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DOES HEALTH IT ADOPTION LEAD TO BETTER INFORMATION OR WORSE INCENTIVES?

Gautam Gowrisankaran
Keith A. Joiner
Jianjing Lin

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We have received helpful comments from Sebastian Fleitas, Ben Handel, Jeff McCullough, Jessamyn Schaller, Bob Town, and seminar participants at several institutions. This paper was previously distributed and presented under the title "Does Hospital Electronic Medical Record Adoption Lead to Upcoding or More Accurate Coding?" The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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ABSTRACT

We evaluate whether hospital adoption of electronic medical records (EMRs) leads to increases in billing where financial gains are large or where hassle costs of complete coding are low. The 2007 Medicare payment reform varied both financial incentives and hassle costs of coding. We find no significant impact of financial incentives on billing levels, inconsistent with bill inflation. However, the reform led to increases in reported severity for medical relative to surgical patients at EMR hospitals, consistent with EMRs decreasing coding costs for medical patients. Greater post-reform completeness of coding with EMRs may increase Medicare costs by $689.6 million annually.

Gautam Gowrisankaran
Department of Economics
University of Arizona
P.O. Box 210108
Tucson, AZ 85721-0108
and HEC Montreal
and also NBER
gowrisankaran@eller.arizona.edu

Jianjing Lin
Tulane University
302 Richardson Hall
6823 St. Charles Avenue
New Orleans, LA 70118
jlin7@tulane.edu

Keith A. Joiner
Center for Management Innovations in Healthcare
PO Box 210108
Tucson, AZ 85721
kjoiner@email.arizona.edu

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 found that EMRs 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 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 both their benefits and the value of government policies that encourage EMR adoption.

This paper has three goals. First, to evaluate whether EMR adoption leads to increases in billing for hospitalized Medicare patients. Second, to evaluate if any increases in billing stem from upcoding (caused by worse incentives), more complete coding (caused by better information), or other explanations.[2] Third, to provide general evidence on the extent to which reimbursement systems and health IT change incentives in the health care sector. While we examine only hospitalized Medicare patients, our results may be more broadly applicable, as other payors use similar payment mechanisms.

We consider four different potential explanations for how EMR adoption might increase billing. First, EMRs might facilitate upcoding by hospitals, where hospitals inflate bills in response to financial incentives. Second, EMRs might lead hospitals to code more completely—a practice that is sometimes called "charge capture"— by lowering the hassle costs of complete coding. Third, EMR hospitals might provide more services.[3] Finally, hospitals with EMRs might select different patients. For instance, patients may perceive a hospital with EMRs as

[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`

[2] Coding is the process of transforming patient diagnoses and procedures into billing codes.

[3] For instance, Clemens and Gottlieb (2014) show that physicians respond to increased financial incentives by providing more care.

being higher quality and hence the hospital may attract a more severely ill patient mix upon adopting EMRs.

Both the upcoding and complete coding explanations imply that EMRs would increase hospital billing. Yet, the two explanations have different implications in other dimensions. If hospitals upcode based on financial incentives, we would expect to see hospitals report more severe illnesses when the relative reimbursement for reporting a high severity illness increases. Furthermore, if EMR adoption helps with upcoding, then this effect should generally be larger for EMR hospitals. Thus, we can detect upcoding based on financial incentives by evaluating whether hospitals change reported severity in response to changes in incentives, and further detect upcoding by EMR hospitals by examining whether the reaction to incentive changes is larger for EMR hospitals than for other hospitals. In contrast, if EMRs lower the hassle costs of complete coding then, following a change in hassle costs, billing for EMR hospitals should increase the most where the hassle costs drop the most. Thus, variation in financial incentives and in hassle costs can help separate upcoding from complete coding.

To further understand our identification, it will be useful to first explain the mechanics of Medicare inpatient hospital reimbursement. Medicare reimburses hospitals a single amount for each admission. This amount is based on the diagnostic related group (DRG) and specifically, is a linear function of the DRG weight. CMS divides DRGs into the categories of "medical" and "surgical." A surgical DRG is for a procedure while a medical DRG is for the management of a disease or alternately put, a medical condition. DRGs are grouped into *base DRGs* based on the patient's primary diagnosis (for medical DRGs) or primary procedure (for surgical DRGs).[4] 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, which have higher weights and hence higher reimbursements. Qualifying for a CC or MCC is costly, requiring both specifying the secondary condition and documenting the supporting medical evidence in the patient chart. The different DRGs within a base DRG are called *severity subclasses*.[5] We

[4]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* diagnoses.

[5]For example, the mouth procedures base DRG contains two severity subclasses, "mouth procedures

refer to the highest weight DRG in a base DRG as the *top code*.

In 2007, Medicare reformed the DRG classification system. The major intent of the reform was to better align reimbursements with the costs of treatment, accomplished through changes in reimbursements across DRGs and by revising the list of CCs and MCCs.[6] The reform altered the extra reimbursements for CCs and MCCs differently across base DRGs. It also significantly reduced the fraction of patients with secondary conditions that would qualify for CCs or MCCs by eliminating many common diagnoses from the list.

Around the same time, many hospitals implemented EMRs, due in part to federal subsidies. EMRs help accurately translate conditions into bills. But, EMRs can only code conditions to the extent that physicians document them. "Medical" physicians (i.e., those that treat medical DRGs) are largely trained to document conditions in detail, which by definition include CCs and MCCs. Surgeons are trained to document procedures in detail. If surgeons are not fully documenting secondary conditions (none of which are procedures), EMRs cannot help document them more completely. Hence, CCs and MCCs may not be fully captured for surgical patients, even with EMRs.

The reform created variation in both the financial incentives and the hassle costs of complete coding. First, by changing the incremental DRG weights for CCs and MCCs differently across base DRGs, the reform created variation in the extra reimbursements for top coding. Under an upcoding story, following the reform, EMR hospitals should increase their top coding disproportionately for base DRGs with higher incremental DRG weights for CCs and MCCs. Second, the reform created variation in the hassle costs of complete coding. To see this, note first that the costs of complete coding are lowered by the complement of EMRs and medical admissions, since medical physicians document conditions in more detail and EMRs better translate these conditions to billing codes. The reform increased this complementarity by increasing the hassle costs of qualifying for top codes. Specifically, while the number of diagnoses on the CC/MCC list actually increased with the reform—going from 3,326 to 4,922 unique conditions—the percent of patients who qualified for CCs or MCCs

without CC/MCC" and "mouth procedures with CC/MCC."

[6] Prior to the reform, MCCs were not a separate category from CCs.

dropped from 78% to 40% (Office of the Federal Register and National Archives and Records Service, 2007, p. 47,153, 47,162). This implies that the reform replaced broader conditions with more narrowly-defined ones. While these conditions are likely harder to code, EMRs, particularly for medical physicians, might mitigate this additional cost. Thus, under a hassle cost story, the interaction of the reform, EMR hospitals, and medical DRGs should predict more top coding.

We investigate the impact of the reform on top coding using a panel of data from 2006 to 2010. We use the universe (100% sample) of Medicare inpatient hospital claims data.[7] 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, among other sources.

Each observation is a unique combination of base DRG, hospital, and year. From our universe of claims, we keep all patients with base DRGs that have two or more severity subclasses and have an identical description before and after the reform. This comprises 19.4% of the patients in the overall Medicare sample. Our main dependent variable is the fraction of top codes among patients in a base DRG at a hospital and year. A simple difference-in-difference shows that EMR hospitals have 1.6 percentage points more top codes following the 2007 payment reform than other hospitals.

To separate the explanations for greater top coding, our main analysis then separates the sample into medical and surgical DRGs and regresses the fraction of top codes 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.

We find an increase in top codes for medical DRG following the reform for hospitals that adopted EMRs, an effect that is bigger for early EMR adopters. In contrast, we find no significant change in top codes for surgical DRGs. We also find no evidence that top coding

[7]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.

increased for base DRGs where the financial incentives to top code increased, either overall or for EMR hospitals relative to others. The fact that there is an increase in top codes for medical DRGs at EMRs following the payment reform, but no significant change for surgical admissions, is consistent with EMRs lowering the hassle costs of complete coding for medical admissions. The fact that the changes in coding do not follow financial incentives is inconsistent with upcoding by hospitals based on financial incentives. The magnitude of our results suggests that the 2007 reform led to 0.47 percent, or $689.6 million, more in Medicare hospital claims costs in 2016 from greater charge capture by EMR hospitals.

We also consider the third and fourth explanations noted above for increases in billing following EMR adoption. We examine whether EMRs might cause hospitals to provide more services to patients, by estimating whether the length-of-stay of patients or the number of procedures changes in the post-reform period, for EMR hospitals. We find little that is significant here. We also examine whether EMRs might cause hospitals to select different patients post-reform. Though there is no significant evidence on patient distance traveled or number of diagnoses per patient, we do find that EMR hospitals select patients with more severe base DRGs (based on the lowest weight for the base DRG) in the post-reform period.

