

# BMJ Open Impact of differential copayment on patient healthcare choice: evidence from South Korean National Cohort Study

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## ABSTRACT

**Objective** We evaluate the effectiveness of mild disease differential copayment policy aimed at reducing unnecessary patient visits to secondary/tertiary healthcare institutions in South Korea.

**Design** Retrospective study using difference-in-difference design.

**Setting** Sample Research database provided by the Korean National Health Insurance Service, between 2010 and 2013.

**Participants** 206 947 patients who visited healthcare institutions to treat mild diseases during the sample period.

**Methods** A linear probability model with difference-in-difference approach was adopted to estimate the changes in patients' healthcare choices associated with the differential copayment policy. The dependent variable was a binary variable denoting whether a patient visited primary healthcare or secondary/tertiary healthcare to treat her/his mild disease. Patients' individual characteristics were controlled with a fixed effect.

**Results** We observed significant decrease in the proportion of patients choosing secondary/tertiary healthcare over primary healthcare by 2.99 per cent point. The decrease associated with the policy was smaller by 14% in the low-income group compared with richer population, greater by 19% among the residents of Seoul metropolitan area than among people living elsewhere, and greater among frequent healthcare visitors by 33% than among people who less frequently visit healthcare.

**Conclusion** The mild disease differential copayment policy of South Korea was successful in discouraging unnecessary visits to secondary/tertiary healthcare institutions to treat mild diseases that can be treated well in primary healthcare.

## INTRODUCTION

Excess demand for secondary and tertiary hospitals is a major healthcare challenge in many countries (eg, China, Australia), resulting in overcrowding, long wait list, safety and inefficiency issues in public health.<sup>1–3</sup> The South Korean government has also recognised it as a major problem and taken steps to address it.<sup>4–6</sup> In most countries, each tier of healthcare has its own role. In the case of South Korea (see Ministry of Health and Welfare Notification No. 2011-69), primary

## Strengths and limitations of this study

- The control group of this study provided a good counterfactual benchmark to precisely measure the change associated with the policy.
- Since the policy of this study pertains to mild diseases only, we could avoid the omitted variable problem due to unobserved disease severity.
- This study limited the subjects to similar pairs of mild diseases to construct a comparable control-treatment group setting.

care should deal with outpatients for mild and common diseases, secondary care should deal with general hospitalizations and surgical care, and tertiary care should deal with treatments requiring high-level medical specialty. However, substantial proportion of mild disease patients visit secondary/tertiary hospitals. 'Mild diseases' refer to the diseases with minor symptoms or illnesses designated by the Ministry of Health and Welfare and these diseases can mostly be treated well in primary healthcare.<sup>7</sup> In 2011, 4.7% of total patient visits to treat mild diseases were at secondary/tertiary healthcare facilities while the number of secondary/tertiary healthcare facilities was 319 (1.1%) and that of primary healthcare was 30 197 (98.9%). As patient visits to treat mild diseases increase, secondary/tertiary healthcare needs to allocate more resources to meet the demand, generating the inefficiency in attaining its main goal (ie, to focus on severe or complicated cases).<sup>8,9</sup> Lee *et al*<sup>4</sup> reported that among the outpatient usage of secondary/tertiary hospitals, approximately 85% can be sufficiently treated in primary healthcare.

A frequently used policy to tackle the excess demand problems in secondary and tertiary healthcare by governments is strengthening the gatekeeping role of the primary healthcare sector.<sup>10,11</sup> In many countries (eg, the UK and the Scandinavian countries), patients cannot directly access secondary



or tertiary healthcare without referral from primary healthcare.<sup>12</sup> Similarly, in South Korea, treatment at secondary or tertiary healthcare requires a referral letter from a primary care doctor. However, referral letters are frequently written at a patient's request and do not always reflect an actual need for care from higher level hospitals.<sup>13</sup> Since the referral has no expiration date, the patient no longer needs a new referral when she/he visits to treat different diseases at the same department of the same hospital later. All in all, the South Korean referral system has failed in the gatekeeping role.

