Cracking the Codes: Do Electronic Medical Records Facilitate Hospital Revenue Enhancement?

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Abstract

Electronic Medical Records (EMR) have great potential to improve the efficiency and effectiveness of patient care delivery. However, the use of EMR could enable hospitals to engage in "revenue-enhancing practice" such as upcoding, thereby raising health care expenditures and potentially jeopardizing quality. This study uses a longitudinal multi-state patient discharge dataset to examine the effect of EMR adoption on medical coding and billing in inpatient settings. I find that the fraction of patients who are assigned to higher-paying DRGs increases significantly after EMR adoption. I estimate that this type of billing change alone increases the reimbursement for inpatient services by $1.3 billion annually. The effect of EMR on coding and billing is particularly strong among for-profit hospitals, financially distressed hospitals, Medicare patients, and billing codes where upcoding potential was previously less exploited. Hospitals document more diagnoses but do not perform more procedures. These findings together reveal that hospitals are sophisticated in their use of EMR as a tool to boost revenue.

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1 Introduction

Electronic Medical Records (EMR) are promising in increasing health care efficiency and improving quality. The HITECH Act introduced in 2009 mandated a gradual shift to EMR in the healthcare industry and marked an unprecedented investment of $20 billion in health IT by the federal government, in the hope that adopting EMR will help providers reduce duplicate medical tests, improve care coordination, and eventually reduce costs and improve quality. In reality, however, there is a lack of consistent evidence that EMR actually delivers the expected benefits. Instead, increasing concerns have emerged that adopting EMR is likely to make it easier for providers to switch patients to higher-paying billing codes, thereby potentially contributing to rising health expenditures and jeopardizing quality of care. In this paper, I use multistate patient discharge data to examine the effect of EMR adoption on hospitals' revenue-enhancing behavior.

In September 2012, a *New York Times* front-page article documented multiple cases of sharp rises in the highest-paying claims after providers adopted EMR and detailed the ways in which EMR use might be contributing to a rise in Medicare billing (Abelson et al., 2012). A *Washington Post* article discussed the fact that EMR vendors explicitly advertise that their products will help providers fuel the level of billing codes: "one electronic medical records company predicts on its web site that its product will result in an increase of one coding level for each patient visit"(Schulte et al., 2012). Providers responded to such accusations of "upcoding" by claiming that previously they had been "undercoding" and that the increase in the number of patients in higher-paying billing codes simply reflects a general change in practice, which has lead to better documentation of what was previously done but not recorded. These debates have also received substantial attention from the government. In September 2012, the Obama Administration warned US hospitals that there were "troubling indications" of abuse in the way hospitals use electronic records to bill for Medicare and Medicaid reimbursement(US Department of Health and Human Services & US Department of Justice, 2012). Despite all the debates and concerns, there is no systematic research linking EMR use to hospitals' revenue-enhancing practices or estimating the magnitude of the effect.

Inflated billing codes have an extensive impact on various aspects of the healthcare industry. First, it leads to a boost in medical payments that may not be justified by clinical benefits. Second, if payers realize that more healthy patients are assigned with higher-paying billing codes and decide to recalibrate reimbursement amount, providers that do not engage in such revenue-enhancing behavior would be financially punished. Third, it also undermines the reliability of quality measures. Quality measures are risk adjusted, hence a false increase in case-mix indices would lead to a false improvement in quality measures. This is especially concerning when different hospitals inflate their billings differently. Fourth, fraudulent upcoding could destroy data integrity and compromise the quality of care in the long run. Unlike previous upcoding studies (Coulam and Gaumer, 1991; Bowblis and Brunt, 2013; Brunt, 2011; Dafny, 2005), which examine changes in the the benefits of upcoding in a certain subpopulation of patients, EMR adoption reduces the cost of upcoding and could potentially affect care provision among all patient populations and settings.

This study assembles patient discharge data from six states (AZ, CA, CO, MA, NJ, and WA) from 1998 to 2010, along with information on hospitals' EMR adoption as well as hospital and patient characteristics over the same period. I measure the extent of hospitals' revenue-enhancing practice using *fraction*, the share of patients who are assigned the higher-paying code within each DRG pair; the two codes within each pair share the same primary diagnosis but differ in the presence of complications (e.g., diabetes with complications and diabetes without complications). Figure 1 shows the trend of this measure in the raw data. I regress *fraction* on dummy variables indicating the years relative to the adoption year without any controls and plot the coefficients. The figure shows that there is a general upward trend in *fraction*, which is consistent with the phenomenon of "DRG creep"[1] documented in literature, but the slope is steeper after EMR adoption, indicating that EMR adoption facilitates such revenue enhancement.

