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ORIGINAL RESEARCH

Cost Shifting in Lung Cancer Inpatient Care Under Diagnosis-Intervention Packet Reform: A Pilot Study in China

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Purpose: China has developed and widely implemented an innovative case-based payment method for inpatient services under a regional global budget, termed the "Diagnosis-Intervention Packet" (DIP). This study aims to examine cost-shifting behaviour in lung cancer inpatient care under the DIP reform.

Methods: This study examines the impact of the DIP reform in Zunyi, a national pilot city, using double machine learning (DML). Specifically, we analyze the effects on the total health expenditures (THS), individual payments excluding reimbursement (IPER), proportion of IPER, copayments for category-B, proportion of copayments for category-B, copayments for category-C and proportion of copayments for category-C per case for LC inpatients in tertiary hospitals.

Results: The results indicate a significant reduction in THS per case after the DIP reform ($\beta = -0.0778$, $p < 0.001$). Following the reform, there was a significant increase in IPER ($\beta = 0.0689$, $p < 0.05$), copayments for category-B ($\beta = 0.1682$, $p < 0.01$), and the proportion of copayments for category-B ($\beta = 0.0039$, $p < 0.05$). Conversely, the proportion of copayments for category-C significantly decreased ($\beta = -0.0108$, $p < 0.001$). Notably, significant heterogeneity in the cost-containment and cost-shifting effects was observed across different hospital categories, teaching types, and insured classifications.

Conclusion: The DIP reform significantly reduced the THS per case for LC inpatients, while shifting in-policy expenditures to IPER. The cost-shifting primarily occurred through the redistribution of copayments from category-C to category-B. It is imperative for policymakers to establish differentiated regulatory policies tailored to various cost categories, hospital types, and insured classifications to optimize the effectiveness of the DIP reform.

Keywords: payment reform, diagnosis-intervention packet, lung cancer, cost containment, cost shifting, China

Introduction

Lung cancer (LC) is the leading cause of cancer incidence and mortality globally.[1] According to the International Agency for Research on Cancer (IARC), since 2022, LC has topped the list with 2,480,308 new cases, representing 12.4% of all new cancer cases, and 1,817,131 deaths, accounting for 18.7% of total cancer deaths.[2]

China records the highest number of new LC cases and deaths worldwide. In 2022, IARC reported 1,060,584 new LC cases in China, constituting 22.0% of the country's total new cancer cases; additionally, 733,291 LC-related deaths were reported, comprising 26.7% of all cancer deaths in China.[2] These high incidence and mortality rates place a significant economic burden on patients, families, and the healthcare system.[3]

In comparison, LC treatment costs in the United States and European countries represent 15–20% of total cancer treatment expenses.[4,5] In China, LC inpatient treatment costs alone account for 11.0% of the total cancer inpatient payments, the highest proportion of inpatient costs.[6] Furthermore, projections indicate that by 2030, the total economic burden of LC in China will increase by CNY 53.4 billion, amounting to 0.146% of the GDP.[7,8] Zhu et al highlighted that inpatient expenditures represent 96% of the annual treatment costs for LC, with approximately 67% of these services

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provided in tertiary hospitals. Additionally, in China's basic medical insurance system, individual payments excluding reimbursement (IPER) consist of copayments for Category-B and Category-C services, as well as deductibles. A major challenge for the Chinese healthcare system is controlling the growth of LC inpatient expenditures and IPER.[9]

Fee-for-Service (FFS) is widely regarded as a principal contributor to the rapid increase in hospital medical costs in China.[10] In response, China has implemented a "dual-track" payment system, integrating both diagnosis-related group (DRG) and diagnosis-intervention packet (DIP) methods, to replace the traditional FFS and control inpatient costs.[11] DIP is an innovative case-based payment method for inpatient services under a regional global budget.[12] Different from DRG, DIP offers a more uniform resource utilization across groups, features a simpler design, allows dynamic grouping, and aligns reimbursement values closely with actual treatment pathways and costs, facilitating easier implementation.[13] Consequently, DIP has been quickly adopted throughout mainland China, with the number of cities implementing DIP being twice that of those adopting DRG.[14]

The cost-containment effects of the DIP reform have gained increasing attention in recent years, although research conclusions are inconsistent. For instance, Lai et al observed that total health expenditures (THS) and drug expenditures for inpatients decreased following the DIP reform.[12] Similarly, Tan et al reported significant reductions in THS for CHD inpatients in tertiary hospitals after implementing DIP.[15] In contrast, Ying et al found that the average expenditures for inpatients with high severity increased by 8.5% after the DIP reform. Previous studies have primarily examined the cost-containment effects of the DIP payment system from a general population and all-disease perspective, with limited focus on lung cancer. Furthermore, research on cost-shifting pathways under DIP remains scarce.[14] Existing theories mainly address cost shifts between insured and uninsured patients, across departments (eg, inpatient to outpatient), or institutions (eg, hospitals to clinics or nursing homes), yet often overlook shifts within a single hospitalisation between insured and uninsured costs.[16–19] Therefore, investigating cost shifts within IPER during a single hospitalisation under the DIP reform provides valuable insights into cost-shifting theory.