Our paper builds on a literature that examines upcoding based on whether the proportion of top-code DRGs changes in response to financial incentives (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 CC to qualify for a top code. Following the change, the older patients were also only top coded based on CCs. Using a difference-in-difference design, Dafny finds that coding responded to hospital incentives, with a relative increase in top codes for the age 70 or older patients when the spread was higher between the DRG weight with and without CCs. Hence, she finds that top coding responds to hospital incentives. In contrast, our results show no such response, perhaps because coding systems are quite different today than during the time of these studies, for instance effectively including much more severe penalties for fraud.

Our paper also builds on a recent literature on coding 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 that either upcoding or more complete coding is occurring, and thus propose explanations to separate upcoding from complete coding. 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, their results may, in part, be driven by changes induced by the payment reform rather than by EMR adoption.

Few papers explicitly consider the hassle cost of complete coding. Most closely related is Sacarny (2014), who find that hospitals sometimes use an unspecified code for heart failure even when *any* specified code would yield a higher reimbursement, implying that there is a hassle cost of complete coding.

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. A hospital's base rate varies based on the costs in the area. For instance, in 2008, a hospital may receive anywhere from \$2,807 to \$8,218 for treating a patient with DRG weight 1, depending on its area cost factor.[8] By reimbursing hospitals a flat rate instead of a cost-based amount, PPS aimed to reward efficiency and lower expenditure growth.

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 on admission, 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.[9] 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 surgical base DRG. Subsequently, the admission is coded to an exact 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

[8] Authors' calculations based on FY2008 data.

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

and MCCs. CCs and MCCs all indicate the presence of secondary *conditions*.

With a few exceptions, the lists of CCs and MCCs are always based on diagnoses and never on procedures—even if the DRG is surgical—and are the same across base DRGs. However, there is variation across base DRGs in the severity subclasses. Specifically, there are four types of 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 substantial variation across base DRGs in the additional weights (and hence payments) from higher severity subclasses.

As an example of the role of CCs and MCCs, consider patient A admitted for poorly controlled diabetes, and patient B admitted for coronary bypass surgery. If either patient suffers from kidney stones, then the hospital can claim a CC. If either patient suffers end-stage renal disease, 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.[10] Thus, the presence of end-stage renal disease does not add to the reimbursement for patient B relative to kidney stones but it does for patient A.

Figure A1 in the Appendix lists the most common CCs and MCCs. The CCs and MCCs are categorized by organ system and/or by general physiologic functions and are all *conditions*. They represent a small subset of the post-reform total of 4,922 CCs and MCCs. An example of a dysfunction of an organ system is heart failure, which, as noted in Figure A1, 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 that contains ketones. Either one was evaluated as making hospital treatment more complex.

The exact DRG 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). Prior to the reform, base DRGs had a maximum of two DRGS, w/ CCs and w/o CCs. The

[10] These weights are for FY2008.

reform replaced the 538 pre-reform DRGs with 745 MS-DRGs. CMS started planning for the reform based on 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, the presence of a chronic disease was sufficient to justify a CC. Following the reform, a new acute manifestation of a chronic disease or a new acute disease—both of which reflect a more severe illness—generally became necessary to justify a CC or MCC.[11] 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, 77.7% of admissions had at least one CC present under the pre-reform criteria, while only 40.3% had a CC or MCC under the post-reform criteria.[12] As noted in Section 1, the number of conditions that qualified for a CC or MCC actually increased, confirming that, post reform, CCs or MCCs were for much narrowly-defined conditions.

Table 1 quantifies the effects of the reform on EMR and non-EMR hospitals by comparing the percent top codes between these two types of hospitals before and after the reform, using our main estimation sample. 72.3% of patients were coded into top tiers among EMR hospitals before the reform while the number dropped to 29.4% after the reform. The decrease is larger for hospitals without EMRs in 2006. A simple difference-in-difference calculation suggests that EMR hospitals see 1.6 percentage points more top codes after the reform than non-EMR hospitals. Since EMRs appear to help achieve top codes following the reform, this suggests the presence of either upcoding or more complete coding.

[11] There are exceptions to this rule including, most prominently, for heart failure. See Office of the Federal Register and National Archives and Records Service (2007) p. 47,153 and Sacarny (2014).

[12] See Office of the Federal Register and National Archives and Records Service (2007), p. 47,153-4.

Table 1: Mean percent top codes by 2006 EMR status

	With EMR in 2006	Without EMR in 2006
Pre-reform (2006) top codes	72.3%	72.5%
Post-reform (2008-10) top codes	29.4%	28%
Difference	−42.9%	−44.5%
Difference-in-difference between hospitals with and without EMR	1.6%	

Note: calculations based on in-sample hospitals as described in Section 3, for the years 2006 and 2008-10, and for all matched base DRGs with 2 severity subclasses before the 2007 payment reform and 2 or 3 severity subclasses after the reform.

2.2 Medical and Surgical Admissions

There are well-understand differences in culture between the physicians of record for medical and surgical DRGs (King et al., 1975). "Medical" physicians are likely to be internal medicine specialists or hospitalists. 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. 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. Patient care includes pharmaceutical therapy and other non-surgical management. For medical admissions, more so than for surgical admissions, the physician must make a continuous series of decisions regarding patient care and management, which evolve during different points in the hospital stay, and are heavily influenced by the comorbid conditions of the patient. Thus, medical physicians will likely spend a lot of effort to learn and document complications and comorbid conditions.

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 post-operative care needed for optimal outcomes, it nonetheless is reflective of the surgical mindset. Since the surgeon is relatively likely to focus on the details of the procedure performed, she may not code comoborbidities as completely.

To address the fact that surgical training has not typically focused on the complete coding of comorbidities, a number of documentation and coding interventions seek to improve coding for resident physicians. The results of such interventions, which are most commonly conducted on resident physicians specializing in surgical services, are mixed.[13] Some studies show improvements in documentation and coding accuracy following the intervention, and some show no effect. Overall, the interventions demonstrate that complete coding of comorbidities is not one of the primary focuses of surgeons.

Table A1 in the Appendix 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, Coding, and Hassle Costs

The coding of a DRG for an inpatient admission derives from the patient chart. The patient chart starts with the admission note, which describes the status of the patient and the diagnoses that are known upon admission. The chart also includes patient progress notes, which are made on a daily basis. These list the patient's course, test results, changes in medication,

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

and other relevant information. Finally, the chart includes the discharge summary, which provides a brief synopsis of the patient's stay and disposition.

In the absence of EMRs, the patient chart will be on paper. In this case, the attending physician or resident preparing progress notes must refer back to previous notes to ensure that diagnoses are carried through the record so that they ultimately 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. Less comprehensive notes will summarize progress on the most active subset of the admitting diagnoses. The least comprehensive notes will provide only cursory information on the status of the primary diagnosis. Figure A2 in the Appendix provides an example of a progress note for a medical patient while Figure A3 in the Appendix provides an example of a progress note for a surgical patient. These examples show how medical and surgical progress notes may differ in their level of detail.

Figure A4 in the Appendix provides an example of a blank discharge summary. Usually dictated after discharge by the attending physician or by a resident who was involved in the care of the patient, the discharge summary is mostly based on the patient progress notes. 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, pertinent laboratory data, and plans for follow-up care. The discharge summary provides information to providers seeing the patient in outpatient settings as well as for any subsequent hospital admissions. In the absence of EMRs, the ideal is for the discharge summary to be sent as a hard copy or fax to other providers, including the patient's primary care provider. In reality, transmittal of this information without EMRs is hit-or-miss, and often delayed.

For surgical admissions, an operative note is also prepared. This note documents in significant detail the procedure(s) that were performed. Figure A5 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.

EMRs have changed hospital treatment and billing in several ways. According to the Healthcare Information and Management Systems Society (HIMSS), the following components are key to perform the meaningful use of EMR: Clinical Data Repository (CDR), Clinical Decision Support Capabilities (CDS), and Computerized Physician/Provider Order Entry (CPOE) (McCullough et al., 2010). 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. Typically, physicians do not interact with CDR, but instead interact with CDS and CPOE. 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 CDS to offer more sophisticated drug safety features such as checking for drug allergies, cross-drug interactions, or dosage adjustments. Both CDS and CPOE require physician involvement to provide real-time support on a range of diagnosis- and treatment-related information.

An EMR system will typically record the hospital course, providing templates to aid the physician in documentation. 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 her 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 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. The EMR can also 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. With EMRs, the patient chart still exists. However, the EMR records diagnoses in particular fields on the (now electronic) patient chart.

Figure A6 in the Appendix shows a picture from one of the leading EMR vendors. It shows that the general illness of angina may correspond to multiple ICD diagnosis codes depending on the specific disease. In the absence of EMRs, it is likely that the physician would not always write down the words that correspond to the precise ICD code, simply noting instead that a patient suffers from angina. Figure A7 in the Appendix shows another picture from the EMR vendor. In this case, the well-understood medical term of *aortic stenosis* does not show up as a potential diagnosis.

Regardless of the presence of EMRs, the coding of a discharge from the patient chart to a DRG is done by a hospital's coding staff or outsourced to a separate health analytics firm. The staff will rely principally on the discharge summary and operative note. In general, coding staff will not communicate with physicians except for clarification requests. CMS requires documentation in the chart (whether paper or electronic) to substantiate each billed CC or MCC. The criteria specified by CMS typically include a combination of results from the patient history, physical examination, laboratory tests, medical imaging, specialty consultations, hospital course, and more. A central role of the coding staff is to verify the substantiation of every ICD code used in billing, and to not bill based on unsubstantiated codes. Even in the absence of EMRs, since roughly the 1990s, the coders then feed the substantiated codes and other information into grouper software, which outputs the appropriate DRG for Medicare billing purposes.

