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Keywords: Reference-dependent preferences; prospective payment scheme; collective decisions

JEL codes: D90, D70, H51, I11

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1. Introduction

Prices for goods and services can vary widely, because they are influenced not only by factors such as consumer preferences and production costs, but also by market frictions such as information asymmetry and market power. To mitigate market distortions caused by these frictions, regulators frequently implement prospectively fixed payment policies. For instance, schools in some countries receive funding based on student enrollment, regardless of actual resource usage; ridesharing drivers are paid predetermined rates for completed trips; and healthcare providers commonly operate under prospective payment systems (PPS), in which hospitals or physicians receive a fixed payment for services related to a specific diagnosis. These fixed payment policies aim to reduce distortions by eliminating marginal incentives for the over- or undersupply of services.

However, the introduction of a fixed payment can lead to behavioral distortions due to individuals' reference-dependent preferences. With such preferences, individuals assess outcomes relative to a reference point. For example, they may hold a reference point for profits based on previously earned profits. When a newly introduced fixed payment is lower than their previous revenue, it threatens to push profits below the reference point. Due to loss aversion (Kahneman & Tversky, 1979), decision-makers may respond by cutting costs much more aggressively than they would when the fixed payment exceeds prior revenue. These asymmetrical responses to the policy shift may generate unintended consequences.

In this study, we investigate the optimal payment level of the prospectively fixed payment policy. While the level of the fixed payment is critical in shaping policy outcomes, the microeconomic foundations of determining the payment level are often overlooked by both researchers and policymakers. In practice, the level of the fixed payment is typically determined on an accounting basis and anchored to historical averages before the policy change, because neoclassical economics theory posits that individuals' decisions are determined by their marginal incentives. To set the optimal level of the prospectively fixed payment, it is essential to consider how payment levels influence the incentive compatibility of decision-makers on both the demand and supply sides given their reference-dependent preferences.

We focus on the PPS in healthcare markets, which is designed to reduce the overprovision of healthcare services and control rising healthcare expense (Christianson & Conrad, 2011). The PPS was first introduced in the U.S. in the early 1980s, has since been adopted in most developed countries, and is increasingly common in developing countries (Christianson & Conrad D, 2011). We develop and structurally estimate a model of collective medical decision-making under a PPS. The model has two novel features: (1) patients and physicians jointly make medical decisions and

(2) physicians have reference-dependent preferences. Based on the model, we investigate the optimal payment level under the PPS.

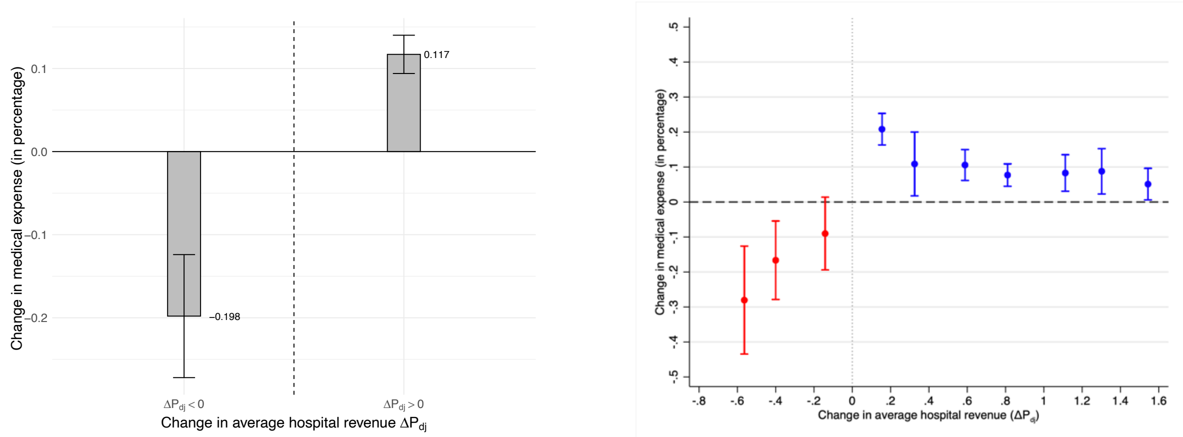
A 2015 policy reform in China offers an ideal setting for our study. This reform targets rehabilitation care, for which global demand is substantial and growing due to the rapidly aging population and increasing prevalence of noncommunicable diseases (Cieza et al., 2020). At the beginning of 2015, the urban employee basic medical insurance (UEBMI) changed both the hospital payment scheme and patient reimbursement structure for rehabilitation care. Before the reform, the UEBMI used a fee-for-service (FFS) scheme, under which hospitals were paid by the UEBMI for each service provided. Patients paid out of pocket based on the total medical expense, their deductible, and the reimbursement rate. Since the reform, hospitals are paid under the PPS and receive a fixed payment for a rehabilitation admission, regardless of the actual amount of care provided. The fixed payment is prospectively set by the UEBMI based on the diagnostic category. The UEBMI covers a fixed share of this payment (85% or 90%, determined by retirement status), and patients paying the remainder.

This context provides four advantages for our research. First, the reform induces perceived gains for some physicians but losses for others, which vary across diagnoses and hospitals. Since physicians and hospitals are closely integrated in China, changes in hospital payments simultaneously change physician revenue.[6] Before the reform, physician revenue depends on the medical expense, which varied significantly across diagnoses and hospitals. After the reform, a uniform payment applies to all hospitals for all diagnoses in a category, which leads to revenue increases for some physicians but decreases for others even in the same hospital. Second, the reform eliminates marginal OOP expenses for patients and marginal revenue for physicians, which enables us to explore the incentive compatibility between the two in collective medical decisions. Third, in our context, most patients undergo rehabilitation only once and are unlikely to be aware of pre-reform OOP expenses, which renders it plausible that only physicians exhibit reference dependence. This simplifies our model and enables us to conduct welfare analyses and investigate optimal PPS payment. Fourth, the rehabilitation system in China limits the scope for selection by either patients or physicians, and thus mitigates concerns regarding potential spillovers caused by the reform.

Our analysis draws on administrative UEBMI enrollment and claims data for Changsha, the capital city of Hunan province in China, from 2013 to 2015. Figure 1 reveals a key pattern that motivates our analysis. Panel (a) plots changes in the amount of care across the reform separately

[6] A physician's revenue is generally tied to the revenue she generates for the hospital through patient treatments. We provide a detailed explanation in Section 2.1.

for admissions with negative and positive changes in average physician revenue.[7] Panel (b) further classifies admissions into 10 classes based on their magnitude of revenue changes from low to high, and plots the mean changes in care amount for each class. Both panels show that the amount of care decreases for admissions for which physicians receive lower average revenue, but increases when they receive higher revenue.



(a) Expense changes across two admission classes (b) Expense changes across ten admission classes

Figure 1. Changes in medical expense across the reform (raw data)

Notes: This figure presents the changes in medical expense across the reform for admissions with different values of physician's revenue changes (ΔP_{dj}). ΔP_{dj} is formally defined in Eq. (3) in the main text. We limit the sample to admissions exposed to the reform (i.e., the treatment group). In panel (a), we divide admissions in the treatment group into two classes: the first (second) includes admissions with negative (positive) changes in average physician revenue. In panel (b), we divide admissions in the treatment group into 10 classes, ordered from low to high based on their ΔP_{dj} values, with each class spanning a bandwidth of 0.25 in ΔP_{dj} (see in Section 4.1 for detailed classification method). Both panels plot the mean change in medical expense across the reform for each class and its 90% confidence intervals, based on raw data.

To substantiate the reduced-form facts, we use a difference-in-differences (DID) estimator to identify the heterogeneous impacts of the reform on care amounts, with untreated hospitals serving as the control group. We find that the reform reduces care by 21% for admissions where the post-reform fixed payment is lower than the average pre-reform physician revenue for the same diagnosis in the same hospital, but increases care by 12% for admissions where the fixed payment is higher. These heterogeneous effects are robust to alternative specifications, control groups, and measures of care. However, we do not observe significant differences based on whether the fixed OOP expense is above or below the pre-reform average.

We examine several plausible explanations for the heterogeneous impacts, including (1) hospital selection, (2) heterogeneity in service composition across admissions, (3) heterogenous policy impacts across hospitals, patients, or diagnoses, (4) mean reversion of medical expense, and (5) anchoring effects. Overall, we do not find supporting evidence for these interpretations.

[7] The change in the amount of healthcare is measured by the change in medical expense. A detailed explanation is provided in Section 3.2.

We then propose a model of collective medical decisions to explain our reduced-form facts. The patient and physician jointly choose the amount of care to maximize their collective utility, which is the weighted average of the patient's and physician's utilities. The weights capture their relative bargaining powers. The patient values his health benefits and OOP expense, and the physician cares about her profit. Importantly, the physician, who has a reference-dependent preference, is loss-averse to profits that fall below her reference point.

We adopt a collective model to capture the active roles of both the patient and the physician in medical decision-making. The reform eliminates the patient's marginal OOP expense and the physician's marginal revenue. If decisions were made unilaterally by the patient (physician), the amount of care would increase (decrease) across all admissions, contrary to the heterogeneous effects we document. Moreover, if decisions were made solely by an altruistic and reference-dependent physician, she would be loss-averse to reform-induced increases in patients' OOP expenses, leading to differential impacts of the reform depending on whether post-reform OOP expenses exceed their pre-reform average. We find no such differential impacts.

Our model effectively explains the reduced-form findings. Following the literature on backward-looking reference points (DellaVigna et al., 2017) and associative memory (Bordalo et al., 2020), we assume that when a physician encounters an admission, she refers to her average profit from admissions for the same diagnosis in previous years. This historical profit serves as her reference point. Before the reform, the physician had adapted to a steady state, in which the optimal amount of care ensured the profit at her reference point. After the reform, the patient has an incentive to raise the amount of care and the physician has a counterincentive to reduce it. The post-reform optimal amount of care depends not only on their incentives and bargaining weights, but also on the fixed payment level. Crucially, the physician's reference point remains anchored to her pre-reform profit. If the fixed payment is lower than her pre-reform revenue, her loss aversion relative to the reference point amplifies her incentive to reduce care. In such cases, the physician's incentive has a greater impact on the collective decision than the patient's, and leads to a reduction in the optimal amount of care. Conversely, when the fixed payment exceeds the pre-reform revenue, the patient's incentive is more influential, which results in an increase in the optimal amount of care.

After introducing our behavioral collective model, we also ask whether the reform's heterogenous impacts could instead be rationalized by a neoclassical collective model in which the physician is not reference-dependent. We show that a neoclassical collective model with heterogeneity in the relative bargaining weights between the physician and patient can, in theory, account for these heterogeneous impacts.

We then structurally estimate both our behavioral collective model and this neoclassical collective model using maximum likelihood estimation, and evaluate which better fits the data. We combine the policy change with the structural model to identify key parameters. Our main findings are as follows. (i) The behavioral collective model, despite having fewer parameters, better fits the data than the neoclassical collective model. (ii) The patient has a higher bargaining weight than the physician, consistent with the medical literature that emphasizes the patient's active role in rehabilitation care (Baker et al., 2011). (iii) The physician places a weight on losses that is approximately 3.5 times greater than on gains.

Based on estimates of our behavioral collective model, we first perform simulation analyses to quantify the reform's impacts on treatment and welfare outcomes. We find that the reform increases both the UEBMI payment and OOP expense, but it does not improve overall patient welfare. Physicians are likely the primary beneficiaries, as the reform substantially raises their profit. We then quantify the impacts of loss aversion on treatment and welfare outcomes. It reduces the amount of care per admission by 23%, which adversely impacts both patient health benefits and welfare. However, loss aversion increases physicians' profit by over 100%, because it incentivizes their strong cost-cutting response.

According to the above findings, the fixed payment level under the PPS crucially affects treatment and welfare outcomes. We proceed to investigate the optimal payment level. Following the tradition in the health economics literature (Skinner, 2011; Gaynor et al., 2023), we assume that the social planner considers the trade-off between patient health benefits and total healthcare expense. The social planner's problem is to prospectively choose the optimal fixed payment—which covers the total expense for an admission—to maximize its objective, subject to the incentive compatibility for the patient and physician.

To illustrate, we solve the optimal payment for stroke rehabilitation in two scenarios: (i) a single fixed payment for all admissions and (ii) separate fixed payments for admissions to hospitals in different tiers. In both cases, adjusting the fixed payment to the optimal level reduces UEBMI payments and OOP expenses while improving patient and social welfare. Tier-specific payments yields greater benefits than a uniform payment, because it accounts for physician's differing reference points across hospital tiers. By fine-tuning physicians' perceptions of gains or losses, this approach reduces expenses without compromising patient outcomes.

This study makes several contributions to the behavioral economics literature on reference-dependent preferences. First, we are the first to study reference dependence in collective decisions that involve multiple agents. Second, we offer the first field evidence of reference dependence in healthcare and structurally estimate the degree of loss aversion among physicians using administrative data, extending the empirical scope beyond previously studied areas (Crawford & Meng, 2011; Engström et al., 2015; DellaVigna et al., 2017; Andersen et al., 2022; Brown et al., 2024). Third, leveraging the healthcare context, we explore the welfare implications of reference dependence—a topic largely avoided in the literature (O'Donoghue & Sprenger, 2018).[8] Fourth, through welfare analyses, we investigate the optimal design of prospectively fixed payment policies. This echoes DellaVigna (2009) and Chetty (2015), who highlight the importance of accounting for reference dependence in policymaking.

We also demonstrate an innovative application of the collective model from family economics (Cherchye et al., 2015; Chiappori et al., 2022) to a healthcare context by integrating reference-dependent preferences into this framework. Also, while the health economics literature has long examined the effects of PPS on various outcomes (see Rosenberg & Browne, 2001; Tan & Melendez-Torres, 2018 for reviews), few studies focus on the level of the fixed payment. We develop a model that offers a microeconomic foundation for solving the optimal payment level, which have broader implications for prospectively fixed payment policies in other sectors.

2. Institutional Background

In this section, we first briefly introduce the healthcare system, the urban employee basic medical insurance (UEBMI), and key aspects of rehabilitation care in China (see Appendix B for further details). We then provide a detailed description of the 2015 reform in Changsha, a provincial capital in central China. Changsha is the capital city of Hunan province, where the healthcare system and public health insurance are representative of China as a whole. In 2014, Changsha had a population of 8.13 million, comparable to mid-sized European countries such as Sweden or Denmark. The GDP per capita in Changsha was 15,056 USD in 2014—more than twice the national average (NBS, 2015).[9]

2.1 The Healthcare System

Public hospitals deliver more than 80% of healthcare services in China, and public hospitals operate within a three-tiered hospital system: tier-1 hospitals provide primary and preventive care, and tier-2 to tier-3 hospitals provide convalescent to critical care (Ministry of Health, 1989). There is no gatekeeping referral system, so patients usually visit hospitals on a walk-in (self-referral) basis (Burns & Liu, 2017; Milcent, 2018).

Public hospitals in China have strong financial incentives. Since the economic reforms in the 1980s, government subsidies for public hospitals have dropped to less than 10% of their total

[8] A notable exception is Reck and Seibold (forthcoming), who theoretically explore the welfare economics of reference dependence.
[9] 1 RMB≈0.16 USD in our sample period.

revenue, which compels hospitals to rely heavily on revenue from patient care to survive financially (Milcent, 2018). As a result, hospitals' revenue primarily comes from patients' OOP expenses and payments from public health insurance, which are determined by the patient reimbursement structure and hospital payment scheme adopted by public insurance.

Physicians are closely integrated with hospitals in China, because almost all physicians are salaried employees in public hospitals (Burns & Liu, 2017). To ensure that physicians' decisions align with hospitals' interests, hospitals frequently provide training to physicians. More importantly, physicians' bonuses—which comprise up to three-quarters of their income—are tied to hospital revenue and costs associated with treating patients (Milcent, 2018). Therefore, throughout our analysis, we assume that the hospital and physician share the same financial incentive—to increase the hospital's profit—and treat them as a single agent. Appendix B.1 provides detailed discussion of physicians' training, employment and income in China.

2.2 Urban Employee Basic Medical Insurance

Public health insurance covers over 95% of the population in China. It consisted of two schemes in 2015: urban employee basic medical insurance (UEBMI) and urban and rural resident basic medical insurance (URRBMI). Our analysis focuses on UEBMI, which is a mandatory insurance for employees and retirees (and their family members) with urban *hukou*.[10] UEBMI is financed and managed by the Healthcare Security Administration (HSA) at county, city, or province level.

2.3 Rehabilitation Care

Rehabilitation is defined as "a set of clinical interventions designed to optimize functioning and reduce disability in individuals with health conditions in interaction with their environment" (WHO, 2017). For example, for patients with stroke, rehabilitation after acute treatment can increase their probability of being able to walk by about 90%, and improve their performance with respect to movement and cognition by about 65% (Ottenbacher, 1993). Appendix B.2 details the health conditions that require rehabilitation and the typical rehabilitation process.

Distinct from acute treatment, rehabilitation has three unique features. First, it necessitates intensive physician-patient interaction throughout the entire treatment process. Rehabilitation care typically lasts several weeks, and closer physician-patient collaboration during this process significantly improves the treatment outcomes of rehabilitation care (Baker et al., 2011). Second, patients are actively involved in rehabilitation, as they often assume responsibility for daily training and medication management rather than relying exclusively on physicians. Third, the price

[10] Hukou is a household registration system in China. Each Chinese citizen is assigned either a rural or urban hukou, according to their registered place of residence and parents' registration status. Changes in hukou are rare. Hukou status may affect a person's eligibility for social benefits provided by the government (Milcent, 2018).

elasticity of demand for rehabilitation care (-0.55) is significantly higher than the overall price elasticity of demand for healthcare (-0.2) (Ziebarth, 2010).

With aging population and the rising prevalence of chronic diseases, the clinical need for rehabilitation is massive not only in China worldwide (Cieza et al., 2020, Feng et al., 2020). However, a key challenge that hampers the global promotion of rehabilitation is that patients typically lack knowledge of rehabilitation and tend to undervalue its benefits (WHO, 2017). Rehabilitation care in China is mainly supplied in large cities and high-tier hospitals.

2.4 The 2015 Reform in Changsha

At the beginning of 2015, the HSA of Changsha changed both the hospital payment scheme and UEBMI patient reimbursement structure for rehabilitation care. Following the gradual implementation strategy commonly adopted in China's healthcare reforms, this reform is piloted in 7 designated hospitals.[11]

This reform covers rehabilitation care for five diagnostic categories: (1) stroke, (2) traumatic brain injury, (3) spinal cord injury, (4) recovery from brain tumor surgery, and (5) recovery from hip/knee replacement. The categories mainly involve care related to neurological disorders and musculoskeletal disorders, which are the top two conditions that require rehabilitation (Cieza et al., 2020).

The five categories contain 110 diagnoses:[12] 44 diagnoses in the category of stroke, 28 in traumatic brain injury, 29 in spinal cord injury, 6 in recovery from brain tumor surgery, and 3 in recovery from hip/knee replacement. Different diagnoses within a category signify similar conditions with different causes and severity levels. For instance, in the category of stroke, the diagnosis of cerebral infarction is the result of disrupted blood flow to the brain, while intracerebral hemorrhage is caused by bleeding within the brain tissue itself.

The reform changes the payment scheme for hospitals. Before the reform, hospitals were paid under an FFS scheme. The hospital revenue for an admission is $R = E$, where E is the medical expense for the admission. After the reform, the hospital revenue from an admission in category g becomes

$$R = P_g, \tag{1}$$

where P_g is the fixed payment for admissions in category g, which is set by the HSA of Changsha. P_g varies across categories, but remains constant across diagnoses within a category.

[11] The selection of pilot hospitals was made by the HSA of Changsha. According to policy documents and interviews with local officials, hospitals were chosen primarily based on administrative readiness and service capacity in rehabilitation care, such as the presence of established rehabilitation departments and sufficient admission volumes. Before the reform, the 7 pilot hospitals accounted for approximately 28% of all rehabilitation admissions in Changsha for the five targeted diagnostic categories.

[12] Diagnoses are defined by 6-digit ICD-10 codes.

The reform also changes the reimbursement structure for patients. Before the reform, the OOP expense (p) is determined by the medical expense (E), claimable expense (Clm), deductible (Dud), and reimbursement rate (re), based on the following formula:

$$p = \begin{cases} E - (Clm - Dud) \cdot re & if\ Clm \geq Dud \\ E & if\ Clm < Dud \end{cases}, \tag{2}$$

The HSA sets Dud and re, which vary across hospital tiers and differ by whether the patient is retired. Hospitals determine E and Clm.[13] Under this reimbursement structure, the patient's OOP expense increases with E. After the reform, for an admission in category g, the patient's OOP expense is $p = \delta P_g$, where δ equals 15% for employees (and their family members) and 10% for retirees (and their family members). P_g is defined the same as in Eq. (1).

The reform has two features. First, it changes the financial incentives for both hospitals and patients. The reform eliminates both the marginal revenue received by hospitals and the marginal OOP expense paid by patients. Therefore, hospitals are incentivized to provide less care, whereas patients are motivated to demand more care.

Second, the reform results in varying changes in average hospital revenue per admission across diagnoses and hospitals. Specifically, for an admission with diagnosis d in hospital j, the change in average hospital revenue varies from a decrease of 86% to an increase of 158% across the reform. To illustrate these varying changes, we use stroke rehabilitation as an example. Table 1 presents the average revenue per admission for stroke rehabilitation at diagnosis-by-hospital level before and after the reform. We list the top 20 most common diagnoses in the category of stroke.[14] Before the reform, the average revenue for tier-2 hospitals ranged from 5,589 to 20,063 RMB across diagnoses, while for tier-3 hospitals it ranges from 8,075 to 34,661 RMB. After the reform, a fixed payment of 18,000 RMB is paid to all hospitals for each admission for stroke rehabilitation.[15] Therefore, for an admission with diagnosis d, some hospitals receive higher average revenue, while others receive lower.

The reform also changed the average OOP expense paid by patients for an admission. Across the reform, changes in average OOP expense for a rehabilitation admission with diagnosis d in

[13] Only medicines and medical services listed by the national HSA are claimable. The listed medicines and services are intended to meet the most essential medical needs of enrollees. Their prices, which are regulated by the government, are low (Milcent, 2018).

[14] 96.4% of admissions for stroke rehabilitation have the 20 most common diagnoses before the reform.

[15] To our knowledge, UEBMI set the fixed payment (18,000 RMB) higher than the pre-reform average medical expense per admission (14,454 RMB) to increase the resource input for stroke rehabilitation. This practice is similar to the PPS reform for post-acute care in the US from 1998 to 2003, which also increased the average payment to post-acute care facilities (Sood et al., 2013). The higher payment level helps mitigate the reduced marginal incentives inherent in the PPS and discourages providers from avoiding high-severity patients.

hospital j varies from a decrease of 75% to an increase of 113% (see Appendix Table A1 for details).

Table 1. Hospital revenue per admission for stroke rehabilitation before and after the reform

The 20 most common diagnoses in stroke	Before		After
	Tier-2 hospitals	Tier-3 hospitals	Fixed payment
Cerebral arteritis	5,589	8,075	18,000
Moyamoya disease	5,882	12,506	
Hemiplegia and hemiparesis following cerebral infarction affecting right non-dominant side	6,307	9,598	
Cerebral infarction due to unspecified occlusion or stenosis of precerebral arteries	6,411	11,017	
Cerebral artery dissection, traumatic	6,511	7,960	
Cerebral infarction due to embolism of cerebral arteries	6,529	8,799	
Hemiplegia and hemiparesis following cerebral infarction affecting right dominant side	7,578	10,995	
Subarachnoid hemorrhage following cerebral infarction	9,396	20,978	
Hemiplegia and hemiparesis following cerebral infarction affecting left non-dominant side	9,702	10,356	
Cerebral infarction due to embolism of unspecified cerebral artery	9,946	23,390	
Hemiplegia and hemiparesis following cerebral infarction affecting left dominant side	10,214	12,666	
Basal ganglia hemorrhage	10,946	28,187	
Cerebrovascular accident	11,056	16,882	
Cerebral infarction due to embolism of precerebral arteries	11,183	16,020	
Subarachnoid hemorrhage following unspecified cerebral infarction	12,912	34,661	
Intracerebral hemorrhage in hemisphere	20,063	32,963	
Cerebral infarction due to thrombosis of precerebral arteries	--	22,645	
Occlusion and stenosis of unspecified cerebral artery	--	21,022	
Cerebral artery dissection, non-traumatic	--	32,398	
Cerebral artery occlusion	--	25,158	

Notes: This table presents an example of hospital revenue per admission for stroke rehabilitation before and after the reform. We separately calculate average hospital revenue for admissions with the 20 most common diagnoses. We include admissions in both treatment and control groups in the calculations. Hospital revenue is adjusted to 2015 prices using the medical care consumer price index. The unit for hospital revenue is RMB.

3. Data

3.1 Data Sources and Sample

Our empirical analysis draws on administrative UEBMI enrollment and claims data in Changsha from 2013 to 2015. The claims data record detailed information on each inpatient admission, such as admission and discharge dates, diagnostic codes (ICD-10), treatment procedures, and charges. The financial information is comprehensive, and covers the medical expense, OOP expense, and expenses broken down by medical services. The claims data also include basic information on the hospital where the patient was admitted, such as the hospital's name, tier, type, and number of beds. The enrollment data contain the basic demographic characteristics of all enrollees, including age and gender, along with the monthly salary for employees and pension for retirees. We merge claims and enrollment data based on each enrollee's unique ID.