In this paper, we analyze inpatient claim data from Zunyi, a national pilot city for DIP in western China, using a quasi-natural experimental design. We compare Zunyi with Guiyang—a city where Zunyi's insured residents frequently seek medical treatment but which has not yet implemented DRG or DIP reforms. Guiyang serves as the control group, allowing us to evaluate the cost-containment and cost-shifting effects of DIP payment reform on LC care. This method effectively circumvents the endogeneity problem typically associated with cost shifting. Our study thus contributes to and broadens the existing literature on the cost-shifting behaviors of prospective payment systems (PPS) in middle- and low-income countries.

Institutional Background

DIP Payment in Zunyi

Located in southwest China, adjacent to Guiyang City, Zunyi comprises three districts, seven counties, two ethnic autonomous counties, and two administratively subordinate cities. In 2022, Zunyi's GDP reached 440.1 billion RMB, and the year-end permanent population was approximately 6.6 million. Zunyi was selected as one of the first national pilot cities for the DIP reform in November 2020. By October 2021, the DIP reform had been implemented across 70 secondary hospitals and 10 tertiary hospitals throughout the city. Table 1 shows the policy elements and mechanisms of Zunyi DIP payments.

Hospital Responses Under DIP Payment

In the general theoretical model of physician behavior, the magnitude of the income effect is a key determinant of how healthcare providers respond to price changes.[22] Under this effect, hospitals might adjust their service mix across different DIP categories based on profitability, aiming for economies of scale and scope. This adjustment leads to observable own-price and negative cross-price effects.[23] Additionally, hospitals may decrease service intensity per patient through marginal payment and average compensation effects to minimize their cost burden and deter treatment of unprofitable patients.[24,25]

Table 1 Policy Elements and Mechanisms of DIP Payment

Policy Element	Mechanism	Policy Content
Regional Global Budget(RGB)	Budget Gaming Mechanism	▪ Similar to the DRG in France and Thailand, the DIP payment sets a regional level global budget.[20,21] ▪ Zunyi RGB is determined by combining the total health expenditure of hospital diseases included in the DIP payment from the previous year with the weighted growth rate of hospitalization fund expenditure over the last three years.
DIP Grouping	Disease Classification Mechanism	▪ The DIP classification system mainly uses information on primary diagnoses and procedures to form DIP groups. In 2021, Zunyi Medical Insurance Bureau developed 4,281 DIP groups by clustering primary diagnosis codes (first 4 digits of ICD-10) and surgery and operation codes (ICD-9-CM-3)
DIP point volume	Point Volume Competition Mechanism	▪ Similar to DRG, DIP established a point schedule to reflect the relative resources consumed by each case group. Zunyi Medical Insurance Bureau determined the points for a disease group by calculating the weighted average expenditure of a certain disease group against the average expenditure of all DIP disease groups in the city, based on the weighted health expenditures (excluding hospital costs) over the last three years.
DIP Point Value (PV)	Point Value Fluctuation Mechanism	▪ In DRG, the absolute reimbursement amount per case is fixed in advance. Unlike DRG, the PV in DIP is variable and is determined post hoc according to the RGB and the total points of all hospital cases in the city. PV depends on the predetermined total regional budget and the total points of all hospital cases.
DIP settlement provision	Settlement Separation Mechanism	▪ The DIP settlement in Zunyi is divided into patient-side settlement and insurance-side settlement. Insured residents hospitalized within Zunyi are settled on the patient-side by FFS, while the insurance-side is settled by DIP. Insured residents seeking medical treatment outside Zunyi are settled on both the patient-side and the insurance-side by FFS.

Under the financial incentives of DIP, hospitals strive to maximize target income and surplus for each inpatient case, primarily through competitive point, cost control, and cost shifting.[26,27] Furthermore, medical institutions engage in cost control by implementing measures such as early discharge and reducing the intensity of diagnosis and treatment to decrease per-hospitalization resource use. This minimizes financial risks associated with exceeding the insurance payment.[15] Cost-shifting behaviors typically involve shifting coverage of reimbursement to IPER to lower the actual reimbursement ratio for patients, thereby increasing the end-of-year settlement point value. This creates a substitution effect between coverage of reimbursement and IPER. The absence of real-world cost data for specific diseases further encourages these behaviors. Nonetheless, the internal shifts in IPER, specifically within category-B and category-C copayments, are not well-documented and remain an area for further investigation.

Data and Methods

Data

This study utilises three data sources

1. Inpatient claim data, which include patient demographics (age, gender and insured classifications), visit dates (admission and discharge times), disease characteristics (type of diagnosis and treatment, main diagnosis, complications, surgery status and length of hospital stay), hospital characteristics (hospital name, hospital code and grade) and hospitalisation expenditures (THS, IPER, copayments for category-B, copayments for category-C, deductibles), were obtained from the Zunyi Health Insurance Bureau.

(2) Supplementary hospital characteristics in Zunyi: Data on additional characteristics of hospitals in Zunyi, such as category, ownership, and teaching status, were acquired from the Zunyi Health Commission.

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(3) Supplementary hospital characteristics in Guiyang: Information regarding hospital category, ownership, and teaching status was collected from the official hospital websites or local government websites of Guiyang and Chongqing, primarily through manual searches.

