ist} = \alpha_{is} + \lambda_{st} + \beta^M (Treat_{is} \times Post_{st}) + u_{ist}, \quad (10)$$

where Y_{ist} is the outcome for patient i in calendar month t when that patient appears in matched set s . The term α_{is} is a separate fixed effect for each patient within each matched set. It accounts for differences between the treated patient and matched controls that do not change over time. The term λ_{st} is a separate fixed effect for each matched set and calendar month. It accounts for changes shared by all patients in set s during month t .

The coefficient β^M compares the treated patient's change in utilization after g_s with the corresponding change among the matched controls over the same calendar months. It therefore summarizes the matched difference between outcomes during months 1 through 11 after the index month and outcomes during months 1 through 11 before it. Each specification applies its corresponding matching weights. Because matching is conducted with replacement, the same patient may appear in multiple matched sets. Standard errors are therefore clustered by the original patient identifier.

Compared with the pooled benchmark, the matched design uses fewer eligible controls and changes which treated patients are included and how the comparisons are weighted. It also makes the groups more similar in their observed pre-transition characteristics. The next checks examine whether other choices in the design or unusually large outcome values affect the estimates.

6.5 Mechanism Tests

The monthly data are especially useful for discussing short-run mechanisms. Health conditions may evolve over time, but gradual health change is less likely to explain an abrupt pattern over a few months. We therefore examine whether the observed increase in

use is accompanied by changes in insurance payments, the timing and breadth of care, or indicators related to health attention and recorded conditions.

First, the analysis examines changes in the price patients pay. Retiree insurance status may raise the reimbursement rate calculated from the bill or make it more likely that a monthly bill reaches the coinsurance segment. The analysis estimates the retirement effect on both measures. It then adds coinsurance-segment status in the same month to the fixed-effects model and examines how the coefficient for retirement changes.

Second, retirement may make it easier to arrange care without changing medical need. The analysis tests whether the timing of registrations and visits shifts between weekdays and weekends or among morning, afternoon, and off-hour periods. It also counts the departments and diagnosis groups used each month. With fewer scheduling conflicts related to work, patients may find it easier to obtain a broader range of care.

Third, the analysis examines attention to health and recorded conditions. The theoretical model allows retirement to increase the value a patient places on health care. The analysis therefore tests mean registration fees and the shares of spending on examinations and laboratory tests, which may be associated with greater attention to health. We also compare diagnosis text with the patient's pre-retirement text in the same department. If these measures change little, the main response would be more consistent with patients seeking care more often or more broadly than with a sudden change in health or care intensity.

6.6 Robustness Analyses

The robustness analyses address these three concerns in sequence. Alternative event months assess whether the estimates depend on when retiree status first appears in the hospital records. The group-time ATT estimator uses different comparison groups and weights from the pooled two-way fixed-effects model. The upper-tail check asks whether a small number of very large observations drive the benchmark results.

6.6.1 Alternative Retirement Months

This exercise addresses possible timing error in the observed retirement month; it is not a placebo test. A standard alternative-measure placebo replaces the main explanatory variable and asks whether the estimated effect disappears. Here, in contrast, the first hospital record with retiree status may appear after the patient has actually retired. We therefore examine two plausible placements of the underlying retirement month.

First, G_i^L is the statutory retirement-age month, namely the calendar month in which patient i turns 60. This is the most extreme correction: it assumes that retirement occurs

exactly when the patient reaches the statutory age. Second, G_i^R is drawn at random from the calendar months between G_i^L and the observed retirement month G_i . A fixed random seed makes this assignment reproducible. This second measure places retirement after age 60 but before retiree status first appears in the hospital records.

For each alternative $A \in \{L, R\}$, define relative event time as $k^A = t - G_i^A$ and the post-transition indicator as

$$D_{it}^A = \mathbf{1}(t \geq G_i^A). \quad (11)$$

We reestimate the static specification using observations satisfying $-11 \leq k^A \leq 11$. Because neither G_i^L nor G_i^R is defined by the hospital visit that first reveals retiree status, month $k^A = 0$ is retained as a post-retirement month. All other parts of the model remain unchanged. The results show how the estimates change after plausible corrections for timing error; they do not identify the exact administrative retirement date.

6.6.2 Heterogeneity-Robust Group-Time ATT

When patients transition in different calendar months, a conventional two-way fixed-effects model can compare an earlier-transitioning patient with a patient who has already transitioned. If retirement effects differ across cohorts or over time, these comparisons can make the pooled estimate difficult to interpret. The analysis therefore follows [Callaway and Sant'Anna \(2021\)](#) to report a heterogeneity-robust DID estimate.

We implement this approach using the Stata command `csdid`. For each observed retirement cohort and calendar month, the method uses patients whose retirement transition has not yet been observed as the comparison group. The observed retirement month is omitted, and the cohort-specific estimates are summarized over months 1–2 and months 1–11 after retirement. This provides a robustness check that avoids using already-transitioned patients as controls.

6.6.3 Robustness to Long Tails

For both primary outcomes, a small number of observations are much larger than most others. This gives their distributions long right tails. The linear fixed-effects model remains the primary specification because it estimates the change in monthly spending and visits across all months, including months with no use. As a robustness check, we calculate each outcome's 99th percentile using the retained pre-transition months and replace larger values with that cutoff. We do not drop these observations.

7 Empirical Results

The preceding section described several approaches that differ in how they show the post-transition pattern, form comparison groups, and handle the outcome distributions. We now apply these approaches in sequence. We begin with pooled two-way fixed-effects estimates as a benchmark and then use the event study to show when healthcare use changes. Next, we test whether the full-window estimates remain positive under matching, alternative event-month definitions, and group-time estimates that use only not-yet-transitioned patients as controls. Finally, we test whether the benchmark results are driven by a small number of very large observations.

7.1 Main Results

We first estimate the average change in healthcare use within the common event window and then show the change separately for each relative month. The pooled model provides a benchmark estimate. The event study shows whether the change lasts or is concentrated around the recorded insurance-status transition.

