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Impacts of the diagnosis-intervention packet reform on costs and healthcare resource utilization: evidence from Guangzhou, China

Bingxue Fang[1] and Yawen Jiang[1*]

Abstract

Background The diagnosis-intervention packet (DIP) payment reform, utilizing big data for patient classification and payment standardization, was initially developed and piloted in China. Guangzhou, the pilot mega-city, rolled out DIP payment reform in 2018 to regulate medical expenditures. We estimated the impacts of DIP on costs and healthcare resource utilization in Guangzhou using a nine-year panel data set of Guangzhou and other regions between 2018 and 2020.

Methods By employing the synthetic difference-in-difference (SDID) method, we captured changes in outcome variables before and after DIP implementation in Guangzhou and non-reforming regions.

Results DIP payment reform increased per-episode inpatient costs by CNY 1574.735 (95% CI: 148.330 to 3001.140, $P<0.05$), CNY 1583.413 (95% CI: 247.356 to 2919.470, $P<0.05$), and CNY 1448.065 (95% CI: -132.051 to 3028.181.140, $P<0.1$) among all hospitals, public hospitals, and private hospitals, respectively. In contrast, DIP had little effect on the average length of stay (LOS) among all hospitals from 2018 to 2020. Although DIP did not impact in-hospital mortality (IHM) overall, it increased IHM by 0.330 percentage points (95% CI: 0.008 to 0.652, $P<0.05$) and 0.311 percentage points (95% CI: 0.158 to 0.463, $P<0.01$) among private hospitals and secondary hospitals.

Conclusions Our results suggest that the effects of DIP payment reform were mixed. While it did increase healthcare costs, its impacts on quality and operation efficiency varied significantly across different types of hospitals.

Keywords Diagnosis-intervention packet (DIP), Payment reform, Per-episode inpatient costs, Healthcare resource utilization, Guangzhou

Introduction

There is a pressing need for payment systems to address the issue of rising medical costs and to regulate healthcare provider behaviors. Prospective payment systems (PPS), such as diagnosis-related groups (DRG), can reduce unnecessary uses and improve healthcare outcomes compared with retrospective payment systems [1, 2]. Under the PPS model, hospitals charge a fixed fee regardless of the actual cost of treating patients, and make payments for each insured patient based on their assigned disease diagnosis related group, resulting in a bundled payment for the entire treatment stage [3–5]. Studies in the literature have consistently reported that PPS has effectively curbed the rapid escalation of medical expenses and improved the allocation efficiency of medical resources [6, 7]. Importantly, PPS aligns the incentive of insurers with those of hospitals, creating a framework that encourages cost-effective and patient-centric care delivery [8, 9].

*Correspondence:
Yawen Jiang
jiangyw26@mail.sysu.edu.cn
[1] School of Public Health (Shenzhen), Sun Yat-Sen University, 66 Gongchang Road, Guangming District, Shenzhen, Guangdong, China

DRG is a payment schedule implemented by the public and private payers globally to control cost and improve quality. The assignment of DRG groups took patient demographics and procedure complexity into account [10]. The implementation of DRG-based payment led to more than $50 billion in savings in Medicare hospital payments through 1990 [11]. China was one of the earliest developing countries to introduce DRG-based payment [3]. Nevertheless, previous literature on DRG-based payment provided mixed findings on costs and resource utilization, partially due to variations in institutional backgrounds before the policy change [1, 3, 12]. The differences in development levels among provinces and cities in China, along with incomplete discharge records in underdeveloped regions, further delays the adoption of DRG. In addition, the lack of consensus on clinical pathways across regions has made the classification resource-consuming and inflexible for future changes [13].

Since 2009, the growth rate of Chinese basic medical insurance expenditures outpaced that of income by approximately 2.43 percentage points. The swift increase in medical expenditures has placed a heavy burden on the medical insurance fund. To alleviate these issues, the "diagnosis-intervention packet" (DIP) payment with global budget was developed and piloted in China. The DIP payment system is a bundled payment model with data-driven payment standards by utilizing historical medical records to align medical services with payment. Encouraged by the central government, Guangzhou successfully implemented DIP payment reforms since January 1, 2018.

The current study estimated the impacts of DIP payment reform on inpatient costs and healthcare utilization in Guangzhou by using region-level discharge data. Specifically, we employed the synthetic difference-in-differences (SDID) method, which was data-driven and could account for time-varying exogenous covariates. By constructing a synthetic Guangzhou, we compared per-episode inpatient costs, average length of stay (LOS), and in-hospital mortality (IHM) in Guangzhou versus those in non-reforming regions before and after DIP implementation to provide valuable insights into the impacts of DIP payment reform. Beyond the main outcomes, this study conducted an exploratory analysis of cost-manipulation behaviors and anticipatory effects.

Institutional background and literature review

The medical insurance payment system serves as an effective policy tool to promote value-based healthcare and optimize the allocation of medical resources. Since 2009, the Chinese government has shown an intention to explore alternative payment approaches to fee-for-service (FFS) [14]. Supply-side cost control policies have been developed and adopted to address rising medical expenses in various settings [13]. In 2012, the capital city, Beijing, launched the first broad adoption of DRG payment with a global budget [15]. Jian et al. found DRG payment led to reductions of 6.2 percent points and 10.5 percent points, respectively, in medical costs and out-of-pocket payments by patients per episode. Although the DRG payment in China has proved effective in reducing medical expenditures, its rollout and implementation have been slow due to several challenges in implementation conditions and patient classification [1, 3, 12].

DIP is different from DRG in that it relies on a standardized method to classify patients based on the direct combination of both principal diagnoses and procedure codes, whereas DRG only takes patient demographics and procedure complexity into account for classification. With over 10,000 groups, DIP also defines patient classification with more granularity than DRG. Each DIP group is assigned points reflecting its relative resource utilization, and unit prices are subsequently determined based on the total volume of points in conjunction with the global budget of the city [13, 16]. Primarily targeting inpatient stays, DIP payment reform has gained rapid adoption across China, with 12 pilot cities by the end of 2021.[1] Remarkably, Guangzhou was one of the first cities to do so in China, and it remains the largest city that deployed city-wide DIP reforms as of the submission of the current work. The DIP reform covered 361 designated medical institutions providing inpatient services in Guangzhou, with all medical facilities with hospitalization capacity enveloped in the program in principle. In contrast, other pilot cities employed the DIP payment reform only among selected hospitals. Therefore, the selection of Guangzhou had the representativeness of DIP effect.

