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Should We Do More To Police Medicaid Fraud? Evidence on the Intended and Unintended Consequences of Expanded Enforcement

Victoria Perez

Coady Wing

Victoria Perez (corresponding author) viperez@indiana.edu, Coady Wing, School of Public and Environmental Affairs at Indiana University.

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I. Introduction

Audit studies suggest that fraudulent and inappropriate reimbursements cost the Medicaid program about $61 billion per year across all states (CMS, 2016). Those figures imply that the total bill for fraudulent Medicaid services is worth more than the entire Medicaid program in every state except New York ($62 Billion) and California ($82 billion) (Henry J. Kaiser Family Foundation, 2016). In an effort to reduce fraud and recoup losses, the federal and state governments spent an average of $259 million per year on Medicaid fraud enforcement between 2006 and 2016.[1] The money supports Medicaid Fraud Control Units (MFCUs), which are state agencies that operate independently of the Medicaid program, and investigate and prosecute cases of Medicaid fraud and abuse. Some MFCU investigations involve financial fraud, such as billing for services that were never provided, billing separately for services that should be submitted as a bundle, and kickback payments. Other investigations involve patient abuse crimes such as: providing unnecessary services, direct abuse or neglect, or the indiscriminate prescribing of controlled substances. In 2016, MFCU investigations recovered more than $7 for every $1 spent (Levinson, 2017).

In this paper, we study the effects of MFCU spending on fraud enforcement outcomes, and on measures of hospital treatment intensity for a set of fraud prone health conditions that are often the target of MFCU investigations. We develop a simple theory in which the provision of fraud prone health services generates revenues for the hospital but also increases the risk of triggering a costly MFCU investigation. We use the theory to understand some of the ways in which MFCU enforcement might affect the production of health services. The model helps clarify arguments about how MFCU effort levels could discourage both fraudulent and legitimate health services.

Our empirical analysis combines data from MFCU annual reports and hospital inpatient data from 2006 to 2014. We start by using a Difference-in-Differences (DD) design to study the effects of within-state changes in MFCU budgets on Medicaid fraud investigations, convictions, and recoveries. This work sheds light on the likely consequences of changes in MFCU spending on the enforcement activities that actually take place in a state. Then we turn to the effects of MFCU spending on hospital treatment decisions. Our analysis of treatment intensity focuses on a set of health services that are considered prone to fraud because these services are mostly likely to attract the interest of MFCU investigators.

The set of fraud prone conditions we examine are derived from previous research. Specifically, in the late 1990s, the US Health Care Financing Administration (now the Centers for Medicare and Medicaid Services) conducted a mixed method study to identify the set of health care conditions that were most susceptible to fraud and abuse. We focus on measures of treatment intensity for the six disease groups that those investigators identified as "fraud prone" (Department of Health and Human Services, 1998). The results in the report are consistent with the stated beliefs of fraud investigators, and there is public knowledge that MFCUs' approach to detecting fraud is guided by this report. We work under the assumption that increased MFCU budgets are most likely to affect the production of these services, which are most likely to arouse the suspicion of MFCU investigators.

The basic DD design, which exploits within state variation in MFCU budgets, could still be misleading if there are unmeasured factors that change within states over time, and that affect both the production of fraud prone health services and the

1 Authors' own analysis of MFCU annual reports. All in-text references are adjusted to be in 2016 dollars, using the CPI inflation factor.

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level of MFCU expenditures in the state. To minimize bias from these threats to validity, we include additional control groups that should not be affected by MFCU spending, but should respond to many of the same within-state factors that might affect fraud prone activity. One comparison group consists of a set of disease groups that are easy to verify and therefore unlikely to arouse the suspicion of MFCU investigators. Another comparison group consists of health conditions that have historically had a production level comparable to the production levels associated with fraud prone health services. We use both of these comparison groups in a triple difference framework to study the effects of MFCU spending on the production of fraud prone health services.

Our results suggest that increases in fraud enforcement spending do generate more investigations and convictions for fraudulent and inappropriate Medicaid billing. We do not find any evidence that MFCUs use their expanded enforcement budgets to investigate less severe cases. Our analysis of treatment intensity suggests that – at least at current margins – increases in MFCU funding do not lead to substantial changes in treatment intensity or patient outcomes associated with fraud prone health conditions. The results imply that the returns to fraud enforcement spending are primarily restricted to the financial value of direct recoveries from individual investigations, which appear to be substantial at current margins. To our knowledge, this is the first study to consider how differences in Medicaid fraud enforcement funding affect investigative effort and outcomes and to estimate the causal effects of Medicaid fraud enforcement spending on treatment intensity in the Medicaid program.

II. Related Research

Several studies have considered the role of fraudulent or deceptive practices in the context of public insurance programs, including workers' compensation insurance, disability insurance, and unemployment insurance (e.g. Meyer et al., 1995; Crocker and Tennyson, 2002; and Meyer and Mok, 2014). Fraud and deception are credible possibilities in these programs because it is difficult to verify the authenticity and legitimacy of claims for covered events. People may file disability insurance and worker's compensation claims because of injuries and illnesses diagnosed mainly through clinical assessments that are hard to verify using laboratory tests, which may be viewed as more objective. Fraud that exploits hard-to-verify events is also an important concern in many private insurance markets, such as car insurance (Tennyson and Salsas-Forn, 2002; Derrig et al., 2006) and credit card fraud (Barker et al., 2008; Dal Pozzolo et al., 2014).

There is also a small literature on the effects of the False Claims Act on fraud in public insurance programs. The False Claims Act (FCA) is designed to encourage whistleblowers to bring suit on behalf of the government. Among cases involving defendants directly involved in health care delivery since the mid-1990s, hospitals were among the most frequent types of defendant, representing one-third of defendants accused of fraud, waste, and/or abuse (Kesselheim and Studdert, 2008; Murrin, 2016). Forlines and Yelowitz (2017) study the effects of fraud enforcement efforts on off-label use of prescription medication. Their work suggests that whistleblower-initiated civil suits reduce Medicaid spending on prescription drugs and off-label prescription drug use. Similarly, Heese et al. (2015) examine cases of civil fraud filed by whistleblowers against California

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hospitals. They find that teaching hospitals, which provide high levels of charity care, tend to receive weaker punishments than other hospitals. Finally, Nguyen and Perez (2018) study the effect of the FCA on MFCU enforcement strategy.

Other studies have tried to measure the rate of fraud in the Medicaid and Medicare programs. Fang and Gong (2017) find that physicians who bill the Medicare Part B program for services that amount to more than 100 hours of labor per week submit more high-intensity service codes than other physicians, which corresponds to higher marginal revenue gain. Silverman and Skinner (2004) report a higher prevalence of upcoding among private hospitals, relative to public hospitals, throughout the 1990s.

Our study is most related to Becker et al. (2005), which examines the effects of Medicaid fraud enforcement funding on treatment intensity among Medicare patients. They find that increases in fraud enforcement spending reduce length of stay among younger Medicare enrollees. Becker et al. (2005) justify their focus on the effect of Medicaid fraud enforcement on Medicare patients by arguing that stepped up enforcement in Medicaid is likely correlated with stepped up enforcement in Medicare. However, they present no evidence that this correlation exists. One reason to think that Medicaid fraud enforcement and Medicare fraud enforcement efforts are not highly correlated is that the two programs organize enforcement quite differently. Each state operates its own Medicaid Fraud Control Unit (MFCU), and MFCU budgets vary across states and time periods. In contrast, the federal government operates Medicare Strike Force Teams, which are multi-state entities. Given the different geographical organization of Medicaid and Medicare enforcement efforts, we think that unmeasured Medicare enforcement efforts is not an important source of omitted variable bias in our study. In that case, a reasonable interpretation of the results in Becker et al. is that they represent the spillover effect of Medicaid enforcement on Medicare patients. However, if Medicaid and Medicare efforts are correlated, even after adjusting for state and year fixed effects, then it would be appropriate to interpret both our estimates and the estimates in Becker et al. as some average of the effects of enforcement efforts in these two public insurance programs.

The literature on physician responses to medical malpractice reforms also offers some insight into the way that hospitals may respond to increased Medicaid fraud enforcement activity. That literature examines the possibility that physicians may practice defensive medicine by overtreating patients to protect themselves against the threat of a medical malpractice law suit (Kessler and McClellan, 1996; Sloan and Shadle, 2009; Paik et al., 2017). In the case of Medicaid fraud enforcement efforts, hospitals may respond by reducing their production of both legitimate and illegitimate health care services in order to avoid raising enforcement agency suspicions.

III. Medicaid Fraud and Fraud Enforcement

The Social Security Act requires every state to operate an independent Medicaid Fraud Control Unit (MFCU) to police and mitigate Medicaid fraud and abuse.[2] Usually, the MFCU is part of the state attorney general's portfolio. The Act also creates a

2 States may make a compelling case that instances of Medicaid fraud in the state are rare enough that an MFCU would not be cost effective. At the moment, only North Dakota has done so.

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matching grant program that provides federal financial support for 75% of MFCU budgets.[3] Budget size depends on the amount requested by the state governor and/or attorney general.

Between 2006 and 2016, total MFCU spending increased by about 37%, from around $190 million to almost $260 million. The total amount of money recovered by MFCUs exceeds expenditures. However, recoveries are much more variable from year to year than expenditures. In the average year, MFCU investigations recover nearly $2 billion per year nationally. MFCU budgets also vary substantially across states. In 2016, the median MFCU had a budget of $2 million and employed about 21 people. However, some MFCUs are large operations. In 2016, California's MFCU had a total budget of $63.6 million, employed 336 people, and conducted 1,448 investigations (Levinson, 2017). MFCUs often publicize recovered losses, prosecutions, and penalties as measures of productivity. For example, in 2017, a single investigation of health care fraud and opioid scams identified over 400 providers who had falsely billed Medicaid and Medicare over $1.3 billion in total (Gurman, 2017). Despite this, there are few studies that evaluate the effects of MFCU investigation efforts on the actual level of fraud.[4]

MFCUs investigate and prosecute a range of deceptive or inappropriate billing practices. Some MFCU investigations involve providers who submit Medicaid claims for services that were never performed. In other cases, providers falsely diagnose a person and then submit claims for medical services that are justified by the false diagnosis, submit duplicate bills for a single service, or submit claims for a service that is more costly than the service actually provided (Sparrow, 2008). There are also cases of patient abuse and neglect. For example, a patient may develop complications from medically unnecessary procedures.

MFCUs receive reports of suspected provider fraud via three channels: directly from consumers; from Medicaid or other agencies, such as the Department of Justice; and from data mining Medicaid enrollee claims (Dixit, 2016). Little detailed information is available on the specific ways in which MFCUs investigators identify suspicious transactions. A detailed public account comes from testimony that Special Agent Abjit Dixit gave to the OIG Office of Investigations. In his testimony, Dixit (2016) explains that MFCU investigations often originate because a provider or group of providers are statistical outliers in terms of the number of services provided or total reimbursements received relative to the other providers in the state. This type of outlier analysis typically focuses on claims for health care conditions that have previously been identified as fraud prone (Department of Health and Human Services, 1998).

IV. Theory

We develop a model of hospital responses to the possibility of a MFCU investigation, which is similar to models of tax evasion and crime (Allingham and Sandmo, 1972; Yitzhaki, 1987; Becker, 1968). In our model, the conditional probability of a MFCU investigation is higher when the MFCU has a larger budget, and higher at hospitals that produce a large number of fraud prone claims. We assume that complying with the investigation imposes administrative costs on the hospitals, and we examine how profit-maximizing hospitals respond to these incentives.

3 This share is capped at a maximum of 0.25% of the total cost of the state Medicaid program, but states tend to request less than this limit.
4 Figures are based on authors' own analysis of the data and are presented in 2016 dollars.

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A. MFCU Investigations

Assume that a state MFCU uses its budget to monitor and investigate the billing and treatment practices of a set of hospitals. The MFCU observes a vector of Medicaid insurance claims submitted by each hospital. It cannot distinguish legitimate and fraudulent claims from the data alone. The only way to learn more is to initiate a costly investigation. However, some claims records are more suspicious than others. Specifically, the MFCU considers Medicaid claims for a set of hard-to-verify health conditions to be fraud prone and is more likely to investigate hospitals that submit a large amount of those claims (Department of Health and Human Services, 1998). Hospitals that submit an unusually high number of claims for fraud prone conditions are more likely to be scrutinized.

Let v_i be the vector of claims originating from hospital i. The MFCU's data analytics team computes a summary statistic $F_i = h(v_i)$, which measures the quantity of fraud prone claims activity at the hospital relative to industry-wide norms. Higher values of F_i indicate that the hospital submitted an unusually high number of claims for fraud prone health conditions. Let $I_i = 1$ if the MFCU opens an investigation into the hospital's practices. $I_i = 0$ if the MFCU decides not to investigate. Finally, let G be the MFCU's budget.

$Pr(I_i = 1|F_i; G_t) = I(F_i; G)$ is a conditional probability function, which describes the investigation rate across different levels of the fraud prone activity index and the MFCU budget. $I(F; G)$ is weakly increasing in both arguments. Larger budgets will allow the MFCU to conduct more investigations and it is likely to investigate hospitals with a relatively high number of fraud prone claims. However, the investigation function must flatten out as it approaches the extreme values of 0 and 1. That implies that the second derivatives of the investigation function are positive over some range of values, but eventually become negative. For example, if we approximate $I(F_i; G)$ as a logit function so that the probability of investigation is an s-curve in F_i and G. In the real world, prevailing MFCU investigation rates are fairly low: the maximum number of total investigations is well below the smallest state's population of active providers. This suggests that the most relevant part of the investigation function is at the bottom of the s-curve, where the second derivatives are positive. Therefore, throughout the theory section, we assume that I_F, I_G, I_{FF}, I_{GG}, and I_{FG} are all weakly positive.