My main analysis regresses *fraction* on EMR adoption, controlling for a rich set of hospital and patient characteristics, as well as hospital, DRG-pair and year fixed effects, to examine whether the adoption of EMR systems leads to a higher level of revenue-enhancing practice in hospitals. The key identification assumption is that EMR adoption is uncorrelated with any time-varying unobservable factors that are correlated with the fraction of patients assigned the higher-paying DRGs within each pair. I further explore the heterogeneity in the effect of EMR across different types of hospitals, patient populations, and billing codes. I also examine changes in diagnosis codes and treatment intensity to show what exactly hospitals do to generate additional reimbursements.

I find that hospitals are more likely to assign patients higher-paying billing codes after adopting EMR. The adoption of EMR is associated with a 1.1 percentage point increase in the fraction of patients assigned the higher-paying DRGs. This can be translated into an annual increase of $1.3 billion in the reimbursement for inpatient care alone. The adoption of EMR does not have the largest effect right away but an increasing effect over at least three years after the adoption year. This is consistent with findings in Dranove et al. (2013), which shows that there is a delay in the expected effect of EMR due to the complementary inventions

[1]This term refers to the phenomenon that patients are increasingly coded into DRGs with higher weights over the past few decades

needed to make new IT more productive in specific settings.

I also find substantial heterogeneity in such effect of EMR on hospital billing. Consistent with previous studies (Dafny, 2005; Silverman and Skinner, 2004), I find that the effect of EMR adoption is larger in for-profit hospitals and financially distressed hospitals, which are likely to place more weight on financial returns or be more willing to risk detection. In addition, the effect is more prominent among Medicare patients, where the monitoring of coding is likely to be less compared with private payers.

In addition, I also find heterogeneity across DRG codes with different financial incentives for upcoding. In contrast to previous evidence (Dafny, 2005), I find that EMR adoption has less of an effect on DRG pairs with larger financial incentives to upcode. The fraction of patients in the higher-paying DRG codes has been constantly rising over the past three decades, yet the potential for upcoding is not infinite. The larger the financial incentives for upcoding are, the higher the pre-adoption coding level is and the smaller the additional boost due to EMR adoption is likely to be. This phenomenon is consistent with the *ceiling effect*—providers seem to exploit more of the upcoding potential where the financial return is larger even without EMR. Since upcoding is increasingly costly, there is not as much potential for further revenue-enhancing behavior compared with the codes that started at a lower level before EMR adoption.

By running the same model using the measures of documented diagnosis and treatment intensity as dependent variables, I find that hospitals document more diagnoses after adopting EMR but do not perform more procedures. This is consistent with the hospitals' incentive under the DRG payment system, which pays more for sicker patients but not for performing more procedures.

This study has important policy implications. Policy makers, researchers, and health professionals have been debating whether EMR can indeed improve quality or reduce costs. My findings provide a potential explanation for why we often do not see the expected benefits of EMR in practice. The evidence of providers actively using EMR as a tool to boost billing suggests an urgent need of increasing the level of monitoring and audits at the payer side, as well as the need of properly regulating the way vendors design their EMR products. In addition, the heterogeneity in such effects of EMR across hospital types, patient types and DRG pairs also provides extra information regarding the particular areas that audits should target.

The paper also contributes to the stream of literature about upcoding. Since the introduction of the PPS system in 1984 and the major adjustment in the DRG rules in 1988, it is fairly rare to have a shock, that could potentially change providers' coding behavior. Adopting EMR is not simply picking up a new piece of technology; it is an enterprise-wide adjustment of practice, including coding and billing. In addition, most previous studies focus on upcoding behavior incentivized by increasing financial benefits—largely involving the reimbursement rules in certain DRG codes—while this paper looks at providers' responses to changes in the *cost* of upcoding. Lastly, this study documents evidence consistent with "ceiling effects", which has not been observed in previous studies.

The rest of the paper proceeds as follows: Section 2 describes the institutional setting for EMR and upcoding. Section 3 presents a conceptual framework for how EMR may effect upcoding and how this effect could be heterogeneous across different settings. Section 4 introduces the data sets that I use and defines key measures. Section 5 discusses the empirical strategy and results. Section 6 presents the results of robustness check. Section 7 discusses the policy implications and concludes.

