

Goel, Rajeev K.

Article — Published Version

Medical professionals and health care fraud: Do they aid or check abuse?

Managerial and Decision Economics

Provided in Cooperation with:

John Wiley & Sons

Suggested Citation: Goel, Rajeev K. (2019) : Medical professionals and health care fraud: Do they aid or check abuse?, Managerial and Decision Economics, ISSN 1099-1468, Wiley, Hoboken, NJ, Vol. 41, Iss. 4, pp. 520-528, <https://doi.org/10.1002/mde.3117>

This Version is available at:

<https://hdl.handle.net/10419/233655>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<http://creativecommons.org/licenses/by-nc-nd/4.0/>

RESEARCH ARTICLE

Medical professionals and health care fraud: Do they aid or check abuse?

Rajeev K. Goel^{1,2} 

¹Department of Economics, Illinois State University, Normal, Illinois, USA

²Knowledge Creation and Growth, Kiel Institute for the World Economy, Kiel, Germany

Correspondence

Rajeev K. Goel, Illinois State University, Normal, Illinois, USA; or Kiel Institute for the World Economy, Kiel, Germany.
Email: rkgoel@ilstu.edu

This paper examines the role of health care professionals in combating health care fraud. It is not overall clear whether the share of the health professionals help control abuse. Using data across U.S. states, our econometric results show that greater employment of nurses consistently reduced health fraud, whereas more physicians did not have a significant impact. Further, more urbanized states and states with a greater proportion of the elderly experienced greater health scams. Identity thefts facilitated health care fraud, whereas different dimensions of health insurance (including the share of the population with Medicare, managed care, and no insurance) and hospital occupancy rates did not matter.

1 | INTRODUCTION

Cost containment in the health sector has been a concern for the industry, regulators, and consumers. An important component of the overall cost reduction of health services is the checking of fraud and abuse. Reports of health fraud include actors that are both internal and external to the health care industry.¹ The importance of cutting waste and abuse in health care services has been noted by several scholars (see, for example, Berwick & Hackbarth, 2012; Morris, 2009; Wilson, Geis, Pontell, Jesilow, & Chappell, 1985). An earlier study by Hyman (2001) estimates that health care fraud and abuse to account for 10% of total health care spending (about \$120 billion per year; also see Morris, 2009; Sparrow, 2000). These numbers most likely have gone up in recent years.²

Health care-related fraud or scams take several forms including, but not limited to, fraudulent or artificially inflated procedures, offers for (fake) insurance cards, stolen health information, or various other scams involving medications, and so forth (see Krause, 2004 for an example). Examples of fraud and efforts to caution the public proliferate on the internet, with involvement by the government, industry, and consumer welfare organizations (see <https://www.consumer.ftc.gov/articles/0171-medical-identity-theft>; https://www.fraud.org/medical_id_theft; <https://oig.hhs.gov/fraud/medical-id-theft/>; <https://www.insurancefraud.org/scam-alerts-medical-id-theft.htm>). According to Beaton (2017), health professionals figured prominently in health care fraud, with the five main types of fraud related to: (a) billing for medically unnecessary services or for services that were not

performed; (b) falsifying insurance claims or diagnoses; (c) participating in illegal patient referrals or kickbacks; (d) prescribing unnecessary medications to patients; and (e) entering codes for expensive and medically unwarranted services. Furthermore, health care fraud is rampant in both the private sector and in the government-administered health systems like Medicaid and Medicare (see, for example, <https://oig.hhs.gov/oei/reports/oei-09-18-00180.pdf>). Yet, health professionals might prove to be sentinels against fraud when they prevent and report abuse by insurance companies and consumers.

The instances of medical fraud are not limited to the United States. Stelfox and Redelmeier (2003) found evidence of abuse in Canada where drug benefits for seniors were claimed more than one year after their death. In a number of instances, health care professionals have been accused of participating in medical fraud—for example, overbilling, treatments to those who do not deserve, and so forth (Jesilow, Pontell, & Geis, 1993; Joudaki et al., 2016; Morris, 2009). Over the spectrum of health professionals, however, it is not clear whether health professionals aid or check fraud in the medical sector and the present work will provide some evidence.

More broadly, formal research on the drivers of health scams is scarce, limited primarily by the dearth of relevant data. This paper attempts to partly address this deficiency, employing recent data on health fraud across U.S. states.

Two key questions we address are:

- Do health care professionals aid or check health care fraud?

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

© 2019 The Authors. Managerial and Decision Economics published by John Wiley & Sons Ltd.

- Are different types of health care workers equally effective as sentinels against health care scams?

The issue of fraud control in medical care is of obvious policy importance as policymakers try to control medical costs of public health and try to make care more widely available and accessible to those in genuine need.

This paper studies the effectiveness of health care professionals in combating health care scams across states in the United States. Estimation results show that greater employment of nurses consistently reduced health scams, whereas more physicians did not have a significant impact. Further, more urbanized states and states with a larger elderly population experienced a greater incidence of medical fraud. Identity thefts facilitated health care scams, signifying spillovers from identity thefts to health care fraud. Implications for health policy are discussed.

The structure of the rest of the paper includes the model, data, and estimation in Section 2, followed by results and conclusions.

