Original Article

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Catastrophic and Socioeconomic Disparities Across Different Payment Schemes in Lung Cancer Treatment: A Cross-Sectional Single-Centre Analysis from Thailand

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Abstract:

Objective: To identify the magnitude of catastrophic health expenditure (CHE) and medical impoverishment across three payment schemes and compare the within-scheme financial disparity.

Material and Methods: A cross-sectional analysis of CHE and medical impoverishment among lung cancer patients was conducted at a university hospital in Thailand. A total of 367 lung cancer patients drawn from three payment schemes were included. The clinical data were collected from the hospital's Electronic Medical Records, while the socioeconomic data, including cost details, were collected via an interview-based questionnaire from November 2020 to June 2022. Economic analyses were performed using concentration curves and logistic regression modeling.

Results: There were 38%, 21% and 27% impoverished patients belonging to the Universal Coverage Scheme (UCS), Social Security Scheme (SSS) and Civil Servant Medical Benefit Scheme (CSMBS), respectively, and approximately further 30% in each scheme became impoverished owing to medical-related expenses. Socioeconomic disparities in CHE; concentration index; CI=-0.36 UCS, -0.59 CSMBS and -0.47 UCS, and medical impoverishment; CI=0.16 UCS, -0.15 CSMBS and 0.10 UCS, were evident in all schemes. These inequities were more pronounced among CSMBS patients. Moreover, if not impoverished already, the probability of medical impoverishment in all payment schemes peaked in the middle quintile and declined thereafter.

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Conclusion: Across all payment schemes, CHE and medical impoverishment occurred at rates of around 60% and 30%, respectively, among lung cancer patients in Thailand. The gradient of CHE probability was more prominent among CSMBS patients.

Keywords: non-small cell lung cancer, catastrophic health expenditure, disparity

Introduction

Cancers cause significant health burdens, and lung cancer ranks as one of the leading causes of health burden in males and one of the top five cancers in females worldwide. Lung cancer-related deaths account for one-fifth of total cancer-related deaths and bring a huge financial burden to patients and their families, the healthcare system, and society. These financial toxicities are not only due to direct medication/non-medication costs but also from indirect costs[1]. Cancer treatment costs can result in household impoverishment or catastrophic health expenditure (CHE) despite wide coverage of social health insurance, especially among patients who are elderly, with low education, living in a rural area and with low household income[2,3].

Sun et al. reported high percentages of CHE from lung cancer treatment in China—about 73-84%, depending on the type of compensation[4].

Cancer treatment costs can result in household impoverishment or CHE despite wide coverage of social health insurance especially among patients who are elderly, with low education, living in a rural area, and with low household income[3,5-7].

Since 2002, the Thai Government has established the Universal Coverage Scheme (UCS) Act applying to all Thai citizens not otherwise covered. It aims to improve the quality of life, health security, equity, and universal access to healthcare of the citizen of the country[8].

However, there are three main payment schemes in Thailand. First, the Civil Servant Medical Benefit Scheme (CSMBS) covers government officers and their dependents and pays healthcare facilities on a fee-for-service basis. Second, the Universal Coverage Scheme (UCS) covers the majority of the Thai population. Finally, the Social Security Scheme (SSS) covers the working-age people employed by private companies. Together, these form the expanded health insurance system in Thailand.

Based on the payment scheme, patients in Thailand could be classified into three groups. Patients belonging to the CSMBS group, which comprise 4.4-4.5 million people working for the government and their parents and immediate family; they can access the new standard treatments via the well-established Oncology Prior Authorization Program (OCPA) even though the regimens are not listed in the Thai National Drug List. The payment methods are fee-for-service for out-patient costs and diagnostic-related groups with multiple cost bands for in-patient costs.[8,9] Patients in the UCS group, the largest group comprising 48-60 million people, can be reimbursed for the cost of treatment only for the regimens/treatments on the National Drug List. Otherwise, they must pay by themselves (out-of-pocket, OOP). Reimbursed payment methods for patients in UCS are based on capitation for out-patient costs and diagnostic-related groups with a global budget with free schedule for specific high-cost procedures for in-patient costs[8,9]. Patients in the SSS group, consisting of mostly people working for a private company and accounting for 8.2-10.6 million people, are younger than the patients in CSMBS and UCS groups. The treatment options for patients in this group are almost the same as for those in the UCS

group. For the SSS group, the capitation for reimbursed costs is implemented for in-patients and diagnostic-related groups with a global budget applied for out-patients[8,9].

By rationale, the poorest patients in each scheme have a higher chance of getting financial problems related to healthcare compared with more wealthy patients.

We hypothesized that the expanded health insurance system improves the financial protection for cancer patients in Thailand. However, in clinical practice, there are cases of financial limitation or inability to pay for drug/treatment costs on the part of patients under these health coverage schemes, which may lead to substandard treatment for some patients. These patients, especially those in the lowest QTE, tend to face a severe financial burden after treatments, which may have multiple sequelae for the patients, their relatives, and the society at large.

In Thailand, a few studies have examined the healthcare disparities among people with chronic diseases such as hypertension, cardiovascular diseases, chronic obstructive pulmonary disease, and chronic kidney disease. However, there is limited evidence regarding the socioeconomic disparities in treatment and financial protection among lung cancer patients following Thailand's health system reform in 2002.

The primary research question was whether there is any difference in financial burden among these three payment schemes and their QTE.

This study aimed to: (1) identify the magnitude of financial toxicities, defined as CHE and medical impoverishment, across the three payment schemes, and (2) compare the within-scheme financial toxicity across the three payment schemes. We hope our findings will be found helpful by the scientific community, policymakers, and healthcare providers.

