Does Hospital Electronic Medical Record Adoption Lead To Upcoding or More Accurate Coding?

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Abstract

This paper seeks to evaluate whether the adoption of electronic medical records (EMRs) leads to *upcoding* for hospitalized Medicare patients, defined as categorizing a condition as more serious than justified in order to inflate bills, or more accurate coding. We use a triple difference: (1) between EMR and non-EMR hospitals; (2) before and after the 2007 Medicare payment reform, which made obtaining high payments harder; and (3) between medical and surgical admissions. For medical admissions, we find that the interaction of Medicare payment reform and EMR hospitals leads to higher codes, regardless of the financial incentive to upcode. For surgical admissions, we find no significant effect. While there is no evidence of upcoding, EMRs lead to higher billing by increasing the accuracy of coding for medical admissions.

JEL Codes:
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1 Introduction

Over the past decade, many hospitals in the U.S. have adopted electronic medical records (EMRs), spurred in part by the HITECH Act of 2009, which provided $27 billion to promote health information technology. On one hand, researchers have found that EMRs have led to higher patient quality (Miller and Tucker, 2011; Parente and McCullough, 2009), higher productivity (Lee et al., 2013), and in some cases, lower costs (Dranove et al., 2014). On the other hand, there is a concern that EMRs may lead hospitals to inflate their bills, in order to seek a higher rate of reimbursement than justified—a practice that is called *upcoding* — by lowering the cost to physicians of adding inadequately-documented diagnoses to patient records.[1] To the extent that EMRs cause upcoding, this is a hidden cost of EMRs that limits their benefits and the benefits of government policies that encourage EMR adoption.

The goal of this paper is to evaluate whether the adoption of EMRs leads to upcoding in the market for hospitalized Medicare patients, and also to provide general evidence on whether there is upcoding in this market. Although our results pertain solely to upcoding with Medicare, payment mechanisms for most inpatient hospital services are based on similar criteria to Medicare, and hence we believe that they apply there. More generally, our study may provide evidence on the extent to which reimbursement systems change incentives in the healthcare sector.

We consider four different potential explanations for how EMR adoption might affect billing. First, EMRs might facilitate upcoding by hospitals. Second, EMRs might allow hospitals to code more accurately, a practice that is sometimes called "charge capture." Third, hospitals with EMRs might select different patients. For instance, a hospital might adopt EMRs at the same time that it upgraded other facilities or technologies, thereby selecting a different, and maybe more severely ill, patient mix. Finally, EMR hospitals might provide a different amount of services to the same patients. For instance, Clemens and Gottlieb (2014) show that physicians respond to increased financial incentives by providing

[1] The popular press has also highlighted that EMRs may lead to outpatient upcoding. See, for instance, http://www.nytimes.com/2012/09/22/business/medicare-billing-rises-at-hospitals-with-electronic-records.html?_r=0

more care.

Upcoding and accurate coding would result in similar features in the data. Notably, the explanations given in the literature for how EMRs help hospitals upcode—such as by populating diagnosis fields—may also lower the costs of charge capture. Thus, in both cases, we would expect that EMR adoption would lead to more billing. Yet, the two have very different policy implications. For instance, increased enforcement of Medicare fraud will help limit upcoding but may not impact accurate coding. Thus, it is necessary to separate these two explanations (as well as the others presented).

In order to provide evidence that separates upcoding from charge capture and other explanations, we use what we believe is a novel identification strategy. Our identification is based on a triple difference. Our first difference is between EMR and non-EMR hospitals. Our second difference is before and after the Medicare payment reform that occurred in 2007. The 2007 payment reform made it harder to obtain high reimbursements. But, it also likely made it relatively less hard for hospitals with EMRs to obtain high reimbursements. Our third difference is between medical and surgical admissions. Why is this difference important? Physicians who are dealing with medical admissions are trained to document conditions. Surgeons are trained to document procedures, and hence may not document all medical conditions of their patients in the same detail. EMRs can only code conditions to the extent that physicians document them. As described below, upcoding in the hospital is entirely dependent on medical and not surgical secondary conditions, of the sort preferentially documented during medical admissions. By far the easiest way to influence Medicare reimbursements is from claiming secondary conditions, regardless of whether an admission is medical or surgical. To our knowledge, this third difference has not been exploited in the literature on upcoding.

Overall, the three differences allow us to separately identify strategic upcoding from accurate coding in a way that has not been done before. If hospitals upcode based on their incentives, hospitals with EMRs will tend to increase higher codes following the reform specifically for patients for whom the financial incentives increase the most. However, if EMRs help hospitals code more accurately, then they will result in greater selection of higher codes following the reform for medical instead of surgical admissions, rather than based on financial incentives. Thus, to the extent that EMRs help with charge capture, they will have different effects on medical admissions from surgical ones.

To understand our methodology and results further, it will be useful to summarize the mechanics of Medicare hospital reimbursement. Medicare reimburses hospitals for inpatient care based on a diagnostic related group (DRG). Each DRG has an associated weight. Medicare payments to a hospital for treating a patient are based on the DRG weight multiplied by a cost factor that is specific to the area. For instance in 2008, a hospital may receive anywhere from \$2,807.35 to \$8,217.91 for treating a patient with DRG weight 1, depending on their cost factors.[2] But, a given hospital will always receive twice as much for treating a patient with DRG weight 2 as from a patient with DRG weight 1. CMS divides DRGs into the categories of "medical" and "surgical." A surgical DRG is for a procedure, such as a bypass surgery, while a medical DRG is for the management of a disease.

DRGs are grouped into *base DRGs* based on the patient's primary diagnosis (for medical DRGs) or primary procedure (for surgical diagnoses). For example, "mouth procedures" is an example of a base DRG. Each base DRG contains between 1 and 3 DRGs, which differ in the patient's *secondary* conditions (or equivalently, secondary diagnoses). CMS issues lists of secondary conditions that, when present, would allow a patient to qualify for a "with complications/comorbid conditions (CC)" or "with major complications/comorbid conditions (MCC)" DRG. The different DRGs within a base DRG are called the *severity subclasses*. For example, the mouth procedures base DRG contains two severity subclasses, "mouth procedures without CC/MCC" and "mouth procedures with CC/MCC." Prior to the 2007 payment reform, there were 284 base DRGs with one severity subclass, and 127 base DRGs with two severity subclasses. The reform added MCC as the third potential severity subclass. Following the reform there were 65 base DRGs with one severity subclass, 110 with two severity subclass and 153 with three severity subclass. We refer to the highest weight DRG contained in a base DRG as the *top code*.

Our paper follows from a the literature that examines upcoding based on whether the

[2] Authors' calculations based on FY2008 data.

proportion of top code DRGs changes following the payment reform (Dafny, 2005; Silverman and Skinner, 2004). Dafny (2005) examines upcoding by considering a Medicare reimbursement change that occurred in 1988. Prior to the change, patients age 70 or older were automatically top-coded, while younger patients, 65-69, had to have a secondary condition that was in the CC list. Following the change, the older patients were only top-coded if they also had a secondary condition that was in the list. Using a difference-in-difference design, Dafny finds that, from 1988 on, hospitals increased the 70+ top codes more for those DRGs for which the weight increased more. Hence, she finds that top-coding responds to hospital incentives. Moreover, this effect was more pronounced for for-profit and distressed hospitals. We test for upcoding by examining whether top-coding follows incentives in this way. However, this literature examines data that are now 20 or more years old and reimbursement and coding systems are quite different today than during the time of these studies, for instance effectively including much more severe penalties for fraud. Thus, we would not necessarily expect incentives to have remaining the same over time.

Our paper also builds on a recent literature on upcoding and EMRs (Qi et al., 2015; Li, 2014; Ganju et al., 2015; Adler-Milstein and Jha, 2014). Papers in this literature have also used a difference-in-difference design, evaluating the change in reported codes for hospitals after they adopt EMR. Two of the papers (Li, 2014; Qi et al., 2015) use the percent of top-coded DRGs, similarly to us. We argue above that a higher percent top-coded may be indicative of that either upcoding or more accurate coding is occurring, and thus propose separate explanations to test for upcoding. The other two (Ganju et al., 2015; Adler-Milstein and Jha, 2014) use the patient-weighted mean DRG weight at the hospital, also called the "case-mix index." A change in case-mix index following EMR adoption does not necessarily separately identify the four different explanations that we noted above. Moreover, three of the four studies use data from before and after the 2007 payment reform. Since the payment reform drastically changed the nature of top-codes and was contemporaneous to a huge increase in EMR adoption, difference-in-difference results may be driven by changes induced by the payment reform.

We investigate the separate impact of EMR adoption and the 2007 payment reform on medical and surgical DRGs using a panel of data from 2006 to 2010. We use the universe (100% sample) of Medicare inpatient hospital claims data.[3] We link our data with hospital characteristics data from the American Hospital Association (AHA) annual survey and with EMR adoption data from the Healthcare Information and Management Systems Society (HIMSS) Analytics Database. Last, we combine these data with information from CMS on DRG type and weights.

Each observation is one unique combination of base DRG, hospital, and year. From our universe of claims, we keep all patients with base DRGs that have two associated DRGs before the reform; these transitioned into either two or three DRGs after the reform. This comprises 20.3% of the patients in the overall Medicare sample. Our main dependent variable is the percent of top codes among patients with a DRG associated with this base DRG at a hospital and year. Our analysis regresses this variable on fixed effects at the hospital-base DRG and year levels, EMR adoption interacted with the payment reform, and early EMR adoption (2006 or prior) interacted with the payment reform. We cluster standard errors at the hospital and base DRG levels with two-way clustering.

Our main findings are that there is an increase in medical DRG top codes following the payment reform for hospitals that adopted EMRs. This effect is bigger for hospitals that adopted EMRs before the payment reform, in 2006 or earlier. Unlike the results in Dafny (2004), there is no evidence that the increase in top codes occurs where the payment increased more. In contrast, there is no significant change in surgical DRG top codes. We also examine medical base DRGs with two post-reform subclasses where CCs and MCCs are lumped together, and medical base DRGs with one post-reform subclass. In both cases, there is absolutely no financial incentive to upcode. Yet, we find an increase in the coding of diagnostic codes that would lead to an MCC severity subclass even in some of these cases.

The fact that there is a change in top codes for medical DRGs following the reform suggests that EMRs allow hospitals to either upcode or charge capture. The fact that there is no significant change in top codes for surgical DRGs and that the pattern does not follow

[3]The data do not include Medicare Advantage claims. Medicare Advantage is the privately-provided option to Medicare. During our sample period, 16-24% of Medicare enrollees were in Medicare Advantage plans.

financial incentives suggests that this is not done strategically but rather simply where possible. This in turn suggests that EMRs allow hospitals to code more accurately, and are not facilitating upcoding. Our finding that hospitals may be leaving money on the table by not coding accurately is also supported by Sacarny (2014), who finds that hospitals sometimes use an unspecified code for heart failure even when *any* specified code would lead to a higher payment.