To construct our analytic sample, we focus on admissions for rehabilitation with diagnoses in the five categories outlined in Section 2.4. The treatment group contains admissions to the 7 hospitals involved in the reform. These hospitals include two tier-2 hospitals and five tier-3 hospitals, with the mean number of admissions per year ranging from 53 to 1,397 before the reform. We obtain 9,174 admissions in the treatment group. For the control group, we use admissions to other hospitals in Changsha. To ensure comparability, we exclude cases in (1) tier-1 hospitals and (2) hospitals with a yearly average number of admissions before the reform of fewer than 50. The final control group contains 21,984 admissions in 22 hospitals. In a robustness analysis, we construct an alternative control group using rehabilitation admissions from the same 7 hospitals in the treatment group but with different diagnoses.

3.2 Variables

Medical expense (E_{ijt}). We use the medical expense for an admission to measure the amount of healthcare throughout the analyses. For administrative purposes, the hospital calculates, records, and reports the medical expense for each admission to the Changsha HSA both before and after the reform. The medical expense of patient i in hospital j in year t (E_{ijt}) is calculated as $E_{ijt} = \sum_{m \in M} P_{mjt} \times Q_{imjt}$, where P_{mjt} is the listed price of service m in hospital j in year t and Q_{imjt} is the quantity of service m provided to the admission. In the claims data, the medical expense consists of expenses for three types of services: (1) pharmaceuticals and medical supplies, (2) diagnostic tests (e.g., laboratory tests, X-rays, MRIs), and (3) general routine care (e.g., daily rehabilitative therapy, medical rounds, nursing). The listed prices of service m did not change during our sample period ($P_{mjt} = P_{mj}$). Therefore, for service m provided to an admission, the percentage change in expense across years reflects the percentage change in quantity. The percentage change in medical expense for the admission is a weighted average of percentage changes in the quantities of services:

$$\frac{E_{ijt',1} - E_{ijt,0}}{E_{ijt,0}} = \sum_{m \in M} s_{imjt,0} \times \frac{Q_{imjt',1} - Q_{imjt,0}}{Q_{imjt,0}},$$

where the subscript $0(1)$ indexes a time period before (after) the reform, and t (t') denotes a calendar year before (after) the reform. $s_{imjt,0}$ is the share of expense for service m out of total medical expense for the admission before the reform. Thus, the impact of the reform on medical expense informs us of the impact on the amount of care provided.

Appendix Table A2 shows that the mean medical expense per admission is 12,691 RMB. It is 12,515 and 12,764 RMB, respectively, for admissions in the treatment and control groups.

Length of stay (LOS). The mean LOS for an admission is 14.23 days, with 14.69 days for admissions in the treatment group and 14.03 days for those in the control group.

Change in average hospital revenue (ΔP_{dj}). For an admission with diagnosis d treated in hospital j in the treatment group, we define the change in average hospital revenue following Cutler (1995):

$$\Delta P_{dj} = \frac{P_g - E_{dj0}}{E_{dj0}}. \quad (3)$$

P_g is the fixed payment for category g, which includes diagnosis d. E_{dj0} is the average medical expense for the admission before the reform. $\Delta P_{dj} > 0$ ($\Delta P_{dj} < 0$) if hospital j receives higher (lower) revenue from the admission after the reform. In the treatment group, 17% of admissions have $\Delta P_{dj} < 0$ and 83% have $\Delta P_{dj} > 0$, with the mean ΔP_{dj} equal to 0.49. Appendix Figure A1 (a) presents the distribution of ΔP_{dj} for these admissions. We define $\Delta P_{dj} = 0$ for admissions in the control group, because the payment scheme to hospitals in the control group did not change during our sample period.

Remark 1: We measure the change in average hospital revenue per admission, ΔP_{dj}, by averaging it at diagnosis-by-hospital level. Within category g, the variation in ΔP_{dj} arises from differences in average medical expense across diagnoses and hospitals before the reform (E_{dj0}). The variation in fixed payments (P_g) across categories introduces extra variation in ΔP_{dj}.

Change in the average OOP expense (Δp_{dj}). Likewise, we define the change in average OOP expense. For an admission with diagnosis d in category g treated in hospital j in the treatment group, the change in OOP expense paid by patients is

$$\Delta p_{dj} = \frac{\delta P_g - p_{dj0}}{p_{dj0}},$$

where δ equals 15% for employees and 10% for retirees. p_{dj0} denotes the average OOP expense for the admission before the reform. In the treatment group, 62% of admissions have $\Delta p_{dj} < 0$ and 38% have $\Delta p_{dj} > 0$, with the mean Δp_{dj} equal to -0.10. The distribution of Δp_{dj} for these admissions is presented in Appendix Figure A1 (b). We define $\Delta p_{dj} = 0$ for admissions in the control group. Similar to the change in average hospital revenue, we measure Δp_{dj} by averaging it at employment-status-by-diagnosis-by-hospital level.

Patient characteristics. Appendix Table A2 presents summary statistics for patient characteristics—gender, age, employment status, monthly income, and measures for latent patient health.

4. Reduced-form Facts

4.1 Heterogeneous Impacts by Change in Average Hospital Revenue

Main analysis. We employ a difference-in-differences (DID) method to investigate the impacts of the reform on medical expense for admissions. As discussed in Section 3.2, we use percentage changes in the medical expense to measure percentage changes in the amount of care.

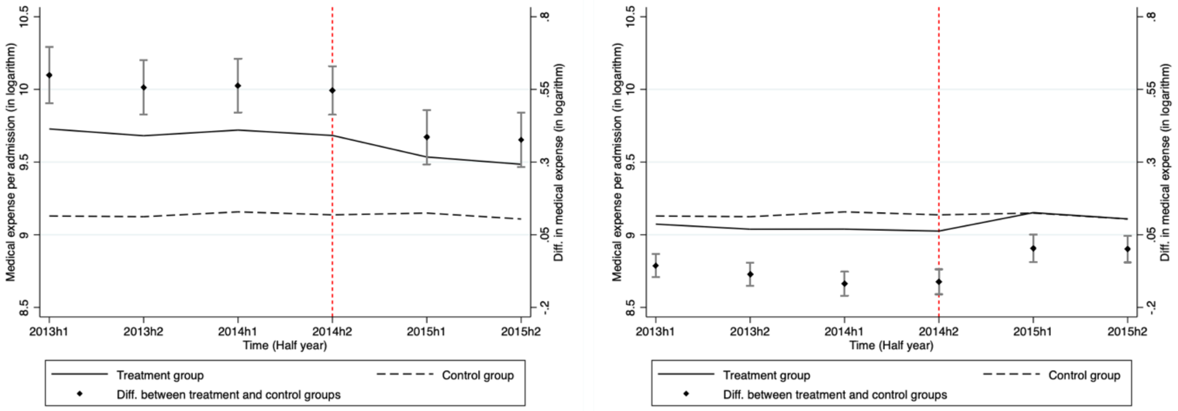
Motivated by the stylized fact in Figure 1, we separately examine the impact of the reform for admissions in two classes. The first class ($k = 1$) contains admissions with diagnosis d in hospital j for which the average hospital revenue decreases ($\Delta P_{dj} < 0$), and the second class ($k = 2$) includes admissions where the average revenue increases ($\Delta P_{dj} > 0$):

$$\ln\left(E_{idjt}\right) = \beta_0 + \sum_{k=1}^{K} \beta_1^k \, \mathbb{I}\left\{class_{dj} = k\right\} \times Post_t + \sum_{k=1}^{K} \beta_2^k \, \mathbb{I}\left\{class_{dj} = k\right\} + \boldsymbol{X_{it}}\gamma$$
$$+\zeta_t + \zeta_j + \zeta_d + \epsilon_{idjt}, \tag{4}$$

where subscript i indexes admission, d diagnosis, j hospital, and t time. The dependent variable $\ln\left(E_{idjt}\right)$ denotes the logarithm of medical expense of the admission. $\mathbb{I}\left\{class_{dj} = k\right\}$ is an indicator that equals 1 if the admission is in class k and 0 otherwise. For admissions in the control group, $\mathbb{I}\left\{class_{dj} = k\right\}$ equals 0 for all k. $Post_t$ is a dummy variable that equals 1 if patient i is admitted in 2015 and 0 otherwise. $\boldsymbol{X_{it}}$ is a vector of the patient's characteristics. We control for time (year-by-month) fixed effects (ζ_t). Despite that our sample covers only 7 hospitals in the treatment group and 21 hospitals in the control group, the main explanatory variable, ΔP_{dj}, exhibits rich variation at the diagnosis-by-hospital level. This enables us to control for hospital fixed effects (ζ_j) and diagnosis fixed effects (ζ_d). In alternative specifications, we further add diagnosis-by-year fixed effects and hospital-by-diagnosis fixed effects. ϵ_{idjt} is the error term. Standard errors are clustered at hospital-by-diagnosis level.

We are interested in the coefficients of β_1^1 and β_1^2, which capture the causal impacts of the reform on medical expense for admissions with $\Delta P_{dj} < 0$ and $\Delta P_{dj} > 0$, respectively. The identification assumption is that in the absence of the reform, trends in the medical expense would be the same for admissions with $\Delta P_{dj} < 0$, $\Delta P_{dj} > 0$, and those in the control group. This assumption is highly plausible in our context. On the demand side, all patients in our sample receive rehabilitation care for diagnoses in the same 5 categories. These patients are either employees or retirees living in the urban area of Changsha, and therefore they share the same socioeconomic environment. On the supply side, hospitals in the treatment and control groups are either tier-2 or tier-3 hospitals of similar sizes. Appendix Figure A2 shows that hospitals in both groups are interspersed with each other in the center of Changsha. To our knowledge, no other policies differentially affect rehabilitation for admissions with $\Delta P_{dj} < 0$, $\Delta P_{dj} > 0$, and those in the control group during the sample period.

To statistically investigate the identification assumption, we separately plot the mean medical expense (in logarithms) for admissions with $\Delta P_{dj} < 0$ ($\Delta P_{dj} > 0$) and that for admissions in the control group in Figure 2(a) (2(b)). Figure 2(a) shows that, before the reform, the mean medical expenses (in logarithms) are stable for both admissions with $\Delta P_{dj} < 0$ and those in the control group, with their difference remaining at approximately 0.55. This suggests a common pre-trend in medical expense for the two groups. Figure 2(b) confirms that the common pre-trend also holds for admissions with $\Delta P_{dj} > 0$ and the control group.[16]



(a) Admissions with $\Delta P_{dj} < 0$ (b) Admissions with $\Delta P_{dj} > 0$

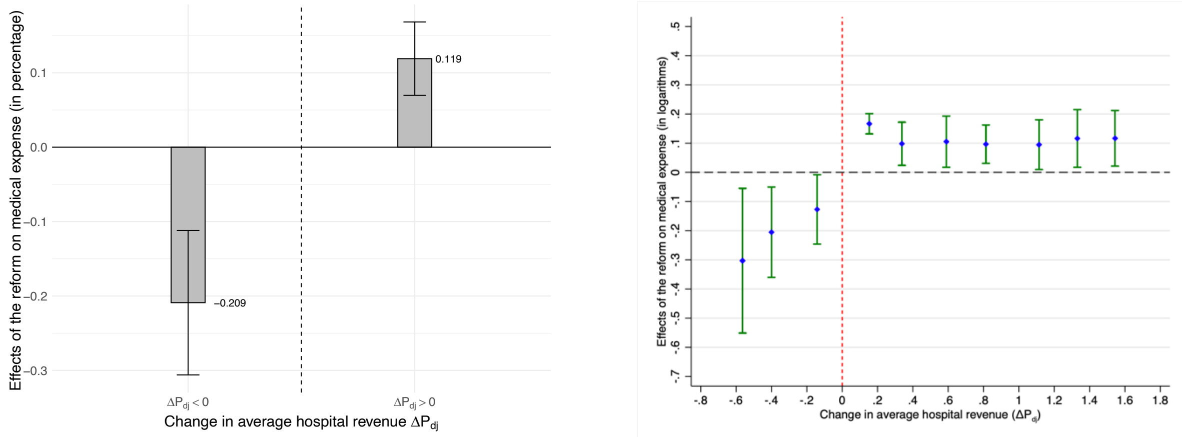
Figure 2. Changes in mean medical expense across time

Notes: Figure (a) ((b)) separately plots average medical expense per admission (in logarithm) for admissions with $\Delta P_{dgj} < 0$ ($\Delta P_{dgj} > 0$) and admissions in the control group by half-year. This figure also plots the difference in medical expense (in logarithms) between the treatment and control groups, along with the corresponding 95% confidence intervals, by half-year.

We find that the reform has heterogeneous impacts on medical expense associated with changes in ΔP_{dj}. Figures 2(a)-(b) show that after the reform, the mean medical expense falls dramatically for those with $\Delta P_{dj} < 0$ and increases for those with $\Delta P_{dj} > 0$; in contrast, the mean medical expense for admissions in the control group remains stable. Figure 3(a) plots the estimates of β_1^1 and β_1^2 in Eq. (4). It suggests that the reform decreases the medical expense by 20.9% for admissions with $\Delta P_{dj} < 0$, but increases it by 11.9% for admissions with $\Delta P_{dj} > 0$. Both estimates are statistically significant at the 1% level. Table 2 Panel (a) reports estimates of Eq. (4), which

[16] The pre-reform mean medical expense mechanically differs between admissions with $\Delta P_{dj} < 0$ and $\Delta P_{dj} > 0$, since it is higher (lower) than the fixed payment for admissions with $\Delta P_{dj} < 0$ ($\Delta P_{dj} > 0$). To address concern that the two classes of admissions are not comparable to the same control group, we compute ΔP_{dj} for admissions in the control group using Eq. (3), and classify them based on whether their $\Delta P_{dj} < 0$ or $\Delta P_{dj} > 0$. Appendix Figure A3(a) (A3(b)) shows that the mean medical expense for admissions with $\Delta P_{dj} < 0$ ($\Delta P_{dj} > 0$) in the control group is close to, and parallel with, that for those in the treatment group before the reform, and remains stable afterward.

show that the results remain robust when we consecutively control for diagnosis-by-year fixed effects and diagnosis-by-hospital fixed effects in Columns (2)-(3).



(a) Reform's impacts for two admission classes (b) Reform's impacts for ten admission classes

Figure 3. Reduced-form estimates of the reform's impacts on medical expense

Notes: This figure presents the heterogeneous impacts of the reform on medical expense by ΔP_{dj}, with ΔP_{dj} defined in Eq. (3) in the main text. In Panel (a). we divide admissions in the treatment group into two classes: the first (second) includes admissions with $\Delta P_{dj} < 0$ ($\Delta P_{dj} > 0$). In Panel (b), we divide admissions in the treatment group into 10 classes, ordered from low to high based on their ΔP_{dj} values. The classification method is illustrated in Section 4.1. Both panels plot the estimate of β_1^k from Eq. (4) and its 90% confidence interval. We additionally control for diagnosis-by-year fixed effects in the regressions. Standard errors are clustered at hospital-by-diagnosis level.

An alternative specification. To address concern that the estimated heterogeneous impacts of the reform in the main analysis are driven by only a small subset of observations, we further categorize admissions in the treatment group into 10 classes, ordered from low to high based on their ΔP_{dj} values. The value of ΔP_{dj} ranges from -0.863 to 1.581. The first class ($class_{dj} = 1$) includes admissions with $\Delta P_{dj} \leq -0.5$. Each subsequent class is defined by an increase of 0.25 in ΔP_{dj}. The last class ($class_{dj} = 10$) includes admissions with ΔP_{dj} >1.5. By this definition, the first 3 classes contain admissions with $\Delta P_{dj} < 0$, and the remaining 7 classes contain admissions with $\Delta P_{dj} > 0$. Based on this finer classification, we estimate Eq. (4) with $K = 10$. The estimate of β_1^k measures the reform's impact on medical expense for admissions in class k.

The results confirm that the reform decreases the medical expense for admissions with $\Delta P_{dj} < 0$, but increases the medical expense for admissions with $\Delta P_{dj} > 0$. Figure 3(b) plots the estimate of β_1^k and its 90% confidence interval against the mean value of ΔP_{dj} in class k. The figure shows that for admissions with $\Delta P_{dj} < 0$, the estimates of β_1^k are all negative and the negative impacts of the reform become more pronounced as the average hospital revenue decreases to a greater extent across the reform. For admissions with $\Delta P_{dj} > 0$, estimates of $\beta_1^k$are all positive and statistically significant at the 10% level. Table 2 Panel (b) reports the estimates of Eq. (4). Results remain robust when we consecutively add diagnosis-by-year fixed effects and hospital-by-diagnosis fixed effects in Columns (2)-(3).

Table 2. Effects of the reform on medical expense of the admission

Dependent variable		Medical expense of the admission (in logarithm)		
		(1)	(2)	(3)
Panel (a)				
$\Delta P_{dj} < 0$	$\mathbb{I}\{class = 1\} \times Post$	-0.209	-0.216	-0.161
		(0.059)	(0.065)	(0.057)
$\Delta P_{dj} > 0$	$\mathbb{I}\{class = 2\} \times Post$	0.119	0.119	0.126
		(0.030)	(0.023)	(0.021)
	R-squared	0.350	0.355	0.401
Panel (b)				
$\Delta P_{dj} < 0$	$\mathbb{I}\{class = 1\} \times Post$	-0.330	-0.303	-0.264
		(0.138)	(0.151)	(0.159)
	$\mathbb{I}\{class = 2\} \times Post$	-0.192	-0.205	-0.154
		(0.083)	(0.094)	(0.080)
	$\mathbb{I}\{class = 3\} \times Post$	-0.100	-0.127	-0.096
		(0.068)	(0.072)	(0.066)
$\Delta P_{dj} > 0$	$\mathbb{I}\{class = 4\} \times Post$	0.206	0.167	0.177
		(0.022)	(0.021)	(0.019)
	$\mathbb{I}\{class = 5\} \times Post$	0.093	0.098	0.102
		(0.049)	(0.045)	(0.036)
	$\mathbb{I}\{class = 6\} \times Post$	0.098	0.105	0.051
		(0.033)	(0.053)	(0.036)
	$\mathbb{I}\{class = 7\} \times Post$	0.081	0.097	0.076
		(0.027)	(0.040)	(0.026)
	$\mathbb{I}\{class = 8\} \times Post$	0.078	0.095	0.127
		(0.049)	(0.052)	(0.049)
	$\mathbb{I}\{class = 9\} \times Post$	0.121	0.116	0.116
		(0.071)	(0.060)	(0.045)
	$\mathbb{I}\{class = 10\} \times Post$	0.060	0.117	0.137
		(0.052)	(0.058)	(0.042)
	R-squared	0.354	0.359	0.402
	Individual controls	Yes	Yes	Yes
	Year-month FE	Yes	Yes	Yes
	Hospital FE	Yes	Yes	No
	Diagnosis FE	Yes	No	No
	Diagnosis-by-year FE	No	Yes	Yes
	Hospital-by-diagnosis FE	No	No	Yes
	Observations	31,158	31,098	31,085

Notes: This table reports estimates for the effects of the reform on medical expense per admission. Panels (a)-(b) report he estimates of Eq. (4), with the total number of classes (K) equal to 2 and 10, respectively. The dummy variable for class k in the treatment group (i.e., $\mathbb{I}\{class = k\}$), individual controls, year-month fixed effects, hospital fixed effects, and diagnosis fixed effects are controlled for in regressions across all columns. We consecutively add diagnosis-by-year fixed effects and hospital-by-diagnosis fixed effects to regressions in Columns (2)-(3). Dummy variables $\mathbb{I}\{class = k\}$ $(k = 1,..,K)$ are omitted from regressions once we control for hospital-by-diagnosis fixed effects. Standard errors are clustered at hospital-by-diagnosis level.

An alternative control group. Our main DID strategy compares medical expenses for admissions in the same 5 diagnostic categories but in different hospitals across the reform. To alleviate concern that the results are driven by time-variant cross-hospital heterogeneity, we construct a new control group using admissions for rehabilitation care within the 7 hospitals involved in the reform but with different diagnoses. Specifically, we focus on diagnoses of neurological disorders because they are among the most prevalent conditions that require rehabilitation care. We identify diagnoses for the control group based on established sources that list neurological diseases that require rehabilitation care (Cieza et al., 2020).[17] Our new control group contains 1,501 admissions in the same 7 hospitals from 2013 to 2015.

Results based on the treatment and new control group are consistent with those in the main analysis, which suggests that the heterogeneous policy impacts are not driven by time-variant cross-hospital heterogeneity. Appendix Figures A4 (a)-(b) replicate Figures 2 (a)-(b), respectively. Appendix Table A3 replicates Table 2. Since we compare different diagnoses within same hospitals in this analysis, the consistent results suggest that changes in medical expenses of the treatment group across the reform are likely driven by physician-level decisions rather than hospital-level changes. This finding confirms that, in our context, physicians typically understand policy changes thoroughly and adjust their strategies accordingly to align with the hospital's interests, as discussed in Section 2.1.

Alternative measure of healthcare amount. In this robustness analysis, we measure the healthcare amount using the LOS. Appendix Table A4 replicates Table 2, using the LOS (in logarithm) as dependent variables. The results remain robust: the reform reduces the LOS for admissions with $\Delta P_{dj} < 0$, but increases it for admissions with $\Delta P_{dj} > 0$.

4.2 Impacts of the Reform by Change in Average OOP Expense

Since the reform also results in varying changes in the average OOP expense paid by patients (Δp_{dj}), we now examine whether the reform's impact on medical expense differs by whether $\Delta p_{dj} < 0$ or $\Delta p_{dj} > 0$ for an admission.

Overall, we do not find significant evidence for such difference. Specifically, we first limit the treatment group to admissions with $\Delta P_{dj} > 0$ to disentangle potential heterogeneous impacts with respect to Δp_{dj} from heterogeneous impacts with respect to ΔP_{dj}, since Δp_{dj} strongly correlates with ΔP_{dj} across admissions (see Appendix Figure A5(a)). We then replicate Figure 3 in Appendix Figure A5(b) to examine the reform's impact on admissions with different values of Δp_{dj}. In the left panel of Appendix Figure A5(b), admissions in the treatment group are classified into two classes based on whether their $\Delta p_{dj} < 0$ or $\Delta p_{dj} > 0$. In the right panel, admissions in the

[17] We include the following diagnoses: (1) Alzheimer's disease and dementia, (2) Parkinson's disease, (3) cerebral palsy, (4) Guillain-Barré syndrome, (5) multiple sclerosis, (6) motor neuron disease, (7) transient ischemic attacks, and (8) Bell's palsy.

treatment group are divided into 10 classes, ordered from low to high based on their Δp_{dj} values.[18] The two figures consistently show that, across admissions with different values of Δp_{dj}, the reform increases the medical expense, with estimates hovering around 10%. This increase is due to the fact that the policy removes the marginal OOP expense, as discussed in Section 2.4.

These results indicate that patients do not show heterogeneous responses to changes in average OOP expenses. A plausible reason could be that 88% of patients undergo rehabilitation only once in our study context, and therefore patients admitted after the reform may lack knowledge of the average OOP expense for similar cases before the reform.[19]

4.3 Plausible Interpretations

From the above analyses, we find that the reform's impact on the amount of care for an admission differs by whether the physician receives a higher or lower payment relative to pre-reform revenue from the admission. Before introducing our model to explain these heterogeneous impacts, we now examine several plausible interpretations. These include (1) hospital selection, (2) heterogeneity in service composition across admissions with different ΔP_{dj}, (3) heterogenous policy impacts across hospitals, patients, or diagnoses, (4) mean reversion of medical expense, and (5) anchoring effects.

Hospital selection. We first examine two types of hospital selection that could potentially account for the heterogeneous impacts. The first type is based on diagnoses. To raise total profit, hospitals may respond to the reform by trying to admit more patients whose diagnoses now yield higher hospital revenue. To attract these newly lucrative patients, hospitals may provide more care to admissions with $\Delta P_{dj} > 0$. Conversely, care for admissions with $\Delta P_{dj} < 0$ might be reduced due to capacity constraints. To test this interpretation, we calculate the number of admissions at diagnosis-by-hospital level, and examine whether treated hospitals admit more cases with $\Delta P_{dj} > 0$ and fewer with $\Delta P_{dj} < 0$ compared with hospitals in the control group across the reform. Appendix C.1 details the analysis. Appendix Figure A6, Panels (a)-(b) and Table A5 suggest that the reform does not have significant impacts on the number of admissions with $\Delta P_{dj} < 0$ or that with $\Delta P_{dj} > 0$.[20]

The second type of hospital selection is based on patient severity. Because they are paid at a fixed payment per admission after the reform, hospitals may avoid admitting severely ill patients

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[18] The first class includes admissions with $\Delta p_{dj} \leq -0.3$, each subsequent class is defined by an increase of 0.1 in Δp_{dj}, and the last class includes admissions with Δp_{dj} >0.5.

[19] Our results in Section 4.1 remain robust when we exclude patients who undergo multiple rehabilitation admissions during the sample period.

[20] The PPS may trigger upcoding (Dafny, 2005), but this is unlikely in our context. First, fixed payment is uniform across diagnoses within each category, and it is the same for all categories involved in the reform except stroke. Second, patients are disincentivized from upcoding due to higher OOP expenses for higher-priced diagnoses. Finally, patients are generally aware of their diagnoses after receiving acute care prior to rehabilitation.

to avoid high treatment costs. Since patients with more severe conditions typically have diagnoses associated with higher medical expenses before the reform, these patients are more likely to be admissions with $\Delta P_{dj} < 0$. Consequently, this type of selection may reduce the average severity, as well as the amount of care required, for admissions with $\Delta P_{dj} < 0$ to greater extents than for those with $\Delta P_{dj} > 0$.[21] To test this, we separately examine the reform's impacts on the average patient severity for admissions with $\Delta P_{dj} < 0$ and $\Delta P_{dj} > 0$. Following the literature (Finkelstein et al., 2016; Alexander, 2020), we proxy for patient severity using (1) the Charlson comorbidity index and (2) the number of chronic diseases. Appendix C.2 provides details of the analysis. Appendix Figure A6 Panels (c)-(f) and Table A6 suggest that the reform does not have a significant impact on average severity for admissions with $\Delta P_{dj} < 0$ or $\Delta P_{dj} > 0$.

