Shall We Blame Health IT for Medicare Overpayments? New Evidence from Medicare Recovery Audit Program

Keith A. Joiner * Jianjing Lin †

September 19, 2021

Abstract

We study how the adoption of electronic medical records (EMRs) affects Medicare payments for hospitalization. Increasing Medicare bills for inpatient care associated with the rapid diffusion of EMRs can arise from the following two mechanisms: (1) EMRs inflate Medicare bills to a higher level than justified, and (2) EMRs facilitate complete documentation to recover more billable services than before. Prior studies based on claims data may not distinguish between these two mechanisms, as both of them lead to similar patterns. Using data on audit outcomes from a national audit program, we examine how the overpayments / underpayments for hospitalization in a state change as the adoption rate of EMRs varies. We find no significant correlation between EMR adoption and overpayments, while underpayments decrease with more rapid EMR adoption, supporting the complete-coding mechanism.

JEL Codes: H51, I13, I18, O33
Keywords: Healthcare expenditure, improper billing, audits, health IT, hospital inpatient care

*University of Arizona
†Rensselaer Polytechnic Institute; Email: linj17@rpi.edu

1 Introduction

The rapid diffusion of electronic medical records (EMRs)—the central component of health IT—in the last decade is partly due to the aggressive promotion from the U.S. federal government as well as its potential in improving productivity and quality of care. However, the fundamental reason for healthcare providers to adopt this technology is to optimize reimbursements, especially given the complexity in medical billing. The widespread adoption of EMRs is described as a contributor to the growth of Medicare bills. This could occur in the following two fashions: (1) the *bill-inflation* mechanism, where EMRs facilitate healthcare providers submitting bills that are not medically justifiable in response to financial incentives ("upcoding"); and (2) the *complete-coding* mechanism, where EMRs enable providers to code more completely so as to recover more billable services than before (a practice that is called "charge capture").[1] Prior studies examining claims data may not separate these two mechanisms, as both of them could lead to similar patterns. We revisit this topic using information on audit outcomes from the Medicare fee-for-service Recovery Audit Program, which could help identify which is the dominant mechanism.

To illustrate why this is the situation, we present an example reflecting a common clinical situation leading to hospitalization—heart failure. The reimbursement for inpatient care is based on the recorded diagnostic related group (DRG), which is first determined by a patient's base diagnosis/procedure and then adjusted to the corresponding severity level—with higher payments for a more severe level—according to the accompanying complicating conditions. Consider a patient admitted to a hospital because of heart failure. The diagnosis for this patient can be selected from a series of 27 codes related to heart failure, that discriminate between functional abnormalities, anatomic abnormalities, and acuity, in various combinations. Codes are associated with different levels of severity, and associated reimbursements. Differentiation between these codes requires documentation in the EMR, using history (past and present), physical examination, laboratory and imaging tests, response to therapy and more. For example, coding "acute systolic heart failure" as the base diagnosis, which justifies reimbursements several thousand dollars greater than "heart failure, unspecified," requires additional supporting documentation, from echocardiography (showing

[1] Upcoding occurs when a healthcare provider submits an incorrect billing code for higher reimbursements than justified.

an ejection fraction of <25%) and use of a diuretic.[2] *Down-coding* (*Upcoding*) would occur if the physician did (did not) perform the additional test and service and the unspecified (specific) code was submitted, which would lead to an *underpayment* (*overpayment*).

Accurate documentation of the base diagnosis of acute systolic heart failure, as described above, is *only* one component of the final process of coding. Of equal if not more importance in coding and reimbursement is the presence or absence of a complication or comorbidity (CC) or major complication or comorbidity (MCC), modifying the base diagnosis by reflecting greater resource use for management. For example, if the individual with acute systolic heart failure also developed acute renal (kidney) failure, a consequence of poor blood flow to the kidneys, this would justify modifying the base diagnosis with an MCC, which would further increase the reimbursement. Down-coding (Upcoding) would occur if acute renal failure was (was not) documented and the admission was coded without (with) an MCC, leading to an underpayment (overpayment).

Of key importance, analysis of a Medicare claim for the above hospitalization cannot distinguish whether the documentation in the medical record was sufficient or insufficient to justify the base diagnosis or the presence of the MCC. Neither the results from the echocardiogram, the administration of a diuretic, the clinical or laboratory data indicating acute renal failure, nor other features of the clinical course can be verified from the claim. The requested reimbursement could be accurate, or could reflect overpayment or underpayment. The only way to evaluate the accuracy of the information is a direct review of the medical record. For the individual patient, this is done by the coders who prepare the claim for submission.[3] Regardless of the analytical methods used to evaluate the accuracy of coding using large data sets, chart audits are required for direct verification (Bauder et al., 2017).

A common intuition that the primary incentive in coding is to maximize revenue, leading to upcoding, belies the complexity interplay of factors involved.[4] When information is left out or erroneously recorded, providers or coders tend to choose a lower billing code to avoid the scrutiny

[2]Coding refers to a process of translating medical information—that includes diagnosis, procedures, medical services and equipment—into universal medical alphanumeric codes for documentation and medical billing purposes.

[3]Healthcare coders are the staff mainly responsible for coding.

[4]See https://www.nytimes.com/2017/03/29/magazine/those-indecipherable-medical-bills-theyre-one-reason-health-care-costs-so-much.html.

by insurers or auditors.[5] Sacarny (2018) also finds that hospitals face large frictions in using the appropriate level of billing codes but instead using a more general billing code that leads to lower reimbursements.

Prior studies that examine the correlation between EMR adoption and billing mainly use claims data (Adler-Milstein and Jha, 2014; Li, 2014; Gowrisankaran et al., 2019; Ganju et al., 2021). However, both the complete-coding and bill-inflation mechanisms result in very similar patterns in claims data—in particular, more reported CC and MCC among EMR hospitals.

In this paper, we use information on review decisions of medical claims from the Medicare fee-for-service (FFS) Recovery Audit Program (RAP), to examine the extent to which EMRs affect improper billing and to distinguish the bill-inflation mechanism from the complete-coding mechanism. RAP is one of the auditing strategies by the Centers for Medicare and Medicaid Services (CMS) to evaluate the accuracy of Medicare payments; almost all Medicare FFS claims are subject to recovery auditors' review.[6] Recovery auditors (RAs) are paid a fraction of identified improper payments and must return the fee if the audit determination is overturned in an appeal. As a result, they have incentives to ensure the accuracy of the review decision.

If it is the bill-inflation mechanism that dominates, we expect more overpayment determinations among EMR hospitals, as RAs are likely to detect inappropriate billing practices, especially after the complex review of all supporting documents.[7] If, instead, the complete-coding mechanism plays a more important role, we expect no significant difference in audit findings (especially for overpayments) between EMR and non-EMR hospitals, as EMRs simply facilitate complete documentation which should comply with the reimbursement criteria.

We are one of the first studies using Medicare audit data to understand the underlying effect of EMRs on hospital billing and coding practices. The results of the analysis may lead to different policy implications. The presence of the bill-inflation mechanism may call for greater fraud enforcement to deter improper billing and policy interventions to ensure that electronic documenta-

[5]See https://www.todayshospitalist.com/Breaking-the-downcoding-habit/.

[6]See https://www.cms.gov/Research-Statistics-Data-and-Systems/Monitoring-Programs/Medicare-FFS-Compliance-Programs/Recovery-Audit-Program/Downloads/RAC-SOW-Regions-1-4-clean-November-30-2016.pdf.