7.1.1 Two-Way Fixed-Effects Estimates

Table 2 presents the pooled two way fixed effects estimates within the common event window. Monthly total expenditure at the study hospital is 81.035 yuan higher after the observed transition, while the number of monthly outpatient visits is higher by 0.250. Both coefficients are statistically significant at the 1% level. Relative to the overall sample means of 149.961 yuan and 0.465 visits reported in Table 1, these estimates correspond to 54.0% and 53.8% of typical monthly utilization, respectively. In months with recorded outpatient use, the estimated change in monthly total expenditure is only 3.053 yuan and is not statistically different from zero. This suggests that, once a patient uses care, spending in that month does not increase by a statistically detectable amount. Panel B reports patient-payment outcomes separately: monthly out-of-pocket payment increases by 32.419 yuan, and monthly expenditure outside insurance increases by 6.109 yuan. Both estimates are statistically significant at the 1% level.

Table 2 contains 38,074 patient-month observations from the 1,903 men in the sample. We do not require every patient to contribute all 22 months surrounding the observed transition. For each patient, we retain the available observations during the 11 months before and the 11 months after the transition, excluding the transition month itself. Patients whose event windows extend beyond the available observation period therefore contribute fewer months.

Table 2: Two-Way Fixed-Effects Estimates within the Common Event Window

	Monthly total expenditure	Monthly visits	Monthly total expenditure, positive-use months
Post-retirement	81.035*** (10.414)	0.250*** (0.028)	3.053 (21.443)
Patient fixed effects	Yes	Yes	Yes
Calendar-month fixed effects	Yes	Yes	Yes
Observations	38,074	38,074	10,466
R^2	0.391	0.413	0.500
<i>Panel B: Patient payments</i>			
	Monthly out-of-pocket payment	Monthly expenditure outside insurance	
Post-retirement	32.419*** (7.059)	6.109*** (2.123)	
Patient fixed effects	Yes	Yes	
Calendar-month fixed effects	Yes	Yes	
Observations	38,074	38,074	
R^2	0.263	0.110	

Notes: Panel A reports the two main outcomes using all patient-months in the estimation sample. It also reports total expenditure using only months with recorded outpatient use. Panel B reports patient-payment outcomes. The estimation sample includes all available patient-month observations from the 11 months before and the 11 months after the observed retirement month. The observed retirement month itself ($k = 0$) is excluded, and patients are not required to contribute observations in all 22 event months. Standard errors are clustered by patient and reported in parentheses below coefficients. $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

Consequently, the number of patient-month observations is below the maximum of 41,866.

The post-transition indicator uses one coefficient for all retained post-transition months. The estimates in Table 2 therefore give one average benchmark. They do not mean that the change is the same in every post-transition month. The event study below examines when the estimated changes emerge and how long they persist.

7.1.2 Dynamic Effects

Figure 4 presents the dynamic estimates relative to month $k = -1$. Before the observed transition, the coefficients for both outcomes generally fluctuate around zero without a clear upward or downward pattern. The joint test p -values for the coefficients from $k = -11$ through $k = -2$ are 0.262 for monthly total expenditure and 0.255 for monthly visits. We therefore cannot reject the null that the pre-transition coefficients are jointly zero. These results provide no evidence of a systematic rise or decline in utilization as the observed transition approaches.

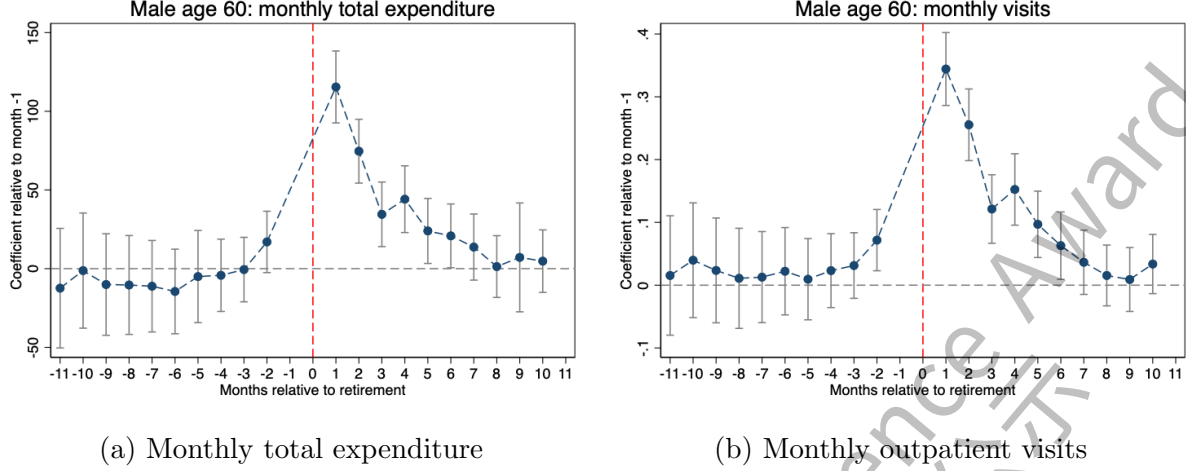


Figure 4: Dynamic Effects Before and After Retirement: Common Event Window
Notes: Month -1 is the reference period and the observed retirement month is removed. The displayed coefficients run from $k = -11$ to $k = -2$ and from $k = 1$ to $k = 10$; $k = 11$ is not plotted because it is perfectly collinear with the event-time indicators and fixed effects in the finite common-window estimation. Error bars are 95% confidence intervals with standard errors clustered by patient.

The post-transition estimates show an immediate increase followed by a gradual decline. In month $k = 1$, monthly total expenditure increases by 115.444 yuan and monthly visits increase by 0.344 relative to month $k = -1$. In month $k = 2$, the corresponding increases are 74.636 yuan and 0.255 visits. All four estimates are statistically significant at the 1% level. The coefficients for both outcomes are generally positive and statistically significant through month $k = 6$, but become markedly smaller and statistically indistinguishable from zero from approximately month $k = 7$ onward. The final identified post-transition coefficient is $k = 10$.