B. Hospital Production Under The Threat of Investigation

A hospital chooses a level of fraud prone health services given the MFCU budget and investigation function. We start with a simple version of the model in which the hospital does not distinguish between the production of legitimate and illegitimate health services for fraud prone health conditions.

Let p be the unit price the hospital receives in return for providing fraud prone health services. Let c be the cost the hospital incurs to produce a unit of fraud prone health services. Let A represent a fixed cost the hospital incurs whenever it has to respond to an MFCU investigation. β is the share of revenue for the fraud prone health service that the hospital expects to repay if the MFCU investigation discovers fraud. The hospital's expected profit from fraud prone health service production is:

$$\pi_i = I(F_i; G)[pF_i - cF_i - \beta pF_i - A] + (1 - I(F_i; G))(pF_i - cF_i) \tag{1}$$

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The hospital receives net revenue of $(p-c)F_i$ in the absence of an investigation. If there is an investigation, the hospital receives this net revenue minus the expected recoveries and fixed costs of complying with the investigation. The first order condition for profit maximization is:

$$\pi_F = p - c - I(F_i; G)\beta p - I_F(\beta p F_i + A) \tag{2}$$

If the probability of an investigation is increasing in the number of fraud prone claims at an increasing rate ($I_F > 0$ and $I_{FF} > 0$) then setting the first order condition to zero is a maximum. Rearranging the first order condition gives:

$$p - c = I(F_i; G)\beta p + I_F(\beta p F_i + A) \tag{3}$$

This shows that the hospital increases its production of fraud prone health services until the net revenue from the services $(p-c)$ is just equal to the expected costs it will incur from an MFCU investigation. The expected investigation costs rise with the level of fraud prone service production because service production increases the likelihood of an investigation and exposes more of the hospital's revenue to the recovery and penalty consequences of an investigation.

Totally differentiating the first-order condition uncovers $dF/dG = -(\partial\pi_F/\partial G)/(\partial\pi_F/\partial F)$, which represents the change in fraud prone service production required to maintain the profit maximization condition in the face of an MFCU budgetary change. The partial derivatives of the first-order condition are $\partial\pi_F/\partial F = 2I_F\beta p + I_{FF}(\beta p F_i + A)$ and $\partial\pi_F/\partial G = I_G\beta p + I_{FG}(\beta p F_i + A)$. Combining them gives

$$\frac{dF}{dG} = -\frac{I_G\beta p + I_{FG}(\beta p F_i + A)}{2I_F\beta p + I_{FF}(\beta p F_i + A)} \tag{4}$$

If I_G, I_{FG}, I_F, and I_{FF} are all positive given the prevailing MFCU investigation rates, then we would expect that $dF/dG < 0$. Increases in the MFCU budget will lead hospitals to reduce their production of fraud prone health services.

C. Legitimate and Illegitimate Fraud Prone Services

Even when focusing on fraud-prone health conditions, the MFCU cannot distinguish between legitimate and fraudulent services without investigating. It is unclear whether hospital management systems can independently control the hospitals production of fraudulent and legitimate fraud-prone health services. If the hospital does have independent control over illegitimate and legitimate activity, then an interesting question is how changes in MFCU budgets will affect the hospitals behavior with respect to these two separate types of activity. That is, in response to a MFCU expansion, will hospitals reduce only their fraudulent activities? Or will they also reduce their production of legitimate health services for the fraud-prone health conditions that attract MFCU attention? To study the possibility of such defensive practice patterns in more detail, we augment the basic model to allow hospitals to produce a mix of legitimate and illegitimate health services for fraud prone health conditions.

Suppose that the MFCU's fraud prone activity index is $F_i = l_i + z_i$, where li represents legitimate service production and z_i represents illegitimate service production. Assume that the hospital receives the same revenue and incurs the same costs

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from both types of services. However, the recoveries and penalties from successful investigations only apply to illegitimate services. Then, the hospital's profit function is:

$$\pi_i = I(F_i; G)[p(l_i + z_i) - c(l_i + z_i) - \beta p z_i - A] + (1 - I(F_i; G))(p(l_i + z_i) + c(l_i + z_i)) \tag{5}$$

Setting the first-order condition to zero shows that the hospital produces legitimate fraud prone health services up to the point where net revenues are equal to the expected costs of an investigation. The hospital produces fewer legitimate health services than it would in the absence of the threat of an MFCU investigation because it is concerned about paying the fixed compliance costs and about lost revenue if its illegitimate activity were discovered. The presence of fixed compliance costs means that even hospitals that do not submit any illegitimate claims will tend to produce fewer legitimate services than they would in the absence of any enforcement effort. To characterize the hospital's response to an increase in the MFCU budget, we differentiate the first-order condition to obtain $dl_i/dG = -(^{\partial \pi_l}/_{\partial G})/(^{\partial \pi_l}/_{\partial F})$, where π_l represents the first order condition with respect to legitimate fraud prone health services. In this case, the partial derivatives of the first-order condition are $\partial \pi_l/\partial l = I_{FF}(\beta z_i p + A)$ and $\partial \pi_l/\partial G = I_{FG}(\beta z_i p + A)$. Combining the two yields:

$$\frac{dl_i}{dG} = -\frac{I_{FG}(\beta z_i p + A)}{I_{FF}(\beta z_i p + A)} \tag{6}$$

Since I_{FG} and I_{FF} are both positive, other things equal, an increase in the MFCU budget will lead hospitals to produce fewer legitimate health services for fraud prone health conditions. A parallel argument shows that the MFCU budget could also reduce illegitimate health services. To see this, totally differentiate the first-order condition and substitute the relevant partial derivatives:

$$\frac{dz_i}{dG} = -\frac{I_{FG}(\beta p z_i + A) + I_G \beta p}{I_{FF}(\beta p z_i + A) + 2 I_F \beta p} \tag{7}$$

If I_{FG}, I_G, I_{FF}, and I_F are all positive, then $dz_i/dG < 0$, which implies that profit maximizing hospitals should submit fewer illegitimate claims for fraud prone health conditions in response to an increase in the MFCU budget.

D. Heterogeneity by Hospital Type

In practice, some hospitals may adjust their production of health services for fraud prone health conditions more than others. For example, some hospitals may treat a large population of Medicaid patients, and many of these patients may have fraud prone health conditions. Without a qualitative change in the mission and structure of the hospital, it may be the case that a good fraction of the hospital's production of fraud prone health services might be considered "non-discretionary'.' A hospital with a fixed patient population or inflexible cost structure that provides a high level of non-discretionary fraud prone health services may be more likely to be investigated by an MFCU and less able to respond to changes in the MFCU budget. Our model does not include production and cost functions for the supply of fraud prone health services. Heterogeneous production and cost functions would lead some hospitals to be more responsive to MFCU budget levels than others.

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V. Data

A. Hospital Inpatient Data From HCUPnet

We use public use data on hospital inpatient events from the Healthcare Cost and Utilization Project's (HCUP) HCUPnet database. HCUPnet allows users to compute aggregate tabulations from the individual records contained in HCUP's State Inpatient Databases (SID) from 36 states from 2006 to 2014. Twenty-nine states appear in every year of the study period: Arizona, Arkansas, California, Colorado, Florida, Hawaii, Iowa, Kansas, Kentucky, Maine, Maryland, Michigan, Minnesota, Mississippi, Nevada, New Jersey, New York, North Carolina, Oklahoma, Oregon, Rhode Island, South Carolina, Tennessee, Utah, Vermont, Washington, West Virginia, and Wisconsin. Three states are missing one year: Massachusetts (2014), Texas (2006), and Wyoming (2006). Four states appear for 3 to 6 years of the panel: Illinois, Indiana, New Hampshire, and New Mexico. (See Table A1 for specific years). We construct aggregate measures of treatment intensity and discharge status for Medicaid patients at the $state \times year \times DRG$ level.

We measure Medicaid treatment intensity in $state \times year \times DRG$ cells as the number of hospital stays, hospital charges associated with each inpatient stay, and average length of stay. Measures related to charges and length of stay were collected as the average value across hospitals and within a DRG-state-year. Measures of total inpatient admissions and discharge status were collected as counts across hospitals and within a DRG-state-year level. The measure of hospital charges available in the HCUPnet excludes professional fees because Medicaid reimburses these fees directly to the provider. These charges reflect the total amount billed by the hospital to the Medicaid program in a specific DRG-state-year cell. While professional fees are the most accurate measure of physician compensation, they represent only 20% of total charges and are highly correlated with hospital charges (Peterson et al., 2015). Thus, hospital charges observed in the data are a credible way to proxy for provider decisions on treatment intensity. We measure discharge status in the same cells using the rate of routine discharges transfers to other facilities (acute-care hospitals, nursing homes, and skilled nursing facilities). Routine discharges occur when the patient is discharged to their home or self care.5

We also use HCUPnet to form measures of the mixture of patient and hospital characteristics in the $state \times year \times DRG$ cells. Specifically, we measure hospital teaching status, ownership type (government, private for-profit, private nonprofit), and size (based on beds and geographic region: Northeast, Midwest, Southern, or Western). Appendix A includes additional details on sample construction.

The focus of our study is the effects of fraud enforcement efforts on treatment intensity for a set of six disease groups that the Health Care Financing Administration (HCFA) has identified as prone to fraudulent overbilling based on its retrospective analysis of claims submitted in the 1990s. The disease categories are: respiratory infections and pneumonia; chronic obstructive pulmonary disease (COPD) and generalized respiratory disorders; circulatory system disorders; kidney disorders and renal failure; diabetes and nutritional or metabolic disorders; and cerebrovascular disorders or stroke. Together, these disease groups represent 22 distinct conditions and 31 sets of Diagnosis-related group (DRG) codes based on case severity.

5 Other types of discharges, which we don't study due to their low occurrence, are discharges against medical advice and patients who die in an inpatient setting.

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The HCUPnet data have several advantages for our research. First, the data are reported at the DRG level within each state and year. This is important because the estimated effect of enforcement is likely to be sensitive to the specific DRG analyzed. We expect enforcement efforts to matter most for treatment intensity of fraud prone health conditions. The ability to separately measure treatment intensity by DRG category makes this type of focus possible. The data also allow us to isolate hospital inpatient records for Medicaid patients. This means we can investigate the effects of Medicaid enforcement efforts on Medicaid treatment intensity directly. Finally, observing outcomes by DRG and state allows us to leverage the variation in treatment patterns that may be caused by state-specific aspects of the Medicaid program.

To control volume of care, hospitals may adjust the types of patients they admit, the typical length of stay, or the intensity with which they treat patients during a stay. Treatment intensity outcomes among fraud prone conditions include length of stay, average hospital charges, the number of inpatient stays, and charges per stay. These outcomes map directly to the volume of fraud prone care described in the conceptual framework. Discharge status outcomes indicate the effects of changes in treatment intensity and the extent to which hospitals adjust criteria for admitting patients. Hospitals could respond to the threat of investigations by cream-skimming patients at entry to avoid admitting those with fraud prone conditions. An increased share of healthier patients would increase the prevalence of routine discharges and decrease the use of secondary facilities. Becker et al. (2005) find that younger Medicare patients receive less intensive services in high Medicaid enforcement states and conclude that enforcement reduces inpatient admission rates among healthy patients. In our study, such a change in hospital behavior would decrease the number of routine discharges and increase the number of transfers to post-acute care settings, such as home health and skilled nursing facilities, because the average admitted patient after the enforcement increase would be sicker than the average patient prior to the change.

B. Medicaid Fraud Control Unit Budget Data

The treatment variable is the level of funding for the MFCU in each state over time. Becker et al. use this measure, scaled by the Medicare population. We modify this approach because direct investigator testimony indicates that surveillance occurs at the provider rather than the patient level (Dixit, 2016). Therefore, we scale the annual MFCU federal grant by the number of providers in the state. Providers include hospitals, individual physicians, and any other health care practitioner that bills Medicaid. We do not limit the number of active NPIs to hospital NPIs because MFCUs monitor all providers. Data on provider numbers is based on the number of unique National Provider Identification (NPI) numbers in the Centers for Medicare and Medicaid Services (CMS) National Plan and Provider Enumeration System that were active in the state and year. This approach may overstate the number of providers under MFCU surveillance as not all providers accept Medicaid. However, we find our results are not sensitive to this choice in scaling.

The OIG MFCU Annual Reports contain measures of MFCU grant funding, Medicaid spending, and the number of civil and criminal cases, indictments, and judgments pursued by the MFCUs, from 2006 to 2014. We exclude North Dakota from the analysis because because it does not operate an MFCU or provide information about Medicaid fraud enforcement. Our sample is further limited to exclude discharges in states that did operate an MFCU, but did not participate in the HCUPnet.

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In the case that effort is not monitored at the provider level, we consider the alternative strategy whereby the MFCU pursues fraud based on abnormal treatment patterns at the patient level (Appendix B). In this scenario, measures of enforcement effort are the number of dollars granted to the MFCU per Medicaid enrollee. Data on Medicaid enrollment is extracted from public reports published by CMS and the Kaiser Family Foundation.

VI. Research Design and Econometric Methods

We study the effects of MFCU budgets on Medicaid fraud enforcement activity using a difference in difference framework based on within-state variation in MFCU budgets over time. To study the effects of MFCU budgets on treatment intensity in the Medicaid program, we developed two broad research design strategies. The first approach is a difference in difference strategy that exploits within-state variation in MFCU budgets per provider on measures of treatment intensity. The key weakness of the design that it relies on the common trends assumption that – in the absence of changes in MFCU budgets – treatment intensity for fraud prone conditions would have changed in parallel across states over time. We test the sensitivity of our results to this assumption by including state-specific linear trends; however, this approach has low power. We then relax this assumption further by estimating two triple difference designs that incorporate comparison conditions that differ from the fraud prone conditions. The comparison and fraud prone conditions should share a common, possibly state-specific, time trend. But only the fraud prone conditions should respond to changes in MFCU spending in the state.