We also examine the third and fourth explanations for changes in billing following EMR adoption that are noted above. First, we examine whether EMRs might cause hospitals to provide more or less services to patients, by examining whether the length-of-stay of patients or the number of procedures changes, following the implementation of EMRs. We find little that is significant here. Second, we examine whether EMRs might cause hospitals to select different patients, by examining whether EMRs lead hospitals to select patients in different base DRGs. Here we find that EMR hospitals select patients with more severe base DRGs in the post-reform period. This is attributable either to EMRs adoption or the payment reform leading to patient selection.

The remainder of the paper is structured as follows. Section 2 provides a background on the market. Section 3 discusses our data. Section 4 discusses our analytic framework and testable hypotheses. Section 5 provides our results. Section 6 concludes.

2 Background

2.1 Medicare Payments and the 2007 Payment Reform

In 1983, the Health Care Financing Administration (now CMS, the Centers for Medicare and Medicaid Services), developed a flat-rate payment system based on DRGs, known as the "Prospective Payment System" (PPS). Under PPS, a hospital assigns a single DRG for each patient stay using the primary diagnosis, additional diagnoses, primary procedure, additional procedures, and discharge status. Each DRG has a weight, which is set by CMS to reflect the average resources used to treat Medicare patients in that DRG. Medicare then reimburses the hospital a flat rate for the admission, calculated as the hospital's base rate multiplied by the DRG weight. By reimbursing hospitals a flat rate instead of a cost-based amount, PPS aims to reward efficiency and lower expenditure growth. The process of transforming patient diagnoses and procedures into billing codes is called *coding*.

DRGs can be either medical or surgical. A patient who underwent a surgical procedure can qualify for either a medical DRG, based on her primary diagnosis, or a surgical DRG, based on her primary procedure. Patients who did not have surgery can only qualify for medical DRGs. Surgical DRGs almost always have a higher weight (and hence payment) than the DRG for the diagnosis for which the surgery is indicated and hence hospitals will generally choose the surgical DRG when a surgery is performed. Essentially, then, medical DRGs are for patients who did not undergo surgery.

The coding of an inpatient admission into a DRG uses the following logic. Diagnoses are identified by ICD-9 diagnosis codes. Surgical procedures are identified by ICD-9 procedure codes.[4] Hospitals report to Medicare up to 10 diagnosis and 6 procedure codes per patient. Each hospital stay is characterized by one primary diagnosis and at most one primary procedure.

Using the ICD-9 codes, an admission is first coded into the base DRG using the primary diagnosis code (for medical base DRGs) or the primary procedure code (for surgical base DRGs). An example of a medical base DRG is "Heart Failure and Shock" while "Spinal Fusion Except Cervical" is an example of a base surgical DRG. Subsequently, the admission is coded to an exact DRG among the DRGs associated with this base DRG, based exclusively on the presence or absence of complicating/comorbid conditions (CCs) and major CCs (MCCs). Each base DRG has one to three associated DRGs (also called *severity subclasses*), which differ only in the presence of CCs and MCCs. CCs and MCCs all indicate the presence of secondary conditions.

Importantly, the lists of CCs and MCCs are the same across base DRGs and are always based on diagnoses and never on procedures, even if the DRG is surgical. However, there is variation across base DRGs in the severity subclasses. Specifically, there are four types of

[4] Starting in October, 2015, both diagnoses and procedures are identified with ICD-10 codes.

base DRGs. The first type of base DRG type has three severity subclasses: without CCs, with CCs, and with MCCs; the second type has two severity subclasses: without CC/MCCs and with either CCs or MCCs; the third type also has two severity subclasses but separates admissions with MCCs from all others; and the fourth type has a single severity subclass. There is also variation across base DRGs in the additional weights (and hence payments) across severity subclasses.

A few exceptions to our above description are worth noting. First, for a few base DRGs, other factors such as the in-hospital death of the patient may factor into the determination of the severity subclass. Second, also for a few base DRGs, a procedure may be a substitute for a CC or MCC. For instance, for major head and neck procedures, the presence of a major device such as a cochlear implant is equivalent to a CC/MCC. Third, we have only described the hospital component of payments; physicians are reimbursed separately, generally on a fee-for-service basis. Fourth, a few base DRGs exclude certain CCs/MCCs in their determination of the severity subclass. This circumstance arises when the diagnosis from the CC/MCC list effectively constitutes the primary diagnosis. Finally, there are a number of hospitals that receive payments in other forms, such as rural Critical Access Hospitals (CAHs), hospitals involved in the Medicare Shared Savings Program, and hospitals involved in bundled payment pilot programs.

As an example of the role of CCs and MCCs, consider patient A admitted for poorly controlled diabetes with underlying cardiac disease, and patient B admitted for coronary bypass surgery. If either patient suffers from acute myocardial ischemia (poor blood flow to heart muscle with no permanent heart damage) without an acute myocardial infarction (permanent damage to heart muscle), then the hospital can claim a CC. If either patient suffers an acute myocardial infarction, then the hospital can claim an MCC. For coronary bypass surgery, the DRG weights are (approximately) 6.45 and 4.92, for w/ MCC and w/o MCC respectively, while for diabetes, they are 1.09, 0.8, and 0.67 for w/ MCC, w/CC and w/o CC/MCC respectively.[5] Thus, the presence of acute myocardial ischemia does not add to the reimbursement for patient A but it does for patient B.

[5]These weights are for FY2008.

Figure 1 in the Appendix lists the principal CCs and MCCs. The CCs and MCCs are organized by organ system and/or by general physiologic functions. An example of a dysfunction of an organ system is heart failure, which, as noted in Figure 1, is part of the cardiovascular system. An example of a physiologic MCC is diabetic ketoacidosis, which refers to poorly controlled diabetes resulting in acidic blood with ketones. Either one was evaluated as making hospital treatment more complex. Importantly, the CCs/MCCs are all secondary diagnoses, not procedures.

The system described above, with up to three severity subclasses, was implemented by CMS starting in Q4:2007, and is known as Medicare Severity DRGs (MS-DRGs). CMS started planning for the reform according to the recommendations made by the Medicare Payment Advisory Commission (MedPAC) in its "Report to the Congress, Physician-Owned Specialty Hospitals" in March 2005 and announced the final rule in August, 2007. CMS implemented this 2007 reform in order to better align payments with the resources used by a hospital. A realignment was deemed necessary because many conditions that previously needed costly and lengthy hospitalizations could now be managed in an outpatient setting using drug or other therapies. The reform also added MCCs, to address the fact that tertiary care hospitals were not being compensated adequately for treating very ill patients. Prior to the reform, base DRGs had a maximum of two DRGS, w/ CCs and w/o CCs. Overall, the reform replaced the 538 pre-reform DRGs with 745 MS-DRGs.

As an example of the impact of the reform, consider again heart failure. Prior to the reform, both chronic and acute systolic and diastolic heart failure were considered CCs. Following the reform, chronic systolic and diastolic heart failure were included in the CC list while acute systolic and diastolic heart failure were considered MCCs. Following the reform, an acute manifestation of a chronic disease or a new acute disease most often became necessary to justify a CC or MCC DRG, although heart failure is an exception to this, where chronic heart failure was sufficient for a CC due to the complexity of treating patients with chronic heart failure (72 Federal Register 47153, Office of the Federal Register and National Archives and Records Service, 2007). Overall, the intent of the 2007 reform was to lower the fraction of admissions that would qualify for a CC or MCC code. Using the universe of 2006 patients, 77.66% of admissions had at least one CC present under the pre-reform criteria, while only 40.34% had a CC or MCC under the post-reform criteria.[6]

Two final points regarding the 2007 reform are worth noting. First, the reform changed the relative weights for top codes. This is useful because we can use the change in DRG weights to identify changes in incentives to upcode. E.g., hospitals should have a greater incentive to upcode following the reform for base DRGs with a greater increase in the relative weight. Second, the new DRGs were phased in over a three year period, starting in October, 2007. This implies that the new weights were not fully active until October, 2009, which also creates variation in incentives over time.

2.2 Medical and Surgical Admissions

By the 2000s, by far the greatest number of admissions with medical DRGs were urgent. Very frequently, a medical admission results from an acute exacerbation of a chronic disease, such as cancer, stroke, heart disease, lung disease, or diabetes. Elective and semi-elective medical admissions are less common, as diseases are increasingly managed in the outpatient setting. In contrast, admissions for surgical DRGs can be urgent, semi-elective, or elective. An example of an urgent surgical admission is for trauma; an example of a semi-elective admission is cancer surgery; and an example of an elective admission is a hip replacement.

There are well-understand differences in culture between "medical" physicians and surgeons (King et al., 1975). Admission to medical services is typically associated with a substantial attention to documenting the reason for admission, i.e. the primary diagnosis. In some cases, the primary diagnosis may be unclear, given uncertainty from the history, physical examination, and test results. In this case, the admitting note will include a list of potential primary diagnoses, also termed the differential diagnosis. During the course of the admission, as additional information is accumulated, the primary diagnosis will usually become clear. Patient progress notes, which are updated throughout the admission, list the various underlying and complicating conditions that will impact the care of the patient,

[6]See 72 Federal Register 47153, 47154, Office of the Federal Register and National Archives and Records Service (2007).

including pharmaceutical therapy and other non-surgical management. Documentation of these complications and comorbid conditions is considered of high if not equal importance to the primary diagnosis, given their impact on patient disposition. For medical admissions, more so than for surgical admissions, decisions regarding patient care and management are made on a continuum, evolving during different points in the hospital stay, and are heavily influenced by the comorbid conditions of the patient.