Inpatients with LC in tertiary hospitals were identified using the main diagnostic codes from ICD-10 (C34, C78, D02, and Z85). As THS and IPER are core variables, inpatients with missing data were excluded, resulting in a final sample of 8,386 inpatients from 33 tertiary hospitals, including 7,388 in the treatment group and 998 in the control group. To ensure privacy, all identifiable patient information, such as names, ID numbers, addresses, and inpatient numbers, was removed before the data were made available to the research team.

Measurements

Outcome Variables

This study primarily assesses the cost-containment and cost-shifting effects of the DIP. THS per case were used as a proxy for cost-containment, while IPER and copayments served as proxies for cost-shifting. Additionally, the copayments for category-B, proportion of copayments for category-B, copayments for category-C, and proportion of copayments for category-C were computed to analyse specific pathways of cost-shifting.

Explanatory Variable

In this study, all LC inpatients in tertiary hospitals in Zunyi were considered the treatment group, while those in Guiyang's tertiary hospitals served as the control group. October 2020 to September 2021 and October 2021 to December 2022 were set as the pre- and post-policy intervention periods, respectively, to exclude the impact of the COVID-19 pandemic. A value of 1 was assigned to the post-policy intervention period for the treatment group, with all others assigned a value of 0.

Control Variables

Control variables were constructed across three dimensions: patient demographics, hospital characteristics, and disease characteristics. Patient demographics included age, gender (female = 0, male = 1), and insured classifications, with urban and rural residents' basic medical insurance (URRBMI) coded as 0 and Urban Employee Medical Insurance (UEMI) as 1. Hospital characteristics encompassed hospital category (general hospital [GH] = 0, traditional Chinese medicine [TCM] hospital = 1), ownership (public = 0, private = 1), and teaching status (teaching = 0, non-teaching = 1). Disease characteristics covered the presence of complications (no = 0, yes = 1), surgery status (no surgery = 0, underwent surgery = 1), and length of hospital stay.

Statistical Analyses

The double machine learning (DML) model aims to leverage machine learning algorithms, such as random forests, to efficiently handle nuisance parameters in high-dimensional data, thereby enabling robust estimation of causal effects. Conventional causal inference methods, including Difference-in-Differences (DID), Instrumental Variables (IV), and Regression Discontinuity (RD), rely on strict assumptions and predefined linear relationships between variables, which limit their applicability. In contrast, DML model offers superior capability in estimating causal effects under nonlinear relationships, interactions, and high-dimensional settings, providing more precise and robust results.[28]

A DML model based on the random forest algorithm was used to assess the impact of the DIP reform on the THS, IPER, proportion of IPER, copayments for category-B, proportion of copayments for category-B, copayments for category-C and proportion of copayments for category-C per case for LC inpatients in tertiary hospitals. Specifically, a partially linear DML model was constructed based on the research findings of Chernozhukov et al[28] and Farbmacher et al:[29]

$$Y_{it} = \alpha E\text{vent}_{it} + g(X_{it}) + U_{it} \tag{1}$$

$$E(U_{it}|Event_{it},\ X_{it}) = 0 \tag{2}$$

where i represents the hospitalised patient, t represents the month and Y_{it} is the dependent variable, including the THS, IPER, proportion of IPER, copayments for category-B, proportion of copayments for category-B, copayments for category-C and proportion of copayments for category-C. All these expenditure variables were estimated in logs due to the skewed distribution of health expenditure. $Event_{it}$ is the explanatory variable, where LC inpatients in the treatment group after the DIP policy intervention are assigned a value of 1, whilst all others are assigned a value of 0. This study focused on α, which is the event coefficient. X_{it} is a set of high-dimensional control variables, including patient demographics, hospital characteristics, disease characteristic variables and the square of these variables. The specific form must be estimated using machine learning algorithms $\hat{g}(X_{it})$. U_{it} is the error term, which has a conditional mean of 0.

In the specific parameter estimation process, the coefficient estimate of $Event_{it}$ introduces regularisation bias due to the regularisation term in the machine learning model, which reduces variance but can introduce bias. Therefore, constructing auxiliary equations is necessary, as shown in Equation (3):

$$Event_{it} = m(X_{it}) + V_{it},\ E(V_{it}|Event_{it}, X_{it}) \tag{3}$$

In Equation (2), the random forest algorithm must estimate $m\ (X_{it})$ to obtain the estimate of this function $\hat{m}(X_{it})$, and the residuals Vit are then estimated, as shown in Equation (4):

$$\hat{V}_{it} = Event_{it} - \hat{m}(X_{it}), \tag{4}$$

where $\hat{V}_{it}$can be used as an insαtal variable for $Event_{it}$, and the estimates for $\hat{g}(X_{it})$ and $\hat{\alpha}$ can be obtained through random forest algorithm, as shown in Equation (5):

$$\hat{\alpha} = (\frac{1}{n}\sum_{i\in It\in T} \hat{V}_{it}\, Event_{it})^{-1} \frac{1}{n}\sum_{i\in It\in T} \hat{V}_{it}\left(Y_{i(t+1)} - \hat{g}(X_{it})\right) \tag{5}$$

where n is the total sample size. In this study, the sample split ratio is set at 1:5.