A. Enforcement Activity: Difference in Differences

Let R_{st} be a measure of enforcement activity (investigations, convictions, recoveries) in state s in year t. E_{st} is a measure of MFCU funding in state s in year t per active NPI in each state-year, logged. We study the effects of MFCU funding on Medicaid enforcement activities using regression models with the following form:

$$R_{st} = \delta E_{st} + \theta_s + \theta_t + \epsilon_{st} \tag{8}$$

θ_s and θ_t are state and year fixed effects, and δ represents the effect of the enforcement spending on enforcement activity. The specification assumes that, in the absence of enforcement spending variation, enforcement activity in each state would follow a common national trend. It also assumes that within-state changes in enforcement spending from year to year are strictly exogenous in the sense that they are independent of the history of changes in the outcome variable over time.

B. Treatment Intensity: Difference in Differences

Let Y_{std} be a measure of Medicaid treatment intensity in state s, year t, and health condition d. Y_{std} represents treatment intensity and discharge status for Medicaid patients admitted for condition d in state s and year t. Treatment intensity outcomes are the average hospital charges, length of stay, total number of inpatient stays ("discharges"), total charges, and charges per inpatient stay. Charges are recorded in nominal dollars.[6] Discharge status outcomes are binary indicators that indicate the

6 The regressions included year fixed effects, which allays concerns about inflation.

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type of discharge patients receive: routine discharges, discharges with a referral to home health agencies, transfers to other acute-care hospitals, or transfers to other skilled nursing facilities.

H_{std} is a vector of hospital characteristics associated with the average discharge for health condition d in each state s and year t. Likewise, P_{std} is a vector of average patient characteristics. The difference in difference model is a fixed effects regression:

$$Y_{std} = E_{st}\delta + H_{std}\alpha + P_{std}\beta + \theta_s + \theta_t + \epsilon_{std} \tag{9}$$

δ is the difference-in-differences parameter that measures the relationship between fraud enforcement and outcomes among fraud prone conditions. The main threat to the internal validity of the estimated effect of MFCU spending on treatment intensity comes from unmeasured factors that change within states over time.

C. Treatment Intensity: Triple Differences

To mitigate possible bias from state-specific time trends, we augment the basic model using a comparison group of non-fraud prone health conditions that we expect would share state-specific time trends with the fraud prone measures but would not be affected by Medicaid fraud enforcement. Let FP_d be a binary variable set to 0 for non-fraud prone health conditions and set to 1 for fraud prone health conditions. Then the triple difference version is:

$$Y_{std} = \delta(E_{st} \times FP_d) + H_{std}\alpha + P_{std}\beta + \theta_s + \theta_t + \theta_d + \gamma_{st} + \gamma_{sd} + \gamma_{dt} + \epsilon_{std} \tag{10}$$

where δ is the triple difference estimate of the effect of fraud enforcement spending on treatment intensity for fraud prone health conditions. γ_{st} represents a $state \times year$ fixed effect that is intended to capture state-specific time trends common across both fraud prone and non-fraud prone conditions. The full model allows us to control for $state \times DRG$ and $DRG \times year$ fixed effects as well. These factors are represented as γ_{sd} and γ_{dt} in the equation.

To implement the triple difference design, we construct a comparison group of health conditions that might plausibly share common trends with the fraud prone conditions but are unlikely to be affected by the MFCU fraud enforcement efforts. We use two methods to construct comparison groups: selection based on verifiability of conditions and selection based on prevalence and cost structure.

The first group consists of five disease groups that are objectively verifiable and therefore likely to be unaffected by MFCU enforcement efforts. They include cancer (tumor), childbirth, and organ transplants (See Table A3 for the complete list) and encompass 24 conditions and 31 sets of DRG codes. The idea is simply to exploit the apparent fact that MFCUs monitor these conditions less carefully because they were not considered fraud prone in earlier studies. The disease groups that we chose involve health services that would be difficult to fake or provide n ecessarily. For example, a claim of childbirth submitted by an obstetrician is verifiable with claims associated with a new infant, who would be automatically eligible for Medicaid for at least 30 days after the birth and on whose behalf claims would be submitted by another provider, a pediatrician.

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The second comparison group consists of conditions that are not part of the fraud prone conditions list but have similar levels of spending and prevalence. Fraud prone conditions are among the most common inpatient DRGs, but they are less expensive to treat than other common conditions. An ideal control condition is one that is not fraud prone but which otherwise follows similar trends in treatment intensity over time within states. To identify these conditions, we use state DRG-level Medicare inpatient charges from 2014. We used Medicare data to avoid the potential endogeneity of selecting conditions prone to over-billing based on charges within the same population. To form the matches, we construct a $state \times DRG$ level data set based on 2014 Medicare discharges. Then we code each cell as either fraud prone or non-fraud prone. We fit logistic regression models of the fraud prone status of the cell on the prevalence of the condition and the treatment costs of the condition. The predicted probabilities serve as propensity scores. We match each fraud prone condition to the two closest control conditions without replacement. The matched comparison group consists of 13 disease groups, which encompass 33 conditions and 34 DRG codes. The list includes disorders related to the nervous system and respiratory system (See Table A4 for the complete list). The advantage of this second control group is that it resembles the treatment group in terms of the distribution of claims and costs. However, these conditions were not identified in the HCFA report as being fraud prone.

D. Hospital-Specific Effects

To examine the possibility that the effects of Medicaid enforcement effort vary by hospital type, we estimate the triple difference specification of the previous section, while limiting the sample to observations for specific hospital types: government, private nonprofit hospitals, and for-profit hospitals. Private hospitals may be more responsive to changes in fraud enforcement than government-run hospitals because the potential returns to fraud and perceptions of incidence of fraud are higher in the private sector.

VII. Results

A. Medicaid Enforcement Activity

Table 1 summarizes MFCU enforcement activity from 2006 to 2014 for the states in our sample. The average MFCU operated on a budget of $6.8 million dollars per year; the median MFCU budget was $2.4 million. The average MFCU received a federal grant of $5.1 million; the median grant was of $1.8 million. The distribution of funding is partly explained by state size. When scaled by the number of active providers (NPIs), states spent an average of $1,963 per NPI, and 50% of states spent at least $1,554 per NPI. A similar pattern of right-skewed distributions is observed across all stages of fraud enforcement activity: investigations, indictments, civil judgments, convictions, and amounts recovered. The highest return to Medicaid fraud enforcement spending in a given year was over $200 per dollar spent.

Table 2 shows the sample means of the independent and dependent variables for the fraud prone conditions and the two control group conditions used in the triple difference designs. Relative to DRGs matched on verifiability, fraud prone DRGs involved more inpatient stays of shorter length and lower cost. Relative to conditions in the second control group, they involved similar inpatient stays of equivalent length, yet their average cost per stay was higher ($1,420 for fraud prone DRGS vs. $300

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for the second control group). Fraud prone DRGs consistently had higher rates of routine discharges and transfers to secondary facilities, such as nursing homes and rehabilitation centers. Patient demographics and hospital characteristics were similar in terms of race and age across the sets of DRGs.

This first stage of the analysis establishes that fraud enforcement budgets are not driven by previous levels of suspected or verified fraud. However, it is possible that budgets are affected by the perception of undetected fraud. We are unable to directly measure this perception and acknowledge it as a source of uncertainty. An alternative theory is that increases in MFCU funding are driven by a political will to take a more serious approach to crime. Signaling commitment to a "zero-tolerance" approach to fraud may be conveyed by expanding the size of a state's MFCU, an expansion that is not necessarily correlated to actual or suspected levels of fraud.

Table 3 shows estimates of the effects of MFCU spending on the numbers of cases opened, indictments, provider exclusions, and settlements and convictions. Higher levels of MFCU funding led to higher numbers of opened cases (52.3, $p < 0.05$), indictments (9.36, $p < 0.001$), and settlements/convictions (2.61, $p < 0.05$). In other words, increasing the average MFCU budget in 2015 by 20 percent (approximately $400,000) would have yielded, on average, an additional 21 cases, 4 indictments, or an additional conviction or settlement. We do not find any causal effect on the number of excluded providers. Overall, the results imply that MFCU funding does lead to substantial increases in MFCU activity, but not to any significant change in the severity of the cases taken on.

B. Difference in Difference Effects of MFCU Spending

Table 4 reports estimates from the difference in difference analysis, which relies on within-state variation in MFCU budgets per NPI. The top panel shows effects on measures of treatment intensity. The bottom panel shows effects on measures of discharge status. Each column represents a different outcome,and each row in the table is a different specification. The difference-in-differences specification only includes data on fraud prone health conditions.

In the simplest specification – estimated without control variables or fixed effects – we observe significantly longer stays (column 1: 0.085, $p < 0.001$) of higher treatment intensity (column 2: 0.21, $p < 0.05$), but fewer numbers of discharges (column 3: -0.39, $p < 0.001$). These results are consistent with the prediction that higher fraud enforcement reduces the profitability of admitting less severe cases of fraud prone conditions. The pattern of results does not change when state fixed effects are included. However, when we include state and year fixed effects, the effect of the MFCU budget per NPI becomes very small in magnitude and statistically insignificant. Fraud enforcement spending has no significant effect on treatment intensity once the model controls for state and year fixed effects, which may adjust for omitted variable bias generated from national trends in federal law enforcement and time-invariant state factors. The standard errors do not change much across the specifications. The estimates become statistically insignificant because the parameter estimates are much closer to zero. We find similar results in the models of discharge status. In the base model, which does not include state and year fixed effects or control variables, the enforcement effort appears to increase the prevalence of each type of discharge. (These estimates are noisy, so we can only reject the null of no effect at the 10% level.) When we add additional controls and state and year fixed

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effects, the pattern disappears entirely. Taken together, the difference-in-differences model implies that there is no significant effect of fraud enforcement effort on treatment intensity or discharge status.

A key assumption of the difference in difference design is that changes in fraud enforcement effort are independent of changes in the trajectory of the outcome variables over time. The main threat to the validity of the design is that state policy makers may decide to apply for larger MFCU grants in response to increases in the level of Medicaid fraud. We explore this possibility by regressing MFCU funding levels on lagged measures of the number of open cases (suspected fraud) and convictions (confirmed fraud).[7] The regressions suggest that lagged measures of potential fraud and verified fraud are not predictive of current fraud enforcement. Civil judgments are one possible exception. An additional civil judgment reduces predicted MFCU funding by $9,200 (Column 4, Table 5). However, even the civil judgement effect is not statistically significant in the full model, which controls for all of the lagged measures of fraud-related activity. Overall, the results support the assumption that within state changes in MFCU funding are not an endogenous response to previous levels of fraud activity.

C. Triple Difference Effects of MFCU Spending

The top panel of Table 6 presents the triple difference estimator that incorporates variation between the treatment (fraud prone DRGs) and control groups, constructed based on DRG verifiability. The base model is a difference in difference model that exploits difference in the cross-sectional variation in enforcement spending across fraud prone and non-fraud prone health conditions. These models allow for much more variation in MFCU spending because they do not rely on within-state changes for identification. The estimates imply that increased fraud enforcement spending reduces inpatient stays for fraud prone conditions (column 3: -0.81, $p< 0.001$). This effect persists as state fixed effects, year fixed effects, and state-by-year fixed effects are incorporated into the model. This finding is consistent with the theory's prediction that fraud enforcement reduces treatment intensity for fraud prone services, either due to deterring fraudulent use or because hospitals reduce the provision of fraud prone services in order to avoid the risk of an investigation. However, once state-specific trends in fraud prone conditions are introduced, the fraud enforcement spending per NPI does not significantly affect discharges. Further – in the full model, which also allows for fraud-specific time trends, there is no evidence of a change in any of the treatment intensity outcomes. Similar to the difference-in-differences model, controlling for more elaborate sources of omitted variable bias reduces the size of the parameter estimate and does not lead to large increases in the standard errors.

The bottom panel of Table 6 presents the triple difference estimates, which incorporates variation between the treatment and control groups constructed based on cost and prevalence. The simplest versions of the model (without fixed effects) show increases in length of stay and costs that are similar to those observed in the early stages of the difference-in-differences model. But the point estimates approach 0 and become statistically insignificant as the full set of fixed effects is included. Effects on discharges are an exception: we find that a one percent increase in fraud enforcement spending per NPI is associated with a 0.28 percent reduction in the number of fraud prone discharges ($p< 0.05$) in the fully specified model. Given the overall patterns across groups, this is fairly weak evidence of a deterrent effect on treatment intensity.

7 We assume a one-year lag to be an appropriate gap because it corresponds to the annual application of MFCU grants. If funding were renewed biannually, then we would present the effects going back two years.

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Table 7 presents the estimated effects of fraud enforcement on patient discharge status. In the fully specified model, higher enforcement spending reduces the number of fraud prone routine discharges (column 1: -0.22, $p < 0.05$) and transfers to home health (column 2: -0.22, $p < 0.05$) and skilled nursing facilities ("Other firm," column $4: -0.13$, $p < 0.05$). If fraud enforcement encourages hospitals to admit relatively sicker patients, then the reduction in routine discharges is consistent with the theory. However, it is hard to interpret simultaneous reductions in discharges to different post-acute care agencies because there is insufficient data to measure the effects of fraud enforcement on other types of discharge status, such as mortality. Overall, we conclude there is no evidence of strategic shifts in discharge status resulting from fraud enforcement. Relative to conditions of similar prevalence and treatment costs, which are more likely to be related to public health needs, the effect of fraud spending is not statistically significant.

D. Effects by Hospital type

The absence of a deterrent effect may be due to hospital-level differences in risk aversion to investigations and in the ability to screen patients and influence physicians. We test this possibility by separately estimating the full triple-difference specification by hospital ownership.