Material and Methods

Data source

Data were extracted from the Hospital Information System (HIS) of Songklanagarind Hospital and face-to-face questionnaires were administered during interviews of all pathologically-proven lung cancer patients, who visited the oncology clinic from November 9, 2020 to June 6, 2022. The data from HIS comprised clinical information as well as data concerning height, weight, performance status, treatment options, histology, treatment regimen, and clinical response. The questionnaires covered the following domains: demographics, health status and functioning, healthcare scheme, income and consumption, and work loss of patients and their relatives. Together, the data provided information on the patients' tertiary healthcare center utilization, which included information related to the demographics, and the clinical, social, and economic status of persons with lung cancer, and also related to healthcare service utilization and costs.

Indicators

Medical expenditure information was collected during the interviews; it included total expenditure, reimbursement, and out-of-pocket expenditures for out-patient visits in the previous month and in-patient visits during the previous year. For the analysis of economic-related disparity, the annual household consumption expenditure, which included the domains of food, entertainment, education, and traveling, was used as a proxy to indicate the household economic status.

To measure the degree of financial risk, we used the CHE, which was defined as annual household health payments exceeding 40% of the capacity-to-pay (CTP), defined as non-food household costs, and medical

impoverishment, which was defined as total spending less than the computed subsistence expenditure plus the total out-of-pocket payments (OOP) health payments and not meeting the criteria for being poor.

According to previous studies, there are two types of CHE measurement OOP over 40% of the household's capacity to pay, or over 10% of total household expenditure. In this study, we defined CHE using the OOP/capacity-to-pay method[10]. Furthermore, the household's capacity to pay (denominator) was defined as the household's expenditure on non-food consumption, and the OOP expenditure (numerator) was defined as the sum of the respondents' and their spouses' medical OOP expenditure for out-patient and in-patient care over the previous year. CHE was coded as "yes" if the proportion was over 40% and "no" if it was not. The factors of age, sex, healthcare scheme, current and initial stage of lung cancer, type of current treatment, and the quintile of economic status were included as covariates.

Statistical analysis

Categorical data are presented in numbers (%). All of the cost data, discounted by the inflation adjustment factor (IAF) to be values in the year 2022, are presented as geometric means (S.D.) because of their right skewness property. QTE were created using ranking within each payment scheme. Chi-square tests were used to analyze the socio-demographic differences in treatment type, health service use, CHE, and medical impoverishment among our lung cancer participants. Concentration curves (CC) and concentration indexes (CI) were used to assess economic-related disparities among the health coverage schemes. The farther the CC lied from the equality line (45-degree line), the greater the degree of disparities in healthcare and expenditure were understood to be. The extension of the concentration index was simplified to the Erreygers index, which was used as an indicator of the degree of disparity[11,12].

Various logistic regression models were used to evaluate the effect of the QTE on the outcomes, including CHE and medical impoverishment. Firstly, the determinants of interest, QTE and payment schemes, were included in the model. Then, the interaction of QTE and payment schemes was added. Finally, other variables potentially associated with the outcomes were added and selectively removed using a backward stepwise procedure. Only for the medical impoverished outcome, the quadratic effect of QTE was added in the final two models. AIC, BIC, and AUC of logistic-ROC were used as an indicator of model performance.

Multivariable logistic regression models were applied to estimate the impacts of cancer treatment on CHE and medical impoverishment among the quintiles of total expenditure in each of the three main payment schemes after controlling for potential predictors of the outcomes. The probability of outcomes is presented graphically using the Delta-Margins method from the adjusted logistic regression. All statistical analyses were conducted using STATA 17.0. p-values of less than 0.05 were considered statistically significant.

Endnotes

US dollar was used as the currency of this study, and the exchange rate on June 7, 2022 was: 1 USD=30.72 THB.

Data sharing

Data sharing is applicable; please contact the author for data requests. Please note that all personal information such as the participants' names, addresses, ID numbers, and telephone numbers have been removed from the dataset.

Ethics approval and consent to participate

Ethical approval was obtained from the Human

Research Ethics Committee (HREC), Prince of Songkla University. The research protocol was reviewed, approved, and then implemented strictly throughout the study. The private information of patients, including name, address, ID number, and phone number, were removed from the dataset, and the participants' confidentiality was protected according to HIPPA criterea (Health Insurance Portability and Accountability Act of 1996).

Results

Sample characteristics

A total of 367 lung cancer patients were enrolled; their demographic characteristics are shown in Table 1. In total, 51% of patients were male, the median age of 65 years, and 56% were undergoing active treatment. The current medication regimens were chemotherapy (44%) and targeted/immune-oncotherapy [TKI/IO] (31%). The others were not receiving any medical treatment. Fifty-five percent initially presented as stage IV lung cancer. The histological subtypes were adenocarcinoma, squamous cell carcinoma and small cell carcinoma (86%, 8% and 3%, respectively). Fifty-five percent had no/unknown driver mutation, and 38% of the patients had the EGFR mutation. Paclitaxel-carboplatin (Pac/Cb) was the most commonly prescribed first-line treatment comprising 38% of cases, followed by 18% gefitinib and 15% erlotinib. Forty-four percent of patients were treated with docetaxel in the second-line setting.

Expenditure data

The total annual OOP payment comprised drug costs that were not reimbursed, non-medical costs, food costs, supplements costs, accommodation costs, transportation costs, in-patient costs, house improvement/facility costs, and caregiver costs (Table 2). The geometric means (geometric standard deviation, GSD) of the total annual costs were 1513 (4.6), 1674 (3.0), and 1252 (7.1) in UCS, CSMBS, and SSS, respectively. Most costs were not statistically different between the payment schemes except for supplements costs and extra-medical costs for hospitalized patients, which were highest in the CSMBS group.