2 Background

2.1 EMR use in US hospitals

EMR are not a specific type of software but a catchall expression used to characterize a collection of information technologies used by hospitals to keep track of utilization, costs, outcomes, and billing. Various software applications (or modules) are integrated into an enterprise-wide EMR system, and some of these applications perform overlapping tasks. The following are the major EMR applications: *Clinical Decision Support (CDS)* integrates patient data, pre-established rules, and clinical guidelines to generate diagnostic and treatment advice; *Clinical Data Repository (CDR)* is a centralized database that integrates disparate information about patients, such as clinical, financial, and administrative data from various applications across the organization, into one single file; *Order Entry* replace faxes and paper forms with electronic documents to streamline hospital operations; *Computerized Provider Order Entry (CPOE)* involves realtime electronic entry of physician treatment orders that can be communicated to the pharmacy, lab, and other departments, and it also provides error checking for duplicate or incorrect doses or tests; *Physician Documentation (PD)* provides structured templates to help physicians generate meaningful documentation and valid diagnostic codes. Together, these EMR applications collect, organize and report patients' diagnostic information, test results, services, and medications and are often linked to administrative data such as demographics and insurance information.

Most hospitals purchase EMR systems from a range of commercial vendors. For inpatient EMR, there are around ten major vendors who together represent more than 90% of the national market, and they all offer the major EMR applications mentioned above. Hospitals can purchase individual applications from different vendors or adopt a whole suite of applications from the same vendor. There are large variations in prices depending on bed size, functionality, vendor, and negotiation, ranging from hundreds of thousands to tens of millions of dollars. Hospitals pay an upfront fee as well as an additional one-seventh to one- fifth annually as a maintenance fee. After purchasing the system, hospitals need to work together with the vendor and/or hire external consultants to configure it based on their own needs and integrate it in their legacy IT systems by building interfaces. EMR systems of different hospitals are not interoperable unless special interfaces are built or both sides are using particular software such as Care Everywhere from Epic; in general, however, such a scenario is still relatively rare especially for unaffiliated hospitals.

If implemented under ideal conditions and executed according to the highest standards, EMR can lead to lower personnel costs, higher diagnosis accuracy, fewer unnecessary and duplicate tests, and superior outcomes with fewer costly complications. There is a general belief that health information technology has the potential to create a more-efficient, safer, and higher-quality care system. This belief is also reflected in the Health Information Technology for Economic and Clinical Health Act (HITECH Act) passed in 2009, which committed an unprecedented $20 billion to promote the adoption and use of health information technology (HIT) and especially electronic health records (Blumenthal, 2009).

However, the use of IT in the US health care industry has lagged far behind other industries (Jha et al., 2009). There are many reasons for this: Physicians, as the most important end users, resist the adoption of EHR technologies because they are perceived as a potential threat to their professional autonomy (Walter and Lopez, 2008). From the product side, most EMR products are poorly designed and not user-friendly. But of all the reasons, one of the most significant ones is the lack of consistent evidence that EMR could actually generate sufficient benefits, such as lower costs or higher quality, to warrant such a significant investment by providers. Since HITECH, the adoption rate has climbed but the debate on whether EMR are worth the money and why we often do not see the promised benefits has not relented.

There are many studies trying to evaluate the effect of EMR over the past two decades. A lot of them are based on case studies of individual institutions, certain subpopulations, of patients or cross-sectional data (Bates et al., 1999; Javitt et al., 2008; Himmelstein et al., 2010). A few more-recent studies use longitudinal data at the national level in trying to establish a causal relationship between EMR adoption and potential effects. Agha (2012) uses Medicare claims data to examine the effect of EMR adoption on costs and quality of care. She finds that adopting HIT is associated with an initial 1.3% increase in billed charges and there is no evidence of cost savings afterwards; furthermore, HIT has little impact on the quality of care. McCullough et al. (2013) go one step further and show heterogeneity in the effects of EMR by focusing on technological and organizational complements that affect EMR's value. They find that the benefits of EMR are mainly experienced by patients whose diagnoses require cross-specialty care coordination and extensive clinical-information management. Dranove et al. (2013) stress the need to adapt enterprise IT to local circumstances in order to realize costsavings. They show that there is a lag in the expected benefits of EMR due to coinvention activities. EMR adoption eventually leads to savings in hospitals' operation costs if the adopters already have access to complementary assets, but there is a delay of three years before the cost savings are realized.