2 | MODEL, DATA, AND ESTIMATION

2.1 | Model

There are a number of laws and regulations such as the federal civil False Claims Act, the federal Anti-Kickback statute, the Ethics in Patient Referral Act as well as numerous state statutes, that are aimed at controlling health care fraud and abuse (Kalb, 1999). However, their effectiveness seems limited given the wide prevalence and the magnitude of such fraud.

2.1.1 | Related work

Whereas the academic literature has noted the need for containment of health care costs and provided some rationale for the behavior driving abuse (for examples, see Berwick & Hackbarth, 2012; Hyman, 2001; Kalb, 1999; Krause, 2004; Morris, 2009), we lack specific guidance from this literature about a formal model or framework to test the determinants of health fraud. Given this shortcoming, the literature on health scams can be placed in the larger literature on white-collar crimes (Goel & Saunoris, 2017).

To anchor the theoretical background for our empirical study, one can draw on the seminal work of Becker (1968) on the drivers of criminal behavior. Becker viewed criminals as rational, who considered the relative costs and benefits of their actions. In the context of the present study, the criminals would be scammers trying to abuse/exploit the health care system, and their perceived payoffs would be the benefits (e.g., unauthorized health care access) they could get by scamming. The costs would be the punishment, given the chances of apprehension/detection.³ Furthermore, the unemployed and those without medical insurance would have incentives to access medical benefits via legal or illegal means. On the other hand, some transaction

(information) costs of conducting fraud might be lower for those in the medical profession (as would be the costs for them to prevent fraud). Rai (2001) has argued, for instance, that some of the abuse in public health might be related to the type of payment structure being used.

An important dimension may be the market power of medical professionals, notably physicians. Such market power might increase the propensity to commit abuse (see McGuire, 2000 for a detailed survey). A related recent study by Crea, Galizzi, Linnosmaa, and Miraldo (2019) studied the tendencies towards physician altruism, where altruism was gauged by the tendencies towards prescribing generic drugs over brand-name drugs. No evidence of physician altruism was found, based on Finnish data.

Thornton, Mueller, Schoutsen, and Hillegersberg (2013) noted that Medicaid in the United States has been particularly prone to fraud and Rudman, Eberhardt, Pierce, and Hart-Hester (2009) provided a number of specific examples of health care fraud. A strand of the related literature has focused on effective techniques for medical fraud detection (see Thornton et al., 2013 and Verma, Taneja, & Arora, 2017, and Li, Huang, Jin, & Shi, 2008 provided a survey).

Although not focusing on health care fraud directly, an interesting recent study by Goel and Mazhar (2019) studies the effectiveness of the death penalty in reducing white-collar crimes across nations. Another related strand of the literature examines the role of the internet on various white-collar crimes (Goel, 2018, 2019). Many medical services, such as patient records, physician contact, and so forth are moving to the internet and it would be interesting to see, given appropriate data, whether such moves increase medical fraud or aid in providing greater transparency.

An earlier review of the literature by Rashidian et al. (2012) underscored the need for “studies using robust research methodologies” to inform and combat health care fraud. The present research can be seen as contributing to that endeavor, focusing especially on the role of health professionals.

2.1.2 | The model

With subscript i denoting a state, the general form of the estimated equation to explain the determinants of health care fraud is the following, with the main focus being on the role of health care professionals:

$$\text{Health care related fraud (HealthSCAM}_i) = f(\text{Health care professional}_{ij}, \text{ (1) Medical/Insurance factors}_{s_{jk}}, \text{ Economic factors}_{im}, \text{ Demographic factors}_{s_{jk}}, \text{ Foreign border}_{iz})$$

where j denotes NURSES and PHYSICIANS; k denotes NOinsure, ManCARE, MediCARE, HOSPocc, DISAB; m denotes GDP, UNEMP; x denotes URBAN, POP65PLUS, EDU, DISAB; and z denotes the dummy variables for states bordering Canada (CANDum) or Mexico (MEXDum).

The dependent variable is measured via the victims of health scams per state in the year 2015. As is true for other types of crimes as well, these statistics are somewhat truncated in the sense that,

given unreported and/or undetected instances, they fail to capture the true related criminal incidence.⁴

We try to explain health scams using five sets of factors: (a) health care professionals; (b) medical/insurance factors; (c) economic factors; (d) demographic factors; and (e) foreign borders.

Health professionals, with their knowledge of medical science and first-hand interactions with patients, are better able to detect and report abuses in health care. More professionals might also check fraud when there is a greater chance of others looking over the abusers' shoulders (network effect). Yet, the confidential nature of the information they possess (e.g., patient records and diagnoses) presents opportunities for abuse (Beaton, 2017) —“agency effect,” (McGuire, 2000). So, we would expect more health professionals to reduce health care-related scams if the former effect is dominant and to increase fraud if the latter effect is dominant. In this study, we consider the number of nurses (NURSES) and the number of physicians (PHYSICIANS) as health professionals. The main hypothesis would be to test whether the impact of medical professionals on health care fraud is positive or negative.

Formally,

H1: More medical professional would check medical fraud due to network effects or might increase fraud because of agency issues.