CHE and medical impoverishment

CHE was experienced by 64%, 66% and 59% in UCS, CSMBS and SSS, respectively. Among patients under UCS, 38% were already impoverished, and a further 28% became impoverished owing to medical-related expenses. The corresponding values among CSMBS patients were 21% and 28%, and among SSS patients, they were 27% and 32%.

One-fourth (28.4%) of the patients met the criteria for being poor before incurring healthcare costs, and about 90% of the lowest quintiles were also in the poor group. Medical impoverishment was experienced by 9.6% in the lowest quintile groups; the proportion of such patients rose to 42.7% and 41.3% in the second and third quintiles, respectively. After that, the percentages of medical impoverishment decreased to 31.7% and 16.4% in the highest two quintiles (Table 3).

Concentration curve and concentration index

The inequity related to CHE (Figure 1A) and medical impoverishment (Figure 1B) are presented as concentration curves. In CHE, the upper-left shift of concentration curves from the line of equity (diagonal line) in all payment schemes indicated that CHE occurred more frequently in less wealthy patients. The concentration curve for CHE in the CSMBS group was far from the line of equity, meaning that there was more inequity in the CSMBS group. The concentration indices were -0.36, -0.59, and -0.47 in UCS, CSMBS, and SSS, respectively. The difference in the CI among payment schemes was statistically significant only between UCS and CSMBS groups (diff.=-0.226, p-value 0.037).

Table 1 Demographic data

Variable	UCS (n=158)	CSMBS (n=187)	SSS (n=22)	Total (N=367)	p-value
Stage of treatment, n=367					0.371
Early	56 (35.4)	56 (29.9)	7 (31.8)	119 (32.4)	
First-line	71 (44.9)	78 (41.7)	11 (50.0)	160 (43.6)	
Second-line or more	31 (19.6)	53 (28.3)	4 (18.2)	88 (24.0)	
Current status, n=367					0.680
Active Rx	85 (53.8)	109 (58.3)	13 (59.1)	207 (56.4)	
Complete Rx	73 (46.2)	78 (41.7)	9 (40.9)	160 (43.6)	
Current Rx type, n=367					0.507
No	40 (25.3)	44 (23.5)	6 (27.3)	90 (24.5)	
CMT	76 (48.1)	78 (41.7)	8 (36.4)	162 (44.1)	
Tki/IO	42 (26.6)	65 (34.8)	8 (36.4)	115 (31.3)	
Sex, n=367					0.306
Male	76 (48.1)	102 (54.5)	9 (40.9)	187 (51.0)	
Female	82 (51.9)	85 (45.5)	13 (59.1)	180 (49.0)	
Initial stage, n=367					0.647
1A	27 (17.1)	29 (15.5)	4 (18.2)	60 (16.3)	
1B	6 (3.8)	16 (8.6)	3 (13.6)	25 (6.8)	
2A	2 (1.3)	6 (3.2)	1 (4.5)	9 (2.5)	
2B	10 (6.3)	6 (3.2)	1 (4.5)	17 (4.6)	
3A	11 (7.0)	14 (7.5)	2 (9.1)	27 (7.4)	
3B	9 (5.7)	13 (7.0)	0 (0.0)	22 (6.0)	
3C	3 (1.9)	2 (1.1)	0 (0.0)	5 (1.4)	
4A	55 (34.8)	51 (27.3)	7 (31.8)	113 (30.8)	
4B	35 (22.2)	50 (26.7)	4 (18.2)	89 (24.3)	
T stage, n=367					0.485
1a	5 (3.2)	3 (1.6)	0 (0.0)	8 (2.2)	
1b	15 (9.5)	22 (11.8)	1 (4.5)	38 (10.4)	
1c	28 (17.7)	34 (18.2)	7 (31.8)	69 (18.8)	
2a	21 (13.3)	28 (15.0)	7 (31.8)	56 (15.3)	
2b	18 (11.4)	21 (11.2)	1 (4.5)	40 (10.9)	
3	29 (18.4)	32 (17.1)	2 (9.1)	63 (17.2)	
4	42 (26.6)	47 (25.1)	4 (18.2)	93 (25.3)	
N stage, n=367					0.458
0	71 (44.9)	83 (44.4)	10 (45.5)	164 (44.7)	
1	12 (7.6)	15 (8.0)	1 (4.5)	28 (7.6)	
2	33 (20.9)	51 (27.3)	3 (13.6)	87 (23.7)	
3	42 (26.6)	38 (20.3)	8 (36.4)	88 (24.0)	
M stage, n=367					0.902
0	71 (44.9)	86 (46.0)	11 (50.0)	168 (45.8)	
1	87 (55.1)	101 (54.0)	11 (50.0)	199 (54.2)	
Pathology, n=367					0.242
Adenocarcinoma	128 (81.0)	165 (88.2)	22 (100.0)	315 (85.8)	
Squamous cell CA	16 (10.1)	15 (8.0)	0 (0.0)	31 (8.4)	
SCLC	6 (3.8)	6 (3.2)	0 (0.0)	12 (3.3)	
NSCLC NOS	3 (1.9)	0 (0.0)	0 (0.0)	3 (0.8)	
Adenosquamous CA	3 (1.9)	1 (0.5)	0 (0.0)	4 (1.1)	
LCNET	2 (1.3)	0 (0.0)	0 (0.0)	2 (0.5)	
Biomarker, n=367					0.646
NOS/unknown	95 (60.1)	93 (49.7)	13 (59.1)	201 (54.8)	
EGFR	55 (34.8)	78 (41.7)	7 (31.8)	140 (38.1)	
ALK	8 (5.1)	14 (7.5)	2 (9.1)	24 (6.5)	
MET14	0 (0.0)	1 (0.5)	0 (0.0)	1 (0.3)	
ROS1	0 (0.0)	1 (0.5)	0 (0.0)	1 (0.3)	