[7]Most of the identified improper payments come from the complex review conducted by healthcare coders or clinicians.

tion is valid, accurate, and complete.[8] Conversely, the finding that the complete-coding mechanism dominates may suggest that compliance with Medicare billing requirements is costly and EMRs make this process less challenging. Given the difficulty in and importance of complying with the documentation criteria, policy makers may consider offering appropriate guidance and incentives to encourage proper documentation among providers.

In this paper, we study how EMR adoption affects improper payments in the Medicare FFS program, including overpayments and underpayments. Because the payment data is at the state level, we estimate how the collected amount of overpayments/understatements in a state changes as this state's EMR adoption rate varies over time. We use the fixed effects model after controlling for a rich set of state variables that may influence state-level adoption and the occurrence of improper payments at the same time. We find that, in general, the level of EMR adoption has no correlation with the amount of improper payments.

We also estimate the heterogenous effects by RAs' capabilities. Certain RAs have developed capabilities of detecting the use of copy-and-paste entries and over-documentation in EMRs.[9] We expect RAs with such capabilities are more likely to identify overpayments if the bill-inflation mechanism dominates. Our results indicate no effects of EMRs on overpayments, regardless of the RA's capabilities. Interestingly, we find that the diffusion of EMRs is associated with an average decrease of 11.8% in underpayments, with the reduction mainly from the regions assigned to the less capable RAs. It may suggest that EMR hospitals are more capable of using the right level of billing codes and thus capturing a greater amount of revenue. The finding of no significant effect on overpayments along with lower underpayments in states with more prevalent EMR usage is somewhat consistent with the finding in previous studies that EMRs result in greater revenue, but through charge capture.

Finally, we use the audit outcomes from the Comprehensive Error Rate Testing (CERT) program—another Medicare audit program—to compare the differences in improper payments between hospital inpatient care (billed on DRG base) and other FFS-billing services, given the

[8] Such policy interventions may include rules or guidance on authorship validation, document amendments, auditing the record for documentation validity, and so on.

[9] Over-documentation refers to "the practice of inserting false or irrelevant documentation to create the appearance of support for billing higher-level services" (Levinson, 2014, Page 2).

completely different reimbursement mechanism between them. The results suggest that underpayments are more prevalent in hospitalization care than the other types of services, implying the coding complexity in inpatient care, which further substantiates the complete-coding mechanism.

Related literature. Our paper is related to three strands of literature. First, it contributes to the research studying the effect of EMR adoption on hospital billing and coding practices. This literature has found mixed results. Adler-Milstein and Jha (2014) find that EMR hospitals do not increase billing to Medicare to a greater extent than non-EMR hospitals, whereas Li (2014) and Ganju et al. (2021) find relatively more patients reported with severe conditions in EMR hospitals. Another paper by Qi and Han (2020) examines the effect of a broader set of health ITs and find that the adoption of these technologies boosts patient revenue. Of importance, none of these papers distinguishes between the upcoding and complete coding mechanisms. Our paper complements these studies by separating the two mechanisms.

Second, our paper contributes to the broader literature on hospital upcoding behavior.[10] An influential paper by Dafny (2005) leverages an exogenous change in DRG price and finds that hospitals coded more patients to the severe category when the reimbursement increment was larger. Silverman and Skinner (2004) find that for-profit hospitals experienced the largest percentage increase in patients assigned to the most generous DRG for pneumonia and respiratory infections, which is aligned with the goal of the administration in these hospitals. A more recent paper by Cook and Averett (2020) find that approximately three percent of reimbursements could be attributed to upcoding after the DRG restructuring in 2008. Such findings are not unique in the U.S. healthcare system (Jürges and Köberlein, 2015; Januleviciute et al., 2016; Barros and Braun, 2017; Verzulli et al., 2017). While it is inarguable that hospitals have incentives for enhancing revenues, the observation of increasing Medicare bills could also arise from a reduction in down-coding, due to improved efficiency in documentation and billing, especially after the rapid diffusion of EMRs and the multiple DRG reforms implemented by CMS to ensure thoroughness and standardization in documentation. Our paper contributes to this literature by using the data from a national audit program, in the hope of identifying the underlying mechanism in the more recent context.[11]

[10]There are other studies examining upcoding in settings other than hospitals, such as Brunt (2011), Bowblis and Brunt (2014), Fang and Gong (2017) and Geruso and Layton (2020).

[11]Our ongoing work also aims to separate the two mechanisms but using Medicare claims data and has similar

Finally, our paper also contributes to a small strand of literature that explores the cost of complete coding. A related study by Sacarny (2018) finds that hospitals sometimes pick a generic code for heart failure instead of specifying the type, even though any specific code could generate greater reimbursements, which may imply the cost of complete documentation. In other words, hospitals may down-code because the cost of complete coding is substantial.

The rest of the paper proceeds as follows. Section 2 describes industry and institutional background. Section 3 introduces the datasets and reports summary statistics. Section 4 presents the empirical strategy. Section 5 discusses the estimation results. The last section concludes and points out limitations.

2 Background

2.1 Medicare inpatient billing and the role of EMRs

Hospital inpatient admissions are paid based on a flat-rate payment system, known as the inpatient prospective payment system (IPPS). A hospital assigns a single DRG for each patient stay based on the primary and additional diagnoses/procedures. Each DRG is associated with a weight that reflects average resources used to treat Medicare patients in that DRG. Medicare reimburses the hospital a flat rate for the admission, which is proportional to the DRG weight plus some adjustments reflecting hospital and region specifics. Typically, the base DRG is first determined, according to the patient's primary diagnosis/procedure. It is likely that several DRGs share a common base DRG. For instance, DRGs 637 – 639 are "Diabetes w MCC," "Diabetes w CC," and "Diabetes w/o CC/MCC," respectively. All three belong to the same base DRG—diabetes. The base DRG can be modified depending on the presence or absence of a CC or MCC, which increases the weight of the DRG and hence the reimbursement.

Justification for selecting a specific base DRG, with or without a CC or MCC, depends on appropriate and adequate documentation. CMS requires documentation in the chart (whether paper or electronic) to substantiate each billed CC or MCC. The criteria specified by CMS typically

findings to this paper (Gowrisankaran et al., 2019).

include a combination of results from the patient history, physical examination, laboratory tests, medical imaging, specialty consultations, hospital course, and more. As a result, compliance with Medicare billing criteria requires substantial efforts and time from healthcare providers.

The following processes could lead to scrutiny by auditors: (1) selecting a base DRG with a higher weight than justified; (2) coding a CC or MCC modifying the base diagnosis that is not present/not sufficiently documented; (3) services that are not medically justified by the clinical situation; (4) coding selected diagnoses as present on admission when they were not, and (5) unbundling services/procedures that are bundled under a single DRG.

The adoption of EMRs has substantially changed the way how hospitals provide treatments and bill services. According to the Healthcare Information and Management Systems Society (HIMSS), the following are the main components for an EMR system: clinical data repository (CDR), clinical decision support capabilities (CDS), order entry (OE), computerized physician order entry (CPOE), and physician documentation (PD). CDR is a centralized database that collects, stores, accesses, and reports health information, including demographics, lab results, radiology images, admissions, transfers, and diagnoses. OE is an automated process of entering order information into an electronic billing system. The orders are usually associated with ancillary services such as lab work and radiology. CDS assists clinicians in decision-making tasks, namely determining the diagnosis or setting treatment plans. CPOE is a more advanced type of electronic prescribing that can link to the adverse drug event system to avoid potential medication errors. PD offers physicians structured templates to document a patient's daily progress, operative notes, consultation notes, emergency department visits, discharge summary, and other relevant information during the course of a hospital admission.