All analyses were performed using Stata 17.0 and Python 3.9.13 for Windows. 0.1%, 1% and 5% were used as the significance levels.

Sensitivity Checks

This study employs three methods for robustness checks: (1) Altering the machine learning model: Initially, the random forest algorithm was used. For robustness, re-estimations were conducted using alternative algorithms including gradient boosting, neural networks, and the LASSO algorithm. (2) Adjusting the split ratio: The sample split ratio was changed from 1:5 to 1:3 for re-estimation purposes. (3) Modifying the estimation method: Instead of relying solely on the machine learning model, the Difference in Differences (DID) method was also employed for re-estimation.

Heterogeneity Analyses

Previous theoretical and empirical literature widely demonstrates that different types of hospitals and insurance types exhibit varied response strategies to prepayment reforms.[15,19,30,31] Consequently, this study explores the heterogeneity of cost-containment and cost-shifting effects of DIP across different hospital categories, teaching types, and insured classifications.

Results

Descriptive Statistics

Table 2 presents the results of the descriptive statistical analysis. After DIP reform, the treatment group saw decreases in THS, IPER, and copayments for category-B and category-C per case by CNY 1,935, 36, 388 and 301, respectively. The proportions of IPER and category-C copayments per case increased by 0.64% and 0.78%, respectively, while the proportion of category-B copayments per case decreased by 0.12%. In contrast, the control group experienced decreases in THS, IPER, and copayments for category-B and category-C per case by CNY 4,414, 266, 688, and 375, respectively. The proportions of IPER and category-C copayments per case decreased by 0.75% and 0.92%, respectively, while the proportion of category-B copayments per case increased by 0.24%. These findings suggest that the trends in sample size, THS, IPER, copayments, and their proportions before and after the DIP reform were generally consistent between the treatment and control groups.

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Table 2 Summary Statistics

Variables	Treatment Group			Control Group		
	Before DIP Reform (2020.10–2021.9)	After DIP Reform (2021.10–2022.12)	Mean Diff	Before DIP Reform (2020.10–2021.9)	After DIP Reform (2021.10–2022.12)	Mean Diff
THS	14810	12875	1935***	23207	18,793	4414***
IPER	2270	1882	388***	4283	3595	688*
Copayments for category-B	926	851	75*	1640	1367	273**
Copayments for category-C	1317	1016	301***	2570	2195	375
Proportion of IPER	0.1440	0.1500	−0.0064	0.1880	0.1810	0.0075
Proportion of copayments for category-B	0.0544	0.0622	−0.0078***	0.0650	0.0674	−0.0024
Proportion of copayments for category-C	0.0890	0.0877	0.0012	0.1220	0.1130	0.0092

Notes: *** p<0.001, ** p<0.01, * p<0.05.
Abbreviations: DIP, diagnosis-intervention packet; THS, total health expenditures; IPER, individual payments excluding reimbursement.

Baseline Regression

Table 3 presents the estimated results of the cost-containment and cost-shifting effects of the DIP reform. Column 1 shows the impact of the DIP reform on THS per case, where THS per case in Zunyi decreased by 7.49% (=1-exp$^{(-0.0778)}$, $p < 0.001$) post-reform. Columns 2 and 3 detail the effects on IPER and their proportion per case, respectively. Specifically, IPER per case increased significantly by 7.13% (=exp$^{(0.0689)} - 1$, $p < 0.05$), while the proportion of IPER per case showed a non-significant decrease of 0.69% ($p > 0.05$). Columns 4 and 5 explore the impacts on copayments and

Table 3 The Cost-Containment and Cost-Shifting Effects of the DIP Reform

Variables	ln (THS)	ln(IPER)	Proportion of IPER	ln(copayments for Category-B)	Proportion of Copayments for Category-B	ln(Copayments for Category-C)	Proportion of Copayments for Category-C
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DIP payment	−0.0778***	0.0689*	−0.0069	0.1682**	0.0039***	−0.1029	−0.0108***
	(0.0157)	(0.0630)	(0.0032)	(0.0572)	(0.0009)	(0.0600)	(0.0032)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Squared of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,386	8,386	8,386	8,386	8,386	8,386	8,386

Notes: Robust standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05.
Abbreviations: DIP, diagnosis-intervention packet; THS, total health expenditures; IPER, individual payments excluding reimbursement; FE, fixed effect.

their proportion in category-B per case. Post-reform, copayments in category-B per case increased significantly by 18.32% (=$\exp^{(0.1682)} - 1$, $p < 0.01$), and the proportion of these copayments also increased significantly by 0.39% ($p < 0.05$). Columns 6 and 7 report on category-C copayments and their proportion per case. The copayments in category-C per case decreased by 9.78% (=1-$\exp^{(-0.1029)}$), which was not statistically significant ($p > 0.05$). However, the proportion of copayments in category-C per case significantly decreased by 1.08% ($p < 0.001$).

Sensitivity Checks

Sensitivity checks were conducted by altering the machine learning model, adjusting the sample split ratio, and modifying the estimation method. Supplementary Table 1 presents the regression results using different approaches, including the gradient boosting, neural network, LASSO algorithms, and DID method. The findings indicate that the DML estimation results align closely with the baseline regression, demonstrating the stability of the outcomes across various analytical methods. This consistency underscores the reliability of the research findings.