Another approach used to mitigate the excess demand problem is that of differential copayment.<sup>14–16</sup> In fact, the Korean government implemented a mild disease differential copayment policy in 2011. The policy imposed differential coinsurance rate on the prescribed medication when a patient visits healthcare due to mild disease. Before the policy, patients paid 30% of the prescribed medication cost regardless of the tier of healthcare he or she visited. After the implementation of the policy, patients paid 40% (50%) of the cost when the prescription was issued at secondary (tertiary) healthcare. The coinsurance rate was maintained at 30% when the prescription is issued at primary healthcare. That is, the copayment for medication increased by 33% or 67% when patient visited secondary or tertiary healthcare due to mild disease. Given the differential roles of secondary and tertiary healthcare, larger increase in the coinsurance rate was imposed on tertiary healthcare. The policy does not involve any cap on the cost of medication or the length of time the medication is required (In South Korea, prescriptions are usually valid for 3 days from the issued date. Medical institutions usually prescribes drugs for 14 days on average).<sup>17</sup> The rationale for the policy was that since the selected 52 diseases were mild ones that could be treated well in a primary healthcare, the extra cost would discourage patients from visiting secondary/tertiary healthcare institutions to treat these diseases.

The results from previous studies on the effects of differential copayment policies have been mixed.<sup>15 18 19</sup> Moreover, some study results should be interpreted with caution because many of them used aggregate measures (eg, annual number of visits, total expenditures) without controlling for potential confounding effects. Huang and Tung<sup>18</sup> investigated if elderly Taiwanese patients' hospital tier choices have changed due to differential user charge using simple statistical tests ( $\chi^2$  test, analysis of variance, Scheffé test). They found that the impact was too small to be practically significant. Rosen *et al*<sup>20</sup> investigated the effect of differential copayment on specialist visits in Israel using the difference-in-difference (DID) approach where they assigned medical beneficiaries who are exempted from the cost sharing as the control group. They found that the differential copayment policy failed to restrain visits to specialist physicians. As they noted, however, there were systematic differences between treatment group (non-medical beneficiaries) and control group (medical beneficiaries) and potential confounding was

not ruled out. There have been a few empirical studies that investigated the effect of differential copayment policy of South Korea but they had the same limitations as the above cited papers—namely, no rigorous handling of the confounding effects.<sup>21–23</sup> Hone *et al*<sup>24</sup> performed a systematic review to evaluate the impact of introducing differential user charges on healthcare service utilisation. They found that the introduction of or increase in user charges for secondary care are associated with decreased secondary care utilisation. However, they concluded that the impact of introducing differential user charges on primary care utilisation remains uncertain.

The main goal of this study is to examine the effectiveness of the differential copayment policy aimed at reducing unnecessary patient visits to secondary/tertiary healthcare institutions using detailed and representative individual-level data provided by the Korea National Health Insurance Services (KNHIS) and a DID approach.

## DATA

This study used the Sample Research Data Base provided by the KNHIS, which provides mandatory social health insurance to all Koreans.<sup>25 26</sup> The dataset was designed and sampled to provide representative information regarding the healthcare usage of Koreans. Lee *et al*<sup>27</sup> provided detailed explanation on the dataset. The 14-year cohort Sample Research Data Base includes socioeconomic and demographic variables (eg, gender, residential area, income level) and detailed information on medical treatments (eg, medical diagnosis, type of medical facilities visited) for approximately 1 million people (2.2% of the total population) collected from 2002 to 2013. Recorded diagnoses follow the Korean Standard Classification of Diseases-6 (KCD-6) code, which is a slightly modified version of International Statistical Classification of Diseases and Related Health Problems, 10th revision.<sup>28</sup>

On 1 October 2011, the Korean government implemented a differential copayment policy with the most common 52 diseases. In 2018, the policy was extended to include additional 48 mild diseases to strengthen the effort to discourage unnecessary visits to secondary/tertiary healthcare to treat mild diseases by expanding the list.<sup>29</sup> We measured the impact of the policy by focusing on the initial implementation (sample period: January 2011–December 2012). Specifically, we constructed a set of treatment observations by selecting patient visits for the treatment of mild diseases selected from the set specified in 2011 (we refer to these as 'treatment diseases') during the sample period. To construct a set of control observations, we selected patient visits whose purpose was to treat 'control diseases' during the same sample period. The selected control diseases were similar to the treatment diseases (both belonged to the same middle-level categories in KCD) and had been newly added in the 2018 extension (see [table 1](#)). Consequently, our control observation provided a good counterfactual benchmark to precisely measure the change in patient