Table 1: Most common base DRGs

	Medical			Surgical		
Rank	Title	Weight	Percent	Title	Weight	Percent
1	Rehabilitation	1.2388	6.05%	Major joint replacement or reattachment of lower extremity	3.3282	3.36%
2	Heart failure and shock	1.4609	4.36%	Percutaneous cardiovascular procedure w/ drug-eluting stent	3.0955	1.19%
3	Simple pneumonia and pleurisy	1.4378	3.64%	Hip and femur procedures except major joint	2.8752	0.97%
4	Chronic obstructive pulmonary disease	1.2076	3.43%	Major small and large bowel procedures	5.1396	0.94%
5	Septicemia or severe sepsis w/ mechanical ventilation 96+ hours	5.8007	3.26%	Other vascular procedures	2.9443	0.84%
6	Psychoses	0.8899	2.73%	Permanent cardiac pacemaker implant	3.5878	0.68%
7	Esophagitis, gastroenteritis and misc digest disorders	1.0958	2.54%	Laparoscopic cholecystectomy w/o common duct exploration	2.405	0.54%
8	Kidney and urinary tract infections	1.2122	2.50%	Spinal fusion except cervical	6.1506	0.50%
9	Cardiac arrhythmia and conduction disorders	1.2188	2.36%	Back and neck procedure except spinal fusion	1.7718	0.44%
10	Renal failure	1.6422	2.05%	Major cardiovascular procedures	5.0355	0.44%

Admission to surgical services is based on the need for, or the recovery from, a surgical procedure. Substantial and appropriate attention is placed on accurate and thorough documentation of the surgical procedure. Less attention is paid to documenting underlying complications or comorbid conditions, particularly in those situations where the surgical procedure provides a definitive solution to the primary surgical indication. One reflection of this mindset is the saying “a chance to cut is a chance to cure.” While overly dismissive of the appropriate pre-operative and postoperative care needed for optimal outcomes, it nonetheless is reflective of the surgical mindset. One approach is to provide training for residents in training on documentation and coding. Results of such studies, most commonly conducted for residents on surgical services, are mixed.[7] Some demonstrate studies show improvements in documentation and coding accuracy following the intervention, and some show no effect.

Table 1 provides the ten most common medical and surgical base DRGs in 2010, along with the highest weight for that base DRG. With the exception of rehabilitation, the most common medical DRGs represent acute medical problems that require urgent admission, such as heart failure, pneumonia, and septicemia (bloodstream infection). Because of the acute nature, often with concurrent underlying disease, management requires attention to the full range of functional abnormalities. Most commonly, surgical DRGs represent elective or semi-elective procedures, such as hip replacements, cardiac pacemaker implants, and spinal fusions. The admissions are very targeted, and organized around the procedure, with the expectation of rapid recovery. Less attention is generally needed or paid to the other functional disabilities or abnormalities.

2.3 EMRs and Billing

The presence of EMRs has significantly affected hospital billing practices. We first discuss billing for hospitals in the absence of EMRs and then discus how EMRs have changed billing practices.

In the absence of EMRs, for inpatient admissions, coding is derived directly from the medical chart. The bulk of a medical chart is typically patient progress notes, which are made on a daily basis. The medical chart starts with the admission note, which describes the status of the patient upon admission and lists diagnoses. On a periodic basis, the chart lists the patient's course, test results, changes in medication, and other relevant information. Coding mostly uses the part of the medical chart that is called the "discharge summary." The discharge summary is usually dictated by the attending physician of record or by a resident

[7] See Marco and Buchman (2003); Tinsley (2004); As-Sanie et al. (2005); Novitsky et al. (2005); Fakhry et al. (2007).

who was involved in the care of the patient after discharge. The discharge summary lists the primary and secondary diagnoses, summarizes the status of the patent on admission, the hospital course and the disposition, including medications and plans for follow-up care.

Figure 2 in the Appendix provides an example of a blank discharge summary. The discharge summary is a brief synopsis of the hospital admission. It includes the identifying information for the patient and the physician of record, and may list other physicians involved in the patients care. The diagnoses are listed, starting with the primary diagnoses, followed by secondary diagnoses. The history, physical examination, and pertinent laboratory data on admission are summarized briefly, followed by a description of the hospital course. Medications on discharge as well as instructions to the patient, including follow-up appointments, are listed. The discharge summary provides information to providers seeing the patient in outpatient follow-up as well as for any subsequent hospital admissions.

For surgical admissions, in addition to the discharge summary, an operative note is prepared, documenting in detail the procedure(s) that were performed. The operative note provides significant detail on the procedure performed. Figure 3 in the Appendix provides an example of an operative note. While a discharge summary is also prepared for a surgical admission, the focus, particularly for elective or semi-elective procedures, is mostly on the operative note. The operative note lists precise details of the surgery performed.

In the absence of EMRs, discharge summaries and operative notes list most of the information in words and not in codes. Physicians preparing these documents are generally only familiar with a subset of the ICD-9 codes that they encounter. Hospital coding staff then access these documents and select and/or verify the appropriate ICD-9 codes. Even in the absence of EMRs, since roughly the 1990s, the coders then feed in the codes and information to grouper software, which outputs the appropriate DRG for billing purposes. In general, hospital coding staff will not communicate with physicians except for clarification requests.

Without EMRs, the knowledge of secondary diagnoses is highly variable, particularly for patients with extensive medical histories. A necessary condition for documentation is knowledge and hence the knowledge of secondary diagnoses is also highly variable. Sometimes, the admitting physician can learn about comorbidities from previous medical encounters, but this information is not always available. Consultations from specialty services, often related to comorbidities, are included in the body of the medical chart, but may or may not be entered into the main running list of diagnoses. In other words, the attending physician or resident preparing the progress notes on the medical chart must refer back to previous notes to ensure that diagnoses are carried longitudinally through the record so that they end up in the discharge summary. Progress notes for medical services are typically much more detailed than progress notes for surgical services. The most comprehensive progress notes will address, on a daily basis, the status of each of the diagnoses listed in the admission note by name. Less comprehensive notes will summarize progress on the the most active subset of the admitting diagnoses, The least comprehensive notes will provide only cursory information on the status of the primary diagnosis.

We now explain the role of EMRs. According to the Healthcare Information and Management Systems Society (HIMSS), a solid EMR foundation should include the following key components: Clinical Data Repository (CDR), Clinical Decision Support Capabilities (CDS), and Computerized Physician/Provider Order Entry (CPOE). CDR is a centralized database that collects, stores, accesses, and reports health information, including demographics, lab results, radiology images, admissions, transfers, and diagnoses. Its goal is to provide a full picture of the care that is received by a patient. CDS assists clinicians in decision-making tasks, namely determining the diagnosis or setting treatment plans. It combines computable biomedical knowledge and individual data to recommend specific interventions and assessments, and provide other forms of guidance to clinicians. CPOE is a more advanced type of electronic prescribing. It is generally connected with some type of CDS to offer more sophisticated drug safety features such as checking for drug allergies or drug/drug interactions. Both CDS and CPOE require physician involvement to provide real-time support on a range of diagnosis- and treatment-related information.

The CDR component of EMR systems records the hospital course, providing templates to aid the physician in documentation. With EMRs, preparation of the admission note is aided by pre-population of fields with information on the patient's primary and secondary diagnoses from previous inpatient or outpatient encounters. These diagnoses can be readily selected for inclusion. The availability of separate pull-down menus by disease category, with associated ICD-9 codes, prompts the physician to select the most appropriate diagnoses, with the proper lexicon for ultimate billing purposes. The EMR can be used to "clone" information, including diagnoses and patient status, from one note to another for a given patient, so that the physician does not need to reenter the information. Even though EMRs facilitate population with existing diagnoses, they do not automatically enter new diagnoses: new diagnoses must be directly entered by the medical professional, again with the assistance of the pull-down menus. Additionally, preparation of the discharge summary is facilitated by the "master list" of primary and secondary diagnoses. Finally, as in the case without EMRs, a coding staff must transform the (now-electronic) medical chart into a DRG.

We now examine how coding differs in the presence of EMRs. With EMRs, the medical chart still exists. However, the EMR specifically records diagnoses in particular fields on the chart. At the time of admission, assuming the patient being admitted has previously been seen in the system, a list of pre-existing diagnoses populates a window in the EMR. The admitting physician, or resident entering information on their behalf, can choose any or all of those diagnoses, along with any new diagnoses prompting the admission. The latter are chosen from a pop-up list organized by organ system or functional abnormality, which appears after text is entered by the physician. In some cases, the pop-up list will contain the precisely correct diagnosis, reflecting one of many ICD-9 or ICD-10 codes. Because of the precise lexicon reflected in these codes, the appropriate choice may not appear in the pop-up window, and different text terms must be chosen, to generate a new pop-up window. Depending upon the circumstances, the physician entering the information may simply choose not to pursue this path.

3 Data

The data are constructed by pooling information from various sources. Our primary dataset is the Medicare Provider Analysis and Review (MedPAR) File. For our purposes, this dataset contains information on all inpatient hospital stays for Medicare beneficiaries. Each observation in these data represents one patient stay and contains information on the hospital, the beneficiary's home zip code, age, gender, date of services, reimbursement amount, dates of admission and discharge, Diagnostic Related Group (DRG), and principal and secondary diagnosis and procedure codes. Our main dependent variable is the percent of patients with documented CCs or MCCs within a particular base DRG, hospital, and year. We focus on the years 2006, and 2008-10, omitting 2007 since the reform occurred in Q4:2007.

Table 2: Summary statistics at patient level

Variable	2006	2008	2009	2010
	Overall Medicare patients			
Number of discharges	15,935,018	17,237,514	17,387,460	17,793,107
Mean age	74.1	74.1	73.9	73.8
Case mix index (mean DRG weight)	1.34	1.41	1.46	1.46
	Patients in base DRGs with 2 DRGs pre-reform and 2 DRGs post-reform (w/o CC/MCC and w/ CC/MCC)			
Number of discharges	232,515	229,735	228,582	218,037
% top-code patients	49	33.3	34.1	34.4
	Patients in base DRGs with 2 DRGs pre-reform and 2 DRGs post-reform (w/o MCC and w/ MCC)			
Number of discharges	995,660	984,533	981,206	982,775
% top-code patients	61.2	21.7	24	24.4
	Patients in base DRGs with 2 DRGs pre-reform and 3 DRGs post-reform			
Number of discharges	2,039,958	2,220,273	2,271,718	2,312,746
% top-code patients	80.4	29.6	31.6	31.3
% middle-code patients	-	38.1	37.8	38.9
	Patients in base DRGs with 2 DRGs pre-reform and 2 or 3 DRGs post-reform			
Number of discharges	3,268,133	3,434,541	3,481,506	3,513,558
% top-code patients	72.2	27.6	29.7	29.6
	Patients in base DRGs with 1 DRG pre-reform and post-reform			
Number of discharges	1,066,684	1,221,839	1,196,443	1,207,051
% patients with secondary diagnoses coded as MCCs	62.6	19.4	17.6	24.6

Table 2 provides summary statistics on our patient sample. The first panel in Table 2 there were more than 15 million Medicare discharges in each of the four years in our data. The mean age of a Medicare patient discharged from a hospital was about 74 years during our sample and the mean DRG weight was rising over time, from 1.34 in 2006 to 1.46 in 2010. The second through the last panel presents the number of discharges and percentage in different severity subclasses according to the type of base DRGs. For instance, the second panel displays the statistics for the sample of patients admitted to the base DRGs always with two subclasses and particularly divided as without CC/MCCs and with either CCs or MCC after the reform. For this group, the number of discharges was about 233,000 in 2006 and 218,000 in 2010. The percent top codes decreased from 49% in 2006 to 34.4% in 2010. Such a reduction in the percent top codes occurred in all the other subsamples, in large part due to the different and more stringent set of diagnoses that generate top-codes.