Heterogeneity Analyses

Hospital Category

Table 4 details the heterogeneity in the cost-containment and cost-shifting effects of the DIP reform across different hospital categories.

Columns 1 and 2 reveal the impact on THS per case. In GHs, there was a significant decrease of 7.36% (=1-$\exp^{(-0.0765)}$, $p < 0.001$), while in TCM hospitals, the decrease was a non-significant 4.23% (=1-$\exp^{(-0.0432)}$, $p > 0.05$).

Columns 3 to 6 analyze the effects on IPER and their proportions. IPER per case in GHs increased by 2.96% (=$\exp^{(0.0292)} - 1$, $p > 0.05$) and in TCM hospitals by 10.97% (=$\exp^{(0.1041)} - 1$, $p > 0.05$). However, the proportion of IPER per case in GHs decreased significantly by 0.76% ($p < 0.05$), whereas in TCM hospitals, it decreased by 0.17% ($p > 0.05$).

Columns 7 to 10 examine the impact on category-B copayments and their proportions. In GHs, copayments and their proportion per case increased significantly by 16.69% (=$\exp^{(0.1567)} - 1$, $p < 0.05$) and 0.37% ($p < 0.001$), respectively. In contrast, TCM hospitals saw increases of 11.62% (=$\exp^{(0.1099)} - 1$, $p > 0.05$) and 0.27% ($p > 0.05$), respectively.

Columns 11 to 14 detail the changes in category-C copayments and their proportions. In GHs, there were significant decreases of 16.63% (=1-$\exp^{(-0.1787)}$, $p < 0.01$) in copayments and 1.13% ($p < 0.01$) in their proportion. Conversely, in TCM hospitals, both the copayments and their proportion in category-C per case showed insignificant decreases of 0.12% (=$\exp^{(-0.0012)} - 1$, $p > 0.05$) and 0.12% ($p > 0.05$), respectively.

Hospital Teaching Types

Table 5 outlines the heterogeneity in the cost-containment and cost-shifting effects of the DIP reform across different types of teaching hospitals.

Columns 1 and 2 show the impact of the DIP reform on THS per case, with teaching hospitals experiencing a non-significant decrease of 0.43% (=1-$\exp^{(-0.0043)}$, $p > 0.05$). In contrast, non-teaching hospitals saw a significant decrease of 17.77% (=1-$\exp^{(-0.1957)}$, $p < 0.001$).

Columns 3 to 6 analyze the effects on IPER and their proportions per case. In teaching hospitals, IPER per case increased significantly by 53.99% (=$\exp^{(0.4317)} - 1$, $p < 0.001$), and the proportion of IPER slightly increased by 0.85% ($p > 0.05$). For non-teaching hospitals, IPER per case decreased significantly by 38.66% (=1-$\exp^{(-0.4887)}$, $p < 0.010$) and the proportion of IPER significantly decreased by 3.38% ($p < 0.001$).

Columns 7 to 10 examine the impact on category-B copayments and their proportions. In teaching hospitals, copayments and their proportion in category-B increased significantly by 64.18% (=$\exp^{(0.4958)} - 1$, $p < 0.001$) and 0.85% ($p < 0.001$), respectively. Conversely, non-teaching hospitals experienced significant decreases of 27.28% (=1--$\exp^{(-0.3185)}$, $p < 0.001$) in copayments and a decrease of 0.29% in their proportion ($p < 0.05$).

Columns 11 to 14 detail the changes in category-C copayments and their proportions. Teaching hospitals saw an increase of 20.96% (=$\exp^{(0.1903)} - 1$, $p < 0.05$) in copayments and a non-significant increase of 1.13% in their proportion ($p > 0.05$). In non-teaching hospitals, copayments and their proportion significantly decreased by 44.89% (=1-$\exp^{(-0.5959)}$, $p < 0.001$) and 3.09% ($p < 0.01$), respectively.

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Table 4 The Cost-Containment and Cost-Shifting Effects of DIP Across Different Hospital Categories

Variables	**ln (THS)**		**ln(IPER)**		**Proportion of IPER**		**ln(Copayments for Category-B)**		**Proportion of Copayments for Category-B**		**ln(Copayments for Category-C)**		**Proportion of Copayments for Category-C**	
	GH	**TCMH**	**GH**	**TCMH**	**GH**	**TCMH**	**GH**	**TCMH**	**GH**	**TCMH**	**GH**	**TCMH**	**GH**	**TCMH**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
DIP payment	−0.0765***	−0.0432	0.0292	0.1041	−0.0076*	0.0017	0.1567*	0.1099	0.0037***	0.0027	−0.1787**	−0.0012	−0.0113**	−0.0012
	−0.0172	−0.0356	−0.0687	−0.0884	−0.0034	−0.0058	−0.0625	−0.0829	−0.001	−0.0016	−0.0648	−0.0061	−0.0035	−0.0061
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Squared of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,121	862	7,121	862	7,121	862	7,121	862	7,121	862	7,121	862	7,121	862

Notes: Robust standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05.
Abbreviations: DIP, diagnosis-intervention packet; THS, total health expenditures; IPER, individual payments excluding reimbursement; FE, fixed effect; GH, general hospital;TCMH, traditional Chinese medicine hospital.