The nexus of insurance and fraud is longstanding (see, for example, Goel, 2014) and health insurance is no different. We consider three dimensions—NOinsure, MediCARE, and ManCARE. Folks without health insurance (NOinsure) might resort to fraudulent means to obtain health care, and those with government-assisted insurance, such as Medicare (MediCARE), would be vulnerable to fraud as others try to gain fraudulent access to their benefits (Jesilow et al., 1993 provide some related evidence; also see Rai, 2001). In this respect, we also compare the relative vulnerabilities of those with Medicare with those with some sort of managed care health insurance (ManCARE).

With regard to the attributes of the medical sector, we consider hospital occupancy rates (HOSPocc). Higher occupancy rates, signifying excess demand for hospital services and related congestion, might induce some to resort to fraudulent means to gain access or to expedite their access to services.

State economic prosperity (GDP) and unemployment rate (UNEMP) are the economic factors we consider. More prosperous states would have better vigilance against fraud, although such states might attract more fraudsters. Furthermore, the unemployed, generally lacking health insurance, would have incentives to obtain access to health care via legal or illegal means, although they might not have the resources to undertake/set up expensive scams.

With respect to the demographic attributes that might impact health-related scams, greater urbanization (URBAN) would be associated with networking and (lower) information acquisition costs that could make it easier for scammers. Detection of perpetrators might also be challenging in more urbanized areas. Greater literacy (EDU) could, however, act as a check against fraud—both by better informing the public about their rights and abilities to guard their private information and to report abuse. The elderly might be especially vulnerable to fraud—for example, someone stealing their information

to get health benefits, and so forth. Accordingly, we employ the percentage of state population over the age of 65 (POP65PLUS) as a regressor. Are the elderly more vulnerable to health care scams? Another related dimension by the way of the percent of the disabled population (DISAB) is considered to see if scammers take undue advantage of them.

Finally, states bordering foreign nations, in this case, Canada and Mexico, might face heightened scam activity either because of greater chances of flight of domestic scammers or the possibility of foreign nationals trying to avail of the U.S. health care benefits.⁵ In other words, the consideration of foreign borders is accounting for possible fraud spillovers across national borders.

We discuss next the data employed to estimate Equation (1).

2.2 | Data

The dataset for this study was compiled from reputed sources that are listed in Table 1. The main variable of interest, health care-related scam victims by state (HealthSCAM), comes from the U.S. Department of Justice's 2015 Internet Crime Report (https://pdf.ic3.gov/2015_IC3Report.pdf). This source lists health-related scams as, “A scheme attempting to defraud private or government health care programs, which usually involve health care providers, companies, or individuals. Schemes may include offers for (fake) insurance cards, health insurance market place assistance, stolen health information, or various other scams and/or any scheme involving medications, supplements, weight loss products, or diversion/pill mill practices. These scams are often initiated through spam email, Internet advertisements, links in forums/social media, and fraudulent websites” (p. 228).

In 2015, on average, there were about six victims of health care scams in a state. The complainants included individuals, companies, and health care providers (see Table 1). There was, understandably, considerable variation across individual states (range 0 to 49). The detail in our state-level data, however, comes at a cost—this information is currently only publicly available for a single year (2015), which limits us to a cross-sectional analysis.

In other variables of key interest, the number of nurses (NURSES) and physicians (PHYSICIANS), the number of registered nurses were on average three times as many as there were physicians (786 per 100,000 population versus 253 per 100,000 population, respectively; see Table 1). Details about the variables, including definitions, summary statistics, and data sources, are provided in Table 1.

2.3 | Estimation

Given the cross-sectional nature of our state-level data, we estimated all the models using the robust regression. The results with robust regressions are somewhat more reliable than those with OLS, as they are less sensitive to outliers. The overall fit of all the models is decent, as denoted by the statistically significant *F* values and *R* squares that

TABLE 1 Variable definitions, summary statistics, and data sources

Variable	Definition (mean; std. dev.)	Source
HealthSCAM	Health care-related scams, "A scheme attempting to defraud private or government health care programs, which usually involve health care providers, companies, or individuals. Schemes may include offers for (fake) insurance cards, health insurance market place assistance, stolen health information, or various other scams and/or any scheme involving medications, supplements, weight loss products, or diversion/pill mill practices. These scams are often initiated through spam email, Internet advertisements, links in forums/social media, and fraudulent websites" (p. 228), victims by state, per capita, 2015 (8.29e-07; 6.55e-07)	[3]
IDtheft	Identity theft, victims by state, per capita, 2015 (0.0006; 0.00002)	[3]
UNEMP	Unemployment rate (%), population aged 16 and over, 2015 (5.92; 1.34)	[1]
EDU	Educational attainment, percent of population aged 25 and over with high school graduate or higher, 2015 (88.74; 2.92)	[2]
POP	State population, 2015 (6302330; 7201100)	[1]
POP65PLUS	Percent of state population over the age of 65, 2015 (0.15; 0.02)	[2]
URBAN	Percent of state population residing in urban areas, 2000, (72.25; 15.28)	[2]
NURSES	Registered nurses in health care and social assistance industry, per 100,000 resident population, 2013 (785.64; 170.39)	[8]
PHYSICIANS	Physicians (in patient care), Excludes doctors of osteopathy, per 100,000 resident population, 2013 (252.51; 77.86)	[8]
HOSPocc	Percentage of beds occupied (number of nursing home residents per 100 nursing home beds), 2015 (80.56; 8.76)	[7]
DISAB	Total population with disability per capita, 2015 (0.13; 0.03)	[1]
ManCARE	Managed care enrollment per capita, 2014 (0.0001; 0.00007)	[6]
MediCARE	Total Medicaid enrollment per capita, 2014 (0.0002; 0.00007)	[6]
NOinsure	Percentage of people without health insurance coverage at the time of the interview, 2015 (8.72; 3.17)	[1]
RGDP	Real state GDP per capita, in millions of 2009 \$, 2014, (0.05; 0.02)	[4]
EF	Index of state economic freedom, higher values imply greater economic freedom, 2014, (-0.04; 0.26)	[5]
POLICE	Number of state and local police officers per capita, 2015 (2.75e-06; 4.57e-07)	[1, 2]
CANdum	Canada dummy = 1 if state shares border with Canada, (0.20; 0.40)	
MEXdum	Mexico dummy = 1 if state shares border with Mexico, (0.08; 0.27)	