The dynamic estimates therefore indicate that the increase in outpatient utilization is concentrated in approximately the first six months after the observed transition rather than persisting at a constant level throughout the entire post-transition window. The estimates in Table 2 provide one average benchmark, while the event study shows that the increase is immediate and temporary. The next analyses ask whether its size changes when we use different comparison groups or allow the effect to differ across transition cohorts and calendar months.

7.2 Matched DID Results

The pooled estimates use the timing comparisons available in the common event window but do not require earlier- and later-transitioning patients to have similar pre-transition utilization histories. Matching makes the comparison more specific by pairing each treated

Table 3: DID Results under Three Nearest-Neighbor Matching Specifications

	One nearest neighbor	Five nearest neighbors, equal weights	Five nearest neighbors, inverse-distance weights
<i>Panel A: Monthly total expenditure</i>			
Post-retirement × treated	21.569*	27.032***	28.421***
	(12.350)	(9.779)	(9.627)
R^2	0.722	0.635	0.638
Observations	57,324	171,972	171,972
Fixed effects	Matched-set-by-patient; matched-set-by-calendar-month		
<i>Panel B: Monthly outpatient visits</i>			
Post-retirement × treated	0.061**	0.065**	0.068**
	(0.030)	(0.030)	(0.029)
R^2	0.724	0.623	0.626
Observations	57,324	171,972	171,972
Fixed effects	Matched-set-by-patient; matched-set-by-calendar-month		
<i>Panel C: Post-match pre-transition balance (absolute SMD)</i>			
Mean monthly visits before transition	0.049	0.069	0.067
Mean monthly expenditure before transition	0.039	0.058	0.056
Share outside insurance before transition	0.034	0.074	0.067
Months with a visit before transition	0.001	0.008	0.007
Months in coinsurance segment before transition	0.005	0.007	0.007
Mean department types before transition	0.021	0.030	0.029
Mean diagnosis types before transition	0.017	0.025	0.024

Notes: All three specifications use the same broad patient groups, matching variables, and common event window. Matching is with replacement. Each observation in Panels A and B is a record for one patient in one month within a particular matched set. The same original patient may appear more than once. Standard errors are clustered by original patient and reported below coefficients. Panel C reports absolute standardized mean differences (SMDs) between treated and weighted control observations after matching; conventionally, $|SMD| < 0.10$ indicates good comparability in observed pre-transition characteristics.

patient with later-transitioning patients who are similar in observed characteristics before the treated patient's transition month. The balance checks show how similar the matched groups are. The matched DID estimates then show how the full-window results change with this comparison group.

Before interpreting the matched DID coefficients, we examine whether matching makes the comparison groups comparable before the transition. The matching procedure produces matched sets for 1,328 treated patients. The one nearest neighbor specification therefore contains 1,328 matched pairs, while each of the two five neighbor specifications contains 6,640 links between treated patients and controls. Panel C of Table 3 reports the weighted balance diagnostics for all three specifications. The seven matching variables cover pre-transition utilization, financial burden, the number of months with visits, the number of months with coinsurance-segment records, and department and diagnosis types. Every absolute standardized mean difference is below 0.10. The largest is 0.049 under one-neighbor matching, 0.074 under five-neighbor equal-weight matching, and 0.067 under inverse-distance weight-

ing. Thus, the subsequent DID estimates compare treated patients with controls that are balanced on the observed pre-transition characteristics used for matching.

Table 3 reports positive coefficients across all three matching specifications. Monthly total expenditure increases by 21.569 yuan under one nearest neighbor matching, 27.032 yuan under five neighbor matching with equal weights, and 28.421 yuan under five neighbor matching with inverse distance weights. The first estimate is statistically significant at the 10% level, while the two five neighbor estimates are significant at the 1% level. Monthly visits increase by 0.061, 0.065, and 0.068, respectively, with all three estimates significant at the 5% level. The point estimates are therefore stable across the three matching choices. Using five controls reduces the standard errors for expenditure, while the improvement in precision for visits is modest.

The matched estimates are substantially smaller than the benchmark two way fixed effects estimates in Table 2. We should not attribute this difference only to matching on pre-transition use. The stacked analysis also changes the treated sample, restricts controls to patients who remain pre-transition throughout the follow-up period, and uses different comparison weights. The results instead show that the estimated change over the full event window is sensitive to the construction of the comparison group. Nevertheless, all three matching models produce positive estimates when treated patients are compared with similar patients who transition later.

7.3 Mechanism Tests

7.3.1 Price Mechanism

Retirement may change patients' insurance benefits and therefore the price they pay for healthcare. Previous research shows that coinsurance, deductibles, and insurance prices that change over time can affect both how much care patients use and when they use it (Aron-Dine et al., 2015; Baicker et al., 2015; Brot-Goldberg et al., 2017). More broadly, changes in public insurance benefits can substantially affect health care utilization (Card et al., 2008). The analysis first estimates the following equation for two monthly outcomes, an indicator for being observed in the coinsurance segment and the average reimbursement rate:

$$M_{it} = \alpha_i + \lambda_t + \pi D_{it} + \varepsilon_{it}, \quad (12)$$

where M_{it} is one of the two insurance outcomes for patient i in month t . The coinsurance indicator records whether the patient is observed in that segment at this hospital and is analyzed using the full patient-month panel. The reimbursement rate is insurance payment

Table 4: Insurance-Benefit Mechanism: Insurance-Use Information and Retirement Effects Controlling for Coinsurance-Segment Status