The reform could also incentivize selection by patients. For example, patients who need to pay higher OOP expense in treated hospitals after the reform (i.e., those with $\Delta p_{dj} > 0$) may sort into hospitals in the control group. Since these patients generally have less severe conditions, such selection could raise the average severity, as well as the amount of care required, for admissions in treated hospitals. However, patient selection based on Δp_{dj} is unlikely to explain the heterogeneous impacts of the reform by ΔP_{dj}. Also, our findings do not support this patient selection, because we do not find heterogeneous impacts of the reform on medical expense between admissions with $\Delta p_{dj} < 0$ and $\Delta p_{dj} > 0$, nor do we find changes in latent patient health due to the reform.

Overall, we do not find evidence of selection, which also alleviates concerns about potential spillovers across hospitals induced by the reform. This finding is highly plausible in our study context. As discussed in Section 2.3, most patients have little knowledge about the rehabilitation services and providers, and decisions regarding whether and where to receive rehabilitation are typically made during the acute treatment phase. In practice, these decisions are primarily guided by the attending physicians in acute-care departments, rather than by physicians in rehabilitation departments (WHO, 2017). Moreover, due to the absence of a formal referral system in China, patients who require rehabilitation after acute treatment are usually transferred directly to the rehabilitation department within the same hospital. This process leaves little room for selection by either physicians in the rehabilitation department or patients themselves.

Heterogeneity in service composition across admissions with different $\boldsymbol{\Delta P_{dj}}$. Another interpretation of our findings relates to heterogeneity in service composition across admissions. Treating patients with different conditions can require different technological and labor inputs, and

[21] The increased care for these patients could also be driven by their increased demand for rehabilitation care by patients, since the marginal OOP expense is eliminated after the reform.

thus incur different marginal costs. Since higher marginal costs dampen incentives for care provision both before and after the reform, time-invariant differences in service composition across admissions cannot account for the differential policy impacts on care amount between admissions with $\Delta P_{dj} < 0$ and $\Delta P_{dj} > 0$. Our estimated heterogenous policy impacts could possibly be explained if the services provided to admissions with $\Delta P_{dj} < 0$ become more costly than those to admissions with $\Delta P_{dj} > 0$ across the reform. In this case, the marginal cost for admissions with $\Delta P_{dj} < 0$ would increase by more than that for admissions with $\Delta P_{dj} < 0$, which incentivizes physicians to reduce the care amount to a greater extent for the former group.

We empirically investigate this interpretation. We first plot the average pre-reform expense shares for pharmaceuticals and medical supplies, diagnostic tests, and general routine services across the 10 classes of admissions defined in Section 4.1. Appendix Figure A7 shows that service compositions are similar across admission classes before the reform. We then re-estimate Eq. (4) using service-specific expense shares as dependent variables. The results, reported in Appendix Table A7, show that for both admissions with $\Delta P_{dj} < 0$ and $\Delta P_{dj} > 0$, the reform's impacts on expense shares are close to zero and statistically insignificant. This result suggests that the reform alters the overall amount of care without changing the composition of services. Accordingly, we find no evidence that the heterogeneous policy impacts in Section 4.1 are driven by differential changes in service composition following the reform across admissions with different values of ΔP_{dj}.

Heterogeneous policy impacts across hospitals, patients, or diagnoses. Our finding in Section 4.1 could also arise if admissions with $\Delta P_{dj} < 0$ and those with $\Delta P_{dj} > 0$ are treated in different hospitals, involve different patients, or correspond to different diagnoses, and if the policy impact varies systematically across hospitals, patients, or diagnoses.

As discussed in Section 2.4, the reform incentivizes hospitals to provide less care, while simultaneously stimulating patients to demand more care. The net effect on the amount of care therefore depends on the relative strengths of hospital and patient responses. If hospitals treating admissions with $\Delta P_{dj} < 0$ respond more strongly than those treating admissions with $\Delta P_{dj} > 0$, or if patients associated with $\Delta P_{dj} > 0$ respond more strongly than those with $\Delta P_{dj} < 0$, the resulting net policy impacts would be consistent with our empirical finding in Section 4.1. Such systematic variation in hospital or patient responses may arise from unobserved heterogeneity in hospital financial incentives, patient price sensitivity, or diagnosis-specific decision-making processes. For example, hospitals with stronger financial incentives or patients who are more sensitive to OOP expense may respond more strongly to the reform; also, patients with different diagnoses may differ in their degree of involvement in medical decision-making, which could further shape the relative strength of their responses.

To assess whether these interpretations hold, we sequentially focus on admissions with $\Delta P_{dj} < 0$ and $\Delta P_{dj} > 0$ within the same hospital, among patients with the same characteristics, and with the same diagnosis. If unobserved heterogeneity in hospitals, patients, or diagnoses were driving our results, the reform's differential impacts should attenuate or disappear under these controlled conditions. Appendix C provides the detailed analysis. The results show that the differential impacts still hold and statistically significant within each treated hospital, among patients with the same socioeconomic characteristics (gender, age, and income), and for admissions with the same diagnosis of single cerebral infarction.

We also examine whether variation in pre-reform cost-sharing rates could account for the estimated heterogeneous policy impacts. A higher pre-reform cost-sharing rate implies a larger reduction in OOP expenses across the reform, which may induce stronger patient responses to the reform. We test this interpretation by comparing pre-reform cost-sharing rates between admissions with $\Delta P_{dj} < 0$ and those with $\Delta P_{dj} > 0$. Appendix Figure A9 shows no such difference between the two admission classes.

Mean reversion. Another plausible interpretation for the heterogeneous policy impacts could be mean reversion of medical expenses. As shown in Figures 2(a)-(b), the average medical expense is relatively high for admissions with $\Delta P_{dj} < 0$ and low for those with $\Delta P_{dj} > 0$ before the reform.[22] Mean reversion would imply an increase in medical expense for admissions with $\Delta P_{dj} > 0$ and a decrease for those with $\Delta P_{dj} < 0$ over time, even without the reform.

If this interpretation holds, the medical expense for the control group would exhibits similar changes across the reform. To test this, we compute ΔP_{dj} for admissions in the control group using Eq. (3), assigning them fixed payment P_g after the reform as if they were exposed to the reform. We then regress the medical expense for an admission on ΔP_{dj}, a dummy that indicates years after the reform ($Post_t$), and their interaction ($\Delta P_{dj} \times Post_t$), using only admissions in the control group. Mean reversion would predict a positive coefficient of the interaction term.[23] However, Appendix Table A8 shows that this coefficient is close to zero and statistically insignificant, which does not support the mean reversion interpretation.

[22] This is mechanical. As shown in Eq. (3), the pre-reform average medical expense is higher (lower) than the fixed payment for admissions with $\Delta P_{dj} < 0$ ($\Delta P_{dj} > 0$).

[23] If mean reversion were present, medical expenses for admissions with $\Delta P_{dj} < 0$—which are relatively high before the reform—would be expected to decrease, while those for admissions with $\Delta P_{dj} > 0$ would be expected to increase. Thus, the direction of changes in medical expense aligns with the sign of ΔP_{dj}.

Anchoring effects. The fixed payment after the reform could influence medical decisions through anchoring effects (Tversky & Kahneman, 1974). That is, physicians may interpret the fixed payment as an implicit suggestion by the government and regard it as a psychological "anchor" in medical decisions. Consequently, physicians tend to adjust medical expenses to align with the fixed payment: they increase (decrease) the amount of care for admissions with pre-reform medical expense lower (higher) than the fixed payment. Since anchoring tends to push medical expenses for all admissions toward the fixed payment after the reform, it would result in bunching at the payment (Bernheim et al., 2015). Appendix Figure A8(a) plots the distributions of medical expense for stroke rehabilitation admissions in the 7 treated hospitals before and after the reform. The figure shows no evidence of increased bunching at the fixed payment (18,000 RMB) after the reform relative to the distribution before the reform.

5. Theory

In this section, we propose a model of medical decisions to explain the heterogeneous impacts of the reform. The model has two novel features: (i) medical decisions are collectively made by patients and physicians and (ii) physicians have reference-dependent preferences. We assume that patients are not reference-dependent in medical decisions for two reasons. First, we do not find evidence that the reform's impact significantly differs by whether patients pay higher or lower OOP expense on average after the reform. Second, most patients undergo rehabilitation only once in our study context, and thus lack prior experience that would form a reference point.

At the end of this section, we also discuss how the reform's heterogeneous impacts could be rationalized by a neoclassical model in the absence of reference dependence. This discussion shows that multiple theoretical models could be consistent with our reduced-form findings, motivating the structural estimation that follows.

5.1 Model Setup

We consider a representative patient treated by a representative physician.[24] The amount of care received by the patient is measured by the medical expense, E. Following Finkelstein et al. (2016), the patient's utility is

$$u(E) = \frac{1}{\alpha} h(E, \omega) - p, \tag{5}$$

where $h(E, \omega)$ is the health benefit for the patient after receiving healthcare E, and ω represents his health conditions. α measures his price sensitivity, which converts the health benefit into a monetized value. We make three standard assumptions about $h(E, \omega)$: (i) the patient's health benefit from the first unit of care is sufficiently large, so that both the patient and physician agree

[24] We abstract from heterogeneities in patients, physicians, and diagnoses in our model.

to start the rehabilitation (i.e., $\frac{\partial h}{\partial E}|_{E=0} > T$, where T is a sufficiently large constant); (ii) the marginal health benefit decreases with E_{ij} (i.e., $\frac{\partial^2 h}{\partial E^2} \leq 0$); and (iii) the marginal health benefit can be negative when E is sufficiently large (i.e., $\frac{\partial h}{\partial E}|_{E=\infty} < 0$). p denotes the patient's OOP expense for the admission.

The physician's profit for providing care E is

$$\pi(E) = R(E) - C(E),$$

where $R(E)$ and $C(E)$ are the revenue and cost functions, respectively.[25] We assume that the physician has a reference-dependent preference: her utility depends on her reference point for the profit. Following Koszegi and Rabin (2006), the physician's utility is

$$v(E|r) = \begin{cases} \frac{1}{1+\eta}\pi(E) + \frac{\eta}{1+\eta}\big(\pi(E) - \pi(r)\big),\ if\ \pi(E) \geq \pi(r) \\ \frac{1}{1+\eta}\pi(E) + \lambda\frac{\eta}{1+\eta}\big(\pi(E) - \pi(r)\big),\ if\ \pi(E) < \pi(r) \end{cases}, \tag{6}$$

where $\pi(r)$ is the profit at the reference point, and r is the critical amount of care that enables her to achieve a profit at the reference point. The physician's utility is composed of two parts: the intrinsic utility derived from the profit $\pi(E)$ and the gain-loss utility from $\pi(E) - \pi(r)$. Relative to the intrinsic utility, the importance of the gain-loss utility is η. When the profit exceeds the reference point ($\pi(E) > \pi(r)$), the physician experiences a gain utility $\pi(E) - \pi(r) > 0$; conversely, when the profit falls below the reference point ($\pi(E) < \pi(r)$), she experiences a loss utility $\pi(E) - \pi(r) < 0$. The parameter $\lambda > 1$ represents the degree of loss aversion; that is, the marginal utility from losses is greater than that from gains. This utility function builds on the prospect theory of Kahneman and Tversky (1979). For simplicity, we do not model the diminishing sensitivity and probability weighting in this utility function.

Collective medical decisions. Borrowing the collective model from the economics of the family (Cherchye et al., 2015; Chiappori et al., 2022), we assume that the optimal amount of care is chosen to maximize the following collective utility of the patient and physician:

$$\mathbb{U}(E|r) = \theta u(E) + (1-\theta)v(E|r), \tag{7}$$

where θ and $1-\theta$ are the bargaining weights of the patient and physician, respectively. Since the physician is reference-dependent, the joint utility also depends on her reference point.

Our adoption of a collective model is motivated by the empirical findings in Section 4. First, Section 4.1 documents heterogeneous impacts of the reform, which indicates active involvements

[25] We assume that the physician's revenue (cost) aligns with that of the hospital where she works. This assumption is reasonable in our context, in which the physician and her affiliated hospital share the same financial incentive. As discussed in Section 2.1, the physician's bonus is tied to hospital revenue and costs associated with patient care. While she may not know the exact bonus from a specific admission, she understands that increasing revenue or reducing costs for the hospital contributes to a higher bonus.

of both the patient and physician in medical decision-making. The reform eliminates the patient's marginal OOP expenses and physician's marginal revenue. If decisions were made solely by the patient (physician), regardless of whether the decision-maker is loss-averse or not, the amount of care would increase (decrease) for all admissions. Second, our findings in Section 4.2 does not support a model in which the medical decision is made unilaterally by an altruistic and reference-dependent physician. In such a model, the physician would be loss averse to the increase in average OOP expense induced by the reform. This predicts differential impacts of the reform between admissions with increases and decreases in average OOP expense. However, we do not such differential impacts.

The collective utility specified in Eq. (7) implies that the decision jointly made by the patient and physician and is Pareto efficient.[26] This is highly plausible in our context. As discussed in Section 2.3, rehabilitation care often involves repetitive therapeutic training and requires intensive interactions between the patient and physician. Such sustained interactions enable the patient and physician to exhaust all possibilities for Pareto improvements.

To our knowledge, we are the first to apply the collective model in the healthcare context. We find that the collective framework provides a natural way to capture key features of medical decisions highlighted in the literature. First, it emphasizes the joint influences of patient and physician incentives on medical decisions (Xiang, forthcoming). Second, the model acknowledges the information asymmetry between physician and patient (McGuire, 2000) by capturing it through their relative bargaining weights.[27] Third, while our model assumes a profit-based physician utility in Eq. (6), it can easily be adapted to incorporate physician altruism in medical decisions (Li et al., 2017; Li et al., 2022).

5.2 Optimal Amount of Care before the Reform

We first consider the optimal amount of care before the reform. The patient reimbursement structure is specified in Eq. (2). For simplicity of illustration, we rewrite the OOP expense as $p_0 = \delta_0 E$, where the subscript 0 denotes the period before the reform and δ_0 is the patient cost-sharing rate. The patient utility is

$$u_0(E) = \frac{1}{\alpha} h(E, \omega) - \delta_0 E.$$

Under the FFS scheme, the physician's profit is

$$\pi_0(E) = (1 - c)E, \tag{8}$$

[26] As suggested by Browning et al. (2014), a key advantage of the collective model is that it characterizes decisions that yield Pareto-efficient outcomes, without requiring explicit assumptions about the underlying decision-making process. This model does not necessarily imply a cooperative decision process, as Pareto-efficient outcomes can also arise in non-cooperative interactions, such as alternating-offer bargaining (Rubinstein, 1982) or Bayesian persuasion (Cao et al., 2025).

[27] For a general modeling of information asymmetry in a collective decision process, please see Cao et al. (2025).

where for tractability, we follow Alexander (2020) and assume that the cost function is linear in E: $C(E) = cE$ ($c \in (0,1)$. This assumption is plausible in our context. Empirically, we find that the composition of services is stable across admissions with different ΔP_{dj} and unaffected by the reform (see Appendix Figure A7 and Table A7), which is consistent with marginal cost not varying with the amount of care provided.[28] The profit increases with E. The physician's reference point for her profit is

$$\pi_0(r_0) = (1-c)r_0,$$

where r_0 is the critical amount of care required to achieve a profit at the reference point. We discuss the formation of $\pi_0(r_0)$ at the end of this subsection. The physician's utility $v_0(E|r)$ depends on both the absolute level of profit $\pi_0(E)$ and the comparison between $\pi_0(E)$ and $\pi_0(r_0)$. The optimal amount of care (E_0^*) maximizes the collective utility (Eq. (7)). Appendix Table A9 Panels (a)-(c) list the patient's, physician's, and their collective utilities, respectively. It shows that the physician's utility differs by whether the physician perceives gains or losses, and this difference carries over to the collective utility.

We consider E_0^* separately in the gain and loss domains. Let $\mathbb{U}_0^G$ ($\mathbb{U}_0^L$) denote the collective utility function in the gain (loss) domain. The optimal amount of care in the gain domain, denoted by E_0^{G*}, is uniquely determined by the following first-order condition:[29]

$$\frac{\partial \mathbb{U}_0^G}{\partial E} = \theta\left(\frac{1}{\alpha}\frac{\partial h}{\partial E} - \delta_0\right) + (1-\theta)(1-c) = 0. \tag{9}$$

Similarly, the optimal expense in the loss domain, E_0^{L*}, is uniquely determined by

$$\frac{\partial \mathbb{U}_0^L}{\partial E} = \theta\left(\frac{1}{\alpha}\frac{\partial h}{\partial E} - \delta_0\right) + (1-\theta)\frac{1+\lambda\eta}{1+\eta}(1-c) = 0. \tag{10}$$

Due to loss aversion ($\lambda > 1$), the physician provides more care to raise her profit when perceiving losses than when experiencing gains, which leads to $E_0^{G*} < E_0^{L*}$. Consequently, we need only to consider E_0^* in three scenarios in the following proposition.

Proposition 1: The optimal amount of care before the reform (E_0^*) depends on the critical amount of care that allows the physician's profit to meet the reference point (r_0). Specifically,

i. If $r_0 < E_0^{G*} < E_0^{L*}$, $E_0^* = E_0^{G*}$;
ii. if $r_0 > E_0^{L*} > E_0^{G*}$, $E_0^* = E_0^{L*}$;
iii. if $E_0^{G*} \le r_0 \le E_0^{L*}$, $E_0^* = r_0$.

[28] In Appendix D.3, we show that the model predictions remain consistent with our reduced-form findings under more general cost function specifications. In the structural estimation, we further show that our key results—particularly the estimate of λ—are robust to allowing for flexible heterogeneity in marginal costs.
[29] The existence and uniqueness of E_0^{G*} is guaranteed by the three properties of $h(E, \omega)$, as outlined in Section 5.1.

Appendix D.1 provides the proof. The intuition is as follows. When $r_0 < E_0^{G*} < E_0^{L*}$, increasing E from r_0 leads to a perceived gain for the physician and increases collective utility in the gain domain until it reaches its maximum at $E_0^* = E_0^{G*}$. When $r_0 > E_0^{L*} > E_0^{G*}$, decreasing E from r_0 results in a perceived loss for the physician and simultaneously increases collective utility in the loss domain until $E_0^* = E_0^{L*}$. When $E_0^{G*} \leq r_0 \leq E_0^{L*}$, any decrease (increase) in E from r_0 leads to a perceived loss (gain), and both deviations reduce the collective utility. Therefore, $E_0^* = r_0$.

Following the literature on backward-looking reference points (DellaVigna et al., 2017) and associative memory (Bordalo et al., 2020), we make the following assumption.

Assumption 1. The physician sets a reference point for profit from an admission based on her average profit from previous admissions for the same diagnosis.

According to Assumption 1, in the steady state, the physician's reference point for profit equals the profit she earns:

$$\pi_0(r_0) = \pi_0(E_0^*) \Rightarrow r_0 = E_0^*. \tag{11}$$

Before the reform, she had adapted to this steady state, since the FFS scheme had been implemented in Changsha for over 10 years. In this stationary environment, the amount of care for the admission was stable, as shown in Figure 2. Thus, by Eq. (11) and Proposition 1-(iii),

$$E_0^* = r_0 \in [E_0^{G*}, E_0^{L*}].$$

This constitutes a personal equilibrium (PE) (Koszegi & Rabin, 2006), where the critical amount of care required to meet the physician's reference point is consistent with the optimal choice given the reference point she holds.

5.3 Optimal Amount of Care after the Reform

We consider the optimal amount of care after the reform. The reform changed the patient reimbursement structure. The patient's OOP expense becomes $p_1 = \delta_1 P$, where the subscript 1 indicates the period after the reform. δ_1 equals 10% (15%) if he is a retiree (an employee). P is the fixed payment for the admission, which is prospectively determined by the HSA of Changsha. Thus, the patient's utility becomes

$$u_1(E) = \frac{1}{\alpha} h(E, \omega) - \delta_1 P.$$

The reform also changed the hospital payment scheme from FFS to a diagnosis-based scheme, and therefore, the physician's profit becomes

$$\pi_1(E) = P - cE. \tag{12}$$

Given the patient utility function and physician profit function after the reform, the patient and physician jointly choose the optimal amount of care (E_1^*) to maximize their collective utility.

Following the same logic as used pre-reform, we derive the optimal amounts of care in the gain and loss domains, denoted by E_1^{G*} and E_1^{L*}, respectively. E_1^{G*} is uniquely determined by

$$\frac{\partial \mathbb{U}_1^G}{\partial E} = \theta \frac{1}{\alpha}\frac{\partial h}{\partial E} - (1-\theta)c = 0, \tag{13}$$

while E_1^{L*} is determined by

$$\frac{\partial \mathbb{U}_1^L}{\partial E} = \theta \frac{1}{\alpha}\frac{\partial h}{\partial E} - (1-\theta)\frac{1+\lambda\eta}{1+\eta} c = 0. \tag{14}$$

Due to loss aversion ($\lambda > 1$), the physician feels worse about her cost when facing losses than when experiencing gains, which leads to $E_1^{G*} > E_1^{L*}$.

Remark 2: We note that, while $E_0^{G*} < E_0^{L*}$, $E_1^{G*} > E_1^{L*}$. This arises because, although the physician always has stronger incentives to raise her profit when experiencing losses than when perceiving gains, her profit increases with E before the reform but decreases with E after the reform (i.e., $\pi_0'(\cdot) > 0$, $\pi_1'(\cdot) < 0$).

We now derive r_1—the critical amount of care required for the physician to achieve a profit at the reference point. By Assumption 1, the physician holds a reference point for her profit after the reform equal to the maximum profit before the reform:

$$\pi_1(r_1) = \pi_0(E_0^*),$$

By Eqs. (8) and (12), we derive

$$r_1 = \frac{(P - E_0^*)}{c} + E_0^*. \tag{15}$$

We note that r_1 increases with P to maintain a given value of profit at the reference point. Conversely, r_1 decreases with E_0^*, as $\pi_0'(\cdot) > 0$ and $\pi_1'(\cdot) < 0$.

Based on Remark 2, we consider the optimal amount of care after the reform in three scenarios in the following proposition.

Proposition 2. The optimal amount of care after the reform (E_1^*) depends on the critical amount of care that allows the physician's profit to meet the reference point (r_1). Specifically,

i. If $r_1 < E_1^{L*} < E_1^{G*}$, $E_1^* = E_1^{L*}$;
ii. if $r_1 > E_1^{G*} > E_1^{L*}$, $E_1^* = E_1^{G*}$;
iii. if $E_1^{L*} \leq r_1 \leq E_1^{G*}$, $E_1^* = r_1$.

The intuition is similar to that for Proposition 1, except that after the reform, increasing E from r_1 leads to a perceived loss for the physician, while decreasing E from r_1 induces a perceived gain.

Remark 3: Table A9 Panel (d) summarizes the determinants of both E_0^* and E_1^*. Compared with E_0^*, E_1^* is no longer influenced by the patient's marginal OOP expense or the physician's marginal revenue, as intended by policymakers. However, the reform has an unintended consequence due to the physician's reference-dependent preference: the fixed payment level (P) now affects E_1^*. According to Proposition 2, E_1^* varies depending on whether the physician perceives a loss or a gain when making the collective decision and her perception is determined by r_1, which is a function of P.

Figure 4 plots the relationship between E_1^* and P for a given E_0^*. When $P \in [P^{L*}, P^{G*}]$ ($\Leftrightarrow r_1 \in [E_1^{L*}, E_1^{G*}]$),[30] the optimal amount of care is chosen to maintain the physician's profit at her reference point (i.e., $E_1^* = r_1$). In this scenario, E_1^* decreases as P declines. When P drops below P^{L*} ($\Leftrightarrow r_1 < E_1^{L*}$), E_1^* stabilizes at E_1^{L*} and stops decreasing. This occurs because any further reduction in E below E_1^{L*} would make the marginal benefit from the patient side ($\theta \frac{1}{\alpha}\frac{\partial h}{\partial E}$) exceed the marginal cost from the physician side ($(1-\theta)\frac{1+\lambda\eta}{1+\eta}c$), which induces the collective decision to favor a higher amount of care. Following similar logic, when P increases above P^{G*} ($\Leftrightarrow r_1 > E_1^{G*}$), E_1^* stabilizes at E_1^{G*}.

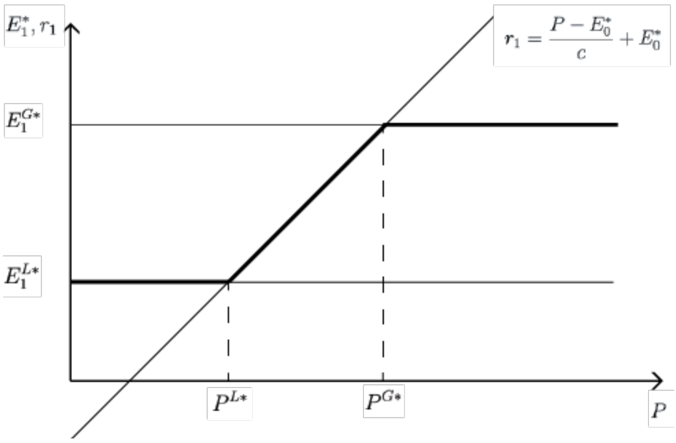

Figure 4. Optimal amount of care (E_1^*) and the fixed payment (P) after the reform

Notes: This presents the relationship between the optimal amount of care (E_1^*) and the fixed payment (P) after the reform following Proposition 2. $P^{L*} = E_0^* + c(E_1^{L*} - E_0^*)$, and $P^{G*} = E_0^* + c(E_1^{G*} - E_0^*)$.