Overall, it is costly to obtain and record accurate information on secondary diagnoses with or without EMRs. 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 patient chart, but may or may not be entered into the patient's list of diagnoses. Even if the physician knows of a secondary diagnosis, the substantiation of this diagnosis in a way that conforms to CMS guidelines can require substantial effort.

Importantly, EMRs may disproportionately lower the hassle costs of complete coding for medical admissions relative to surgical ones because of the different role of conditions across these two types of admissions. As discussed in Section 2.2, documentation of secondary conditions is generally considered more integral to care for medical patients than for surgical patients. Because EMRs force medical physicians to choose diagnoses from drop-down menus that correspond directly to billing codes, this will then help ensure that the chosen diagnoses are most likely interpretable by the coding staff. In addition, with EMRs, accurate specification of secondary conditions may be necessary to justify appropriate treatments for medical admissions. Typically, medical admissions are associated with more prescribed medications, imaging procedures, and laboratory testing. The reason for this is that the treatment of medical admissions most commonly consists of medications (whereas the treatment of a surgical admission may be the surgery itself). Determining which medications to use for medical admissions commonly involves imaging procedures and laboratory testing. With EMRs, placing an order for a specialized procedure, test, or medication may require the entry of a diagnosis justifying the order. If the ordering physician had not previously entered the justifying diagnosis, she will be prompted to do so when placing the order. Finally, because EMRs will be available to a patient post-discharge, a physician may have a greater incentive to accurately code diagnoses with EMRs, in order to help patients in their post-discharge treatments.

Another difference in hassle costs is the physician's time cost of entering secondary diagnoses, which may differ across medical and surgical physicians. Specifically, as noted above, a typical limitation of EMR systems is a unique lexicon that does not always correspond to common medical terminologies. Thus, EMRs may also disproportionately lower the hassle costs of complete coding for medical physicians because these physicians would generally have more knowledge of the appropriate terminologies, since all CCs and MCCs are conditions rather than procedures. While a medical physician might be likely here to search for related terms that would generate a match in the EMR system, a surgeon might be relatively more likely to simply skip reporting this diagnosis. Indeed, we are aware of many physicians, often surgeons, who have admitted to being frustrated enough in trying to find the terminology used by their EMR system to describe a condition of their patient, that they have simply given up trying to code this condition. Finally, since surgeons, unlike medical physicians, can generate more revenue by performing additional surgeries, it is likely that their incentives from hospital management are to spend more time doing surgeries rather than coding.

3 Data

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, dates of service, reimbursement amount, dates of admission and discharge, Diagnostic Related Group (DRG), and principal and secondary diagnosis and procedure codes. We drop admissions to Critical Access Hospitals (CAHs) as these hospitals receive cost-based reimbursement from Medicare, instead of prospective DRG-based payments. 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. We also construct other dependent variables using these data, including the distance traveled, length of stay, case mix index, and numbers of diagnoses and procedures. The distance between each patient and the hospital is calculated based on the latitude and longitude of the zip code where the patient and hospital are located.

We merge two datasets on hospitals to our main analysis data. First, we merge technology adoption data from the Healthcare Information and Management Systems Society (HIMSS) Analytics Database, which is the most comprehensive national source of hospital IT adoption data. We use the Medicare provider number as a crosswalk 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.

There are several components of EMRs and no uniform definition across studies of which components constitute a functional EMR system. For instance, Jha et al. (2009) divide EMR systems into 32 functionalities, of which they view eight (including some parts of CPOE) as necessary for "basic" EMR operation. Miller and Tucker (2009) measure EMR adoption by whether a hospital has installed an "enterprise EMR" system, which they state is a "basic" system that underlies CDR, CDS, and CPOE. Recent studies defined EMR capabilities by either enterprise EMR or CPOE (Lee et al., 2013; McCullough et al., 2016; Ganju et al., 2015). We define a hospital to have adopted EMRs if either CPOE or CDS is live and operational within the organization. CPOE is generally paired up with CDS[14] to improve medication safety. Both of these key components require physician training and involvement. We chose these components because physicians typically interact with them, and hence they are most relevant for our models, which regard physician behavior.

Second, we merge the American Hospital Association (AHA) Annual Survey data, using the Medicare provider number as the primary crosswalk. In cases where the Medicare provider number was missing, we merge the databases using the hospital's name and exact address. We match approximately 3,300 non-CAH hospitals across the three datasets. The AHA data include a rich set of hospital-specific features such as number of beds, system affiliation, and profit status.

Finally, we merge a number of other smaller datasets. We use data that map diagnosis codes into CCs and MCCs. These data are derived from the CC and MCC lists published by CMS.[15] 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 the coding of diagnoses (and not just of DRGs) changes after the payment reform. We also use information on DRGs, including the type and weights, from the Centers for Medicare and Medicaid Services (CMS).

In order to assess hospital financial status, we merge our data with the Medicare Cost Reports, using the Medicare Provider Number field. Following the literature (Dafny, 2005;

[14] See https://psnet.ahrq.gov/primers/primer/6/computerized-provider-order-entry

[15] 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 for providing us with these data.

Li, 2014), we use the debt-to-asset ratio as a measure of financial health. We construct this measure by dividing current liabilities by total assets, both of which are listed in the cost reports. We define a hospital as financially distressed if its debt-to-asset ratio is above 75th percentile and as financially healthy if this ratio is below 25 percentile.

Table 2: Summary statistics on patient sample

Variable	2006	2008	2009	2010
Panel 1: 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
Panel 2: 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	219,735	216,054	214,306	204,114
% top-code patients	49.2	32.8	33.4	33.7
Panel 3: Patients in base DRGs with 2 DRGs pre-reform and 2 DRGs post-reform (w/o MCC and w/ MCC)				
Number of discharges	984,484	970,779	968,304	970,215
% top-code patients	61	21.8	24.2	24.6
Panel 4: Patients in base DRGs with 2 DRGs pre-reform and 3 DRGs post-reform				
Number of discharges	1,983,485	2,162,007	2,218,236	2,259,083
% top-code patients	80.6	30	32	31.7
% middle-code patients	-	38.1	37.8	38.9
Panel 5: Patients in base DRGs with 2 DRGs pre-reform and 2 or 3 DRGs post-reform				
Number of discharges	3,187,704	3,348,840	3,400,846	3,433,412
% top-code patients	72.4	27.8	29.9	29.8
Panel 6: Patients in base DRGs with 1 DRG pre-reform and post-reform				
Number of discharges	1,038,983	1,060,897	1,038,651	1,054,228
% patients with secondary diagnoses as MCC	67.2	21.1	19.4	20.1

Table 2 provides summary statistics on our patient sample. The first panel in Table 2 shows 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 (or case-mix index) was rising over time, from 1.34 in 2006 to 1.46 in 2010. This rise suggests an increase in top coding, a phenomenon we will explore in more detail below. Panels 2-6 of Table 2 split these data into the different subsamples used in our estimation. Panel 2 lists statistics on base DRGs which represent the same primary diagnosis or procedure before and after the reform, which have two severity subclasses before, and which combine CCs with MCCs in one severity subclass after the reform. For this group, the number of discharges was about 219,735 in 2006 and 204,114 in 2010. The percent top codes decreased from 49.2% in 2006 to 33.7% in 2010, due to the different and more stringent set of diagnoses that generate top codes. Panels 3 and 4 consider base DRGs for which only MCCs generate a top code following the reform. Not surprisingly, they show a greater reduction in the percent top codes than Panel 2. Panel 4 considers base DRGs with three severity subclasses. Similar to Panel 2, the sum of the percent of top codes (MCCs in this case) and middle codes (CCs) is smaller post-reform than the percent top codes pre-reform. Panel 5 combines Panels 2-4 and Panel 6 reports data on matched base DRGs with one severity subclass pre- and post-reform.

From the universe of Medicare discharges, our main sample keeps the observations in Panel 5, which represent 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 hospital/base DRG fixed effects for these base DRGs. Among the DRGs we consider, the number of discharges ranges from 1,345 to 416,821 in each base DRG. For our main sample, the percent of top code patients declined from 72.4% in 2006 to 27.8% in 2008, following the reform.

Table 3 reports EMR adoption rates of hospitals in our sample during 2006-2010. Only 54.1% of hospitals had adopted EMRs in 2006, a figure that had increased to 92.4% 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. Well in advance of the passage of the HITECH Act in 2009, President George W. Bush outlined a plan in 2004 under which most Americans would have electronic health records within 10 years. The president's FY2005 budget proposal included funding of $100 million for demonstrative projects to test the effectiveness of health IT. The Office of the National Coordinator for Health Information Technology (ONC) and the American Health Information Community (AHIC) were established after this proposal and organized a number of meetings with the public and private sectors in 2006-2007 to discuss the prototypes of the Nationwide Health Information Network (NHIN) and strategies to support health IT. Thus, the increase in EMR adoption starting in 2007 may be caused in part by the expectation of future subsidies.