Panel A: Retirement and insurance-use information				
	Observed in coinsurance segment this month		Average reimbursement rate this month	
Post-retirement	0.104***		0.108***	
	(0.008)		(0.012)	
Observations	38,074		9,366	
R ²	0.406		0.690	
Fixed effects	Patient; calendar month			
Panel B: Monthly total expenditure and monthly outpatient visits				
	Monthly total expenditure		Monthly outpatient visits	
	Baseline	Controls for coinsurance	Baseline	Controls for coinsurance
Post-retirement	81.035***	16.858*	0.250***	0.082***
	(10.414)	(8.816)	(0.028)	(0.024)
Observed in coinsurance segment this month		615.027***		1.607***
		(19.499)		(0.039)
Observations	38,074	38,074	38,074	38,074
R ²	0.391	0.517	0.413	0.552
Fixed effects	Patient; calendar month			

Notes: The average reimbursement rate is insurance payment divided by monthly total expenditure and is calculated only when valid outpatient expenditure is observed in that month; it therefore has fewer observations. Standard errors are clustered by patient and reported below coefficients. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

divided by monthly total expenditure and is calculated only when valid outpatient expenditure is observed in that month. If changes in insurance benefits after retirement contribute to increased health care use, both the probability of observing a coinsurance-segment record and the average reimbursement rate are expected to rise after retirement.

The analysis then estimates the baseline model in Equation (8) alongside a specification that controls for current coinsurance-segment status:

$$Y_{it} = \alpha_i + \lambda_t + \beta^C D_{it} + \gamma Copay_{it} + u_{it}. \quad (13)$$

If adding $Copay_{it}$ greatly reduces the retirement coefficient and the coinsurance variable is positively related to healthcare use, the results suggest a strong association between higher post-retirement healthcare use and use in the coinsurance segment.

Panel A of Table 4 shows that the probability of observing a coinsurance-segment record at this hospital rises by 10.4 percentage points after retirement. Among patient-months with valid outpatient expenditure, the average reimbursement rate rises by 10.8 percentage points; both coefficients are significant at the 1% level. This pattern is consistent with higher

Table 5: Retirement and the Timing of Registration and Outpatient Visits

	Weekend share	Morning share	Afternoon share	Off-hour share	Average time
<i>Panel A: Registration time</i>					
Post-retirement	−0.001 (0.012)	0.003 (0.018)	0.017 (0.017)	−0.019* (0.011)	0.134 (0.092)
Observations	10,466	10,466	10,466	10,466	10,466
R^2	0.537	0.442	0.506	0.625	0.585
Fixed effects	Patient; calendar month				
<i>Panel B: Visit time</i>					
Post-retirement	−0.003 (0.012)	0.001 (0.018)	0.013 (0.017)	−0.014* (0.007)	0.136 (0.093)
Observations	10,376	10,376	10,376	10,376	10,376
R^2	0.533	0.470	0.488	0.447	0.544
Fixed effects	Patient; calendar month				

Notes: Panel A uses months with a registration record, and Panel B uses months with a visit record. Average time is measured in hours. The models control for patient and calendar-month fixed effects, and standard errors are clustered by patient and reported below coefficients.

insurance benefits after retirement and patients bearing a smaller share of the cost.

Panel B compares the baseline model with the model controlling for current coinsurance-segment status. After the coinsurance variable is included, the retirement coefficient falls from 81.035 yuan to 16.858 yuan for monthly total expenditure and from 0.250 to 0.082 for monthly visits. Being observed in the coinsurance segment during the month is positively associated with both monthly total expenditure and monthly visits. The retirement coefficient falls substantially after controlling for coinsurance status. This pattern is consistent with changes in insurance benefits and use in the coinsurance segment being closely associated with higher healthcare use after retirement.

7.3.2 Timing of Health Care Use

Leaving the labor force may reduce conflict between work time and health care use. For each timing outcome T_{it} , the analysis estimates the same fixed-effects model as Equation (8), replacing Y_{it} with T_{it} . Outcomes include the shares of registrations or visits occurring on weekends, in the morning, in the afternoon, and outside regular daytime hours, as well as average registration and visit times. These measures are calculated only for months with at least one corresponding record. They therefore describe when patients use healthcare in months when they use it.

Table 5 shows no significant changes after retirement in the shares of weekend registrations or weekend visits, morning or afternoon shares, or average times. The shares of

Table 6: Retirement and the Structure of Department and Diagnosis Text

<i>Panel A: Raw types and coverage of aggregated categories</i>				
	Raw departments	Aggregated departments	Raw diagnoses	Aggregated disease groups
Post-retirement	0.178*** (0.015)	0.116*** (0.012)	0.177*** (0.015)	0.160*** (0.016)
Observations	38,074	38,074	38,074	38,074
R^2	0.382	0.299	0.367	0.427
Fixed effects	Patient; calendar month			
<i>Panel B: Number of distinct text tokens</i>				
	Department tokens	Diagnosis tokens		
Post-retirement	0.240*** (0.022)	0.426*** (0.036)		
Observations	38,074	38,074		
R^2	0.387	0.429		
Fixed effects	Patient; calendar month			

Notes: The common event window retains relative months $-11, \dots, -1, 1, \dots, 11$ and excludes the observed retirement-transition month. Panel A and Panel B variables are constructed from current-month records and are set to zero in months without an outpatient visit at this hospital. The models control for patient and calendar-month fixed effects, and standard errors are clustered by patient and reported below coefficients.

off-hour registrations and visits decline by 1.9 and 1.4 percentage points, respectively, but are significant only at the 10% level. Overall, the results provide only descriptive evidence of a small shift from off-hour to regular-hour healthcare use. They do not show a large change in how visits are divided across weekdays or times of day after retirement.

7.3.3 Department and Diagnosis Structure

Healthcare use may also increase because demand for care changes or patients receive a different mix of services. Table 6 uses the same fixed-effects model as Equation (8). The three sets of outcomes are counts of raw department and diagnosis types, counts of broad categories represented after manual grouping, and counts of distinct text tokens. The analysis uses the common event window from 11 months before through 11 months after the observed transition, excluding the transition month itself. All outcomes are constructed from current-month records and are set to zero in months without a recorded outpatient visit. Thus, the post-retirement coefficient compares average outcomes in months +1 through +11 with those in months -11 through -1 , conditional on patient and calendar-month fixed effects.

