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ORIGINAL ARTICLE

Do Fraud Investigations Impact Healthcare Expenditures of Medical Institutions?: An Interrupted Time Series Analysis of Healthcare Costs in Korea

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Background: The aim of our study was to review the findings of health insurance fraud investigations and to evaluate their impacts on medical costs for target and non-target organizations. An interrupted time series study design using generalized estimation equations was used to evaluate changes in cost following fraud investigations.
Methods: We used National Health Insurance claims data from 2009 to 2015, which included 20,625 medical institutions (1,614 target organizations and 19,011 non-target organizations). Outcome variable included cost change after fraud investigation.
Results: Following the initiation of fraud investigations, we found statistically significant reductions in cost level for target organizations (–1.40%, $p < 0.001$). In addition, a reduction in cost trend change per month was found for both target organizations and non-target organizations after fraud investigation (target organizations, –0.33%; non-target organizations of same region, –0.19%; non-target organizations of other regions, –0.17%).
Conclusion: This study suggested that fraud investigations are associated with cost reduction in target organization. We also found similar effects of fraud investigations on health expenditure for non-target organizations located in the same region and in different regions. Our finding suggests that fraud investigations are important in controlling the growth of health expenditure. To maximize the effects of fraud investigation on the growth of health expenditure, more organizations needed to be considered as target organizations.

Keywords: Fraud; Health expenditures; Cost savings; Health policy

INTRODUCTION

Over the past decades, the growth of healthcare spending in South Korea has increased rapidly. As a result, healthcare expenditures, which accounted for 2.8% of growth of the gross domestic product (GDP) in 1970, increased to 7.2% in 2013, faster than the growth of the GDP [1]. The increase in healthcare expenditures has been attributed to multiple factors, including aging of the population, the introduction of new technologies, changes in health insurance reimbursements, and political changes [2-4]. Given the trend of increasing costs and the magnitude of healthcare expenditures, this issue has been a major concern for policymakers. Both policymakers and insurers share an interest in reducing waste to control these costs.

In Korea, the National Health Insurance Service (NHIS) program operates as a single-payer system. At the initiation of this program, the NHIS paid reimbursements to health care providers that submitted claims for medically necessary services or items. However, this system relied upon the judgments of healthcare providers regarding the necessity and appropriateness of the care provided. The system was vulnerable to fraud by unscrupulous providers claiming inappropriate medical costs for personal profit.

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Under these circumstances, fraud was considered to be one cause of increasing healthcare expenditures [5,6]. To reduce inappropriate healthcare expenditures and promote the appropriate submission of insurance claims, the government instituted annual medical insurance fraud investigations since 2003. To detect occurrences of fraud and abuse, insurance claims are reviewed and used to identify suspicious medical institutions for targeted claims reviews [7-9]. Target organizations for these claims reviews include all types of medical institutions. Approximately 1% of all medical institutions undergo targeted fraud investigation annually.

Previous research suggests that fraud investigation is important for reducing waste in healthcare expenditures [10-13]. In addition, researchers have looked at methods for discouraging fraud schemes [14-16]. Although fraud investigation results are published regularly in government reports, these provide only the amounts of the fraudulent costs recovered and the penalties imposed on the target institutions. Whether fraud investigations have had a broader effect on healthcare costs is not clear. Korea has a highly competitive medical environment, and collaborative networks have been established as a strategy to survive in this dynamic environment [17]. Given the pressures of the healthcare environment and the interconnectedness of institutions, we hypothesized that fraud investigations might have impacts even on the practices of medical institutions not targeted for investigation, and that these effects might impact medical institutions of all sizes, ranging from clinics to long-term care facilities and hospitals.

Thus, the aim of our study was to assess the effects of fraud investigations on medical costs. We assumed that changes in the claim pattern, such as a reduction in inappropriate or fraudulent claims, will result in a change in medical expenditure after a fraud investigation, and that these changes will be impacted not only by target medical institutions but also by other medical institutions. In addition, we evaluated whether the effects of fraud investigations varied according to the type of medical institution.