Based on the historical medical cost data between 2015 and 2017, the DIP point schedule incorporates higher prices for procedures in Guangzhou. Under different diagnosis-intervention groups, there may be instances of coding bias and patient selection by healthcare providers. Under the same diagnosis-intervention group, hospital may also seek to reduce the treatment cost for each patient, acquiring more point values at a lower cost. The transition to DIP payment system may lead to a decline in the average LOS and certain healthcare service items [17]. The reduction in LOS may not necessarily improve the quality of inpatient care, while an increase in medical costs and admissions could potentially reduce

[1] Based on the experience of reform operations in Guangzhou, China has designated 12 pilot cities to promote the DIP reform. The 12 pilot cities in China including Xingtai, Liaoyuan, Huaian, Suzhou, Xiamen, Ganzhou, Dongying, Yichang, Shaoyang, Guangzhou, Luzhou, and Zunyi.

operational efficiency. The intensity of these incentives depends on the impact of institutional inertia on hospital behaviors. The establishment of an auxiliary directory within the DIP payment system can supervise and curb behaviors such as readmissions and super-long hospitalizations. Additionally, healthcare providers' behaviors may be affected by the anticipatory effects of DIP payment reform. In the literature, anticipatory effects are defined as emotional states that people experience while anticipating significant outcomes [18]. Under the DIP scheme, the anticipatory effects are straightforward and embodied by healthcare providers. They may have adjusted and manipulated their behaviors for diagnoses and procedures to maximize their surplus. After anticipating potential revenue loss, they could deliver more profitable services for patients within a given DIP group. In our empirical analysis, we will test the existence of these strategic behaviors.

Data

The study primarily used official statistical summary data on hospitals discharges from 21 cities[2] in Guangdong province (where Guangzhou is located) from 2012 to 2020. We included additional panel data from 33 provinces and province-level cities in China (hereinafter referred to as regions)[3] to verify our primary findings. The data was directly derived from the China Statistical Yearbook (2012–2020) [19], China Health Statistical Yearbook (2012–2020) [20], Guangdong Health Statistical Yearbook (2012–2020) [21], Guangzhou Statistical Yearbook (2012–2020) [22], and Shenzhen Statistical Yearbook (2012–2020) [23]. We extracted inpatient costs and LOS among all hospitals,[4] the data of which were later stratified by public hospitals and private hospitals in Guangzhou and other regions. In addition, we adjusted the costs using the annual healthcare consumer price index (CPI). We also collected data including IHM, occupancy rate of hospital beds, discharge volume, and outpatient visits from 2012 to 2020. As the part of the heterogeneity analysis, we include data from tertiary hospitals, secondary hospitals and primary hospitals. After addressing missing data through multiple imputation, we obtained a strongly balanced panel data set covering 21 cities in Guangdong province.

Methods

Measures

To analyze the impacts of DIP on costs, length of stay, and quality of inpatient care, we selected per-episode inpatient costs, the average LOS, and IHM as outcome variables [24, 25]. Additionally, we examined the resource utilization of inpatient care by using three metrics: occupancy rate of hospital beds, discharge volume, and inpatient visits [26–28]. Specifically, we investigated whether DIP increased inpatient discharges or shifted outpatient services to inpatient services. To explore those possibilities, we conducted additional analyses on the changes of discharge volume per day and inpatient visits per day. To control for region-level confounding, the per-ten thousand-population numbers of hospitals, doctors, beds and medical insurance participants[5] were included as covariates. In addition, we controlled the gross domestic product (GDP) per capital. Specific definitions of the variables were summarized in the Table S1.

Empirical strategies

The primary purpose of this study was to evaluate the policy effects of DIP payment reform in Guangzhou. To that end, the counterfactual question of interest was "what would have happened to Guangzhou without the implementation of DIP". We used a balanced panel with N regions and T time periods in the study, where outcomes for region i in period t are denoted by Y_{it} and exposure to the binary treatment is denoted by $W_{it} \in \{0, 1\}$. T_{pre} represents the time periods before DIP implementation (2012–2017), while T_{post} represents the ones after DIP implementation (2018–2020). N_{co} denotes the control regions, and N_{tr} equals $N\text{-}N_{co}$, which represents the treated region. A premise of conducting the SDID analysis is that the outcomes of control regions are not affected by the implementation of DIP in the treated region.

We discuss the SDID estimates in the context of block treatment assignment. This $N \times T$ assignment matrix

[2] Guangzhou is the capital of Guangdong Province, which is one of provinces in China. There are 21 cities in Guangdong province, including Chaozhou, Dongguan, Foshan, Heyuan, Huizhou, Jieyang, Jiangmen, Maoming, Meizhou, Qingyuan, Shantou, Shanwei, Shaoguan, Shenzhen, Yangjiang, Yunfu, Zhanjiang, Zhaoqing, Zhongshan, Zhuhai, and Guangzhou.

[3] The robustness check of this study uses panel data from 32 regions in China (except Guangzhou), including Anhui, Beijing, Chongqing, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Liaoning, Ningxia, Qinghai, Shandong, Shanghai, Shanxi, Shenzhen, Sichuan, Tianjin, Tibet, Shaanxi, Xinjiang, Yunnan, and Zhejiang. Shenzhen and Guangzhou are comparable, because they are both part of Guangdong province, have similar economic growth levels, and share similar policy foundations. Simultaneously, Shenzhen has similar regional weights to other provincial regions while constructing the synthetic Guangzhou (see Fig. 1 and Figure S1). As such, the robustness check of the current study included 31 provincial administrative regions, Shenzhen and Guangzhou.

[4] All hospitals here include public hospitals and private hospitals.

[5] Medical insurance refers to the universal health insurance of China, including employee basic medical insurance (UEBMI), urban resident basic medical insurance (URBMI), and the new rural cooperative medical system (NCMS).

could be simplified to the following outcome matrix with four blocks:

$$Y_{it} = \begin{bmatrix} Y(0)_{co,pre} & Y(0)_{co,post} \\ Y(0)_{tr,pre} & Y(1)_{tr,post} \end{bmatrix} \tag{1}$$

Where $Y(0)_{co,pre}$ denotes the pre-treatment control group, which is a $(N-1)\times(T-1)$ matrix, $Y(0)_{co,post}$ denotes the post-treatment control group, which is a $(N-1)\times 1$ matrix, $Y(0)_{tr,pre}$ denotes the pre-treatment treated group, which is a $1\times(T-1)$ matrix, $Y(1)_{tr,post}$ denotes the post-treatment treated group, which is a 1×1 matrix. To identify the effect of DIP payment reform, the missing potential outcome $\widehat{Y}(0)^{sdid}_{tr,post}$ was needed.