5.4 Impact of the Reform on the Amount of Care

We assess the impact of the reform on the amount of care by comparing E_1^* and E_0^*. For illustration, we assume that $E_0^* = E_0^{G*}$, which is a preferred personal equilibrium (PPE)—the PE that yields the highest collective utility (Koszegi & Rabin, 2006). Based on this assumption, we derive the impact of the reform in the following proposition.[31]

Proposition 3. The impact of the reform on the optimal amount of care varies in the following three scenarios. Specifically:

i. If $\theta\delta_0 \leq (1-\theta)$, the reform decreases the amount of care ($E_1^* < E_0^*$);

ii. if $\theta\delta_0 \geq (1-\theta)[1 + \frac{(\lambda-1)\eta}{1+\eta}c]$, the reform increases the amount of care ($E_1^* > E_0^*$);

[30] By Eq. (15), $P^{L*} = E_0^* + c(E_1^{L*} - E_0^*)$, and $P^{G*} = E_0^* + c(E_1^{G*} - E_0^*)$.

[31] In Appendix D.2, we allow E_0^* to be any specific value in $[E_0^{G*}, E_0^{L*}]$ and derive a proposition regarding the impact of the reform on the amount of care (Proposition 3.1) that is analogous to Proposition 3.

iii. if $(1-\theta) < \theta\delta_0 < (1-\theta)[1+\frac{(\lambda-1)\eta}{1+\eta}c]$, the reform decreases the amount of care $(E_1^* < E_0^*)$ when $(P-E_0^*) < 0$, but increases it $(E_1^* > E_0^*)$ when $(P-E_0^*) > 0$.

We provide the proof for Proposition 3 in Appendix D.3.

To understand the intuition behind Proposition 3, we first discuss the how the reform alters the marginal collective utility. The second row in Appendix Table A9 Panel (c) lists the marginal collective utilities both before and after the reform. By eliminating the patient's marginal OOP expense, the reform increases the marginal collective utility by $\theta\delta_0$ for all E. Conversely, by removing the physician's marginal revenue, the reform decreases the marginal collective utility. This decrease differs by whether the physician perceives a gain or a loss after the reform, due to her reference-dependent preference. As we consider $E_0^* = E_0^{G*}$, the physician experiences a gain before the reform. In this case, the decrease is $(1-\theta)$ for E in the gain domain, but $(1-\theta)[1+\frac{(\lambda-1)\eta}{1+\eta}c]$ for E in the loss domain after the reform.

The impact of the reform on the amount of care depends on the change in marginal collective utility. If $\theta\delta_0 \leq (1-\theta)$, the reform results in a net decrease in marginal collective utility for all E, which motivates the patient and physician to collectively choose a lower optimal amount of care. If $\theta\delta_0 > (1-\theta)[1+\frac{(\lambda-1)\eta}{1+\eta}c]$, the reform raises marginal collective utility for all E, which encourages a higher optimal amount of care. If $(1-\theta) < \theta\delta_0 < (1-\theta)[1+\frac{(\lambda-1)\eta}{1+\eta}c]$, the reform raises marginal collective utility for E in the gain domain, but lowers it for E in the loss domain after the reform. In this scenario, the collective decision yields a higher optimal amount of care when the physician experiences a gain (i.e., when $(P-E_0^*) > 0$), but a lower optimal amount when she perceives a loss (i.e., when $(P-E_0^*) < 0$). Our empirical result in Section 4.1 is consistent with the theoretical prediction in Scenario iii.

5.5 A Neoclassical Collective Model as an Alternative Interpretation

In this section, we discuss how the reform's heterogenous impacts could be rationalized by alternative collective models in which the physician does not exhibit reference-dependent preferences. We refer to this type of models as neoclassical collective models. While we empirically preclude a set of plausible interpretations in Section 4.3, we now theoretically examine potential explanations within the collective decision-making framework.

We start from a model with the same setup as our model in Section 5.1 except that we set $\lambda = 1$. Before the reform, according to Eqs. (9)-(10), the optimal amount of care (E_0^*) is determined by:

$$\frac{\theta}{1-\theta}\frac{1}{\alpha}\frac{\partial h}{\partial E} - \frac{\partial C}{\partial E} = \delta_0\frac{\theta}{1-\theta} - 1. \quad (16)$$

Similarly, from Eqs. (13)-(14), the optimal amount of care after the reform (E_1^*) satisfies

$$\frac{\theta}{1-\theta}\frac{1}{\alpha}\frac{\partial h}{\partial E} - \frac{\partial C}{\partial E} = 0. \quad (17)$$

We do not impose a functional form on the physician's cost function $C(E)$ here. Given the properties of $h(E, \omega)$ outlined in Section 5.1, we assume that the left-hand side of Eqs. (16)-(17) decreases in E (i.e., $\frac{\theta}{1-\theta}\frac{1}{\alpha}\frac{\partial^2 h}{\partial E^2} - \frac{\partial^2 C}{\partial E^2} \leq 0$), ensuring the existence and uniqueness of E_0^* and E_1^*. Comparing Eqs. (16) and (17) yields[32]

$$E_0^* > E_1^* \text{ if } \delta_0\theta < 1 - \theta,$$
$$E_0^* < E_1^* \text{ if } \delta_0\theta > 1 - \theta.$$

The intuition is similar to that for Proposition 3 in Section 5.4: the collective decision yields a lower (higher) E^*, when the increase in marginal collective utility due to eliminating the patient's marginal OOP expense, $\delta_0\theta$, is smaller (larger) than the decrease in marginal collective utility resulting from the removal of the physician's marginal revenue, $1 - \theta$.

Therefore, the reform's heterogeneous impacts could be alternatively explained by a neoclassical collective model in which $\delta_0\theta < (1 - \theta)$ for admissions with $(P - E_0^*) < 0$ and $\delta_0\theta > (1 - \theta)$ for those with $(P - E_0^*) > 0$. However, we do not find systematic difference in pre-reform cost-sharing rates (δ_0) between admissions with $\Delta P_{dj} < 0$ and those with $\Delta P_{dj} > 0$ (Appendix Figure A9). Accounting for the heterogeneous impacts using the neoclassical model would require the physician's bargaining weight relative to the patient's ($\frac{1-\theta}{\theta}$) to differ systematically between the two classes of admissions. At present, it is not obvious what economic mechanisms would generate such systematic variation in relative bargaining weights based on whether physicians receive higher or lower average revenue following the reform. Nevertheless, it is interesting to empirically explore whether such heterogeneity exists. In the following section, we structurally estimate both our behavioral collective model and a neoclassical collective model that allows for rich heterogeneity in $\frac{1-\theta}{\theta}$, and we evaluate which better fits the data.

6. Structural Estimates

6.1 Parameterization

To estimate the behavioral collective model, we make three assumptions. First, for a patient i with diagnosis d treated by hospital j in year t, his health benefit is

$$h(E_{idjt}, \omega_{idjt}) = -\frac{1}{2\alpha}\left(E_{idjt} - \omega_{idjt}\right)^2.$$

Second, the patient's health condition (ω_{idjt}) is

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[32] A sufficient but not necessary condition for $\frac{\theta}{1-\theta}\frac{1}{\alpha}\frac{\partial^2 h}{\partial E^2} - \frac{\partial^2 C}{\partial E^2} \leq 0$ is that the cost function is convex (i.e., $\frac{\partial C}{\partial E} \geq 0$ and $\frac{\partial^2 C}{\partial E^2} \geq 0$). More generally, as long as the assumption $\frac{\theta}{1-\theta}\frac{1}{\alpha}\frac{\partial^2 h}{\partial E^2} - \frac{\partial^2 C}{\partial E^2} \leq 0$ is satisfied, neither the functional forms of $h(\cdot)$ and $C(\cdot)$ nor their potential heterogeneity across admissions affects the sign of $(E_1^* - E_0^*)$.

$$\omega_{idjt} = \boldsymbol{X}_{it} \cdot \phi + \kappa_d + \kappa_j + \kappa_t, \tag{18}$$

where the vector of $\boldsymbol{X}_{it}$ includes patient age (x_{it}^1), age squared (x_{it}^2), gender (x_{it}^3), annual income (x_{it}^4), an indicator for being a civil servant (x_{it}^5), diagnosis fixed effects (κ_d), hospital fixed effects (κ_j), and time (half-year) fixed effects (κ_t).

Third, the observed medical expense, E_{idjt}^o, contains measurement errors, υ_{idjt}, such that

$$\ln\left(E_{idjt}^o\right) = \ln\left(E_{idjt}\right) + \upsilon_{idjt}.$$

We assume that the measurement error, υ_{idjt}, is independent and identically distributed, following a normal distribution with a mean of 0 and a standard deviation σ:

$$\upsilon_{idjt} \sim N(0, \sigma).$$

As a result, E_{idjt}^o follows the lognormal distribution

$$\ln\left(E_{idjt}^o\right) \sim N\left(\ln\left(E_{idjt}\right), \sigma\right). \tag{19}$$

This lognormal distribution effectively captures the right-skewed distribution of the observed medical expense, as shown in Appendix Figure A8(b).

For the neoclassical collective model, we maintain the same three assumptions.[33] In addition, we allow the relative bargaining weight between to the physician and patient to vary with patient characteristics, diagnoses, hospitals, and time:[34]

$$\frac{1-\theta_{idjt}}{\theta_{idjt}} = \boldsymbol{X}_{it} \cdot \psi + \kappa_d + \kappa_j + \kappa_t. \tag{20}$$

6.2 Maximum Likelihood Estimation

We separately estimate the two models using maximum likelihood estimation (MLE). In our behavioral collective model, the optimal amount of care (E_{idjt}) is summarized as follows:

(i) For admissions before the reform or those in the control group,[35]

$$E_{idjt} = E_{idjt,0}^{G*} = \omega_{idjt,0} - \alpha\delta_{idjt,0} + \alpha\frac{1-\theta}{\theta}(1-c). \tag{21a}$$

(ii) For admissions in the treatment group after the reform, according to Proposition 2, $E_{idjt} = min\{E_{idjt,1}^{G*}, max\{E_{idjt,1}^{L*}, r_{idjt,1}\}\}$, where

$$E_{idjt,1}^{G*} = \omega_{idjt,1} - \alpha\frac{1-\theta}{\theta}c, \tag{21b}$$

$$E_{idjt,1}^{L*} = \omega_{idjt,1} - \alpha\frac{1-\theta}{\theta}c\frac{1+\lambda\eta}{1+\eta}, \tag{21c}$$

[33] The physician's cost function in the neoclassical model is assumed to be linear: $C(E) = cE$. As discussed in Section 5.5, this assumption is without loss of generality for our purpose.

[34] In both Eqs (18) and (20), we include diagnosis fixed effects at the level of 3-digit ICD code rather than the 6-digit level, as the latter would substantially increase the dimensionality of the parameter space and render the structural estimation computationally intractable. At the 3-digit level, we have 29 diagnoses in total.

[35] While we abstract from heterogeneities in diagnoses and hospitals in the theoretical model, our structural estimation employs rich data variations across diagnoses, hospitals, and years.

$$r_{idjt,1} = \frac{1}{c}(P_g - E^*_{dj,0}) + E^*_{dj,0}. \tag{21d}$$

The subscript t indexes calendar year, $0(1)$ indexes treatment status, and g denotes the diagnostic category that includes diagnosis d. $E^*_{dj,0}$ is the average amount of care for admissions with the same diagnosis in hospital j before the reform. We normalize the physician's weight on gain-loss utility (η) as 1; hence, our estimate of the loss-aversion parameter λ can be interpreted as the overall weight on the losses.[36]

In the neoclassical collective model, the optimal amount of care (E_{idjt}) for admissions before the reform or those in the control group is

$$E_{idjt} = \omega_{idjt,0} - \alpha\delta_{idjt,0} + \alpha\frac{1-\theta_{idjt,0}}{\theta_{idjt,0}}(1-c), \tag{22a}$$

and for admissions in the treatment group after the reform is

$$E_{idjt} = \omega_{idjt,1} - \alpha\frac{1-\theta_{idjt,0}}{\theta_{idjt,0}}c. \tag{22b}$$

For both models, given the lognormal distribution of the observed medical expense (E^o_{idjt}) (Eq. (19)), the density of $\ln(E^o_{idjt})$ is

$$\varrho[\ln(E^o_{idjt})] = \frac{1}{\sigma\cdot\sqrt{2\pi}}\cdot e^{-\frac{1}{2}\left[\frac{\ln(E^o_{idjt})-\ln(E_{idjt})}{\sigma}\right]^2}.$$

The log-likelihood function is

$$LL(\Omega) = \sum_i\sum_j\sum_d\sum_t 1_{idjt}\log\{\varrho[\log(E^o_{idjt})]\},$$

where 1_{idjt} is an indicator that patient i with diagnosis d is treated by physician j in year t. Ω denotes the vector of parameters to be estimated.

Compared with the neoclassical collective model, our behavioral collective model introduces one additional behavioral parameter—the degree of loss aversion λ—but assumes no heterogeneity in θ. Overall, our behavioral model has 67 fewer parameters than the neoclassical model, as the latter allows rich heterogeneity in $\frac{1-\theta_{idjt}}{\theta_{idjt}}$.[37]

6.3 Identification

Behavioral collective model. We first discuss identification of the four key parameters of interest in the behavioral collective model: the patient's price sensitivity (α), the patient's bargaining weight (θ), the physician's marginal cost (c), and the degree of loss aversion (λ). Identifying parameters related to patient health conditions (ω_{idt}) and the standard deviation (σ) is standard in

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[36] η and λ could be separately identified if we could observe some physicians switching from the loss to the gain domain and others switching from the gain to the loss domain across the reform. However, we only observe the latter case.

[37] We include 69 parameters to capture the heterogeneity in $\frac{1-\theta_{idjt}}{\theta_{idjt}}$ in Eq. (20).

the literature. Our discussion of the source of the identification for each parameter is for illustrative purposes only. All parameters are estimated simultaneously when conducting the estimation.

We combine the policy change with our structural model to carry out the identification in four steps. First, for each admission in the treatment group after the reform, we determine whether the amount of care falls into the gain domain ($E^{G*}_{idjt,1}$), into the loss domain ($E^{L*}_{idjt,1}$), or at the critical value to meet the reference point ($r_{idjt,1}$). This is accomplished by examining the *correlation* between the amount of care for the admission after the reform ($E^{*}_{idjt,1}$) and the average pre-reform care amount for admissions with the same diagnosis in the same hospital before the reform ($E^{*}_{dj,0}$). Eqs. (21b)–(21d) show that when $E_{idjt,1} = r_{idjt,1}$, the amount of care changes with $E^{*}_{dj,0}$; in the other two scenarios, it does not directly depend on $E^{*}_{dj,0}$. The other two scenarios are easily distinguishable, because for admissions with the same observed characteristics, the amount of care is higher in the gain domain than in the loss domain.

Second, we identify c using admissions with $E_{idjt,1} = r_{idjt,1}$. As shown in Figure 4, when the fixed payment $P_g \in [P_g^{L*}, P_g^{G*}]$, the optimal amount of care is always chosen to keep the physician's profit at her reference point. For these admissions, the optimal amount of care is determined by the fixed payment (P_g), the pre-reform average amount of care ($E^{*}_{dj,0}$), and the marginal cost (c) (see Eq. (21d)). A one-unit decrease in ($P_g - E^{*}_{dj,0}$) induces the physician to reduce $E_{idjt,1}$ by $\frac{1}{c}$ to offset the revenue shortfall. This helps identify c.

Third, we identify α and θ based on admissions for which the amount of care remains in the gain domain across the reform. According to Eqs. (21a) and (21b), the change in care for these admissions is

$$\Delta E^{G*}_{idjt} = \left(\omega_{idjt,1} - \omega_{idjt,0}\right) + \alpha\delta_{idjt,0} - \alpha\frac{1-\theta}{\theta}.$$

Conditional on patient health conditions ω_{idjt}, This change in care results from (i) the change in the patient's marginal OOP expense from $\delta_{idjt,0}$ to 0 and (ii) the change in the physician's marginal profit from $(1-c)$ to $(-c)$. With ω_{idjt} estimated using Eq. (18), the correlation between ΔE^{G*}_{idjt} and $\delta_{idjt,0}$ helps identify α, which in turn allows us to isolate the contribution of the change in patient incentives ($\alpha\delta_{idjt,0}$) from that of the change in physician incentives ($\alpha\frac{1-\theta}{\theta}$). The magnitude of the latter then helps identify θ. The identification of α and θ is in the same spirit as that of the literature on collective models (Cherchye et al., 2015, Chiappori et al., 2022), exploiting the differential shifts in patient and physician marginal incentives due to the reform.

Fourth, we identify λ by leveraging the difference in the amount of care between the gain and loss domains after the reform, since this difference is induced by λ, as shown by comparing Eqs. (21b) and (21c).

Neoclassical collective model. In estimating the neoclassical collective model, our objective is to compare its model fit with our behavioral model, rather than to precisely recover all structural parameters. With this goal in mind, we note that we cannot identify two parameters in the neoclassical model— c and α. First, we lack the identification source of c in the neoclassical model. As shown in Eqs. (22a)-(22b), both the optimal amount of care before and that after the reform include the term $-\alpha\frac{1-\theta_{idjt,0}}{\theta_{idjt,0}}c$, and c cancels out in the change in care amount due to the reform; in addition, the neoclassical model does not predict admissions for which $E_{idjt,1} = r_{idjt,1}$, eliminating an alternative source of variation that could identify. Second, when we incorporate rich heterogeneity in $\frac{1-\theta_{idjt}}{\theta_{idjt}}$ as specified in Eq. (20), both $\frac{1-\theta_{idjt}}{\theta_{idjt}}$ and $\delta_{idjt,0}$ vary with patient characteristics, diagnoses, and hospitals.[38] As a result, the variation in ΔE^*_{idjt} induced by $\delta_{idjt,0}$ can be mostly absorbed by variation in $\frac{1-\theta_{idjt}}{\theta_{idjt}}$, which prevents us from precisely identifying α.

We therefore calibrate c and α using the estimates from the behavioral collective model. While the calibrated values influence the estimates of other model parameters, they do not affect the model fit.[39] Given the calibrated c and α, estimation of the parameters related to ω_{idt}, $\frac{1-\theta_{idjt}}{\theta_{idjt}}$, and σ is standard in the literature.

6.4 Results

Table 3 presents estimates of the key parameters. Almost all estimates are statistically significant at the 1% level when we compute standard errors using 200 replications of bootstrap.[40] Column (1) reports estimation results for the behavioral collective model. The physician's marginal cost is 0.72, which is close to the cost-to-revenue ratio in the annual report of Chinese hospitals.[41] The estimate of θ is 0.87. That is, the bargaining weight for patients is 0.87, while that for physicians is 0.13. This result highlights the importance of active patient involvement in rehabilitation care, consistent with evidence from the medical literature (Baker et al., 2011).

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[38] $\delta_{idjt,0}$ varies by hospital tier, the patient's retirement status, and the share of medical expense that is claimable (see Eq. (2)).

[39] The fact that c and α are not identifiable in the neoclassical collective model implies that, for any given values of c and α, there exist corresponding values of the remaining model parameters that leave the value of the log-likelihood function unchanged.

[40] Only the coefficients of income (in logarithm) are not statistically significant in both columns.

[41] The data, collected by the National Health Commission, provide information on the total cost and revenue from inpatient admissions for each hospital in Sichuan province in China in 2015. On average, the total cost is 81% of total revenue.

The estimate of α is 37.2, which suggests that a one percentage point increase in the coinsurance rate leads to a decrease in the amount of care by 372 RMB.[42] Given the mean coinsurance rate of 21% and mean medical expense of 12,518 RMB before the reform, we calculate the price elasticity of demand to be -0.62. This is close to the estimated price elasticity of the demand for rehabilitation (-0.55) by Ziebarth (2010). Estimates for patient health conditions indicate that patient severity first decreases with age, then increases; also, males and non-civil servants typically exhibit worse health conditions.

Table 3. Parameter estimates of structural models

		(1)	(2)
		Behavioral model	Neoclassical model
Physician's marginal cost	c	0.719	0.719
		(0.252)	-
Patient's price sensitivity	α	37.203	37.203
		(1.121)	-
Patient's bargaining weight	θ	0.871	Rich
		(0.003)	heterogeneity
Loss aversion	λ	3.529	1
		(1.596)	-
Health conditions	$\mathrm{Age}/10$	-2.260	-1.885
		(0.214)	(0.192)
	$\mathrm{Age}^2/100$	0.168	0.146
		(0.016)	(0.014)
	Female	-0.418	-0.449
		(0.048)	(0.049)
	Income (in logarithm)	0.112	0.029
		(0.058)	(0.033)
	Civil servant	-2.037	-1.332
		(0.146)	(0.094)
	Diagnosis fixed effects	Yes	Yes
	Hospital fixed effects	Yes	Yes
	Year-month fixed effects	Yes	Yes
	Log-likelihood values	-95,295	-95,354
	Number of parameters	157	224
	Number of observations	31,158	

Notes: This table reports structural estimates of key parameters in the model. The unit of the dependent variable is 1,000 RMB in the structural estimation. Column (1) reports estimates for the behavioral collective model and Column (2) for the neoclassical collective model. As discussed in Section 6.3, we calibrate c and α in the neoclassical model using the estimate of c in Column (1). Standard errors in parentheses are computed using 200 replications of bootstrap.

The estimate of λ is 3.53, which suggests that the physician places a weight on loss utility that is approximately 3.5 times greater than that on gain utility. Our estimate of λ is comparable to estimates in the behavioral economics literature (Engström et al., 2015; DellaVigna et al., 2017; Andersen et al., 2022; Brown et al., 2024).

[42] The unit of medical expense in the structural estimation is 1,000 RMB.

In the baseline estimation for the behavioral collective model, we abstract from the potential heterogeneity in c, α, and θ across admissions. To assess the robustness of our findings to this assumption, we conduct three additional exercises. First, we allow the marginal cost to vary by service composition by modeling c as a function of expense shares on different service types. Second, we allow c, α, and θ to vary with patient and hospital characteristics. Third, we separately estimate the model for admissions with different diagnoses, focusing on the three most common diagnoses. Appendix Table A10 reports estimates of key parameters. Across all three exercises, we obtain precise and statistically significant estimates of λ, with values ranging from 3.18 to 4.96. These results indicate that our key finding—physicians exhibit loss aversion—is robust to allowing for heterogeneity in marginal cost, price sensitivity, and bargaining weights.

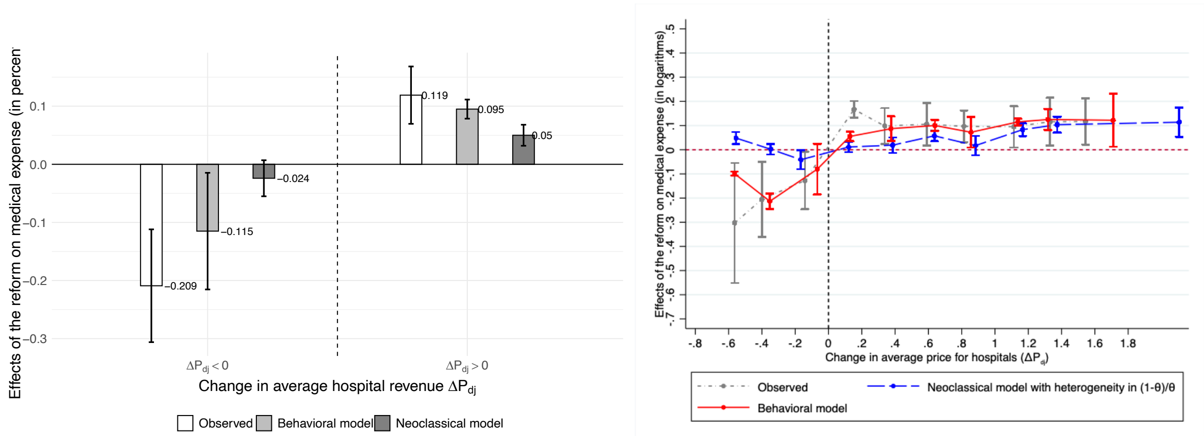
Table 3, Column (2) reports the estimates for key parameters in the neoclassical collective model. The estimates for patient health conditions are in the same sign of those in the behavioral collective model. The value of the log-likelihood function is lower than that for the behavioral collective model.

6.5 Model Fit

To evaluate model fit, Figure 5 compares empirically estimated impacts of the reform with the impacts predicted by the two models. Despite having fewer parameters, the behavioral collective model provides a better fit to the data than the neoclassical collective model.

Panel (a) plots the reform's impacts for two classes of admissions: those with $\Delta P_{dj} < 0$ and those with $\Delta P_{dj} > 0$. White bars represent estimates of β_1^k in Eq. (4) using the observed medical expense (in logarithm) as the dependent variable. Dark gray and light gray bars report the same estimates using medical expense (in logarithm) predicted by the behavioral and neoclassical collective models, respectively. For both admission classes, the reform's impacts predicted by the behavioral model fall within the 90% confidence intervals of the empirical estimates. In contrast, although the neoclassical model incorporates rich heterogeneity in $\frac{1-\theta_{idjt}}{\theta_{idjt}}$, it predicts a negative impact for admissions with $\Delta P_{dj} < 0$ that is close to zero and statistically insignificant, and it substantially underestimates the positive impact for admissions with $\Delta P_{dj} > 0$.