An EMR system will typically record the hospital course, providing templates to aid the physician in documentation. For instance, at the time of admitting a patient, the admitting physician can enter a new diagnosis by selecting one from a pop-up list organized by organ system or functional abnormality or simply choose from a populating list of pre-existing diagnoses if the patient has previously been seen in the system. On the one hand, the presence of pop-up lists, preloaded templates, and autofill functions reduces the probability of missing information during the hospital course and makes generating complete medical records much easier. But on the other hand, these

functionalities may facilitate inappropriate billing practices, such as enabling "cloning" information that includes diagnoses and patient status from one note to another for a given patient.[12]

2.2 Medicare FFS Recovery Audit Program

The CMS uses a variety of auditing strategies to ensure the accuracy of Medicare payments, including the Comprehensive Error Rate Testing (CERT) program, Recovery Audit Program (RAP), Medicare Administrative Contractors (MACs), Supplemental Medical Review Contractors (SMRCs), and the Zone Program Integrity Contractor (ZPIC) audits.[13] As one of the contractors to ensure providers follow Medicare reimbursement policy, the primary task of a recovery auditor is to examine paid claims under Medicare Parts A and B and identify whether the claim contains any improper payments (overpayments or underpayments). The RAP started as a demonstration in six states between March 2005 and March 2008, and was expanded nationwide by 2010. It is unique and distinct from other programs because of its ability to conduct widespread post-payment review.

The CMS contracts the recovery audit work with four independent contractors, each of which is responsible for claims in a geographically defined region that is about one-quarter of the country.[14] RAs perform three types of review: automated, semi-automated, and complex. The first two approaches are mainly based on claims data analysis, with the latter sometimes requiring providers to submit supporting documents for substantiation. Complex reviews must be conducted by a qualified healthcare coder or clinician, who must review supporting medical records before making the determination. While most of the reviews are performed in an automated way, on average, over 88 percent of the improper payments are identified from complex review. When an improper payment is identified, the involved provider will receive a notification letter with the rationales for the

[12] This leads to upcoding. There are also discussions on EMRs leading to upcoding in outpatient care. See http://www.nytimes.com/2012/09/22/business/medicare-billing-rises-at-hospitals-with-electronic-records.html?_r=0.

[13] ZPICs were formerly known as the Program Safeguard Contractors (PSCs). See the Medicare Program Integrity Manual (https://www.cms.gov/Regulations-and-Guidance/Guidance/Manuals/Internet-Only-Manuals-IOMs-Items/CMS019033). Beginning in Fiscal Year (FY) 2016, CMS developed the Unified Program Integrity Contractor (UPIC) strategy to consolidate the integrity efforts of many of the above programs. See https://www.lilesparker.com/unified-program-integrity-contractor-upic-audits-investigations/. The fiscal year is the accounting period for the federal government, from the fourth quarter of the previous year to the third quarter of the current year.

[14] Appendix Figure A1 displays the map of the four RAP regions.

determination. After that, the provider either fulfills the payments or initiates a discussion or an appeal process.[15]

RAs are paid based on a contingency fee basis, a percentage of the corrected payments, ranging from 9.0 – 12.5 percent for all claim types except for claims on durable medical equipment.[16] Note that RAs will get paid in *both* cases of overpayments and underpayments, but need to return the fee if the determination is overturned at all levels of appeal. As a result, RAs are incentivized to accurately identify improper payments, which is confirmed by the recovery audit validation contractor who reviews a monthly random sample of claims that RAs adjudicated improperly paid and finds that the assessment of RAs are accurate in over 90% of the time.

The majority of improper payments are overpayments, and most of the corrected payments—81% of the overpayments and 76% of the underpayments—arise from inpatient claims. Thus, the billing and documentation in inpatient hospital care plays an important role in ensuring the compliance with Medicare's payment criteria and documentation and billing requirements, which is also the focus of the discussion in this paper. According to the RAP reports, the most common reasons for improper payments are related to the services (1) for which the documentation submitted does not support the services rendered; or (2) that do not meet Medicare's coverage and medical necessity criteria; or (3) that are incorrectly coded (Recovery Audit Program, 2011 – 2014).[17] The results of the RAP help CMS identify program vulnerabilities and point out directions on future corrective actions that can be implemented to reduce improper payments.[18]

3 Data and Summary Statistics

We obtain the data on overpayments and underpayments from the Reports to Congress—Recovery Auditing in Medicare for FY 2011 – 2016 (Recovery Audit Program, 2011 – 2016). The appendices of these reports document the collected amount of overpayments and underpayments by state,

[15] In case of an underpayment, the provider will be notified in the letter about the repayment process.

[16] The rate went up to 10 – 14.4 percent in FY 2016 after the procurement and contract modification.

[17] These are the key areas in proper billing and documentation that CMS emphasizes and other audit contractors (such as the CERT program) also focus on.

[18] Vulnerability is defined as a claim type or series of related claim types that are more susceptible to improper payments and thus impose greater financial risk to the Medicare FFS program (Recovery Audit Program, 2012).

which we use as our main outcome measures.

Overpayments					
FY	Mean	Std. Dev.	Min	Max	National total
2011	15,027,971	21,583,408	344,655	143,133,739	766,426,560
2012	44,575,305	56,533,167	3,345,195	366,953,650	2,273,340,416
2013	71,019,268	87,784,946	4,798,836	516,927,724	3,621,982,720
2014	45,094,535	52,875,609	913,447	261,036,006	2,299,821,312
2015	7,865,145	10,422,682	181,665	50,244,702	401,122,400
2016	7,767,808	11,634,131	211,893	62,723,109	396,158,240
Underpayments					
FY	Mean	Std. Dev.	Min	Max	National total
2011	2,729,836	4,017,589	63,675	25,385,403	139,221,648
2012	2,107,355	3,359,027	139,216	22,206,906	107,475,088
2013	1,895,550	3,002,785	67,408	18,467,227	96,673,040
2014	2,668,948	3,531,411	66,526	14,233,159	136,116,336
2015	1,426,992	1,662,128	1,548	7,980,722	72,776,592
2016	1,265,075	1,909,218	18,417	10,679,471	64,518,836

Table 1: Summary statistics for overpayments and underpayments ($)

Table 1 reports the summary statistics of the corrected payments. The upper panel shows the statistics for overpayments. The total amount of overpayments nationwide (shown in the last column of the first panel) increased substantially from FY 2011 to FY 2013, and started to fall from FY 2014. An important reason is that RAs were prohibited to review inpatient hospital patient status on claims with admission dates between FY 2014 and FY 2015 because of the implementation of the Two-midnight Rule (Recovery Audit Program, 2014 – 2015).[19] In August 2013, CMS published the final rule, specifying the standard by which inpatient hospital admissions generally qualify for Part A payments and established the Probe and Educate process to provide educations to providers on this rule, before reinstituting RA analysis of inpatient claims. Note that improper payments from inpatient hospital patient status reviews accounted for a substantial portion in the

[19]RAs did not perform such reviews in FY 2016 as well (Recovery Audit Program, 2016).

collections in RAP during previous years.[20]

The collected overpayments also differ substantially by states, as can be seen from the large standard deviations. For instance, in 2011, the smallest amount of recovered overpayments is \$0.345 million in West Virginia, which is only 0.24% of that compared with the largest state, California. The amount of underpayments is much smaller than that of overpayments and also fluctuates less over time, but the difference by state remains substantial. All these variations constitute important sources for our identification.