SDID is a relatively new method for estimating causal effects with panel data developed by Arkhangelsky et al. [29]. We investigated the average treatment effect (ATT) of DIP payment reform in Guangzhou from 2018 to 2020, denoted by τ, as follows:

$$(\widehat{\tau}^{sdid}, \widehat{\mu}, \widehat{\alpha}, \widehat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - (\mu + \alpha_i + \beta_t + \tau DIP_{it}))^2 \widehat{\lambda}^{sdid}_t \widehat{\omega}^{sdid}_i \right\} \tag{2}$$

where the coefficient τ captures the effects of DIP, which are the primary focuses of the study. The key explanatory variable DIP_{it} is a dummy variable indicating DIP payment reform status of region i at time t to identify the effects of DIP payment reform.

The Eq. (2) includes both regional fixed effects α_i and time fixed effects β_t as well as weights, where the weights are the product of regional weights and time weights, with both sets of weights derived from data. The regional weights, $\widehat{\omega}^{sdid}_i$, align the pre-implementation trend in control regions with it in Guangzhou. The time weights of $\widehat{\lambda}^{sdid}_t$ balance the pre-implementation time periods with the post-implementation ones in control regions. The use of weights in the SDID estimates effectively makes the two-way fixed effect regression "local" [29]. The concomitant use of $\widehat{\omega}^{sdid}_i$ and $\widehat{\lambda}^{sdid}_t$ allows the parallel trends across observed Guangzhou and the synthetic control unit both region-wise (parallel trends vertically) and time-wise (parallel trends horizontally), thereby mirroring the DID approach. Of note, the method differs from the synthetic control (SC) method in which only synthetic parallel trends vertically (time-wise) were exploited to control time-invariant confounding [30]. As such, SDID inherits robustness properties from both traditional DID and SC methods, making it a promising approach applicable in settings where DID and SC would traditionally be used [29]. We also tested the balance between Guangzhou and synthetic Guangzhou before DIP implementation using the mean and maximum absolute standardized mean difference (ASMD) [31].

To explore heterogeneity in τ, Eq. (2) is separately estimated for various hospital subgroups and each time period after DIP implementation. Dynamic causal effects of DIP payment reform could be identified for each post-treatment period [32–35]. Accordingly, we introduced dynamic SDID to estimate the causal effects in each DIP year. We tested the sensitivity of our estimates by augmenting Eq. (2) with the inclusion of time-varying exogenous covariates [36].

Additionally, this study extends preceding works in several ways. First, we utilized region-level discharge data with an extensive time span. Second, we investigated the effects of DIP among not only public hospitals but also private hospitals, both of which covered primary hospitals, secondary hospitals, and tertiary hospitals. Third, we explored the effects of DIP on IHM and occupancy rate of hospital beds, which reflect the quality and resource utilization of healthcare. Finally, we explored the possibility of cost-manipulation behaviors and anticipatory effects.

All hypothesis tests adopted a two-tailed α = 0.1 threshold for statistical significance.

Results

Costs, LOS, and IHM

Table 1 and Table S2 displays sample statistics before and after DIP implementation in Guangzhou and other control regions for all hospitals, public hospitals and private hospitals, respectively. We observed an average increase in inpatient costs and discharge volume for all regions across hospital subgroups from 2012 to 2020. Based on the descriptive statistics of outcome variables in Table 1, Guangzhou had an increase in costs (CNY 4305.396 vs. CNY 2363.955) and discharge volume per day (1601.888 vs. 281.254) compared with control regions. A downward trend was observed in the occupancy rate of hospital beds for all regions from 82.842% (SD: 6.834%) in 2012–2017 to 77.852% (SD: 7.444%) in 2018–2020. There was an opposite trend in the figure for Guangzhou and control regions on average LOS and IHM. The average LOS of Guangzhou decreased from 9.633 (SD: 0.333) days in 2012–2017 to 9.400 (SD: 0.755) days in 2018–2020, while the figure for control regions increased from 8.543 (SD: 0.893) days to 8.553 (SD: 0.786) days. Guangzhou witnessed a slide in IHM by 0.050 percentage points after DIP implementation, compared with slight increase in

Table 1 Descriptive statistics of outcome variables among all hospitals ($N = 189$)

	Before DIP implementation (2012–2017)			After DIP implementation (2018–2020)		
	All regions (1)	**Guangzhou (2)**	**Control regions (3)**	**All regions (1)**	**Guangzhou (2)**	**Control regions (3)**
Per-episode inpatient costs (CNY)	8180.676 (2153.038)	15,562.306 (1620.964)	7811.595 (1369.020)	10,637.081 (2761.779)	19,867.702 (1904.385)	10,175.550 (1828.462)
Average length of stay (days)	8.595 (0.905)	9.633 (0.333)	8.543 (0.893)	8.594 (0.799)	9.400 (0.755)	8.553 (0.786)
In-hospital mortality (%)	0.553 (0.266)	0.871 (0.031)	0.537 (0.263)	0.592 (0.250)	0.821 (0.072)	0.581 (0.250)
Occupancy rate of hospital beds (%)	82.842 (6.834)	89.333 (1.935)	82.517 (6.831)	77.852 (7.444)	81.300 (8.235)	77.680 (7.437)
Discharge volume (episode)	1436.159 (1320.196)	6205.418 (783.5497)	1197.696 (775.118)	1780.300 (1638.879)	7807.306 (756.334)	1478.950 (929.371)
Outpatient visits (episode)	45,703.730 (59,457.160)	248,650.100 (13,213.280)	35,556.410 (39,058.440)	48,305.150 (58,392.830)	247,675.800 (28,149.320)	38,336.620 (37,869.030)

Means and standard deviations (in parentheses) are reported for Guangzhou and control regions between 2012 and 2020. All regions include Guangzhou and control regions. Control regions refer to 20 cities in Guangdong Province except Guangzhou, including Chaozhou, Dongguan, Foshan, Heyuan, Huizhou, Jieyang, Jiangmen, Maoming, Meizhou, Qingyuan, Shantou, Shanwei, Shaoguan, Shenzhen, Yangjiang, Yunfu, Zhanjiang, Zhaoqing, Zhongshan, and Zhuhai

IHM by 0.044 percentage points for control regions. Table S9 (Additional file) list all 21 control regions and their assigned weights.

The estimated effects of DIP payment reform on inpatient costs, LOS, and IHM are shown in Table 2. DIP was associated with an average increase in per-episode inpatient costs by CNY 1574.735 (95% CI: 148.330 to 3001.140, $P < 0.05$) from 2012 to 2020. The estimates are robust to the inclusion of covariates. After adding covariates to SDID estimates, DIP increased per-episode inpatient costs by CNY 1469.410 (95% CI: 428.699 to 2510.121, $P < 0.01$). The estimated effect of DIP on LOS among all hospitals was not statistically significant and small (SDID estimates: 0.049, 95% CI: −1.363 to 1.462, $P > 0.1$). The IHM decreased by 0.031 percentage points (95% CI: −0.185 to 0.122, $P > 0.1$) after DIP implementation, corresponding to a decrease of 3.559% (0.031 / 0.871). But the estimates were not statistically significant.