Table 5 The Cost-Containment and Cost-Shifting Effects of DIP Across Different Types of Teaching Hospitals

Variables	**ln (THS)**		**ln(IPER)**		**Proportion of IPER**		**ln(Copayments for Category-B)**		**Proportion of Copayments for Category-B**		**ln(Copayments for Category-C)**		**Proportion of Copayments for Category-C**	
	Teaching Hospitals	**Non-Teaching Hospitals**	**Teaching Hospitals**	**Non-Teaching Hospitals**	**Teaching Hospitals**	**Non-Teaching Hospitals**	**Teaching Hospitals**	**Non-Teaching Hospitals**	**Teaching Hospitals**	**Non-Teaching Hospitals**	**Teaching Hospitals**	**Non-Teaching Hospitals**	**Teaching Hospitals**	**Non-Teaching Hospitals**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
DIP payment	−0.0043	−0.1957***	0.4317***	−0.4887***	0.0085	−0.0338***	0.4958***	−0.3185***	0.0085***	−0.0029*	0.1903*	−0.5959***	0.0001	−0.0309***
	−0.0201	−0.0255	−0.0854	−0.0876	−0.0046	−0.0038	−0.0771	−0.0799	−0.0012	−0.0012	−0.0806	−0.0846	−0.0047	−0.0037
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Squared of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,098	3,288	5,098	3,288	5,098	3,288	5,098	3,288	5,098	3,288	5,098	3,288	5,098	3,288

Notes: Robust standard errors in parentheses, *** p<0.001, * p<0.05.
Abbreviations: DIP, diagnosis-intervention packet; THS, total health expenditures; IPER, individual payments excluding reimbursement; FE, fixed effect.

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Insured Classifications

Table 6 outlines the heterogeneity of the DIP reform's cost-containment and cost-shifting effects across different insured classifications.

Columns 1 and 2 report the impact on THS per case for URRBMI and UEMI, with significant decreases of 6.80% (=1-exp$^{(-0.0704)}$, $p < 0.001$) and 15.06% (=1-exp$^{(-0.1632)}$, $p < 0.01$), respectively.

Columns 3 to 6 analyze the effects on IPER and their proportions per case. For URRBMI, IPER per case increased by 9.19% (=exp$^{(0.0879)}$ − 1, $p > 0.05$), and the proportion of IPER decreased slightly by 0.62% ($p < 0.05$). In contrast, for UEMI, IPER per case decreased significantly by 38.66% (=1-exp$^{(-0.4887)}$, $p < 0.010$) and the proportion of IPER significantly decreased by 23.78% (=1-exp$^{(-0.2716)}$, $p < 0.001$) and 1.90% ($p < 0.05$), respectively.

Columns 7 to 10 examine the impact on category-B copayments and their proportions. For URRBMI, there were significant increases of 21.45% (=exp$^{(0.1943)}$ − 1, $p < 0.01$) in copayments and 0.42% ($p < 0.001$) in their proportion. For UEMI, however, copayments decreased by 17.65% (=1-exp$^{(-0.1942)}$, $p < 0.05$), while the proportion of copayments increased significantly by 0.42% ($p < 0.001$).

Columns 11 to 14 detail the effects on category-C copayments and their proportions. URRBMI experienced a decrease of 8.63%(=1-exp$^{(-0.0902)}$, $p > 0.05$) in copayments and a significant decrease in their proportion by 1.04% ($p < 0.01$). UEMI saw a significant decrease of 38.16% (=1-exp$^{(-0.4807)}$, $p < 0.001$) in copayments, but a non-significant decrease of 1.73% in their proportion ($p > 0.05$).

Discussion

This study in mainland China is the first to use a quasi-natural experiment to evaluate the cost-shifting effects of the DIP reform. The results indicate that the DIP reform significantly reduced the THS per LC inpatient case in tertiary hospitals, while shifting in-policy expenditures to IPER. Simultaneously, the cost-shifting primarily occurred through the redistribution of copayments from category-C to category-B.

Rising costs can be mainly attributed to inappropriate incentives for healthcare providers.[32] Reforming the payment method of health insurance is the most critical "lever" for controlling medical expenditures.[33] Similar to the United States, oncology is a focal area for healthcare payment reform efforts in China.[34] However, payment reforms introduce new uncertainties for oncologists.[35] Many middle- and low-income countries have established DRG payment systems for emergency hospitalisation costs.[36] In October 2021, Zunyi shifted from FFS to DIP for inpatient services. Similar to DRG, DIP helps control expenditures by bundling all goods and services provided during hospitalisation into one unit for payment.[37]

The estimated results show that the DIP reform led to a significant reduction of 7.49% ($p < 0.001$) in the THS per case, aligning with findings by Lai et al,[12] Tan et al.[15] However, the marginal effect of THS reduction for LC inpatients in this study is higher than those previously found. This difference can be attributed to the focus on LC inpatients in tertiary hospitals, while previous studies by Lai, Ding included all disease types across various hospital levels. Research indicates that inpatient expenditures for LC patients are significantly higher than for those without cancer,[38] and expenditures in tertiary hospitals exceed those in secondary and primary facilities.[39] Historical data show that hospitals with higher per-case expenditures tend to reduce costs more significantly under PPS.[40] These findings underscore a substantial cost-containment effect of the DIP reform for LC inpatients in tertiary hospitals.