From the universe of Medicare discharges, our main sample keeps base DRGs for which there was an exact match before and after the reform and for which there were at least two severity subclasses prior to and after the reform. Our main sample does not use base DRGs with one severity subclass prior to or after the reform because one cannot identify the reform effect separately from the hospital/base DRG fixed effect for these base DRGs. Among the DRGs we consider, the number of discharges ranges from 1,288 to 356,642 in each base DRG. For our main sample, the percent of top code patients declined from 72.2% in 2006 to 27.6% in 2008, following the reform.

We also use data that maps diagnosis codes into CCs and MCCs. These data are derived from the CC and MCC list from CMS.[8] We use these data to identify patients with CCs and MCCs for base DRGs which do not record these severity subclasses. These data allow us to understand whether patients are coded with different levels of CCs and MCCs following EMR adoption in the absence of any financial incentives to do so.

We also construct other dependent variables to test for alternative explanations, such as the distance from each patient to the hospital at which she received treatment, length of stay, case-mix index (mean DRG weight at a hospital), and mean numbers of diagnoses and procedures.

We obtain technology adoption data from the Healthcare Information and Management

[8] The codes are provided at `https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Acute-Inpatient-Files-for-Download-Items/CMS1247844.html` We thank Adam Sacarny from providing us with these data.

Systems Society (HIMSS) Analytics Database, which is the most comprehensive national source of hospital IT adoption data. We use the Medicare provider number to connect to the claims data. The database covers the demographic and automation information of the majority of U.S. hospitals, and includes purchasing plan details for over 90 software applications and technologies. It is the most complete, detailed and longest running survey recording the choice and evolution of a hospital's IT capacities.

Table 3: Summary statistics on EMR adoption rates

Variable	Obs	Mean
% hospitals with EMR, 2006	4,518	46.4
% hospitals with EMR, 2008	4,488	68.2
% hospitals with EMR, 2009	4,509	84.2
% hospitals with EMR, 2010	4,511	87.3

There is no consensus on how to define adoption of EMRs for a hospital. Jha et al. (2009) used a very comprehensive definition. From a list of 32 potential functionalities of an inpatient electronic health record, they asked an expert panel to define the functionalities that constitute a basic and comprehensive electronic system respectively. Miller and Tucker (2009) measured EMR adoption by whether a hospital is installing or has installed the enterprise EMR system. In our paper, a hospital is defined to have adopted EMRs if either CPOE or CDS is live and operational within the organization. Both of these key components require greater level of physician training and involvement. Since we pay special attention to how Health IT alters physicians' behavior in response to the payment reform, the adoption status of these components are most relevant to identify the effect. Table 3 reports the adoption rate over the sample periods. Only 46.4% of hospitals had adopted EMRs in 2006, a figure that had increased to 87.3% by the end of our sample. The significant expansion of EMRs mainly arose from the strong push from the federal government, through the HITECH Act of 2009, which was part of the American Reinvestment and Recovery Act (ARRA), also known as the stimulus bill.

We complement the claims and HIT data with the American Hospital Association (AHA) Annual Survey, using the Medicare provider number and geographic information to perform

Table 4: Summary statistics on hospital characteristics by EMR use

	Hospital characteristics among EMR adopters, 2006 or earlier	Hospital characteristics among EMR adopters, 2007-10	Hospital characteristics among EMR non-adopters, through 2010
Bed size	226	139	63.5
Total outpatient visits	182,292	107,363	37,838
Total admissions	10,454	5,969	1,919
FTE physicians and dentists	25.8	13.0	3.76
Total number of births	1,171	683	175
% teaching hospital	11	3.5	0.53
% Medicare discharge	46.0	50.1	54.6
% Medicaid discharge	18.3	16.5	14.1
% for-profit	17.4	15.1	23.0
% not-for-profit	66.8	59.3	35.4
% public hospitals	15.8	25.6	41.6
Number of hospitals	1,810	2,068	563

Note: For each set of hospitals, table reports the mean value of statistic over years in our data.

the linkage. About 4,500 hospitals can be matched between the three datasets, covering more than 70% of the U.S. hospitals. The AHA data includes a rich set of hospital-specific features such as number of beds, system affiliation, profit status, etc. Table 4 provides summary statistics for the main hospital characteristics according to EMR adoption status of hospitals. Hospitals that adopted EMRs in 2006 or earlier are on average larger and more likely to be teaching and not-for-profit hospitals. For instance, the bed size of early adopters is 62% larger than that of hospitals adopting EMRs between 2007 and 2010, and more than twice of that of hospitals adopting EMRs later than 2010. The numbers of outpatient visits and inpatient admissions are more than four times of those of hospitals without adoption through 2010. The fact that early EMR adopters have very different observables from later EMR adopters suggests that separating the treatment effects of EMR by early and later adopters may be helpful.

Finally, we use information on DRGs, including the type and weights, from the Centers for Medicare and Medicaid Services (CMS). The third row in Table 2 reports the overall Case mix index, calculated by summing the DRG weights of all Medicare discharge divided by the total number of discharges. It reflects the relative cost or resources to treat a mix of patients. It is relatively stable over the sample period. Table 5 shows the mean DRG weights and

Table 5: Summary statistics on the payment reform

Variable	Obs	Mean	Std. Dev.
DRG weight, 2006	559	1.47	1.86
DRG weight, 2008	743	1.99	1.93
DRG weight, 2009	743	2.02	2
DRG weight, 2010	744	2.02	2.01
Mean spread, 2 to 2, 2006	29	0.519	0.516
Mean spread, 2 to 2, 2008	29	0.545	0.496
Mean spread, 2 to 2, 2009	29	0.872	0.761
Mean spread, 2 to 2, 2010	29	0.886	0.787
Mean spread, 2 to 3, 2006	59	0.886	0.489
Mean spread, 2 to 3, 2008	59	1.13	0.595
Mean spread, 2 to 3, 2009	59	1.76	0.871
Mean spread, 2 to 3, 2010	59	1.78	0.873

Note: Spread measures the difference between the weight in the top and bottom codes.

spread for the base DRGs considered in this paper. "Spread" is defined to be the difference between the weight in the top and bottom codes. The overall DRG weights increased by 35% after the reform and stayed relatively stable since then. The mean spread for DRGs with two severity subclasses before and after the reform went up by 60% in 2009, while the spread for DRGs transitioning from 2 to 3 severity subclasses increased significantly in both 2008 and 2009. These changes are useful in creating variation to detect the impact of financial incentives on hospitals' coding behavior.

4 Analytic Framework

4.1 Model

Our model focuses primarily on the decision of a hospital regarding the coding of a given patient stay. We also consider the hospital's decision regarding procedures to perform on a patient and indirectly, the decision of the patient or her physician on which hospital to choose. For any patient stay, there are eight potential hospital environments, each combination of (1) medical or surgical admission; (2) EMR or no EMR; and (3) pre- or post-2007 reform. We now describe the potential impacts of each of the above three factors. We focus primarily on the impact of these factors on coding within a base DRG. Our principal outcome variable is the percent of patients within a base DRG that are coded with the highest severity subclass, which we call the *top code*.

Consider first whether the patient is admitted for a medical or surgical DRG. If the patient is admitted for a surgical DRG, the physician who will create the discharge summary is a surgeon. The surgeon's principal role is to perform surgery and ensure appropriate pre- and post-operative care. The surgeon is relatively likely to focus on the details of the procedure performed and may miss particular comoborbidities that could lead to a higher code. If the patient is admitted for a medical DRG, the physician who will create the discharge summary is a "medical" physician, likely an internal medicine specialist or hospitalist. The medical physician's principal role is to make a series of smaller decisions to aid the patient recover from her illness. The medical physician is likely to document patient comoborbidities in detail as this will help with these decisions.

Both surgeons and medical physicians may have financial incentives to state comorbidities that are not present, since this would increase hospital bills, which hospitals could potentially pass on to their employed or contracted physicians, through explicit or implicit arrangements. Hospital coding staff may have similar incentives. These individuals may also have incentives to *not* state comorbidities that are not present, since, if identified as part of an audit, they and the hospitals may face high criminal and civil penalties from bill inflation. Conditional on a given set of incentives, we would expect that medical physicians will record more secondary diagnoses than surgeons, since this recoding is more integral to their processes of care. If hospitals are upcoding, we would expect that they would be more likely to do so for diseases where the incremental reimbursements from upcoding are higher.

We now turn to the role of EMRs. For both surgeons and medical physicians, the physician records patient information on a medical chart. Without EMRs, physicians will enter information directly into the patient chart. This information is used by coders to verify that sufficient documentation is provided to justify billing for a particular primary or secondary diagnosis, as reflected in the discharge summary. There is a significant possibility that diagnoses will be recorded in part of the chart but not described in the discharge summary or not described in a precise way. EMRs force "medical" physicians to enter diagnoses in precise ways. Thus, EMRs will help in transforming a potentially inaccurate written comorbidity into an accurate one. For instance, a physician with an EMR system would be forced to enter the diagnosis with a series of pull-down menus, rather than writing words on paper that may not correspond exactly to particular codes and that may not be translated accurately. Thus, EMRs will help with accurate coding, but will only do so to the extent that the physician is recording and documenting the evidence for the comoborbidities that lead to higher severity subclasses. Since medical physicians are more likely to code comorbidities completely than surgeons, this suggests that EMRs will increase top codes for medical DRGs relatively more than for surgical DRGs by increasing the relative accuracy of coding for medical DRGs.

EMRs may also potentially facilitate upcoding by making it easier for physicians to report diagnoses for which there is no justification provided. For instance, EMRs allow physicians to clone diagnoses across records. They also allow physicians to code a diagnosis by clicking on a button, rather than writing down the patient's exact symptoms. Physicians or coding staff may perceive a lower cost of inflating diagnoses when clicking on a button than when writing down inaccurate words. Importantly, the upcoding caused by EMRs should be based on financial incentives rather than being biased towards either medical or surgical DRGs.

EMRs may also have at least two other impacts: they may lead to different procedures being performed and/or may change the selection of patients. For instance, the Clinical Decision Support capabilities may lead hospitals to perform procedures that are useful but which they otherwise would not have thought of performing, or conversely, to not perform procedures that would are of little use. Patients with severe illnesses may also be more likely to seek care at a hospital with EMRs, perceiving that the quality of care will be higher due to the ability to more accurately record and interpret diagnoses and suggest "best practice" treatments. Note also that hospitals which seek to upgrade their quality in other ways may simultaneously invest in EMRs, thus implying that one cannot determine the treatment effects of EMRs on patient selection from a simple fixed effects regression.