Our results offer weak evidence that the effects of fraud enforcement on treatment intensity varies significantly across hospital types (Table 8). Across both control groups, treatment intensity does not vary with fraud enforcement effort among government hospitals. Among nonprofit hospitals, increases in fraud enforcement spending increase treatment intensity when comparing fraud prone conditions to verifiable conditions. A one-percent increase in fraud enforcement spending per NPI increases charges per discharge by 0.5 percent ($p < 0.05$), total discharges by 0.7 percent ($p < 0.01$), and total charges by 1.2 percent ($p < 0.001$). However, these results are not replicated in the second control group. Similarly we do not observe consistent patterns of change within hospital type across control groups for measures of discharge status. When compared to conditions of similar prevalence and cost, the marginal effects of MFCU funding on rates of discharge to different sources are statistically insignificantly different from zero. In some cases the confidence intervals around these estimates are small enough to rule out substantive effects. In other cases, the confidence intervals are very wide, making it difficult to draw firm conclusions.

E. Robustness Checks

The research designs rely on the assumption that within-state changes in the level of MFCU funding are strictly exogenous of the history of Medicaid treatment intensity in the states. To evaluate this assumption, we examine the relationship between contemporaneous MFCU funding and lagged measures of suspected and verified fraud. We also test the sensitivity of our results in several ways, but find no substantial differences from the main results.

In the main specifications, we measure MFCU effort levels using MFCU grant dollars-per-provider. We test the stability of our results when effort is measured in terms of dollars per Medicaid enrollee, similar to Becker et al. (2005) (Appendix B). The results demonstrate a similar absence of a deterrent effect with the full specification.

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We consider the possibility that enforcement effort may be more observable to providers when measured as lagged MFCU actions. For instance, large settlements in the previous year may be a stronger signal of high fraud enforcement effort than spending levels of the fraud enforcement unit itself because these settlements receive considerably more media attention (Appendix C). We also use several measures of MFCU activity that are likely to receive media attention: the total number of convictions, fraud settlements, criminal convictions, the average amount recovered per case, the average civil settlement per fraud case, and the average amount recovered from criminal convictions. The results are unaffected by these alternative signals of enforcement effort.

Third, we test the sensitivity of our results to the inclusion of conditions that have undergone major changes in prevalence or treatment. For example, the rise of opioid addiction may have influenced the treatment intensity of drug rehabilitation conditions, which are included as a set of control conditions. We present the results excluding this class of DRGs from the control group (Appendix D). We observe no noticeable shift in results.

An additional concern with our strategy is that effects of fraud enforcement may accumulate over time. We test this possibility by including lagged levels of fraud enforcement for up to four years. Finally, as a falsification test, we consider the effect of fraud enforcement on hospitalizations paid for by private insurance. If main effects are biased by broader changes in medical practice and technology, then MFCU enforcement would appear to affect private insurance treatment intensity. We find no evidence of such effects.

VIII. Conclusions

Scandals in public agencies and programs raise uncomfortable questions: does the scandal signal deeply rooted corruption in a public agency, or merely ineffective monitoring? Perceptions of fraud and inappropriate use of public resources can weaken public support for specific social programs and even reduce the level of trust people have in government more broadly. Promises to reduce fraud and abuse are a staple of campaign speeches, but there is little evidence indicating that the resources governments devote to investigating and punishing fraud in public programs actually reduce fraudulent activity.

One concern associated with attempts to detect and deter fraud within public programs is that high fraud enforcement can result in defensive practices that reduce social welfare. Not all incidences of fraud prone care are fraud. Given that conditions requiring fraud prone care can quickly evolve into life-threatening complications if they are not treated, timely and appropriate provision of care is welfare-improving. An anti-fraud program that succeeded in reducing fraud only to discourage the provision of legitimate care would be very unappealing.

This paper provides new evidence on fraud enforcement effects. First, we demonstrate that deterrence efforts previously observed in the Medicare population from Medicaid fraud enforcement do not appear to have major effects within the Medicaid program. Second, we present a model of hospital behavior that describes how defensive medicine in the context of fraud enforcement results in lower treatment intensity, as opposed to the higher treatment intensity seen in cases of medical malpractice (Kessler and McClellan, 1996; Sloan and Shadle, 2009).

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Our work has important policy implications for fraud enforcement within the Medicaid program. It suggests that – at current levels of enforcement – hospitals do not appear to adapt their admission decisions or treatment intensity with respect to levels of fraud enforcement efforts within the Medicaid program. This suggests that devoting more money to Medicaid fraud enforcement efforts is unlikely to lead to (undesirable) defensive medicine effects. Of course, they also appear unlikely to actually deter fraud.

In addition, our analysis of the effects of increased MFCU spending on MFCU activity suggests that giving MFCUs more resources allows them to open more investigations but does not appear to alter the likelihood that a physician will be excluded from the program due to the investigation. These results suggest that expanding the MFCUs does not lead them to investigate less severe cases of suspected fraud. If increasing MFCU funding lowered the probability of provider exclusion, then it would imply that marginal cases of fraud detected in states with high fraud enforcement spending are less severe than those in states with low enforcement spending.

It seems likely that Medicaid fraud enforcement programs have not exhausted the value of provider-side fraud enforcement efforts. Our estimates of MFCU recoveries suggest that states can raise revenue by expanding MFCU budgets. One reason to avoid expanding MFCU operations is that theory suggests that hospitals may respond by reducing both illegitimate health services as well as legitimate health services for the fraud-prone conditions that attract MFCU attention. However, we found little evidence that increases in MFCU spending affect hospital treatment intensity. One implication of our results is that states could increase MFCU spending as a way to increase revenue, without substantially altering provider behavior or patient care. Of course, at some margin of enforcement intensity, it is possible that both deterrence effects and defensive medicine effects would begin to matter.

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IX. Tables

TABLE 1.: Summary Statistics of Medicaid Fraud Control Units (MFCUS), Providers, and Medicaid Spending

	Mean	Std. Dev.	Min	Median	Max
	MFCU Funding and Effort				
Federal grant award ($ M)	5.10	9.06	0.37	1.80	47.7
State MFCU funding ($ M)	1.70	3.02	0.12	0.60	15.9
Staff	41.8	66.0	4	17	336
Total investigations	308.8	325.2	22	177	1448
Fraud investigations	243.2	259.3	19	146	1262
Abuse/Neglect investigations	65.6	99.6	1	29	558
Total indictments	30	38.0	0	16	190
Fraud indictments	20.5	27.2	0	10	157
Abuse/Neglect indictments	9.46	14.1	0	4	80
Civil Settlements and Judgments	18.1	27.3	0	13	226
Total convictions	27.0	33.1	0	15	197
Fraud convictions	18.2	23.1	0	9	120
Abuse/Neglect convictions	8.18	10.7	0	5	65
Total recoveries ($ M)	41.8	74.2	0.015	17.3	504.0
Criminal recoveries ($ M)	5.65	21.9	0	0.40	212.2
Civil recoveries ($ M)	44.0	71.5	0.035	21.7	406.1
	Enforcement Outcomes				
Excluded providers (any)	144.5	183.6	6	76	1009
Excluded physicians	10.8	17.2	0	4	118
Fed. Grant: Convictions& Judgements	0.099	0.083	0.0087	0.078	0.99
State Spending: Convictions& Judgements	0.033	0.028	0.0029	0.026	0.33
Recoveries: Fed. Grant	9.12	8.20	0.011	6.97	76.6
Recoveries: State Spending	27.3	24.6	0.032	20.9	229.9
	Public Insurance Population				
Medicaid enrollment (M)	2.97	6.88	0	0.98	69.4
Enforcement $/Medicaid enrollee	2.88	1.83	0.098	2.63	9.58
Total Medicaid spending	10643.1	13675.8	602.4	6348.5	70380.2
Enforcement $/Medicaid enrollee ($1,000)	5.6	2.9	0.41	6.1	12
Medicare enrollment	1035986.1	1050096.1	74113	729147	5482813
Enforcement $/Medicare enrollee	4.01	2.46	1.11	3.39	16.3
	Provider Characteristics				
Physicians	1373.0	1329.2	83	791	5326
Enforcement $/Physician	3347.6	2229.7	616.7	2573.2	12456.0
NPIs	2235.9	2043.5	168	1761	8260
Enforcement $/active NPI	1963.3	1312.7	367.9	1554.6	6569.8
Hospital count	72.4	71.6	6	52	335
Enforcement $/hospital	58641.6	44770.3	15594.0	46814.6	289849.6

Note: (1) Observations are at the state-year level. (2) Years: 2006-2014.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE 2.: Average Characteristics at the DRG-State-Year Level by Treatment Group

	Outcomes: Utilization		
	Fraud-Prone DRGs	Verifiable DRGs	Prevalence & Cost
Charges ($1,000)	1.42	4.36	0.03
	(42.19)	(71.12)	(0.02)
Length of stay (Days)	4.94	8.80	4.16
	(3.94)	(11.01)	(2.24)
Total discharges	172.98	96.81	187.69
	(215.90)	(179.77)	(219.03)
	Outcomes: Discharge Status		
Routine	16.83	3.87	13.28
	(106.54)	(48.65)	(91.15)
Home health transfers	5.90	4.13	4.69
	(23.16)	(20.99)	(22.36)
Hospital transfers	2.08	0.26	1.66
	(10.01)	(2.93)	(8.10)
Other firm transfers	5.65	0.87	5.32
	(24.39)	(14.27)	(30.10)
	Patient demographics		
White	0.41	0.25	0.40
	(0.37)	(0.35)	(0.37)
Black	0.17	0.14	0.15
	(0.22)	(0.25)	(0.21)
Hispanic	0.09	0.09	0.09
	(0.16)	(0.18)	(0.16)
Asian	0.03	0.03	0.03
	(0.12)	(0.11)	(0.11)
18-44	0.19	0.24	0.21
	(0.22)	(0.35)	(0.23)
45-64	0.41	0.26	0.35
	(0.36)	(0.39)	(0.34)
65-84	0.04	0.01	0.03
	(0.10)	(0.05)	(0.09)
85-plus	0.01	0.00	0.01
	(0.04)	(0.01)	(0.04)
	Hospital characteristics		
Teaching hospital	0.43	0.39	0.41
	(0.34)	(0.39)	(0.34)
Small hospital	0.12	0.08	0.10
	(0.18)	(0.20)	(0.17)
Large hospital	0.47	0.39	0.44
	(0.37)	(0.42)	(0.37)
Private for-profit	0.11	0.07	0.10
	(0.19)	(0.17)	(0.19)
Private non-profit	0.54	0.42	0.51
	(0.40)	(0.43)	(0.41)

Note: (1) Observations are at the DRG-state-year level. Enforcement measures are at the state-year level. (2) Years: 2006-2014.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE 3.: Effect of Enforcement Funding on MFCU Activity

	(1) Cases	(2) Indictments	(3) Excl. Providers	(4) Convictions/Settlements
MFCU Funding ($M)	52.3*	9.36***	−1.76	2.61*
	(23.0)	(2.47)	(3.74)	(1.01)
DV Mean	309	32	128	26
Obs.	300	300	499	499
Years available	2010-2016	2010-2016	2006-2016	2006-2016
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Omitted States	ND		ND & IA (2006)	

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: (1) The independent variable is the total amount of MFCU funding in millions of dollars. The dependent variables are stages and outcomes of MFCU activity: opened cases, indictments, excluded providers, and the number of civil settlements obtained. (2) Notes (2)-(3) for Table 5 apply.

Source: Office of the Inspector General.

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TABLE 4.: Difference-in-Differences: Effect of Enforcement Effort on Treatment Intensity and Patient Status Among Fraud prone Conditions

	Utilization Outcomes			
Enforcement effort ($/NPI)	LOS	Charge/Discharge	Discharges	Total Charges
Base model:	0.085***	0.21*	-0.39***	0.39
	(0.016)	(0.088)	(0.10)	(0.38)
+State FE	0.21***	0.95***	-0.28**	0.11
	(0.041)	(0.13)	(0.090)	(0.18)
+Year FE	0.0064	-0.024	-0.083	0.84***
	(0.034)	(0.069)	(0.11)	(0.18)
+DRG FE	0.0064	-0.0047	-0.085	-0.0060
	(0.029)	(0.050)	(0.11)	(0.13)
+Patient/Hospital traits	0.0020	-0.0012	-0.18	-0.0060
	(0.027)	(0.044)	(0.11)	(0.13)
Dep. Variable Mean	5.4 days	$24,500/stay	83.9 stays	$8,200
Dep. Variable SE	1.5 days	$2,000/stay	4.9 stays	$7,600
Obs.	6931	6936	6931	6931

	Discharge Status			
	Routine discharges	Home health	Hospital	Other firm
Base model:	0.21+	0.43+	0.31+	0.45+
	(0.11)	(0.22)	(0.17)	(0.23)
+State FE	-0.020	0.035	0.085	-0.043
	(0.057)	(0.047)	(0.068)	(0.048)
+Year FE	0.015	0.042	-0.0064	0.027
	(0.060)	(0.067)	(0.082)	(0.056)
+DRG FE	0.0029	0.0064	-0.029	-0.035
	(0.056)	(0.059)	(0.083)	(0.057)
+Patient/Hospital traits	-0.015	-0.040	-0.026	-0.067
	(0.044)	(0.046)	(0.041)	(0.050)
Dep. Variable Mean	1.9	1.5	1.3	0.38
Dep. Variable SE	2.7	3.1	2.3	3.0
Obs.	7316	8028	8034	7920

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Note: (1) Base model: $Y_{std} = E_{st} + \epsilon_{std}$, where Y_{std} are the log of measures of spending and utilization. (2) Years: 2006-2014. Observations are at the state-year-DRG level. (3) Standard errors are clustered at the state level.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE 5.: Effect of Previously Detected Fraud on Enforcement Funding

Lagged:	(1)	(2)	(3)	(4)	(5)
Cases	0.0012				0.0012
	(0.00095)				(0.00095)
Excluded providers		0.00069			−0.0012
		(0.00095)			(0.0015)
Convictions			0.0044		−0.00046
			(0.0052)		(0.0058)
Civil judgments				−0.0092*	−0.013
				(0.0036)	(0.013)
Obs.	250	450	449	449	250
Years available	2010-2016	2006-2016	2006-2016	2006-2016	2010-2016
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Omitted States	ND	ND & IA (2006)	ND	ND	ND

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: (1) The dependent variable is the total amount of MFCU funding in millions of dollars. (2) Observations are at the state-year level. (3) Standard errors are clustered at the state level.