The cost-containment effect of DIP meets the expectations of this study. A fixed price system transfers financial risk from insurers to healthcare providers,[41] promoting rational behavior among hospitals to minimize costs under yardstick competition.[42] This behavior holds true across all hospital types, regardless of income constraints, allowing hospitals to profit by controlling medical expenditures. The relative prices for different DIP disease groups are set, but the actual compensation—based on the price per PV—is determined post-hoc. Each hospital's annual reimbursement is also calculated post-hoc, depending on its service volume, the service volumes at other hospitals, and the regional medical insurance budget. This macro-level regulatory mechanism, although designed to manage costs, creates an opaque environment that complicates hospitals' financial planning due to unpredictable annual budget adjustments tied to service volume changes. Without clear price signals and benchmark cost data, hospitals are forced to focus on balancing their financial accounts.[21] In such a competitive

Table 6 The Cost-Containment and Cost-Shifting Effects of DIP Across Different Insured Classifications

Variables	**ln (THS)**		**ln(IPER)**		**Proportion of IPER**		**ln(Copayments for Category-B)**		**Proportion of Copayments for Category-B**		**ln(Copayments for Category-C)**		**Proportion of Copayments for Category-C**	
	URRBMI	**UEMI**	**URRBMI**	**UEMI**	**URRBMI**	**UEMI**	**URRBMI**	**UEMI**	**URRBMI**	**UEMI**	**URRBMI**	**UEMI**	**URRBMI**	**UEMI**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
DIP payment	−0.0704***	−0.1632**	0.0879	−0.2716***	−0.0062	−0.0190*	0.1943**	−0.1942*	0.0042***	−0.0024	−0.0902	−0.4807***	−0.0104**	−0.0173
	−0.0165	−0.0509	−0.0696	−0.0823	−0.0034	−0.009	−0.063	−0.0818	−0.001	−0.0024	−0.0654	−0.1097	−0.0034	−0.0096
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Squared of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,795	1,591	6,795	1,591	6,795	1,591	6,795	1,591	6,795	1,591	6,795	1,591	6,795	1,591

Notes: Robust standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05.
Abbreviations: DIP, diagnosis-intervention packet; THS, total health expenditures; IPER, individual payments excluding reimbursement; FE, fixed effect; URRBMI, urban and rural residents' basic medical insurance;UEMI, Urban Employee Medical Insurance.

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environment, the price per point decreases as hospitals strive to increase total point values. Importantly, the reimbursement rules under DIP specifically incentivize tertiary hospitals to enhance cost control on the health insurance side.

Different from the reimbursement rules of France, the basic medical insurance of China only reimburses costs within the coverage of reimbursement.[43] Our study found that after the DIP reform, IPER per case in tertiary hospitals significantly increased by 7.13% ($p < 0.05$), demonstrating a significant cost-shifting effect under DIP. This cost-shifting behavior aligns with the expectations of this study, where tertiary hospitals manage to reduce the actual reimbursement ratio for inpatients by shifting costs from coverage of reimbursement to IPER, thus enhancing the year-end settlement point value. Importantly, the implementation of a RGB under DIP alters the budget gaming rules among hospitals, mitigating the financial risks associated with incurring a high proportion of costs not covered by the policy. Previously, under an individual institution budget similar to France, medical institutions had incentives to shift costs from services covered by insurance to those paid out-of-pocket by patients to avoid exceeding annual cost limits.[15] Such strategies might include intentionally exceeding the annual budget to secure a larger budget for the next fiscal year. However, this approach carries risks as exceeding the budget can lead to deductions by the health security administration from the amount over the allocated budget, ultimately reducing the hospital's overall income. With the transition to a RGB under DIP, tertiary hospitals now have the opportunity to gain additional points through their competitive advantage, without the risk of budget overruns, ensuring financial stability and potentially more effective cost management.

Furthermore, the pathways of cost-shifting following the DIP reform were examined. The analysis revealed that the absolute and relative values of copayments for category-B per case significantly increased by 18.32% and 0.39%, respectively. Conversely, both the absolute and relative values of copayments in category-C per case decreased, showing reductions of 9.78% and 1.08%, respectively. This cost-shifting effect is primarily achieved by transferring copayments from category-C to category-B. Despite the increases in category-B being larger than the reductions in category-C, the IPER did not significantly increase. This is attributed to the "base effect", where the initial amount of copayments in category-C is larger than those in category-B. This finding suggests that the Zunyi health security administration should particularly focus on monitoring the copayments for category-B in the future.

This study found that the cost-containment and cost-shifting effects of the DIP reform vary across different hospital categories. Specifically, DIP reform significantly contains costs in GHs, while these effects are absent in TCM hospitals. In terms of cost-shifting, GHs saw significant increases in both the amount and proportion of category-B copayments, while category-C copayments and their proportions significantly decreased. Conversely, in TCM hospitals, changes in both category-B and category-C copayments and their proportions were insignificant, indicating minimal cost-shifting effects. These findings suggest that cost-shifting in GHs is primarily achieved by transferring costs from category-C to category-B, and subsequently from IPER to coverage of reimbursement. The lack of significant cost-shifting effects in TCM hospitals could be due to several factors. One possibility is the competitive landscape among Chinese hospitals, where GHs, due to their dominant market position, have more strategic flexibility to respond to DIP reform. Another factor could be the mismatch between DIP's disease classification, which is based on Western medicine, and the diagnoses and procedures used in TCM, limiting the ability of TCM hospitals to strategically respond to the reform.