These studies investigating how the adoption of EMR affects care quality and costs have largely focused on mechanisms such as (1) quality improvements through enabling informed medical decision making and facilitating provider-provider communication, and (2) cost savings through eliminating duplicate tests and improving efficiency. None of the existing studies, however, has taken into account potential detrimental effects introduced by EMR adoption as a result of EMR-induced "upcoding". The work reported in my paper fills this critical gap by studying how hospitals' new coding behavior in the EMR era might increase costs and jeopardize care quality. In addition, both Agha (2012) and McCullough et al. (2013) only focus on the Medicare population, while the dataset I use allows for a more comprehensive examination of both Medicare and non-Medicare populations. Heterogeneity among these subpopulations reveals additional information about the level of sophistication in hospitals' revenue-enhancing behavior.

2.2 How do EMR facilitate hospital revenue enhancement?

The adoption of EMR comes with many changes in practice that could potentially boost billing. Some of them are brought on by the technology itself. For example, like other digitization technology, EMR lowers the costs of documentation and easily generates more-complete medical records. Physicians and nurses no longer need to write down patients' medical records word by word. Instead, with a slew of "time-saving" tricks introduced by EMR, such as generic pick lists, preloaded macro, and autofill, providers can generate comprehensive medical records with a few clicks. For instance, doctors used to have to fill out a checklist for every step in a physical exam. Now, they can click one button that automatically places a comprehensive normal physical exam in the record. Another click brings up a normal review of systems — the series of screening questions to ask patients about anything from nasal congestion to constipation. Sometimes the automatically populated fields are not clinically relevant, have not typically been billed in the past, or even contain obvious mistakes. For example, audits have shown that the use of some preloaded macros for the physical examination created automatic documentation indicating that females had received prostate exams and males had had negative pap smears (Thurston et al., 2009). Many EMR systems combine the documentation and coding processes into one, making such errors more difficult to detect. Together, these changes result in a tendency of more documentation, and inflated documentation often triggers a higher level of billing codes.

At the same time, EMR may also lead to more procedures performed. EMR often has clinical protocols built into the system. If physicians do not pay enough attention to uncheck all unrelevant boxes, the system will automatically order a battery of tests. Some of them are preventive care, recommended by clinical guidelines, and may have long-term benefits, but others may not be clinically necessary.

In addition to the changes due to the nature of the technology itself, there are also ways in which hospitals can use EMR to strategically game the system by switching patients to higher-paying billing codes.

(1) Computerized algorithms monitoring physicians' coding behavior and suggesting higher levels of coding to them: In the pre-EMR era, physicians enter medical documentation, and coders then turn the text-based documentation into corresponding billing codes for reimbursement from insurers. Physicians usually were not clear about what document is needed in order to justify certain codes. After purchasing a commercially sold EMR, hospitals can configure the system based on their individual needs. Computerized algorithms can be built into the system to monitor physicians' coding behavior. Via prompts and alerts, it produces "recommendations" for additional items to record in order to trigger higher-paying billing codes. In a whistle-blower lawsuit filed in 2007, a doctor contended that a new EMR system rolled out in his hospital in 2006 prompted doctors to click a box that indicated that a thorough review of patients symptoms had taken place, even though the exams were rarely performed (Abelson et al., 2012).

(2) "Cloning" is a term referring to the behavior of copying and pasting information from previous encounters or other patients' records. The use of the copy-and-paste functionality is not necessarily noncompliant or fraudulent, but there are substantial concerns and preliminary evidence that physicians may be using cloned notes to inflate their medical claims by copying documentation that is corresponding to a higher billing code than necessary from one visit to the next, or repeating a service that was provided during an initial visit but not during the subsequent consult Abelson and Creswell (2014). As discussed in an article by Hartzband and Groopman (2008) in the *New England Journal of Medicine*, "many times, physicians have clearly cut and pasted large blocks of text, or even complete notes, from other physicians;" According to a testimony by the American Health Information Management Association (AHIMA), "some EHR systems are designed to facilitate cloning with options such as 'make me the author' to assume the content of another person's entry or 'demo recall' to copy and forward vital signs."