Finally, we consider the impact of the 2007 payment reform. The reform made it harder to obtain top codes, by lowering the number of top codes, tightening the criterion for top codes, and splitting MCCs from CCs, implying the need to code more precisely. Overall, the payment reform should lower the percent of top codes for both medical and surgical DRGs. If EMRs help with accurate coding then, for medical DRGs, the payment reform should have a smaller negative effect for hospitals with EMRs than for hospitals without EMRs. Alternately put, the interaction of EMRs and the payment reform on the percent of top codes should be positive. If EMRs disproportionately help with accurate coding for medical DRGs then, for surgical DRGs, the interaction term should be much smaller in magnitude.

If EMRs facilitate hospital upcoding, then we should see EMR hospitals shift their coding practices in response to the payment reform in ways that relate to their incentives, relative to non-EMR hospitals. Specifically, we should observe that EMR hospitals top codes increase the most where the weight difference increased the most. For base DRGs where CCs and MCCs are in the same severity subclass, we should see no movement towards top coding. We should not expect to see any systematic differences between medical and surgical DRGs if upcoding is the main explanation for the changes.

4.2 Testable Hypotheses

The model described above leads to several testable hypotheses. We now enumerate these hypotheses.

1. If EMRs lead to more accurate coding, then for medical DRGs, we would expect to see a post-reform increase in top codes for EMR hospitals, relative to non-EMR hospitals. For surgical DRGs, if this interaction effect is positive, we would expect it to be smaller than for medical DRGs.

2. If EMRs lead to upcoding, then we would expect to see a relative increase in post-reform top codes for EMR hospitals for base DRGs where the spread between the bottom and top codes increases the most post-reform.

3. If EMRs lead to upcoding and not accurate coding, then we would expect to see no

increase in top codes where there is no incentive to top code. Specifically, we should see no increase in diagnoses that qualify for MCCs for base DRGs where CCs and MCCs are lumped together or for base DRGs where w/o CCs/MCCs, CCs and MCCs are all lumped together.

4. If EMRs are correlated with different procedures being performed or differential patient selection, we would expect to see hospitals change their numbers of procedures or their patient lengths-of-stay upon EMR adoption.

5. If EMRs are correlated with differential patient selection, we would expect to see different base DRGs upon EMR adoption. For instance, if EMR adoption is correlated with having more severely ill patients, we would expect to see base DRGs with higher weights, upon EMR adoption.

One important point regarding the above list of hypotheses is that we have not directly considered the impact of EMR adoption by a hospital on its coding practices. Rather, we are examining the interaction of EMR adoption and the 2007 payment reform. There are two reasons for this. First, if we considered EMR adoption itself, then differential patient selection would yield similar implications to upcoding or more accurate coding. In contrast, the payment reform occurred to all hospitals and hence, we can avoid this source of endogeneity. Second, EMR adoption mostly occurred in the immediate post-reform period. Hence, to achieve identifying variation, we have to control for the effects of the reform.

4.3 Estimation and Identification

Our regression specifications for Hypothesis 1 considers the percent of patients within a base DRG coded to the top severity subclass of a base DRG. Our estimation approach is built on the following base specification:

$$Y_{jgt} = \beta_1 EMR_{jt} \times Post_t + \beta_2 EarlyEMR_{jt} \times Post_t + \beta_3 X_{jt} + FE_t + FE_{jg} + \varepsilon_{jgt}$$

where Y_{jgt} denotes the percent of patients coded to the top severity subclass of base DRG g in hospital j in year t; $Post_t$ is an indicator, equal to 1 when t is after the 2007 reform; EMR_{jt} is an indicator for whether hospital j had adopted EMR at period t; $EarlyEMR_{jt}$ is an indicator for whether hospital j had adopted EMR at or before 2006; X_{jt} includes hospital characteristics, specifically bed size, total outpatient visits, total admissions, total number of births, the number of full-time physicians and dentists, percentage Medicare, percentage Medicaid, profit status, and a teaching hospital indicator; FE denotes fixed effects at different levels; and ε_{jgt} represents the error term.

We allow the effect of the reform to vary for early and later EMR adopters. Early adopters, which installed the technology at least two years prior to the reform, may have accumulated a greater knowledge base of the technology and behave differently in response to the reform than new users in terms of their top-coding behavior. Also, early EMR adopters are systematically different from later adopters in observable characteristics (as shown in Table 4), and hence they may also have patients with different underlying comorbidities, which would provide a different reason for a difference in the treatment effects.

The main variables of interest are $EMR_{jt} \times Post_t$ and $EarlyEMR_{jt} \times Post_t$. β_1 and β_2 measure the marginal effects of using EMRs on coding behavior following the 2007 reform, with β_2 particularly capturing the effect for early adopters. For instance, $\beta_2 > 0$ would imply that hospitals which installed EMR earlier than 2007 experienced a greater increase in top codes following the reform. The magnitude measures the percentage change in fraction that is associated with adoption.

We also include both hospital/base DRG fixed effects and year fixed effects, in order to control for time-invariant unobservable heterogeneity in these dimensions. Specifically, the inclusion of hospital/base DRG fixed effects allows for the possibility that hospitals have different case-mix indices and also that hospital case-mix indices vary across base DRGs. For instance, we allow for the possibility that a hospitals treats a relatively high fraction of bypass surgery patients with CCs or MCCs but a relatively low fraction of mouth procedure patients with CCs or MCCs. Our inclusion of year fixed effects allows for different baseline effects of the reform across year. This is important to capture because weights changed in the reform across years.

Given the inclusion of both these fixed effects, our identification is purely within a base DRG: we will identify positive effects on $EMR_{jt} \times Post_t$ if the fraction of top codes at individual hospitals within base DRGs rises post-reform. In some specifications, we interact EMR_{jt} with each post-reform year, which allows us to separate the effect of the reform by year.

Our sample for Hypothesis 1 is all base DRGs with two severity subclasses before the reform and two or three severity subclasses after the reform. The reason that we exclude base DRGs with only one severity subclass before or after the reform is that we cannot really identify the within-base-DRG change in top-coding that occurred with the reform.

Note also that our specification here does not directly include terms for the base effects of EMR adoption or the reform. This is because these effects are subsumed by the other fixed effects in the model. The reform effect is subsumed by the year dummies. The EMR adoption effect is also subsumed by the other fixed effects, because we only have one year of data pre-reform. Specifically, a potential indicator variable EMR_{jt} is exactly equal to the sum of the hospital/base DRG fixed effects for all hospitals which are early adopters, plus $EarlyEMR_{jt} \times Post_t$ minus $EMR_{jt} \times Post_t$.

Finally, note that we cluster the standard errors at both the hospital and base DRG levels. This allows for dependence in the residuals for different base DRGs across the same hospital and for different hospitals across the same base DRG.

Our regression specification for Hypothesis 2 employs the same dependent variable as does Hypothesis 1. However, here, we also include a variable called $Spread_{jgt}$ and interactions of $Spread_{jgt}$ with EMR_{jt} and $EarlyEMR_{jt}$. $Spread_{jgt}$ measures the difference between the DRG weight for the highest and lowest severity subclass within the base DRG. Because we employ hospital/base DRG fixed effects, the coefficient on $Spread_{jgt}$ will identify how the change in spread affects top-coding.

Our regression specification for Hypothesis 3 employs a different dependent variable to Hypothesis 1 and uses different samples. Specifically, for Hypothesis 1 (and Hypothesis 2), the dependent variable is calculated as the percent of admissions within the top severity subclasses, by hospital and base DRG. There, the dependent variable is constructed directly from the severity subclass for each patient, which is a function of the DRG. For Hypothesis 3, we are checking whether hospitals code CCs and MCCs differently even when there is no separate DRG for this. In other words, we focus on base DRGs for which CCs and MCCs are lumped together, and ones where CCs, MCCs and w/o CC/MCCs are all lumped together. Thus, our sample here includes base DRGs with 2 DRGs pre-reform and 2 DRGs post-reform where CCs and MCCs are lumped together, and base DRGs with 1 DRG pre- and post-reform. Note also that we need to code the CCs and MCCs ourselves. We do this based on the secondary diagnoses.

Our regression specifications for Hypothesis 4 examine whether hospitals perform more procedures or select different patients following EMR implementation. The unit of observation is the same as for the previous hypotheses. The specification is very similar except that, instead of percent top code, we use the average length of stay and number of procedures performed within the hospital/base DRG as the dependent variables. Note that here, we are interested in the base coefficient on EMR. Since we have only one year pre-reform, we can only identify this for the non-early adopters, and for these hospitals, the $EMR_{jt} \times Post_t$ coefficient will pick up the base coefficient, although the effect will also pick up any effect of the reform on procedures performed or selection of patients.

Finally, our regression specifications for Hypothesis 5 examine whether there is a change in the composition of base DRGs following EMR adoption. Specifically, we use the average patient-to-hospital distance and the number of diagnoses as the outcome measures within a base DRG. We use the mean DRG weight of the lowest severity subclass within a base DRG as a measure of the patient case mix in a hospital. Here, the unit of observation is the hospital/year, since we are looking at substitution across base DRGs. We do not use the actual reported DRG weight because we would like this effect to be robust to misreporting of severity subclasses, which form our main hypotheses, Hypotheses 1-3. The main regressors are the same as those in the previous specifications except that we only include hospital and year fixed effects for the last outcome measure, given the unit of observation.

5 Results

We now test the above hypotheses using our sample of Medicare claims data. In this section, we discuss the results and implications for different hypotheses. We also provide an estimate of the potential cost to the government, associated with the adoption of EMRs.

5.1 Hypotheses 1–3: Strategic Behavior or More Accurate Coding

We start by considering Hypothesis 1. Our base specification here examines the impact of EMR adoption status, the payment reform, and the type of base DRG, medical or surgical, on the percent top codes. The estimation is performed on base DRGs with different number of subclasses, separated by medical and surgical base DRGs. Each observation is a combination of a base DRG, hospital and year. The key variables of interest are $EMR \times Post$, the interaction of post-reform dummy and EMR adoption, as well as $EarlyEMR \times Post$, the interaction of post-reform dummy and EMR adoption in 2006 or earlier. Both variables measure the impacts of EMRs on coding practices according to adoption status following the reform. We also control for hospital/base DRG and year fixed effects and a rich set of hospital characteristics. Standard errors are clustered at both hospital and base DRG levels, with two-way clustering. Each regression is weighted by the total number of visits per hospital/base DRG.

Table 6 shows the regression coefficients for the key variables of interest and year fixed effects. Each column of numbers reports the results from one regression, with the samples varying across regressions. Considering the columns that pertain to medical DRGs, there is a significant and positive effect of hospitals adopting EMRs. For instance, for the base DRGs with 2 DRGs pre- and post-reform, there is an 0.6% increase in patients in medical DRGs classified into top codes following the reform for late adopters. The number increases by 2.3 percentage points for hospitals adopting EMRs in 2006 or earlier. These results are robust across the sample of base DRGs with 2 DRGs pre-reform and 3 DRGs post-reform, and the combined sample.