METHODS

1. Database and data collection

To investigate the effects of fraud investigation on medical institutions, we reviewed data published for medical fraud investigations conducted between 2010 and 2014, monthly aggregated National Health Insurance (NHI) claims data to hospital level from July 2009 to May 2015, and national medical institution data. First, we selected a non-target organization for evaluating the effects of medical fraud investigations using the nationwide medical institution registry. In Korea, the administrative districts consist of 17 geopolitical areas that are further divided into 257 municipal districts (called si-gun-gu). In our study, region was defined according to the municipal districts. Propensity score matching (ratio = 1:3) was used to select non-target organization by matching medical institutions annually based on information of target organization. Since we assumed that the effects of the fraud investigation would be in the same or nearby medical institution, we used information from region, institution type, and ownership status. Second, we matched medical institution data with NHI claims data for medical institutions that had been the focus of on-site investigations (target organizations). Between 2010 and 2014, a total of 2,505 on-site investigations of medical institutions were performed. The month of investigation was defined as the index month and varied by medical institution, occurring between 2010 and 2014. We then selected periods of 12 months before and after based on the index month of the on-site investigation for several reasons. (1) We wanted to reduce any possible confounding effect due to other investigations. Each on-site investigation was performed continuously throughout the month, and there was a possibility that long observation periods (over 12 months) would overlap with investigations taking place in the surrounding years, meaning that the general trends could be affected by other investigations. (2) There was a possibility of switching from the target organization to a non-target organization. (3) We considered the punishment of the fraud investigation. According to the type of fraud, the medical institute received a form of suspension, meaning that there was no claim from the medical institute during this period. For these reasons, we limited the observational period to within 12 months based on the on-site investigation. Third, we created a single index date and month for the target organization by institution type and region. Fourth, we then selected a non-target organization from the same period as the target organization, matched according to institution type, ownership status and region. Non-target organizations were classified as being from the same or other region. Same-region facilities were those from the same area as the on-site investigation in the index year. Other regions were defined as areas that did not have on-site investigations within their geopolitical boundaries and in which fraud had never been detected. Finally, we excluded medical institutions with incomplete period data. A total of 20,625 medical institutions (1,614 target institutions and 19,011 non-target

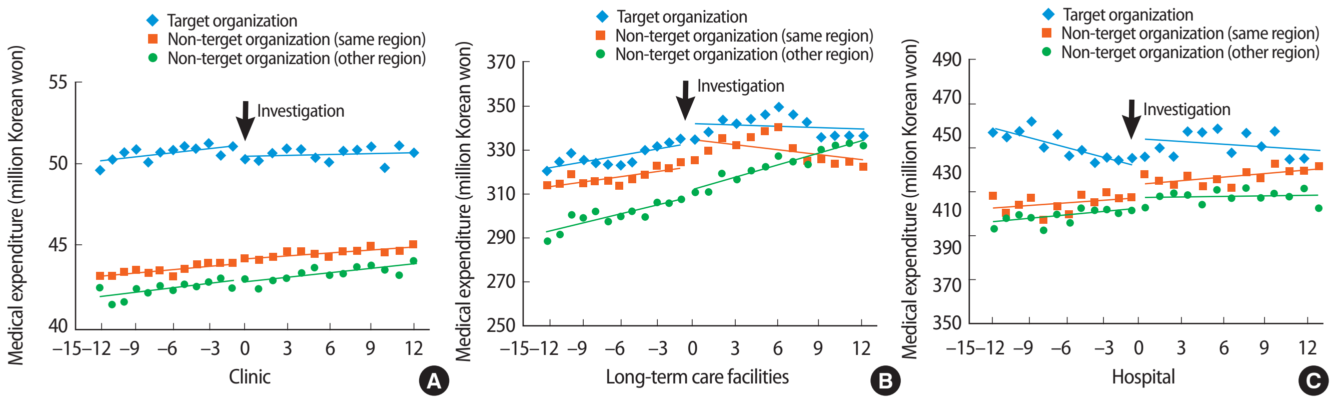

Figure 1. Changes in average medical expenditure before and after fraud investigation by type of hospital. Data is shown as mean cost per medical institution. Medical institutions that did not receive fraud investigations were classified as non-target organizations (same region, other region). Data was based on National Health Insurance claim data. (A) Clinic. (B) Long-term care facilities. (C) Hospital.

institutions) were included in the analysis of changes in medical costs per month (Figure 1A).

2. Variables

To evaluate the effects of fraud investigations, the outcome variable in our study was healthcare costs per medical institution. Cost data was obtained from the NHI claims database per month and included the combined costs of inpatient and outpatient care. There is no data related to patient information. Outpatient costs included all health service costs except medication, due to the adoption of separate prescribing and dispensing drug systems in South Korea. Inpatient costs included reimbursements for health services, including medications. In addition, uncovered benefits were not included in our data. Uninsured benefits were not reimbursed by the NHI system; thus, this information was not included in the claim data. We have adjusted total price inflation. In other words, it looks like the total cost ratio has remained unchanged by 2014.