Table 3: Summary statistics on EMR adoption rates

Variable	Obs	Mean
% hospitals with EMR, 2006	3,465	54.1
% hospitals with EMR, 2008	3,318	75.7
% hospitals with EMR, 2009	3,337	90.4
% hospitals with EMR, 2010	3,306	92.4

Table 4 provides summary statistics for the main hospital characteristics according to EMR adoption status. 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 36% larger than that of hospitals adopting EMRs between 2007 and 2010, and more than one and a half times that of hospitals adopting EMRs later than 2010. The numbers of outpatient visits and inpatient admissions are more than three times those of hospitals without adoption through 2010. Early EMR adopters also had a lower debt-to-asset ratio than 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 EMRs by early and later adopters may be helpful.

Table 5 shows the mean DRG weights for all DRGs and the changes in spread for the base DRGs considered in this paper. *Spread* is defined to be the difference between the weight of the top and bottom codes. For base DRGs with three severity subclasses, *Spread* measures the difference in weight between the highest and lowest tier. While it became harder to

Table 4: Summary statistics on hospital characteristics by EMR use

	Hospital characteristics		
	EMR adopters $\leq$2006	EMR adopters 2007-10	EMR non-adopters through 2010
Bed size	252	186	100
Total outpatient visits	202,066	139,984	57,971
Total admissions	11,794	8,321	3,707
FTE physicians and dentists	29	16	6
Total number of births	1,328	957	356
% teaching hospital	12.1	5.29	1.24
% Medicare discharge	44.6	46.5	49.8
% Medicaid discharge	18.9	18.4	17
% for-profit	19.5	20.4	44.8
% not-for-profit	67.5	61.6	31.6
% public hospitals	13	18	23.6
Debt-asset ratio	0.659	0.647	0.83
Number of hospitals	1,771	1,186	242

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

obtain a top code after the reform, the mean DRG weight increased from before the reform to after the reform.

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	744	2.02	2
DRG weight, 2010	744	2.02	2.01
$\Delta Spread$, 2 to 2, 2006 to 2008	27	0.03	0.143
$\Delta Spread$, 2 to 2, 2008 to 2009	27	0.346	0.279
$\Delta Spread$, 2 to 2, 2009 to 2010	27	0.017	0.102
$\Delta Spread$, 2 to 3, 2006 to 2008	59	0.248	0.291
$\Delta Spread$, 2 to 3, 2008 to 2009	59	0.626	0.302
$\Delta Spread$, 2 to 3, 2009 to 2010	59	0.021	0.123

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

The mean spread for DRGs with two severity subclasses before and after the reform increased by 0.03 in 2008 and 0.346 in 2009, indicating that the reform had varied impacts throughout the time period of our sample. Similarly, the mean spread for DRGs transitioning from 2 to 3 severity subclasses increased 0.248 in 2008 and 0.626 in 2009. There is also a large standard deviation in the change in weights between years. These changes are useful in creating variation to detect the impact of financial incentives on hospitals' coding behavior.

4 Analytic Framework

4.1 Model

We model the decision of a hospital regarding the top coding of a given patient stay. Let EMR_{jt} be an indicator for whether hospital j had adopted EMRs at time t and let $Spread_{dt}$ denote the spread between top and bottom codes for base DRG d at time t.[16]

We first consider a model of upcoding. Why might hospitals upcode? Physicians may have financial incentives to list comorbidities that are not adequately documented, 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 and may coordinate with physicians. For instance, Dafny (2005) interviewed a medical resident who was asked by coding personnel "to reconsider her diagnosis of 'urinary tract infection' and replace it with 'septicemia' ... as the hospital is 'underpaid' and 'needs' the funds to provide care for the uninsured."

However, these parties may also have incentives to *not* list comorbidities in the absence of appropriate documentation. If identified through an an audit, they and the hospitals may face high criminal and civil penalties from bill inflation. Overall, since upcoding is about financial incentives, if hospitals are upcoding, we would expect that they would be more likely to do so when the incremental reimbursements from upcoding increase.

EMRs may also potentially increase upcoding. They may make it easier for physicians to report diagnoses for which no justification is provided. For instance, EMRs allow physicians to clone diagnoses across records. They also allow physicians to enter a diagnosis by clicking on a button, rather than writing down the diagnosis, which may lower the perceived cost of

[16]For ease of exposition, our model only considers base DRGs with two severity subclasses.

diagnosis inflation. Importantly, the upcoding caused by EMRs should be based on financial incentives rather than being biased towards either medical or surgical DRGs.

Recall that the 2007 payment reform varied the incremental reimbursement $Spread_{dt}$ significantly across base DRGs, thus providing identifying power for the upcoding model. To formalize, we consider a patient i being treated by hospital j for base DRG d at time t, who does not merit a top code for base DRG d given her diagnoses. The net utility to the hospital from upcoding this patient is:

$$u_{ijdt}^{upcode} = \text{FinBenefits}(Spread_{dt}, EMR_{jt}, d, X_{jt}) - \text{Costs}(EMR_{jt}, d, X_{jt}) + e_{ijdt}. \quad (1)$$

From (1), the mean benefits from upcoding, FinBenefits, are a function of the spread between top and bottom codes at time t, EMR adoption, the base DRG d, and hospital characteristics X_{jt}. The mean costs from upcoding, Costs, which reflect the potential penalties from audits among other factors, are a function of EMR adoption, d, and X_{jt}. The hospital will upcode this patient if and only if $u_{ijdt}^{upcode} > 0$.

Importantly, we assume that the costs of upcoding are not a function of *Spread*. If enforcement increases when *Spread* increases, then this assumption may not be accurate. However, while enforcement may indeed be higher for base DRGs with higher *Spread*, we would not expect enforcement to change quickly or completely in response to changes in *Spread*. So long as the magnitude of the cost increase from a change in *Spread* is less than the gain in financial benefits from the change, the overall implications of our model would not change.

We make two further assumptions regarding the payoffs, consistent with the roles of financial incentives and EMRs in upcoding. First, we assume that FinBenefits is increasing in $Spread_{dt}$. This assumption stems from the fact that the spread is proportional to the additional financial benefits which accrue to the hospital from upcoding. Second, we assume that the costs of upcoding are lowered by EMRs, conditional on the base DRG.

Given these assumptions, the utility that a hospital obtains from upcoding a given patient will be higher if *Spread* is higher or if the hospital adopts EMRs. This implies that, with upcoding, we should see an increase in the probability of top-coding if *Spread* increases for a patient, holding all else equal. The payment reform provides within-hospital/base DRG variation in *Spread* that we can use to test for upcoding in this way.

Under further regularity conditions, there will be a complementarity between upcoding and EMR adoption. In other words, in response to an increase in *Spread*, the probability of upcoding a given patient increases more for a hospital which has adopted EMRs than for a hospital which has not. To see this, suppose that e_{ijdt} is distributed type 1 extreme value and that the probability of upcoding a patient (based on equation (1)) is always less than 50%, which seems probable given the magnitudes of upcoding found in other studies. Finally, suppose that $\text{FinBenefits}(Spread_{dt}, EMR_{jt}, d, X_{jt}) = \alpha_1 Spread + \alpha_2 EMR_{jt} + \alpha_3 X_{jt}$, so it is linear in its components. In this case, the increase in utility from EMR adoption will lead to an increased baseline upcoding probability, which will imply that the hospital will react more strongly to an increase in *Spread*.[17] Thus, we further test for whether EMR hospitals respond more strongly to changes in *Spread* than other hospitals.

Finally, note that $\text{FinBenefits}(Spread_{dt}, d, X_{jt})$ may vary with observable hospital characteristics. For instance, hospitals in financial distress or for-profit hospitals may have a more immediate use for extra resources, which may magnify their implicit financial incentives from a high *Spread*. In these cases, we would expect that these hospitals would also respond more strongly to changes in *Spread* than other hospitals.

We now turn to the role of EMRs on the hassle costs of complete coding. As noted in Section 2.3, there are a variety of reasons that suggests that EMRs will reduce the hassle costs of complete coding for medical patients more than for surgical patients. Thus, we assume that the complement of EMR and MED (i.e., medical DRGs) reduces hassle costs. In addition, comparing the set of diagnoses that were top codes after the reform to those that were top codes before the reform, the conditions after the reform were much less common and more specific in their coding, e.g., requiring an acute exacerbation of a chronic disease.

[17] Specifically, if the probability of upcoding increases from p_1 to p_2 with EMR adoption for a given level of *Spread*, a marginal increase in *Spread* would change the upcoding probability from $\alpha_1 p_1(1 - p_1)$ to $\alpha_1 p_2(1 - p_2)$ given EMR adoption. So long as $p_1 < p_2 < \frac{1}{2}$, this change will be positive.

Thus, we further assume that the complement of EMR and MED lower the hassle costs for the diagnoses that generate top codes after the reform relative to the diagnoses that generate top codes before the reform.

Although we believe that the hassle costs of coding top codes after the reform are higher than before the reform, even if the codes were no more stringent, if there were a sunk cost of coding completely, the same model would apply. In particular suppose that before the reform, a surgeon had learned how to code completely over time. Following the reform, she would then have to learn how to code the new codes completely. So the hassle cost would be higher in this case by virtue of the codes being new rather than them being more complex.