Table 1 (continued)

Variable	UCS (n=158)	CSMBS (n=187)	SSS (n=22)	Total (N=367)	p-value
Definite surgery, n=367					0.115
No	112 (70.9)	121 (64.7)	11 (50.0)	244 (66.5)	
Sx	46 (29.1)	66 (35.3)	11 (50.0)	123 (33.5)	
Curative XRT, n=367					0.540
No	151 (95.6)	181 (96.8)	22 (100.0)	354 (96.5)	
Curative XRT	7 (4.4)	6 (3.2)	0 (0.0)	13 (3.5)	
Adjuvant CMT, n=367					0.437
No	139 (88.0)	169 (90.4)	18 (81.8)	326 (88.8)	
Adj CMT	19 (12.0)	18 (9.6)	4 (18.2)	41 (11.2)	
CCRT, n=367					0.218
No	141 (89.2)	172 (92.0)	22 (100.0)	335 (91.3)	
CCRT	17 (10.8)	15 (8.0)	0 (0.0)	32 (8.7)	
First-line, n=244					0.107
Afatinib	13 (12.9)	6 (4.7)	2 (13.3)	21 (8.6)	
Alectinib	0 (0.0)	2 (1.6)	1 (6.7)	3 (1.2)	
Atezo Tirago	0 (0.0)	1 (0.8)	0 (0.0)	1 (0.4)	
Atezolizumab	0 (0.0)	1 (0.8)	0 (0.0)	1 (0.4)	
Brigatinib	0 (0.0)	1 (0.8)	0 (0.0)	1 (0.4)	
CAV	1 (1.0)	0 (0.0)	0 (0.0)	1 (0.4)	
Carbo_Eto	0 (0.0)	1 (0.8)	0 (0.0)	1 (0.4)	
Ceritinib	4 (4.0)	7 (5.5)	1 (6.7)	12 (4.9)	
Cis Eto	3 (3.0)	2 (1.6)	0 (0.0)	5 (2.0)	
Crizotinib	1 (1.0)	3 (2.3)	0 (0.0)	4 (1.6)	
Docetaxel	2 (2.0)	1 (0.8)	0 (0.0)	3 (1.2)	
Durvalumab	1 (1.0)	0 (0.0)	0 (0.0)	1 (0.4)	
Erlotinib	20 (19.8)	13 (10.2)	4 (26.7)	37 (15.2)	
Eto Cb	0 (0.0)	1 (0.8)	0 (0.0)	1 (0.4)	
Gefitinib	4 (4.0)	39 (30.5)	0 (0.0)	43 (17.6)	
Gemcitabine	2 (2.0)	1 (0.8)	0 (0.0)	3 (1.2)	
MEDI5752	1 (1.0)	1 (0.8)	0 (0.0)	2 (0.8)	
Osimertinib	2 (2.0)	2 (1.6)	0 (0.0)	4 (1.6)	
Pac Cb	43 (42.6)	44 (34.4)	7 (46.7)	94 (38.5)	
Pac Cb Beva	1 (1.0)	1 (0.8)	0 (0.0)	2 (0.8)	
Pac Cb Pemb	1 (1.0)	0 (0.0)	0 (0.0)	1 (0.4)	
Pem Cb	0 (0.0)	1 (0.8)	0 (0.0)	1 (0.4)	
Pem Cb Osimer	1 (1.0)	0 (0.0)	0 (0.0)	1 (0.4)	
Pem Cb Pemb ACZ	1 (1.0)	0 (0.0)	0 (0.0)	1 (0.4)	
Second-line, n=86					0.076
Afatinib	3 (10.3)	0 (0.0)	0 (0.0)	3 (3.5)	
Ceritinib	0 (0.0)	2 (3.8)	0 (0.0)	2 (2.3)	
Docetaxel	12 (41.4)	13 (24.5)	1 (25.0)	26 (30.2)	
Erlotinib	1 (3.4)	1 (1.9)	0 (0.0)	2 (2.3)	
Gefitinib	0 (0.0)	5 (9.4)	2 (50.0)	7 (8.1)	
Osimertinib	1 (3.4)	8 (15.1)	0 (0.0)	9 (10.5)	
Pac_Cb	12 (41.4)	22 (41.5)	1 (25.0)	35 (40.7)	
Pem Cb	0 (0.0)	1 (1.9)	0 (0.0)	1 (1.2)	
Pem Cis	0 (0.0)	1 (1.9)	0 (0.0)	1 (1.2)	

Table 1 (continued)

Variable	UCS (n=158)	CSMBS (n=187)	SSS (n=22)	Total (N=367)	p-value
Third-line, n=25					0.220
Afatinib	1 (25.0)	0 (0.0)	0 (0.0)	1 (4.0)	
Atezolizumab	1 (25.0)	1 (5.6)	1 (33.3)	3 (12.0)	
Docetaxel	1 (25.0)	9 (50.0)	1 (33.3)	11 (44.0)	
Erlotinib	1 (25.0)	1 (5.6)	0 (0.0)	2 (8.0)	
Gefitinib	0 (0.0)	3 (16.7)	0 (0.0)	3 (12.0)	
Gemcitabine	0 (0.0)	0 (0.0)	1 (33.3)	1 (4.0)	
Osimertinib	0 (0.0)	1 (5.6)	0 (0.0)	1 (4.0)	
Pac Cb	0 (0.0)	1 (5.6)	0 (0.0)	1 (4.0)	
Pemetrexed	0 (0.0)	2 (11.1)	0 (0.0)	2 (8.0)	