Based on the hospital subgroups results presented in Table 3, we found that DIP was associated with an average increase in per-episode inpatient costs by CNY 1583.413 (95% CI: 247.356 to 2919.470, $P < 0.05$) among

Table 2 Impacts of DIP using the SDID method without covariates and with covariates

	(1) [effect estimates (95% CI)]	**(2)** [effect estimates (95% CI)]
Per-episode inpatient costs (CNY)	1574.735** [148.330, 3001.140]	1469.410*** [428.699, 2510.121]
Average length of stay (days)	0.006 [−1.362, 1.374]	0.049 [−1.363, 1.462]
In-hospital mortality (%)	−0.031 [−0.185, 0.122]	−0.023 [−0.210, 0.163]
Occupancy rate of hospital beds (%)	−4.431 [−14.387, 5.524]	−5.018 [−1.362, 1.374]
Discharge volume (episode)	86.422 [−159.158, 332.002]	246.104* [−15.172, 507.380]
Outpatient visits (episode)	−5264.290*** [−8790.790, −1737.790]	−7293.225*** [−11500.000, −3129.997]
Control variables	No	Yes
Observations	189	189

Abbreviations: DIP Diagnosis-intervention packet, *SDID* synthetic difference-in-differences, *CNY* ChiNa Yuan

***, **, and * denote the significance at the 1%, 5%, and 10% level. 95% confidence intervals in brackets. The SDID estimates use panel data from the other 20 cities in Guangdong Province to synthesize Guangzhou. The first column is the average casual impacts of DIP using the SDID method without covariates. The third column is the average casual impacts of DIP using the SDID method with covariates. Covariates include the per-unit-population numbers of hospitals, doctors, beds and medical insurance participants, and the gross domestic product (GDP) per capital

Table 3 Impacts of DIP on costs, LOS, and IHM by hospital subgroups using the SDID method without covariates

	Per-episode inpatient costs (CNY)	Average length of stay (days)	In-hospital mortality (%)
All hospitals	1574.735** [148.330, 3001.140]	0.006 [−1.362, 1.374]	0.031 [−0.185, 0.122]
Public hospitals	1583.413** [247.356, 2919.470]	−0.123 [−1.243, 0.998]	−0.071 [−0.230, 0.087]
Private hospitals	1448.065* [−132.051, 3028.181]	1.965 [−2.528, 6.459]	0.330** [0.008, 0.652]
Tertiary hospitals	988.493 [−1047.165, 3024.151]	0.264 [−1.533, 2.060]	−0.029 [−0.277, 0.219]
Secondary hospitals	1080.636* [−106.338, 2267.610]	3.022* [−0.148, 6.192]	0.311*** [0.158, 0.463]
Primary hospitals	959.746 [−1010.504, 2929.996]	0.191 [−2.815, 3.196]	0.1 [−0.959, 1.159]

Abbreviations: DIP diagnosis-intervention packet, *LOS* length of stay, *IHM* in-hospital mortality, *SDID* Synthetic difference-in-differences, *ATT* Average treatment effect

***, **, and * denote the significance at the 1%, 5%, and 10% level. 95% confidence intervals in brackets

public hospitals. Additionally, an upward trend was seen in per-episode inpatient costs across other four hospital subgroups, but the estimates were not statistically significant. The LOS-reducing effects of DIP were limited to public hospitals (SDID estimates: −0.123, 95% CI: −1.243 to 0.998, $P > 0.1$), although the estimates were not statistically significant. Notably, DIP was associated with an increase in IHM by 0.330 percentage points (95% CI: 0.008 to 0.652, $P < 0.5$) and 0.311 percentage points (95% CI: 0.158 to 0.463, $P < 0.01$) among private hospitals and secondary hospitals. The magnitudes of changes in IHM were greater among private hospitals and secondary hospitals compared to other types of hospitals. In contrast, DIP reduced IHM by 0.160 percentage points (95% CI: −0.651 to 0.331, $P > 0.1$) and 0.071 (95% CI: −0.230 to 0.087, $P > 0.1$) percentage points among all hospitals and public hospitals although the estimates were not statistically significant.

The variations in per-episode inpatient costs, average LOS, and IHM in Guangzhou and synthetic Guangzhou between 2012 and 2020 are depicted in Fig. 1. For per-episode inpatient costs, DIP was associated with an 8% to 15% increase across all types of hospitals from 2018 to 2020. For average LOS, the overall trend declined between 2012 and 2020, but it rose significantly in 2018 and then fell in 2019. The dynamic effects of the DIP payment reform over years are reported in Table 3 and Fig. 2. It corroborates the changing trend of per-episode inpatient costs, average LOS, and IHM depicted in Fig. 1. The results indicate that the effects of DIP on costs in the second and third year were generally stronger than those in the first year across hospital subgroups (Table 3). We also estimated an approximately half-day increase in the average LOS in the first year of DIP payment reform among all hospitals and public hospitals, however, the estimates were not statistically significant.

Healthcare resource utilization

The effect of DIP payment reform on healthcare resource utilization, including occupancy rate of hospital beds, discharge volume, and outpatient visits, was listed in Table 2. Changes in the occupancy rate of all hospital beds in response to DIP were not statistically significant and trivial in size (SDID estimates: −0.031, 95% CI: −0.185 to 0.122, $P > 0.1$). Discharge volume per day in Guangzhou saw an upward trend from 2012 to 2020 (Table S3). DIP increased discharge volume per day by 61.414 (95% CI: 5.148 to 117.680, $P < 0.05$) among private hospitals. In contrast, DIP decreased outpatient visits per day by 5264.290 (95% CI: −8790.790 to −1737.790, $P < 0.01$) among all hospitals. After adding covariates to SDID estimates, outpatient visits per day decreased by 7293.225 (95% CI: −11,500.000 to −3129.997, $P < 0.01$), which is consistent with estimates based on the SDID method without covariates. Additionally, DIP reduced outpatient visits per day by 10,600.000 (95% CI: −14,100.000 to −6993.910, $P < 0.01$) and 34,300.000 (95% CI: −50,200.000 to −18,400.000, $P < 0.01$) among pubic hospitals and tertiary hospitals, respectively. The estimated effect among tertiary hospitals was about three times of that among public hospitals (Table 4).