Table 6 shows significant increases after retirement in the number of raw department types, aggregated department categories, raw diagnosis combinations, and aggregated disease-group coverage. The numbers of distinct department and diagnosis text tokens also increase

by 0.240 and 0.426, respectively. Because these monthly counts are set to zero in months without a visit, their increases may reflect both a broader range of health care use and, in part, more outpatient visits.

7.3.4 Service Composition

To distinguish a change in the amount of care from a change in the composition of spending, Table 7 uses each service category’s expenditure divided by total monthly expenditure as the outcome. These shares are defined only in months with positive total expenditure. The estimates therefore describe the mix of spending only in months when patients receive outpatient care. They do not show changes in the use of each category across all months.

Table 7: Retirement and Expenditure Shares by Service Category

	Western medicine	Chinese patent medicine	Chinese herbal medicine	Examination	Laboratory tests	Treatment
Post-retirement	-0.010 (0.010)	0.011 (0.009)	0.002 (0.009)	-0.006* (0.003)	0.000 (0.004)	-0.003 (0.007)
Observations	10,466	10,466	10,466	10,466	10,466	10,466
R^2	0.727	0.578	0.789	0.278	0.322	0.627
Fixed effects	Patient; calendar month					

Notes: Each outcome is category expenditure divided by total monthly expenditure and is defined only for months with positive total expenditure. The models use the common event window, omit the observed retirement month, include patient and calendar-month fixed effects, and cluster standard errors by patient.

The conditional shares are stable across most service categories. The examination share decreases by 0.6 percentage points at the 10% level, while the remaining estimates are statistically insignificant. Thus, the increase in total spending does not appear to come from a large shift among the six recorded service categories.

7.3.5 Other Mechanisms

Table 8 examines changes in health demand using two within-department measures. Panel A uses the number of distinct Chinese- and Western-medicine diagnosis-text combinations divided by the number of raw departments used in the month. It measures the average number of diagnosis-text combinations associated with each department used and is defined only for months with at least one department. If the increase in utilization after retirement mainly reflected more complex or more diverse disease records within the same department, this outcome would be expected to increase.

Panel B directly compares current diagnosis text with the patient’s own prior text in the same raw department. The unit of observation is a patient–department–month, not a

Table 8: Retirement and Within-Department Diagnosis Complexity and Continuity

Panel A: Diagnosis-text combinations per department			
	Diagnosis-text combinations per department		
Post-retirement	-0.002		
	(0.012)		
Observations	10,466		
R ²	0.233		
Fixed effects		Patient; calendar month	
Panel B: Continuity of diagnosis text within prior departments			
	TF-IDF cosine similarity	Jaccard similarity	Share of new tokens
Post-retirement	0.013	0.012	-0.011
	(0.013)	(0.013)	(0.014)
Observations	5,504	5,504	5,504
R ²	0.776	0.788	0.735
Fixed effects		Patient-department; calendar month	

Notes: Panel A uses the common event window, retaining relative months $-11, \dots, -1, 1, \dots, 11$. Its outcome is the number of distinct Chinese- and Western-medicine diagnosis-text combinations in a month divided by the number of raw departments, and it is defined only for months with at least one department. Panel B uses one patient–raw-department–month observation for each return to a raw department with a diagnosis-text baseline from months -12 through -7 . It compares months -6 through -1 with months $+1$ through $+6$, excluding month 0. Panel B includes patient–department and calendar-month fixed effects; Panel A includes patient and calendar-month fixed effects. Standard errors are clustered by patient.

patient-month aggregate. For each patient–raw-department pair, valid diagnosis text from months -12 through -7 forms a fixed reference. The estimation sample contains returns to that same department in months -6 through -1 and $+1$ through $+6$, excluding month 0. Patient–department fixed effects therefore compare each patient’s recorded diagnosis content in the same department before and after retirement. Calendar-month fixed effects remove common changes in documentation or hospital practice. TF-IDF cosine similarity measures how similar the weighted diagnosis texts are. Jaccard similarity measures how much the sets of diagnosis tokens overlap. The share of new tokens measures how much of the current token set is absent from the department-specific reference.

Table 8 shows no significant change in diagnosis-text combinations per department after retirement. In the patient–department–month comparison sample, the estimated changes in TF-IDF similarity, Jaccard similarity, and the share of new tokens are 0.013, 0.012, and -0.011 , respectively, and none is statistically significant. The available evidence therefore does not support the view that higher healthcare use is mainly driven by systematically greater disease complexity or changes in recorded diagnosis content within the same department.

Table 9 provides an additional check using mean registration fees. Mean registration fee equals total registration fees in a month divided by the number of registration records and is

defined only for months containing at least one registration. If patients systematically shifted toward higher-priced registration services after retirement, this outcome would increase.

Table 9: Retirement and Mean Registration Fee

	Mean registration fee
Post-retirement	0.221 (0.570)
Patient fixed effects	Yes
Calendar-month fixed effects	Yes
Observations	10,466
R^2	0.746

Notes: Mean registration fee is total registration fees in a month divided by the number of registration records and is defined only for months containing at least one registration. The model controls for patient and calendar-month fixed effects, and standard errors are clustered by patient and reported below the coefficient.

Table 9 shows no significant change in mean registration fees after retirement. Together with the largely unchanged examination and laboratory-test shares in Table 7, this result provides no evidence that retirement increases attention to health, as represented by a higher ω in the model. The available evidence does not indicate that patients systematically shift toward more expensive registration services after retirement.

7.3.6 Summary of Mechanism Evidence

The mechanism results can be compared with the model's predictions about the price patients pay and the time and inconvenience of seeking care. The evidence is clearest for lower out-of-pocket prices. After the observed transition to retiree health-insurance status, patients are more likely to enter the coinsurance segment and have higher reimbursement rates calculated from their bills. Controlling for coinsurance-segment status in the same month substantially reduces the estimated post-retirement increases in both outpatient visits and medical expenditure. These patterns are consistent with the model's prediction that a lower effective out-of-pocket price, represented by a lower θ_R , increases outpatient healthcare utilization.