**Table 1** Selected diseases and descriptive statistics

		Treatment disease	Control disease
		(B35.2–6, 8, 9) Dermatophytosis	(B35.0, 1) Dermatophytosis
		(H60.1, 3, 5, 8, 9) Otitis externa	(H60.0) Abscess of external ear
		(J20.9) Acute bronchitis, unspecified	(J20.0–2] Acute bronchitis
		(J30.0–4] Vasomotor and allergic rhinitis	(J31.0) Chronic rhinitis
		(J31.1, 2) Nasopharyngitis and pharyngitis	(K52.1) Toxic gastroenteritis and colitis
		(K52.2, 3, 8, 9) Other noninfective gastroenteritis and colitis	(L20.0) Besnier’s prurigo
		(L20.8, 9) Atopic dermatitis	(L23.0–7] Allergic contact dermatitis
		(L23.8,9) Allergic contact dermatitis	(M50.3) Other cervical disc degeneration
		(M50.9) Cervical disc disorder, unspecified	(M54.0, 1–6] Dorsalgia
		(M54.8, 9) Dorsalgia	(M77.2, 3, 5) Other enthesopathies
		(M77.8, 9) Other enthesopathies	(M79.2) Neuralgia and neuritis, unspecified
		(M79.1, 4, 6, 8, 9) Neuralgia and neuritis, unspecified	(S63.5) Sprain and strain of wrist
		(S63.6, 7) Dislocation, sprain and strain of joints and ligaments (hand)	
		(S93.5, 6) Dislocation, sprain and strain of joints and ligaments (ankle/foot)	
Variable	Categories of variable	Patients in treatment group (n=201 256)	Patients in control group (n=5691)
Gender	Male	44.1%	42.6%
	Female	55.9%	57.4%
Age	Age_group1 (<20)	35.6%	14.4%
	Age_group2 (20s)	12.0%	8.8%
	Age_group3 (30s)	17.1%	17.8%
	Age_group4 (40s)	15.4%	23.8%
	Age_group5 (5’s0s)	14.8%	26.2%
	Age_group6 (60s)	5.2%	9.1%
Income	Low (1–2 decile)	11.7%	12.9%
	Middle (3–8 decile)	55.4%	53.4%
	High (9–10 decile)	33.0%	33.8%
Residential area	Seoul-metro. area	55.9%	55.1%
	Other areas	44.1%	44.9%
Differential copayment policy (visit)	Pre-policy (1/1/2010–9/30/2011)	Count: 394 316 (secondary/tertiary: 5.0%, primary: 95.0%)	Count: 6452 (secondary/tertiary: 3.0%, primary: 97.0%)
	Post-policy (10/1/2011–12/31/2012)	Count: 307 920 (secondary/tertiary: 4.0%, primary: 96.0%)	Count: 6113 (secondary/tertiary: 5.0%, primary: 95.0%)

Korean Standard Classification of Diseases-6 (KCD-6) code is shown in brackets. Detailed information on the selected disease is provided in online supplemental material A.

behaviour associated with the policy. We discuss key observations from summary statistics in online supplemental material A.

We collected patient records of healthcare visits to treat the selected diseases between 2011 to 2012. Since we mainly examined the type of healthcare patients visited (ie, primary vs secondary/tertiary) and the change in this associated with the focal policy, we included initial visits to treat mild diseases in our sample but follow-up visits to treat the same disease in the same hospital were excluded. Moreover, we focused on primary diagnosis in

the categorisation of our observations. As a main empirical approach, we used a DID method with patient fixed effect (we will provide more details in the next section). To this end, we included patients with two or more healthcare visits (follow-up visits are not counted)—specifically, at least one visit before the policy and one visit after the policy. Note that patients with only one visit are cancelled out in the fixed effect estimation. Also, we only included patients younger than 65 years old since seniors (65+) are subject to a different cost sharing and insurance system. For the same reason, patients at the lowest income level



(ie, medical aid beneficiaries) were also excluded from the analysis. Key descriptive statistics of the selected samples are provided in [table 1](#).

## METHODOLOGY

Our dataset has an unbalanced panel structure and the unit of analysis is a patient visit. We adopted a linear regression model with patient-level fixed effect in our analysis. Accordingly, cluster standard errors were used in all inferences and the standard errors were clustered at individual patient level.<sup>30</sup> The dependent variable was whether the afflicted patients selected primary healthcare or secondary/tertiary healthcare in their visit to treat the focal diseases; thus, it is represented as a binary dummy variable (1 if secondary/tertiary healthcare was chosen and 0 if primary healthcare was chosen). This modelling approach is categorised as a linear probability model (LPM), where the estimated dependent variable can be interpreted as the probability of visiting secondary/tertiary healthcare rather than primary healthcare.<sup>31–33</sup>

We applied a DID approach to measure the change in healthcare choice associated with the differential copayment policy. This method has been widely applied in previous studies to measure the impact of policies because it eliminates the effects of unobservable external factors by using control observations as counterfactuals.<sup>18 34 35</sup>

Before applying the DID approach, we checked the validity of our control observations by performing a parallel trend test to check whether the treatment and control observations followed the same pattern before the differential copayment policy and confirmed that they had the same trend (see online supplemental material C).