There was an opposite trend in the figure for discharge volume per day and outpatient visits per day from 2018 to 2020 (see Table S4). Discharge volume per day slightly increased by 223.408 (95% CI: 70.895 to 375.921, $P < 0.01$) in 2018 and 409.709 (95% CI: 80.879 to 738.539, $P < 0.05$) in 2019, respectively, after which it declined by 373.852 (95% CI: −746.000 to −1.306, $P < 0.05$) in 2020. In contrast, outpatient visits per day decreased by 2994.347

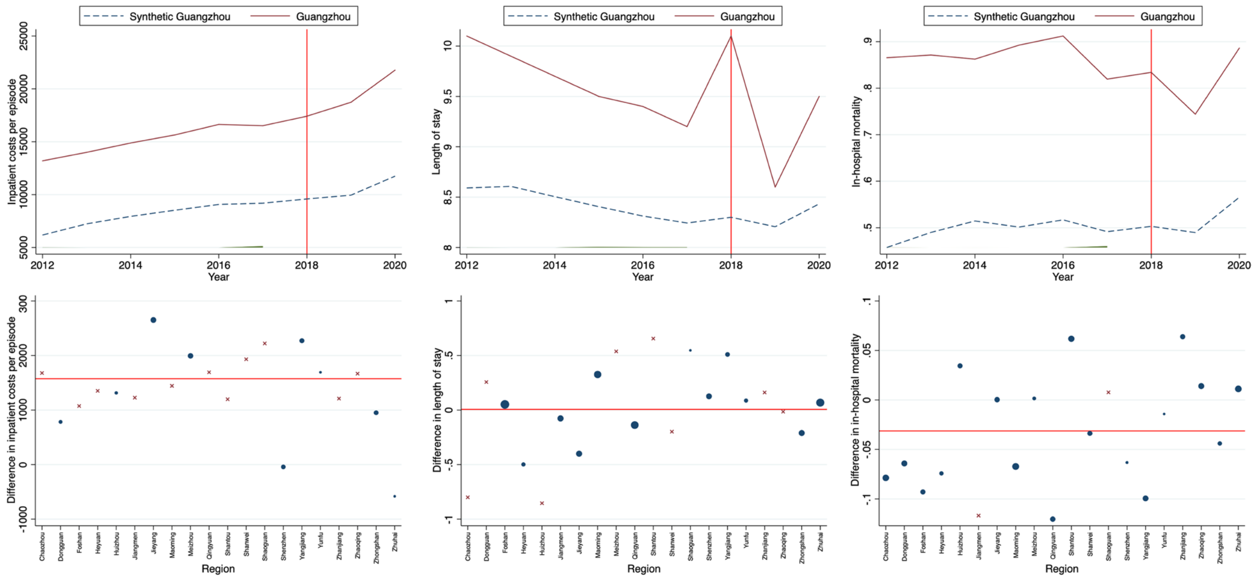

Fig. 1 Estimated causal effects of the DIP on inpatient costs, length of stay, and in-hospital mortality using the SDID method. Notes: Each panel of each column is a separate SDID estimates without covariates. In the first row, we show trends in inpatient costs, length of stay, and in-hospital mortality for Guangzhou and synthetic Guangzhou in 2012–2020. The weights used to synthesize pre-treatment periods of candidate regions are presented at the bottom of the graphs. The red vertical bar indicates when DIP starts to be implemented. In the second row, we show the region-by-region adjusted outcome difference. The weights are indicated by dot size. The weighted average of these differences, namely the estimated effect, is indicated by a horizontal line. Observations with zero weight are denoted by an × -symbol

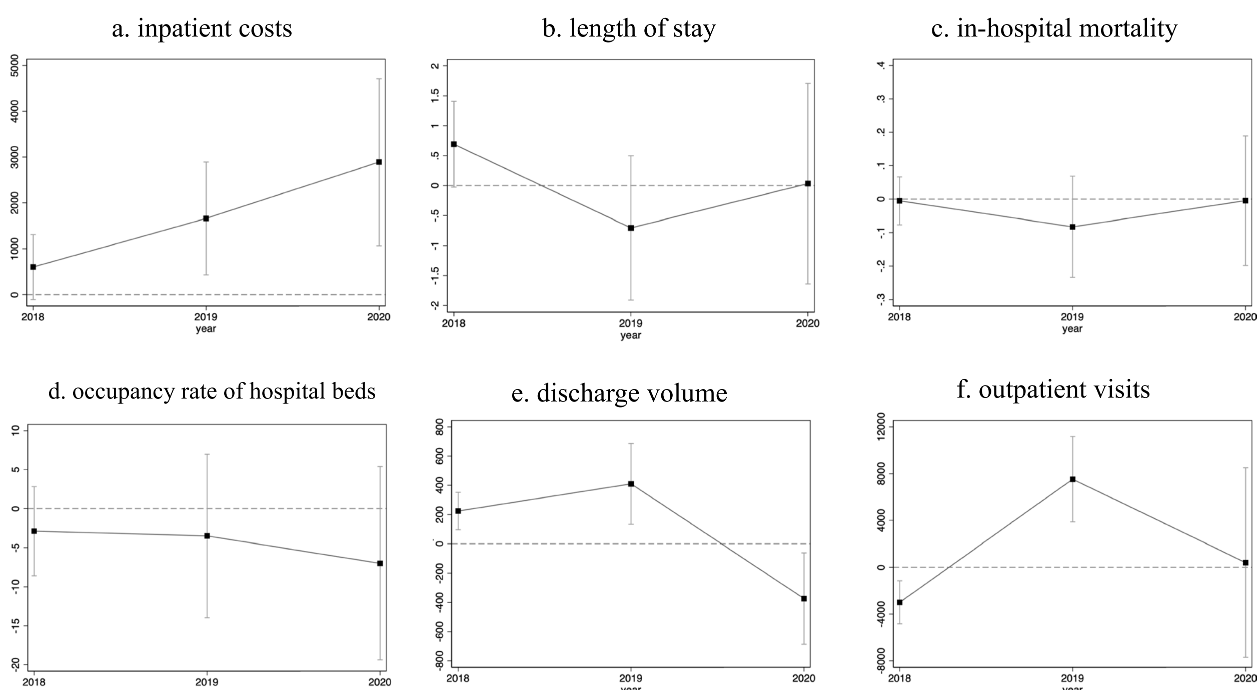

Fig. 2 Variations in the impacts of the diagnosis-intervention packet (DIP) payment reform among all hospitals over years (2018–2020)

Table 4 The dynamic impacts of DIP on costs, LOS, and IHM using the SDID method without covariates (2018–2020)

	Per-episode inpatient costs (CNY)	Average length of stay (days)	In-hospital mortality (%)
ATT (2018–2020)	1574.735** [148.330, 3001.140]	0.006 [−1.362, 1.374]	−0.031 [−0.185, 0.122]
ATT_1 (2018)	603.296 [−241.000, 1450.000]	0.691 [−0.163, 1.545]	−0.005 [−0.090, 0.080]
ATT_2 (2019)	1662.495** [198.425, 3130.000]	−0.705 [−2.138, 0.728]	−0.083 [−0.263, 0.097]
ATT_3 (2020)	2889.953*** [719.63588, 5060.000]	0.033 [−1.962, 2.028]	−0.005 [−0.235, 0.226]

Abbreviations: DIP diagnosis-intervention packet, *LOS* length of stay, *IHM* in-hospital mortality, *SDID* synthetic difference-in-differences, *ATT* average treatment effect

*** , **, and * denote the significance at the 1%, 5%, and 10% level. 95% confidence intervals in brackets. The SDID estimates use panel data from the other 20 cities in Guangdong Province to synthesize Guangzhou. 2018 was the first year of DIP implementation, 2019 was the second year of DIP implementation, 2020 was the third year of DIP implementation

(95% CI: −5190.000 to 801.000, $P<0.01$) in 2018, before rising steadily by 7519.013 (95% CI: 3170.000 to 11,900.000, $P<0.01$) in 2019.