The primary variable of interest in this study was the level of cost change in organizations targeted for fraud investigation and overall change trend after fraud investigation. The period of fraud investigation of the medical institutions studied varied by index date, so we created a dummy variable for unified time. We used the dummy variable based on the index date to denote the time before and after, ranging from 12 months before to 12 months after investigation (–12 to 12, respectively). To investigate the changes in cost per medical institution following fraud investigation, the time before the fraud investigation was defined as zero, and the time after the investigation concluded was defined as one. In addition, our analysis of trends looked at linear changes after investigation. Baseline trends varied by the index date of fraud investigation and include data from July 2009 to May 2015.

We adjusted the data for other medical institution characteristics when analyzing the changes in costs after fraud investigation. Human resources data (doctors, nurses), institution type (clinic, long-term care, hospital), medical institution ID, total patients per medical facility, proportion of medical aid patients, number of fraud investigation per region, number of fraud detections per region, medical service department, and year were included in our analysis.

3. Statistical analysis

The distribution of each categorical variable was examined by an analysis of frequencies and percentages, and χ^2 tests were performed. Analysis of variance was also performed to compare average values and standard deviations for the continuous variables. To evaluate the changes in cost after fraud investigation, we used an interrupted time series study design using generalized estimating equations (GEE) by target organization [18-21]. In this study, the error term for GEE with correlation structure was autoregressive (AR1) and used repeated outcome measurement. We used log transformations on costs to reflect the original scale of skewed data and to measure changes in the dependent variables in response to percentage changes in the explanatory variable [22-25]. In addition, subgroup analyses were performed by institution type. All statistical analyses were performed using SAS ver. 9.4 (SAS Institute Inc., Cary, NC, USA). All p-values less than 0.05 were considered to indicate statistical significance.

RESULTS

The data we used in our study consisted of 20,625 medical institutions. Among these, 1,614 of the included sites were target organizations for fraud investigations and 19,011 were non-target organizations (same region, 12,236; other region, 6,775). Among the included sites, 16,731 (81.12%) were clinics, 1,993 (9.66%) were long-term care facilities, and 1,901 (9.22%) were hospitals. Mean medical costs per month were highest in target organizations (164 million Korean won [KRW]) and lowest in non-target organizations located in same region (77 million KRW) (Table 1).

The overall trend of average cost per month seemed to be increasing in clinics and long-term care facilities in both target and non-target organizations before fraud investigation began. After fraud investigation, the general trend of average cost decreased in the target organizations. In addition, a similar trend was observed

Table 1. General characteristics of hospital (n = 20,625)