UCS=Universal Coverage Scheme, CSMBS=Civil Servant Medical Benefit Scheme, SSS=Social Security Scheme, Rx=treatment, CMT=chemotherapy, CA= carcinoma, SCLC=small cell lung cancer, NSCLC=non-small cell lung cancer, NOS=not, LCNET=large cell neuroendocrine tumor, EGFR=epidermal growth factor receptor, ALK=anaplastic lymphoma kinase, MET14=MET exon 14 skipping mutation, ROS1=ROS 1 mutation, XRT=radiotherapy, CCRT=concurrent chemoradiotherapy, CAV=cyclophosphamide/adriamycin/vincristine, ACZ=canakinumab, Sx=surgery

Table 2 Demographic cost data in USD (geometrics mean)

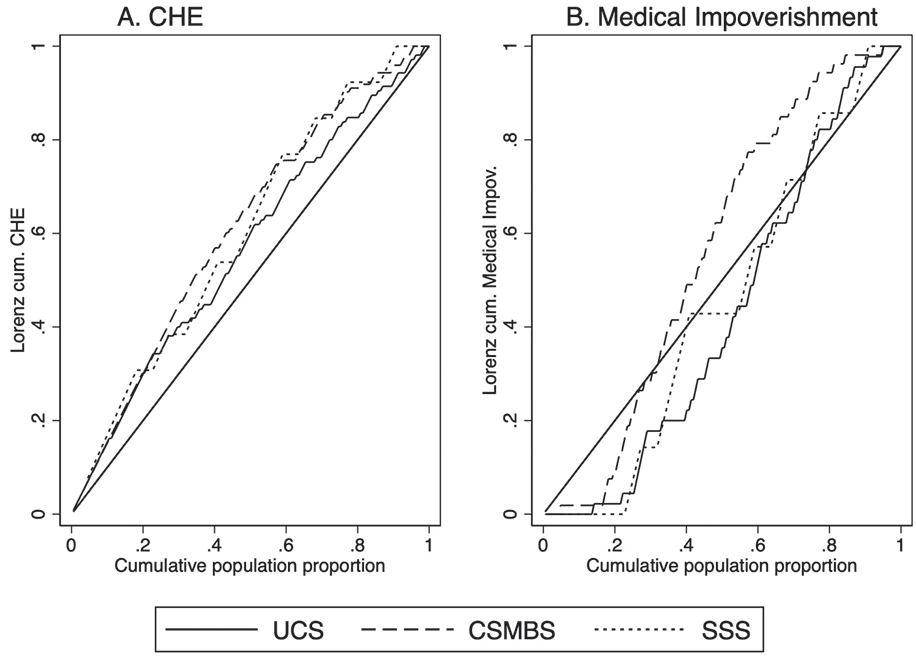
Variable	UCS (n=158)	CSMBS (n=187)	SSS (n=22)	Total (N=367)	p-value
Annual extra-medical cost for OPD, n=367	1,091.1 (22.1)	112.0 (28.9)	1,209.4 (40.5)	433.2 (30.3)	0.186
Annual extra-medical cost for OPD visit at other hospital, n=367	1,723.5 (6.2)	464.5 (4.7)	720.4 (1.8)	905.3 (5.4)	0.920
Annual drug cost outside hospital, n=367	50.5 (3.5)	58.6 (3.4)	60.8 (1.8)	55.6 (3.3)	0.527
Annual herbal supplement cost, n=367	359.4 (2.7)	236.9 (3.8)	324.7 (5.1)	267.2 (3.5)	0.524
Annual supplement cost, n=367	456.8 (2.3)	593.3 (2.7)	451.3 (2.8)	527.0 (2.5)	<0.001
Annual extra-medical cost for IPD, n=223	92.8 (6.0)	210.8 (3.9)	63.7 (9.3)	144.7 (5.2)	<0.001
Annual OOP for medical cost, n=367	686.3 (7.6)	834.1 (4.2)	776.6 (10.7)	764.5 (5.8)	0.059
Annual non-medical cost for OPD visit at study hospital, n=367	357.7 (3.6)	307.4 (3.4)	372.8 (5.7)	330.9 (3.6)	0.786
Annual food cost for OPD visit at study hospital, n=348	84.0 (3.7)	82.4 (3.2)	110.0 (3.7)	84.3 (3.4)	0.945
Annual stay cost for OPD visit at study hospital, n=348	294.9 (8.5)	675.0 (4.5)	1237.1 (3.1)	465.1 (6.5)	0.379
Annual non-medical cost for OPD visit at study hospital, n=367	357.7 (3.6)	307.4 (3.4)	372.8 (5.7)	330.9 (3.6)	0.786
Annual IPD cost, n=367	45.9 (2.1)	37.0 (2.4)	27.9 (2.3)	39.7 (2.3)	0.676
Annual house improvement and facility cost, n=367	409.8 (4.7)	475.3 (4.8)	309.3 (3.8)	439.6 (4.6)	0.798
Annual cost of formal caregiver, n=367	692.4 (4.6)	2,933.6 (2.5)	811.5*	1,486.3 (4.0)	0.992
Annual OOP for non-medical expenses, n=367	453.0 (3.9)	477.2 (3.8)	317.5 (5.7)	455.8 (3.9)	0.284
Total annual OOP, n=367	1,512.9 (4.6)	1,674.2 (3.0)	1,251.6 (7.1)	1,575.4 (3.9)	0.321