In contrast, the coefficients on top-coding for surgical DRGs are generally not significant.

Table 6: Base results: top-coding by EMR adoption and payment reform

	Dependent variable: percent top code within a base DRG					
	2 to 2		2 to 3		Combined	
	MED	SURG	MED	SURG	MED	SURG
$EMR \times Post$	.582**	−.507	.403*	.135	.445**	−.35
	(.237)	(.313)	(.239)	(.257)	(.22)	(.271)
$EarlyEMR \times Post$	2.25***	−.44**	1.13***	−.0438	1.37***	−.0607
	(.419)	(.216)	(.359)	(.31)	(.364)	(.333)
Year 2008	−55.6***	−25.6***	−52.8***	−49.1***	−53.4***	−36.7***
	(7.49)	(4.06)	(4.08)	(1.39)	(3.55)	(3.43)
Year 2009	−52.9***	−23.8***	−50.3***	−48.1***	−50.9***	−35.2***
	(7.52)	(4.11)	(4.2)	(1.33)	(3.64)	(3.59)
Year 2010	−52.7***	−23.2***	−50.6***	−48.2***	−51.1***	−34.9***
	(7.53)	(4.13)	(4.2)	(1.35)	(3.65)	(3.7)
Observations	119,911	94,993	284,969	276,047	404,880	371,040

Unit of observation: hospital/base DRG/year
Standard errors clustered at both hospital and base DRG levels
Other regressors: bed size, total outpatient visits, teaching hospital, total admissions, full-time physicians and dentists, percentage Medicare, percentage Medicaid, profit status, total number of births, hospital/base DRG fixed effects, and year fixed effects.

In one case, the coefficient for early adopters in the post-reform period is actually significantly negative. The coefficients on top-coding for surgical DRGs are also much smaller in magnitude than the coefficients on medical DRGs.

Table 7: Robustness results: top-coding by EMR adoption and payment reform

	Dependent variable: percent top code within a base DRG					
	2 to 2		2 to 3		Combined	
	MED	SURG	MED	SURG	MED	SURG
$EMR \times Post$	.0383	$-.657^{*}$	.225	.123	.19	$-.364$
	(.238)	(.36)	(.259)	(.287)	(.237)	(.312)
$EarlyEMR \times Post$	2.3^{***}	$-.293$	1.1^{***}	$-.122$	1.35^{***}	$-.0139$
	(.401)	(.291)	(.4)	(.331)	(.396)	(.347)
$EMR \times 2009$	2.48^{***}	.399	$.826^{*}$	.398	1.2^{**}	.0282
	(.507)	(.732)	(.498)	(.479)	(.501)	(.468)
$EarlyEMR \times 2009$	$-.18$	$-.114$	.0316	$-.00422$	$-.0107$	$-.0578$
	(.312)	(.353)	(.228)	(.201)	(.201)	(.221)
$EMR \times 2010$	2.53^{***}	$-.0859$	1.23^{**}	.664	1.53^{***}	$-.396$
	(.451)	(1.02)	(.592)	(.621)	(.555)	(.617)
$EarlyEMR \times 2010$	$-.0914$	$-.264$	.0061	.178	$-.00476$	$-.0515$
	(.319)	(.329)	(.202)	(.223)	(.195)	(.246)
Observations	119,911	94,993	284,969	276,047	404,880	371,040

Unit of observation: hospital/base DRG/year.
Standard errors clustered at both hospital and base DRG levels.
Other regressors: bed size, total outpatient visits, teaching hospital, total admissions, full-time physicians and dentists, percentage Medicare, percentage Medicaid, profit status, total number of births, hospital/base DRG fixed effects, and year fixed effects.

Table 7 presents a robustness check on Table 6, by including additional regressors that interact adoption status with indicators for the post-reform years 2009 and 2010. Since the payment reform involved a transition period during which the relative weights of each DRG were a blend of the old and new weights, this table allows us to understand if the changes in top-coding for EMR hospitals phased in gradually over time. Consistent with the findings in the base specification, there is a higher fraction of medical patients coded to more severe categories among EMR hospitals. Also, early adopters consistently saw such an increase throughout the post-reform periods while hospitals adopting the technology in 2008 or later experienced the increase only in 2009, likely due to the complexity of integrating EMR technology. The results suggest that new users were facing some knowledge and resource barriers to assimilating EMRs. The results on surgical DRGs continued to be statistically insignificant and smaller in magnitude.

The fact that we find effects of greater top-coding by EMR hospitals post-reform suggests that there is either upcoding or more accurate coding. The fact that the effects are only for medical DRGs suggests that this is due to more accurate coding rather than upcoding: if the results were due to bill inflation, hospitals would likely do this for surgical DRGs as well. In the case of upcoding, we would not have seen such an asymmetric difference in the effect between medical and surgical diagnoses.

Table 8: Top-coding based on payment spread

	Dependent variable: Percent top code within a base DRG, 2 to 2			
	MED		SURG	
Spread	8.72	(32.1)	-26.2^{***}	(9.24)
$Spread \times EMR$	28	(22.8)	5.33	(6.87)
$Spread \times EarlyEMR$	-2.15	(1.41)	.626	(.9)
$EMR \times Post$	-10.9	(7.71)	-5.28	(6.12)
$EarlyEMR \times Post$	9.83^{*}	(5.7)	3.3	(4.8)
Observations	119,911		94,993	

Unit of observation: hospital/base DRG/year
Standard errors clustered at both hospital and base DRG levels
Other regressors: bed size, total outpatient visits, teaching hospital, total admissions, full-time physicians and dentists, percentage Medicare, percentage Medicaid, profit status, total number of births, hospital/base DRG fixed effects, and year fixed effects.

In order to further examine the evidence on upcoding, we next test Hypothesis 2. This table considers the role of financial incentives induced by differential reimbursements between low and high codes across base DRGs. In particular, we try to understand whether there are incentive effects that point to upcoding and not just coding more accurately. Following Dafny (2005), we consider whether top coding is occurring with greater frequency when there is a greater financial incentive to top code. For each base DRG, the "spread" measures the weight difference between the top and bottom codes. We use this measure to identify hospitals' "upcoding" incentive in response to the payment reform. We only focus on DRGs with two severity subclasses for which the "spread" is clearly defined. The key variables of interest are the interaction terms involving spreads, EMR adoption status and post-reform dummies.

Table 8 presents the results. None of the estimated coefficients on the interaction between *Spread* and EMR adoption is significant. In other words, for both medical and surgical diagnoses, there is no significant effect of EMR hospitals having more top codes based on financial incentives. Early-adopting hospitals are still predicted to receive a significant increase in top codes for medical diagnoses, regardless of the magnitude of the spread. However, the effects are insignificant for surgical diagnoses. Thus, we find no evidence that EMR hospitals top code patients based on financial incentives after the reform.

Finally, Table 9 considers tests based on Hypothesis 3. Here, we use data that maps diagnosis codes into CCs and MCCs. We focus on two types of base DRGs: those with a single severity subclass pre- and post-reform and those with two severity subclasses that separate admissions without CC/MCCs from those with either CCs or MCCs post reform. Both of these lump MCCs together with less severe levels and thus there is no financial incentives to assign patients to MCCs. Table 9 reports the estimated coefficients for the key variables as well as the year fixed effects. For the 2 to 2 subclass, we find results that match our base results: there is a larger proportion of patients coded to MCCs following EMR adoption for medical DRGs only. This occurs even though there is no financial incentive to do so or even report the MCCs. Interestingly, for the 1 to 1 subclass, we do not find any effect for medical DRGs but find a positive and statistically significant effect for surgical DRGs.

Following the literature, we also examine differences in coding for hospitals in financial distress and for-profits. A hospital is defined as financially-distressed if its debt-to-asset

Table 9: Coding MCCs in the absence of a separate DRG

	Dependent variable: percent of patients with MCC within a base DRG			
	2 to 2		1 to 1	
	MED	SURG	MED	SURG
$EarlyEMR \times Post$	-6.42	.116	$-.226$	.525
	(4.67)	(.0956)	(.412)	(.65)
$EMR \times Post$	8.1^{***}	.0888	.06	2.54^{**}
	(3.03)	(.18)	(.304)	(1.14)
Year 2008	12.9^{***}	2.8^{***}	-52.2^{***}	-35.8^{***}
	(2.72)	(.262)	(1.6)	(5.35)
Year 2009	12.4^{***}	2.75^{***}	-53.0^{***}	-44.9^{***}
	(3)	(.322)	(2.46)	(5.92)
Year 2010	16.1^{***}	3.5^{***}	-47.3^{***}	-23.7^{***}
	(3.18)	(.319)	(1.49)	(4.98)
Observations	3,222	58,436	174,790	51,105

Unit of observation: hospital/base DRG/year.
Standard errors clustered at both hospital and base DRG levels.
Other regressors: bed size, total outpatient visits, teaching hospital, total admissions, full-time physicians and dentists, percentage Medicare, percentage Medicaid, profit status, total number of births, hospital/base DRG fixed effects, and year fixed effects.

ratio is above the 75th percentile and not financially-distressed if it is below 25 percentile.[9] Table 12 and 13 in the Appendix report the results. We do not find evidence that EMRs facilitate upcoding in for-profit hospitals or hospitals in financial distress.

Overall, our results for Hypotheses 2 and 3 support the fact that EMRs facilitate accurate coding instead of upcoding. We find significant increase in top codes for medical diagnoses and such a pattern does not follow financial incentives. EMRs seem to bring in greater "charge capture" rather than assist in revenue-enhancing practices. We find no evidence of upcoding based on financial incentives.

5.2 Hypotheses 4 and 5: Services and Patient Selection

Table 10: Evidence on amount of services provided

	2 to 2							
	Length of Stay				# Procedures			
	MED		SURG		MED		SURG	
EMR×Post	−3.67	(2.63)	.783	(2.83)	.936	(.586)	−.307	(.922)
EarlyEMR×Post	2.47	(3.86)	.649	(1.9)	−1.43	(1.16)	2.55**	(1.01)
N	119,911		194,993		119,911		194,993	
	2 to 3							
	Length of Stay				# Procedures			
	MED		SURG		MED		SURG	
EMR×Post	−2.35	(1.67)	1.26	(3.03)	.564	(.601)	.448	(.989)
EarlyEMR×Post	.84	(2.16)	1.46	(3.07)	.132	(1.13)	.729	(1.22)
N	284,969		276,047		284,969		276,047	

Unit of observation: hospital/base DRG/year.
Standard errors clustered at both hospital and base DRG levels.
Other regressors: bed size, total outpatient visits, teaching hospital, total admissions, full-time physicians and dentists, percentage Medicare, percentage Medicaid, profit status, total number of births, hospital/base DRG fixed effects, and year fixed effects.