By contrast, evidence for lower time and inconvenience costs is weaker. After retirement, outpatient visits do not show a clear, systematic shift between weekdays and weekends or across most times of day. At the same time, patients visit more departments and receive

diagnoses from more disease groups. This broader use of care is consistent with retirement giving patients more time and greater flexibility to seek different types of outpatient care.

However, lower time costs are not the only possible explanation for the wider range of departments and disease groups. This expansion could also reflect worsening health or greater attention to health after retirement. The remaining mechanism tests, however, provide little support for these alternative explanations. Expenditure shares across service categories remain broadly stable, mean registration fees do not increase, and both diagnosis complexity and diagnosis-text content within the same department remain largely unchanged. These findings are consistent with the model's benchmark assumption that medical need remains relatively stable. They provide little evidence of a substantial increase in attention to health, represented by a higher ω , around the transition.

Overall, the evidence is most consistent with retirement increasing outpatient use by reducing the combined time, inconvenience, and out-of-pocket costs patients face. The evidence is strongest for lower out-of-pocket prices. Direct evidence for lower time and inconvenience costs is weaker, although its direction is consistent with the broader range of care observed after retirement.

7.4 Robustness Analyses

The matched results show that the choice of comparison group affects the size of the full-window estimate. The robustness analyses now examine three other parts of the empirical design. First, the alternative-event-month specifications examine whether the estimates depend on the month in which retiree status first appears in hospital records. Second, the group-time ATT estimator replaces the pooled two-way fixed-effects comparisons with cohort-specific estimates that use not-yet-transitioned patients as controls. Third, the upper-tail assesses whether the benchmark coefficients are driven by extreme observations in the two primary outcomes.

7.4.1 Alternative Retirement Months

Table 10 reports estimates using two plausible ways to correct timing error. In both cases, the alternative event month is included in the post period. When the event is placed in the statutory retirement-age month, monthly expenditure increases by 29.806 yuan and monthly visits by 0.083, both significant at the 1% level. When the reproducibly drawn intermediate month is used, the corresponding coefficients are 80.247 yuan and 0.246 visits. The statutory-age placement produces smaller estimates, as expected when some post-retirement months are reclassified as pre-retirement months. Nevertheless, both exercises retain a positive and

statistically significant retirement effect. Thus, possible timing error changes the estimated magnitude, but does not remove the central post-retirement increase in utilization.

Table 10: Alternative Retirement Months: Full-Window Estimates

	Statutory retirement-age month		Random month within interval	
	Monthly visits	Monthly total expenditure	Monthly visits	Monthly total expenditure
Post-retirement	0.083*** (0.022)	29.806*** (8.544)	0.246*** (0.022)	80.247*** (8.780)
Observations	40,997	40,997	40,740	40,740
R^2	0.384	0.367	0.382	0.367
Patient fixed effects			Yes	
Calendar-month fixed effects			Yes	

Notes: The statutory retirement-age month is the birth month plus 60 years. The random month is reproducibly drawn between the statutory month and the observed transition month. The sample uses a common window covering 11 months before and after each alternative event month. Both alternative event months are retained and included in the post period from event month 0 onward. Standard errors are clustered by patient and reported below coefficients. *** $p < 0.01$.

Using the statutory retirement-age month as the event month produces smaller estimates than the benchmark specification centered on G_i , whereas using the random intermediate month produces estimates closer to the benchmark. Neither alternative identifies the patient's actual retirement date. These results only show how the estimates change when we choose a different event month.

7.4.2 Heterogeneity-Robust Group-Time ATT

Table 11 reports the heterogeneity-robust estimates obtained with `csdid`. Following the approach of Callaway and Sant'Anna (2021), each retirement cohort is compared only with patients whose transition has not yet been observed in the same calendar month. This avoids using already-transitioned patients as controls.

Table 11: Heterogeneity-Robust Group-Time ATT: Common Event Window

	Months 1–2 after retirement		Months 1–11 after retirement	
	Monthly visits	Monthly total expenditure	Monthly visits	Monthly total expenditure
Average ATT	0.293*** (0.030)	90.452*** (10.849)	0.085*** (0.029)	19.879* (11.203)
Comparison group	Patients not yet retired in the current period			
Estimator	Callaway–Sant’Anna group–time ATT; Stata <code>cstdid</code>			

Notes: The estimates are produced using Stata’s `cstdid` command. The observed retirement month is removed, and the same common 11-month event window as in the main analysis is used. Standard errors are in parentheses. Fixed effects and R^2 are not reported because this is not a conventional two-way fixed-effects regression. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

The heterogeneity-robust estimates remain positive. During months 1–2 after retirement, monthly expenditure increases by 90.452 yuan and visits by 0.293; both estimates are significant at the 1% level. Over months 1–11, the estimated increases are 19.879 yuan for expenditure and 0.085 for visits. Thus, the `cstdid` results confirm a short-run increase in outpatient utilization while showing that the full-window average is smaller than the benchmark two-way fixed-effects estimate.

Taken together, the analyses point to a consistent pattern over time rather than a single common coefficient. Outpatient visits and expenditures rise most sharply during the first two months after the observed transition and then diminish. Positive estimates remain under matching, alternative event time definitions, and the group and time estimator. However, the estimated average over months 1–11 is considerably smaller under the matched and group and time specifications than under the benchmark two way fixed effects model. The most stable conclusion is that outpatient utilization increases immediately but temporarily around the observed retirement transition. The estimated average increase over the full event window depends on event timing, how the comparison groups are constructed, and the weights used to average the estimates.

7.4.3 Robustness to Long Tails

The long-tail check confirms that the main finding is not driven solely by a small number of extreme observations. Capping each outcome at the 99th percentile of its pre-transition distribution changes the expenditure coefficient from 81.035 to 80.479 yuan and the visit coefficient from 0.250 to 0.243. Both remain significant at the 1% level.