UCS=Universal Coverage Scheme, CSMBS=Civil Servant Medical Benefit Scheme, SSS=Social Security Scheme, OPD=out patient department, OOP=out-of-pocket, IPD=in patient department
*only one patient in SSS group had a formal caregiver

Table 3 Impoverishment by TE Quintile: all, n (col %)

Variable	UCS (n=158)	CSMBS (n=187)	SSS (n=22)	Total (N=367)	p-value
Pre-OOP impoverishment, n=367	60 (38.0)	39 (20.9)	6 (27.3)	105 (28.6)	0.002
Medical impoverishment, n=367	44 (27.8)	53 (28.3)	7 (31.8)	104 (28.3)	0.928
CHE, n=367	102 (64.6)	123 (65.8)	13 (59.1)	238 (64.9)	0.820

UCS=Universal Coverage Scheme, CSMBS=Civil Servant Medical Benefit Scheme, SSS=Social Security Scheme, OOP=out-of-pocket, CHE=catastrophic health expenditure



CHE=catastrophic health expenditure, UCS=Universal Coverage Scheme, CSMBS=Civil Servant Medical Benefit Scheme, SSS=Social Security Scheme

Figure 1 Concentration curves for payment schemes and cumulative proportions of catastrophic health expenditure (A) and medical impoverishment (B)

The medical impoverishment concentration curves started below the diagonal line. Then they moved closer to the line of equity only in UCS and SSS; the CI line, on the other hand, crossed above the line of equity in CSMBS. The concentration indexes for medical impoverishment were 0.16, −0.15, and 0.10 in UCS, CSMBS, and SSS, respectively. Only the CI of CSMBS showed a statistically significant difference from that of UCS (diff.=−0.310, p-value 0.005).

Logistic regression modeling

The results of the logistic regression models for CHE are shown in Table 4. The multivariable-adjusted

interaction model had the best fit based on AIC/BIC and also the highest discriminating power (AUC=0.82).

Figure 2A shows the probabilities of CHE computed from the final-adjusted logistic model with the interaction of QTE and payment schemes with the adjusted covariates mentioned above. In the lowest quintile, the probability of CHE was highest in the CSMBS group (0.94 [0.89–0.98]), followed by SSS (0.84 [0.62–1.01]), and UCS (0.83 [0.75–0.92]). The probability of CHE gradually decreased as the QTE increased. In the highest quintiles, the probabilities of CHE were highest in UCS (0.42 [0.29-0.55]), but it had a value of about one-fifth in CSMBS and SSS.

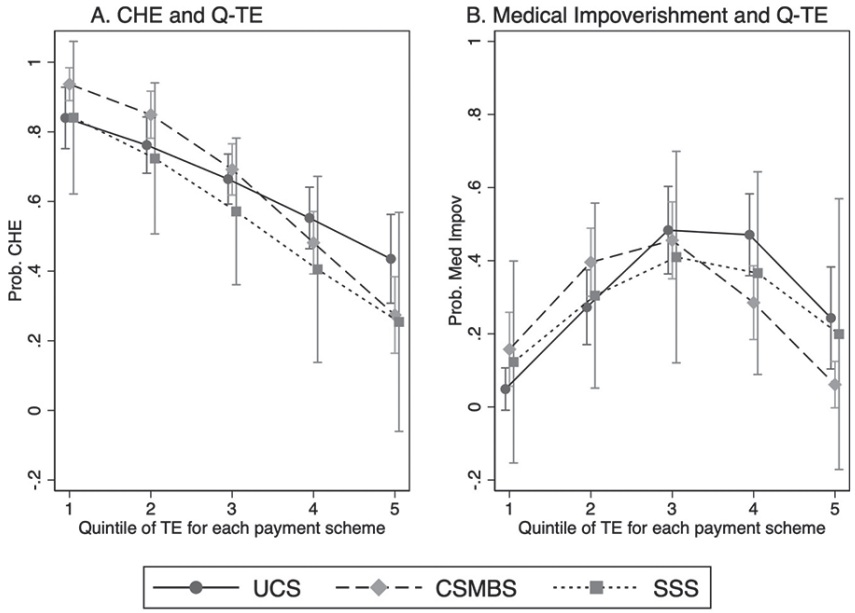
The logistic regression models for medical impoverishment are illustrated in Table 5. The multivariable-adjusted interaction with a quadratic term of the QTE model showed the best fit and the highest discriminating power (AUC=0.81).

Figure 2B shows the probabilities of medical impoverishment computed from the multivariable-adjusted interaction with a quadratic term for the QTE model. The probabilities of medical impoverishment in the lowest quintile were low in all payment schemes—0.05 [0–0.11] in UCS, 0.14 [0.04–0.24] in CSMBS, and 0.12 [-0.15–0.39] in SSS. For each payment scheme, they reached the highest levels at the third quintile—0.47 [0.35–0.60] in UCS, 0.46 [0.36–0.57] in CSMBS, and 0.41 [0.12–0.70] in SSS.