Sources: [1] U.S. Census Bureau, American Community Survey, <https://factfinder.census.gov/>

[2] Statistical Abstract of the U.S., various years

[3] U.S. Department of Justice, 2015 Internet Crime Report, https://pdf.ic3.gov/2015_IC3Report.pdf

[4] U.S. Department of Commerce, Bureau of Economic Analysis

[5] Cato Institute, <https://www.cato.org/policy-report/novemberdecember-2016/freedom-50-states>

[6] U.S. Centers for Medicare and Medicaid Services, Medicaid Managed Care Enrollment and Program Characteristics, 2014, Spring 2016, <https://www.medicare.gov/medicaid/managed-care/enrollment/index.html>

[7] U.S. National Center for Health Statistics, Health, United States, 2016, May 2017, <http://www.cdc.gov/nchs/hus.htm>

[8] American Medical Association, Chicago, IL, Physician Characteristics and Distribution in the U.S., 2015 Edition, annual.

Note. All the above sources are in the public domain, so no copyright permission is required.

are at least 0.30. Furthermore, the mean variance inflation factors (VIFs) are below 2.9, alleviating concerns about possible multicollinearity. Section 3.3.1 discusses results from 2SLS estimation that addresses possible endogeneity concerns. We turn to a discussion of the results next.

3 | RESULTS

3.1 | Baseline models

The baseline results are presented in Table 2. The baseline models exclude medical professionals (nurses and physicians) as regressors. The idea is to first see how the models perform without the key variables of interest. Results with two models are reported including economic, demographic, and geographic factors. Because literacy and

unemployment are likely negatively correlated, we do not include these variables in the same model.

We find that states with greater economic prosperity had a lower incidence of health care scams. This is consistent with greater prosperity increasing the opportunity costs of crimes and with better checks and balances in wealthier states. Furthermore, more urbanized states experienced greater health scams. This may be due to lower transaction costs for scammers in urbanized areas (both of obtaining information to scam and it being relatively easier to conceal their identity after scamming), and greater networking.

The influences of literacy, unemployment and the elderly population were statistically insignificant. The strength of these relations will be reexamined with other factors taken into account in subsequent robustness checks reported below.

Addressing the question, Are states bordering Canada and Mexico more susceptible to health care fraud?, the effects of foreign borders

TABLE 2 Medical professionals and health care fraud: Baseline models (Dependent variable: HealthSCAM)

Model	2.1	2.2
RGDP	-0.00001 ^{**} (2.4)	-0.00001 ^{**} (2.1)
UNEMP	7.48e-08 (1.2)	
EDU		-4.65e-08 (1.4)
URBAN	2.38e-08 ^{**} (4.0)	2.55e-08 ^{**} (4.3)
POP65PLUS	5.76e-06 (1.2)	5.96e-06 (1.3)
CANdum	-6.40e-08 (0.3)	-1.61e-08 (0.1)
MEXdum	-4.97e-08 (0.2)	-2.60e-08 (0.8)
N	51	51
F value	4.44 ^{**}	4.67 ^{**}
R ²	0.30	0.31
Mean VIF	1.31	1.48

Note. See Table 1 for variable definitions. Constant included but not reported. The numbers in parentheses are (absolute) t-statistics based on robust regressions.

^{*}Statistical significance at the 10% level.

^{**}Statistical significance at the 5% (or better) levels.

(captured via dummy variables identifying states bordering Canada (CANdum) and Mexico (MEXdum), were statistically insignificant.

Next, we consider attributes of the health care sector (including employment [physicians, nurses], insurance [Medicare, managed care, no insurance], and hospital occupancy) and other demographic aspects in terms of their impact on health care scams. The focus on the health sector, especially the behavior of medical professionals forms the main focus of this work.

3.2 | Influence of health care professionals and attributes of the medical sector

Considering first the main variables of interest, we focus on the number of nurses (NURSES) and the number of physicians (PHYSICIANS) as health care professionals. Due to their knowledge of medicine (e.g., which procedures are required and which may be optional) and their first-hand interactions with patients, nurses and physicians would be in a good position to identify and report health fraud. The results bear out these attributes—the coefficients on NURSES and PHYSICIANS are negative in all cases; however, only NURSES attain statistical significance at the usual levels.⁶ The greater effectiveness of nurses might be due to the greater time they spend with patients and the paperwork afterward, which enables them perhaps to better identify scams. Another explanation might be that nurses are more effective at keeping doctors and patients honest by mitigating the issues with information asymmetry that engender fraud.⁷ This finding supports the network effect discussed in H1 above. Overall, the results point to the fraud mitigation impact of medical professionals, with stronger support for the role of nurses relative to that of physicians.