Next, we defined the ‘*Treat*’ dummy variable as 1 if a patient visit was to treat one of the treatment diseases and 0 if it was to treat one of the control diseases. We defined the ‘*Post*’ dummy variable as 1 if the visit occurred after the policy implementation and 0 if it occurred before. We also included month dummy variables to capture time trends and/or seasonal variations in the dependent variable. To account for the differences in selected mild diseases, disease dummies are included. The change in healthcare choice associated with the differential copayment policy was measured using the coefficient of the interaction of ‘*Treat*’ and ‘*Post*.’

Furthermore, we added interaction terms to the base model to investigate how the changes in healthcare choices associated with the policy varied with key demographic variables. We refer to this model as Heterogenous DID Model (or model 2). Specifically, we considered demographic variables such as gender, income (low/middle/high) and residential area as categorical dummy variables. With respect to residential area, we looked at whether the patients lived in the Seoul metropolitan area or not. This was of interest because about 25 million people (50% of the country’s population) live currently in the Seoul metropolitan area, where healthcare facilities and resources are highly concentrated.<sup>36</sup>

As stated, we define ‘*Treat*’ variable based on whether the patient visit was to treat treatment disease or control disease. Accordingly, a patient can serve as treatment group in a visit but as control group in another visit. In contrast, in model 3, we select patients who belong to only one group during the entire sample period and perform heterogenous DID analysis using them. Note that the assignment of treatment vs control is at the individual patient level in this model. Next, we used inverse probability of treatment weighting (IPTW) to remove confounding from observable variables and then estimated the heterogeneous DID model (model 4).

The specifications for the above-stated models are provided below.

DID with fixed effect (model 1)

$$Y_{it} = \alpha_i + \beta_T \cdot Treat_{it} + \beta_P \cdot Post_{it} + \beta_{DID} \cdot Treat_{it} \times Post_{it} + \tau_{Month} + \delta_{Disease} + u_{it} \quad (1)$$

Heterogenous did with fixed effect (model 2, model 3, model 4)

$$\begin{aligned} Y_{it} = & \alpha_i + \beta_T \cdot Treat_{it} + \beta_P \cdot Post_{it} \\ & + \beta_{DID} \cdot Treat_{it} \times Post_{it} + \beta_{Male} \cdot Male_i \times Treat_{it} \times Post_{it} \\ & + \beta_{LI} \cdot LowInc_i \times Treat_{it} \times Post_{it} \\ & + \beta_{HI} \cdot HighInc_i \times Treat_{it} \times Post_{it} \\ & + \beta_{Metro} \cdot Metro_i \times Treat_{it} \times Post_{it} + \tau_{Month} + \delta_{Disease} + u_{it} \end{aligned} \quad (2)$$

where  $i$  and  $t$  denote patient and healthcare visit, respectively, and  $Y_{it}$  is a binary indicator variable which takes the value of one if secondary/tertiary healthcare is visited by  $i$  at  $t$  and zero otherwise (ie, primary healthcare visit).  $\alpha_i$  is a patient-fixed effect which account for patient-specific characteristics in healthcare choice.  $\tau_{month}$  and  $\delta_{Disease}$  are month-fixed and disease-fixed effects to account for seasonality, time trend and disease-specific variations.  $Male_i$ ,  $LowInc_i$  and  $Metro_i$  are indicator variables denoting whether  $i$  is a male or not,  $i$  belongs to the low-income group or not, the high-income group or not, and  $i$  resides in the Seoul-metro area or not, respectively.  $t$  is an idiosyncratic error.

## Patient and public involvement

No patient involved.