Table 4 Odds ratio and 95% confidence interval for catastrophic health expenditure from various logistic models

Variable	Naive	IntAct	IntAct_Adj
QTE for each payment scheme	0.500 (0.417, 0.599)	0.620 (0.482, 0.798)	0.574 (0.435, 0.757)
CSMBS	1.039 (0.637, 1.696)	4.704 (1.200, 18.437)	4.859 (1.124, 21.006)
SSS	0.721 (0.263, 1.973)	1.106 (0.090, 13.554)	1.262 (0.092, 17.283)
CSMBS x QTE for each payment scheme		0.635 (0.433, 0.931)	0.627 (0.416, 0.944)
SSS x QTE for each payment scheme		0.882 (0.421, 1.848)	0.802 (0.361, 1.783)
Complete Rx			0.217 (0.127, 0.368)
Progression			5.679 (1.525, 21.148)
Intercept	16.308 (8.062, 32.986)	8.027 (3.314, 19.442)	20.047 (7.008, 57.342)
AIC	416	415	377
BIC	432	438	409
LROC_AUC	0.751	0.750	0.820

Naïve – the logistic model with QTE and payment schemes as determinators for catastrophic health expenditure, IntAct – the logistic model with QTE interaction with payment schemes as determinators for CHE, IntAct_Adj – the logistic model with QTE interaction with payment schemes as determinators for CHE and backward stepwise removal of other covariates, CSMBS=Civil Servant Medical Benefit Scheme, SSS=Social Security Scheme, QTE=quintile of total expenditure, AIC=akaike information criterion, BIC=Bayesian Information Criterion, LROC_AUC=area under the curve of logistic model



UCS=Universal Coverage Scheme, CSMBS=Civil Servant Medical Benefit Scheme, SSS=Social Security Scheme, CHE=catastrophic health expenditure, Q-TE=quintile of total expenditure

Figure 2 Delta-Margin probabilities of catastrophic health expenditure (A) and medical impoverishment (B) according to logistic regression models

Table 5 Odds ratio and 95% confidence interval for medical impoverishment according to various logistic models

Variable	Naive	Int_L_qTE_noAdj	Int_Q_qTE_noAdj	Int_qTE_Adj
QTE for each payment scheme	1.028	1.342	24.360	52.162
	(0.876, 1.207)	(1.041, 1.730)	(4.282, 138.568)	(7.707, 353.017)
CSMBS	1.026	4.702	5.735	6.214
	(0.640, 1.643)	(1.496, 14.773)	(0.222, 148.393)	(0.187, 206.350)
SSS	1.211	1.797	4.420	10.711
	(0.463, 3.171)	(0.175, 18.406)	(0.011, 1727.284)	(0.011, 1.1e+04)
CSMBS x QTE for each payment		0.601	0.719	0.632
scheme		(0.426, 0.848)	(0.076, 6.783)	(0.057, 7.045)
SSS x QTE for each payment scheme		0.886	0.530	0.236
		(0.444, 1.769)	(0.009, 33.010)	(0.002, 27.583)
QTE for each payment scheme x QTE for each			0.632	0.565
payment scheme			(0.486, 0.822)	(0.422, 0.755)
CSMBS x QTE for each payment scheme x QTE for			0.931	0.944
each payment scheme			(0.650, 1.334)	(0.642 ,1.388)
SSS x QTE for each payment scheme x QTE for			1.067	1.198
each payment scheme			(0.555, 2.053)	(0.562, 2.551)
Complete Rx				0.258
				(0.123, 0.539)
Progression				8.372
				(2.275, 30.804)

Table 5 (continued)

Variable	Naive	Int_L_qTE_noAdj	Int_Q_qTE_noAdj	Int_qTE_Adj
1B				1.458 (0.386, 5.512)
2A				2.532 (0.394, 16.258)
2B				1.333 (0.302, 5.882)
3A				2.846 (0.870, 9.316)
3B				0.908 (0.220, 3.751)
3C				1.599 (0.191, 13.413)
4A				1.005 (0.386, 2.615)
4B				1.600 (0.597, 4.289)
Equivalence of household size				0.514 (0.278, 0.951)
EGFR				0.770 (0.406, 1.462)
ALK				3.419 (1.076, 10.863)
MET 14				1.000
Intercept	0.355 (0.196, 0.643)	0.155 (0.064, 0.379)	0.003 (0.000, 0.049)	0.005 (0.000, 0.107)
AIC	445	440	408	381
BIC	461	464	443	467
LROC_AUC	0.518	0.592	0.697	0.810

Naïve – the logistic model with QTE and payment schemes as determinators for medical impoverishment, Int_L_qTE_noAdj – the logistic model with QTE interaction with payment schemes as determinators for medical impoverishment, Int_Q_qTE_noAdj – the logistic model with quadratic-QTE interaction with payment schemes as determinators for medical impoverishment, Int_qTE_Adj the logistic model with quadratic-QTE interaction with payment schemes as determinators for medical impoverishment and backward stepwise removal of other covariates
CSMBS=Civil Servant Medical Benefit Scheme, SSS=Social Security Scheme, QTE=quintile of total expenditure, EGFR=Epidermal Growth Factor Receptor, ALK=anaplastic lymphoma kinase, AIC=akaike information criterion, BIC=Bayesian Information Criterion, LROC_AUC=area under the curve of logistic model

Discussion

The percentage of poverty ranked from highest to lowest in UCS, SSS and CSMBS, respectively, but there was no substantial difference in the proportion of patients becoming impoverished owing to medical expenses; in each scheme, that proportion was around 30%. Socioeconomic disparities based on CHE and medical impoverishment were evident in each payment scheme, but the gradient of CHE probability was more marked among CSMBS patients. If not impoverished already, the probability of medical impoverishment reached a peak in all payment schemes in the middle quintile and declined thereafter.

An unexpected finding was the greater socio-economic disparity in the experience of CHE and medical impoverishment among CSMBS compared to UCS participants. One possible explanation is that CSMBS patients included the parents of people who work for the government, which was not the case for UCS patients,

and the definition of CHE is based on the ratio of the total OOP cost to the total substantial non-food expenditure, which is usually low among the elderly living alone. Another possible explanation is that the CSMBS patients, even those in the lower quintile, as a result of their sociodemographic characteristics, may tend to prefer premium services or be more willing to pay for comfort and convenience in comparison to their UCS counterparts; this entails supplementary and extra medical costs as suggested by the data presented in Table 2.