Characteristic	Fraud investigation			Total	*p*-value
	Done	None			
		Same region	Other region		
Institution type					< 0.0001
Clinic	1,059 (6.33)	11,006 (65.78)	4,666 (27.89)	16,731 (81.12)	
Long-term care facilities	305 (15.30)	643 (32.26)	1,045 (52.43)	1,993 (9.66)	
Hospital	250 (13.15)	587 (30.88)	1,064 (55.97)	1,901 (9.22)	
Medical cost*	164.98 ± 222.47	77.12 ± 135.92	141.86 ± 210.81	100.38 ± 168.12	< 0.0001
No. of doctors	2.21 ± 2.66	1.56 ± 1.90	2.27 ± 3.27	1.85 ± 2.52	< 0.0001
No. of nurses	4.56 ± 9.67	1.83 ± 6.31	4.54 ± 10.41	2.94 ± 8.27	< 0.0001
Patients per medical institution	1,867 ± 1,810	1,875 ± 1,580	1,947 ± 1,800	1,898 ± 1,674	0.014
No. of fraud investigation per region	2.66 ± 1.88			2.66 ± 1.88	
No. of detected fraud per region	1.92 ± 1.85			1.92 ± 1.85	
Proportion of medical aid	13.7 ± 14.57	7.75 ± 9.55	10.72 ± 12.45	9.19 ± 11.19	< 0.0001
Medical service department					< 0.0001
General practitioner	658 (9.98)	3,546 (53.77)	2,391 (36.25)	6,595 (31.98)	
Internal medicine	155 (6.07)	1,731 (67.83)	666 (26.10)	2,552 (12.37)	
Neurology	7 (5.51)	83 (65.35)	37 (29.13)	127 (0.62)	
Psychiatry	68 (7.52)	602 (66.59)	234 (25.88)	904 (4.38)	
Surgery department	39 (5.50)	451 (63.61)	219 (30.89)	709 (3.44)	
Orthopedics	109 (6.99)	1,044 (66.97)	406 (26.04)	1,559 (7.56)	
Neurosurgery	22 (7.51)	194 (66.21)	77 (26.28)	293 (1.42)	
Cardiothoracic surgery	1 (3.23)	16 (51.61)	14 (45.16)	31 (0.15)	
Anesthesia	31 (6.61)	293 (62.47)	145 (30.92)	469 (2.27)	
Obstetrics and gynecology	38 (4.99)	522 (68.50)	202 (26.51)	762 (3.69)	
Pediatrics	26 (3.32)	522 (66.75)	234 (29.92)	782 (3.79)	
Ophthalmology	30 (3.78)	540 (68.01)	224 (28.21)	794 (3.85)	
Otorhinolaryngology	39 (4.32)	605 (67.00)	259 (28.68)	903 (4.38)	
Dermatology	21 (3.52)	419 (70.18)	157 (26.30)	597 (2.89)	
Urology	12 (2.02)	409 (68.97)	172 (29.01)	593 (2.88)	
Radiology	7 (4.90)	101 (70.63)	35 (24.48)	143 (0.69)	
Laboratory medicine	1 (25.00)	3 (75.00)	0	4 (0.02)	
Rehabilitation	17 (5.63)	175 (57.95)	110 (36.42)	302 (1.46)	
Nuclear medicine	1 (33.33)	2 (66.67)	0	3 (0.01)	
Family medicine	27 (5.29)	335 (65.69)	148 (29.02)	510 (2.47)	
None†	305 (15.30)	643 (32.26)	1,045 (52.43)	1,993 (9.66)	
Year‡					< 0.0001
2010	344 (8.14)	2,711 (64.14)	1,172 (27.73)	4,227 (20.49)	
2011	361 (8.78)	2,459 (59.83)	1,290 (31.39)	4,110 (19.93)	
2012	251 (6.21)	2,176 (53.87)	1,612 (39.91)	4,039 (19.58)	
2013	292 (6.95)	2,425 (57.72)	1,484 (35.32)	4,201 (20.37)	
2014	366 (9.04)	2,465 (60.89)	1,217 (30.06)	4,048 (19.63)	
Total	1,614 (7.10)	12,236 (53.85)	6,775 (32.85)	20,625 (100.00)	

Values are presented as number (%) or mean ± standard deviation.
*Korean won (unit: 1 million). †'None' indicates long-term care. ‡Index year of fraud investigation.

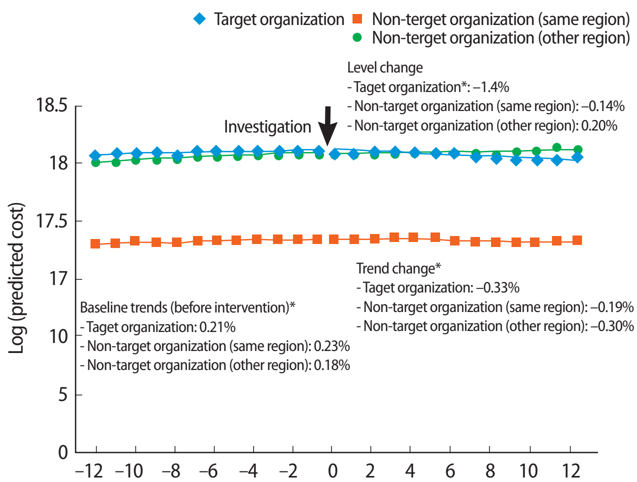

Figure 2. The results of predicted cost before and after fraud investigation for each group. Adjusted for type of hospital, number of doctors, number of nurses, patient per medical institute, number of fraud investigations per region, number of detected fraud per region, proportion of medical aid, medical service department, year, and region. Data was analyzed based on the data of National Health Insurance claim. *Statistically significant.