In Panel (b), we further divide admissions in the treatment group into 10 classes, using the same classification method as in Figure 3(b). The dotted gray line plots the empirically estimated impacts for the 10 classes of admissions, and the solid red (dashed blue) line plots the impacts predicted by the behavioral (neoclassical) collective model. Consistent with Panel (a), the behavioral model closely tracks the empirical estimates across all 10 classes, but the neoclassical model fails to predict the negative impacts on medical expense for admissions with $\Delta P_{dj} < 0$.



(a) Reform's impacts for two admission classes (b) Reform's impacts for ten admission classes

Figure 5. Observed vs. predicted impacts of the reform on medical expense

Notes: This figure plots both the empirically estimated and model-predicted impacts of the reform on medical expense, as well as their 90% confidence intervals. In Panel (a), we divide admissions in the treatment group into two classes: the first (second) includes admissions with $\Delta P_{dj} < 0$ ($\Delta P_{dj} > 0$). In Panel (b), we divide admissions in the treatment group into 10 classes, ordered from low to high based on their ΔP_{dj} values. The classification method is illustrated in Section 4.1. We additionally control for diagnosis-by-year fixed effects in the regressions. Standard errors are clustered at hospital-by-diagnosis level.

6.6 Simulation Analyses

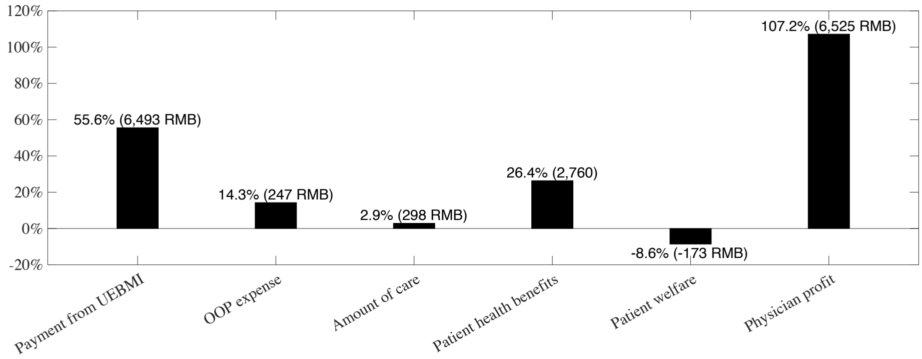
We now conduct simulation analyses using estimates from the behavioral collective model.

Impacts of the reform. In the first analysis, we quantify the impacts of the reform on (1) payment from UEBMI, (2) OOP expense, (3) amount of care, (4) patient health benefits, (5) patient welfare, and (6) physician's profit. Based on model estimates, we simulate these outcomes for each admission under two scenarios—one with the reform in place and one without—and compare outcomes between the two scenarios.

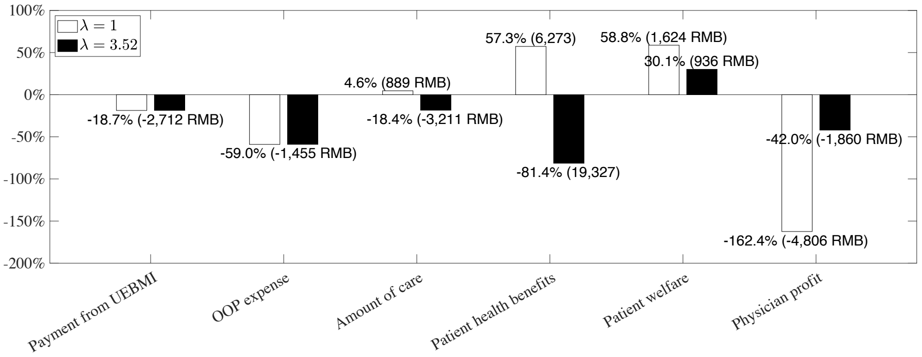
Figure 6(a) reports the mean change in each outcome due to the reform for all admissions. The reform raises both the UEBMI payment and OOP expense, consistent with the fact that the fixed payment after the reform is set above the average pre-reform expense per admission.[43] The percentage increase in the OOP expense (14.3%) is smaller than that in the UEBMI payment (55.6%), because the mean coinsurance rate decreases across the reform. Additionally, the amount of care per admission, measured by the medical expense, increases by 2.9% (≈298 RMB), which raises the average patient health benefits by 26.4%. Patient welfare decreases by -8.6% (≈173 RMB), because the increased disutility from the increase in OOP expense outweighs the utility gain from the increase in health benefits. The physician's profit increases substantially by 107.2% (≈6,525 RMB). This figure indicates that, while both the UEBMI and patients spend more on rehabilitation care due to the reform, patient welfare does not improve on average. Physicians are

[43] As explained in Section 2.4, before the reform, the total of the UEBMI payment and OOP expense for an admission equals its medical expense; after the reform, the total equals the fixed payment for the admission.

likely the primary beneficiaries of the reform. Appendix Figure A10 further plots the reform's impacts separately for admissions with $\Delta P_{dj} < 0$ and $\Delta P_{dj} > 0$. For admissions with $\Delta P_{dj} > 0$, changes in the six outcomes due to the reform align with the changes illustrated above; however, for admissions with $\Delta P_{dj} < 0$, the changes all occur in the opposite direction. Such difference is induced by physician's loss aversion.



(a) Reform's impacts on treatment and welfare outcomes for all admissions



(b) Impacts of loss aversion

Figure 6. Model fitness and simulation analyses

Notes: Figure (a) plots the simulated reform's impacts on the six outcomes for all admissions. Figure (b) plots the simulated reform's impacts in the scenario in which $\lambda = 1$ and those in the scenario in which $\lambda = 3.52$, limiting the sample to admissions with $\Delta P_{dj} < 0$.

Impacts of loss aversion. Our second analysis quantifies the impacts of loss aversion on treatment and welfare outcomes. According to our behavioral collective model, loss aversion plays an important role in driving physicians' responses for admissions with $\Delta P_{dj} < 0$. Focusing on these admissions, we simulate the reform's impacts on the six outcomes in two scenarios: one in which physicians are loss averse (λ =3.52) and another in which physicians do not exhibit loss aversion (λ =1). We then compare the reform's impacts between the two scenarios.

Figure 6(b) reports the results. White bars represent changes in outcomes due to the reform under the scenario in which λ =1. Black bars depict those in the scenario with λ =3.52. The UEBMI payment and OOP expense are not affected by physicians' loss aversion, because they are determined by the hospital payment scheme and patient reimbursement structure. If physicians do not exhibit loss aversion (λ =1), the reform would increase the amount of care for admissions with

$\Delta P_{dj} < 0$, similar to the impact for admissions with $\Delta P_{dj} > 0$. However, due to physicians' loss aversion (λ =3.52), the care amount for these admissions decreases by 23% (4.6%+18.4%), or approximately 4,100 RMB. This reduction adversely impacts patient health benefits and welfare, and decreases them by 132.8% and 26.3%, respectively. Also, the loss aversion leads to a 102.2% (≈2,946 RMB) increase in physicians' profit by incentivizing their strong cost-cutting response.

7. Optimal Payment under the PPS

Despite global adoption of the PPS, few studies have investigated the optimal level of the fixed payment. In a neoclassical framework, in which physicians do not exhibit reference-dependent preferences, medical decisions are entirely determined by the marginal incentives of patients and physicians, which are unaffected by payment level. However, we find that the behavioral collective model provides a substantially better explanation of our reduced-form findings than the neoclassical alternative. When physicians exhibit reference dependence, payment levels become crucial in determining the treatment and welfare outcomes of medical decisions. We now investigate the optimal payment under the PPS, taking the reference dependence of physicians into consideration. We focus on admissions for stroke rehabilitation in this analysis, which account for 93% of all admissions in our sample.[44]

To derive the optimal level of the fixed payment, we first define the social planner's problem. Following Skinner (2011) and Gaynor et al. (2023), we assume that the social planner considers the trade-off between patient health benefits and total healthcare expense, in which the latter includes both the payment from UEBMI and OOP expense for patients.[45] The social planner prospectively sets a fixed payment (P) to cover the total expense for a stroke rehabilitation admission, knowing how patients and physicians will respond. The same as the post-reform reimbursement structure in reality, patients need to pay a fixed share (δ^1) of P, and the remaining is paid by UEBMI.[46] The social planner chooses the optimal payment (P^*) to maximize its utility, subject to incentive compatibility for both patient and physician:

$$\max_P \frac{1}{\alpha_s} h(E_1^*, \omega) - P$$

$$\text{s.t.} E_1^* = \arg\max_E \theta u_1(E) + (1-\theta) v_1(E|r_1),$$

[44] We use stroke rehabilitation as an example to illustrate our analytical framework of deriving the optimal payment. Our framework can easily be adapted to other diagnoses or diagnostic categories.
[45] The assumption that the social planner's objective does not include the supply side's profit is common in contexts with market frictions, such as principal-agent problems and monopolistic markets.
[46] We assume that δ^1 is 15% for employees and 10% for retirees. Our framework can be extended to analyze the optimal policy when the social planner can simultaneously choose both P and δ^1.

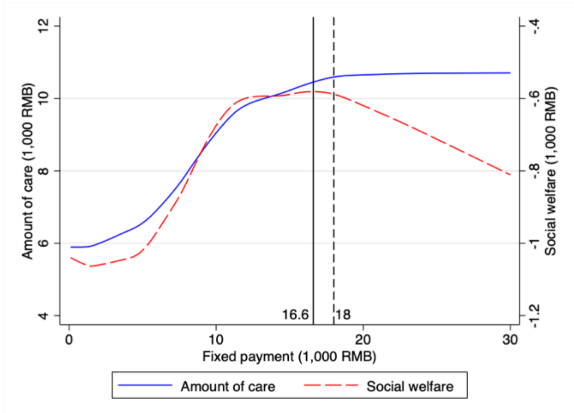
where $h(E_1^*, \omega)$ is patient health benefits, as defined in Eq. (5). $\frac{1}{\alpha_s}$ is the social planner's weight on patient health benefits relative to expense. This may differ from the patient's weight ($\frac{1}{\alpha}$), since patients may underutilize healthcare without insurance due to liquidity constraints, lack of information, or myopia. Notably, the underuse of rehabilitation care is a global issue, mainly because patients typically lack knowledge about their need for rehabilitation and tend to undervalue its benefits (WHO, 2017). E_1^* is the amount of care that maximizes the collective utilities of the patient and physician, which we solve for in Section 5.3. As shown in Figure 3, E_1^* is responsive to the choice of P.

Based on estimates of our behavioral collective model, we conduct a counterfactual analysis to solve the optimal payment level. Specifically, holding physicians' reference points unchanged, we hypothetically change P, and simulate E_1^* as well as the social planner's welfare under each value of P. We solve the optimal payment that maximizes the social welfare. We also examine the impacts of switching the fixed payment from the observed to the optimal level on treatment and welfare outcomes.

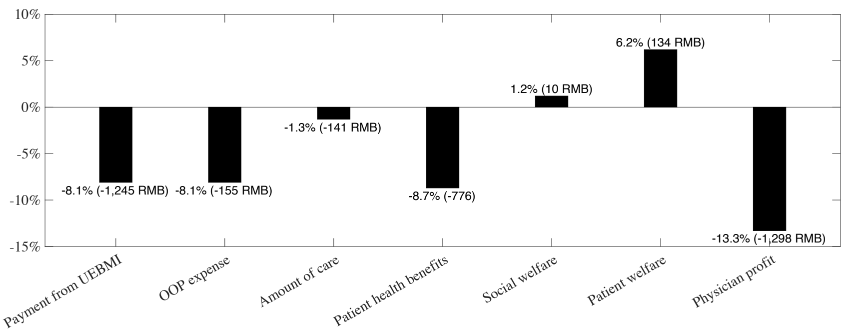
Before the simulation, we need to set a value for α_s. Following Gaynor et al. (2023), we calibrate a value for α_s based on the value of a statistical life year, the relationship between the amount of care and mortality risk that is estimated leveraging the 2015 reform, and assumptions that allow us to relate these quantities to social welfare (see Appendix E for detailed analysis). The resulting value is 0.75, which is lower than the patient's price sensitivity, which means that the social planner places a much higher weight on patient health than patients do, as might be expected. This calibrated value of α_s may explain why the government sets a fixed payment of 18,000 RMB for stroke rehabilitation, which is substantially higher than the pre-reform average medical expense (12,979 RMB). Based on our model estimates, the reform would increase patient health benefits by 4,078 units if we ignore the physician's reference dependence. If the government is willing to achieve this health benefit gain at an additional cost of 5,021 RMB (18,000−12,797), α_s should be no more than 0.81 ($\frac{4{,}078}{5{,}021}$). This value is close to our calibrated α_s of 0.75.

Notably, our framework for solving the optimal payment under the PPS is readily applicable to alternative values of α_s or alternative specifications of the social planner's objective function. One limitation of this framework is that we do not model the evolvement of physicians' reference points over time. If reference points adjust dynamically, the optimal payment path may differ from the static benchmark derived here. Nevertheless, our analytical framework remains useful for optimal payment design, as it can accommodate alternative formulations or values of physicians' reference points without altering its core structure.

A single fixed payment. We first investigate the optimal payment in a scenario in which a single fixed payment is applied to all stroke rehabilitation admissions, as in the post-reform situation observed in reality. Figure 7(a) plots the simulated optimal amount of care (solid blue line) and social welfare (dashed red line) under different values of fixed payment for a stroke rehabilitation admission. We obtain two observations from the figure. First, the optimal amount of care changes with the fixed payment, which is consistent with our model predictions. Second, the optimal payment that maximizes social welfare is 16,600 RMB, which is lower than the current fixed payment of 18,000 RMB in reality.



(a) A uniform optimal payment



(b) Observed payment vs. a single optimal payment

Figure 7. The optimal payment level for stroke rehabilitation

Notes: Limiting the analytic sample to stroke rehabilitation admissions, Panel (a) plots the simulated optimal amount of care (solid blue line) and social welfare (dashed red line) under different values of fixed payment, Panel (b) presents the impacts of reducing the fixed payment from the observed (18,000 RMB) to the optimal level (16,600 RMB) on average treatment and welfare outcomes per admission.

We further investigate the impacts of reducing the fixed payment from 18,000 RMB to 16,600 RMB on treatment and welfare outcomes per admission. Specifically, we separately simulate the outcomes under the two payment levels, holding physicians' reference point unchanged, and compute the mean change for each outcome when the fixed payment is reduced from 18,000 RMB to 16,600 RMB.

Figure 7(b) presents the results. This reduction of 1,400 RMB in the fixed payment reduces both the UEBMI payment and OOP expense by 8.1%. It also reduces the amount of care by 1.3% ($\approx$141 RMB), which decreases patient health benefits by 8.7%. Despite this, social welfare increases by 1.2% (≈ 10 RMB), since the savings in total expense outweigh the loss in patient health benefits. Patient welfare increases even more, by 6.2% (≈ 134 RMB), because patients place a lower weight on health benefits relative to expense compared with the social planner. Physician profit decreases by 13.3% (≈1,298 RMB).

Separate fixed payments by hospital tier. The optimal payment may differ by hospital tier, because physicians in hospitals of different tiers may form different reference points. As shown in Table 1, the pre-reform medical expense for stroke rehabilitation is systematically higher in tier-3 hospitals than in tier-2 hospitals.

To solve the optimal payment by hospital tier, we replicate the simulation analysis from Figure 7(a) separately for admissions in tier-2 and tier-3 hospitals. Appendix Figure A11(a) presents the results, which shows that the optimal payment is 7,200 RMB for tier-2 hospitals and 17,100 RMB for tier-3 hospitals. Appendix Figure A11(b) further shows that, for admissions in both tiers of hospitals, reducing the fixed payment from the observed to their optimal levels lowers the UEBMI payment and OOP expense, which improves patient and social welfare.

Does setting payments based on hospital tier achieve better outcomes than applying a uniform payment for all hospitals? To answer this, we compare the average treatment and welfare outcomes of an admission under two scenarios: one in which all hospitals are paid 16,600 RMB per admission for stroke rehabilitation and another in which tier-2 hospitals are paid 7,200 RMB and tier-3 hospitals are paid 17,100 RMB. Figure 8 reports the results. Compared with a single payment for all admissions, setting payments by hospital tier reduces the total expense by 7.8% (≈1,248 RMB), but only decreases the amount of care and patient health benefits by 0.1% and 0.8%, respectively. Therefore, hospital-tier-specific payments results in greater gains in social and patient welfare. The reduction in total expense mainly translates into a reduction in physician profit (≈1,241 RMB).[47]

We conclude that, from the social planner's perspective, hospital-tier-specific payments are preferable than a uniform payment across all hospitals. The former acknowledges the difference in physicians' reference points across hospital tier, and enables more precise management of their perceived gains or losses. Using tier-specific payments, we can avoid setting payment at levels that induce widespread loss perceptions among physicians or, alternatively, levels at which the amount of care no longer responds to payment changes. As a result, this approach can reduce expenses without compromising patient health benefits.

[47] The outcome per admission in the second scenario is calculated as the weighted average of the outcomes in tier-2 and tier-3 hospitals. In our sample, 18% of admissions are in tier-2 hospitals and 82% are in tier-3 hospitals.

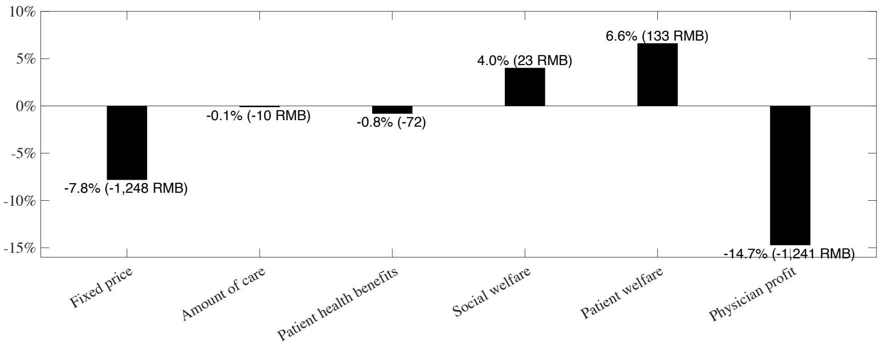


Figure 8. The impacts of payment level on treatment and welfare outcomes

Notes: This figure reports the impacts of changing the fixed payment from a single price of 16,600 RMB to hospital-tier-specific prices (7,200 RMB for tier-2 hospitals and 17,100 RMB for tier-3 hospitals).

Greater gains in social welfare could be achieved by further refining payments based on admission diagnoses or other patient characteristics, such as diagnosis-related groups (DRGs). Our optimal pricing framework is readily adaptable to finer classifications of admissions. However, this refinement comes with certain drawbacks: increased payment granularity can raise management costs for healthcare regulators. Additionally, finer payments may lead to serious issues such as upcoding, as highlighted in the literature (Dafny, 2005).

8. Future Extensions

This paper is the first to examine the implications of reference dependence in collective medical decisions that involve two agents and to explore optimal payment setting under the PPS. Two extensions may be worth considering for future research. First, our study focuses on the reference-dependent preferences of the physician, since this assumption is plausible in the context of rehabilitation care. Future studies could investigate the reference-dependent preferences of both physicians and patients in other settings, such as chronic disease management. This could not only enhance our understanding of incentive compatibility in collective decision-making, but also offer new insights for optimizing hospital payment schemes and patient reimbursement structures.

Second, we assume that the physician's reference point is shaped by past experiences, given our focus on the short-term period following the reform. Future research could explore the dynamic evolution of reference points under the PPS over longer time horizons. Recent studies in behavioral economics (O'Donoghue & Sprenger, 2018; DellaVigna, 2018; Bordalo et al., 2020) actively investigate how reference points are formed. Over time, factors such as memories of past experiences, expectations of future profits, and psychological anchoring to fixed payments may influence these updates. Examining these factors could provide valuable insights into the endogenous formation of reference points.

We relegate these two extensions—theoretical modeling and welfare analysis for reference-dependent preferences of both patients and physicians and the dynamic evolution of reference points after the reform in the long run—to our future research agenda.

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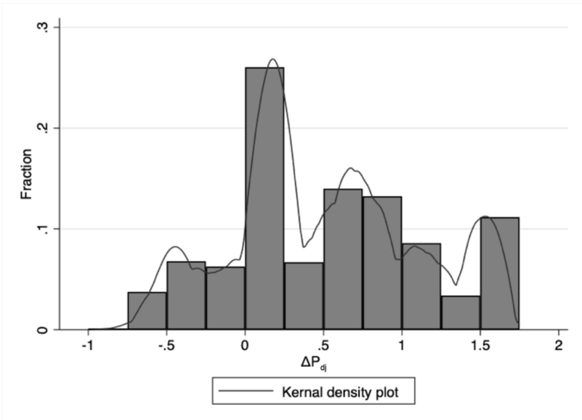
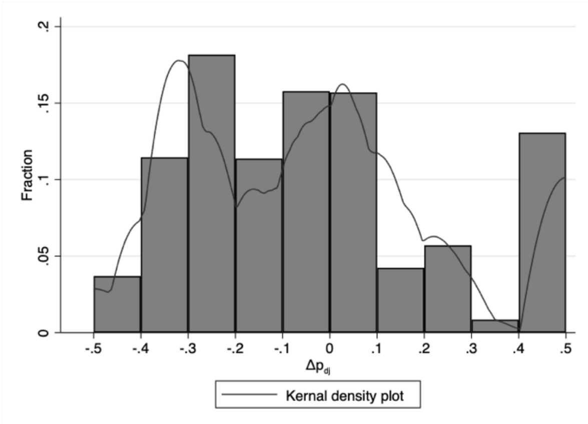
Appendix A. Figures and Tables



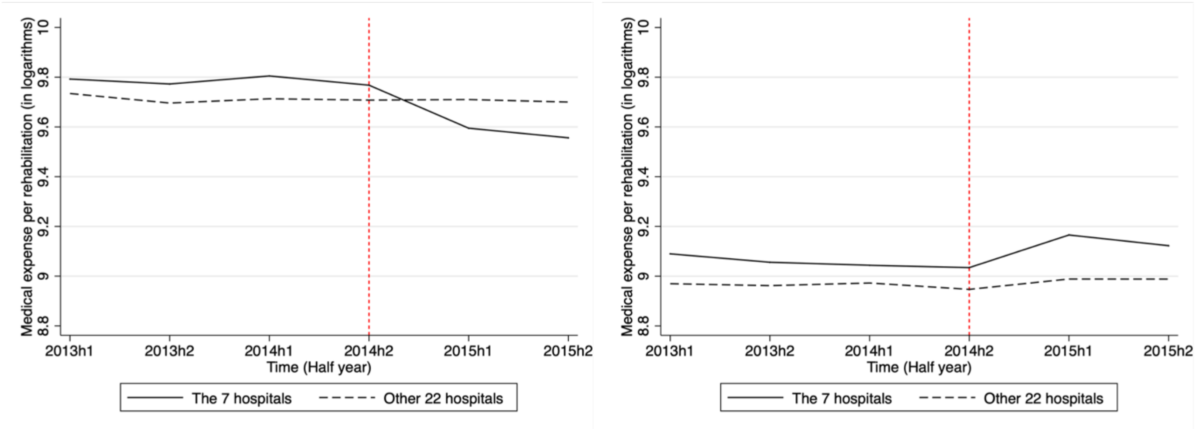


(a) Distribution of ΔP_{dj} (b) Distribution of Δp_{dj} for admissions with $\Delta P_{dj} > 0$)

Figure A1. Distributions of ΔP_{dj} and Δp_{dj}

Notes: Figure (a) presents the histogram and kernel density plot for changes in average physician revenue (ΔP_{dj}), and Figure (b) presents the histogram and kernel density plot for changes in average OOP expense paid by patients (Δp_{dj}) for admissions with $\Delta P_{dj} > 0$. The bandwidth is 0.5 in Figure (a) and 0.1 in Figure (b).

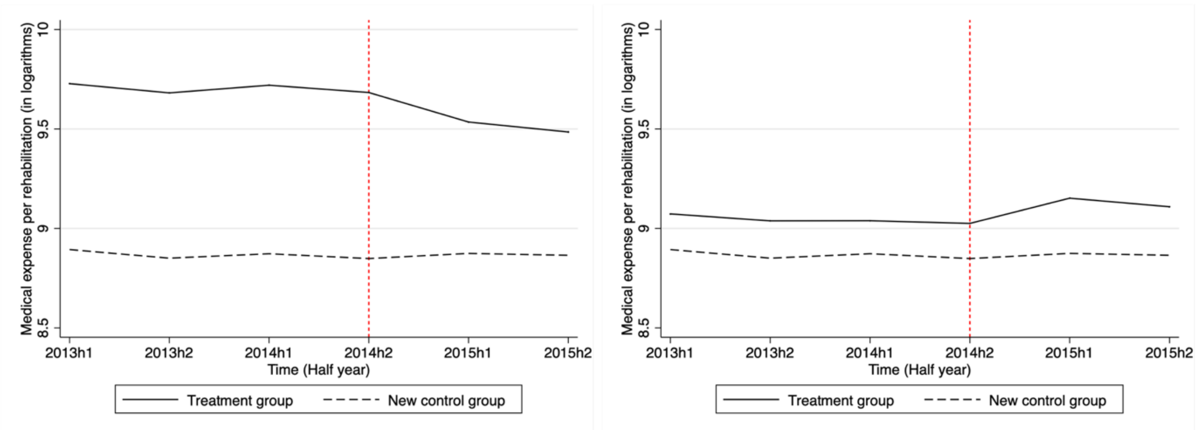
Figure A2. Locations of hospitals in the treatment and control groups in Changsha



(a) Admissions with $\Delta P_{dj} < 0$ (b) Admissions with $\Delta P_{dj} > 0$

Figure A3. Mean medical expense per admission by half-year

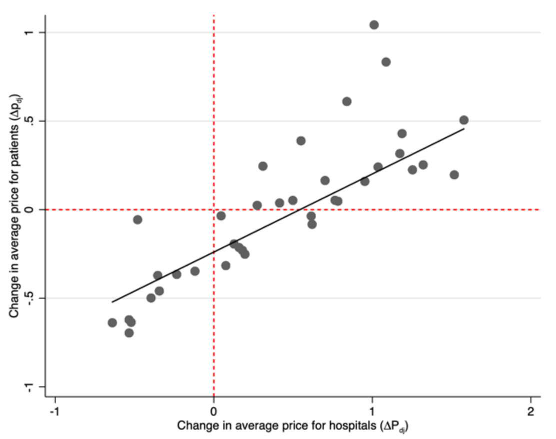
Notes: This figure plots the mean medical expense (in logarithm) per admissions by half-years. We first compute the value of ΔP_{dj} for admissions in both the treatment and control groups according to Eq. (3). We then classify all admissions into two groups: those with $\Delta P_{dj} < 0$ and those with $\Delta P_{dj} > 0$. Figure (a) ((b)) plots average medical expense per admission (in logarithm) for admissions with $\Delta P_{dj} < 0$ ($\Delta P_{dj} > 0$).