To formalize our model of complete coding based on hassle costs, consider a patient i being treated by hospital j for base DRG d at time t who merits a top code code for base DRG d given her diagnoses. Suppose further that the hospital is not making its coding decisions based on financial incentives. The net utility to the hospital from completely coding comorbidities for this patient is:

$$u_{ijdt}^{complete} = \text{Benefits}(EMR_{jt}, d, X_{jt}) - \text{HassleCosts}(EMR_{jt}, d, X_{jt}, Post_t) + e_{ijdt}, \quad (2)$$

where $Post_t$ is an indicator for being in the post-reform period.

The model is very similar to the model of upcoding specified in equation (1). We assume that HassleCosts are a function of EMR adoption, conditional on a base DRG. However, we assume that the benefits from complete coding, Benefits, are not a function of the financial incentives and hence do not vary with financial incentives. Also, we assume that the costs of top-coding are due to the hassle costs of complete coding and are a function of $Post_t$ interacted with d. Our main testable assumption is that the reform lowered hassle costs for the complement of MED, EMR, and $Post$. Hence, EMR hospitals should have relatively more top codes after the reform for MED than for SURG (i.e., surgical DRGs) compared to non-EMR hospitals.

Note that our model of hassle costs does not allow for firms to strategically invest resources in more complete coding based on changes in financial incentives over time. If firms do invest resources in this manner, we would find upcoding rather than complete coding. However, this explanation would be somewhat different than from our model: our model of upcoding specifies that the strategic investment is for patients who do not merit top codes while this model assumes that the strategic investment is for people who do merit top codes. Thus, to the extent that we find evidence of upcoding, this does not necessarily imply that there is unjustified bill inflation, but could also be due to firms strategically top-coding based on financial incentives. In contrast, our model of complete coding specifies top coding based on hassle costs, which are not systematically related to the financial benefits from top coding.

EMRs may also have at least two other impacts which we examine. First, 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 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 any finding here regarding the causal impact of EMRs in affecting patient demand should be interpreted with caution.

4.2 Testable Hypotheses

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

1. Complete coding:

    (a) If EMRs lead to more complete coding, then for medical DRGs, there will be a post-reform increase in top codes for EMR hospitals relative to non-EMR hospitals.

(b) For surgical DRGs, if this interaction effect is positive, it will be smaller than for medical DRGs.

(c) The increase in top codes for the interaction of EMRs and MED should be due, at least in part, to a change in diagnoses coded.

2. Upcoding:

   (a) If upcoding exists, then the probability of a top code should increase when the spread in the DRG weight between the bottom and top codes increases.

   (b) If EMRs lead to upcoding, then EMR hospitals should increase their top code probability more than other hospitals when the spread increases.

   (c) If upcoding exists, then hospitals in financial distress and for-profit hospitals should increase their top code probabilities more than other hospitals when the spread increases.

3. Service mix:

   If EMRs leads to different procedures being performed, hospitals should change their patient lengths-of-stay and numbers of procedures following EMR adoption.

4. Patient selection:

   If EMRs lead to the selection of more severely ill patients, patients will travel further, have more secondary diagnoses, and have higher DRG weights (using the lowest DRG weight of the base DRG to eliminate coding effects) upon EMR adoption.

4.3 Estimation and Identification

Our regression specifications for Hypotheses 1a and 1b 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:

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

where Y_{jdt} denotes the percent of patients coded to the top severity subclass of base DRG d 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_{jdt} is an unobservable.

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. 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 and hence behave differently in response to the reform than new users. They may also interact differently with their EMR system due to their differences in observable characteristics (Table 4).

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 hospital 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.

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 Hypotheses 1a and 1b includes patients with base DRGs with exact matches before and after the reform, and that had two severity subclasses before the reform and two or three severity subclasses after the reform. The reason that we exclude base DRGs that had only one severity subclass before or after the reform is that we cannot identify the within-base-DRG change in top-coding that occurred with the reform for these base DRGs.

Note also that our specifications here and later do 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 $EMR_{jt} \times Post_t$ minus $EarlyEMR_{jt} \times Post_t$.

Finally, note that we cluster the standard errors at both the hospital and base DRG levels (Cameron et al., 2012; Thompson, 2011). 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 1c employs a different dependent variable to Hypothesis 1. Specifically, we can partition patients into one of four sets. Set A contains patients who would qualify for top codes both before and after the reform, set B contains patients who would qualify for top codes before only, set C contains patients who would qualify for top codes after only, and set D contains patients who would never qualify for top codes. We code patients into these categories based on their reported secondary diagnoses. Our dependent variables are the percents of patients in each set A, B, and C (with D excluded).[18] This hypothesis allows us to examine whether the payment reform caused EMR hospitals to disproportionately shift people between these four sets—consistent with changes in coding due to hassle costs—or whether the different types of hospitals simply had different proportions in the different sets ex ante.

Our regression specifications for Hypothesis 2a and 2b employs the same dependent vari-

[18]For 13 base DRGs, top coding is determined by slightly different criteria, e.g., “complicating diagnoses” rather than “complicating conditions.” We exclude patients with these base DRGs for this hypothesis.

able as does Hypothesis 1. However, here, we also include a variable called $Spread_{dt}$ and interactions of $Spread_{dt}$ with EMR_{jt} and $EarlyEMR_{jt}$. $Spread_{dt}$ 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 $Spread_{dt}$ will identify how the change in spread affects top coding.

Our regression specification for Hypothesis 2c are similar to our specification for Hypotheses 2a but we interact $Spread_{dt}$ with measures of financial health—$Distressed$ (bottom 25%) and $FinHealthy$ (top 25 %)—or with whether the hospital is for-profit or not-for-profit, with the omitted category being public hospitals.

Our regression specifications for Hypothesis 3 examine whether hospitals keep patients longer or perform more procedures 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 or number of procedures within the hospital/base DRG as the dependent variables.

Finally, our regression specifications for Hypothesis 4 examine whether there is a change in the composition of patients 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 also 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. For this third outcome measure, 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. 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.

Table 6: Base results on complete coding (Hypotheses 1a and 1b)

	Dependent variable: percent top code within a base DRG					
	2 to 2		2 to 3		Combined	
	MED	SURG	MED	SURG	MED	SURG
EMR×Post	.329	−.495	.259	.144	.278	−.367
	(.315)	(.309)	(.196)	(.257)	(.202)	(.268)
$EarlyEMR$×Post	1.78***	−.394**	.803**	−.0707	1.01***	−.0874
	(.453)	(.19)	(.317)	(.313)	(.334)	(.316)
Year 2008	−54.8***	−25.7***	−52.2***	−49.1***	−52.8***	−36.6***
	(7.65)	(4.08)	(4.17)	(1.4)	(3.63)	(3.45)
Year 2009	−52***	−23.8***	−49.6***	−48.1***	−50.2***	−35.1***
	(7.66)	(4.12)	(4.3)	(1.34)	(3.72)	(3.6)
Year 2010	−51.7***	−23.2***	−50***	−48.2***	−50.4***	−34.9***
	(7.69)	(4.15)	(4.29)	(1.36)	(3.73)	(3.72)
Observations	105,456	91,932	241,831	265,286	347,287	357,218

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

5 Results

5.1 Hypothesis 1: Evidence on Complete Coding

Table 6 considers Hypotheses 1a and 1b. 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. 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 on top-coding for hospitals that adopted EMRs early on. For instance, for the base DRGs with 2 severity subclasses pre- and post-reform, there is a 1.78 percentage point increase in patients in medical DRGs classified into top codes following the reform for hospitals adopting EMRs in 2006 or earlier. However, this impact is smaller and not statistically significant for late adopters who installed the system later than 2007. The year dummies indicate a significant a drop in the percentage of top-code percents following the reform, reflecting the more stringent criteria for qualifying for a top code post-reform. These results are robust across the sample of base DRGs with 2 subclasses pre-reform and 3 subclasses post-reform, and the combined sample.

In contrast, the coefficients on top-coding for surgical DRGs are generally not significant. In one case, the coefficient for early adopters in the post-reform period is significantly negative, consistent with the explanation that surgeons may be coding fewer comorbidities with EMRs than without EMRs post-reform due to the time cost of doing so. The coefficients on top-coding for surgical DRGs are also much smaller in magnitude than the coefficients on medical DRGs.

Table A2 in the Appendix presents robustness checks to Table 6, by including additional regressors that interact adoption status with indicators for the post-reform years 2009 and 2010. Consistent with the findings in the base specification, there is a higher fraction of medical patients top-coded post-reform at EMR hospitals. Also, early adopters consistently saw such an increase throughout the post-reform period while hospitals adopting EMRs in 2008 or later experienced the increase only since 2009. The results suggest that new adopters faced roughly a year-long lag in successfully integrating EMRs into their coding systems.