Table 2. Subgroup analysis of change in medical expenditure after intervention by institution type

Fraud investigation	Change in level		Change in slope	
	Estimates ± SE	*p*-value	Estimates ± SE	*p*-value
Clinic				
Done	–0.0155 ± 0.0039	< 0.0001	–0.002 ± 0.0009	0.0235
None				
Same region	–0.0015 ± 0.0015	0.3069	–0.0015 ± 0.0003	< 0.0001
Other region	0.0001 ± 0.0018	0.9751	–0.0012 ± 0.0004	0.0031
Long-term care facilities				
Done	–0.0111 ± 0.0047	0.0169	–0.0046 ± 0.0019	0.0134
None				
Same region	–0.0084 ± 0.0036	0.0204	–0.0075 ± 0.0018	< 0.0001
Other region	–0.0067 ± 0.0045	0.1405	–0.0078 ± 0.0016	< 0.0001
Hospital				
Done	0.0016 ± 0.0085	0.8488	–0.0020 ± 0.0022	0.3567
None				
Same region	0.0138 ± 0.0057	0.0152	–0.0035 ± 0.0020	0.0869
Other region	–0.0026 ± 0.0049	0.5912	–0.0059 ± 0.0012	< 0.0001

Estimates are the results of log transformation and interpretable as percentage changes. Adjusted for type of hospital, number of doctors, number of nurses, patients per hospital, number of fraud investigation per region, number of detected fraud per region, proportion of medical aid, year, and region.
SE, standard error.

in non-target organizations, including long-term care facilities of the same region and hospitals located in other regions (Figure 1).

The interrupted analysis of medical cost and average cost per month also showed changes after fraud investigation. The level of change that existed in target organizations (–1.40%, $p < 0.001$) and non-target organizations (same region: –0.15%, $p = 0.2720$; other regions: 0.18%, $p = 0.2993$) demonstrated statistical significance for target organizations. In addition, a significant trend for reduced costs after fraud investigation existed in both target organizations and non-target organizations (target, –0.33%; non-target/same region, –0.19%; non-target/other regions, –0.17%) (Figure 2).

Subgroup analyses by institution type for level change and trend change were performed for both target and non-target organizations. In the case of clinics, significant differences in level change were observed for target organizations (target, –1.55%; non-target/same region, –0.15%; non-target/other regions, 0.01%). The trend change tended to decrease for both target and non-target organizations (target, –0.20%; non-target/same region, –0.15%; non-target/other region, –0.12%). Among long-term care facilities, significant level changes existed for both target and non-target organizations located in the same region (target, –1.11%; non-target, –0.84%). Trend changes after fraud investigation existed for both target organizations (–0.46%) and non-target organizations (same region, –0.75%; other regions, –0.78%). Among hospitals, level changes were statistically significant for non-target organizations of the same region (1.38%). The general trend of average cost per month decreased after fraud investigation (Table 2).

DISCUSSION

In this study, we evaluated the effects of fraud investigations on healthcare costs in both organizations targeted for medical fraud investigations and non-target organizations. We found that fraud investigations were associated with reductions in healthcare costs not only at target organizations but also at non-target organizations. Prior to fraud investigations, both target and non-target organizations had a tendency to raise monthly medical costs. This trend has changed based on the time of the fraud investigations, and the target institution has decreased costs at the time of investigation. Furthermore, the cost trend after fraud investigation tended to decrease in target and non-target organizations. These reduced costs per month could be considered direct effects of the target organization investigation. Medical institutions that have undergone a fraud investigation would be expected to modify their insurance claim practices to ensure accurate claim submissions for health services delivered in their facilities. These changes would be expected to result in decreasing medical costs per month after fraud investigations identified inappropriate insurance claims. In addition, a ripple effect could exist for non-target organizations where the occurrence of a fraud investigation might motivate examination of claims practices. There may be a variety of unmeasured factors that can affect the cost of a medical institution. However, it is difficult to explain the change in trends in non-target institutions that have various points of time based on the specific time point of fraud investigation. Plausible explanations for these phenomena can be associated with the medical industry in Korea [17,26], where medical institutions have developed collaborative networks as a strategy to deal with the highly competitive environment. Investigators think there will be a potential impact of fraud investigations, and information about fraud investigation is expected to spread to other medical institutions that are not subject to investigation. As a result, a single fraud investigation could have broader effects in decreasing costs due to inappropriate insurance claims. In addition, non-target organizations in the same region as target organizations would be expected to show a reduction in costs after fraud investigation faster than non-target organizations in other regions.