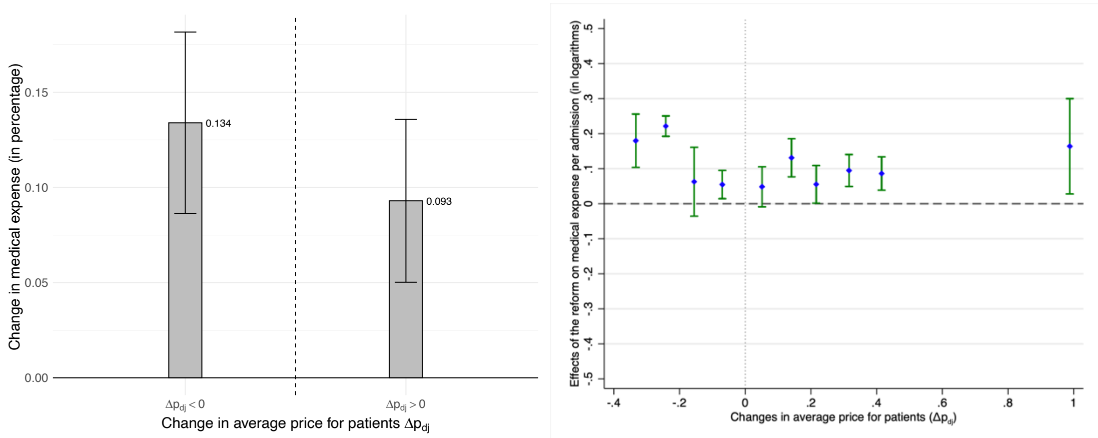
(a) Admissions with $\Delta P_{dj} < 0$ (b) Admissions with $\Delta P_{dj} > 0$

Figure A4. Mean medical expense per admission by half-year

Notes: This figure plots mean medical expense based on admissions in the treatment group and admissions in a new control group. The new control group contains admissions in the 7 hospitals involved in the reform but who receive rehabilitation care for other diagnoses for neurological disorders. Figure (a) separately plots average medical expense per admission (in logarithm) for admissions with $\Delta P_{dj} < 0$ and admissions in the control group. Figure (b) separately plots average medical expense per admission (in logarithm) for admissions with $\Delta P_{dj} > 0$ and admissions in the control group.



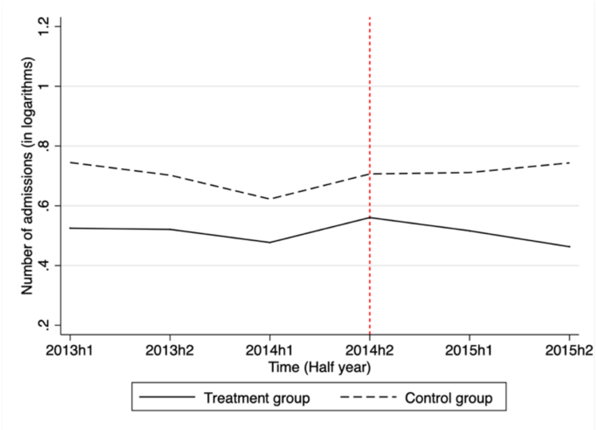
(a) Changes in average prices paid by patients vs. changes in average price received by hospitals



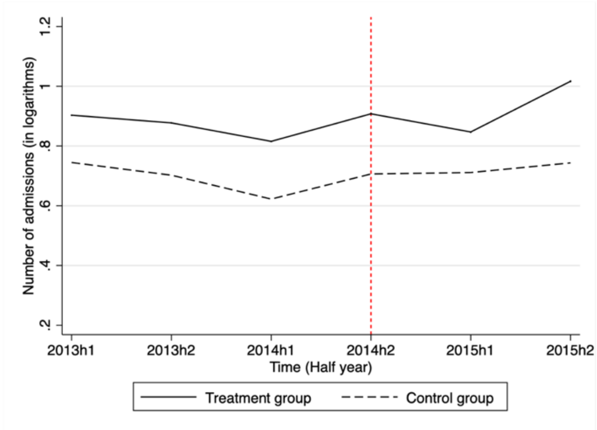
(b) Impacts of the reform on medical expense by Δp_{dj}

Figure A5. Impacts of the reform on medical expense and changes in average prices paid by patients

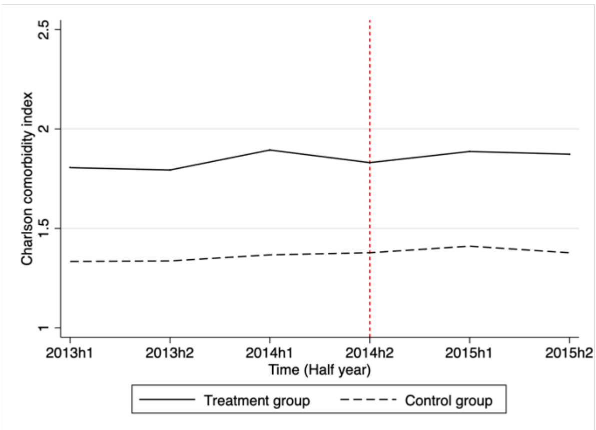
Notes: Figure (a) plots changes in average OOP expense (Δp_{dj}) against changes in average hospital revenue (ΔP_{dj}). We first divide admissions into 60 bins based on their ΔP_{dj} from low to high. We then calculate the mean Δp_{dj} in each bin. The real line is the fitted line. This figure shows that Δp_{dj} positively correlate with ΔP_{dj}. The slope coefficient estimate is 0.441, with a standard error of 0.003. The R-squared is 0.681. Figure (b) plots the impacts of the reform on medical expense across admissions with different values of Δp_{dj}. We limit the sample to admissions with $\Delta P_{dj} > 0$. In the left panel, we divide these admissions into two classes, based on whether $\Delta p_{dj} < 0$ or $\Delta p_{dj} > 0$. In the right panel, we categorize these admissions into 10 classes based on their Δp_{dj} values. The first class includes admissions with $\Delta p_{dj} \leq -0.3$. Each subsequent class is defined by an increase of 0.1 in Δp_{dj}. The last class includes admissions with Δp_{dj} >0.5. Both panels plot the estimate of β_1^k from Eq. (4) and its 90% confidence interval.



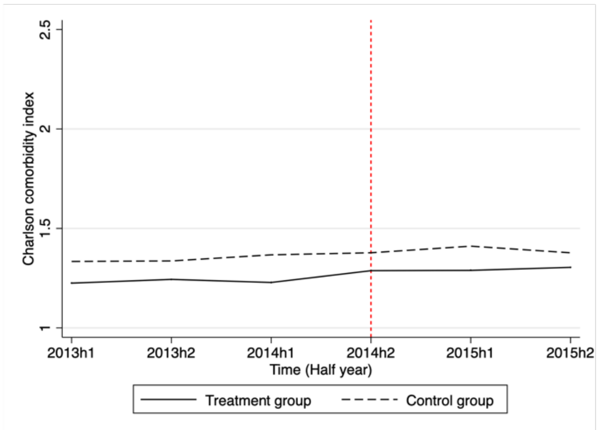
(a) $\Delta P_{dj} < 0$



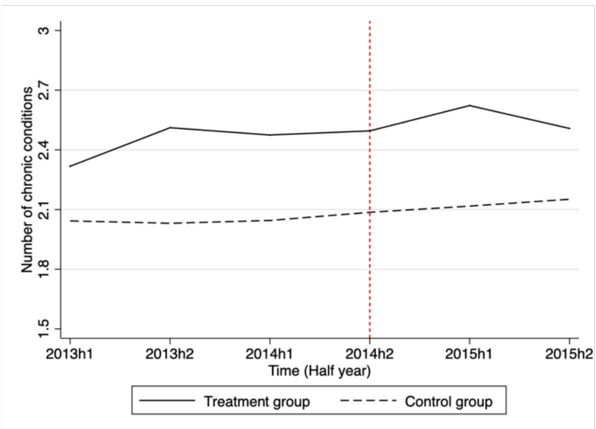
(b) $\Delta P_{dj} > 0$



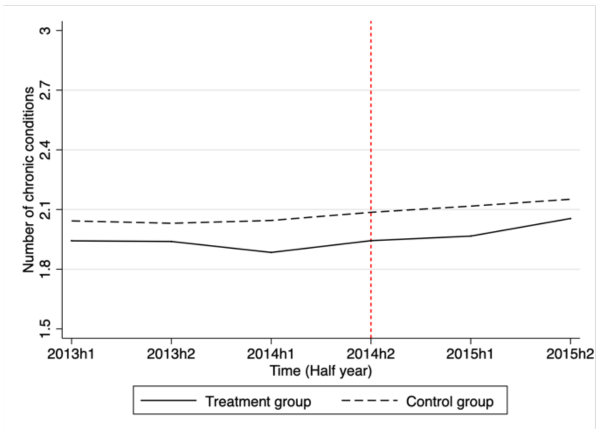
(c) $\Delta P_{dj} < 0$



(d) $\Delta P_{dj} > 0$



(e) $\Delta P_{dj} < 0$



(f) $\Delta P_{dj} > 0$

Figure A6. Mean number of admissions at diagnosis-by-hospital level by half-year

Notes: Figure (a) separately plots the mean number of admissions at diagnosis-by-hospital level for admissions with $\Delta P_{dj} < 0$ and that for admissions in the control group by half-years. Figure (b) separately plots the mean number of admissions at diagnosis-by-hospital level for admissions with $\Delta P_{dj} > 0$ and that for admissions in the control group by half-years. Figure (c) ((d)) separately plots the average Charlson comorbidity index for admissions with $\Delta P_{dj} < 0$ ($\Delta P_{dj} > 0$) and that for admissions in the control group by half-years. Figures (e) and (f) replicate Figures (c) and (d), respectively, using the number of chronic conditions as the dependent variable.

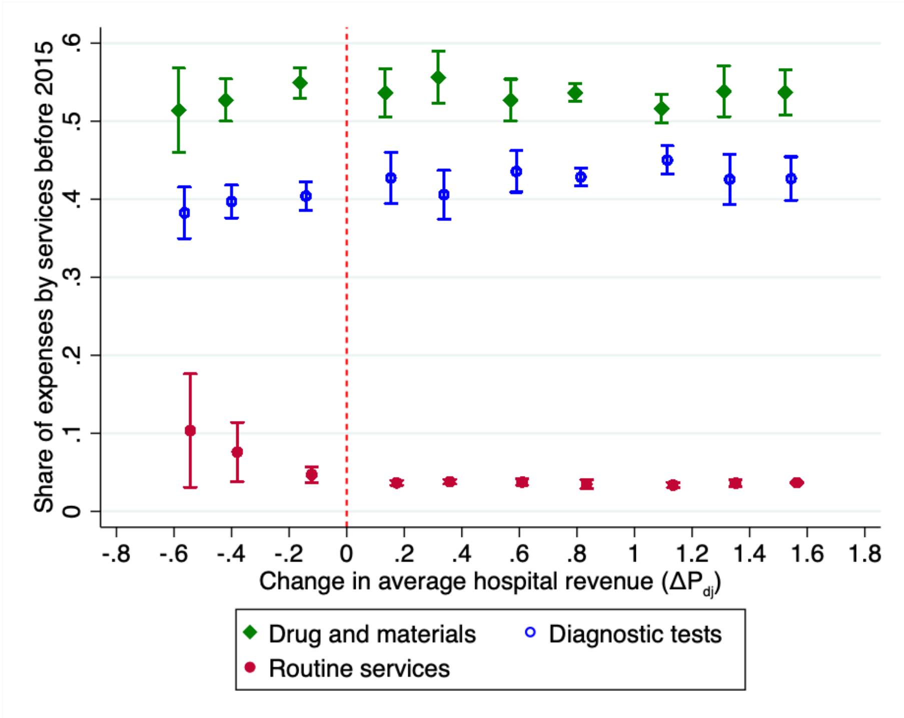
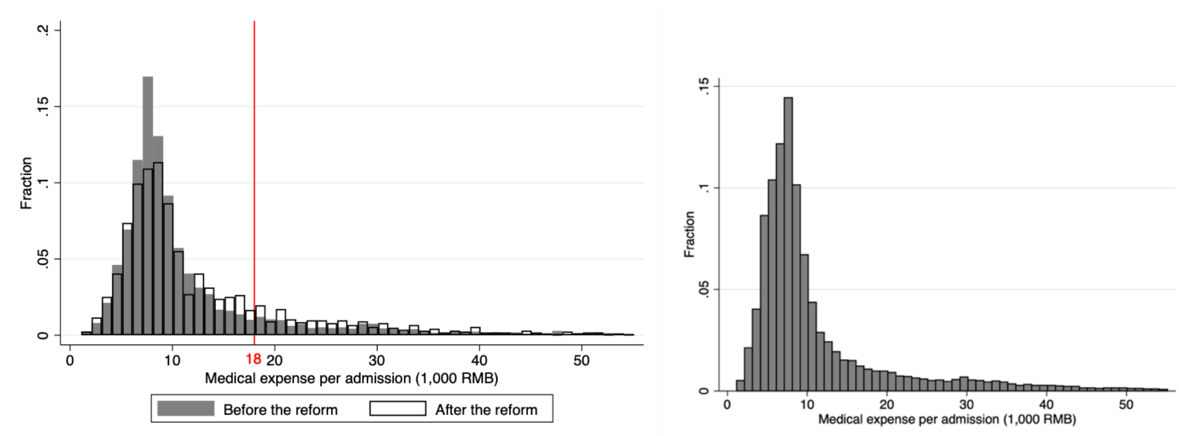


Figure A7. Share of expenses by services before the reform

Notes: In this figure, we first divide admissions in the treatment group into 10 classes based on their value of ΔP_{dj} from low to high, using the method discussed in Section 4.1. For each class, we then plot the mean pre-reform expense shares on three types of services before the reform, along with their 95% confidence intervals. The three types of services are (1) pharmaceuticals and medical supplies, (2) diagnostic tests (e.g., laboratory tests, X-rays, MRIs), and (3) general routine care (e.g., daily rehabilitative therapy, medical rounds, nursing).



(a) Stroke rehabilitation admissions

(b) All admissions

Figure A8. Distribution of medical expense per admission

Notes: Figure (a) presents the distributions of medical expense for stroke rehabilitation admissions before and after the reform separately. Figure (b) presents the distribution of medical expense for all admissions.

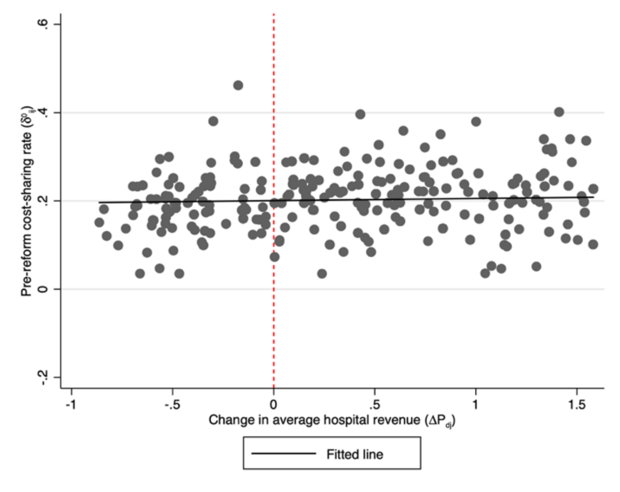


Figure A9. Relationship between the share of the OOP portion of medical expense (δ_{ij}^0) and changes in average hospital revenue (ΔP_{dj})

Notes: This figure plots the relationship between δ_{ij}^0 and ΔP_{dj}, based on admissions in the treatment group before the reform. Since ΔP_{dj} varies across hospitals and across diagnoses within a hospital, we first calculate the mean δ_{ij}^0 at diagnosis-by-hospital level, then plot the mean δ_{ij}^0 against ΔP_{dj}. The slope coefficient estimate is 0.005, with a standard error of 0.001. R-squared is 0.008.

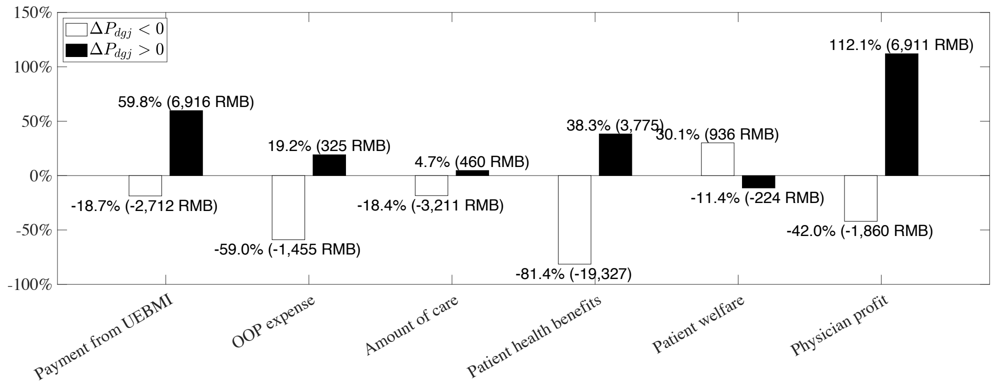
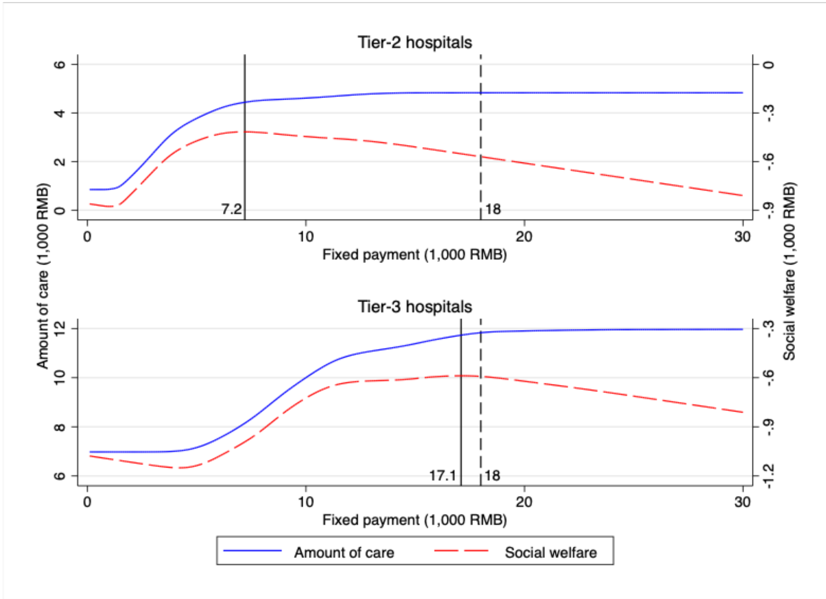
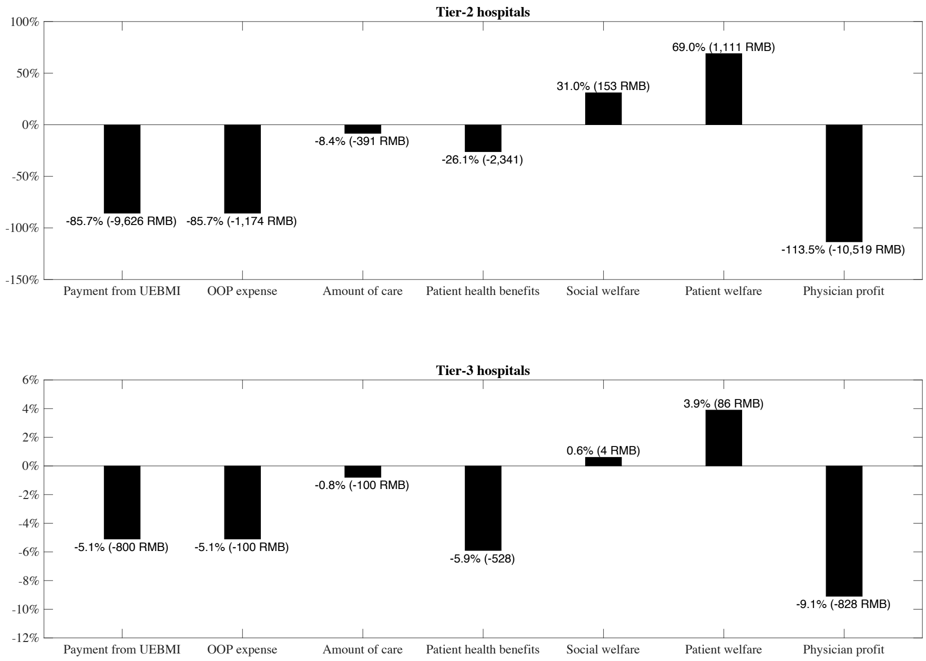


Figure A10. The reform's impacts for admissions with $\Delta P_{dj} < 0$ and $\Delta P_{dj} > 0$

Notes: This figure plots the simulated impacts of the reform separately for admissions with $\Delta P_{dj} < 0$ and $\Delta P_{dj} > 0$.



(a) Different optimal payments by hospital tier



(b) Observed payment vs. optimal payment by hospital tier

Figure A11. Optimal payment levels by hospital tier for stroke rehabilitation

Notes: Figure (a) plots the simulated optimal amount of care (solid blue line) and social welfare (dashed red line) under different values of fixed payment for a stroke rehabilitation admission. Figure (b) presents the impacts of reducing the fixed payment from the observed to the optimal levels on treatment and welfare outcomes per admission. Limiting the analytic sample to stroke rehabilitation admissions, we conduct the simulation analyses separately for admissions in tier-2 and tier-3 hospitals. In both panels, the upper figure is for tier-2 hospitals and the lower one is for tier-3 hospitals.

Table A1. OOP expense per admission for stroke rehabilitation before and after the reform

	The 20 most common diagnoses in stroke	Before		After
		Tier-2 hospitals	Tier-3 hospitals	
Employee	Cerebral arteritis	1,132	2,079	2,700
	Moyamoya disease	1,212	2,134	
	Hemiplegia and hemiparesis following cerebral infarction affecting right non-dominant side	1,260	2,165	
	Cerebral artery dissection, traumatic	1,297	2,433	
	Cerebral infarction due to embolism of cerebral arteries	1,301	2,115	
	Cerebral infarction due to unspecified occlusion or stenosis of precerebral arteries	1,363	4,072	
	Hemiplegia and hemiparesis following cerebral infarction affecting left non-dominant side	1,372	2,070	
	Hemiplegia and hemiparesis following cerebral infarction affecting right dominant side	1,501	1,986	
	Cerebral infarction due to embolism of unspecified cerebral artery	1,522	4,916	
	Subarachnoid hemorrhage following cerebral infarction	1,737	3,653	
	Cerebrovascular accident	1,790	2,699	
	Cerebral infarction due to embolism of precerebral arteries	2,186	5,266	
	Hemiplegia and hemiparesis following cerebral infarction affecting left dominant side	2,574	6,590	
	Subarachnoid hemorrhage following unspecified cerebral infarction	2,662	6,798	
	Basal ganglia hemorrhage	--	8,900	
	Intracerebral hemorrhage in hemisphere	--	--	
	Occlusion and stenosis of unspecified cerebral artery	--	2,994	
	Cerebral infarction due to thrombosis of precerebral arteries	--	4,218	
	Cerebral artery occlusion	--	5,644	
	Cerebral artery dissection, non-traumatic	--	10,828	
Retiree	Cerebral arteritis	1,031	1,795	1,800
	Moyamoya disease	927	2,618	
	Hemiplegia and hemiparesis following cerebral infarction affecting right non-dominant side	662	1,735	
	Cerebral artery dissection, traumatic	1,095	1,774	
	Cerebral infarction due to embolism of cerebral arteries	1,028	1,670	
	Cerebral infarction due to unspecified occlusion or stenosis of precerebral arteries	964	2,091	
	Hemiplegia and hemiparesis following cerebral infarction affecting left non-dominant side	815	1,449	
	Hemiplegia and hemiparesis following cerebral infarction affecting right dominant side	1,074	1,892	
	Cerebral infarction due to embolism of unspecified cerebral artery	1,273	3,241	
	Subarachnoid hemorrhage following cerebral infarction	1,666	2,292	
	Cerebrovascular accident	997	3,567	

Cerebral infarction due to embolism of precerebral arteries	1,284	2,654
Hemiplegia and hemiparesis following cerebral infarction affecting left dominant side	1,098	2,719
Subarachnoid hemorrhage following unspecified cerebral infarction	2,120	5,299
Basal ganglia hemorrhage	--	4,232
Intracerebral hemorrhage in hemisphere	2,401	4,827
Occlusion and stenosis of unspecified cerebral artery	--	2,779
Cerebral infarction due to thrombosis of precerebral arteries	--	5,134
Cerebral artery occlusion	--	5,598
Cerebral artery dissection, non-traumatic	--	4,213

Notes: This table presents an example of out-of-pocket expenses for admissions for stroke rehabilitation care before and after the reform. We separately report the average out-of-pocket expense for employees and retirees. We also separately report the average out-of-pocket expense for admissions with the top 20 most common diagnoses. Out-of-pocket expense is adjusted to 2015 prices using the medical care consumer price index. The unit for out-of-pocket expense is RMB.