## RESULTS

### DID analysis using LPM

While the observations from descriptive statistics supported the effectiveness of the policy, we formally examined this after controlling for other effects such as unobserved patient-level characteristics, seasonal trend, and disease-specific characteristics using the proposed models. After confirming common trend between treatment and control group (see online supplemental material C), the proposed fixed-effect LPM (Eq. 1) was estimated. Note that we used the within-estimator to handle the patient-level fixed effect.<sup>37</sup> The first column (model 1) of [table 2](#) presents the estimation result. Here,

**Table 2** Results of linear probability models on patient healthcare choice

	DID	Heterogenous DID	Using treatment only and control only patients	IPTW
	Model 1 $\beta$ (SE)	Model 2 $\beta$ (SE)	Model 3 $\beta$ (SE)	Model 4 $\beta$ (SE)
Month Dummies	Yes	Yes	Yes	Yes
Disease Dummies	Yes	Yes	Yes	Yes
Patient Fixed Effect	Yes	Yes	Yes	Yes
Post	0.0235 (0.003)†	0.0235 (0.003)†	0.0238 (0.004)†	0.0236 (0.004)†
Treat	-0.3722 (0.277)	-0.3738 (0.276)	-	-0.4257 (0.305)
Post×Treat	-0.0299 (0.004)†	-0.0267 (0.004)†	-0.0270 (0.004)†	-0.0268 (0.004)†
Post×Treat×Male	-	-0.0025 (0.001)*	-0.0026 (0.001)*	-0.0025 (0.001)*
Post×Treat×Low-Income	-	0.0037 (0.002)*	0.0035 (0.002)*	0.0039 (0.002)*
Post×Treat×High-Income	-	-0.0005 (0.001)	-0.0005 (0.001)	0.0005 (0.001)
Post×Treat×Seoul Metro. Area	-	-0.0052 (0.001)††	-0.0052 (0.001)†	-0.0052 (0.001)†
R-square	0.006	0.006	0.006	0.006
Number of observations	714 801	714 801	699 867	714 801
F-statistics	84.22†	77.49†	77.57†	79.21†

The full estimation results are available in online supplemental material D.

\* $P < 0.05$ .

† $P < 0.001$ .

DID, difference-in-difference; IPTW, inverse probability of treatment weighting.

the coefficient of ‘*Treat*’ indicates the estimated mean difference in the probability of selecting secondary/tertiary healthcare between the treatment and control observations. The coefficient of ‘*Post*’ indicates the estimated change in the probability after policy implementation. We captured the effect of the policy through the interaction of ‘*Post*’ and ‘*Treat*’ represented as ‘*Post*×*Treat*’.

In Model 1, the coefficient of ‘*Treat*’ (-0.3722, 95% CI -0.9149 to 0.1705) was not statistically significant, indicating that there is no significant difference between treatment and control observations in choosing secondary/tertiary healthcare over primary healthcare. In contrast, the coefficient of ‘*Post*’ (0.0235, 95% CI 0.0167 to 0.0303) was positive and significant, indicating that the proportion of secondary/tertiary healthcare visits among the control diseases increased after policy implementation. More importantly, the DID term related to the policy effect (‘*Post*×*Treat*’) was negative and significant (-0.0299, 95% CI -0.0368 to -0.0230). That is, the decrease associated with the policy was 2.99% point. From our data, we found that 4.93% of visits to treat mild diseases headed for secondary/tertiary healthcare before the policy. If we use this number as a baseline, the decrease amounts to -60%.

### Heterogeneous policy effect

After verifying the effectiveness of the policy, we conducted additional analyses to examine the heterogeneity associated with the policy among different demographic

groups. To this end, we added triple interaction terms between ‘*Post*×*Treat*’ and dummies for gender, income, and residential area (Eq. 2). The estimation results are reported in table 2 (Model 2).

In Model 2, the coefficient of ‘*Post*×*Treat*’ is highly significant and negative (-0.0267, 95% CI -0.0337 to -0.0197), indicating that the policy was associated with the decrease in the probability of choosing secondary/tertiary healthcare instead of primary healthcare. The coefficient of ‘*Post*×*Treat*×*LowInc*’ (0.0037, 95% CI 0.0007 to 0.0067) was statistically significant, while the coefficient of ‘*Post*×*Treat*×*HighInc*’ (-0.0005, 95% CI -0.0026 to 0.0016) was not statistically significant. This indicates that the differential copayment policy was associated with a smaller decrease in the probability of choosing secondary/tertiary over primary healthcare among people in the low income group than among the others in the middle/high-income group. Specifically, ‘*Post*×*Treat*’ is -0.0267 in Mid-Income group (baseline category) but the estimate becomes -0.0230 (= -0.0267 + 0.0037) in low-income group. We found that 4.23% of visits to treat mild diseases were at secondary/tertiary healthcare in low-income group before the policy. When we use this number as a baseline, the change associated with the policy amounts to -54%.