We use the HIMSS Analytics Database to construct the health IT adoption variable. The database is an annual survey, recording the demographic and automation information of the majority of U.S. hospitals and evaluating 90 software applications and technologies. Specifically, the dataset includes information on a hospital's adoption status, year of adoption, component installed, and the identify of the vendor. We define a hospital has adopted EMRs if any of the key components (among CDR, OE, CDS, CPOE, and PD) is live and operational within the organization. Similar to Dranove et al. (2014) and Li (2014), we also categorize adoptions into the basic and advanced levels, with the former depending on the adoption status of the basic components (CDR, OE, and CDS) and the latter based on the advanced components (CPOE and PD).[21] We then calculate the adoption rate within a state, equal to the total number of beds in adopting hospitals divided by the total number of hospital beds in this state. It is a weighted adoption rate at the state level that accounts for hospital bed size. Our data includes approximately 4500 to 4900 hospitals per year, depending on the year considered, and covers most of the hospitals enrolling in Medicare.[22]

Table 2 reports the adoption rate at the state level during the sample period. The first panel shows the adoption rate based on all components and the last two present the rate for the basic and advanced level, respectively. The overall/basic adoption rate was high, over 90%, at the beginning of our sample, probably because of the ongoing activities to promote health IT at that time.[23]

[20] A reason why the corrected payments in FY 2014 did not drop as much as later years is that RAs are allowed to review claims that were paid within the past three years. It is likely that, in FY 2014, RAs still reviewed patient status in claims for which the admission occurred prior to FY 2014.

[21] Hospitals can install all components at one time or implement individual ones sequentially, but they all have some basic applications at the moment or before they deploy the advanced components.

[22] We only consider hospitals that bill Medicare for the services provided.

[23] The Health Information Technology and Economic and Clinical Health (HITECH) Act—an incentive program promoting the adoption of EMRs—was passed in 2009. Even before the passage of the HITECH Act, there had

Overall				
Year	Mean	Std. Dev.	Min	Max
2010	91.72	7.35	70.38	100
2011	95.54	3.85	81.67	100
2012	97.08	3.54	80.21	100
2013	98.66	2.10	88.85	100
2014	99.52	0.85	96.16	100
2015	99.88	0.30	98.26	100
2016	99.93	0.20	98.93	100
Basic level				
Year	Mean	Std. Dev.	Min	Max
2010	91.38	7.61	70.38	100
2011	95.26	4.19	81.67	100
2012	96.82	3.78	80.21	100
2013	98.38	2.92	84.23	100
2014	99.48	0.93	96.16	100
2015	99.87	0.31	98.26	100
2016	99.90	0.26	98.93	100
Advanced level				
Year	Mean	Std. Dev.	Min	Max
2010	46.18	15.69	12.50	82.97
2011	60.38	15.92	17.42	98.29
2012	71.44	15.53	17.42	100
2013	81.33	11.74	40.40	100
2014	91.76	7.50	65.01	100
2015	95.51	5.47	68.87	100
2016	98.35	1.66	94.12	100

Table 2: Summary statistics for adoption rates (%)

The average adoption rate at the advanced level was relatively low in 2010 but went up rapidly afterwards, to over 98% at the end of the sample period.

Variable	Mean	Std. Dev.	Min	Max
% white	69.8	16.3	21.9	94.1
% black	10.8	10.8	1.00	48.9
% hispanic	11.1	10.1	1.00	47.4
% households with at least one full-time worker	80.2	3.38	73.4	86.4
Median household income ($)	58,723	8,977	41,177	77,259
Hospital expenses per inpatient day ($)	2,056	481	1,207	3,178
Total hospital beds per 1000 population	2.73	0.82	1.70	5.53
% Medicare coverage	12.7	1.91	6.86	17.0
% Uninsured	11.7	3.66	3.43	20.6
% with bachelor's degree or higher	21.9	5.15	15.2	45.1
% in the occupation of medical records and health information	0.0678	0.0191	0.0211	0.124
% in the occupation of healthcare practitioners	2.69	0.50	1.79	4.91
% teaching hospitals in 2010	16.8	12.2	0	51.7
% not-for-profit hospitals in 2010	64.7	19.8	17.0	100
% for-profit hospitals in 2010	15.5	12.7	0	51.5
% affiliated hospitals in 2010	60.6	15.5	3.98	88.2
HHI in 2010	0.0521	0.0518	0.0046	0.2753

Note: Table reports the statistics over the years 2010-2016.

Table 3: Summary statistics for state controls

We supplement our IT adoption data with a rich set of state control variables. We obtain the information on the following state characteristics from the state health facts documented by the Kaiser Family Foundation: employment rate, median household income, race and ethnicity, hospital expenses per inpatient day, percentage of Medicare coverage, uninsurance rate, and total hospital beds.[24] We also control for the occupation-specific employment rates (for the occupation of medical records and health information and healthcare practitioners, respectively) from the Bureau of Labor Statistics and the state education level from the Current Population Survey. Finally, we use the American Hospital Association (AHA) Annual Survey to control for hospital characteristics at the state level, including the share of teaching hospitals, share of affiliated hospitals, and

been ongoing discussions on how to encourage the adoption of the technology. For instance, the Office of the National Coordinator for Health Information Technology and the American Health Information Community organized a number of public-private sector meetings in 2006-2007 to discuss the strategies to support the technology.

[24] See https://www.kff.org/statedata/.

share of for-profit and not-for-profit hospitals. We also calculate the Herfindahl–Hirschman Index using total hospital admissions to measure hospital market concentration at the state level.

Table 3 presents the statistics for the state control variables. For each variable, we first calculate the average across years within a state and then report the statistics across states. In general, states are different in terms of demographic features. Moreover, certain hospital characteristics vary substantially by state, such as hospital profit status and hospital market concentration. As a result, it is important to control these characteristics in the estimation, as they could be related to the diffusion of health IT and the generation of Medicare improper payments at the same time. To sum up, our empirical analysis is based at the state level, covering the years between 2011 and 2016.

4 Empirical Strategy

Our empirical specification is motivated by the two potential mechanisms for how EMRs affect hospital documenting and billing services: the *bill-inflation* mechanism and the *complete-coding* mechanism.[25] These two mechanisms lead to similar patterns in claims data—higher bills among EMR hospitals, but result in different audit findings. If the former is the primary mechanism, RAs are likely to make an improper payment determination after a complex review, because patients' conditions could be mis-reported or inadequately justified. However, if the complete-coding mechanism plays a major role, the original claim determination will probably not change after RAs' examination, because the (complete) documentation should comply with Medicare guidelines and support the level of services billed.