The general trends in inpatient discharges and outpatient visits were illustrated in Figure S3 using the event-study estimates. Discharge volume per day slightly increased by 422.137 (95% CI: 386.262 to 458.012, $P<0.000$), while outpatient visits per day decreased by 7056.32 (95% CI: −7727.905 to −6384.736, $P<0.000$) in 2018 (Figure S3). The estimated results were consistent with the trends of discharge volume and outpatient visits showed in Fig. 2 and Figure S3. As such, it's possible to identify the cost-manipulation behaviors of transferring patients from outpatient services to inpatient services after the first year of DIP implementation.

Validity tests and robustness checks

A comparison between DID, SC, and SDID estimates for the effects of DIP payment reform is listed in Table S5 and Table S6. DIP increased per-episode inpatient costs across all types of hospitals and IHM among private hospitals and secondary hospitals in 2018–2020. Specifically, the DID method provided increased estimates of per-episode inpatient costs: CN¥ 1874.687 (95% CI: 229.348 to 3520.026, $P<0.05$) for all hospitals, CN¥ 1627.340 (95% CI: 65.105 to 3189.575, $P<0.05$) for public hospitals, and CN¥ 4027.378 (95% CI: 1210.128 to 6844.628, $P<0.01$) for private hospitals. The other method, SC, revealed significantly higher inpatient costs compared to the DID estimates. Moreover, DIP increased IHM by 0.693 percentage points (95% CI: 0.301 to 1.084, $P<0.01$) and 0.600 percentage points (95% CI: 0.151 to 1.049, $P<0.01$) among private hospitals using the DID and SC methods, respectively. Similarly, among secondary hospitals, the increase in IHM was 0.469 percentage points (95% CI: 0.260 to 0. 678, $P<0.01$) with the DID method and 0.414 percentage points (95% CI: 0.188 to 0. 639, $P<0.01$) with the SC method. The main results based on the DID and SC method were consistent with SDID estimates, which verified the validity of the causal effects presented in Table 2. Additionally, we conducted sensitivity analyses by iteratively excluding six high-weight regions[6] (Additional file: Table S11), with consistent policy effect estimates.

Additionally, the study summarized SDID estimates for the ATT in Guangzhou after DIP implementation using region-level data collected from 33 regions in China (see Table S7 and Figure S2). The estimated results of per-episode inpatient costs, average LOS, and IHM were consistent with the main results. Notably, DIP increased per-episode inpatient costs and average LOS among private hospitals by CN¥ 1172.763 (95% CI: 222.565 to 2120.000, $P<0.05$) and 4.438 days (95% CI: 1.109 to 7.766, $P<0.05$), respectively. It was noteworthy that DIP was associated with increases in LOS by 0.922 days (95% CI: 0.423 to 1.420, $P<0.01$) and 1.126 days (95% CI: 0.670 to 1.553, $P<0.01$) among all hospitals and public hospitals in 2018. It corroborates the changing trend of LOS depicted in Fig. 1, confirming the validity of our empirical results. Table S8 reports the changes in inpatient costs and LOS in Guangzhou and synthetic Guangzhou between 2012 and 2020 using region-level data collected from 33 regions in China (see Additional file 1). Table S10 (Additional file) report the ASMD metrics for pre-treatment outcomes between Guangzhou and synthetic Guangzhou (2012–2017). All mean ASMD values are < 0.10, satisfying the balance criterion. It indicates that using region-level data to synthesize Guangzhou is reliable.

[6] Six control regions and their assigned average weights were listed: Shenzhen: 0.070, Jieyang: 0.117, Yangjiang: 0.085, Yunfu: 0.021, Zhongshan: 0.082, Zhuhai: 0.089. The weight of these 6 regions was positive among the SDID estimates on three main outcomes.

Discussion and conclusion

Relying on region-level discharge statistics, this study estimated the impacts of DIP payment reform on cost and healthcare resource utilization from 2018 to 2020 by comparing the inpatient costs, LOS, and IHM in Guangzhou versus those in synthetic Guangzhou before and after DIP implementation using the SDID method. Our results showed that DIP significantly increased overall per-episode inpatient costs across all hospitals in 2018–2020. However, the effect on the average LOS and IHM among all hospitals was not statistically significant and small. We also observed that the quality effects of DIP on IHM differed across hospital types, with significant increase in IHM limited to private hospitals and secondary hospitals.

Additionally, we examined whether DIP payment reform triggered cost-manipulation behaviors. The results further indicate that, on average, DIP reduced outpatient visits and increased inpatient discharges among all hospitals. Healthcare providers may have shifted crowded-out utilization from outpatient settings to inpatient settings after DIP implementation. Variations in outpatient visits were different from discharge volume among all hospitals in 2018–2020. Specifically, DIP significantly decreased outpatient visits per day, but increased per-episode inpatient costs among public hospitals from 2018 to 2020, suggesting a potential trend towards selecting more profitable patients. Notably, private hospitals experienced a significant rise in IHM and discharge volume per day simultaneously after DIP implementation (Figure S3 and Figure S4). This aligns with the evidence of public hospitals transferring high-cost, end-stage patients to private hospitals under the cost-shifting incentives of payment reform.

The results also document anticipatory effects by healthcare providers in respond to DIP payment reform in both all hospitals and public hospitals. The current findings reveal a substantial increase in the average LOS among all hospitals and public hospitals in 2018, the first year after DIP implementation, followed by a subsequent decline in 2019 (see Fig. 1). Healthcare providers may have initially increased their procedures after DIP announcement, anticipated potential revenue loss, but subsequently reduced them under constrained measures and stringent supervision by the Guangzhou medical security bureau. And DIP payment reform was announced on November 9, 2017, and officially implemented in 2018. The time lag between policy announcement and its implementation indicated that providers had adequate time to prepare for the anticipated impact on their revenue [37]. This aligns with the "announcement effects-expectations of future event-individual responses" process. Healthcare providers may have adopted strategic behaviors to deliver more cost-effective services and prolong the average LOS in a given DIP group [17], possibly deviating from their patients' best interests to pursue their own economic interests.