2.3 DRG upcoding and the previous literature

The federal government implemented the Prospective Payment System (PPS) in 1984. Before that, hospitals were paid based on their actual costs of providing care by submitting a "cost report," which itemized expenditures incurred in the previous fiscal year. Under this payment system, Medicare's health expenditure increased dramatically. Mandating PPS was a solution introduced in order to control costs. Under PPS, inpatient admission cases are divided into relatively homogeneous categories called diagnosis-related groups (DRGs) and hospitals receive a flat rate per case for inpatient care. The reimbursement amount a hospital can receive for a DRG depends on multiple factors, including the hospital's teaching status, the share of indigent patients, and DRG weights, but most of the variation in that amount is due to DRG weights. DRG weights, which range from 0.0987 (DRG 448 for allergic reactions) to 19.8 (DRG 541 for ECMO or Tracheotomy),[2] reflect the average intensity of resources needed to treat the group of patients in that category. The Health Care Financing Administration (HCFA) uses hospital cost data to recalibrate the weights every year, increasing weights of the DRGs experiencing a relative increase in average costs. Under this system, hospitals are rewarded based on their efficiency relative to the national average. The PPS system soon revealed its own problem, a phenomenon called "DRG creep," i.e. hospitals increasingly assigning patients higher-paying DRG codes.

In reality, there are mainly two ways to detect upcoding behavior. One is to audit medical records, which is time and resource intensive. The other is to compare the case mix across hospitals and over time. Most of these studies are descriptive. A review by Coulam and Gaumer (1991) summarizes the literature about upcoding during the first few years following the implementation of PPS and concludes that there is evidence of upcoding and DRG creep. A frequently cited study that finds evidence of a causal relationship between the reimbursement amount and upcoding is by Dafny (2005). She uses Medicare claims data and a natural experiment to examine hospitals' responses to a policy reform that led to large changes in prices of DRG pairs in 1988. She finds that hospitals responded the prices changes primarily by "upcoding" patients to diagnosis codes with the largest price increases. This response was particularly strong among for-profit hospitals. Silverman and Skinner (2004) find evidence of upcoding for patients with pneumonia and respiratory infections. Both studies find that the upcoding phenomenon is more prominent at for-profit hospitals than nonprofit hospitals. Similar upcoding effects are also examined in other settings such as nursing homes and outpatient visits (Brunt, 2011; Bowblis and Brunt, 2013). All of these studies examine providers' responses to increased benefits of upcoding, while in my study, EMR mainly changes the cost

[2]The DRG range is from year 2005.

of upcoding.

3 Conceptual Framework and Hypotheses

When deciding whether to assign a patient higher-paying billing codes, providers put different weights to added profits, the costs of making additional documentation to justify the code, the increased risk of being challenged by the payer, as well as ethical discomfort. The adoption of EMR significantly decreases the cost of documentation and in particular, the cost of searching for the "right" item to document, therefore shifting providers' optimal behavior towards assigning more patients higher-paying codes. At the same time, new processes take time to adapt, and to the extent that revenue enhancement using EMR is a new process, there could be a delay in the effect of EMR due to the complementary inventions needed to make new IT more productive in specific settings (Dranove et al., 2013). Therefore, the effect is likely to increase after adoption, rather than being instantaneous.

Hypothesis 1: Providers are more likely to assign patients higher-paying billing codes after adopting EMR. This effect is increasing over several years after adoption.

If such revenue-enhancing practices are partially attributable to the hospitals' strategic behavior of using EMR as a tool to receive more reimbursement from payers, there should be heterogeneity among different types of hospitals and patient populations.

For-profit and nonprofit hospitals have different objective functions (see, for example, Dranove (1988)). For-profit hospitals are more likely to engage in such revenue-enhancing practice after EMR adoption due to: 1) for-profit hospitals put more weights on profit than on quality, and/or 2) for-profit hospitals are better at utilizing technology to capture billable items to maximize the reimbursement amount. At the same time, financially distressed hospitals should be more willing to take the risk of being detected in order to boost revenue or improve risk-adjusted quality measures, which could be helpful for attracting patients.

Hypothesis 2: EMR adoption has a larger effect on the billing of for-profit hospitals than nonprofit hospitals.

Hypothesis 3: EMR adoption has a larger effect on the billing of financially distressed hospitals

There is also likely to be heterogeneity in such affect across patient populations. In particular, there are at least two reasons that hospitals are likely to exploit more of the revenue-enhancement potential among the Medicare population: (1) there is in general less auditing and monitoring by public payers than private payers, (2) DRG is the reimbursement system that has primarily been used by Medicare for almost 30 years. The built-in automatic code-generating system of many EMR systems is likely to be the most sophisticated in helping hospitals optimize billing codes for DRG payment systems. Nevertheless, a weaker but nonzero effect should still exist among the non-Medicare population. Many potential mechanisms of EMR leading to inflated billing codes, such as "cloning," have nothing to do with the particular reimbursement rules used, but they allow providers to jack up the overall level of diagnosis codes and/or procedure codes.