Previous research found the occurrence of cost shifting after the implementation of PPS, which is not applicable to all hospitals.[44] This study reveals that the effects of the DIP reform on cost-containment and cost-shifting for LC inpatients vary significantly between teaching and non-teaching hospitals. Specifically, the reform significantly contains costs in non-teaching hospitals, but this effect is not evident in teaching hospitals. Regarding cost-shifting, there was significant movement from coverage of reimbursement to IPER in teaching hospitals, while non-teaching hospitals showed a notable shift from IPER to coverage of reimbursement. The predominant method of cost-shifting in teaching hospitals involves increasing copayments for category-B and category-C, whereas in non-teaching hospitals, it is achieved by reducing these payments. Several factors contribute to these differences: First, Chinese teaching hospitals, which often hold a monopolistic position, do not typically face concerns about patient sources].[45] Second, the DIP pricing model does not account for the additional costs associated with teaching, new technologies, and new projects, which disproportionately affects teaching hospitals, leading to higher uncompensated costs compared to their non-teaching counterparts.[46] Additionally, the detailed grouping in DIP, compared to DRG, provides benefits that are more aligned with the operations of research-focused teaching hospitals.[44] Consequently, teaching hospitals may exhibit less motivation for cost containment compared to non-teaching hospitals.

The fragmented approach to universal health coverage in China has resulted in diverse health insurance schemes.[47] China's basic medical insurance is divided into URRBMI and UEMI, with UEMI typically offering higher reimbursement ratios.[48] Previous studies have indicated that URRBMI Beneficiaries are more likely to incur catastrophic health expenditures and suffer from the economic toxicity of diseases like cancer, compared to UEMI Beneficiaries.[49] The DIP reform has shown to control the THS per case for both URRBMI and UEMI, with a more pronounced cost-containment effect observed for UEMI. Additionally, the reform has led to varying cost-shifting effects depending on the insurance classification: IPER for UEMI significantly decreased, while those for URRBMI increased. Specifically, the copayments for category-B and category-C in UEMI significantly decreased, whereas category-B copayments in URRBMI significantly increased, though the decrease in category-C for URRBMI was not significant. These findings suggest that the DIP reform may exacerbate existing inequalities between URRBMI and UEMI Beneficiaries, particularly in the economic burden faced by LC inpatients.

Policy Implications

Firstly, a micro-regulation system for medical practices in hospitals should be established. This system should focus on monitoring changes in copayments for Category-B and Category-C, aiming to prevent the shift of costs from insurance payments to IPER following the DIP reform, which could increase the financial burden on lung cancer inpatients. Secondly, it is important to align external and internal incentives for medical practices. This includes developing a compensation system under the DIP that reflects the intensity, complexity, and technical risks associated with lung cancer inpatient care. Additionally, the 'shared savings or losses' incentive embedded in the DIP payment system should be utilised to influence hospital behaviour, ensuring that the distribution of surplus aligns with the reform objectives.

Limitations

This study has several limitations. Firstly, it does not investigate the impact of the DIP reform on hospitalization rates for LC patients due to data unavailability. In China's competitive healthcare system, the point-based competition under DIP payments could affect regional budget allocations. Future studies should explore how DIP payments influence hospitalization rates for LC patients. Second, this study covers only the short-term effects of the DIP reform over a 15-month period. Considering evidence from the Netherlands, which suggests that long-term effects of DRG reforms can exceed short-term impacts,[50] it is crucial to continuously monitor the effects of DIP as its implementation progresses. Third, the analysis is limited to the cost-containment and cost-shifting effects for LC only. Since hospitals may respond differently to various diseases, future research should compare these effects across surgical and medical diseases and between complex and simple diseases, based on disease classification.

Conclusions

Overall, the DIP reform has significant cost-containment and cost-shifting effects on LC inpatient in tertiary hospitals. This effect primarily occurs as copayments are shifted from category-C to category-B. However, there is considerable heterogeneity in these effects across different hospital categories, teaching types, and insurance classifications. Given these variations, policymakers must establish differentiated regulatory policies tailored to the specific needs of different hospital categories, teaching types, and insurance classifications under the DIP reform.

Data Sharing Statement

The data that support the findings of this study are available from Zunyi Local Health Security Administration but restrictions apply to the availability of these data, which were used under licence for the current study, and so are not publicly available. However, data are available from the corresponding author upon reasonable request and with permission of Zunyi Health Security Administration.

Ethics Approval and Consent to Participate

The study was approved the institutional review board of the Tongji Medical College, Huazhong University of Science and Technology (No: 2022LSZ-S145). The procedures used in this study adhere to the tenets of the Declaration of Helsinki. All patients had been provided informed consent before participating this study.

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Disclosure

The authors declare no competing interests.

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