While the costs and LOS impacts of DIP have been partially documented in the literature, the results were mixed. Two studies used the difference-in-difference (DID) method to investigate the effects of DIP on healthcare utilization [17, 38]. Lai et al. reported a decrease in per-episode healthcare expenditures, primarily driven by reduced drug expenditures. Qian et al. found that DIP increased inpatient costs and had little impact on LOS. Empirical studies examining DIP's cost effects have demonstrated divergence, potentially attributable to variations in sample selection criteria, temporal coverage, and the counterfactual construction of control groups. Theoretically, provider payment design methods, such as DRGs and bundled payment, are likely to perform better than fee-for-service in cost control. However, according to the Chinese experience so far, little payment reforms has reduced total medical expenditures. More research is needed to explain the gap between theoretical predictions and actual outcomes.

Several limitations should be noted when interpreting the results. First, the impacts of DIP in Guangzhou may differ from other areas in China, which might restrict the generalizability of the implications from the study. Second, out-of-pocket (OOP) costs among insured patients were not estimated due to data availability. Third, the analysis could not further delineate the effects of DIP by diseases within the inpatient setting. Low severity and high severity patients may have different cost patterns and resource utilization. Additionally, the wide confidence intervals in subgroup analyses likely reflect hospital heterogeneity in payment systems across regions and incomplete overlap in pre-reform trends between treatment and control groups. While sample size constraints of the current study may have undermined the precision of the estimates, the stability of point estimates under alternative specifications suggests that our core finding is robust to methodological variations.

Despite such limitations, the current findings carry important implications for healthcare policymaking in China. Based on the current findings, the early stage of the implementation did not necessarily effectively neutralize the growth of hospitalization costs across all hospitals. However, it should be noted that the goal of payment reform should not be limited to cost control. In fact, DIP relies on a unified national medical insurance data infrastructure system, which could alleviate the disparities of medical service across different regions in China by raising the awareness of relatively consistent standards. Therefore, there may be practical meanings of DIP payment reform to the healthcare system beyond cost concerns. In the meantime, the behaviors and the case-mix of patients of public hospitals might have been altered based on the results related to outpatient costs and discharge volumes. To balance fiscal sustainability with care quality, cost-containment policies must systematically integrate performance metrics and outcome data into healthcare system planning. The future payment reform should pay more attention to patient-centric outcomes rather than provider-centric outcomes. More studies should be conducted with a longer time span and take patient characteristics into consideration, including the severity of inpatients. In-depth analysis with physicians to understand their strategies in response to DIP payment reform is also necessary.

Abbreviations

DIP	Diagnosis-Intervention Packet
PPS	Prospective Payment Systems
DRG	Diagnosis-Related Groups
LOS	Length of Stay
SDID	Synthetic Difference-In-Differences
FFS	Fee-For-Service
CNY	China Yuan
OOP	Out-of-Pocket
UEBMI	Urban Employee Basic Medical Insurance
URBMI	Urban Resident Basic Medical Insurance
NCMS	New Rural Cooperative Medical System
ASMD	Absolute Standardized Mean Difference

Supplementary Information

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Additional file 1.

Additional file 2: Figure S1. Estimated causal effects of the DIP on occupancy rate of hospital beds, discharge volume, and outpatient visits using the SDID method. Notes: Each panel of each column is a separate SDID estimates without covariates. In the first row, we show trends in occupancy rate of hospital beds, discharge volume, and outpatient visits for Guangzhou and synthetic Guangzhou in 2012-2020. The weights used to synthesize pre-treatment periods of candidate regions are presented at the bottom of the graphs. The red vertical bar indicates when DIP starts to be implemented. In the second row, we show the region-by-region adjusted outcome difference. The weights are indicated by dot size. The weighted average of these differences, namely the estimated effect, is indicated by a horizontal line. Observations with zero weight are denoted by an×-symbol. Figure S2. Synthetic difference-in difference (SDID) estimates for the effects of DIP on per-episode inpatient costs and the average length of stay using region-level data collected from 33 regions in China. Notes: Each panel of each row and column is a separate SDID estimates without covariates. In the first row, we show trends in per-episode inpatient costs over time for Guangzhou and synthetic Guangzhou, while the second row is about the average length of stay. All hospitals here include public hospitals and private hospitals. Figure S3. Event-study estimates for the effects of DIP on discharge volume and outpatient visits across three hospital types. Notes: All hospitals here include public hospitals and private hospitals. 2018 is the first year after DIP implementation, namely lag0 in the figure. Figure S4. Event-study estimates for the effects of DIP on in-hospital mortality and Occupancy rate of hospital beds across three hospital types. Notes: All hospitals here include public hospitals and private hospitals. 2018 is the first year after DIP implementation, namely lag0 in the figure

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BF conducted literature review and contributed to data analysis and manuscript writing. YJ conceptualized and designed the study, was in charge of the overall study implementation, and contributed to manuscript drafting and revision. Both of the authors approved the final version of the manuscript.

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Data availability
Data directly used in the study are available in the article and the supplementary materials. Details of the codes will be supplied upon request. The data that support the findings of this study are openly available in the (China Statistical Yearbook), (China Health Statistical Yearbook), (Guangdong Health Statistical Yearbook), (Guangzhou Statistical Yearbook), and (Shenzhen Statistical Yearbook) repository, at: (http://www.stats.gov.cn/tjsj./ndsj/), (https://www.gdhealth.net.cn/html/tongjishuju/tongjiziliao/), (http://www.nhc.gov.cn/mohwsbwstjxxzx/tjtjnj/tjsj_list.shtml), (https://lwzb.gzstats.gov.cn:20001/datav/admin/home/www_nj/), and (http://tjj.sz.gov.cn/zwgk/zfxxgkml/tjsj/tjnj/index.html) [20–24].

Declarations

Ethics approval and consent to participate
Not applicable.