Hypothesis 4: The effect of EMR exists in both Medicare and non-Medicare populations, but it is stronger for the Medicare population.

The effect of EMR could also be heterogeneous across different DRG pairs. On the one hand, the larger the difference in the reimbursement amount of the top and bottom code is, the larger the financial incentive of upcoding is, and therefore patients are more likely to be upcoded. On the other hand, however, since providers have been engaging in such revenue-enhancing behavior even before EMR adoption and the upcoding potential is more likely to be exploited first in more profitable areas, the additional effect on billing due to EMR adoption is likely to be less. Put another way, the adoption of EMR allows providers to exploit the potential of revenue enhancement in the area where they did not exploit before.

Hypothesis 5: The effect of EMR is larger in DRG pairs where the financial incentive of upcoding is less.

In the inpatient setting, hospitals' reimbursement is based on the DRG system, which pays a flat rate for each hospital stay according to the DRG code assigned to the patient. Hospitals have incentives to encourage physicians to document more diagnoses hoping that could trigger higher-paying billing codes, while within a certain DRG code, there is no incentive to perform more procedures, as it will not generate additional revenue.

Hypothesis 6: Hospitals document more diagnosis codes after adopting EMR but do not increase treatment intensity.

4 Data and Measures

This study draws on data from a variety of sources: the patient discharge data are from the Healthcare Cost and Utilization Project (HCUP) State Inpatient Data (SID) of six states (AZ, CA, CO, MD, NJ and WA) from 1998 to 2010. The data cover annual inpatient discharge abstracts of all hospitals in these states regardless of insurance payers and contain patient demographics, diagnosis and procedure codes, hospital identifiers, and payer types. EMR adoption information is from the Healthcare Information and Management Systems Society (HIMSS) Analytics Dataset, which reports the current status and implementation history of health IT for more than 5300 healthcare providers nationwide. Hospital characteristics and financial information are from the Annual Survey of Hospitals from American Hospital Association (AHA) and Healthcare Cost Report Information System (HCRIS) data from the Center for Medicare and Medicaid Services (CMS). I also obtain yearly DRG weights from the *Federal Register*.

Dependent variable: Measure of hospital billing level. The primary dependent variable in my main model is the *fraction* of patients who are assigned the higher-paying code within each DRG pair. DRG represents inpatient classifications on the basis of diagnosis code, procedure code, and a set of patient characteristics. About 40% of DRG codes belong to a "pair" of codes that share the same primary diagnosis but are distinguished by the presence of complications (CC). For example, DRG 79 and 80 form a pair, where 79 is "major respiratory infections and inflammations with complications" and 80 is "major respiratory infections and inflammations without complications." In the HCUP data that I use, there are approximately 550 DRGs during the sample period,[3] and 232 of them are in pairs (116 pairs). Each DRG is assigned a weight that reflects the relative resource intensity of admissions within that group and is the main factor that determines the amount of reimbursement that hospitals can receive. The weight of the top code (with CC) in each pair always exceeds that of the bottom code. Therefore, conditional on the same primary diagnosis, providers have incentives to switch patients into higher-paying DRGs in order to receive a higher reimbursement. The *fraction* of patients in the top code represents the level of hospitals' revenue-enhancing practice. To generate the percentage of patients who are assigned the top DRG, I collapse patient-level discharge data to the hospital-year DRG-pair level.

Figure 2 shows the trend of average weights of the top and bottom codes within DRG pairs, weighted by the number of discharges in my dataset. If more and more patients who should be in the bottom code are switched to the top code, the difference between the health expenditure of the two groups should become smaller, and the DRG weights, which are calculated based on aggregated expenditure nationally, should follow the same trend with a lag. The graph indicates that the average weights of the top codes and bottom codes seem to be converging over time, which from a different perspective suggests there is upcoding taking place.