Table A2. Summary statistics

	Full sample		Treatment group		Control group	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	SD	Mean	SD	Mean	SD
Medical expense (RMB)	12,690.561	14,338.403	12,515.497	13,476.209	12,763.616	14,682.915
Length of stay (days)	14.226	14.842	14.687	13.566	14.034	15.339
Change in average hospital revenue (ΔP_{dj})	0.144	0.392	0.490	0.595	0	0
Change in average OOP expense (Δp_{dj})	-0.028	0.218	-0.096	0.393	0	0
Charlson comorbidity index	1.365	0.640	1.360	0.651	1.367	0.636
Number of chronic conditions	2.091	1.582	2.118	1.607	2.080	1.571
Female	0.472	0.499	0.456	0.498	0.479	0.500
Age	67.959	12.088	68.089	12.008	67.905	12.121
Monthly income	2,640.805	1,046.591	2,629.504	944.599	2,645.522	1,086.311
Number of patients	23,097		7,473		16,857	
Observations	31,158		9,174		21,984	

Notes: This table reports summary statistics of the main variables from administrative UEBMI enrollment and claims data in Changsha from 2013 to 2015.

Table A3. Effects of the reform on medical expense of the admission

Dependent variable		Medical expense of the admission (in logarithm)		
		(1)	(2)	(3)
Panel (a)				
$\Delta P_{dj} < 0$	$\mathbb{I}\{class = 1\} \times Post$	-0.189	-0.183	-0.161
		(0.057)	(0.053)	(0.051)
$\Delta P_{dj} > 0$	$\mathbb{I}\{class = 2\} \times Post$	0.124	0.126	0.112
		(0.030)	(0.029)	(0.027)
	R-squared	0.313	0.315	0.346
Panel (b)				
$\Delta P_{dj} < 0$	$\mathbb{I}\{class = 1\} \times Post$	-0.337	-0.354	-0.314
		(0.135)	(0.126)	(0.128)
	$\mathbb{I}\{class = 2\} \times Post$	-0.150	-0.135	-0.138
		(0.078)	(0.069)	(0.063)
	$\mathbb{I}\{class = 3\} \times Post$	-0.084	-0.061	-0.054
		(0.062)	(0.055)	(0.051)
$\Delta P_{dj} > 0$	$\mathbb{I}\{class = 4\} \times Post$	0.201	0.186	0.176
		(0.022)	(0.022)	(0.022)
	$\mathbb{I}\{class = 5\} \times Post$	0.087	0.135	0.123
		(0.046)	(0.062)	(0.060)
	$\mathbb{I}\{class = 6\} \times Post$	0.056	0.071	0.070
		(0.028)	(0.031)	(0.032)
	$\mathbb{I}\{class = 7\} \times Post$	0.076	0.095	0.069
		(0.026)	(0.025)	(0.021)
	$\mathbb{I}\{class = 8\} \times Post$	0.088	0.081	0.088
		(0.051)	(0.052)	(0.056)
	$\mathbb{I}\{class = 9\} \times Post$	0.115	0.151	0.135
		(0.070)	(0.064)	(0.064)
	$\mathbb{I}\{class = 10\} \times Post$	0.048	0.030	0.043
		(0.052)	(0.059)	(0.040)
	R-squared	0.326	0.328	0.347
	Individual controls	Yes	Yes	Yes
	Year-month FE	Yes	Yes	Yes
	Hospital FE	Yes	Yes	No
	Diagnosis FE	Yes	No	No
	Hospital-by-year FE	No	Yes	Yes
	Hospital-by-diagnosis FE	No	No	Yes
	Observations	10,808	10,808	10,779

Notes: This table reports estimates for the effects of the reform on medical expense per admission, based on treatment and new control groups. The new control group, which includes admissions for rehabilitation care in the same 7 hospitals as the treatment group, contains diagnoses for neurological disorders that are not included in the five categories of the treatment group. Panels (a)-(b) report estimates of Eq. (4), with the total number of classes (K) equal to 2 and 10, respectively. The dummy variable for class k in the treatment group (i.e., $\mathbb{I}\{class = k\}$), individual controls, year-month fixed effects, hospital fixed effects, and diagnosis fixed effects are controlled for in the regressions across all columns. We consecutively add hospital-by-year fixed effects and hospital-by-diagnosis fixed effects to the regressions in Columns (2)-(3). The dummy variables $\mathbb{I}\{class = k\}$ $(k = 1, .., K)$ are omitted from regressions once we control for hospital-by-diagnosis fixed effects. Standard errors are clustered at hospital-by-diagnosis level.

Table A4. Effects on the reform on the length of stay (LOS)

Dependent variable		LOS (in logarithm)		
		(1)	(2)	(3)
Panel (a)				
$\Delta P_{dj} < 0$	$\mathbb{I}\{class = 1\} \times Post$	-0.102	-0.097	-0.071
		(0.048)	(0.060)	(0.059)
$\Delta P_{dj} > 0$	$\mathbb{I}\{class = 2\} \times Post$	0.070	0.064	0.094
		(0.026)	(0.025)	(0.022)
	R-squared	0.131	0.136	0.185
Panel (b)				
$\Delta P_{dj} < 0$	$\mathbb{I}\{class = 1\} \times Post$	-0.128	-0.105	-0.095
		(0.095)	(0.101)	(0.118)
	$\mathbb{I}\{class = 2\} \times Post$	-0.062	-0.057	-0.024
		(0.065)	(0.091)	(0.089)
	$\mathbb{I}\{class = 3\} \times Post$	-0.150	-0.149	-0.125
		(0.056)	(0.063)	(0.059)
$\Delta P_{dj} > 0$	$\mathbb{I}\{class = 4\} \times Post$	0.098	0.075	0.086
		(0.036)	(0.037)	(0.039)
	$\mathbb{I}\{class = 5\} \times Post$	0.121	0.118	0.061
		(0.055)	(0.064)	(0.043)
	$\mathbb{I}\{class = 6\} \times Post$	0.101	0.093	0.079
		(0.028)	(0.033)	(0.032)
	$\mathbb{I}\{class = 7\} \times Post$	0.070	0.075	0.064
		(0.022)	(0.038)	(0.036)
	$\mathbb{I}\{class = 8\} \times Post$	0.098	0.100	0.098
		(0.058)	(0.059)	(0.063)
	$\mathbb{I}\{class = 9\} \times Post$	0.087	0.090	0.051
		(0.079)	(0.077)	(0.067)
	$\mathbb{I}\{class = 10\} \times Post$	0.061	0.111	0.212
		(0.055)	(0.065)	(0.046)
	R-squared	0.141	0.145	0.185
	Individual controls	Yes	Yes	Yes
	Year-month FE	Yes	Yes	Yes
	Hospital FE	Yes	Yes	No
	Diagnosis FE	Yes	No	No
	Diagnosis-by-year FE	No	Yes	Yes
	Hospital-by-diagnosis FE	No	No	Yes
	Observations	10,808	10,808	10,779

Notes: This table reports the impacts of the reform on LOS. Panels (a)-(b) report estimates of Eq. (4), with the total number of classes (K) equal to 2 and 10, respectively, using LOS (in logarithms) as the dependent variable. The dummy variable for class k in the treatment group (i.e., $\mathbb{I}\{class = k\}$), individual controls, year-month fixed effects, hospital fixed effects, and diagnosis fixed effects are controlled for in the regressions across all columns. We consecutively add hospital-by-year fixed effects and hospital-by-diagnosis fixed effects to the regressions in Columns (2)-(3). The dummy variables $\mathbb{I}\{class = k\}$ ($k = 1, .., K$) are omitted from regressions once we control for hospital-by-diagnosis fixed effects. Standard errors are clustered at hospital-by-diagnosis level.

Table A5. Effects of the reform on number of admissions at diagnosis-by-hospital level

	Number of admissions (in logarithm)		
	(1)	(2)	(3)
$\mathbb{I}\{\Delta P_{dj} < 0\} \times Post$	-0.049	-0.005	-0.004
	(0.061)	(0.060)	(0.056)
$\mathbb{I}\{\Delta P_{dj} > 0\} \times Post$	-0.007	0.030	0.014
	(0.059)	(0.057)	(0.057)
Individual controls	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	No
Diagnosis FE	Yes	No	No
Hospital-by-diagnosis FE	No	Yes	Yes
Diagnosis-by-year FE	No	No	Yes
Observations	9,056	9,044	8,972
R-squared	0.449	0.706	0.711

Notes: This table reposts effects of the reform on the number of admissions at diagnosis-by-hospital level. We report estimates of Eq. (D1). Dummy variables $\mathbb{I}\{\Delta P_{dj} < 0\}$ and $\mathbb{I}\{\Delta P_{dj} > 0\}$, year-month fixed effects, hospital fixed effects, and diagnosis fixed effects are controlled for in regressions across all columns. We consecutively add hospital-by-diagnosis fixed effects and diagnosis-by-year fixed effects in Columns (2)-(3). Dummy variables $Treat^{-}$ and $Treat^{+}$ are omitted from regressions once we control for hospital-by-diagnosis fixed effects. Standard errors are clustered at hospital-by-diagnosis level.

Table A6. Effects of the reform on patient latent health

	Charlson comorbidity index			Number of chronic conditions		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}\{class = 1\} \times Post$	-0.007	0.007	0.001	-0.016	0.002	-0.021
	(0.019)	(0.019)	(0.020)	(0.073)	(0.087)	(0.087)
$\mathbb{I}\{class = 2\} \times Post$	0.014	0.004	0.002	0.035	0.025	0.004
	(0.017)	(0.018)	(0.019)	(0.057)	(0.042)	(0.042)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	No	Yes	Yes	No
Diagnosis FE	Yes	No	No	Yes	No	No
Diagnosis-by-year FE	No	Yes	Yes	No	Yes	Yes
Hospital-by-diagnosis FE	No	No	Yes	No	No	Yes
Dep. Means (Pre-reform)	1.350	1.350	1.350	2.051	2.052	2.052
Observations	31,158	31,098	31,085	31,158	31,098	31,085
R-squared	0.131	0.136	0.185	0.405	0.411	0.456

Notes: This table reports effects of the reform on patient composition. We report estimates of Eq. (D2). Columns (1)-(3) report results using the Charlson comorbidity index for the admission as the dependent variable. The dummy variable for class k in the treatment group (i.e., $\mathbb{I}\{class = k\}$), year-month fixed effects, hospital fixed effects, and diagnosis fixed effects are controlled for in regressions across all columns. We consecutively add diagnosis-by-year fixed effects and hospital-by-diagnosis fixed effects in Columns (2)-(3). Dummy variables $T\mathbb{I}\{class = k\}$ ($k \in \{1,2\}$) are omitted from regressions once we control for hospital-by-diagnosis fixed effects. Columns (4)-(6) replicate Columns (1)-(3) using the number of chronic conditions for the admission as the dependent variable. Standard errors are clustered at hospital-by-diagnosis level.

Table A7. Effects of the reform on shares of medical expense on different services.

	Pharmaceuticals and medical supplies			Diagnostic tests			Routine services		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{I}\{class = 1\} \times Post$	0.006	0.002	-0.006	0.013	0.002	0.010	-0.018	-0.004	-0.005
	(0.010)	(0.009)	(0.012)	(0.010)	(0.009)	(0.011)	(0.013)	(0.006)	(0.007)
$\mathbb{I}\{class = 2\} \times Post$	-0.003	0.002	0.006	0.004	-0.000	-0.003	-0.001	-0.002	-0.004
	(0.006)	(0.006)	(0.004)	(0.007)	(0.006)	(0.004)	(0.003)	(0.002)	(0.002)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	No	No	Yes	No	No	Yes	No	No
Diagnosis FE	Yes	No	No	Yes	No	No	Yes	No	No
Hospital-by-diagnosis FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Diagnosis-by-year FE	No	No	Yes	No	No	Yes	No	No	Yes
Dep. Means (Pre-reform)	0.572	0.572	0.572	0.382	0.382	0.382	0.046	0.046	0.046
Observations	31,158	31,154	31,085	31,158	31,154	31,085	31,158	31,154	31,085
R-squared	0.293	0.367	0.372	0.270	0.335	0.340	0.395	0.584	0.593

Notes: This table reports effects of the reform on shares of medical expense on different services. The regression is conducted at the admission level. In Column (1), we estimate Eq. (4) using the share of expense on pharmaceuticals and medical supplies of the admission as the dependent variable. The dummy variable for class k in the treatment group (i.e., $\mathbb{I}\{class = k\}$), individual controls, year-month fixed effects, hospital fixed effects, and diagnosis fixed effects are controlled for in the regressions across all columns. We consecutively add hospital-by-diagnosis fixed effects and diagnosis-by-year fixed effects to the regressions in Columns (2)-(3). Columns (4)-(6) and (7)-(9) Columns (1)-(3) using the expense shares of diagnostic tests and general routine care as dependent variables, respectively. Standard errors are clustered at hospital-by-diagnosis level.

Table A8. Impacts of the reform on medical expense for admissions in the control group

Dependent variable	Medical expense of the admission (in logarithm)	
	(1)	(2)
$\Delta P_{dj} \times Post_t$	-0.000	-0.005
	(0.013)	(0.013)
Individual controls	Yes	Yes
Year-month FE	Yes	Yes
Hospital FE	Yes	Yes
Diagnosis FE	Yes	No
Hospital-by-diagnosis FE	No	Yes
Observations	21,980	21,979
R-squared	0.396	0.421

Notes: This table reports the impact of the reform on medical expense for admissions with different ΔP_{dj} in the control group. Limiting the estimation sample to admissions in the control group, we first simulate ΔP_{dj} admissions using Eq. (3), assigning the fixed price P_g after the reform as if they were exposed to the reform. We then regress the medical expense for an admission on ΔP_{dj}, a dummy that indicates years after the reform ($Post_t$), and their interaction. Standard errors are clustered at hospital-by-diagnosis level.

Table A9. Function specifications of the model and determinants of optimal amount of care

	Before		After	
	Gain	Loss	Gain	Loss
Panel (a): Patient				
Monetized health benefit	$\frac{1}{\alpha}h(E,\omega)$		$\frac{1}{\alpha}h(E,\omega)$	
OOP expense	$p_0 = \delta_0 E$		$p_1 = \delta_1 P$	
Utility	$u_0(E) = \frac{1}{\alpha}h(E,\omega) - \delta_0 E$		$u_1(E) = \frac{1}{\alpha}h(E,\omega) - \delta_1 P$	
Panel (b): Physician				
Profit	$\pi_0(E) = (1-c)E$		$\pi_1(E) = P - cE$	
Reference point	$\pi_0(r_0) = \pi_0(E_0^*) \Leftrightarrow r_0 = E_0^*$		$\pi_1(r_1) = \pi_0(E_0^*) \Leftrightarrow r_1 = \frac{(P-E_0^*)}{c} + E_0^*$	
Utility	$v_0^G(E\|r_0) = \frac{1}{1+\eta}\pi_0(E) + \frac{\eta}{1+\eta}\left(\pi_0(E) - \pi_0(r_0)\right)$	$v_0^L(E\|r_0) = \frac{1}{1+\eta}\pi_0(E) + \lambda\frac{\eta}{1+\eta}\left(\pi_0(E) - \pi_0(r_0)\right)$	$v_{1,G}(E\|r_1) = \frac{1}{1+\eta}\pi_1(E) + \frac{\eta}{1+\eta}\left(\pi_1(E) - \pi_1(r_1)\right)$	$v_{1,L}(E\|r_1) = \frac{1}{1+\eta}\pi_1(E) + \lambda\frac{\eta}{1+\eta}\left(\pi_1(E) - \pi_1(r_1)\right)$
Panel (c): Collective decision				
Utility	$\theta u_0(E) + (1-\theta)v_0^G(E\|r)$	$\theta u_0(E) + (1-\theta)v_0^L(E\|r)$	$\theta u_1(E) + (1-\theta)v_1^G(E\|r)$	$\theta u_1(E) + (1-\theta)v_1^L(E\|r)$
Marginal utility	$\theta\left(\frac{1}{\alpha}\frac{\partial h}{\partial E} - \delta_0\right) + (1-\theta)(1-c)$	$\theta\left(\frac{1}{\alpha}\frac{\partial h}{\partial E} - \delta_0\right) + (1-\theta)\frac{1+\lambda\eta}{1+\eta}(1-c)$	$\theta\frac{1}{\alpha}\frac{\partial h}{\partial E} - (1-\theta)c$	$\theta\frac{1}{\alpha}\frac{\partial h}{\partial E} - (1-\theta)\frac{1+\lambda\eta}{1+\eta}c$
Panel (d): Optimal amount of care				
Determinants of optimal amount of care	1. Patient side: price sensitivity (α), marginal health benefit ($\frac{\partial h}{\partial E}$), marginal OOP expense (δ_0); 2. Physician side: marginal revenue (1), marginal costs (c), importance of gain-loss utility relative to intrinsic utility (η), degree of loss aversion (λ); 3. Relative bargaining weights of patient and physician ($\theta/(1-\theta)$)		1. Patient side: price sensitivity (α), marginal health benefit ($\frac{\partial h}{\partial E}$); 2. Physician side: marginal costs (c), importance of gain-loss utility relative to intrinsic utility (η), degree of loss aversion (λ); 3. Relative bargaining weights of patient and physician ($\theta/(1-\theta)$); 4. Fixed payment (P), optimal amount of care pre-reform (E_0^*)	

Table A10. Parameter estimates of behavioral collective models.

	(1)		(2)		(3)	(4)	(5)
	Heterogeneity in c by service composition		Heterogeneity in c, α, and θ by patient and hospital characteristics		Diagnosis I63.902	Diagnosis I67.802	Diagnosis I61.902
Physician's marginal cost (c)	Pharmaceuticals and medical supplies	0.962 (0.035)	Patient: age>65	-0.281 (0.121)	0.635 (0.288)	0.981 (0.061)	0.494 (0.013)
	Diagnostic tests	0.601 (0.152)	Patient: female	-0.211 (0.110)			
	Routine services	0.035 (0.028)	Hospital: above-median size	0.039 (0063)			
			Constant	0.559 (0.129)			
Patient's price sensitivity (α)		37.564 (1.019)	Patient: age>65	22.689 (6.137)	54.260 (10.720)	91.793 (2.014)	1.694 (0.777)
			Patient: female	0.267 (2.349)			
			Hospital: above-median size	-2.574 (0.996)			
			Constant	26.667 (4.539)			
Patient's bargaining weight (θ)		0.870 (0.003)	Patient: age>65	-0.134 (0.100)	0.827 (0.019)	0.883 (0.004)	0.978 (0.053)
			Patient: female	-0.046 (0.182)			
			Hospital: above-median size	-0.002 (0.013)			
			Constant	0.852 (0.009)			
Loss aversion (λ)		3.313 (1.201)		4.963 (1.962)	3.181 (1.681)	4.459 (1.021)	4.779 (0.242)
Number of observations		31,158		31,158	11,520	4,627	2,410

Notes: This table reports key parameter estimates from six structural estimations of the behavioral collective model. Column (1) allows the marginal cost to vary with service composition, specified as $c = \sum_{s=1}^{3} c_s share_s$, where $share_s$ denotes the pre-reform expenditure share on service s. The three types of services are (1) pharmaceuticals and medical supplies, (2) diagnostic tests, and (3) general routine care. In Column (2), we allow c, α, and θ to vary with patient and hospital characteristics, specified as: $x = x_1 \mathbb{I}\{age > 65\} + x_2 female + x_3 \mathbb{I}\{size > median\} + constant$, where x is c, α, or θ. $\mathbb{I}\{age > 65\}$ indicates the patients older than 65. Hospital size is measured by the number of admissions to the hospital over the sample period, and $\mathbb{I}\{size > median\}$ indicates hospitals above the median size. Columns (3)-(5) reports the estimates of the baseline model for admissions with the three most common diagnoses (ICD-10 codes: I63.902, I67.802, and I61.902).

Appendix B. Institutional Background Details

B.1 Hospitals and Physicians in China

The training of physicians is highly organized in China. High school graduates who wish to become physicians are admitted to medical school if they pass the National College Entrance Examination. Students receive either 3 or 5 years of training in medical school and obtain a bachelor's degree.[1] Medical students who spend 7 or more years in training earn master's or doctoral degrees. In 2014, approximately 90% of physicians received at least 3 years of training in medical school (National Health Commission, 2015). Graduates of medical schools must pass the Medical Doctors Licensing Examination to receive a license and practice medicine. Licensed physicians are required to register with the Health Commission of local governments and then work in medical institutions, such as hospitals and clinics (Milcent, 2018). Medical training in China focuses on specialties, which results in essentially no general practitioners in the country.

Physicians in China are primarily specialists who work at a single hospital, which differs from physicians in the United States who are primarily office-based and can be affiliated with multiple hospitals. After 2009, the National Health Commission gradually allowed qualified physicians to work in two or more hospitals. To become qualified, physicians must (1) obtain a license, (2) have at least 5 years of clinical experience, (3) pass their two most recent regular assessments, and (4) obtain consent from their employers and approval from the Health Commission of local governments. At the end of 2015, less than 5% of physicians worked at multiple hospitals (National Health Commission, 2016).

Over 90% of physicians are salaried employees in public hospitals (Burns & Liu, 2017). Their income includes a salary and a bonus, in which the salary is low and the bonus is high. Salary standards in public hospitals are determined at the national level and jointly regulated by the National Health Commission, Ministry of Finance, Ministry of Human Resources, and Social Security. The salary consists of (1) a position salary based on promotion, (2) a seniority salary based on the physician's seniority and performance, and (3) a government subsidy for working in "arduous and remote areas." The average salary of physicians is only about 10% higher than the average salary of all employees in China (Burns & Liu, 2017). The bonus, which is generated by treating patients, usually accounts for as much as three-quarters of physicians' total income (Milcent, 2018). Physicians' bonuses are tied to the profits they generate for the hospital. The bonus amount a physician receives depends on (1) the hospital's total profit from treating patients in that year and (2) the physician's performance based on their contribution to the hospital's total profit from treating patients. For example, some hospital administrators may set profit targets for clinical departments, which in turn set profit targets for their physicians. Physicians would receive a baseline bonus if they reach the target and earn a higher bonus if they exceed the target (Burns & Liu, 2017). Therefore, we assume throughout our analysis that hospitals and physicians have the same financial incentive to increase hospitals' profit. In this paper, we treat the hospital and physician as a single agent.

[1] Students with the 3-year bachelor's degree can become assistant doctors, who resemble physician assistants in the United States; as such, they must work under the supervision of a licensed physician. They can become independent practitioners following 5 years of practice in hospitals and completion of a series of qualifying exams. To meet the growing demand for high-quality physicians, the majority of medical schools now offer 5-year programs (Burns & Liu, 2017).

B.2 Rehabilitation Care

Individuals may suffer long-term physical, mental, intellectual, or sensory impairments after severe health shocks. Rehabilitation aims to help disabled individuals become as independent as possible in everyday activities. The medical literature has identified a wide range of health conditions that require rehabilitation and has documented significant benefits of rehabilitation for patients (O'Sullivan et al., 2019; Cieza et al., 2020). The five most prevalent conditions that require rehabilitation are (1) neurological disorders (e.g., stroke, spinal cord injury, and traumatic brain injury); (2) musculoskeletal disorders (e.g., hip/knee replacement and low back pain); (3) sensory impairments (e.g., hearing loss and vision loss); (4) mental disorders (e.g., developmental intellectual disability and autism spectrum disorders); and (5) cardiovascular diseases (e.g., heart failure and acute myocardial infarction). According to Cieza et al. (2020), patients with the above conditions accounted for over 95% of total demand for rehabilitation care globally in 2019.

Rehabilitation typically begins with the physician assessing the patient's medical history and current condition through physical exams, diagnostic tests, and patient interviews. Based on this assessment, the physician collaborates with the patient to set rehabilitation goals and devise a customized plan. For example, stroke rehabilitation may include mobility training, speech therapy, occupational therapy, and functional electrical stimulation (WHO., 2017). Throughout this process, the physician routinely monitors the patient's progress, adjusting the rehabilitation plan according to their evaluation and the patient's feedback. Evidence suggests that the physician-patient interaction significantly affects treatment outcomes, including functional status and pain relief, as well as other clinical parameters such as blood pressure and blood sugar levels (Dibbelt et al., 2010). Since rehabilitation requires practicing the same tasks repeatedly, the patient often takes over daily management from the physician, and continues training and adapting to lifestyle changes such as regular exercise and medication management (Baker et al., 2011).

Appendix C. Alternative Interpretations

C.1 Hospital Selection Based on Diagnoses

To assess this type of hospital selection, we examine whether hospitals admit more cases with $\Delta P_{dj} > 0$ and fewer with $\Delta P_{dj} < 0$ in response to the reform. We first plot the mean number of admissions at diagnosis-by-hospital level separately for both treatment and control groups by half-years in Figure A6. Panel (a) shows that the trend for admissions with $\Delta P_{dj} < 0$ is parallel with that for admissions in the control group. Panel (b) shows that the parallel trends also hold between admissions with $\Delta P_{dj} > 0$ and those in the control group.