We found evidence that EMR adoption improves coding accuracy in the previous subsection. We now assess the last two hypotheses, Hypotheses 4 and 5, to understand whether

[9] We use the Medicare Cost Reports to measure the level of financial distress. The debt-to-asset ratio is constructed using the total current liabilities and total assets in the cost reports.

Table 11: Evidence of patient selection

	2 to 2				
	Distance		# Diagnoses		Mean base DRG weight
	MED	SURG	MED	SURG	Overall
EMR×Post	50.2	−119	−2.95**	1.19	2.14***
	(105)	(175)	(1.16)	(2.03)	(.435)
EarlyEMR×Post	264	125	1.9	1.07	−.694
	(208)	(150)	(1.68)	(2.56)	(.695)
Observations	119,911	94,993	119,911	94,993	17,079
	2 to 3				
	Distance		# Diagnoses		Mean base DRG weight
	MED	SURG	MED	SURG	Overall
EMR×Post	−108	−129	−1.02	.808	.242*
	(67.2)	(117)	(1.03)	(1.8)	(.129)
EarlyEMR×Post	137*	82.6	.355	1.16	1.89***
	(75.9)	(128)	(1.48)	(2.11)	(.279)
Observations	284,969	276,047	284,969	276,047	17,301

Unit of observation: hospital/year for last column and hospital/base DRG/year for columns.
Standard errors clustered at both hospital and base DRG levels.
Other regressors: bed size, total outpatient visits, teaching hospital, total admissions, full-time physicians and dentists, percentage Medicare, percentage Medicaid, profit status, total number of births, hospital/base DRG fixed effects, and year fixed effects.

EMR hospitals provide more or less services to patients following the reform and whether they select different patients. We test Hypothesis 4 by examining for whether the implementation of EMRs leads to longer stay of patients or more procedures performed within a base DRG. The specifications for Hypothesis 4 are almost the same as the base one except that we use different dependent variables to test for this hypothesis. Table 10 shows the results. The upper panel displays the estimates for base DRGs with two subclasses while the lower for those expanding from two to three subclasses after the reform. We only present the key variables of interest. Note that we are more interested in the baseline EMR effect than the $EMR \times post$ interaction on service provided and patient selection. There is almost no effect on these outcome measures induced by the application of EMRs except for a slight increase in the number of procedures for medical diagnoses in the 2-to-2 cases. It suggests that hospitals perform more or less the same amount of services to patients following EMR adoption.

We test for Hypothesis 5 by examining the mean distance from patients to hospitals and the number of diagnoses within a base DRG. We also investigate whether hospitals moved into different base DRGs as a result of EMRs or the reform. In this last specification, the dependent variable is the mean DRG weight per hospital per year, using the weight of the lowest subclass for each base DRG, weighted by the corresponding number of visits. All of these measures, to some extent, reflect the severity of patient mix either within or across base DRGs. Table 11 shows the results.

Almost none of the estimated coefficients relating to EMR adoption are positive and significant in the first four columns. Thus, we find no selection of patients within base DRGs. However, we do find a positive and significant effect of EMR adopters in the post-reform period, in terms of the mean base DRG weight of a hospital. Thus, there appears to be selection across base DRGs following EMR adoption in the post-reform period. However, the causality of this result is unclear. It is possible that EMR adoption causes patients with more complex illnesses to visit a hospital. However, it is also possible that hospitals that improve their quality of care in a way that attracts patients invest in EMRs at the same time.

5.3 Cost to Government from Charge Capture

In this subsection we derive an estimate of the resulting payments from "charge capture" due to EMR adoption. Based on the estimation results in the sixth column of Table 6, early adopters experience 1.42% increase in medical patients coded to the highest level. On average, there are 3.5 million patients assigned with the DRGs considered in our paper and about 1.4 million of them are medical patients admitted to early-adopting hospitals. The average spread of the DRGs we focus on is 1.02 and the average DRG price is $7,200 per an admission with weight 1. Therefore, the in-sample cost due to "charge capture" associated with EMR adoption is $146 million per year for the U.S. The sample we consider accounts for about one fifth of the Medicare inpatient population. Considering the fact that almost 74% of DRGs have multiple subclasses, we expect the cost amounts to $540 million when extrapolating to the full Medicare sample. Traditionally, Medicare accounts for about 30% of total spending on hospital care. Therefore, the impacts of "charge capture" from adopting EMRs can be translated into $1.8 billion of annual cost in hospitalization.

6 Conclusion

The federal government has provided $27 billion to promote the adoption of EMRs, but its impact on the health care sector remains uncertain. Our paper examines the effect of EMRs on hospital coding behavior. In particular, we try to understand whether the application of this technology leads to upcoding or improved coding accuracy. The recent literature has not reached consensus on whether EMRs lead to upcoding. Our paper uses a triple difference that has never been considered before to test for alternative hypotheses. We find that EMR hospitals see a larger proportion of patients assigned to more severe diagnoses and this increase mainly occurs to medical admissions. Unlike what has been documented in the media in different contexts, we do not find hospitals code patients higher in base DRGs associated with largest reimbursement increment from high coding. We even find similar coding results when there is no high code DRG and hence absolutely no financial incentive to upcode.

Therefore, we believe EMRs improve coding accuracy rather than leading to upcoding. This paper further helps show how EMRs impact the coding process. The potential cost resulting from this type of application amounts to $540 million annually to Medicare and much more to the healthcare system as a whole. The information is potentially important for policy makers to provide better guidance in order to maximize the benefit of EMR technologies and understand the impact of their diffusion.

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Appendix

Figure 1: List of CCs and MCCs

Major Complications and Comorbid Conditions (MCC) & Complications and Comorbid Conditions (CC)

Abbreviated CMS List of MCCs and CCs

Major Complications/Comorbid Conditions

Cardiovascular/Cerebrovascular

❑Congestive Heart Failure, *Acute*
Acute on Chronic
Systolic or Diastolic
❑Cor Pulmonale, *Acute*
❑CVA, Stroke, Cerebral Infarct or Hemorrhage
❑Cerebral Edema
❑Coma
❑Endocarditis or Myocarditis, *Acute*
❑MI, *Acute*
❑Pulmonary Embolism, *Acute*

Respiratory & Infectious Disease

❑Aspiration Bronchitis, Aspiration Pneumonia
❑HIV Disease
❑Peritonitis
❑Pneumonia, Including viral
❑Pulmonary Edema, *Acute, Non-cardiogenic*
❑Respiratory Failure, *Acute*
❑Respiratory Insufficiency
Acute Post-Operative
❑Sepsis, Severe Sepsis, Septic Shock

Other MCCs

❑Acute Renal Failure with
Acute Tubular Necrosis (ATN)
❑Aplastic, Anemia due to
Drugs, Chemo, Infection, or Radiation
❑Diabetic Ketoacidosis or Diabetes with
Hyperosmolarity or Other Coma
❑Encephalopathy
Metabolic or Toxic
Other or Unspecified
❑End Stage Renal Disease
❑GI Disorder With
Hemorrhage, Gastritis, Duodenitis
Or Diverticular Disease
❑GI Ulcer With *Perforation, Hemorrhage or Obstruction*
❑Ischemic Colitis, *Acute*
❑Major Injuries
❑Malnutrition, *Severe*
❑Pancreatitis, *Acute*
❑Peritonitis
❑Pressure Ulcer *Stage III OR IV*
❑Quadriplegia or Functional Quadriplegia
❑SIRS due to Noninfectious Process with
Acute Organ Dysfunction
❑Volvulus

MCC IF Discharged Alive

❑Cardiac Arrest
❑Cardiogenic Shock
❑Respiratory Arrest
❑Ventricular Fibrillation
❑Other Shock *without Trauma*

Complications/Comorbid Conditions

Cardiovascular & Vascular

❑Myocardial Ischemia, *Acute, Without MI*
❑Angina, *Unstable*
❑Complete Block
AV or Mobitz Type II
Trifascicular or BBB
❑Atrial Flutter
❑CAD of Bypass Graft
❑Congestive Heart Failure
Chronic or Unspecified
Systolic or Diastolic
❑Cardiomyopathy *EXCEPT Ischemic*
❑Demand Ischemia
❑Heart Failure, *Left*
❑Hypertension, *Accelerated or Malignant*
❑Hypertensive Heart Disease *with CHF*
❑Hypertensive Encephalopathy
❑In-Stent Stenosis, *Cardiac*
❑Pleural Effusion
❑Post-MI Syndrome
❑Tachycardia, Sustained *PSVT*
❑Thrombophlebitis & Venous Thrombosis
Acute or Chronic

Behavioral, Nervous & Cerebrovascular

❑Alzheimer's Dementia with *Behavioral Disturbance*
❑Aphasia, *NOT Post-Stroke*
❑Delirium, Drug Induced
❑Dementia with
Delirium, Depression or Delusion
Presenile, Senile or Vascular
❑Depression, *Major, Acute*
❑Encephalopathy*, Alcoholic*
❑Hallucinations
Auditory OR Drug/Alcohol-Induced
❑Hemiplegia, Hemiparesis
❑Normal Pressure Hydrocephalus
❑Paraplegia
❑Post-Traumatic Seizures
❑Schizophrenia *EXCEPT Unspecified*
❑Suicidal Ideation
❑TIA
❑Vertebrobasilar Insufficiency
❑Withdrawal, *Drug or Alcohol*

Hematology & Oncology

❑Anemia due to *Acute or Post-Op Blood Loss*
❑Aplastic Anemia
❑Lymphoma, Leukemia *Also In Remission*
❑Malignant Neoplasm, *Most Sites*
NOT Breast or Prostate
❑Pancytopenia
❑Secondary Neuroendocrine Tumor

Metabolic

❑Acidosis/Alkalosis
❑Adult BMI <19 OR ≥40
❑Cachexia
❑Hypernatremia OR Hyponatremia
❑Malnutrition, *Unspecified*
❑Obesity Hypoventilation Syndrome

Complications/Comorbid Conditions

Gastrointestinal

❑Ascites
❑Attention to Gastrostomy
❑C. Difficile Enteritis
❑Cholelithiasis *with Cholecystitis*
❑Colitis, Enteritis or Gastroenteritis
of Presumed Infectious Origin
❑Colitis, *Ischemic or Ulcerative*
❑Colostomy or Enterostomy, Complications
❑Crohn's Disease
❑Diverticulitis
❑Esophagitis, *Acute*
❑Gastroenteritis, *Toxic or due to Radiation*
❑GI Bleed, Melena, Hematemesis, Hemoptysis
❑Hernia *with Obstruction*
❑Ileus
❑Intestinal Infections, *Viral or Bacterial*
❑Intestinal Malabsorption
❑Jaundice
❑Pancreatitis, *Chronic*
❑Ulcer, *Acute Gastric, Duodenal or Peptic*