Source: Office of the Inspector General.

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TABLE 6.: Effect of Enforcement Effort on Spending and Utilization

	Control Group Based on Verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	0.021	-0.0039	-0.81***	-0.095
	(0.049)	(0.082)	(0.19)	(0.21)
+State & year FE	0.033	0.030	-0.84***	0.15
	(0.056)	(0.093)	(0.22)	(0.20)
+Patient/Hospital traits	-0.0050	0.012	-0.62**	-0.088
	(0.045)	(0.056)	(0.18)	(0.090)
+Fraud-specific state FE	0.50***	0.65***	0.19	1.10***
	(0.096)	(0.13)	(0.18)	(0.19)
+Fraud-specific year FE	-0.011	0.14	0.29	0.11
	(0.072)	(0.11)	(0.19)	(0.22)
	Control Group Based on Costs and Prevalence			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	0.030*	0.071***	-0.082	-0.044
	(0.014)	(0.013)	(0.090)	(0.067)
+State & year FE	0.028+	0.060***	-0.088	-0.079
	(0.015)	(0.014)	(0.086)	(0.067)
+Patient/Hospital traits	0.011	0.048**	-0.14	-0.16**
	(0.014)	(0.015)	(0.097)	(0.059)
+Fraud-specific state FE	0.20***	0.18**	-0.56***	0.55**
	(0.036)	(0.051)	(0.12)	(0.18)
+Fraud-specific year FE	-0.0014	-0.047	-0.28*	0.014
	(0.026)	(0.043)	(0.13)	(0.19)
Dep. Variable Mean	1.63	3.20	4.53	1.80
Dep. Variable SE	0.37	0.66	1.53	1.99
Obs.	14335	14344	14335	14335

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: (1) Base model: $Y_{std} = \delta(E_{st} \times FP_d) + E_{st} + FP_d + \epsilon_{std}$, where Y_{std} are the log of measures of spending and utilization. (2) Years: 2006-2014. Observations are at the state-year-DRG level. (3) Standard errors are clustered at the state level.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE 7.: Effect of Enforcement Effort on Discharge Status

	Control Group Based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.13	0.43*	0.31+	0.38+
	(0.11)	(0.18)	(0.16)	(0.20)
+State & year FE	0.20	0.52*	0.37*	0.47*
	(0.12)	(0.19)	(0.16)	(0.21)
+Patient/Hospital traits	0.23+	0.42**	0.32*	0.36*
	(0.13)	(0.12)	(0.13)	(0.14)
+Fraud-specific state FE	-0.0025	0.057	0.0076	-0.0014
	(0.079)	(0.090)	(0.048)	(0.075)
+Fraud-specific year FE	-0.22*	-0.22*	-0.034	-0.13*
	(0.094)	(0.094)	(0.040)	(0.054)
	Control Group Based on Costs and Prevalence			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.15*	0.16	0.098	0.16
	(0.060)	(0.10)	(0.074)	(0.100)
+State & year FE	0.14*	0.14	0.087	0.14
	(0.061)	(0.098)	(0.070)	(0.096)
+Patient/Hospital traits	0.15*	0.13+	0.079	0.14+
	(0.058)	(0.075)	(0.066)	(0.075)
+Fraud-specific state FE	-0.12**	-0.17**	-0.057	-0.12+
	(0.046)	(0.055)	(0.038)	(0.063)
+Fraud-specific year FE	-0.093	-0.022	0.019	-0.034
	(0.086)	(0.057)	(0.081)	(0.077)
Dep. Variable Mean	0.66	0.35	0.23	0.33
Dep. Variable SE	0.95	1.07	0.80	1.04
Obs.	15015	17018	17067	16883

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Note: (1) Base model: $Y_{std} = \delta(E_{st} \times FP_d) + E_{st} + FP_d + \epsilon_{std}$, where Y_{std} is the log of discharge status types. (2) Years: 2006-2014. Observations are at the state-year-DRG level. (3) Standard errors are clustered at the state level.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE 8.: Effect of Enforcement Effort on Spending, Utilization, and Discharge Status by Hospital Ownership Type

	LOS	Charge/Discharge	Discharges	Total Charges
	Control Group Based on Verifiability			
Government	-0.073	-0.080	-0.33	-0.38
	(0.074)	(0.15)	(0.24)	(0.28)
Private non-profit	0.14	0.49*	0.70**	1.21***
	(0.11)	(0.22)	(0.22)	(0.27)
Private for-profit	0.93	1.43+	-1.46	-0.017
	(0.87)	(0.75)	(1.94)	(1.81)
	Control Group Based on Costs and Prevalence			
Government	0.012	-0.014	0.097	0.080
	(0.053)	(0.075)	(0.099)	(0.14)
Private non-profit	0.049	0.045	-0.025	0.014
	(0.040)	(0.046)	(0.21)	(0.22)
Private for-profit	0.88*	0.30	-0.69	-0.40
	(0.30)	(0.56)	(1.55)	(1.57)

	Routine discharges	Home health	Hospital	Other firm
	Control group based on Verifiability			
Government	-0.13+	-0.34	-1.45**	17.6***
	(0.068)	(0.52)	(0.40)	(2.07)
Private non-profit	-0.12	-0.59**	-0.63	-0.97+
	(0.13)	(0.18)	(0.38)	(0.56)
Private for-profit	0.19	-0.0098	-0.022	1.28*
	(0.31)	(0.030)	(0.047)	(0.43)
	Control group based on Costs and Prevalence			
Government	-0.059	-0.19	-0.028	0.48
	(0.043)	(0.22)	(0.32)	(0.59)
Private non-profit	-0.11	0.20	-0.048	-0.015
	(0.096)	(0.14)	(0.18)	(0.30)
Private for-profit	0.075	-0.13**	-0.26	0.038
	(0.14)	(0.037)	(2.21)	(0.10)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: (1) Base model: $Y_{std} = \delta(E_{st} \times FP_d) + H_{std}\alpha + P_{std}\beta + \theta_d + E_{st} + \epsilon_{std}$. (2) Years: 2006-2014. Observations are at the state-year-DRG level. (3) Standard errors are clustered at the state level.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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A. Description of Sample Creation

Our data comes from the HCUPnet FastStats site. The sample consists of all available years of states that had an operating MFCU (Table A1). We have collected data from 2006 to 2014. The sample is limited to DRG-level outcomes among the Medicaid population.

Imputed Zeros: Distinguishing between zero values and missing values is limited in the data for three reasons. First, SID data is censored to exclude values based on 10 or fewer discharges or fewer than 2 hospitals. Second, states may restrict which outcomes are publicly reported with their submitted data. Finally, not all DRGs may be associated with every outcome. For example, childbirth visits rarely result in transfers to nursing home care. To separate out missing values caused by the first two limitations, states missing outcomes across all DRGs are assumed to have not released their data publicly, and the outcome is coded as missing. If a state is missing values for a DRG across all outcomes, we assume there were too few cases or reporting hospitals and the value was censored (assumed 0). If an outcome is missing for a specific DRG across all states, then the most likely reason is that the DRG is not associated with the missing outcome for medical reasons (assumed 0). If observations were initially coded as missing because the state did not report any data for that outcome, we do not impute the value to 0 to avoid skewing the distribution due to variation in reporting.

The effect of this imputation process on the distribution of each outcome is presented in Figure A1.

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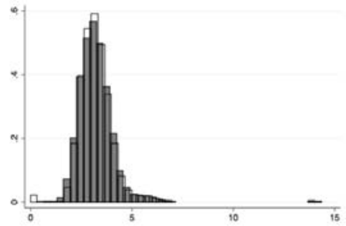
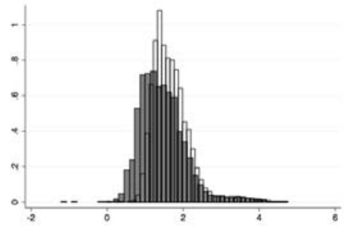
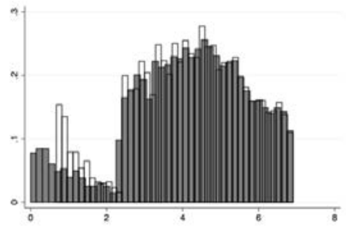
FIGURE A.1.: Outcome Distributions Before and After Imputation



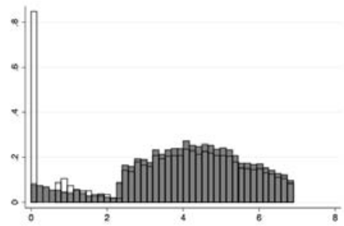
(a) Average charge



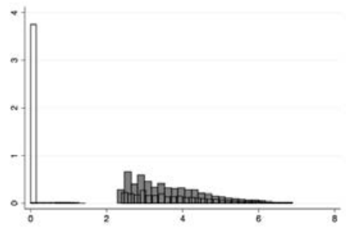
(b) Length of stay



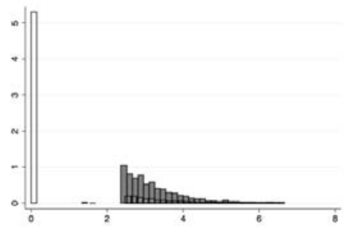
(c) Total stays



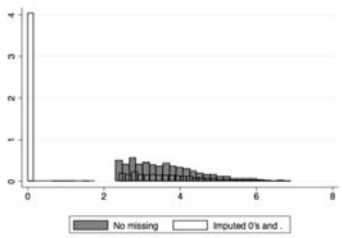
(d) Routine discharges status



(e) Home health transfers



(f) Hospital transfers



(g) Other firm transfers

(1) The histogram presents the log transformation of original distribution of each outcome variable (gray) and of the distribution after the imputation(white). (2) Years: 2006-2014.

Source: Healthcare Cost and Utilization Project.

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TABLE A1.: State Participation in the HCUP State Inpatient Database, 2006 to 2014

State	2006	2007	2008	2009	2010	2011	2012	2013	2014
Arizona	■	■	■	■	■	■	■	■	■
Arkansas	■	■	■	■	■	■	■	■	■
California	■	■	■	■	■	■	■	■	■
Colorado	■	■	■	■	■	■	■	■	■
Florida	■	■	■	■	■	■	■	■	■
Hawaii	■	■	■	■	■	■	■	■	■
Illinois				■	■	■	■	■	■
Indiana						■	■	■	■
Iowa	■	■	■	■	■	■	■	■	■
Kansas	■	■	■	■	■	■	■	■	■
Kentucky	■	■	■	■	■	■	■	■	■
Maine	■	■	■	■	■	■	■	■	■
Maryland	■	■	■	■	■	■	■	■	■
Massachusetts	■	■	■	■	■	■	■	■	
Michigan	■	■	■	■	■	■	■	■	■
Minnesota	■	■	■	■	■	■	■	■	■
Missouri	■	■	■	■	■	■	■	■	■
Nebraska	■	■	■	■	■	■	■	■	■
Nevada	■	■	■	■	■	■	■	■	■
New Hampshire	■	■	■	■					
New Jersey	■	■	■	■	■	■	■	■	■
New Mexico				■	■	■	■	■	■
New York	■	■	■	■	■	■	■	■	■
North Carolina	■	■	■	■	■	■	■	■	■
Oklahoma	■	■	■	■	■	■	■	■	■
Oregon	■	■	■	■	■	■	■	■	■
Rhode Island	■	■	■	■	■	■	■	■	■
South Carolina	■	■	■	■	■	■	■	■	■
Tennessee	■	■	■	■	■	■	■	■	■
Texas		■	■	■	■	■	■	■	■
Utah	■	■	■	■	■	■	■	■	■
Vermont	■	■	■	■	■	■	■	■	■
Washington	■	■	■	■	■	■	■	■	■
West Virginia	■	■	■	■	■	■	■	■	■
Wisconsin	■	■	■	■	■	■	■	■	■
Wyoming		■	■	■	■	■	■	■	■

Source: Hospital Inpatient and Utilization Project. Accessed: January 3, 2017. North Dakota is excluded from this list because it does not operate a MFCU and is excluded from the analysis.

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TABLE A2.: Crosswalk of pre-2008 DRGs, post-2007 DRGs and modified DRG mapping among fraud prone conditions and conditions with high observability.