Because the improper payment data are only available at the state level, we aggregate the adoption data to the state-year cell and conduct all the analyses at this level. Specifically, we examine how the collected overpayments / underpayments change over time as the state adoption rate varies. We estimate the regression equation in the following form:

$$\ln(Y_{st}^{M}) = \text{AdoptRate}_{st-1}\beta^{M} + X_{st-1}\alpha^{M} + \delta_{s}^{M} + \gamma_{t}^{M} + \theta_{r}^{M} \times t + \varepsilon_{st}^{M}, \tag{1}$$

[25] EMRs could affect billing and documentation in other parts of care in the Medicare FFS program. Our discussion focuses on inpatient hospital care, considering that it is the largest contributor to Medicare spending and improper payments.

where Y_{st}^{M} denotes the amount of improper payments per Medicare enrollee at state s and year t and $M = OP\ (UP)$ if we consider overpayments (underpayments). We take the natural log of the dependent variable to reduce the skewness in the payment data. AdoptRate_{st-1} represents the state adoption rate in the previous year. X_{st-1} includes the lagged measure of a set of state characteristics as mentioned above. We use these variables lagged by one year, because RAs are allowed to review claims with admission dates in previous years. We expect most of the reviewed claims from the year before, considering the changes in overpayments in FY 2014 and FY 2015 as a result of the prohibition from performing patient status review, but we also use the measures lagged by more years as a robustness check.[26] We include the state fixed effects, δ_s^M, controlling for any time-invariant factors at the state level that may simultanesouly affect the audit outcomes and the adoption of health IT, such as the persistent patterns of medical practices or unobservables at the state healthcare market. γ_t^M stands for year fixed effects, controlling for any omitted variables at the national level but varying over time, such as new rules in the overall Medicare auditing strategy. Each RA is responsible for a geographic region consisting of multiple states, and $\theta_r^M \times t$ denotes the auditor-/region-specific linear time trend, allowing for differential trends by RAs/regions to capture time-varying unobservables.

The key variable of interest is the state adoption rate, and the associated coefficient, β^M, measures the effect of adoption on the amount of improper payments. In the case of overpayments, we anticipate β^{OP} to be positive if EMRs mainly facilitate inappropriate billing practices, which can be captured in the complex review by auditors. However, β^{OP} is expected be insignificant if the effect on complete documentation dominates. In this latter case, EMRs help capture charges for the services provided by producing supporting documentation adequate to pass audits. In the case of underpayments, we expect β^{UP} to be negative in both mechanisms. For the bill inflation mechanism, hospitals have no desire for down-coding in response to financial incentives. For the complete coding hypothesis, EMRs assist healthcare providers in billing the appropriate level of services, decreasing down-coding. In all, the estimated β's help shed light on which mechanism

[26]Even though the prohibition applied on claims with admission dates starting from FY 2014, the overpayments collected in the same fiscal year dropped by about one third compared with that in FY 2013, but the amount dropped by 89% in FY 2015. As a result, we expect the claims examined by RAs mainly come from the previous year. The main results hold in the robustness check. We provide more details in Section 5.

dominates: the presence of a positive β^{OP} and a negative β^{UP} supports the bill-inflation mechanism, whereas the combination of an insignificant β^{OP} and a negative β^{UP} are in favor of the complete-coding mechanism.

Our estimation strategy relies on a fixed effects approach, and thus, the identification of our key variable of interest is based on within-state variations. The key identifying assumption is that the adoption of EMRs at the state level is mean-independent of the unobserved component ε_{st}^{M}. While we control for time-invariant cross-state heterogeneity using state fixed effects, there may exist unobserved variables that are associated with the change in state-level adoption over time and lead the improper payments to trend differentially between states.[27] In this case, the established correlation may not necessarily imply a cause–effect relationship.

To further explore the bill-inflation mechanism, we estimate the heterogenous effect of EMR adoption based on the capabilities of RAs. As pointed out by Ganju et al. (2021), certain RAs have developed the capabilities of identifying copied language and over-documentation in EMRs and thus are more effective in capturing inflated reimbursements. To verify this implication, we estimate the following equation:

$$\begin{aligned}\ln(Y_{st}^{M}) = {} & \text{Special}_s \times \text{AdoptRate}_{st-1}\beta_1^M + \text{NotSpecial}_s \times \text{AdoptRate}_{st-1}\beta_2^M \\ & + X_{st-1}\alpha^M + \delta_s^M + \gamma_t^M + \theta_r^M \times t + \varepsilon_{st}^M,\end{aligned} \tag{2}$$

where $\text{Special}_s = 1$ ($\text{NotSpecial}_s = 1$) if state s is assigned to the auditors with (without) specialized capabilities.[28] The values of β_1^M reflect the extent to which such capabilities help identifying the improper payments arising due to EMR adoption. If an EMR is more of a tool to game the reimbursement system, especially due to the functionalities of pre-loaded templates and "cloned" records, we expect $\beta_1^{OP} \geq \beta_2^{OP} > 0$. Other variables share the same definitions in Equation (1).

Moreover, the impact from EMRs may vary by the level of adoption. As pointed out by Dranove et al. (2014), basic EMRs establish the underlying infrastructure to collect and report patient

[27] A potential example will be the interaction between provider networks and the private insurance market in a particular state, but we hope that this can be stable within a relatively short time (six years in our data) and picked up by the state fixed effects.

[28] We thank Ganju et al. for providing us the information on the auditors that possess the specialized capabilities.

information at one place and automate the process of creating orders (mostly) for ancillary services. Advanced components, if properly implemented and operated, offer more sophisticated features in documentation (such as built-in structured templates) and provide real-time support on a range of related information when determining diagnosis and prescribing treatments. Advanced EMRs may affect the process of billing and documentation in a more substantive way but are harder to put into effect, as they are more complex, and require a higher level of organization-wide integration, typically involving extensive and costly training for providers and a lag of two or more years before enhanced revenue capture is realized. To examine this, we estimate Equations (1) and (2) separately for basic and advanced adoptions. We cluster all standard errors at the state level and weight our regressions by the size of Medicare population within a state.

5 Results

5.1 Main results

Table 4 presents the estimated coefficients for the key variables of interest from Equations (1) – (2) based on the general adoption definition. The first two coefficient columns suggest that the amount of improper payments, for both overpayments and underpayments, is not significantly correlated with the state-level adoption. We also report the marginal effect of adoption on improper payments, equal to the exponentiated value of the linear prediction for the regression equation multiplied by the coefficient estimate.[29] Similarly, both the estimated marginal effects are statistically insignificant.

The results for overpayments are similar after taking into account whether the RA is capable of identifying the use of over-documentation and copied records in EMRs, as shown in the second panel in Table 4. In the case of underpayments, however, the coefficient on the interaction between adoption rates and the indicator for RAs without the specialized capabilities is significantly negative, suggesting that states assigned to these RAs experience a smaller amount of underpayments when the adoption rate is higher; that is, hospitals with EMRs tend to make fewer "mistakes" that

[29] To achieve this, we first exponentiate both sides of the regression equation to transform the outcome measure to the original level and then calculate the first derivative of the original Y with respect to adoption rate.

lead to underpayments in those states. The estimate corresponds to an average decrease of 11.8 percent in underpayments as a consequence of higher adoption rates.