Similarly, the coefficient of ‘*Post*×*Treat*×*Metro*’ (-0.0052, 95% CI -0.0072 to -0.0032) was significant and negative, revealing that the decrease in the probability of choosing



secondary/tertiary over primary healthcare was larger by 19% among the residents of Seoul metropolitan area than among people living elsewhere. Specifically, *Post×Treat* is  $-0.0267$  in the other areas (baseline category) but the estimate becomes  $-0.0319$  ( $=-0.0267-0.0052$ ) in low-income group. We found that 4.6% of visits to treat mild diseases were at secondary/tertiary healthcare in Seoul metropolitan area before the policy. When we use this number as a baseline, the change associated with the policy amounts to  $-69\%$ .

### Exclusion of patients who have both treatment and control observations

We defined treatment and control observations based on the disease—whether the disease is influenced by the policy or not. Accordingly, a patient can have both treatment and control observations. In model 3, in contrast, we selected the patients who visited healthcare due to treatment diseases only or control diseases only. As a result, our assignment of samples to treatment and control groups was not varying within a patient. The main purpose of this analysis is to tackle a potential problem of diagnosis code change to avoid increased cost due to the policy. If there were frequent and common code changes, many patients in treatment group would have moved to control group after the policy. Therefore, this exclusion of patients who have both treatment/control visits allows us to circumvent the issue of diagnosis code change. First, we note that we dropped only 14934 observations (2% out of 714802 observations) from this additional screening rule. This indicates that the diagnosis

code change, if any, is not frequent. Model 3 in table 2 represents the estimation results from this model. Note that the *Treat* variable became time invariant in model 3 and was absorbed into the fixed effect term. Overall, the main findings from model 3 are highly consistent with those from model 1 and model 2. This adds robustness to our findings.

### Inverse probability of treatment weighting

We used IPTW to remove confounding from observable variables and then estimated the heterogeneous DID model (Eq.2).<sup>38 39</sup> Details on our IPTW procedure is provided in online supplemental material E. Model 4 in table 2 reports the estimation results. We found that a highly significant decrease in the probability of choosing secondary/tertiary over primary healthcare was associated with the implementation of differential copayment policy ( $-0.0268$ , 95% CI  $-0.0343$  to  $-0.0193$ ). Also, almost all estimated coefficients have the same sign and similar magnitude as the estimates from the other models.

### Extended sample period

The policy change may take some time until the actual effect shows up or the effect can be short-lived, disappearing soon after the implementation. To further investigate this aspect of the policy, we extended our sample period from 2011 to 2012 to 2010–2013. We estimated the Heterogeneous DID model (Eq. 2). Model 5 in table 3 provides the estimation results. As in other model results, the coefficient of *Post×Treat* is highly significant and negative ( $-0.0218$ , 95% CI  $-0.0273$  to  $-0.0163$ ). Overall

**Table 3** Results of additional models to check robustness

Model	Extended sample period (2010–13)	Split sample using visit count	
	Model 5 $\beta$ (SE)	# of Visits>5 Model 6 $\beta$ (SE)	# of Visit $\leq$ 5 Model 7 $\beta$ (SE)
Month dummies	Yes	Yes	Yes
Disease dummies	Yes	Yes	Yes
Patient fixed effect	Yes	Yes	Yes
Post	0.0199 (0.003)‡	0.0262 (0.007)‡	0.0230 (0.004)†
Treat	$-0.3628$ (0.153)*	$-0.4919$ (0.356)	$-0.0759$ (0.021)†
Post×Treat	$-0.0218$ (0.003)‡	$-0.0335$ (0.008)‡	$-0.0252$ (0.004)‡
Post×Treat×Male	$-0.0025$ (0.001)†	$-0.0013$ (0.003)	$-0.0027$ (0.001)*
Post×Treat×Low-Income	0.0028 (0.001)*	0.0118 (0.004)†	0.0016 (0.002)
Post×Treat×High-Income	$-0.0001$ (0.001)	0.0001 (0.003)	$-0.0007$ (0.001)
Post×Treat×Seoul Metro. Area	$-0.0066$ (0.001)‡	$-0.0076$ (0.003)†	$-0.0044$ (0.001)‡
R-square	0.006	0.006	0.006
Number of observations	1 077 928	155 418	559 383
F-statistics	116.90‡	31.21‡	54.32‡

The full estimation results are available online in online supplemental material D.