Disease group	Conditions	DRG		
		Pre-2007	Post-2006	Modified
Cerebrovascular disorders and strokes	Degenerative Nervous System disorders	012	056, 057	1
	Intracranial Hemorrhage or Cerebral Infarction	014	064, 065, 066	
	Nonspecific Cerebrovascular disorders	017	071	3
		016	070	4
	Nonspecific CVA and Precerebral Occlusion Infarction	015	067, 068	5
Circulatory system disorders	Angina Pectoris	140	311	6
	Atherosclerosis	132	302	7
		133	303	8
	Cardiac Arrhythmia and Conduction disorders	139	309	9
		138	308	10
	Other Circulatory System diagnoses	145	315	11
		144	314	12
	Syncope and Collapse	141, 142	312	13
Respiratory disorders	Bronchitis and Asthma	096	202	14
		097	203	15
	Chronic Obstructive Pulmonary disease	088	190, 191, 192	16
	Other Respiratory System diagnoses	101	205	17
		102	206	18
	Pulmonary Edema and Respiratory Failure	087	189	19
	Respiratory Signs and Symptoms	099, 100	204	20
Nutritional/metabolic disorders	Diabetes	294	637	21
	Esophagitis, Gastroent. and Digestive disorders	182	391	22
	Nutritional and Metabolic disorders	296	640	23
		297	641	24
Kidney disorders and Renal failure	Kidney and Urinary Tract Signs and Symptoms	326	696	25
	Other Kidney and Urinary Tract diagnoses	332	699	26
		331	698	27
Respiratory infections and pneumonia	Respiratory Infections and Inflammations	080	178	28
	Simple Pneumonia and Pleurisy	090	194	29
		089	193	30
	Respiratory Infections and Inflammations	079	177	31

Source: Center for Medicare & Medicaid Services.

Note: Conditions are assigned a modified DRG number for consistency across time. Nutritional/metabolic disorders include diabetes-related DRGs, excluding diabetic complications(a separate group).

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TABLE A3.: Crosswalk of Pre-2008 DRGs, Post-2007 DRGs, and Modified DRG Mapping among Verifiable Conditions (Control)

Disease group	Conditions	DRG		
		Pre-2007	Post-2006	Modified
Cancer-tumor	Digestive Malignancy	173	375, 376	32
		172	374	33
	Ear, Nose, Mouth and Throat Malignancy	064	146, 147, 148	34
	Malignancy of Hepatobiliary System or Pancreas	203	435, 436, 437	35
	Malignancy, Female Reproductive system	367	755, 756	36
		366	754	37
	Mastectomy For Malignancy	257, 258	582, 583	38
Childbirth	Vaginal Delivery	372	774	39
	Cesarean Section	370	765	40
		371	766	41
	Ectopic Pregnancy	378	777	42
	Vaginal Delivery or Procedure except Sterilization	375	768	43
	Vaginal Delivery or Sterilization	374	767	44
	Vaginal Delivery	373	775	45
Diabetic complications	Amputation of Lower Limb	285	616, 617, 618	46
	Skin Grafts and Wound Debridement	287	622, 623, 624	47
HIV	HIV Extensive O.R. Procedure	488	969, 970	48
	HIV Major Related Condition	489	974, 975, 976	49
	HIV or Other Related Condition	490	977	50
Organ failure	Heart Transplant	103	1	51
		541	2	52
	Kidney Transplant	302	652	53
	Bone Marrow Transplant	512	9	54
	Liver Transplant or Intestinal Transplant	542	5	55
	Lung Transplant or Intestinal Transplant	480	6	56
	Pancreas Transplant	481	10	57
	Simultaneous Pancreas/Kidney Transplant	495	8	58
	Tracheostomy For Face,Mouth and Neck diagnoses	482	012	59
		513	011	60
		482	013	61

Source: Center for Medicare & Medicaid Services.

Note: Conditions are assigned a modified DRG number for consistency across time. Amputation of the lower limb and skin grafts are only those procedures that result from complications associated with endocrine, nutritional, & metabolic diseases.

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TABLE A4.: Crosswalk of Pre-2008 DRGs, Post-2007 DRGs, and Modified DRG Mapping among Conditions Matched on Prevalence and Treatment Costs (Control).

Disease group	Conditions	DRG		
		Pre-2007	Post-2006	Modified
Nervous System Disorders	Craniotomy and Endovascular Intracranial Procedures	3	27	62
	Nervous System Neoplasms	10	54	63
	Transient Ischemia	524	69	64
	Traumatic Stupor and Coma, Coma $<$ 1 Hr	29, 30	86, 87	65
	Other Disorders Of Nervous System	35	92, 93	66
Ear, Nose, Mouth and Throat Disorders	Dysequilibrium	65	149	67
	Otitis Media and Upper Respiratory Infection	68, 69, 70, 71	153	68
Respiratory System Disorders	Pulmonary embolism	78	175, 176	69
	Simple Pneumonia and Pleurisy	91	195	70
	Respiratory System Diagnosis with Ventilator Support $<$ 96 Hours	566	208	71
Circulatory System Disorders	Acute Myocardial Infarction, Discharged Alive	122	281, 282	72
	Acute Myocardial Infarction, Expired	123	283, 284, 285	73
	Circulatory Disorders Except Ami, with Card Catheter	125	287	74
	Peripheral Vascular Disorders	131	300, 301	75
	Major Small and Large Bowel Procedures	570	331	76
Digestive System Disorders	G.I. Obstruction	181	389, 390	77
	Other Digestive System Diagnoses	189	394	78
Hepatobiliary System and Pancreas Disorders	Laparoscopic cholecystectomy without C.D.E.	494	418, 419	79
Musculoskeletal System and Connective Tissue Disorders	Major joint replacement or reattachment of lower extremity	544	469, 470	80
	Hip and Femur Procedures Except Major Joint	212	482	81
	Back and Neck Procedure, Excluding Spinal Fusion	499, 500	490, 491	82
	Signs and Symptoms Of Musculoskeletal System and Connective tissue	247	555, 556	83
	Tendonitis, myositis and bursitis	248	557, 558	84
Skin, Subcutaneous Tissue and Breast Disorders	Cellulitis	278, 279	603	85
Kidney and Urinary Tract Disorders	Kidney and ureter procedures for neoplasm	303	656, 657, 658	86
	Renal failure	316	682, 683, 684	87
	Kidney and Urinary Tract Infections	320	689	88
	Urinary stones without E.S>W. lithotripsy	324	693, 694	89
Blood, Blood Forming Organs, Immunologic Disorders	Red Blood Cell Disorders	396	812	90
Myeloproliferative Disorders, Poorly Differentiated Neoplasms	Lymphoma and leukemia with major O.R. procedure	540	821, 822	91
Infectious and Parasitic Diseases, Systemic or Unspecified Sites	Septicemia Or Severe Sepsis without M.V. 96+ Hours	576	871	92
	Septicemia without M.V. 96+ hours		872	93
Alcohol/Drug Use	Alcohol/Drug Abuse Or Dependence with Rehabilitation Therapy	521, 522	895	94
and Alcohol/Drug Induced Mental Disorders		523	896, 897	95

Source: Center for Medicare & Medicaid Services.

Note: Conditions are assigned a modified DRG number for consistency across time.

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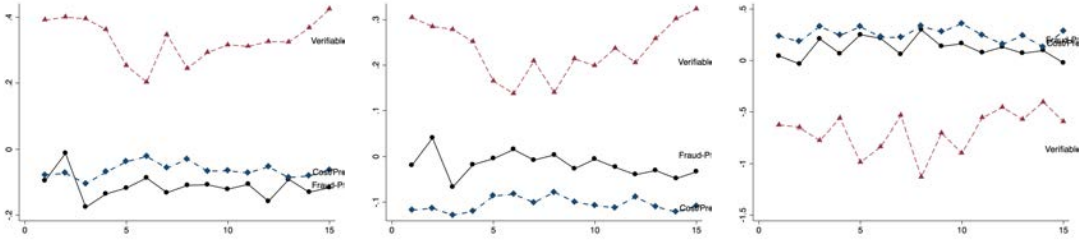
B. Enforcement Effort Measured as Dollars per Medicaid Enrollee

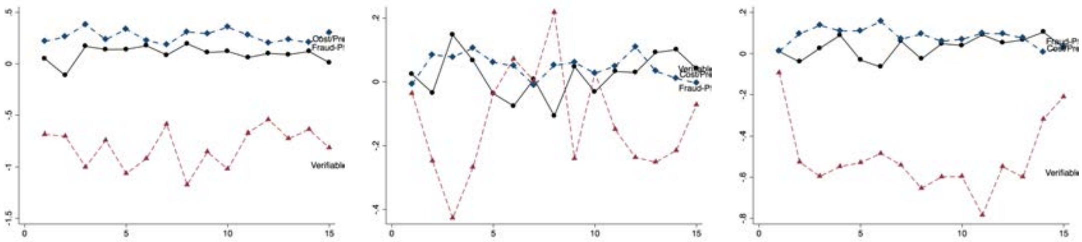


(a) Charges (b) Length of stay (c) Total discharges

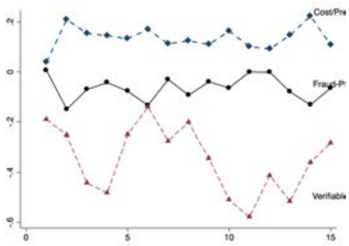
FIGURE B.2.: Average Measures of Treatment Intensity by DRG group

(1) The respective outcomes are levels of spending per NPI (y-axis). (2) The x-axis presents the quintile of the logged enforcement measure, either enforcement dollars per NPI or per Medicaid enrollee. (3) The solid black line indicates verifiable DRG conditions (control); the red dashed line indicates non-verifiable DRG codes (treated); the blue dashed line with dots indicates DRG codes matched to the treatment DRGs based on prevalence and treatment cost. (4) Years: 2006-2014.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.



(a) Routine discharges (b) Transfer: Home health agency (c) Transfer: SNF institutions



(d) Transfer: Short-term hospital

FIGURE B.3.: Average number of discharges by DRG group

(1) The respective outcomes are logged (y-axis). (2) The x-axis presents the quintile of the logged enforcement measure: enforcement dollars per Medicaid enrollee. (3) The solid black line indicates verifiable DRG conditions (control); the red dashed line indicates non-verifiable DRG codes (treated); the blue dashed line with dots indicates DRG codes matched to the treatment DRGs based on prevalence and treatment cost. (4) Years: 2006-2014.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A5.: Effect of Enforcement Effort, Measured as Dollars per Medicaid Enrollee, on Spending and Utilization

	Control group based on verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.082***	-0.20***	-0.42***	-5.36*
	(0.017)	(0.029)	(0.046)	(2.29)
+State & year FE	0.017	0.076*	-0.82***	-14.4**
	(0.021)	(0.032)	(0.056)	(4.24)
+Patient/Hospital traits	-0.040*	0.033	-0.59***	-16.5***
	(0.020)	(0.028)	(0.058)	(3.85)
+Fraud-specific state FE	0.044	0.20+	0.13	-6.45
	(0.079)	(0.11)	(0.23)	(7.24)
+Fraud-specific year FE	-0.078	0.043	0.13	-3.56
	(0.080)	(0.11)	(0.23)	(11.2)
	Control Group Based on Costs and Prevalence			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.040***	-0.066***	0.14***	7.70**
	(0.0060)	(0.011)	(0.024)	(2.25)
+State & year FE	-0.033***	-0.044***	0.11***	6.06*
	(0.0060)	(0.0090)	(0.023)	(2.73)
+Patient/Hospital traits	-0.024***	-0.013	0.072**	6.07*
	(0.0062)	(0.0087)	(0.024)	(2.31)
+Fraud-specific xtate FE	-0.028***	-0.033**	0.12***	11.3***
	(0.0072)	(0.010)	(0.028)	(1.80)
+Fraud-specific year FE	-0.024	-0.031	-0.025	1.85
	(0.037)	(0.052)	(0.14)	(7.05)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: (1) Dependent variables and enforcement measures are logged. (2) Years: 2006-2014. Observations are at the state-year-DRG level. (3) Standard errors are clustered at the state level.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A6.: Effect of Enforcement Effort, Measured as Dollars per Medicaid Enrollee, on Discharge Status

	Control Group Based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Base model	-0.042*	-0.022	0.046***	0.071***
	(0.020)	(0.022)	(0.014)	(0.018)
+State & year FE	0.030	0.060**	0.071***	0.13***
	(0.022)	(0.022)	(0.013)	(0.016)
+Patient/Hospital traits	0.14***	0.12***	0.080***	0.12***
	(0.024)	(0.020)	(0.011)	(0.016)
+Fraud-specific state FE	0.0042	-0.024	-0.0040	0.019
	(0.036)	(0.024)	(0.013)	(0.018)
+Fraud-specific year FE	0.011	-0.036	-0.026	-0.037
	(0.11)	(0.11)	(0.063)	(0.088)
	Control Group Based on Costs and Prevalence			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.067***	0.042*	0.031*	0.071***
	(0.014)	(0.018)	(0.014)	(0.017)
+State & year FE	0.075***	0.057***	0.032*	0.078***
	(0.014)	(0.016)	(0.013)	(0.016)
+Patient/Hospital traits	0.082***	0.061***	0.030**	0.074***
	(0.016)	(0.016)	(0.011)	(0.015)
+Fraud-specific state FE	0.041*	0.032+	0.014	0.042*
	(0.018)	(0.019)	(0.013)	(0.018)
+Fraud-specific year FE	-0.047	0.0033	-0.040	-0.046
	(0.095)	(0.094)	(0.066)	(0.090)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: (1) Dependent variables and enforcement measures are logged. (2) Years: 2006-2014. Observations are at the state-year-DRG level. (3) Standard errors are clustered at the state level.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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C. Enforcement Effort Measured as Lagged MFCU Actions

TABLE A7.: Effect of Enforcement, Measured as Lagged Number of Closed Cases, on Discharge Status