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References

1. Choi JW, Kim S-J, Park H-K, Jang S-I, Kim TH, Park E-C. Effects of a mandatory DRG payment system in South Korea: Analysis of multi-year nationwide hospital claims data. BMC Health Serv Res. 2019;19:776.
2. Liu Y-M, Yang Y-HK, Hsieh C-R. Financial incentives and physicians' prescription decisions on the choice between brand-name and generic drugs: Evidence from Taiwan. J Health Econ. 2009;28:341–9.
3. Jian W, Lu M, Chan KY, Poon AN, Han W, Hu M, et al. Payment reform pilot in beijing hospitals reduced expenditures and out-of-pocket payments per admission. Health Aff (Millwood). 2015;34:1745–52.
4. Yee CA, Pizer SD, Frakt A. Medicare's bundled payment initiatives for hospital-initiated episodes: evidence and evolution. Milbank Q. 2020;98:908–74.
5. Agarwal R, Liao JM, Gupta A, Navathe AS. The impact of bundled payment on health care spending, utilization, and quality: a systematic review: a systematic review of the impact on spending, utilization, and quality outcomes from three centers for medicare and medicaid services bundled payment programs. Health Aff. 2020;39:50–7.
6. Ellis RP, McGuire TG. Provider behavior under prospective reimbursement: Cost sharing and supply. J Health Econ. 1986;5:129–51.
7. Dieleman JL, Squires E, Bui AL, Campbell M, Chapin A, Hamavid H, et al. Factors associated with increases in US health care spending, 1996–2013. JAMA. 2017;318:1668.
8. Rice TH. The impact of changing medicare reimbursement rates on physician-induced demand. Med Care. 1983;21:803–15.
9. Okamura S, Kobayashi R, Sakamaki T. Case-mix payment in Japanese medical care. Health Policy. 2005;74:282–6.

10. Lin H-C, Xirasagar S, Kao S. Association of hospital ownership with patient transfers to outpatient care under a prospective payment system in Taiwan. Health Policy. 2004;69:11–9.
11. Fetter RB. Diagnosis related groups: understanding hospital performance. Interfaces. 1991;21:6–26.
12. Kutz A, Gut L, Ebrahimi F, Wagner U, Schuetz P, Mueller B. Association of the swiss diagnosis-related group reimbursement system with length of stay, mortality, and readmission rates in hospitalized adult patients. JAMA Netw Open. 2019;2:e188332.
13. Ying Y. DIP & DRG: Similarities and differences. China health insurance. 2021:39–42.
14. Li X, Zhang Y, Zhang X, Li X, Lin X, Han Y. Effects of fee-for-service, diagnosis-related-group, and mixed payment systems on physicians' medical service behavior: experimental evidence. BMC Health Serv Res. 2022;22:870.
15. Jian W, Lu M, Liu G, Chan KY, Poon AN. Beijing's diagnosis-related group payment reform pilot: Impact on quality of acute myocardial infarction care. Soc Sci Med. 2019;243:112590.
16. Huang Y, Liu Y, Yang X, Li J, Fang P. Global budget payment system helps to reduce outpatient medical expenditure of hypertension in China. Springerplus. 2016;5:1877.
17. Lai Y, Fu H, Li L, Yip W. Hospital response to a case-based payment scheme under regional global budget: the case of guangzhou in China. Soc Sci Med. 2022;292:114601.
18. Knutson B, Greer SM. Anticipatory affect: neural correlates and consequences for choice. Philos Trans R Soc Lond B Biol Sci. 2008;363:3771–86.
19. National Bureau of Statistic. China statistical yearbook. 1999. Available from: http://www.stats.gov.cn/tjsj./ndsj/. Cited 2022 Nov 17.
20. National Health Commission of the People's Republic of China. China Health Statistical Yearbook. 2011. Available from: http://www.nhc.gov.cn/mohwsbwstjxxzx/tjtjnj/tjsj_list.shtml. Cited 2022 Nov 17.
21. Health Commission of Guangdong Province. Guangdong Health Statistical Yearbook. 2012. Available from: https://www.gdhealth.net.cn/html/tongjishuju/tongjiziliao/. Cited 2022 Nov 17.
22. Guangzhou Statistics Bureau. Guangzhou Statistical Yearbook. 2000. Available from: https://data.cnki.net/area/yearbook/single/N2021120009?dcode=D19. Cited 2022 Nov 17.
23. Shenzhen Municipality Bureau of Statisticscs. Shenzhen Statistical Yearbook. 2013. Available from: http://tjj.sz.gov.cn/zwgk/zfxxgkml/tjsj/tjnj/. Cited 2022 Nov 17.
24. Herbst T, Foerster J, Emmert M. The impact of pay-for-performance on the quality of care in ophthalmology: empirical evidence from Germany. Health Policy. 2018;122:667–73.
25. Zuckerman RB, Maddox KEJ, Sheingold SH, Chen LM, Epstein AM. Effect of a hospital-wide measure on the readmissions reduction program. N Engl J Med. 2017;377:1551–8.
26. Li B, Hu L. Analysis on the effect of inpatient rehabilitation payment reform of medical insurance in Changsha City. Chinese Health Econ. 2024;13:1–7.
27. Hu M, Lu M, Du S, Jian W. The Evaluation of the pilot study on diagnosis related groups and prospective payment system in Beijing. China Health Insurance. 2014;4:48–52.
28. Zhang X, Yan J, Wang R, Lv D, Qian M, Ying X. Study on impact of diagnosis- intervention packet reform on the quality of healthcare. Chinese Hospital Manag. 2023;43:16–9.
29. Arkhangelsky D, Athey S, Hirshberg DA, Imbens GW, Wager S. Synthetic difference-in-differences. Am Econ Rev. 2021;111:4088–118.
30. Abadie A, Diamond A, Hainmueller J. Synthetic control methods for comparative case studies: estimating the effect of california's tobacco control program. J Am Stat Assoc. 2010;105:493–505.
31. Parast L, Hunt P, Grifln BA, Powell D. When is a Match Suflcient? A score-based balance metric for the synthetic control method. 2020;20.
32. Clarke D, Tapia-Schythe K. Implementing the panel event study. Stand Genomic Sci. 2021;21:853–84.
33. Goodman-Bacon A. Difference-in-differences with variation in treatment timing. J Econ. 2021;225:254–77.
34. Sun L, Abraham S. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. J Econ. 2021;225:175–99.
35. Liu M, Xu W, Zhang H, Chen H, Han G, Yu X. Livestock production, greenhouse gas emissions, air pollution, and grassland conservation: quasi-natural experimental evidence. SSRN J. 2022. Available from: https://www.ssrn.com/abstract=4306904. Cited 2024 Jun 18.
36. Kranz S. Synthetic Difference-in-Differences with Time-Varying Covariates. 2022. Available from: https://github.com/skranz/xsynthdid. Cited 2023 Mar 15.
37. Chandra A, Cutler D, Song Z. Who Ordered That? The Economics of Treatment Choices in Medical Care. Handbook of Health Economics. Elsevier; 2011. p. 397–432. Available from: https://linkinghub.elsevier.com/retrieve/pii/B9780444535924000062. Cited 2022 Oct 29.
38. Qian M, Zhang X, Chen Y, Xu S, Ying X. The pilot of a new patient classification-based payment system in China: the impact on costs, length of stay and quality. Soc Sci Med. 2021;289:114415.

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