In terms of relative elasticities, based on Model 3.1 and evaluated at the respective means, $\varepsilon_{\text{HealthSCAM,PHYSICIANS}} = -0.28$; and

$\varepsilon_{\text{HealthSCAM,NURSES}} = -1.22$ (only the latter elasticity is statistically significant—see Table 3). In other words, a 10% increase in nurses would reduce health care scams by about 12%. Thus, the nursing shortage in the United States (<https://www.ncbi.nlm.nih.gov/books/NBK493175/>) is likely having spillovers in terms of heightened health care fraud. It is unclear whether resource allocation decisions to increase the number of nurses are taking account of these spillovers.

The nexus of fraud with insurance is present in many contexts, of which health care-related frauds are a significant dimension. Accordingly, we consider three different dimensions related to insurance: (a) NOinsure—the percentage of the population without health insurance; (b) ManCARE—the percentage of the population with managed care health insurance; and (c) MediCARE—the percentage of the population with government Medicare health insurance. One would expect some of those without health insurance to try to obtain insurance via fraudulent means. On the other hand, scams might be present in both privately administered health insurance (ManCARE) and government-administered care (MediCARE). Our results fail to find a significant effect in any case, (although the signs are all positive).⁸ It could be the case that over time effective oversights against abuse have been developed by insurance companies, especially with the help of digital technologies and the internet.

The supply-side characteristics of the health care markets might also influence the prevalence of health care crimes and we account for the congestion aspect by including hospital occupancy rates (HOSPocc). On average, about 80% of hospital beds were occupied in the United States. The resulting coefficient, although positive and consistent with the notion that greater congestion would engender fraud, fails to attain statistical significance.

Consistent with the findings in Table 2, unemployment failed to have a significant impact on health care crimes. In two other instances, however, the results were different—the effects of economic prosperity were now largely insignificant, whereas the proportion of the elderly in a state contributed to abuses in the health sector. Quantitatively, a 10% increase in the proportion of seniors in a state would increase health care scams by about 17% (Model 3.1). The vulnerability of seniors to scams has been recognized by agencies in the government and elsewhere (<https://www.fbi.gov/scams-and-safety/common-fraud-schemes/seniors>; <https://www.aarp.org/money/scams-fraud/info-2017/elder-fraud-scams-stories.html>). However, a greater proportion of the population with a disability (DISAB) did not have a significant impact. It could be the case that in some cases, the medical records and related information for the disabled are overseen by someone else.

The following section considers synergies between health care scams and identity thefts—two white-collar crimes that are likely to be complementary.

3.3 | Effects of identity theft

It is quite possible that health scams have synergies or complementarities with other white-collar crimes. Thus, we consider the

TABLE 3 Medical professionals and health care fraud: Influences of the medical sector (Dependent variable: HealthSCAM)

Model	3.1	3.2	3.3	3.4	3.5	3.6
NURSES	-1.29e-09** (2.4)	-1.08e-09** (2.0)	-1.28e-09** (2.3)	-1.42e-09** (2.3)	-1.53e-09** (3.0)	-1.27e-09** (2.2)
PHYSICIANS	-9.22e-10 (0.6)	-6.63e-10 (0.4)	-1.04e-9 (0.6)	-1.81e-10 (0.1)	-1.09e-09 (0.8)	-8.44e-10 (0.5)
RGDP	6.48e-07 (0.01)	-3.24e-06 (0.5)	6.42e-07 (0.1)	9.19e-07 (0.1)	-0.00002* (1.8)	1.71e-07 (0.02)
UNEMP	8.53e-08* (1.8)	6.33e-08 (1.3)	7.94e-08 (1.3)		2.03e-08 (0.4)	6.15e-08 (0.9)
URBAN	1.55e-08** (3.0)	1.48e-08** (2.7)	1.57e-08** (2.9)	1.74e-08** (2.9)	2.05e-08** (4.0)	1.79e-08** (2.6)
POP65PLUS	9.16e-06** (2.2)	6.09e-06 (1.4)	9.00e-06** (2.0)	0.00001** (2.3)	8.56e-06** (2.2)	9.13e-06** (2.0)
ManCARE		0.001 (1.5)				
MediCARE			0.0002 (0.2)			
NOinsure				2.43e-08 (0.8)		
HOSPocc					7.00e-09 (0.8)	
DISAB						1.23e-06 (0.4)
N	51	51	51	51	50	51
F value	7.29**	6.07**	5.74**	5.26**	7.91**	5.54**
R ²	0.36	0.38	0.36	0.34	0.37	0.36
Mean VIF	2.44	2.33	2.57	2.71	2.35	2.80

Note. See Table 2. The bold emphasis in these tables identifies the main variables of interest.

*Statistical significance at the 10% level.

**Statistical significance at the 5% (or better) levels.

prevalence of identity theft. Identity thefts are becoming increasingly common in recent years due to the internet (see Goel, 2019). Stolen identities could facilitate health scams.⁹ Do states with a greater prevalence of identity theft experience more health care related fraud?