	Control Group Based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.0055***	0.012***	0.0092***	0.013***
	(0.00097)	(0.0017)	(0.0024)	(0.0025)
+State & year FE	0.0062***	0.012***	0.0092***	0.013***
	(0.0012)	(0.0017)	(0.0024)	(0.0024)
+Patient/Hospital traits	0.0065***	0.0091***	0.0075**	0.011***
	(0.0015)	(0.0010)	(0.0023)	(0.0014)
+Fraud-specific state & year FE	-0.00011	-0.0012	0.0013	0.0015
	(0.00067)	(0.00094)	(0.00090)	(0.0013)
	Control Group Based on Costs and Prevalence			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.0034**	0.0045+	0.0024	0.0052*
	(0.0012)	(0.0022)	(0.0022)	(0.0020)
+State & year FE	0.0036**	0.0046*	0.0024	0.0052*
	(0.0012)	(0.0022)	(0.0021)	(0.0020)
+Patient/Hospital traits	0.0035**	0.0039*	0.0021	0.0045**
	(0.0011)	(0.0017)	(0.0021)	(0.0016)
+Fraud-specific State & Year FE	0.0023	0.0012	0.0023+	0.0028
	(0.0014)	(0.00093)	(0.0013)	(0.0025)
Dep. Variable Mean	0.67	0.37	0.25	0.34
Dep. Variable SE	0.96	1.09	0.83	1.06
Obs.	13269	14704	14739	14593

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Note: (1) Observations are at the DRG-state-year level. (2) Years: 2006-2014. (3) Convictions are the logged sum of criminal convictions and civil judgments obtained.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A8.: Effect of Enforcement, Measured as Lagged Number of Closed Cases, on Utilization

	Control group based on Verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.0021***	-0.0038***	-0.012***	0.010***
	(0.00038)	(0.00060)	(0.0032)	(0.0018)
+State & year FE	-0.0024***	-0.0045***	-0.014***	0.0096***
	(0.00045)	(0.00065)	(0.0034)	(0.0014)
+Patient/Hospital traits	-0.0019***	-0.0025***	-0.011***	0.0012
	(0.00038)	(0.00047)	(0.0029)	(0.0011)
+Fraud-specific state & year FE	-0.00060	-0.00068	-0.0025*	0.00017
	(0.00041)	(0.0015)	(0.0012)	(0.0017)
	Control group based on Costs and Prevalence			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.00036**	0.00022	-0.0037	0.0026*
	(0.00013)	(0.00029)	(0.0024)	(0.0011)
+State & year FE	-0.00041**	0.00011	-0.0035	0.0029**
	(0.00014)	(0.00030)	(0.0024)	(0.00099)
+Patient/Hospital traits	-0.00033*	0.000045	-0.0045*	0.00012
	(0.00015)	(0.00029)	(0.0020)	(0.00085)
+Fraud-specific state & year FE	0.000014	-0.00036	-0.0052+	0.0027
	(0.00024)	(0.00073)	(0.0030)	(0.0021)
Dep. Variable Mean	1.63	3.24	4.53	1.83
Dep. Variable SE	0.36	0.66	1.54	1.99
Obs.	12860	12868	12860	12860

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: Notes (1)-(3) from the previous table apply.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A9.: Effect of Enforcement, measured as Lagged Fraud Convictions, on Discharge Status

	Control group based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.0064**	0.015***	0.010*	0.015**
	(0.0023)	(0.0037)	(0.0048)	(0.0052)
+State & year FE	0.0083*	0.015**	0.0098+	0.016*
	(0.0032)	(0.0049)	(0.0050)	(0.0059)
+Patient/Hospital traits	0.0084*	0.011**	0.0071	0.013**
	(0.0035)	(0.0033)	(0.0043)	(0.0038)
+Fraud-specific state & year FE	-0.00094	-0.00016	0.00081	0.00084
	(0.0015)	(0.0015)	(0.0014)	(0.0028)
	Control group based on Costs and Prevalence			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.0034+	0.0034	0.00079	0.0048
	(0.0019)	(0.0030)	(0.0030)	(0.0029)
+State & year FE	0.0038+	0.0037	0.00072	0.0050+
	(0.0019)	(0.0031)	(0.0030)	(0.0029)
+Patient/Hospital traits	0.0037*	0.0031	0.00035	0.0043+
	(0.0018)	(0.0029)	(0.0029)	(0.0025)
+Fraud-specific state & year FE	0.0015	0.0023	0.0020	0.0037
	(0.0044)	(0.0028)	(0.0024)	(0.0053)
Dep. Variable Mean	0.67	0.39	0.26	0.36
Dep. Variable SE	0.96	1.13	0.85	1.08
Obs.	7333	7827	7748	7717

Note: Notes (1)-(3) from the previous table apply.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A10.: Effect of Enforcement, measured as lagged fraud convictions, on Utilization

	Control group based on Verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.0032***	-0.0070***	-0.015*	0.011**
	(0.00053)	(0.0017)	(0.0057)	(0.0037)
+State & year FE	-0.0040***	-0.0086***	-0.018*	0.011*
	(0.00062)	(0.0018)	(0.0072)	(0.0043)
+Patient/Hospital traits	-0.0025***	-0.0045***	-0.013*	0.00017
	(0.00044)	(0.00086)	(0.0051)	(0.0015)
+Fraud-specific State & Year FE	-0.00072	-0.0012	-0.0035+	-0.0020
	(0.00049)	(0.0015)	(0.0019)	(0.0017)
	Control group based on Costs and Prevalence			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.00049**	0.00074+	-0.0014	0.0031
	(0.00015)	(0.00039)	(0.0031)	(0.0019)
+State & year FE	-0.00060***	0.00075	-0.0012	0.0038*
	(0.00016)	(0.00049)	(0.0031)	(0.0015)
+Patient/Hospital traits	-0.00043**	0.00050	-0.0040	0.00038
	(0.00016)	(0.00050)	(0.0028)	(0.0011)
+Fraud-specific State & Year FE	0.00026	-0.000056	-0.0062	0.0013
	(0.00061)	(0.0014)	(0.0067)	(0.0044)
Dep. Variable Mean	1.64	3.36	4.51	1.95
Dep. Variable SE	0.37	0.67	1.56	2.03
Obs.	7162	7162	7162	7162

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: Notes (1)-(3) from the previous table apply.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A11.: Effect of Enforcement, Measured as Lagged Abuse Convictions, on Discharge Status

	Control Group Based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.018***	0.034**	0.030***	0.042***
	(0.0045)	(0.010)	(0.0082)	(0.011)
+State & year FE	0.022***	0.036***	0.031***	0.044***
	(0.0046)	(0.0098)	(0.0076)	(0.0096)
+Patient/Hospital traits	0.024***	0.025***	0.025**	0.034***
	(0.0058)	(0.0068)	(0.0071)	(0.0063)
+Fraud-specific state & year FE	0.0075**	-0.0046	0.0011	0.0040
	(0.0023)	(0.0041)	(0.0027)	(0.0028)
	Control Group Based on Costs and Prevalence			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.012*	0.015+	0.0095+	0.017*
	(0.0046)	(0.0075)	(0.0048)	(0.0069)
+State & year FE	0.012*	0.014+	0.0087+	0.015*
	(0.0046)	(0.0075)	(0.0047)	(0.0068)
+Patient/Hospital traits	0.012**	0.013*	0.0074+	0.013*
	(0.0042)	(0.0059)	(0.0043)	(0.0058)
+Fraud-specific state & year FE	0.012+	0.0059	0.0035	0.010
	(0.0072)	(0.0060)	(0.0045)	(0.0089)
Dep. Variable Mean	0.67	0.39	0.26	0.36
Dep. Variable SE	0.96	1.13	0.85	1.08
Obs.	7333	7827	7748	7717

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: (1) Observations are at the DRG-state-year level. Enforcement measures are at the state-year level. (2) Years: 2006-2014. (3) Abuse and neglect convictions are criminal cases pursued by the MFCU (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A12.: Effect of Enforcement, Measured as Lagged Abuse Convictions, on Utilization

	Control group based on Verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.0067***	-0.018***	-0.038**	0.032***
	(0.0013)	(0.0031)	(0.013)	(0.0078)
+State & year FE	-0.0078***	-0.019***	-0.046**	0.031***
	(0.0018)	(0.0038)	(0.014)	(0.0057)
+Patient/Hospital traits	-0.0036*	-0.0085**	-0.033**	0.0024
	(0.0014)	(0.0026)	(0.010)	(0.0037)
+Fraud-specific State & Year FE	-0.00095	-0.0044	-0.0094	-0.0019
	(0.0013)	(0.0045)	(0.0083)	(0.0050)
	Control group based on Costs and Prevalence			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.0012*	0.0011	-0.0082	0.0026
	(0.00045)	(0.0010)	(0.0078)	(0.0036)
+State & year FE	-0.0016**	0.00026	-0.0069	0.0020
	(0.00050)	(0.0010)	(0.0077)	(0.0032)
+Patient/Hospital traits	-0.0011*	0.000043	-0.014*	-0.0047
	(0.00053)	(0.00097)	(0.0062)	(0.0032)
+Fraud-specific State & Year FE	-0.00052	-0.0016	-0.022+	0.0038
	(0.00098)	(0.0027)	(0.011)	(0.0079)
Dep. Variable Mean	1.64	3.36	4.51	1.95
Dep. Variable SE	0.37	0.67	1.56	2.03
Obs.	7162	7162	7162	7162

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: Notes (1)-(3) from the previous table apply.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A13.: Effect of Enforcement, Measured as Lagged Recoveries per Action (Civil Settlement and Convictions), on Discharge Status

	Control Group Based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.100**	0.18*	0.11*	0.16*
	(0.033)	(0.079)	(0.051)	(0.066)
+State & year FE	0.11**	0.18*	0.11+	0.15*
	(0.035)	(0.084)	(0.053)	(0.069)
+Patient/Hospital traits	0.087*	0.099	0.050	0.10*
	(0.033)	(0.061)	(0.041)	(0.040)
+Fraud-specific state & year FE	0.0019	0.0044	-0.0014	0.0024
	(0.021)	(0.016)	(0.012)	(0.019)
	Control Group Based on Costs and Prevalence			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.027	0.056	0.021	0.053
	(0.036)	(0.036)	(0.028)	(0.036)
+State & year FE	0.030	0.060	0.022	0.056
	(0.036)	(0.036)	(0.028)	(0.036)
+Patient/Hospital traits	0.033	0.052	0.011	0.048
	(0.038)	(0.032)	(0.024)	(0.028)
+Fraud-specific state & year FE	0.0035	0.0015	-0.0011	0.012
	(0.026)	(0.019)	(0.0085)	(0.013)
Dep. Variable Mean	0.67	0.37	0.25	0.35
Dep. Variable SE	0.96	1.09	0.83	1.06
Obs.	13229	14654	14689	14543

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: Notes (1)-(2) from the previous table apply. (3) Fraud enforcement is the average amount recovered from civil settlements and criminal convictions (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A14.: Effect of Enforcement, Measured as Lagged Recoveries per Action (Civil Settlement and Convictions), on Utilization

	Control Group Based on Verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.058***	-0.12*	-0.078	0.26*
	(0.014)	(0.046)	(0.087)	(0.10)
+State & year FE	-0.066***	-0.13***	-0.098	0.28***
	(0.015)	(0.036)	(0.099)	(0.077)
+Patient/Hospital traits	-0.029+	-0.056*	-0.070	0.13*
	(0.015)	(0.025)	(0.072)	(0.050)
+Fraud-specific state & year FE	0.018+	0.0034	-0.012	-0.022
	(0.0089)	(0.023)	(0.043)	(0.024)
	Control Group Based on Costs and Prevalence			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.0035	0.0054	-0.090*	0.094**
	(0.0070)	(0.015)	(0.038)	(0.029)
+State & year FE	-0.0028	0.0061	-0.084*	0.13***
	(0.0078)	(0.015)	(0.039)	(0.032)
+Patient/Hospital traits	-0.0090	-0.0087	-0.096**	0.10*
	(0.0070)	(0.010)	(0.032)	(0.037)
+Fraud-specific state & year FE	-0.0030	-0.0019	-0.028	0.031+
	(0.0056)	(0.0080)	(0.030)	(0.017)
Dep. Variable Mean	1.63	3.24	4.53	1.83
Dep. Variable SE	0.36	0.66	1.54	1.99
Obs.	12825	12833	12825	12825

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: Notes (1)-(2) from the previous table apply. (3) Fraud enforcement is the average amount recovered from civil settlements and criminal convictions (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A15.: Effect of Enforcement, Measured as Lagged Civil Recoveries per Judgments, on Discharge Status where Enforcement

	Control Group Based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.017	0.049+	0.034	0.049
	(0.013)	(0.026)	(0.023)	(0.034)
+State & year FE	0.032*	0.055+	0.037	0.055
	(0.015)	(0.028)	(0.025)	(0.037)
+Patient/Hospital traits	0.028+	0.028	0.023	0.034
	(0.015)	(0.018)	(0.021)	(0.022)
+Fraud-specific state & year FE	-0.0066	-0.0019	0.0012	-0.00084
	(0.0044)	(0.0029)	(0.0017)	(0.0016)
	Control Group Based on Costs and Prevalence			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.0063	0.017	0.0047	0.018
	(0.015)	(0.019)	(0.013)	(0.019)
+State & year FE	0.0091	0.019	0.0059	0.020
	(0.016)	(0.020)	(0.013)	(0.020)
+Patient/Hospital traits	0.0083	0.012	0.0043	0.014
	(0.015)	(0.016)	(0.012)	(0.017)
+Fraud-specific state & year FE	-0.000049	0.00039	0.0031	0.0038
	(0.0090)	(0.0070)	(0.0041)	(0.0087)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: Notes (1)-(2) from the previous table apply. (3) Fraud enforcement is the average amount recovered from civil cases (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A16.: Effect of Enforcement, Measured as Lagged Civil Recoveries per Judgments, on Utilization