We then estimate the following equation at hospital-by-diagnosis-by-month level:

$$\ln(N_{djt}) = \partial_0 + \partial_1^- \mathbb{I}\{\Delta P_{dj} < 0\} \times Post_t + \partial_1^+ \mathbb{I}\{\Delta P_{dj} > 0\} \times Post_t$$
$$+ \partial_2^- \mathbb{I}\{\Delta P_{dj} < 0\} + \partial_2^+ \mathbb{I}\{\Delta P_{dj} < 0\} + \zeta_t + \zeta_j + \zeta_d + e_{djt} \quad \text{(D1)}$$

where N_{djt} denotes the number of admissions with diagnosis d in hospital j in month t. $\mathbb{I}\{\Delta P_{dj} < 0\}$ ($\mathbb{I}\{\Delta P_{dj} > 0\}$) equals 1 if $\Delta P_{dj} < 0$ ($\Delta P_{dj} > 0$) for the admission and 0 otherwise. Other notations are defined the same as Eq. (4). Standard errors are clustered at hospital-by-diagnosis level.

Table A5 reports estimates of Eq. (D1). Across the columns, estimates of both ∂_1^- and ∂_1^+ are all statistically insignificant, and the estimates become close to zero when we also control for hospital-by-diagnosis fixed effects and diagnosis-by-year fixed effects in Column (3). The result suggests that the reform does not have significant impacts on the number of admissions with $\Delta P_{dj} < 0$ or those with $\Delta P_{dj} > 0$.

C.2 Hospital Selection Based on Health Conditions

To investigate potential hospital selection based on patients' health conditions, we compare latent patient health for admissions in the treatment and control groups across the reform. We first construct two measures for latent patient health. The first proxy is the Charlson comorbidity index (CCI), which is designed to predict 1-year mortality for a patient based on their comorbidities. Patients with higher CCI values are usually in worse health conditions. The second measure is the number of chronic diseases, which measures a patient's total number of chronic diseases based on their past diagnostic records. The two measures have been widely used and validated in the literature (Finkelstein et al., 2016; Alexander, 2020). Section 3.2 describes the construction of and summary statistics for the two measures.

Figure A6(c) separately plots the mean CCI (in logarithm) for admissions with $\Delta P_{dj} < 0$ and admissions in the control group by half-year, and Figure A6(d) separately plots the mean CCI for admissions with $\Delta P_{dj} > 0$ and admissions in the control group by half-year. Figures A6(e) and (f) replicate (a) and (b), respectively, using the mean number of the patient's chronic conditions (in logarithm) as the dependent variable. The four figures consistently show that latent patient health is stable for admissions in both treatment and control groups across half-years.

We then separately estimate Eq. (4) using the two measures for latent patient health of the admission as dependent variables, with the total number of classes K equal to 2. The first class includes admissions with $\Delta P_{dj} < 0$ and the second includes those with $\Delta P_{dj} > 0$. Table A6 reports the results. Columns (1)-(3) report results using the CCI of the admission as the dependent variable. We consecutively add diagnosis-by-year fixed effects and hospital-by-diagnosis fixed effects in Columns (2)-(3). Columns (4)-(6) replicate Columns (1)-(3) using the number of chronic conditions for the admission as the dependent variable. Across columns, estimates of both β_1^1 and β_1^2 are small and statistically insignificant, suggesting that latent patient health for admissions in the treatment group does not change relative to that for admissions in the control group across the reform.

C.3 Heterogeneity in Hospitals

To examine this interpretation, we separately examine the impacts of the reform on medical expense for admissions in three different hospitals, which are the three largest hospitals in the treatment group.[2] We first estimate Eq. (4) using admissions in each of the three treated hospitals and those in the control group, with the total number of classes K equal to 2. The first class includes admissions with $\Delta P_{dj} < 0$ and the second includes those with $\Delta P_{dj} > 0$. Table C1, Columns (1)-(3) report estimates for the three hospitals. We denote the 3 hospitals as hospital A, B, and C. Across columns, the estimates consistently show that the reform

[2] Admissions in the 3 hospitals account for 79.1% of all admissions in the treatment group.

reduces the medical expense for admissions with $\Delta P_{dj} < 0$ but increases the medical expense for those with $\Delta P_{dj} < 0$ within each hospital.

For admissions in hospital j ($j \in \{\mathrm{A}, \mathrm{B}, \mathrm{C}\}$), we then further classify admissions into 8 classes based on their ΔP_{dj} from low to high. The first 3 classes contain admissions with $\Delta P_{dj} < 0$ and the remaining 5 classes contain admissions with $\Delta P_{dj} > 0$. We then estimate Eq. (4) based on admissions in hospital j and admissions in the control group, with $K = 8$. We plot the estimates of β_1^k against the mean value of ΔP_{dj} in class k in Figure C1(a). The figure confirms the heterogeneous impacts of the reform between admissions with $\Delta P_{dj} < 0$ and $\Delta P_{dj} > 0$ within each hospital.

C.4 Heterogeneity in Patients

We test the interpretation by examining the impacts of the reform for patients with the same socioeconomic characteristics, based on the assumption that patients with similar socioeconomic characteristics have similar price sensitivity. If this interpretation held true, we would not observe significant heterogeneous impacts of the reform between admissions with $\Delta P_{dj} < 0$ and admissions with $\Delta P_{dj} > 0$ for patients with the same socioeconomic characteristics.

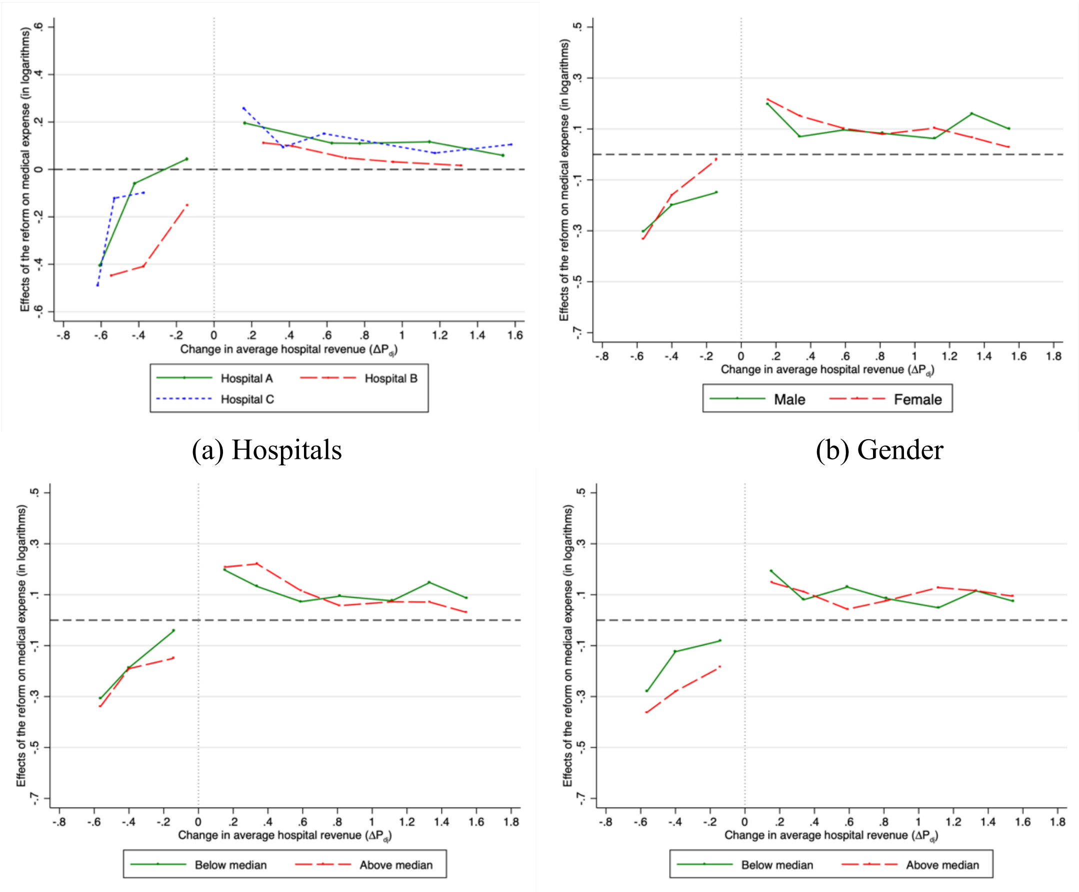
We focus on three socioeconomic characteristics: gender, age, and income. We divide admissions into different subgroups based on the patients' socioeconomic characteristics. We then estimate Eq. (4) for each subgroup, with the total number of classes K equal to 2. The first class includes admissions with $\Delta P_{dj} < 0$ and the second includes those with $\Delta P_{dj} > 0$. Table C1, Columns (4)-(5) report estimates for females and males, respectively; Columns (6)-(7) for patients with age above and below the median; and Columns (8)-(9) for patients with income above and below the median. Across columns, the estimated heterogeneous impacts of the reform are consistent with those in Table 2, Panel (a).

We further classify admissions in each subgroup into 10 classes, and estimate Eq. (4) with $K = 10$. We plot the estimates of β_1^k in Figures C1(b)-(d). The horizontal line shows the mean value of ΔP_{dj} for class k. Figure (b) separately presents estimates for female and male patients. Figures (c) and (d) present estimates for patients in different age and income subgroups, respectively. The figures consistently show that within each subgroup, the impact of the reform is negative for admissions with $\Delta P_{dj} < 0$ but positive for admissions with $\Delta P_{dj} > 0$.

C.5 Heterogeneity in Diagnoses

To test this interpretation, we examine the impacts of the reform for admissions with the same diagnosis, single cerebral infarction. If this interpretation held true, we would not observe different impacts of the reform between admissions with $\Delta P_{dj} < 0$ and those with $\Delta P_{dj} > 0$ with the same diagnosis. The average medical expense for admissions with $\Delta P_{dj} < 0$ (14,167 RMB) is slightly higher than that for admissions with $\Delta P_{dj} > 0$ before the reform (13,295 RMB), but the difference is not statistically significant. We estimate Eq. (4) using admissions with single cerebral infarction, with the total number of classes K equal to 2. The first class includes admissions with $\Delta P_{dj} < 0$ and the second includes those with $\Delta P_{dj} > 0$. Estimates are reported in Table C1 Column (10). It shows that the reform decreases the medical expense by

6.4% for admissions with $\Delta P_{dj} < 0$ but increases the medical expense by 18.0% for admissions with $\Delta P_{dj} > 0$.



(a) Hospitals (b) Gender

(c) Age (d) Income

Figure C1. Heterogeneous effects of the reform on medical expense

Notes: Figure (a) separately plots the effects of the reform on medical expense for admissions in 3 different hospitals. For admissions in hospital j ($j \in \{\text{A}, \text{B}, \text{C}\}$), we divide admissions into 8 classes based on their ΔP_{dj} from low to high. The first 3 classes contain admissions with $\Delta P_{dj} < 0$ and the remaining 5 classes contain admissions with $\Delta P_{dj} > 0$. We then estimate Eq. (4) using the sample that includes admissions in hospital j and admissions in the control group. This figure plots estimates of β_1^k against the mean value of ΔP_{dj} in class k ($k \in \{1,2, \dots ,8\}$). In Figures (b)-(d), we divide admissions into different subgroups based on their gender, age, and income. We then separately estimate Eq. (4) for admissions in these subgroups and plot the estimates of β_1^k. The horizontal line shows the mean value of ΔP_{dj} for class k ($k \in \{1,2, \dots ,10\}$). Figure (b) separately presents the effects of the reform for male and female patients. Figures (c) and (d) plot estimates for patients in different age and income subgroups, respectively.

Table C1. Heterogeneous impacts of the reform on the medical expense

	Heterogeneity in hospitals			Heterogeneity in patients						Heterogeneity in diagnosis
	Hospital A	Hospital B	Hospital C	Female	Male	Above-median age	Below-median age	Above-median income	Below-median income	Diagnosis: single cerebral infarction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{I}\{class = 1\} \times Post$	-0.094	-0.314	-0.148	-0.179	-0.216	-0.227	-0.183	-0.305	-0.153	-0.064
	(0.066)	(0.097)	(0.120)	(0.075)	(0.067)	(0.075)	(0.061)	(0.084)	(0.071)	(0.044)
$\mathbb{I}\{class = 2\} \times Post$	0.110	0.060	0.175	0.112	0.126	0.128	0.105	0.102	0.123	0.180
	(0.052)	(0.030)	(0.039)	(0.035)	(0.030)	(0.036)	(0.028)	(0.040)	(0.031)	(0.020)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	--	--	--	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diagnosis FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	--
Observations	26,184	23,282	23,883	14,696	16,427	15,548	15,569	14,506	16,612	0.164
R-squared	0.371	0.372	0.369	0.386	0.324	0.313	0.394	0.343	0.366	10,755

Notes: This table reports the impacts of the reform on medical expense for different hospitals and patients with different socioeconomic characteristics. In Columns (1)-(3), we separately estimate Eq. (4) by restricting the treatment group to admissions in hospitals A, B, and C. In Columns (4)-(9), we divide admissions into different subgroups based on the patient's socioeconomic characteristics, and estimate Eq. (4) for each subgroup. Columns (4)-(5) report estimates for females and males, respectively; Columns (6)-(7) for patients with age above and below the median; and Columns (8)-(9) for patients with income above and below the median.

Appendix D

D.1 Proof of Proposition 1

We first prove that $E = r_0$ is the unique intersection of $\mathbb{U}_0^L(E|r_0)$ and $\mathbb{U}_0^G(E|r_0)$:

By substituting $E = r_0$ in both $\mathbb{U}_0^L(E|r_0)$ and $\mathbb{U}_0^G(E|r_0)$, we obtain

$$\mathbb{U}_0^L(r_0|r_0) = \mathbb{U}_0^G(r_0|r_0) = \theta u_0(r_0) + (1-\theta)\frac{1}{1+\eta}\pi_0(r_0).$$

Furthermore, $E = r_0$ is the unique intersection because

$$\forall E > r_0, \frac{\eta}{1+\eta}(1-c)(E-r_0) < \frac{\lambda\eta}{1+\eta}(1-c)(E-r_0), \text{ as } \lambda > 1,$$

$$\Rightarrow \mathbb{U}_0^G(E|r_0) < \mathbb{U}_0^L(E|r_0);$$

$$\forall E < r_0, \frac{\eta}{1+\eta}(1-c)(E-r_0) > \frac{\lambda\eta}{1+\eta}(1-c)(E-r_0), \text{ as } \lambda > 1,$$

$$\Rightarrow \mathbb{U}_0^G(E|r_0) > \mathbb{U}_0^L(E|r_0).$$

We then prove Proposition 1:

(i) If $r_0 < E_0^{G*} < E_0^{L*}$,

$$\forall E < r_0, \mathbb{U}_0^L(E|r_0) < \mathbb{U}_0^G(E|r_0) < \mathbb{U}_0^G\left(E_0^{G*}\middle|r_0\right);$$

$$\forall E \geq r_0, \mathbb{U}_0^G(E|r_0) \leq \mathbb{U}_0^G\left(E_0^{G*}\middle|r_0\right),$$

$$\Rightarrow E_0^{G*} = \arg\max_E \mathbb{U}_0(E|r_0).$$

(ii) If $E_0^{G*} \leq r_0 \leq E_0^{L*}$,

$$\forall E < r_0, \mathbb{U}_0^L(E|r_0) < \mathbb{U}_0^L(r_0|r_0), \text{ as } \frac{\partial \mathbb{U}_0^L}{\partial E}|_{E<E_0^{L*}} > 0;$$

$$\forall E > r_0, \mathbb{U}_0^G(r_0|r_0) > \mathbb{U}_0^G(E|r_0), \text{ as } \frac{\partial \mathbb{U}_0^G}{\partial E}|_{E>E_0^{G*}} < 0,$$

$$\Rightarrow r_0 = \arg\max_E \mathbb{U}_0(E|r_0).$$

(iii) If $r_0 > E_0^{L*} > E_0^{G*}$,

$$\forall E < r_0, \mathbb{U}_0^L(E|r_0) \leq \mathbb{U}_0^L(E_0^{L*}|r_0);$$

$$\forall E \geq r_0, \mathbb{U}_0^G(E|r_0) \leq \mathbb{U}_0^L(E|r_0) < \mathbb{U}_0^L(E_0^{L*}|r_0),$$

$$\Rightarrow E_0^{L*} = \arg\max_E \mathbb{U}_0(E|r_0).$$

D.2 The Impact of the Reform on the Optimal Amount of Care

We assume that

$$E_0^* = \frac{1}{a+1}E_0^{G*} + \frac{a}{a+1}E_0^{L*}, \text{ with } a \in [0,1]. \quad \text{(E1)}$$

We have the following proposition, analogous to Proposition 3:

Proposition 3.1. The impact of the reform on the optimal amount of care varies in the following three scenarios:

i. If $\theta_{ij}\delta_{ij}^0 < (1-\theta_{ij})[c_j + \left(1-c_j\right)[\frac{1}{a+1} - \frac{a}{a+1}\frac{1+\lambda\eta}{1+\eta}]$, the reform decreases the amount of care;

ii. if $\theta\delta_0 > (1-\theta)[\frac{1+\lambda\eta}{1+\eta}c + (1-c)[\frac{1}{a+1} - \frac{a}{a+1}\frac{1+\lambda\eta}{1+\eta}]$, the reform increases the amount of care;

iii. if $(1-\theta)[c+(1-c)\left[\frac{1}{a+1}-\frac{a}{a+1}\frac{1+\lambda\eta}{1+\eta}\right] \le \theta\delta_0 \le (1-\theta)[\frac{1+\lambda\eta}{1+\eta}c+(1-c)[\frac{1}{a+1}-\frac{a}{a+1}\frac{1+\lambda\eta}{1+\eta}]$, the reform decreases the amount of care when $(P-E_0^*)<0$ but increases the amount of care when $(P-E_0^*)>0$.

Proof: By combining Eqs. (9), (10) and (E1), we have $\frac{1}{\alpha}\frac{\partial h}{\partial E}|_{E=E_0^*}=\delta_0-\frac{1-\theta}{\theta}(1-c)[\frac{1}{a+1}-\frac{a}{a+1}\frac{1+\lambda\eta}{1+\eta}]$. By Eqs. (13) and (14), we obtain $\frac{1}{\alpha}\frac{\partial h}{\partial E}|_{E=E_1^{G*}}=\frac{1-\theta}{\theta}c$, and $\frac{1}{\alpha}\frac{\partial h}{\partial E}|_{E=E_1^{L*}}=\frac{1-\theta}{\theta}\frac{1+\lambda\eta}{1+\eta}c$.

Under the condition in scenario i, we have $\frac{1}{\alpha}\frac{\partial h}{\partial E}|_{E=E_0^*}<\frac{1}{\alpha}\frac{\partial h}{\partial E}|_{E=E_1^{G*}}$. Since $\frac{\partial h}{\partial E}$ decreases with E, $E_0^*>E_1^{G*}\ge E_1^*$. Therefore, the reform decreases the amount of care.

Under the condition in scenario ii, we have $\frac{1}{\alpha}\frac{\partial h}{\partial E}|_{E=E_0^*}>\frac{1}{\alpha}\frac{\partial h}{\partial E}|_{E=E_1^{L*}}$. Therefore, $E_0^*<E_1^{L*}\le E_1^*$. The reform increases the amount of care.

Under the condition in scenario iii: we have $\frac{1}{\alpha}\frac{\partial h}{\partial E}|_{E=E_1^{G*}}\le\frac{1}{\alpha}\frac{\partial h}{\partial E}|_{E=E_0^*}\le\frac{1}{\alpha}\frac{\partial h}{\partial E}|_{E=E_1^{L*}}$. Therefore, $E_1^{L*}\le E_0^*\le E_1^{G*}$. According to Proposition 2, when $r_1<E_1^{L*}\Leftrightarrow(P-E_0^*)<c\cdot(E_1^{L*}-E_0^*)<0$, the physician is in the loss domain after the reform, and the reform's impact is $E_1^{L*}-E_0^*<0$; when $E_1^{L*}\le r_1\le E_1^{G*}\Leftrightarrow c\cdot(E_1^{L*}-E_0^*)\le(P-E_0^*)\le c\cdot(E_1^{G*}-E_0^*)$, the reform's impact is $r_1-E_0^*=\frac{(P-E_0^*)}{c}$; when $r_1>E_1^{G*}\Leftrightarrow(P-E_0^*)>c\cdot(E_1^{G*}-E_0^*)>0$, the physician is in the gain domain after the reform, and the reform's impact is $E_1^{G*}-E_0^*>0$. (**Q.E.D**)

D.3 Proof of Proposition 3

The proof is the same as that in Section D.2, as Proposition 3 is a special case of Proposition 3.1 with $a=0$.

D.4 Model Predictions with General Cost Function

Our model can still explain the reduced-form findings in Section 4.1 under general cost function specifications. The optimal amount of care before the reform is $E_0^*\in[E_0^{G*},E_0^{L*}]$, where E_0^{G*} is given by

$$\theta\left(\frac{1}{\alpha}\frac{\partial h}{\partial E}-\delta_0\right)+(1-\theta)\left(1-\frac{\partial C}{\partial E}\right)=0,$$

and E_0^{L*} is determined by

$$\theta\left(\frac{1}{\alpha}\frac{\partial h}{\partial E}-\delta_0\right)+(1-\theta)\left(1-\frac{1+\lambda\eta}{1+\eta}\frac{\partial C}{\partial E}\right)=0.$$

The optimal amount of care after the reform is $E_1^*\in[E_1^{L*},E_1^{G*}]$, where E_1^{G*} is determined by

$$\theta\frac{1}{\alpha}\frac{\partial h}{\partial E}-(1-\theta)\frac{\partial C}{\partial E}=0,$$

and E_1^{L*} is determined by

$$\theta\frac{1}{\alpha}\frac{\partial h}{\partial E}-(1-\theta)\frac{1+\lambda\eta}{1+\eta}\frac{\partial C}{\partial E}=0.$$

As discussed in Section D.2, we assume $E_0^*=E_0^{G*}$ without loss of generosity for our purpose. Given the properties of $h(E,\omega)$ outlined in Section 5.1, we assume that $(\frac{\theta}{1-\theta}\frac{1}{\alpha}\frac{\partial h}{\partial E}-\frac{\partial C}{\partial E})$ is decreasing in E (i.e., $\frac{\theta}{1-\theta}\frac{1}{\alpha}\frac{\partial^2 h}{\partial E^2}-\frac{\partial^2 C}{\partial E^2}\le 0$) to ensure the existence and uniqueness of E_0^* and E_1^*. We can therefore get that the following model predictions:

i. If $\delta_0\theta\le 1-\theta$, the reform decreases the amount of care ($E_1^*<E_0^*$);

ii. if $\theta\delta_0 \geq (1-\theta)[1+\frac{(\lambda-1)\eta}{1+\eta}\frac{\partial C}{\partial E}]$, the reform increases the amount of care ($E_1^* > E_0^*$);

iii. if $(1-\theta) < \theta\delta_0 < (1-\theta)[1+\frac{(\lambda-1)\eta}{1+\eta}\frac{\partial C}{\partial E}]$, the reform decreases the amount of care ($E_1^* < E_0^*$) when $(P-E_0^*) < 0$, but increases it ($E_1^* > E_0^*$) when $(P-E_0^*) > 0$.

This is exactly our Proposition 3 in Section 5.4.

Appendix E. Calibration of α_s

The term $\frac{1}{\alpha_s}$ represents the conversion (i.e., marginal rate of substitution) in the government's objective function between patient health benefits—specified as a function of the amount of care—and monetary value in RMB. Following Gaynor et al. (2023), we use information on the relationship between patient health benefits, mortality risk, and an estimate of the value of a statistical life-year (VSLY) to calibrate the value of α_s. Our calibrated value of α_s equates the difference in patient health benefits with the difference in mortality risks multiplied by the VSLY.

Specifically, we limit the sample to admissions for stroke rehabilitation and calibrate the value of α_s in three steps. First, based on our model estimates, we simulate the reform's average impact on patient health benefits for these admissions: The reform increases patient health benefits by 3,390.76 units. Second, we estimate the impact of the reform on mortality risk. UEBMI enrollment data include death records for all enrollees from 2013 to 2015. We identify the policy's impact on mortality 6 months after discharge using the following DID specification:

$$M_{idjt} = \theta_0 + \theta_1 Treat_{idj} \times Post_t + \theta_2 Treat_{idj} + \boldsymbol{X_{it}}\gamma + \zeta_t + \zeta_j + \zeta_d + \epsilon_{idjt},$$

where M_{idjt} is a dummy variable that equals 1 if patient i with diagnosis d admitted in hospital j in year t is dead 6 months after discharge and 0 otherwise.[3] The estimate of θ_1 is -0.0059, which suggests that the reform reduces the mortality rate in 6 months by 0.0059. This difference in mortality rate corresponds to the difference in patient health benefits of 3,390.76.

Third, if we further assume that the government's value of this difference in health comes entirely from the difference in the mortality rate, we can find the monetary value of the difference in health benefits by multiplying the difference in mortality rates by a VSLY estimate. Hao et al. (2019) provide an estimate of VSLY based on 74 major cities in China, which is approximately 1,530,000 RMB. Therefore, we have $\frac{1}{\alpha_s} \times 3390.76 = 0.5 \times 1530000 \times 0.0059$, which yields our calibrated value of $\alpha_s = 0.7451$.

Reference

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Hao, Y., Zhao, M., & Lu, Z. N. (2019). What is the health cost of haze pollution? Evidence from China. *International Journal of Health Planning and Management*, *34*(4), 1290-1303.

[3] We use the mortality 6 months after discharge as the dependent variable due to data limitations. Our estimate provides a lower bound for $\frac{1}{\alpha_s}$, since the benefits of rehabilitation care may extend over 6 months. Our framework for deriving optimal payments under the PPS is readily applicable to alternative values of α_s.