In our sample, the correlation between HealthSCAM and IDtheft was 0.42.¹⁰ Accordingly, we estimated models taking the significant factors from Tables 2 and 3 and by including IDtheft as an additional regressor. In our sample, there were on average six victims of identity theft per 10,000 state population (Table 1). The corresponding estimation results are presented in Table 4.

Results show that greater identity thefts do indeed facilitate health fraud—the resulting coefficient on IDtheft is positive in all

cases and statistically significant in two of the three instances.¹¹ Stolen IDs lower the transaction costs of other crimes by hiding the identities of criminals. In terms of magnitude (Models 4.2 and 4.3), the elasticity of HealthSCAM w.r.t IDtheft (evaluated at respective means) turns out to be 7.24.

The finding of the complementarity between identity thefts and health scams has obvious policy value. Whereas identity thefts and health care-related crimes are being increasingly recognized by the press, corporations, and government agencies, it is not clear whether and how policies to combat the two white-collar crimes are coordinated across agencies. The elastic relation between IDtheft and HealthSCAM that we found shows significant potential dividends in controlling health scams when identity thefts are reduced.

TABLE 4 Medical professionals and health care fraud: Effect of identity theft (Dependent variable: HealthSCAM)

Model	4.1	4.2	4.3
NURSES	-1.41e-09** (2.1)	-1.69e-09** (2.7)	-1.82e-09** (3.0)
PHYSICIANS	-1.31e-09 (0.8)	-6.92e-10 (0.4)	-8.36e-10 (0.5)
RGDP	-8.16e-08 (0.01)	2.53e-06 (0.3)	1.87e-06 (0.2)
EDU		-2.40e-08 (0.9)	
URBAN	1.35e-08** (2.1)		
POP65PLUS	9.25e-06* (1.8)	8.00e-06 (1.5)	6.30e-06 (1.2)
IDtheft	0.006 (1.5)	0.01** (2.3)	0.01** (2.6)
N	51	51	51
F value	5.47**	4.74**	6.48**
R ²	0.35	0.32	0.31
Mean VIF	2.74	2.49	2.71

Note. See Table 2. The bold emphasis in these tables identifies the main variables of interest.

*Statistical significance at the 10% level.

**Statistical significance at the 5% (or better) levels.

The other findings are consistent with what was reported earlier—notably, both a greater number of nurses and physicians reduce health scams, with the effects of nurses attaining statistical significance at the conventional levels.

3.3.1 | Effects of identity theft—Considering possible reverse feedbacks

One could, however, wonder about the direction of causality (i.e., whether the positive effect of identity theft exhibits correlation or causation). In other words, it is possible that more scams in the health care sector could increase identity thefts (e.g., to hide those scams or increase the payoffs for existing scams). Accordingly, we ran sets of 2SLS regressions, allowing IDtheft to be endogenous and be alternately instrumented by (a) a state-level index of economic freedom (EF in Table 1), and the number of state and local police personnel per capita (POLICE in Table 1); and (b) POLICE, CANDUM, and MEXDUM (see Table 1 for details).

In both instances, the test of exogeneity could not reject the exogeneity of IDtheft.¹² Thus, reverse feedbacks from health fraud to IDtheft do not appear to be a significant concern. This finding instills confidence in our earlier results.

Furthermore, as noted in Footnote #6, the number of health professionals could be inflated due to more scams. To alleviate this possibility, the data for nurses and physicians is lagged (see Table 1). The concluding section follows.

4 | CONCLUSIONS

Abuses in the health care industry are rampant, with both monetary and quality of care implications. The perpetrators of fraud have been both from outside the medical establishment (e.g., criminals, fraudsters [see Sparrow, 2000]) and from the inside (e.g., medical professionals [see Jesilow et al., 1993]). This paper studies the effectiveness of health care professionals in combating health care scams. Nurses and physicians are the health professionals we consider and we employ data across U.S. states. The wide prevalence of medical fraud and the high monetary losses involved lend importance to the issue being studied (<https://www.nhcaa.org/resources/health-care-anti-fraud-resources/the-challenge-of-health-care-fraud.aspx>). The focus on state-level fraud and the role of physicians and nurses are key contributions of this work.

Our results show that greater employment of nurses consistently reduced health scams, whereas more physicians did not have a significant impact. Nurses, due to their greater interaction with patients in terms of the time spent and relatively greater exposure to the paperwork (prescriptions, medical notes, etc.) seem better able to control medical abuse. Overall, we do not find statistical support for health professionals aiding medical fraud in the United States. Although some have noted the need for structural or procedural fixes to reduce health care fraud, our results suggest that

increases in the employment of health professionals, notably nurses, would contribute to reducing abuse.¹³

Turning to the two questions posed in Section 1, we are able to provide the following answers:

- Do health care professionals aid or check health care fraud?
Yes, health care professionals, especially nurses, are effective at checking health care fraud. This supports the network effect mentioned in H1.
- Are different types of health care workers equally effective as sentinels against health care scams?
No, different types of health care workers are not equally effective at checking abuse in health care. Nurses seem relatively more effective than physicians.