The results on surgical DRGs continue to be mostly 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 complete coding. The fact that the effects are only for medical DRGs suggests that this is due to more complete 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 7: Evidence of coded diagnoses changing following reform (Hypothesis 1c)

	Dependent variable: percent of patients with diagnoses qualifying for MCCs in different time frame, within a base DRG					
	Set A		Set B		Set C	
	MED	SURG	MED	SURG	MED	SURG
$EMR\times$Post	.279	.139	$-.375^{*}$	.225	$-.0111$	$-.00138$
	(.189)	(.218)	(.21)	(.237)	(.0102)	(.0133)
$EarlyEMR\times$Post	.296	$-.0379$	$-.311$	$-.279$	.0104	$.0171^{*}$
	(.218)	(.215)	(.269)	(.344)	(.0132)	(.00984)
Year 2008	6.3^{***}	3.79^{***}	-8.22^{***}	-6.52^{***}	$.103^{***}$	$.0578^{***}$
	(.538)	(.577)	(.477)	(.49)	(.0205)	(.0202)
Year 2009	9.85^{***}	5.74^{***}	-11^{***}	-8.53^{***}	$.138^{***}$	$.134^{*}$
	(.649)	(.944)	(.518)	(.854)	(.0381)	(.0781)
Year 2010	11.3^{***}	6.44^{***}	-11.9^{***}	-8.79^{***}	$.152^{***}$	$.14^{*}$
	(.755)	(.993)	(.592)	(.891)	(.0516)	(.0743)
Observations	325,328	265,927	325,328	265,927	325,328	265,927

Note: set A are patients with diagnoses that qualify for top codes before and after the reform, set B qualify for top codes only before the reform, and set C only after the reform. Unit of observation is hospital/base DRG/year. Standard errors are clustered at both hospital and base DRG levels. Other regressors are bed size, total outpatient visits, teaching hospital, total admissions, full-time physicians and dentists, percentage Medicare, percentage Medicaid, profit status, total number of births, and hospital/base DRG fixed effects. Sample is patients in base DRGs with 2 severity subclasses before the reform and 2 or 3 severity subclasses after the reform for base DRGs for which the base CC and MCC lists determine severity subclasses.

Table 7 considers Hypothesis 1c. Here, we are interested in understanding whether the positive interaction term on $EMR \times Post \times MED$ is due to EMR hospitals having a different selection of patients all along or to changes in coding practices consistent with hassle costs. We examine as dependent variables the percent of patients with codes that would have qualified for top codes before and after the reform (set A), before the reform only (set B), and after the reform only (set C). We find that EMR hospitals code fewer MED patients in set B after the reform. Though not statistically significant, it appears that they code more MED patients in set A after the reform. In contrast, the interaction terms for set C for MED patients are small and not statistically significant. This implies that our findings in Tables 6 and A2 are not due to EMR hospitals simply having more MED patients in set C but are instead due to changes in coding practices.

Relatedly, the base year effects are all large and statistically significant. While not the focus of our paper, these results imply that, for both MED and SURG patients, coding practices change following the reform irrespective of EMR status.[19]

5.2 Hypothesis 2: Evidence on Upcoding

Table 8: Base results on upcoding (Hypothesis 2a)

	Dependent variable: Percent top code within a base DRG, 2 to 2			
	MED		SURG	
Spread	9.07	(31.5)	-26.2^{***}	(9.26)
$Spread \times EMR$	27.5	(22.8)	5.39	(6.88)
$Spread \times EarlyEMR$	-2.02	(1.51)	.597	(.887)
$EMR\times$ Post	-11	(7.71)	-5.34	(6.16)
$EarlyEMR\times$ Post	9.39	(5.83)	3.39	(4.81)
Observations	105,456		91,932	

Note: unit of observation is hospital/base DRG/year. Standard errors are clustered at both hospital and base DRG levels. Other regressors are 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.

[19]This result is also consistent with Sacarny (2014), who finds changes in coding practices for heart failures following the reform.

Table 8 considers Hypothesis 2, by examining the role of financial incentives induced by changes in the reimbursement spread on top coding across base DRGs. Following Dafny (2005), we consider whether top coding is occurring with greater frequency when there is a greater financial incentive to top code. Because the variable *Spread* captures the variation in reimbursement over time, we do not separately include a post-reform dummy in these interactions. In contrast to the upcoding model, the base coefficients on *Spread* are either not statistically significant or significantly negative. Neither of the $Spread \times EMR$ interactions is statistically significant. Hence, we do not see any evidence that upcoding based on financial incentives exists or that EMRs facilitate this practice.

Table A3 in the Appendix reports the results when *Spread* is interacted with measures of financial health. For hospitals undergoing more financial stress, we do not see a greater proportion of patients coded to higher levels. Instead, financially healthy hospitals are more likely to respond to financial incentives among medical patients. Table A4 in the Appendix presents the coefficients when we add the hospital's profit status as a regressor. Neither for-profit nor not-for-profit hospitals code more aggressively following the increase in reimbursement. However, these two tables suggest that hospitals, in general, see a rise of top-code patients in medical admissions but a reduction in surgical admissions.

Overall, our results here show no evidence of upcoding based on financial incentives and no evidence that EMRs facilitate upcoding. In contrast, consistent with Hypothesis 1, EMRs seem to lead to greater "charge capture" rather than assist in bill inflation.

5.3 Hypotheses 3 and 4: Services and Patient Selection

Table 9 considers Hypothesis 3. The upper panel displays the estimates for base DRGs with two subclasses pre- and post-reform while the lower panel displays estimates for those expanding from two to three subclasses. We find no significant effect of EMR adoption on length of stay or number of procedures except for a slight increase in the number of procedures for medical admissions in the 2-to-2 cases, which is significant at the 10% level. While we cannot identify the baseline effect because we only have one-year data prior to the reform, the

Table 9: EMRs and service provision (Hypothesis 3)

	2 to 2							
	Length of Stay				# Procedures			
	MED		SURG		MED		SURG	
EMR×Post	−3.23	(2.88)	.87	(2.85)	1.03*	(.612)	−.361	(.925)
$EarlyEMR$×Post	3.09	(3.57)	.676	(1.92)	−1.56	(1.23)	2.49**	(.986)
N	105,456		91,932		105,456		91,932	
	2 to 3							
	Length of Stay				# Procedures			
	MED		SURG		MED		SURG	
EMR×Post	−2.07	(1.75)	1.45	(3.03)	.5	(.626)	.42	(1.01)
$EarlyEMR$×Post	1.91	(2.2)	1.93	(3.1)	−.078	(1.15)	.691	(1.21)
N	241,831		265,286		241,831		265,286	

Note: unit of observation is hospital/base DRG/year. Standard errors are clustered at both hospital and base DRG levels. Other regressors are 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 10: EMRs and patient selection (Hypothesis 4)

	2 to 2				
	Distance		# Diagnoses		Mean DRG weight
	MED	SURG	MED	SURG	Overall
EMR×Post	61	−119	−3.11***	1.21	2.17***
	(90.3)	(179)	(1.15)	(2.03)	(.472)
$EarlyEMR$×Post	298	128	2.04	1.13	−.643
	(201)	(150)	(1.68)	(2.55)	(.695)
Observations	105,456	91,932	105,456	91,932	12,562
	2 to 3				
	Distance		# Diagnoses		Mean DRG weight
	MED	SURG	MED	SURG	Overall
EMR×Post	−92.1	−147	−.733	.873	.158
	(84.9)	(114)	(1.08)	(1.8)	(.14)
$EarlyEMR$×Post	157*	91.5	.618	1.31	1.88***
	(82.2)	(135)	(1.52)	(2.13)	(.262)
Observations	241,831	265,286	241,831	265,286	12,671

Unit of observation: hospital/year for last column and hospital/base DRG/year for other columns. Mean DRG weight is calculated using the lowest DRG weight within a base DRG. Standard errors are clustered at both hospital and base DRG levels. Other regressors are 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.

overall lack of significance on the coefficients suggests that this effect may not be significant.

Table 10 considers Hypothesis 4, examining the effect of EMRs on distance from patients to hospitals, the number of diagnoses within a base DRG, and changes in base DRGs. We find no significant evidence of selection of patients traveling further or having more secondary diagnoses.

For the last column, the dependent variable is the mean DRG weight by hospital/year, calculated using the lowest DRG weight for each base DRG. Here, we find a positive and significant effect from EMR adoption on the mean DRG weight following the reform. Thus, EMR hospitals select patients with more severe base DRGs following the reform.

5.4 Economic Magnitudes of Complete Coding

Having established that EMR adoption leads to more complete coding, we now seek to quantify the economic magnitude of this effect. From column 6 of Table 6, early adopters experienced a 1.01 percentage point increase in top-coded medical patients in the post-reform period. On average, there are 3.34 million patients per year with the DRGs considered in our paper, about 1.97 million of whom are medical patients, and about 1.28 million of whom are medical patients admitted to early-adopting hospitals. The average spread of the DRGs on which we focus is 1.19 and the average DRG price is $6,349 for an admission with weight 1. Therefore, the in-sample cost due to the relatively more complete coding from the 2007 reform by early EMR adopters is 1.28 million times $6,349 times 1.19 times 1.01%, which is $97.7 million per year for the U.S.