Table 12: Robustness to Long Tails

	Monthly total expenditure		Monthly visits	
	Baseline OLS	99% upper-tail cap	Baseline OLS	99% upper-tail cap
Post-retirement	81.035*** (10.414)	80.479*** (9.009)	0.250*** (0.028)	0.243*** (0.025)
Observations	38,074	38,074	38,074	38,074
R^2	0.391	0.429	0.413	0.419
Fixed effects	Patient; calendar month			

Notes: We cap each outcome at the 99th percentile of its distribution in months -11 through -1 before retirement, without dropping observations. All models include patient and calendar-month fixed effects. Standard errors are clustered by patient and reported below coefficients. *** $p < 0.01$.

8 Conclusion

Retirement can change outpatient use even when patients' health does not change immediately. It may give patients more time to seek care and may reduce the amount they pay. The model predicts that both visit frequency and medical spending increase when retirement lowers these time and monetary costs. Using monthly outpatient records from a tertiary hospital in Shanghai, the analysis examines 1,903 men whose first claim under retired health-insurance status occurs around age 60. The estimates consistently show higher outpatient use after this observed transition. The most conservative full-window DID specification estimates increases of RMB 19.8 in monthly expenditure and 0.061 visits, equivalent to 13.2% and 13.1% of the corresponding sample means.

The mechanism evidence is broadly consistent with the view that retirement increases outpatient use by lowering the combined time, inconvenience, and out-of-pocket costs patients face. Improved insurance-payment conditions provide the clearest support. Evidence for lower time and inconvenience costs is weaker, but its direction is consistent with the broader range of care observed after retirement. At the same time, there is little evidence that the increase is mainly driven by changes in underlying health or greater attention to health. More importantly, the post-retirement increase in utilization is reflected primarily in more frequent and broader use of outpatient care, rather than in more expensive or more complex treatment within each visit.

The findings have two main policy implications. First, as the population ages, retirement may put pressure on the health insurance system by changing the balance between contribu-

tors and beneficiaries as the retired population grows. Higher healthcare use associated with retirement itself may add to this pressure. Raising the retirement age may therefore ease pressures on labor supply and pension systems. By postponing retirement-related increases in healthcare use, it may also help smooth or moderate pressure on health insurance spending. Second, hospitals and health insurers should also consider how healthcare use changes after retirement. The evidence suggests that the increase mainly reflects more frequent visits and use of a broader range of departments and disease groups, rather than more expensive or more complex care within each visit. Improving access to outpatient appointments, streamlining care processes, and strengthening coordination across departments may therefore be more useful than simply expanding the supply of high-cost specialist services.

This study has several limitations. The exact retirement date is not observed because the event month is defined by the patient's first retired-insurance claim at the study hospital, which may occur after the patient actually retires. Care is also observed at only one tertiary hospital, so a month without a visit does not mean that the patient received no care elsewhere, and some of the estimated increase may reflect patients moving between providers. The sample includes only men retiring around age 60 who have both employed- and retired-insurance claims, so the findings may not apply to women, early retirees, people who do not use this hospital, or patients in other regions. The study also focuses on short-run changes around the retirement transition. It primarily identifies changes in outpatient healthcare use within approximately one year before and after retirement. The findings therefore cannot determine the long-run effects of retirement on health, medical expenditure, or the cumulative financial burden on the health insurance system.

Future research should directly address the limits and policy questions raised by this study. Linking hospital records to complete insurance claims and exact retirement and employment dates would show whether outpatient use increases overall or simply moves between hospitals. Information on work schedules and insurance rules would also help distinguish the role of time costs from that of insurance benefits. Adding measures of disease severity, health outcomes, and longer-term spending would show whether the additional visits represent necessary care that was previously postponed or lower-value care encouraged by better insurance.

References

- Abadie, A. (2005). Semiparametric difference-in-differences estimators. *Review of Economic Studies*, 72(1):1–19.

- Aron-Dine, A., Einav, L., Finkelstein, A., and Cullen, M. R. (2015). Moral hazard in health insurance: Do dynamic incentives matter? *Review of Economics and Statistics*, 97(4):725–741.
- Baicker, K., Mullainathan, S., and Schwartz, J. (2015). Behavioral hazard in health insurance. *Quarterly Journal of Economics*, 130(4):1623–1667.
- Barschkett, M., Geyer, J., Haan, P., and Hammerschmid, A. (2022). The effects of an increase in the retirement age on health: Evidence from administrative data. *The Journal of the Economics of Ageing*, 23:100403.
- Brot-Goldberg, Z. C., Chandra, A., Handel, B. R., and Kolstad, J. T. (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.
- Callaway, B. and Sant’Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.
- Card, D., Dobkin, C., and Maestas, N. (2008). The impact of nearly universal insurance coverage on health care utilization: Evidence from medicare. *American Economic Review*, 98(5):2242–2258.
- Centers for Medicare & Medicaid Services (2023). Health expenditures by age and sex: 2020 highlights.
- Eibich, P. (2015). Understanding the effect of retirement on health: Mechanisms and heterogeneity. *Journal of Health Economics*, 43:1–12.
- Filomena, M. and Picchio, M. (2023). Retirement and health outcomes in a meta-analytical framework. *Journal of Economic Surveys*, 37(4):1120–1155.
- Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J. P., Allen, H., Baicker, K., and Oregon Health Study Group (2012). The oregon health insurance experiment: Evidence from the first year. *Quarterly Journal of Economics*, 127(3):1057–1106.
- Fitzpatrick, M. D. and Moore, T. J. (2018). The mortality effects of retirement: Evidence from social security eligibility at age 62. *Journal of Public Economics*, 157:121–137.
- French, E. (2005). The effects of health, wealth, and wages on labour supply and retirement behaviour. *Review of Economic Studies*, 72(2):395–427.