	Control group based on Verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.022**	-0.069***	-0.066*	-1.40*
	(0.0062)	(0.017)	(0.030)	(0.51)
+State & year FE	-0.021**	-0.055***	-0.088+	-1.34*
	(0.0071)	(0.015)	(0.047)	(0.63)
+Patient/Hospital traits	-0.0093*	-0.028***	-0.054+	-0.84
	(0.0044)	(0.0072)	(0.029)	(0.53)
+Fraud-specific State & Year FE	0.0030	0.0020	0.0026	0.94*
	(0.0024)	(0.0061)	(0.012)	(0.41)
	Control group based on Costs and Prevalence			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.0015	0.00073	-0.013	-0.0068
	(0.0024)	(0.0047)	(0.013)	(0.25)
+State & year FE	-0.00069	0.0042	-0.013	-0.12
	(0.0026)	(0.0047)	(0.015)	(0.28)
+Patient/Hospital traits	-0.0012	0.000047	-0.016	0.041
	(0.0018)	(0.0022)	(0.015)	(0.22)
+Fraud-specific State & Year FE	-0.00050	-0.0014	-0.0067	0.085
	(0.0014)	(0.0027)	(0.011)	(0.51)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: Notes (1)-(2) from the previous table apply. (3) Fraud enforcement is the average amount recovered from civil cases (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A17.: Effect of Enforcement, Measured as Lagged Criminal Recoveries per Conviction, on Discharge Status

	Control Group Based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.13	0.61**	0.13	0.45**
	(0.081)	(0.18)	(0.16)	(0.14)
+State & year FE	0.14	0.52***	0.058	0.38**
	(0.086)	(0.14)	(0.14)	(0.11)
+Patient/Hospital traits	0.11	0.33**	-0.076	0.37***
	(0.070)	(0.12)	(0.11)	(0.080)
+Fraud-specific state & year FE	-0.10*	-0.022	0.040	0.031
	(0.046)	(0.048)	(0.031)	(0.034)
	Control Group Based on Costs and Prevalence			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.036	-0.0045	-0.25+	0.092+
	(0.039)	(0.10)	(0.14)	(0.054)
+State & year FE	0.042	-0.018	-0.26*	0.081*
	(0.040)	(0.076)	(0.12)	(0.039)
+Patient/Hospital traits	0.052	-0.063	-0.26+	0.083*
	(0.049)	(0.093)	(0.13)	(0.038)
+Fraud-specific state & year FE	-0.035	-0.0077	0.10	-0.011
	(0.13)	(0.095)	(0.065)	(0.13)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: Notes (1)-(2) from the previous table apply. (3) Enforcement is presented as the average recoveries per criminal conviction (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A18.: Effect of Enforcement, Measured as Lagged Criminal Recoveries per Conviction, on Utilization where Enforcement

	Control Group Based on Verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.15***	-0.28*	-0.47*	-10.3+
	(0.041)	(0.12)	(0.20)	(5.90)
+State & year FE	-0.21***	-0.37***	-0.46*	-0.37
	(0.050)	(0.091)	(0.18)	(5.33)
+Patient/Hospital traits	-0.13**	-0.28***	-0.26+	-8.92
	(0.042)	(0.060)	(0.15)	(6.45)
+Fraud-specific state & year FE	0.048	-0.015	0.16	13.7+
	(0.059)	(0.051)	(0.11)	(6.90)
	Control Group Based on Costs and Prevalence			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	-0.017	0.044	0.098	-2.53
	(0.021)	(0.051)	(0.14)	(5.86)
+State & year FE	-0.029	0.012	0.14	-2.08
	(0.017)	(0.039)	(0.12)	(6.19)
+Patient/Hospital traits	-0.027*	0.0050	-0.0030	2.04
	(0.011)	(0.034)	(0.063)	(6.22)
+Fraud-specific state & year FE	0.037	0.048	0.024	-6.37
	(0.052)	(0.056)	(0.21)	(17.0)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: Notes (1)-(2) from the previous table apply. (3) Enforcement is presented as the average recoveries per criminal conviction (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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D. Enforcement, Lagged by up to 5 Years

TABLE A19.: Effect of Enforcement on Discharge Status, Lagged 0 to 5 years

	Control Group Based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Fraud X Enforcement	0.23+	0.42**	0.32*	0.36*
	(0.13)	(0.12)	(0.13)	(0.14)
(Lag=1 year)	0.26+	0.45***	0.34*	0.40*
	(0.13)	(0.13)	(0.14)	(0.15)
(Lag=2 years)	0.32*	0.50***	0.36*	0.44**
	(0.15)	(0.14)	(0.14)	(0.16)
(Lag=3 years)	0.31*	0.49***	0.36*	0.44**
	(0.14)	(0.14)	(0.14)	(0.16)
(Lag=4 years)	0.33*	0.48**	0.35*	0.44**
	(0.15)	(0.13)	(0.13)	(0.16)
(Lag=5 years)	0.34*	0.44**	0.32*	0.41*
	(0.15)	(0.14)	(0.13)	(0.15)
	Control Group Based on Costs and Prevalence			
	Routine discharges	Home health	Hospital	Other firm
Fraud X Enforcement	0.23+	0.42**	0.32*	0.36*
	(0.13)	(0.12)	(0.13)	(0.14)
(Lag=1 year)	0.17**	0.14+	0.084	0.15+
	(0.060)	(0.076)	(0.066)	(0.076)
(Lag=2 years)	0.20**	0.17*	0.093	0.17*
	(0.066)	(0.080)	(0.065)	(0.078)
(Lag=3 years)	0.19**	0.17*	0.090	0.17*
	(0.061)	(0.080)	(0.062)	(0.074)
(Lag=4 years)	0.18**	0.16*	0.086	0.16*
	(0.057)	(0.077)	(0.057)	(0.070)
(Lag=5 years)	0.16**	0.14+	0.077	0.15*
	(0.047)	(0.072)	(0.054)	(0.059)

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Note: Notes (1)-(2) from the previous table apply. (3) Enforcement is presented as the average recoveries per criminal conviction (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A20.: Effect of Enforcement on Utilization, Lagged 0 to 5 years

	Control Group Based on Verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Fraud X Enforcement	-0.0050	0.012	-0.62**	-0.62**
	(0.045)	(0.056)	(0.18)	(0.18)
(Lag=1 year)	-0.020	-0.022	-0.66**	-0.66**
	(0.040)	(0.050)	(0.19)	(0.19)
(Lag=2 years)	-0.046	-0.060	-0.67**	-0.67**
	(0.030)	(0.041)	(0.19)	(0.19)
(Lag=3 years)	-0.042	-0.068	-0.67**	-0.67**
	(0.028)	(0.041)	(0.19)	(0.19)
(Lag=4 years)	-0.048+	-0.075	-0.68**	-0.68**
	(0.028)	(0.045)	(0.20)	(0.20)
(Lag=5 years)	-0.036	-0.057	-0.67**	-0.67**
	(0.028)	(0.050)	(0.19)	(0.19)
	Control Group Based on Costs and Prevalence			
	LOS	Charge/Discharge	Discharges	Total Charges
Fraud X Enforcement	-0.0050	0.012	-0.62**	-0.62**
	(0.045)	(0.056)	(0.18)	(0.18)
(Lag=1 year)	0.0041	0.042**	-0.15	-0.15
	(0.012)	(0.014)	(0.099)	(0.099)
(Lag=2 years)	-0.0032	0.037*	-0.15	-0.15
	(0.0097)	(0.015)	(0.10)	(0.10)
(Lag=3 years)	-0.0035	0.039*	-0.13	-0.13
	(0.0094)	(0.016)	(0.10)	(0.10)
(Lag=4 years)	-0.0071	0.038*	-0.10	-0.10
	(0.0086)	(0.016)	(0.098)	(0.098)
(Lag=5 years)	-0.0048	0.042*	-0.093	-0.093
	(0.0083)	(0.017)	(0.093)	(0.093)

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Note: Notes (1)-(2) from the previous table apply. (3) Enforcement is presented as the average recoveries per criminal conviction (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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E. Omitting Drug- and Alcohol-Related DRGs

TABLE A21.: Effect of Enforcement Effort on Spending and Utilization

	Control Group Based on Verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	0.028	-0.0035	-0.80***	-0.080
	(0.053)	(0.091)	(0.18)	(0.22)
+State & year FE	0.040	0.027	-0.83***	0.15
	(0.060)	(0.10)	(0.21)	(0.21)
+Patient/Hospital traits	-0.00017	0.0085	-0.60**	-0.11
	(0.045)	(0.059)	(0.17)	(0.093)
+Fraud-specific state FE	0.52***	0.67***	0.22	1.20***
	(0.099)	(0.13)	(0.19)	(0.20)
+Fraud-specific year FE	-0.014	0.17	0.33+	0.16
	(0.075)	(0.12)	(0.19)	(0.24)
	Control Group Based on Costs and Prevalence			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	0.027+	0.068***	-0.098	-0.092
	(0.013)	(0.013)	(0.096)	(0.067)
+State & year FE	0.025+	0.059***	-0.10	-0.13+
	(0.014)	(0.013)	(0.093)	(0.069)
+Patient/Hospital traits	0.0098	0.046**	-0.15	-0.22**
	(0.013)	(0.014)	(0.10)	(0.064)
+Fraud-specific state FE	0.20***	0.21***	-0.60***	0.39*
	(0.038)	(0.055)	(0.10)	(0.19)
+Fraud-specific year FE	-0.00093	-0.048	-0.30*	-0.028
	(0.027)	(0.044)	(0.11)	(0.20)
Dep. Variable Mean	1.62	3.21	4.51	1.78
Dep. Variable SE	0.36	0.66	1.54	1.99
Obs.	13896	13905	13896	13896

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Note: (1) Base model: $Y_{std} = \delta(E_{st} \times FP_d) + E_{st} + FP_d + \epsilon_{std}$, where Y_{std} is the log of measures of spending and utilization. (2) Years: 2006-2014. Observations are at the state-year-DRG level. (3) Standard errors are clustered at the state level. (4) Fraud enforcement is the logged number of MFCU funding per NPI.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A22.: Effect of Enforcement Effort on Discharge Status

	Control Group Based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.12	0.43*	0.31+	0.37+
	(0.11)	(0.18)	(0.15)	(0.20)
+State & year FE	0.19	0.52*	0.37*	0.46*
	(0.12)	(0.19)	(0.16)	(0.21)
+Patient/Hospital traits	0.22+	0.41**	0.32*	0.34*
	(0.12)	(0.12)	(0.13)	(0.14)
+Fraud-specific state FE	0.0030	0.066	0.0079	0.0035
	(0.082)	(0.094)	(0.050)	(0.077)
+Fraud-specific year FE	-0.22*	-0.24*	-0.041	-0.15*
	(0.099)	(0.10)	(0.039)	(0.060)
	Control Group Based on Costs and Prevalence			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.15*	0.15	0.11	0.16
	(0.059)	(0.10)	(0.076)	(0.10)
+State & year FE	0.14*	0.13	0.096	0.14
	(0.060)	(0.100)	(0.074)	(0.098)
+Patient/Hospital traits	0.15*	0.13	0.092	0.14+
	(0.058)	(0.077)	(0.068)	(0.079)
+Fraud-specific state FE	-0.13**	-0.18**	-0.057	-0.13*
	(0.048)	(0.054)	(0.038)	(0.059)
+Fraud-specific year FE	-0.11	-0.035	0.020	-0.049
	(0.087)	(0.058)	(0.086)	(0.075)
Dep. Variable Mean	0.66	0.36	0.24	0.33
Dep. Variable SE	0.96	1.08	0.81	1.05
Obs.	14574	16496	16594	16414

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Note: Notes (1)-(4) from the previous table apply.

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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F. Falsification Test: Effect of Medicaid Fraud Enforcement on Private Insurance

TABLE A23.: Effect of Enforcement on Discharge Status Among Privately-Insured Patients

	Control Group Based on Verifiability			
	Routine discharges	Home health	Hospital	Other firm
Base model	0.22+	0.42+	0.31+	0.45+
	(0.11)	(0.21)	(0.17)	(0.22)
+State FE	0.053	0.11	0.11	0.020
	(0.056)	(0.068)	(0.066)	(0.069)
+Year FE	0.039	0.068	-0.029	0.047
	(0.075)	(0.11)	(0.094)	(0.10)
+DRG FE	0.036	0.044	-0.047	-0.010
	(0.078)	(0.10)	(0.093)	(0.10)
+Patient/Hospital traits	0.029	-0.022	0.0084	-0.0094
	(0.078)	(0.074)	(0.063)	(0.076)
Dep. Variable Mean	0.66	0.42	0.27	0.39
Dep. Variable SE	1.03	1.16	0.86	1.12
Obs.	7487	8164	8174	7987

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: (1) Observations are at the DRG-state-year level. Enforcement measures are at the state-year level. (2) Years: 2006-2014. (3) Enforcement is presented as the average recovery per criminal conviction (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.

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TABLE A24.: Effect of Enforcement on Utilization Among Privately-Insured Patients

	Control Group Based on Verifiability			
	LOS	Charge/Discharge	Discharges	Total Charges
Base model	0.076***	0.20*	-0.38***	0.42
	(0.015)	(0.089)	(0.096)	(0.36)
+State FE	0.17***	0.98***	-0.12	0.22
	(0.036)	(0.13)	(0.086)	(0.19)
+Year FE	0.024	-0.034	-0.082	0.97***
	(0.035)	(0.066)	(0.14)	(0.21)
+DRG FE	0.025	-0.027	-0.085	-0.085
	(0.033)	(0.049)	(0.14)	(0.14)
+Patient/Hospital traits	0.015	-0.042	-0.11	0.095
	(0.031)	(0.050)	(0.13)	(0.14)
Dep. Variable Mean	1.67	3.22	4.45	2.15
Dep. Variable SE	0.40	0.75	1.59	2.08
Obs.	7125	7131	7125	7125

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: (1) Observations are at the DRG-state-year level. Enforcement measures are at the state-year level. (2) Years: 2006-2014. (3) Enforcement is presented as the average recovery per criminal conviction (logged).

Source: Office of the Inspector General & Healthcare Cost and Utilization Project.