Our sample accounts for about one fifth of the Medicare inpatient population. Considering the fact that almost 89% of patients are in DRGs with multiple subclasses, we expect that the costs for early adopters would amount to $448 million when extrapolating to all DRGs. Moreover, given that almost all hospitals have adopted EMRs by 2016, when considering the full Medicare sample, the costs of the reform for all 2016 EMR hospitals would amount to $689.6 million per year, which is 0.47 percent of total Medicare hospital claims costs.

Note also that, from Table A2, new EMR adopters in 2010 experienced a 1.17 percentage point increase in top coding in 2010. The similarity between this coefficient and our base coefficient of 1.01 from Table 6 implies that the effect of *EMR adoption* on more complete coding post-reform (1.17) is similar to the effect of *the reform* on more complete coding for EMR hospitals (1.01). This in turn implies that EMR adoption likely did not lead to more complete coding pre-reform, perhaps because coding of secondary diagnoses was simpler then.

Finally, Medicare accounts for about 30% of total spending on hospital care. Many private insurers have DRG-based contracts with hospitals (Gowrisankaran et al., 2014). If all hospitals were reimbursed on a DRG basis, the impact of a change to MS-DRGs on extra charge capture from EMR hospitals would translate into approximately $2.3 billion in annual billed costs. Overall, our takeaway is that the costs of complete coding from EMR adoption are a small but significant fraction of one of the largest sectors of the economy, and hence, still substantial in magnitude.

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 billing practices. In particular, we try to understand whether the application of this technology causes upcoding or increased completeness of coding by lowering hassle costs. Both upcoding and more complete coding lead to higher Medicare reimbursements but have very different policy implications. The recent literature has not reached a consensus on the sources of top coding. Our paper is the first to try to separately identify these two effects. We make use of the 2007 Medicare payment reform, which creates variations in both financial incentives and the hassle costs of coding.

We find that, following the payment reform, EMR hospitals see a larger proportion of patients assigned to higher severity subclasses within a base DRG and that this increase occurs only for medical DRGs. We argue that this reflects a relative drop in the hassle costs of complete coding for medical DRGs following the payment reform. Unlike what has been documented in the media in different contexts, we do not find that hospitals top-code patients more when there is a larger reimbursement increment from top coding. Therefore, we believe that EMR adoption allows for increased information transmittal in the form of more complete coding but does not add to any incentives to inflate bills. We do not find any evidence that hospitals provide different services to patients following the reform. Nor do we detect patient selection within a base DRG by EMR hospitals after the reform. EMR hospitals do select patients with more severe base DRGs in the post-reform period.

Our calculations suggests that the potential cost resulting from extra charge capture at EMR hospitals post-reform amounts to $689.6 million annually in billed costs to Medicare and up to $2.3 billion in annual billed costs in the U.S. as a whole. These results are potentially important for policy makers in understanding the impacts of EMR diffusion and how to maximize their benefits.

Finally, our paper provides general evidence on incentives in the health sector. Our lack of substantiation to the proposition that hospitals are engaged in bill inflation suggests that there is limited ability to reduce Medicare hospital expenditures by eliminating upcoding. We also find no evidence that health information technology is contributing to bill inflation.

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Appendix: For On-Line Publication Only

Figure A1: 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`

Table A1: 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%

Figure A2: Sample Patient Progress Note for Medical Admission

Date/Time: MSIII Progress Note - Medicine *(state which service)*

S: *(Subjective)* Patients noted no n/v *(nausea, vomiting)*, no d/c *(diarrhea, constipation)* this am. +fever with shaking chills x 1 this am. Tolerated po *(oral intake)* well. No complaints of dysuria or abdominal pain. Last BM *(bowel movement)* 2 days ago. Patient continues to cough, productive of greenish-yellow sputum. No wheezing, hemoptysis, orthopnea or PND *(paroxysmal nocturnal dyspnea)*, +SOB *(shortness of breath)*, + pain on R side with deep inspiration. Slept poorly.

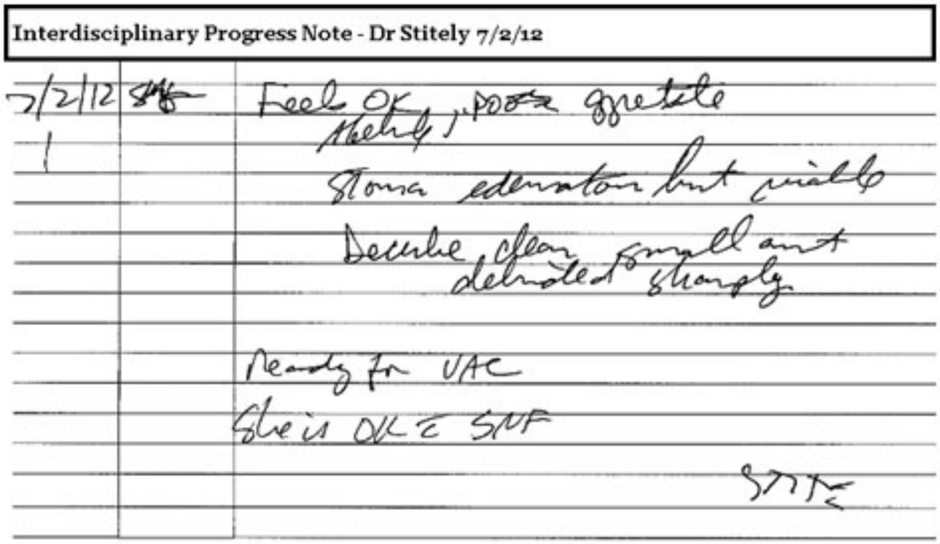
O: *(Objective)*:
PE: *(physical examination)*
VS: *(vital signs)* T: 100.2, Tmax *(maximum temperature)* 102.6, BP 128/82 (115-130/72-84 *(range)*), RR: 20, HR: 98, regular, Pulse Ox 98% on 4L, I/O *(in's and out's)*=1.7/2.2 *(liters)*.
Gen: A+O x 3 *(alert and oriented to person, place, and time)*, flushed, moderate distress. MMM *(mucous membranes moist)*, fair skin turgor; WD/WN *(well-developed/well-nourished)*
HEENT: *(head, ears, eyes, nose, throat -- often combined into one description)*
Head: NC/AT *(normocephalic/atraumatic)*
Eyes: PERRLA *(pupils equal, round, and reactive to light and accommodation)*, EOMI *(extraocular muscles intact)*.
Ears: No erythema, no discharge, tympanic membrane intact.
Throat: No erythema or exudates. Tongue protrudes straight.
Neck: No nuchal rigidity, good ROM *(range of motion)*; No masses/LAD *(lymphadenopathy)*
CV: RRR *(regular rate/rhythm)* S1/S2, no S3 or S4, no m/g/r *(murmurs, gallops, or rubs)*
Pulm: + R lower lobe dullness to percussion; increased tactile fremitis, increase BS *(breath sounds)*, - bronchial BS, + whispered pectoriloquy; +fine crackles R lower third posteriorly. - w/r/r *(wheezes, rubs, or rhonchi)*.
Abd: Soft, NT *(non-tender)* ND *(non-distended)*, +BS *(bowel sounds)*, no rebound, guarding, masses or HSM *(hepatosplenomegaly)*; Heme + *(rectal exam positive for fecal occult blood)*
Ext: no c/c/e *(clubbing, cyanosis, edema)*, 2+ DP/PT *(dorsalis pedis, posterior tibial)*
Neuro: CNI *(cranial nerves intact)*

Labs: None

A: *(Assessment)* 54 y/o white male PMH *(past medical history)* DK +Tob ppd x 20 years, with one day h/o CAP *(community-acquired pneumonia)*.

P: *(Plan)*
1. Pulm: Pneumonia Continue 02 4L, Day I Ceftriaxone I g q12 Codeine prn for pleuritic chest pain, Tylenol prn fever
2. Endocrine: DM Type II Continue Glipizide qd c (*with*) daily accu-checks
3. FEN: *(fluids/electrolytes/nutrition)* Full PO diet/liquids as tolerated. I/0's good, continue D51/2 NS @ 80 cc/hr
4. Dispo: Consult for Smoking Cessation Program

Figure A3: Sample Patient Progress Note for Surgical Admission



Interdisciplinary Progress Note - Dr Stitely 7/2/12

7/2/12 Feels OK, poor appetite

Stoma edematous but viable

Decubitus clean, small amt debrided sharply

Ready for VAC

She is OK c̄ SNF

Figure A4: Sample 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 A5: Sample 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.