\* $P < 0.05$ .

† $P < 0.01$ .

‡ $P < 0.001$ .

results using the extended sample period echoed our earlier findings from the other models. Next, we examined how patients' healthcare choices varied over time after the policy. To this end, we interacted dummies for the months after the policy with 'Treat.' We found that the change associated with the policy showed stable pattern rather than showing increasing or decreasing trends. We provide more detailed description on the model and results in online supplemental material G.

### Policy effect and visit frequency

Patients who visit healthcare facilities more frequently than others would be subject to a greater financial burden if they do not change their behaviour after the policy. In contrast, low-frequency patients might be more willing to pay the increased cost. If this is the case, the policy might be more effective among frequent visitors. To further examine this in our empirical context, we decomposed our sample into two using the number of healthcare visits to treat mild diseases during the sample period: (1) five times or less, (2) above five times. Model 6 and model 7 in table 3 show the estimation results using frequent visitors and the others, respectively. In the frequent visitor sample (model 6), the coefficient of 'Post×Treat' (−0.0335, 95% CI −0.0485 to −0.0185) is much larger than any other models. In contrast, from the less frequent visitor sample (model 7), we found that the coefficient of 'Post×Treat' (−0.0252, 95% CI −0.0330 to −0.0174) is smaller in magnitude than those of model 1, model 2 and model 3. These results imply that the decrease in the visits to secondary/tertiary healthcare associated with the policy was stronger among frequent healthcare visitors. We also found that the coefficient of 'Post×Treat×LowInc' was statistically significant in model 6 (0.0118, 95% CI 0.0035 to 0.0201) while it was insignificant in model 7. This finding indicates that the substantially smaller decrease in visits to secondary/tertiary over primary healthcare among low-income patients was mainly driven by low-income frequent visitors. Both models had significant and negative coefficients of 'Post×Treat×Metro', which is consistent with all the other models.

### Additional robustness checks

In our analysis, the control diseases are very similar to treatment diseases. This setting has some strengths but at the same time may suffer from some potential problems. For instance, doctors may change the diagnoses to ensure patients have low copayments. To mitigate this issue, we selected distinct set of mild diseases as control diseases and treatment diseases in a follow-up analysis (see online supplemental material F) and obtained the high consistent results.

Next, we performed an analysis using seniors with the age of 65 and above in the sample. Note that these group of people are not subject to the policy. Since there is no change in the policy, we do not expect any significant change in their healthcare choices. Moreover, if the significant result of our main model comes from some

other latent effects that change over time, we should also find significant DID effect in the analysis using these seniors. This analysis can be regarded as a placebo test or a pseudo shock test to add validity to our findings. We found that there is no significant change due to the policy in the senior group (see online supplemental material F). All in all, we think that additional analyses have substantially improved the robustness of our findings.

### DISCUSSION

We found that the South Korean government's 2011 differential copayment policy was significantly associated with the decrease in patients' unnecessary choice of secondary/tertiary healthcare over primary healthcare for mild diseases. This finding is consistent with the results from previous empirical studies. For example, researchers found that the introduction of or increase in user charges for secondary care are associated with decreased secondary care utilisation.<sup>40</sup> The changes associated with the policy differed across demographic groups. Specifically, the decrease was smaller among low income patients compared with richer patient groups. This result is distinct from those in several previous empirical studies in which many researchers have found that people with low income are more sensitive to cost sharing changes and that policies based on cost sharing can exacerbate medical inequality.<sup>41–45</sup> For example, Powell-Jackson *et al.*<sup>24 46</sup> reported that user charge intervention increases primary healthcare utilisation only in the lowest and middle income terciles. The distinctiveness of our results can be explained by the Korean differential copayment policy focusing only on mild diseases. Before the policy, people in middle-income and high-income groups visited secondary/tertiary healthcare more frequently than people in the low-income brackets. Since most of the visits by middle-income and high-income people to secondary/tertiary healthcare institutions could have been handled just as well by primary healthcare institutions, their adjustment in healthcare choices after the policy implementation could be more pronounced. This finding is consistent with a stream of research that showed that carefully designed copayment policies can reduce disparity in healthcare access and usage.<sup>47</sup>