	Overall		By RA capabilities	
	OP	UP	OP	UP
Adoption rate	-0.266	0.0679		
	(1.044)	(2.194)		
Adoption rate × RAs **w/** specialized capabilities			-0.333	2.080
			(1.303)	(2.305)
Adoption rate × RAs **w/o** specialized capabilities			-0.0653	-6.044**
			(1.289)	(2.835)
MEs (%): adoption rate	-7.190	0.133		
	(28.17)	(4.292)		
MEs (%): adoption rate × RAs **w/** specialized capabilities			-8.977	4.069
			(35.19)	(4.508)
MEs (%): adoption rate × RAs **w/o** specialized capabilities			-1.762	-11.82**
			(34.81)	(5.546)
N	306	306	306	306

Note: OP (UP) stands for overpayments (underpayments). Other regressors include state fixed effects, year fixed effects, RA-specific time trends, and the following state controls: percentage white, percentage black, percentage hispanic, percentage households with at least one full-time worker, logged hospital expenses per inpatient day, logged median household income, logged hospital beds per 100 population, percentage with bachelor's degree or above, percentage employed in the occupation of medical records and health information, percentage working as healthcare practitioners, percentage Medicare coverage, percentage uninsured, percentage teaching hospitals in 2010 × time trends, percentage for-profit hospitals in 2010 × time trends, percentage not-for-profit hospitals in 2010 × time trends, percentage affiliated hospitals in 2010 × time trends, and HHI in 2010 × time trends. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of EMR adoption on improper payments

We test the sensitivity of the results using the adoption rates two years before, as the RAP reports do not specify which year in the look-back period RAs focus on. The main finding holds, as shown in Appendix Table A1. Also, our data is a short panel, lasting only six years, and thus, a fixed effects model may lead to unusually high variances. For a robustness check, we try alternative specifications, such as removing state fixed effects from our original specifications (results in Appendix Table A2) or drop the state control variables (results in Appendix Table A3).

In general, the estimates are consistent.

Taken together, the finding of insignificant effects of EMR adoption on overpayments, regardless of the capabilities of RAs, along with lower underpayments in states where the technology becomes more prevalent, provides supporting evidence for the complete-coding mechanism. EMRs improve the data collection and documentation during the hospital course and enhance allowable billing. These results are consistent with the findings in prior studies—even those concluding more complicated conditions reported as a result of EMR adoption—in the sense that EMR hospitals are able to bill the appropriate level instead of a lower billing code, given more complete documentation. As a result, RAs identify a disproportionate amount of underpayments in states with less adoption of EMRs. The finding here may represent an upper bound estimate, because the reviews in RAP sometimes focus on the flagged categories from data analysis in other programs (such as the CERT program).[30]

5.2 Effects of basic/advanced EMRs

To investigate whether the effect of EMRs differs by the level of adoption, we rerun the main specifications separately for the definition of basic and advanced EMRs and report the results in Table 5. The findings based on the basic level of adoption are similar to those using the general adoption definition. We do not see any significant impact from basic EMRs on overpayments, but a decrease of almost 12 percent in underpayments as a result of the change in basic adoption among the states whose RAs do not develop the special capabilities.

There is still little evidence showing that EMR adoption is associated with overpayments, in terms of the advanced level. By contrast, the correlation between the adoption of advanced EMRs and underpayments becomes significantly positive in states with more capable RAs. On average, the amount of underpayments increases by 4.3 percent in response to the variations in advanced adoption relative to no or basic adoption in those states.[31] The coefficient estimate on the interaction with the indicator for less capable RAs remains negative and yet insignificant.

[30] Claims reviews by CERT auditors are performed on a random sample.

[31] Note that the aggregated effect of EMR adoption on underpayments remains negative, as suggested by the results from the general adoption definition.

	Basic				Advanced			
	Overall		By RA capabilities		Overall		By RA capabilities	
	OP	UP	OP	UP	OP	UP	OP	UP
Adoption rate	0.346	0.0958			-0.243	1.413		
	(1.120)	(2.128)			(0.538)	(0.965)		
Adoption rate × RAs **w/** specialized capabilities			0.441	1.882			-0.479	2.210*
			(1.395)	(2.172)			(0.656)	(1.104)
Adoption rate × RAs **w/o** specialized capabilities			0.0161	-6.110**			0.680	-1.711
			(1.304)	(2.851)			(0.576)	(1.490)
MEs (%): adoption rate	9.351	0.187			-6.567	2.765		
	(30.23)	(4.163)			(14.52)	(1.888)		
MEs (%): adoption rate × RAs **w/** specialized capabilities			11.92	3.681			-12.92	4.322**
			(37.66)	(4.248)			(17.71)	(2.160)
MEs (%): adoption rate × RAs **w/o** specialized capabilities			0.433	-11.95**			18.36	-3.347
			(35.22)	(5.578)			(15.55)	(2.915)
N	306	306	306	306	306	306	306	306

Note: OP (UP) stands for overpayments (underpayments). Other regressors include state fixed effects, year fixed effects, RA-specific time trends, and the following state controls: percentage white, percentage black, percentage hispanic, percentage households with at least one full-time worker, logged hospital expenses per inpatient day, logged median household income, logged hospital beds per 100 population, percentage with bachelor's degree or above, percentage employed in the occupation of medical records and health information, percentage working as healthcare practitioners, percentage Medicare coverage, percentage uninsured, percentage teaching hospitals in 2010 × time trends, percentage for-profit hospitals in 2010 × time trends, percentage not-for-profit hospitals in 2010 × time trends, percentage affiliated hospitals in 2010 × time trends, and HHI in 2010 × time trends. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of EMR adoption on improper payments, by level of adoption

Taken together, we still find no evidence supporting the bill-inflation mechanism. Moreover, the result of relatively more underpayments identified in states with greater adoption of advanced EMRs may suggest that hospitals face challenges in implementing the sophisticated applications. For instance, the difficulty in deploying and operating CPOE has been well documented in academic research (Kruse and Goetz, 2015). A successful implementation of CPOE requires substantive changes in the work practices of clinicians and staff, as well as the established patterns of interactions between them.[32] Studies find that CPOE could impair the synchronization and feedback mechanism in collaborations between clinicians (Cain and Haque, 2008).[33] As a result,

[32]The Agency for Healthcare Research and Quality also presents emerging lessons of implementing and using CPOE from its funded projects. The agency describes this application as the most difficult component to implement because of "the impact on the culture and workflow." See https://digital.ahrq.gov/key-topics/computerized-provider-order-entry.

[33]Consider an order that is placed by a physician and needs a pharmacist's verification before it can be administered by the nurse. Without CPOE, the operation is likely to be smoother either because the physician usually places the

hospital staff (usually coders) may find it difficult to coordinate the inconsistent information entered by clinicians, which may lead to down-coding.[34] In all, the results suggest that the adoption of basic EMRs improves charge capture for hospitals by making the overall documentation process less difficult, but the value of advanced EMRs has not been fully appropriated given its inherent complexity and the relatively short time of being in place.

5.3 Supplemented evidence from other Medicare audit data

Coding of hospital admissions is a more complicated endeavor than coding for other services through Medicare. There are 330 base DRGs, hundreds of MCCs, and thousands of CCs, which can be coded in hundreds of thousands of combinations. In stark contrast, billing for an ambulatory visit through Medicare Part B is limited to five levels, regardless of the primary diagnosis or comorbidities, but rather based on documentation of effort by the provider. The difference in the complexity of the coding in these two circumstances is enormous. Hence, comparing the ratio of overpayments to underpayments for hospitalization with other services provides further insight into the role of EMRs in the billing process.