Figure A6: Picture of EMR Menu with Diagnoses

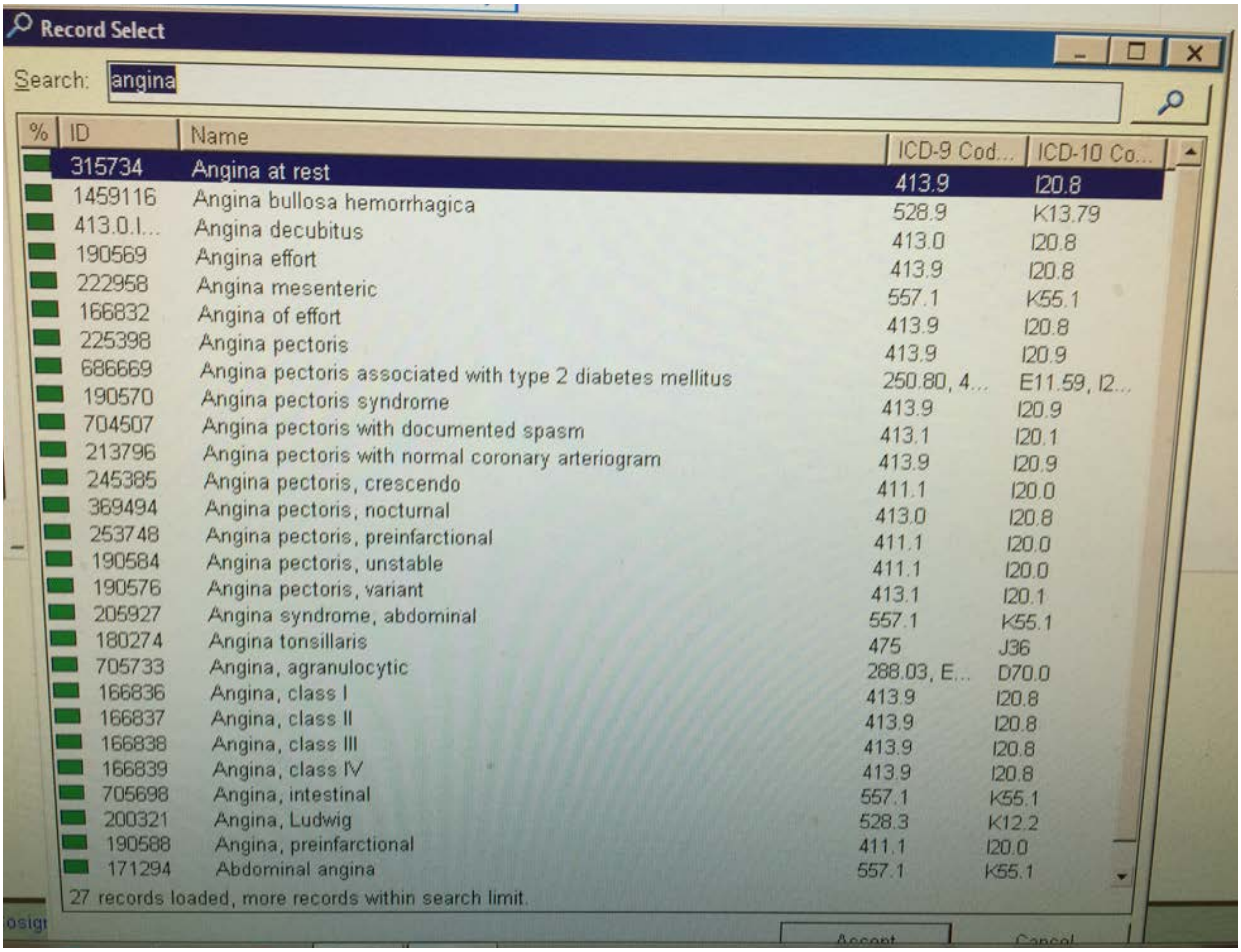


Figure A7: Picture of EMR Menu where Diagnosis is Not Found

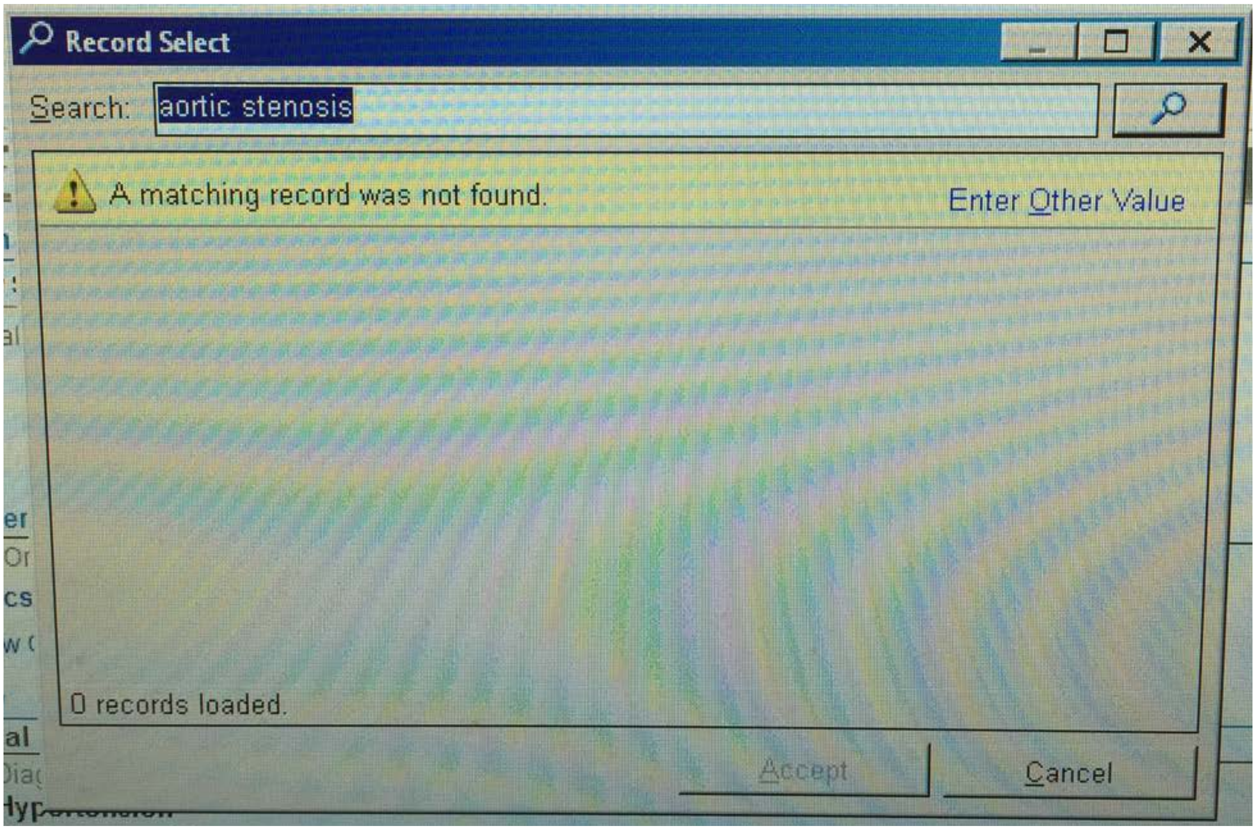


Table A2: Robustness results on complete coding (Hypotheses 1a and 1b)

	Dependent variable: percent top code within a base DRG					
	2 to 2		2 to 3		Combined	
	MED	SURG	MED	SURG	MED	SURG
EMR×Post	−.0946	−.659*	.135	.131	.0903	−.383
	(.285)	(.363)	(.239)	(.293)	(.231)	(.313)
$EarlyEMR$×Post	1.92***	−.243	.834**	−.136	1.06***	−.0265
	(.447)	(.263)	(.371)	(.34)	(.373)	(.332)
EMR×2009	1.71**	.483	.316	.328	.634	−.0153
	(.679)	(.723)	(.514)	(.474)	(.529)	(.47)
$EarlyEMR$×2009	−.266	−.123	−.057	−.0207	−.0994	−.0735
	(.29)	(.353)	(.227)	(.2)	(.198)	(.221)
EMR×2010	1.88***	−.0755	.955	.662	1.17**	−.488
	(.572)	(1.01)	(.611)	(.629)	(.572)	(.615)
$EarlyEMR$×2010	−.168	−.27	−.056	.161	−.071	−.0682
	(.301)	(.331)	(.208)	(.228)	(.198)	(.248)
Observations	105,456	91,932	241,831	265,286	347,287	357,218

Note: unit of observation is hospital/base DRG/year. Standard errors are clustered at both hospital and base DRG levels. Other regressors are 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 A3: Upcoding and financial distress (Hypothesis 2b)

	Dependent variable: Percent top code within a base DRG, 2 to 2			
	MED		SURG	
$Distressed \times$ Post	-1.16^{*}	(.646)	$-.225$	(.427)
$Distressed \times Spread$	$-.0206$	(1.6)	.132	(.374)
$FinHealthy \times$ Post	$-.379$	(.435)	$-.877^{**}$	(.397)
$FinHealthy \times Spread$	1.68^{***}	(.576)	.288	(.305)
$Spread$	36.4^{***}	(12.4)	-19.8^{***}	(4.29)
Observations	102,875		89,820	

Note: unit of observation is hospital/base DRG/year. Standard errors are clustered at both hospital and base DRG levels. Other regressors are 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 A4: Upcoding and for-profit status (Hypothesis 2b)

	Dependent variable: Percent top code within a base DRG, 2 to 2			
	MED		SURG	
$ForProfit \times$Post	$-.514$	(1.55)	.565	(.776)
$ForProfit \times Spread$	$-.45$	(1.68)	.966	(.757)
$NotForProfit \times$Post	.98	(1.01)	$-.55$	(.519)
$NotForProfit \times Spread$	$-.128$	(1.14)	-1.2^{**}	(.485)
$Spread$	36.9^{***}	(13.4)	-19^{***}	(4.32)
Observations	105,456		91,932	

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