- Frimmel, W. and Pruckner, G. J. (2020). Retirement and healthcare utilization. *Journal of Public Economics*, 184:104146.
- Fu, M. and Xu, W. (2023). The effects of retirement on healthcare utilization and medical expenditures among urban employees. *Economic Research Journal*, 58(2):141–157. In Chinese.
- Hallberg, D., Johansson, P., and Josephson, M. (2015). Is an early retirement offer good for your health? quasi-experimental evidence from the army. *Journal of Health Economics*, 44:274–285.
- Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *Review of Economic Studies*, 64(4):605–654.
- Lalive, R., Magesan, A., and Staubli, S. (2023). How social security reform affects retirement and pension claiming. *American Economic Journal: Economic Policy*, 15(3):115–150.
- Li, Y.-P., Propert, K. J., and Rosenbaum, P. R. (2001). Balanced risk set matching. *Journal of the American Statistical Association*, 96(455):870–882.
- Lucifora, C. and Vigani, D. (2018). Health care utilization at retirement: The role of the opportunity cost of time. *Health Economics*, 27(12):2030–2050.
- Ministry of Health, Labour and Welfare of Japan (2025). Overview of national medical care expenditure, fiscal year 2023.
- National Bureau of Statistics of China (2026). China’s economy achieves its expected development targets in 2025.
- Nielsen, N. F. (2019). Sick of retirement? *Journal of Health Economics*, 65:133–152.
- Rabaté, S., Jongen, E., and Atav, T. (2024). Increasing the retirement age: Policy effects and underlying mechanisms. *American Economic Journal: Economic Policy*, 16(1):259–291.
- Shigeoka, H. (2014). The effect of patient cost sharing on utilization, health, and risk protection. *American Economic Review*, 104(7):2152–2184.
- Standing Committee of the National People’s Congress (2024). Decision on implementing the gradual raising of the statutory retirement age.
- Staubli, S. and Zweimüller, J. (2013). Does raising the early retirement age increase employment of older workers? *Journal of Public Economics*, 108:17–32.

- Stuart, E. A., Huskamp, H. A., Duckworth, K., Simmons, J., Song, Z., Chernew, M. E., and Barry, C. L. (2014). Using propensity scores in difference-in-differences models to estimate the effects of a policy change. *Health Services and Outcomes Research Methodology*, 14:166–182.
- Wu, N., Xie, X., Cai, M., Han, Y., and Wu, S. (2023a). Trends in health service needs, utilization, and non-communicable chronic diseases burden of older adults in china: Evidence from the 1993 to 2018 national health service survey. *International Journal for Equity in Health*, 22:169.
- Wu, Y., Pang, J., and Yang, H. (2023b). Effect of retirement on medical reimbursement expenses: Evidence from china. *Health Economics Review*, 13:22.
- Yu, X., Hu, Q., and Shen, Y. (2023). The mechanism and resolution of the retirement–healthcare utilization fluctuation puzzle: Theoretical and empirical analysis from the perspective of institutional linkages. *Management World*, 39(10):94–115. In Chinese.
- Zhang, Y., Salm, M., and van Soest, A. (2018). The effect of retirement on healthcare utilization: Evidence from china. *Journal of Health Economics*, 62:165–177.
- Zhou, Q., Eggleston, K., and Liu, G. G. (2021). Healthcare utilization at retirement in china. *Health Economics*, 30(11):2618–2636.

Acknowledgements

Research background and origin. My interest in economics began through the economics courses I took at school. Ms. Danqing Chen and Ms. Yuewen Gu introduced me to economic reasoning and showed me how economics can be used to explain individual choices and public policy. Their teaching sparked my interest in the field and motivated me to explore economic questions independently. I was also interested in the changes associated with China’s aging population and began thinking about how retirement could affect people’s daily decisions. Specifically, healthcare seemed very relevant because retirement may change both the time available for seeking care and the amount patients need to pay themselves. Based on this interest, I developed the research direction myself and decided to study whether retirement changes outpatient healthcare utilization. I therefore examined the transition from employed to retired health-insurance status around China’s statutory retirement age.

My contribution. This study uses de-identified 2016–2019 outpatient records from a tertiary hospital in Shanghai. Access to the data was facilitated through my adviser. I developed the research question, reviewed and verified the literature, formulated the health care economic model, constructed the sample, conducted the statistical analysis in Stata, interpreted the results, prepared the tables and figures, and drafted and revised the report.

Adviser relationships and contributions. This project had two advisers with distinct roles. Dr. Yating Zhu, my high-school teacher, provided guidance on the competition process and data access. Professor Zhikuo Liu of Fudan University provided guidance on empirical research conventions, and the organization and presentation of an economics paper. Both advisers answered questions and provided feedback when I encountered methodological or presentation issues, while the research direction, analysis, and implementation remained my own. Their guidance was unpaid.

Neither adviser processed the data, wrote code, calculated estimates, or drafted or rewrote the report. Ms. Danqing Chen and Ms. Yuewen Gu contributed through classroom instruction only: their teaching introduced me to economics and inspired my interest in conducting economic research, but they did not participate in the project’s design, analysis, or writing. I retained responsibility for all research decisions, implementation, verification, interpretation, and final wording.

Disclosure of artificial-intelligence use.

Throughout the project, I used OpenAI ChatGPT Pro with web browsing to assist with literature searches, language editing, and identifying potential mistakes in the research design, analysis, and presentation. I treated all of its outputs solely as suggestions. Because OpenAI automatically updates ChatGPT and the models available through the service, the

specific model version used depended on what was available at the time of each interaction. The frequency of use varied across stages of the project. Before August, I used ChatGPT a couple times for literature searches. Since August, during the manuscript-revision stage, I used it approximately once every few days. I checked all referenced sources against the original materials, evaluated every suggested correction, and approved the final wording. ChatGPT did not receive any patient-level, confidential, or unauthorized data. It did not generate the study data, estimates, or conclusions, nor did it make any final research decisions.

I sincerely thank Dr. Yating Zhu for her guidance on the competition process and for helping establish contact with the data source, Professor Zhikuo Liu for his guidance on empirical research conventions and academic writing, and Ms. Danqing Chen and Ms. Yuewen Gu for introducing me to economics and inspiring my interest in economic research.