In other findings, more urbanized states and states with a greater proportion of the elderly population experienced a greater incidence of health scams. This suggests that states like Florida, with a large population of the elderly, would be especially vulnerable to health scams. Identity thefts facilitated health care scams, signifying complementarity between the two types of crimes. Different dimensions of health insurance (including the population with Medicare, managed care, and no insurance) and hospital occupancy rates did not matter. Finally, proximity to foreign borders did not affect medical scams. In other words, fraud in states bordering Mexico and Canada was no different from other states.

Quantitatively, the positive elasticity of health care scams with respect to identity thefts is greater than the negative elasticity with respect to nurses. Thus, the dividends in terms of reduced health scams from increases in nursing employment would be undermined by increases in identity thefts. This suggests some policy coordination across different agencies to effectively bring down health scams. Health workers, especially nurses, can turn out to be effective internal complements/allies to external policy initiatives and enforcement in controlling medical fraud. On the other hand, factors such as urbanization rates and the graying population are less susceptible to policy manipulations, at least in the short term. Nevertheless, effective policymaking can be cognizant of these influences, especially given the scale and scope of the medical fraud problem.

In closing, although this study provides formal insights and new evidence on the role of health professionals in combating health care scams, validation of these findings with data covering a longer time period would be useful.¹⁴ It would also be instructive to examine the role of other medical workers (office staff) in terms of their impact on medical fraud. Finally, alternative fraud detection techniques and classifications might aid in the fight against fraud.¹⁵

ACKNOWLEDGEMENTS

Comments by two referees and research assistance of Abenaa Birago and Srishti Goel are appreciated.

ORCID

Rajeev K. Goel  <https://orcid.org/0000-0001-9580-3196>

ENDNOTES

- ¹ <https://www.courthousenews.com/texas-files-opioid-related-medicaid-fraud-suit-against-johnson-johnson/>; <https://www.wlns.com/news/local-news/michigan-doctor-faces-felony-fraud-charges/>; <https://www.forbes.com/sites/kellyphillips/2019/09/04/scammers-target-genetic-testing-as-medical-tax-benefits-expand/#21e269c740cc>.
- ² More recent estimates from The National Health Care Anti-Fraud Association report that health care fraud costs the nation about \$68 billion annually. <https://www.bcbsm.com/health-care-fraud/fraud-statistics.html>; accessed November 2019.
- ³ Indeed, for the case of Korea, penalties were found effective in lowering medical care costs (Kang, Hong, Lee, & Kim, 2010). Unfortunately, we lack comparable cross-state data on penalties for medical fraud to include this dimension in our analysis.
- ⁴ Although we employ a direct measure of fraud (see Table 1), alternative techniques for detecting insurance fraud using data mining are discussed by Verma et al. (2017), with Al Saidi and Zeki (2019) providing a broader related discussion. Also, see Batra and Kundra (2019).
- ⁵ Later in Section 3.3 we consider the relationship of health care scams with identity thefts.
- ⁶ One could argue that some of the fraud could be perpetrated by health care professionals (Joudaki et al., 2016; Morris, 2009), in which case the number of health professionals could be inflated due to more scams. To alleviate this possibility, the data for nurses and physicians is for a prior year (2013)—see Table 1. Thus, it is unlikely that medical fraud in 2015 would affect the employment of health professionals in 2013.
- ⁷ I thank a referee for this insight.
- ⁸ Note that since the unemployed are likely to be the ones without health insurance, we do not include these two determinants together.
- ⁹ See <https://www.chicagotribune.com/business/sns-201903141631-tms-savingsgctnzy-a20190314-20190314-story.html>; <https://health.usnews.com/health-care/health-insurance/articles/2018-11-13/how-to-avoid-medicare-scams>.
- ¹⁰ The 2015 Internet Crime Report formally defines identity theft as, “Someone steals and uses personal identifying information, like a name or Social Security number, without permission to commit fraud or other crimes, and/or (account takeover) a fraudster obtains account information to perpetrate fraud on existing accounts” p. 228.
- ¹¹ It is possible that both identity thefts and medical fraud result from a general weakness in institutions related to governance (see Goel, 2019 for some evidence related to identity fraud).
- ¹² Additional details are available upon request.
- ¹³ A related aspect, that we are unable to account for, may be the market power of medical professionals (McGuire, 2000).
- ¹⁴ The cross-sectional nature of the analysis prevents us from including state-specific dummy variables that might account for, among other things, the differences in enforcement/laws targeting nurses and physicians accused of fraud (see <https://statalaws.findlaw.com/health-care-laws.html>).
- ¹⁵ See Al Saidi and Zeki (2019), Batra and Kundra (2019), and Verma et al. (2017).

REFERENCES

- Al Saidi W., & Zeki, A. M., (2019). The use of data mining techniques in crime prevention and prediction. 2nd Smart Cities Symposium (SCS 2019), DOI: <https://doi.org/10.1049/cp.2019.0225>.