Nephrology & Genitourinary

❑Acute Renal Failure
❑Calculus of Ureter or Kidney
❑Chronic Kidney Disease*, Stage IV or V*
❑Hydronephrosis or Hydroureter
❑Nephrotic Syndrome
❑Polycystic Kidney
❑Pyelonephritis, UTI

Orthopedic & Skin

❑Cellulits, *EXCEPT Fingers or Toes*
❑Compartment Syndrome, *Non-Traumatic*
❑Complications of Prosthetic Joint
❑Fractures, *Pathologic*
❑Fractures, *Traumatic, Closed/Many Sites*
❑Osteomyelitis, *Acute, Chronic or Unspecified*
❑Stasis Ulcer, *Inflamed or Infected*
❑Ulcer of Skin, *Lower Extremity*

Respiratory

❑Asthma Exacerbation
❑Atelectasis
❑COPD with Acute Exacerbation
❑Emphysema
with Exacerbation of Chronic Bronchitis
❑Hemoptysis
❑Pulmonary Edema, *Non-Cardiogenic*
❑Respiratory Distress, *Acute*
❑Respiratory Failure, *Chronic*
❑Respirator *Weaning or Dependence*

Other

❑Bacteremia
❑Complications of Device, Implant or Graft
❑SIRS due to Non-Infectious Process
❑Thrush
❑Transplant Status, *Most Organs*

e-MedTools.com

Sources: `http://e-medtools.com/drg_modifier.html`

Figure 2: Sample of Discharge Summary

Discharge Summary: General Format

Patient Name:
Medical Record Number:
Admission Date:
Discharge Date:
Attending Physician:
Dictated by:

Primary Care Physician:
Referring Physician:
Consulting Physician(s):
Condition on Discharge:

Final Diagnosis: ***(list primary diagnosis FIRST)***

Procedures: ***(list dates, complications)***

History of Present Illness ***(can refer to dictated/written HPI)***

Laboratory/Data ***(be BRIEF, just the most PERTINENT results that need to be followed)***

Hospital Course ***(by PROBLEM LIST…. NOT BY DATE ---)***

Discharge Medications ***(MOST IMPORTANT – LIST MEDS THAT ARE DIFFERENT FROM ADMISSION MEDICATIONS)***

Discharge Instructions ***(diet, activity, discharged to home/nursing facility, etc)***

Follow up Appointments

Code Status

Dictated by…

Figure 3: Sample of Operative Report

Sample Operative Report

Blair General Hospital
123 Main Street
Anytown, USA 56789

Patient Name: Betty Doe

Date: January 1, 2005

Preoperative Diagnosis: Bilateral upper eyelid dermatochalasis

Postoperative Diagnosis: Same

Procedure: Bilateral upper lid blepharopoasty, (CPT 15822)

Surgeon: John D. Good, M.D.

Assistant: N/A

NAME: Doe, William

Anesthesia: Lidocaine with l:100,000 epinephrine

Anesthesiologist: John Smith, M.D.

Dictated by: John D. Good, M.D.

This 65-year-old female demonstrates conditions described above of excess and redundant eyelid skin with puffiness and has requested surgical correction. The procedure, alternatives, risks and limitations in this individual case have been very carefully discussed with the patient. All questions have been thoroughly answered, and the patient understands the surgery indicated. She has requested this corrective repair be undertaken, and a consent was signed.

The patient was brought into the operating room and placed in the supine position on the operating table. An intravenous line was started, and sedation and sedation anesthesia was administered IV after preoperative P.O. sedation. The patient was monitored for cardiac rate, blood pressure, and oxygen saturation continuously.

The excess and redundant skin of the upper lids producing redundancy and impairment of lateral vision was carefully measured, and the incisions were marked for fusiform excision with a marking pen. The surgical calipers were used to measure the supratarsal incisions so that the incision was symmetrical from the ciliary margin bilaterally.

The upper eyelid areas were bilaterally injected with 1% Lidocaine with 1:100,000 Epinephrine for anesthesia and vasoconstriction. The plane of injection was superficial and external to the orbital septum of the upper and lower eyelids bilaterally.

The face was prepped and draped in the usual sterile manner.

After waiting a period of approximately ten minutes for adequate vasoconstriction, the previously outlined excessive skin of the right upper eyelid was excised with blunt dissection. Hemostasis was obtained with a bipolar cautery. A thin strip of orbicularis oculi muscle was excised in order to expose the orbital septum on the right. The defect in the orbital septum was identified, and herniated orbital fat was exposed. The abnormally protruding positions in the medial pocket were carefully excised and the stalk meticulously cauterized with the bipolar cautery unit. A similar procedure was performed exposing herniated portion of the nasal pocket. Great care was taken to obtain perfect hemostasis with this maneuver. A similar procedure of removing skin and taking care of the herniated fat was performed on the left upper eyelid in the same fashion. Careful hemostasis had been obtained on the upper lid areas. The lateral aspects of the upper eyelid incisions were closed with a couple of interrupted 7 – 0 blue prolene sutures.

At the end of the operation the patient's vision and extraocular muscle movements were checked and found to be intact. There was no diplopia,no ptosis, no ectropion. Wounds were reexamined for hemostasis, and no hematomas were noted. Cooled saline compresses were placed over the upper and lower eyelid regions bilaterally.

The procedures were completed without complication and tolerated well. The patient left the operating room in satisfactory condition. A follow-up appointment was scheduled, routine post-op medications prescribed, and post-op instructions given to the responsible party.

The patient was released to return home in satisfactory condition.

____

John D. Good, M.D.

Table 12: Evidence of upcoding for hospitals in financial distress

	Percent top code within base DRG					
	2 to 2		2 to 3		Combined	
	MED	SURG	MED	SURG	MED	SURG
Distressed×Post	−.743	.873	.847	.655	.508	.402
	(.981)	(.79)	(.532)	(.683)	(.661)	(.624)
Distressed×EMR×Post	.632	−.973	−.522	−.443	−.273	−.295
	(.475)	(.718)	(.515)	(.639)	(.509)	(.585)
Distressed×EarlyEMR×Post	−.881	−.541	.597	−.882	.231	-1.09^{*}
	(.912)	(.571)	(.438)	(.681)	(.541)	(.569)
NotDistressed×Post	.992	-2.7^{***}	−.535	.31	−.182	−1.38
	(.918)	(.972)	(.477)	(.765)	(.49)	(.937)
NotDistressed×EMR×Post	.255	.549	−.476	−.142	−.301	.282
	(.842)	(.576)	(.435)	(.533)	(.466)	(.506)
NotDistressed×EarlyEMR×Post	$-.759^{*}$	1.76^{**}	1.35^{***}	.444	.857	.829
	(.45)	(.796)	(.454)	(.634)	(.559)	(.606)
EMR×Post	.381	−.332	$.631^{**}$	.338	$.571^{*}$	−.00929
	(.431)	(.412)	(.298)	(.319)	(.294)	(.352)
EarlyEMR×Post	2.43^{***}	−.669	.218	.0705	$.731^{*}$	.0742
	(.576)	(.438)	(.281)	(.393)	(.415)	(.466)
Year 2008	-54.2^{***}	-25.3^{***}	-52.4^{***}	-49.4^{***}	-52.8^{***}	-36.8^{***}
	(7.52)	(4.2)	(4.1)	(1.44)	(3.57)	(3.61)
Year 2009	-51.5^{***}	-23.5^{***}	-49.8^{***}	-48.4^{***}	-50.2^{***}	-35.4^{***}
	(7.56)	(4.28)	(4.23)	(1.39)	(3.67)	(3.77)
Year 2010	-51.2^{***}	-22.9^{***}	-50.1^{***}	-48.5^{***}	-50.4^{***}	-35.1^{***}
	(7.6)	(4.33)	(4.21)	(1.42)	(3.68)	(3.89)
Observations	109,578	86,149	226,156	248,993	335,734	335,142

Unit of observation: hospital/base DRG/year
Standard errors clustered at hospital/DRG level
Other regressors: bed size, total outpatient visits, teaching hospital, total admissions, full-time physicians and dentists, percentage Medicare, percentage Medicaid, profit status, total number of births, hospital/base DRG fixed effects, and year fixed effects.

Table 13: Evidence of upcoding for for-profit hospitals

	Percent top code within base DRG					
	2 to 2		2 to 3		Combined	
	MED	SURG	MED	SURG	MED	SURG
ForProfit×Post	3.19*	.424	.771	.391	1.3	3.26**
	(1.71)	(1.98)	(.856)	(.996)	(.995)	(1.31)
ForProfit×EMR×Post	−2.45*	−1.39	−1.03*	−.0823	−1.35**	−2.12**
	(1.45)	(1.67)	(.536)	(.8)	(.617)	(1.04)
ForProfit×EarlyEMR×Post	−1.69*	2.34	−.0771	1.09	−.441	.761
	(.998)	(1.63)	(.93)	(1.2)	(1)	(1)
NotForProfit×Post	3.95***	.132	1.46*	−.872	2.05**	1.3
	(1.24)	(1.68)	(.769)	(.63)	(.805)	(1.05)
NotForProfit×EMR×Post	−2.07***	−1.33	−.399	.0774	−.788	−.868
	(.763)	(1.5)	(.516)	(.518)	(.537)	(.781)
NotForProfit×EarlyEMR×Post	−1.35	−.167	−.802	−.48	−.938	−.7
	(.834)	(1.24)	(.749)	(.798)	(.773)	(.825)
EMR×Post	2.38**	.734	.811	.141	1.18**	.753
	(.987)	(1.5)	(.503)	(.47)	(.525)	(.763)
EarlyEMR×Post	3.5***	−.529	1.69*	.264	2.11**	.478
	(.798)	(1.07)	(.99)	(.759)	(.952)	(.787)
Year 2008	−57.8***	−25.8***	−53.9***	−48.6***	−54.8***	−38.3***
	(6.55)	(3.91)	(4.1)	(1.44)	(3.5)	(2.98)
Year 2009	−55.1***	−24***	−51.4***	−47.6***	−52.3***	−36.8***
	(6.58)	(3.96)	(4.23)	(1.39)	(3.6)	(3.13)
Year 2010	−54.9***	−23.4***	−51.8***	−47.7***	−52.5***	−36.5***
	(6.61)	(3.99)	(4.25)	(1.41)	(3.63)	(3.25)
Observations	131,727	94,993	284,969	276,047	416,696	371,040

Unit of observation: hospital/base DRG/year
Standard errors clustered at hospital/DRG level
Other regressors: bed size, total outpatient visits, teaching hospital, total admissions, full-time physicians and dentists, percentage Medicare, percentage Medicaid, profit status, total number of births, hospital/base DRG fixed effects, and year fixed effects.