Year	Part A IPPS	Part A excluding IPPS	DMEPOS	Part B
2011	22.6	71	177274.9	48.9
2012	13.1	56.3	172530.8	63.7
2013	9.8	58.5	34147	62.8
2014	9.8	270.5	10122.8	55.5
2015	8.5	327.4	1692.3	35.7
2016	6.8	442.8	370.9	20

Note: Calculation based on the reported projected overpayments and underpayments in Medicare FFS Improper Payments Reports 2011 – 2019 (CERT Program, 2011 – 2019).

Table 6: Ratio of overpayments to underpayments by category from CERT

order in the unit of the pharmacist / nurse or because there would be a unit secretary who keeps other clinicians informed of the update of the order. With CPOE, physicians may place the order in multiple locations and both the pharmacist and nurse may fail to follow up immediately.

[34] Sacarny (2018) also points out that an important factor that determines whether hospitals can capture the full revenue through reporting the detailed code for heart failure (i.e., specifying the type of heart failure) is the quality of hospital staff in extracting information from physicians.

We do so by analyzing data from the CERT program—another Medicare audit strategy. The CERT program conducts reviews on a random sample of paid claims from the Medicare FFS program to assess the program accuracy. The advantage of this data is that it reports the projected overpayments and underpayments by claim types, including Part A IPPS (hospitalization), Part A excluding IPPS (skilled nursing facility care, nursing home care, hospice care and home health care), Part B, and Part B durable medical equipment, prosthetics, orthotics and supplies (DMEPOS).[35] DRG-based reimbursement is determined by the principal and accompanying diagnoses, independent of provider efforts, patient risk score, or other factors, whereas billing for physician services under Part B, Part A other than IPPS, and for DMEPOS under Part B FFS is based on provider effort and the need for individual services.

Table 6 reports the the ratio between the projected overpayments to projected underpayments during the same time frame as our sample. We observe two interesting facts. First, the ratio in RAP—obtained from the last column of the top and bottom panels in Table 1—is much closer to that in Part A IPPS than any other service types, probably because the majority of improper payments collected in RAP come from hospital inpatient claims. Second, the radio in Part A IPPS is much smaller than that in the other three categories. This is a consequence of at least two factors: underpayments are relatively more prevalent in Part A IPPS with the complexity of coding, and overpayments are more prevalent in Part B, Part A non-IPPS, and DMEPOS, where the coding is much less complex.

We make the comparison at a highly aggregate level, but it still reflects the potential coding complexity to bill hospital inpatient care, for which the compliance with the billing requirements is very costly. While we acknowledge that a fundamental reason for hospitals to adopt EMRs is to optimize reimbursements, our finding suggests that the complete-coding mechanism dominates in hospital inpatient care, probably because of the specificity in the billing criteria in Part A IPPS.

[35]The projected payments are obtained by extrapolating the sample estimates using proper sampling weight so as to be representative of the population of Medicare FFS claims.

6 Conclusion

We study the correlation between the improper payments collected in a state and the state adoption rate of EMRs. Using audit data allows us to distinguish between the two potential mechanisms: the bill-inflation mechanism and the complete-coding mechanism, which cannot be separated in conventional claims data. Since inpatient hospital care accounts for the largest proportion in Medicare spending, the findings here shed light on the underlying effect of EMR adoption on hospital coding behavior. We find no evidence supporting the proposition that EMRs facilitate bill inflation, but more evidence pointing to the complete-coding mechanism.

Our lack of substantiation to the bill-inflation mechanism suggests that more focus could be concentrated on other more common types of improper payments, as is shown by Joiner et al. (2020), such as the improper payment error of lacking medical necessity or the improper billing in Medicare Part B that is billed under FFS. Instead, compliance with Medicare billing criteria could be costly and the application of EMRs makes the process less complicated. Policy makers might consider providing more guidance to providers and create the right incentive for them to engage in proper documentation.

This paper has a few limitations. First, we only estimate the effect at the state level due to data limitation, but we believe that the established correlation is plausibly causal, based on the state fixed effects model with a rich set of state controls. It is likely that there remain some unobserved characteristics that may affect state EMR adoption and cause improper payments to trend differentially. However, we believe that the bias are limited, as the changes are likely to be small within a short time. Accordingly, our analysis contributes to the current literature by uncovering the underlying mechanism for how EMRs affect hospital billing and documentation practices.

References

Adler-Milstein, J. and Jha, A. K. (2014). No evidence found that hospitals are using new electronic health records to increase Medicare reimbursements. *Health Affairs*, 33(7):1271–1277.

Barros, P. and Braun, G. (2017). Upcoding in a national health service: the evidence from Portugal. *Health economics*, 26(5):600–618.

Bauder, R., Khoshgoftaar, T. M., and Seliya, N. (2017). A survey on the state of healthcare upcoding fraud analysis and detection. *Health Services and Outcomes Research Methodology*, 17(1):31–55.

Bowblis, J. R. and Brunt, C. S. (2014). Medicare skilled nursing facility reimbursement and upcoding. *Health economics*, 23(7):821–840.

Brunt, C. S. (2011). CPT fee differentials and visit upcoding under Medicare Part B. *Health economics*, 20(7):831–841.

Cain, C. and Haque, S. (2008). *Chapter 31, Patient Safety and Quality: An Evidence-Based Handbook for Nurses*. Agency for Healthcare Research and Quality, Rockville, MD.

CERT Program (2011-2019). Medicare fee-for-service improper payments report. *Centers for Medicare and Medicaid Services*.

Cook, A. and Averett, S. (2020). Do hospitals respond to changing incentive structures? Evidence from Medicare's 2007 DRG restructuring. *Journal of Health Economics*, 73:102319.

Dafny, L. S. (2005). How do hospitals respond to price changes? *American Economic Review*, 95(5):1525–1547.

Dranove, D., Forman, C., Goldfarb, A., and Greenstein, S. (2014). The trillion dollar conundrum: Complementarities and health information technology. *American Economic Journal: Economic Policy*, 6(4):239–270.

Fang, H. and Gong, Q. (2017). Detecting potential overbilling in Medicare reimbursement via hours worked. *American Economic Review*, 107(2):562–91.

Ganju, K. K., Atasoy, H., and Pavlou, P. A. (2021). Do electronic health record systems increase medicare reimbursements? The moderating effect of the recovery audit program. *Management Science*.

Geruso, M. and Layton, T. (2020). Upcoding: evidence from Medicare on squishy risk adjustment. *Journal of Political Economy*, 128(3):984–1026.

Gowrisankaran, G., Joiner, K., and Lin, J. (2019). How do hospitals respond to Medicare payment reforms? *NBER Working Paper No. 26455*.

Januleviciute, J., Askildsen, J. E., Kaarboe, O., Siciliani, L., and Sutton, M. (2016). How do hospitals respond to price changes? Evidence from norway. *Health economics*, 25(5):620–636.

Joiner, K. A., Lin, J., and Pantano, J. (2020). Upcoding of hospital admissions in Medicare Part A: Not a significant issue now. *Available at SSRN 3757285*.

Jürges, H. and Köberlein, J. (2015). What explains drg upcoding in neonatology? The roles of financial incentives and infant health. *Journal of health economics*, 43:13–26.

Kruse, C. S. and Goetz, K. (2015). Summary and frequency of barriers to adoption of CPOE in the US. *Journal of medical systems*, 39(2):1–5.

Levinson, D. R. (2014). CMS and its contractors have adopted few program integrity practices to address vulnerabilities in EHRs. *Department of Health and Human Services, Office of Inspector General*.