As expected, CHE in the present study occurred more frequently among the lowest quintile groups. This finding is consistent with a study from China. Leng et al.[3] studied the probability of CHE at the end-of-life period in cancer patients. Even though that study focused only on the end-of-life period, CHE occurred in 100% of the lowest three quintiles, which was much higher than the proportion found in the present study. A possible explanation for this is the severe wealth inequities in China, where the wealthiest 1% own more than 33% of the total national household wealth, while the poorest 25% own less than 2%.

Fu et al.[5] reported post-treatment impoverishment rates of 47%, 15%, 9%, 5% and 3% in cancer patients in China in quintiles one to five, respectively. These proportions include a range similar to that of the proportion of medical impoverishment in the present study but in a different pattern. In the Chinese study, the proportion decreased as the quintile increased, whereas in the present study, the proportions peaked in the middle quintiles. This is because the Chinese study included patients, who were already impoverished before experiencing medical-related expenses. In contrast, in the present study, medical impoverishment patients did not comprise patients, who were already poor.

There are two main methodological issues at play in our research. First, the present study used total expenditure as a proxy for living standard/wealth. It is still debatable whether or not it is appropriate to use expenditure instead of income to determine one's living standard/wealth. Income and expenditure data are both challenging to collect accurately. However, there are a number of people, who do not have formal work or salary, especially in developing countries; meanwhile, there are also those who may be reluctant to expose their true income. On the other hand, it is more convenient to answer a questionnaire about expenditure by referring to purchasing particular goods or services. Second, to define the QTE, the authors decided to rank the quintiles within each payment scheme as an independent variable, which is not directly translatable into real-life meaning, instead of ranking them by overall participants. However, no matter the method of ranking chosen, there are always limitations associated with it.

There are at least three limitations in this study. First, this is a single university hospital study in Thailand; therefore, the patients receiving healthcare treatment there may differ in terms economics, educational level, and expectations from those seeking treatment in private/provincial hospitals around the country. Second, the distribution of the stages of the disease may not resemble the true incidence of the disease because of survival bias, as patients who live longer have a greater chance of being included in such a study than patients who have a shorter survival. Finally, the authors did not adjust for the participant's place of residence; distance from the health facility should affect the commute cost and time spent during the medical follow-up period.

This study employed intensive data extraction and detailed questionnaire interviewing, especially in respect to cost data. Data analyses were performed using multiple patterns of regression and the best fit model chosen.

Conclusion

In all three payment schemes for lung cancer patients in Thailand, CHE and medical impoverishment occurred in

around 60% and 30% of patients, respectively. The gradient of CHE probability was more prominent among CSMBS patients, and, if not impoverished already, the probability of medical impoverishment reached a peak in all payment schemes in the middle quintile and declined thereafter.

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Conflict of interest

Both authors declare that they have no competing interests.

References

1. Cicin I, Oksuz E, Karadurmus N, Malhan S, Gumus M, Yilmaz U, et al. Economic burden of lung cancer in Turkey: a cost of illness study from payer perspective. Health Econ Rev 2021;11:22.
2. Vahedi S, Rezapour A, Khiavi FF, Esmaeilzadeh F, Javan-Noughabi J, Almasiankia A, et al. Decomposition of socioeconomic inequality in catastrophic health expenditure: an evidence from Iran. Clin Epidemiol Glob Health 2020;8:437–41.
3. Leng A, Jing J, Nicholas S, Wang J. Catastrophic health expenditure of cancer patients at the end-of-life: a retrospective observational study in China. BMC Palliat Care 2019;18:43.
4. Sun C yao, Shi J fang, Fu W qi, Zhang X, Liu G xiang, Chen W qing, et al. Catastrophic health expenditure and its determinants in households with lung cancer patients in China: a retrospective cohort study. BMC Cancer 2021;21:1323.
5. Fu W, Shi J, Zhang X, Liu C, Sun C, Du Y, et al. Effects of cancer treatment on household impoverishment: a multicentre cross-sectional study in China. BMJ Open 2021;11:e044322.
6. Zhao Y, Zhang L, Fu Y, Wang M, Zhang L. Socioeconomic disparities in cancer treatment, service utilization and catastrophic health expenditure in china: a cross-sectional analysis. Int J Environ Res Public Health 2020;17:E1327.
7. Zhang X, Liu S, Liu Y, Du J, Fu W, Zhao X, et al. Economic burden for lung cancer survivors in Urban China. Int J Environ Res Public Health 2017;14:308.
8. Tangcharoensathien V, Witthayapipopsakul W, Panichkriangkrai W, Patcharanarumol W, Mills A. Health systems development in Thailand: a solid platform for successful implementation of universal health coverage. Lancet 2018;391:1205–23.
9. Hughes D, Leethongdee S. Universal coverage in the land of smiles: lessons from Thailand's 30 Baht health reforms. Health Aff (Millwood) 2007;26:999–1008.
10. Buigut S, Ettarh R, Amendah DD. Catastrophic health expenditure and its determinants in Kenya slum communities. Int J Equity Health 2015;14:46.
11. O'Donnell O, O'Neill S, Van Ourti T, Walsh B. conindex: Estimation of concentration indices. Stata J 2016;16:112–38.
12. Jenkins S. Estimation and interpretation of measures of inequality, poverty, and social welfare using Stata [monograph on the Internet]. Stata Users Group; 2008 [cited 2022 Jun 7]. Available from: https://econpapers.repec.org/paper/bocasug06/16.htm