The results of the sub-group analysis show that the magnitude of impact differed depending on type of institution. Careful interpretation of the results is needed, as they do not represent the absolute scale of the effect of the fraud investigation; rather, the scale is relative and may change. This means that the results cannot be used to compare each group. One plausible explanation for the magnitude of the effect would be that it is associated with a difference in the type and size of illegal insurance claims submitted for hospital-level care. Clinics are the smallest medical institutions included in this analysis and provide primary care services to patients. Long-term care and hospital facilities are larger and must meet certain criteria, including having over 30 beds for inpatient care. Long-term care institutions provide health services only to stable, residential elderly patients. By contrast, hospitals provide a range of medical services through multiple departments. Thus, the size of illegal insurance claims would be expected to be largest in hospitals compared with other institutions. However, the sum of reduced costs would be expected to be largest when clinic costs are combined, as these represent the largest percentage of medical facilities.

Fraud investigation is an important approach for protecting health expenditures from waste. However, fraud investigations in Korea are performed for only approximately 1% of all medical institutions annually due to limited resources. The effectiveness of fraud investigations would be expected to increase with a greater number of investigations. In Korea, methods of medical fraud include document investigations, data analysis and field investigations, and most investigations are conducted in field investigations using human experts. However, human resources for these reviews are limited, and these investigations are not conducted for a large number of institutions. Thus, methods for improving fraud investigation efficiency and discouraging medical fraud are greatly needed. Like other countries, there has been an attempt to adopt data analysis for fraud detection [27-29], but fewer medical institutions are detected in this way due to their low accuracy. To develop better fraud detection systems, specialized training and time are needed to further improve current administrative processes. Improving methods for fraud detection and prevention would require increasing the number of investigations, as well as maximizing the effects of fraud investigations. Thus, policymakers focusing on healthcare fraud should consider both their human resource plan and pursue improvements in fraud investigation methods. In addition, a systematic long-term plan for fraud prevention should include data analysis on the accuracy of fraud investigations and their outcomes.

There are several strengths in the study. First, to the best of our knowledge, our study is the first to evaluate the impact of fraud investigations on costs in both target and non-target organizations. Previous research and reports have considered the actual effects of investigations, such as penalties and redemptions [13], but no prior study has performed an analysis of the effects of fraud investigations on overall changes in costs per month after investigation. Second, our results provide valuable evidence to policymakers regarding the effects of fraud investigations. Our study characterizes both direct and ripple effects of fraud investigations on healthcare costs and billing practices. Thus, it would be meaningful for policymakers to consider our findings when evaluating ongoing plans for healthcare fraud investigations. Third, this study provides evidence related to the expansion of fraud investigations. Expansion of fraud investigations through a variety of methods, such as the prediction of fraud, may contribute to the reduction of inappropriate medical costs. However, selecting and expanding these methods will require careful consideration.

Despite these strengths, our study does have some limitations. First, the data used in our study included only medical institution characteristics, and we were unable to consider patient characteristics, such as demographic factors, disease severity, and length of stay. Medical costs are influenced by patient factors, particularly severity of disease, health services utilization, and other potential factors [30-32]. However, as our data did not include patient information, we could not control for these factors. We did adjust for health service department type to account for differences between medical institutions that might result from differences in the types of patients being treated in each facility. Second, target organizations chosen for investigation of possibly fraudulent activities included only approximately 1% of all medical institutions. This limited sample lacks generalizability to all institutions. There may also be an error in selecting a non-target medical institution, and this can be a potential bias in our study results. In addition, we did not investigate whether the effects of fraud investigations might be different for other large medical institutions compared with small medical institutions. However, this study was the first attempt to evaluate cost changes for target organizations after fraud investigation, and our results provide meaningful information to policymakers seeking to protect health expenditures from fraud. Third, we could not consider unmeasured factors that may affect fraud investigations, such as the personal characteristics of individual investigators. The data used in our study did not include investigation team members' employment histories or years of working on fraud investigations. These factors also might affect the methods of investigation used for each medical institute and thereby impact changes in medical costs after investigation. In addition, although we selected non-target organizations annually, there was a possibility of overlaps within the study period. To minimize study period overlaps, we limited the period of analysis to 12 months before and after the occurrence of an investigation. Also, non-target organizations were selected based on 257 municipal districts within the 17 geopolitical boundaries. Finally, we did not evaluate uninsured benefits, which were not included in our dataset. Thus, we were unable to measure the change in uninsured benefits and other undocumented costs.

In conclusion, our results support the efficacy of fraud investigations for protecting healthcare expenditures. The impact of the fraud investigations on reducing costs was observed not only for target organizations but also for non-target organizations. Our findings highlight the need for increasing the number of fraud investigations to maximize their effects. Thus, policymakers should consider the available workforce for conducting these investigations as well as alternative methods for fraud investigation to achieve maximal effects.

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