Li, B. (2014). Cracking the codes: Do electronic medical records facilitate hospital revenue enhancement? *Working paper*.

Qi, K. and Han, S. (2020). Does IT improve revenue management in hospitals? *Journal of the Association for Information Systems*, 21(6):7.

Recovery Audit Program (2011-2016). Recovery auditing in Medicare for Fiscal Year 2011 – 2016. *Centers for Medicare and Medicaid Services*.

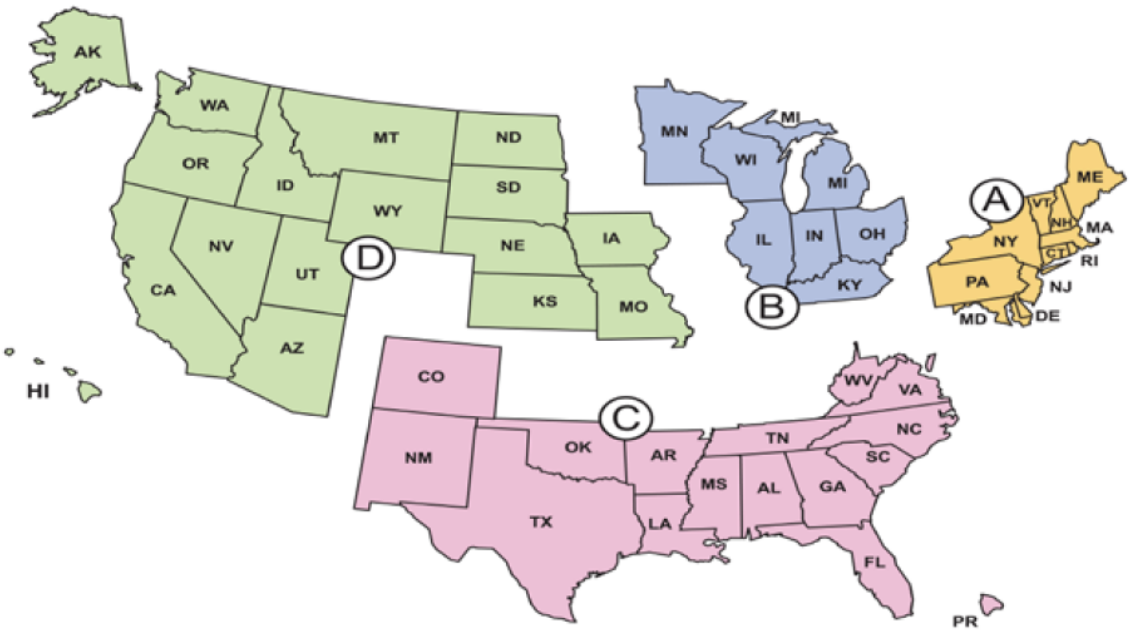
Sacarny, A. (2018). Adoption and learning across hospitals: The case of a revenue-generating practice. *Journal of health economics*, 60:142–164.

Silverman, E. and Skinner, J. (2004). Medicare upcoding and hospital ownership. *Journal of health economics*, 23(2):369–389.

Verzulli, R., Fiorentini, G., Lippi Bruni, M., and Ugolini, C. (2017). Price changes in regulated healthcare markets: Do public hospitals respond and how? *Health economics*, 26(11):1429–1446.

Appendix 1: Extra Figures and Tables

Figure A1: Map of RA regions



Note: Below lists the RA for each region: Performant Recovery for Region A, CGI for Region B, Connolly for Region C, and HealthData Insights (HDI) for Region D.

Table A1: Effect of EMR adoption on improper payments, using two-year lagged adoptions and controls

	Overall		By RA capabilities	
	OP	UP	OP	UP
Adoption rate	0.793	1.462		
	(1.419)	(2.620)		
Adoption rate × RAs **w/** specialized capabilities			1.061	3.445
			(1.613)	(3.119)
Adoption rate × RAs **w/o** specialized capabilities			-0.224	-6.081*
			(2.446)	(3.138)
MEs (%): adoption rate	22.03	2.943		
	(39.41)	(5.273)		
MEs (%): adoption rate × RAs **w/** specialized capabilities			29.46	6.933
			(44.79)	(6.276)
MEs (%): adoption rate × RAs **w/o** specialized capabilities			-6.218	-12.24*
			(67.94)	(6.315)
N	306	306	306	306

Note: OP (UP) stands for overpayments (underpayments). Other regressors include state fixed effects, year fixed effects, RA-specific time trends, and the following state controls: percentage white, percentage black, percentage hispanic, percentage households with at least one full-time worker, logged hospital expenses per inpatient day, logged median household income, logged hospital beds per 100 population, percentage with bachelor's degree or above, percentage employed in the occupation of medical records and health information, percentage working as healthcare practitioners, percentage Medicare coverage, percentage uninsured, percentage teaching hospitals in 2009 × time trends, percentage for-profit hospitals in 2009 × time trends, percentage not-for-profit hospitals in 2009 × time trends, percentage affiliated hospitals in 2009 × time trends, and HHI in 2009 × time trends. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Effect of EMR adoption on improper payments, no state FEs

	Overall		By RA capabilities	
	OP	UP	OP	UP
Adoption rate	0.0378	-0.624		
	(0.810)	(1.835)		
Adoption rate × RAs **w/** specialized capabilities			0.143	1.065
			(1.051)	(2.253)
Adoption rate × RAs **w/o** specialized capabilities			-0.252	-5.291***
			(1.846)	(1.772)
MEs (%): adoption rate	1.017	-1.261		
	(21.82)	(3.709)		
MEs (%): adoption rate × RA **w/** specialized capabilities			3.841	2.154
			(28.28)	(4.556)
MEs (%): adoption rate × RA **w/o** specialized capabilities			-6.788	-10.70***
			(49.68)	(3.583)
N	306	306	306	306

Note: OP (UP) stands for overpayments (underpayments). Other regressors include year fixed effects, RA-specific time trends, and the following state controls: percentage white, percentage black, percentage hispanic, percentage households with at least one full-time worker, logged hospital expenses per inpatient day, logged median household income, logged hospital beds per 100 population, percentage with bachelor's degree or above, percentage employed in the occupation of medical records and health information, percentage working as healthcare practitioners, percentage Medicare coverage, percentage uninsured, percentage teaching hospitals in 2010 × time trends, percentage for-profit hospitals in 2010 × time trends, percentage not-for-profit hospitals in 2010 × time trends, percentage affiliated hospitals in 2010 × time trends, and HHI in 2010 × time trends. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Effect of EMR adoption on improper payments, no state control variables

	Overall		By RA capabilities	
	OP	UP	OP	UP
Adoption rate	0.0414	-1.033		
	(0.959)	(2.187)		
Adoption rate × RAs **w/** specialized capabilities			-0.227	1.275
			(0.984)	(2.917)
Adoption rate × RAs **w/o** specialized capabilities			0.780	-7.378**
			(2.123)	(3.196)
MEs (%): adoption rate	1.038	-1.891		
	(24.04)	(4.002)		
MEs (%): adoption rate × RAs **w/** specialized capabilities			-5.696	2.334
			(24.64)	(5.339)
MEs (%): adoption rate × RAs **w/o** specialized capabilities			19.54	-13.50**
			(53.19)	(5.850)
N	312	312	312	312

Note: OP (UP) stands for overpayments (underpayments). Other regressors include state fixed effects, year fixed effects, and RA-specific time trends. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$