- Batra, B., & Kundra, S. (2019). Naïve classification approach for insurance fraud prediction. *International Journal of Engineering and Advanced Technology (IJEAT)*, 8(5), 2378–2382.
- Beaton, T. (2017). Top 5 Most common healthcare provider fraud activities. *Health Payer Intelligence*, November 13. <https://healthpayerintelligence.com/news/top-5-most-common-healthcare-provider-fraud-activities>.
- Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76(2), 169–217.
- Berwick, D. M., & Hackbarth, A. D. (2012). Eliminating waste in US health care. *Journal of the American Medical Association*, 307(14), 1513–1516. <https://doi.org/10.1001/jama.2012.362>
- Crea, G., Galizzi, M. M., Linnosmaa, I., & Miraldo, M. (2019). Physician altruism and moral hazard: (no) Evidence from Finnish national prescriptions data. *Journal of Health Economics*, 65, 153–169. <https://doi.org/10.1016/j.jhealeco.2019.03.006>
- Goel, R. K. (2014). Insurance fraud and corruption in the United States. *Applied Financial Economics*, 24(4), 241–246.
- Goel, R. K. (2018). Internet diffusion and free riding in insurance markets: An empirical investigation. *Managerial and Decision Economics*, 39(1), 91–96.
- Goel, R. K. (2019). Identity theft in the internet age: Evidence from the U.S. states. *Managerial and Decision Economics*, 40(2), 169–175.
- Goel, R. K., & Mazhar, U. (2019). Does capital punishment deter white collar crimes? *The World Economy*, 42(6), 1873–1897.
- Goel, R. K., & Saunoris, J. W. (2017). The nexus of white collar crimes: Shadow economy, corruption and uninsured motorists. *Applied Economics*, 49(31), 3032–3044.
- Hyman, D. A. (2001). Healthcare fraud and abuse: Market change, social norms, and the trust “reposed in the workmen”. *The Journal of Legal Studies*, 30(S2), 531–567.
- Jesilow, P., Pontell, H. N., & Geis, G. (1993). *Prescription for profit: How doctors defraud Medicaid*. Oakland, California: University of California Press.
- Joudaki, H., Rashidian, A., Minaei-Bidgoli, B., Mahmoodi, M., Geraili, B., Nasiri, M., & Arab, M. (2016). Improving fraud and abuse detection in general physician claims: A data mining study. *International Journal of Health Policy and Management*, 5(3), 165–172.
- Kalb, P. E. (1999). Health care fraud and abuse. *Journal of the American Medical Association*, 282(12), 1163–1168. <https://doi.org/10.1001/jama.282.12.1163>
- Kang, H. C., Hong, J. S., Lee, K. S., & Kim, S. (2010). The effects of the fraud and abuse enforcement program under the National Health Insurance Program in Korea. *Health Policy*, 95(1), 41–49. <https://doi.org/10.1016/j.healthpol.2009.10.003>
- Krause, J. H. (2004). Regulating, guiding, and enforcing health care fraud. *NYU Annual Survey of American Law*, 60(2), 241–282.
- Li, J., Huang, K.-Y., Jin, J., & Shi, J. (2008). A survey of statistical methods for health care fraud detection. *Health Care Management Science*, 11(3), 275–287. <https://doi.org/10.1007/s10729-007-9045-4>
- McGuire, T.G. (2000). Physician agency. In A. J. Culyer, & J. P. Newhouse (Eds.), *Handbook of health economics*, Volume (Vol. 1). Part A, Chapter 9. (pp. 461–536). Amsterdam: Elsevier.
- Morris, L. (2009). Combating fraud in health care: An essential component of any cost containment strategy. *Health Affairs*, 28(5), 1351–1356. <https://doi.org/10.1377/hlthaff.28.5.1351>
- Rai, A. K. (2001). Health care fraud and abuse: A tale of behavior induced by payment structure. *The Journal of Legal Studies*, 30(S2), 579–587.
- Rashidian, A., Joudaki, H., & Vian, T. (2012). No evidence of the effect of the interventions to combat health care fraud and abuse: A systematic review of literature. *PLoS ONE*, 7(8), 1–8. e41988. <https://doi.org/10.1371/journal.pone.0041988>
- Rudman, W. J., Eberhardt, J. S., III, Pierce, W., Hart-Hester, S. (2009). Healthcare fraud and abuse. *Perspectives in Health Information*

- Management*, 6, PubMed PMID: 20169019; PubMed Central PMCID: PMC2804462.
- Sparrow, M. K. (2000). *License to steal: How fraud bleeds America's health care system* (updated ed.). Boulder, Colorado: Westview Press.
- Stelfox, H. T., & Redelmeier, D. A. (2003). An analysis of one potential form of health care fraud in Canada. *Canadian Medical Association Journal*, 169(2), 118–119.
- Thornton, D., Mueller, R. M., Schoutsen, P., & Hillegersberg, J. v. (2013). Predicting healthcare fraud in Medicaid: A multidimensional data model and analysis techniques for fraud detection. *Procedia Technology*, 9, 1252–1264.
- Verma, A., Taneja, A., Arora, A. (2017). Fraud detection and frequent pattern matching in insurance claims using data mining techniques. 2017 Tenth International Conference on Contemporary Computing (IC3), 1, 1-7. DOI:<https://doi.org/10.1109/IC3.2017.8284299>.
- Wilson, P. R., Geis, G., Pontell, H. N., Jesilow, P., & Chappell, D. (1985). Medical fraud and abuse: Australia, Canada, and the United States. *International Journal of Comparative and Applied Criminal Justice*, 9(1-2), 25–34.

How to cite this article: Goel RK. Medical professionals and health care fraud: Do they aid or check abuse? *Manage Decis Econ*. 2020;41:520–528. <https://doi.org/10.1002/mde.3117>