The smaller changes associated with the policy among low-income people might be derived from the difference in the level of health information each group has regarding the policy. People with lower incomes tend to have poorer healthcare information compared with people with higher incomes.<sup>48</sup> Since they are poorly informed regarding the policy and the increase in the cost sharing payment, their adjustment in healthcare choices after the policy could be weak. We also found that the smaller change associated with the policy among low income people was not limited to short period after the policy implementation but lasted for extended period of time (27 months afterward). Moreover, our

analyses indicated that this heterogeneity along with the income was mainly driven by the patients with frequent healthcare visits. This finding implies that the government can fulfil its policy goal more effectively by enhancing information sharing, especially focusing on low-income frequent healthcare visitors.

Another interesting finding from our study was that the change in healthcare choices associated with the policy was greater among the people living in the Seoul metropolitan area than among people living in other areas. Healthcare resources are concentrated in the Seoul metropolitan area. For instance, according to Statistics Korea, the number of doctors per thousand was 3.5 in Seoul area but was only 2.2 in other areas in 2011. Because there are more healthcare facilities overall in the Seoul metropolitan area, people there may find suitable primary healthcare institutions to substitute for secondary/tertiary healthcare institutions more easily than the people in other areas whose choices may be more limited. This might explain the pronounced policy effect in the Seoul metropolitan area. This finding points out that it is important to make primary healthcare outside the Seoul metropolitan area more accessible and attractive to patients.

Our study had several noteworthy strengths. First, we used a quasi-experimental setting with the DID approach to precisely measure the policy's impact. Our control observation provided the ideal counterfactual benchmark to measure the effectiveness of the policy. Moreover, a series of robustness checks add validity to our findings. Second, the focal policy covered only mild diseases, allowing us to circumvent the omitted variable problem due to unobserved severity. Previous studies have looked at the impact of healthcare policies applied to wide variety of diseases for which patients' condition severity may also vary widely but remain unobserved by researchers.<sup>49</sup> In such cases, omitted disease severity becomes a critical challenge in measurement of a policy's effect. In contrast, our study examined a policy on mild diseases with only small variations in severity. Accordingly, we can circumvent the omitted variable problem due to unobserved severity.

A few limitations of this study should be noted. As is the case with most studies using observed data, it is difficult to estimate the causal effect of the policy in a non-experimental setting. Since experimentation in our context had several challenges, including ethical issues, an experimental study was not feasible. Instead, we tried to control the effects of confounding variables by using control variables, fixed effects, and control observations. We also performed a series of robustness tests to check the validity of our findings. In our study, we mainly investigated the changes in healthcare choices associated with a differential copayment policy. Another important variable is the number of consultations. We leave this as a future research agenda. Moreover, future study can investigate whether the patient visits differed between those who attended secondary and tertiary

hospitals. A potential weakness of our sample is that doctors may change the diagnoses to ensure patients have low copayments. To mitigate this issue, we selected distinct set of mild diseases as control diseases and treatment diseases in a follow-up analysis (online supplemental material F). Nevertheless, we acknowledge that the issue of disease code change cannot be fully ruled out. We also assume that there is no spillover effect due to changes in behaviours in our analysis.

## CONCLUSION

We investigated the effect of the mild disease differential copayment policy introduced in South Korea in 2011 using the Sample Research Data Base provided by the KNHIS, conducting a DID analysis with a quasi-experimental design. We found that a significant decrease in the proportion of patients choosing secondary/tertiary healthcare facilities over primary healthcare facilities was associated with the implementation of the policy. The change was pronounced among people with middle/high incomes, those living in the Seoul metropolitan area, and those who frequently visited healthcare facilities to treat mild diseases. We performed a series of robustness checks and found all our results to be highly consistent.

**Contributors** We confirm that all the authors have made substantive intellectual contributions to the paper; SP contributed to the design and the interpretation of the study after reviewing the result of the study. SJ conceptualised the study and analysed the data. DBJ contributed the data acquisition and provided statistical analysis support. All authors supplied critical revisions to the manuscript.

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**Data availability statement** The data can be accessed on the Korean National Health Insurance homepage (<http://nhiss.nhis.or.kr>), but restrictions apply to the availability of the data, which was used with permission for the current study and therefore not publicly available. The data is available from the corresponding author upon reasonable request and with permission of KNHIS. Applications to use the KNHIS data will be reviewed by the inquiry committee of research support and, once approved, raw data will be provided to the applicant with a fee.

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