I explore the mechanism of hospitals' revenue-enhancing practices using changes in diagnosis codes and treatment intensity. The HCUP data include ICD-9-CM diagnosis and procedure codes. These are the standard codes used in inpatient care to document the diag-

[3] There were major changes in the DRG system in 2008. A main adjustment was resequencing the groups by replacing the "with-CC" and "without-CC" pair with a trifurcated design—"without CC", "with CC", and "with major CC"—so the total number of DRG codes rose to 700+. However, the HCUP data I use in this study still include the DRG codes calculated based on the old rule until year 2010, which gives a consistent DRG grouping rule over my whole sample period. As a robustness check, I run the same test using only pre-2007 data.

noses of patients and procedures performed. After patients are discharged, they are converted into corresponding billing codes for reimbursement. There are about 10,000 different diagnosis codes and 3,500 procedure codes. For each patient, a primary diagnosis and a primary procedure (if relevant) are recorded. HCUP also allows up to 29 additional diagnosis codes and 29 procedure codes depending on the state and year[4]. In particular, I use the share of patients for whom 2 plus, 3 plus, 4 plus, or 5 plus diagnosis codes are recorded to examine whether hospitals document more patient conditions after EMR adoption. The measure of treatment intensity include (1) the share of patients with 1 plus, 2 plus, or 3 plus procedures, and (2) the total charges, which is not the amount that patients actually pay, but is correlated with how much work the hospital has done on the patient. As a robustness check, I also measure treatment intensity using the average number of four common procedures per patient.

Key independent variable: EMR adoption. I obtain EMR adoption data from the 2012 release of Healthcare Information and Management Systems Society (HIMSS) Analytics. Previous releases of HIMSS data have been used in various studies about the diffusion and effect of EMR (Fonkych and Taylor, 2005; Hillestad et al., 2005; Miller and Tucker, 2009, 2010; Dranove et al., 2013). The HIMSS survey approximates a comprehensive sample of US hospitals and reports the current status and implementation history of 103 different technologies in 17 categories, such as Ambulatory, Laboratory, Nursing, and Radiology. I focus on the applications in the category Electronic Medical Record. Similarly to Dranove et al. (2013), I aggregate these applications into two broad categories: *basic* EMR—having either a clinical data repository, clinical decision support system (CDS), or order communication and result reports; and *advanced* EMR—having either computerized practitioner order entry (CPOE) or physician documentation. Applications within each of these categories involve similar costs of adoption. Advanced EMR are in general more difficult to implement and operate than basic EMR, because its proper functioning requires a relatively high level of enterprise-wide integration of different IT elements, including *basic* EMR applications. *Advanced* EMR also requires greater physician training as well as involvement.

Hospitals may adopt all applications together or adopt individual applications at different times, but they all have some basic EMR applications before or at the time they adopt advanced applications. Table 1 shows the adoption rate of each application in the baseline year and final year over the sample period. There are significant increases in adoption rates of all technologies. By the end of 2010, around 89.6% of hospitals have adopted one or more basic EMR systems, and more than 61.4% have adopted some advanced EMR applications.

Other control variables. HCUP data also include patients' basic demographic information such as age and gender. For additional controls on hospital characteristics and financial

[4]The number of diagnosis codes and procedures that are allowed to record varies by states and year.

information, I merge HCUP data and HIMSS data to the Annual Survey of Hospitals by the American Hospital Association (AHA) and hospital cost reports from the Center for Medicare and Medicaid Services (CMS) based on AHA IDs and Medicare IDs. The sample is also matched to DRG weights from the *Federal Register*.

Other measures. I use the debt:asset ratio before the adoption year to measure the level of financial distress. The debt:asset ratio is calculated using the current liability and current assets from hospitals' cost reports. Following Dafny (2005), I define a hospital as financially distressed if its debt:asset ratio is above the 75th percentile and not financially distressed if it is below the 25th percentile. The Medicare population is identified based on the payer information in the HCUP data. The hospitals' profit status is from AHA data.

Sample generation. The primary sample I use consists of all patients who are assigned to one of the 232 DRG codes that are in pairs. In the HCUP data I use, there are 29,954,649 discharge records that belong to the 232 paired DRG codes (116 pairs). After dropping those with a missing hospital ID (0.5%), the patient discharge data are collapsed to 672,361 observations at hopsital-year-DRG pair level, so each observation represents the group of patients assigned either code of a DRG pair in a given hospital-year. 523,966 observations are matched with HIMSS data and AHA data. I further exclude one hospital that adopts the advanced EMR before basic EMR (881 observations), and 1 federal hospital (225 observations). The final sample consists of around 435,297 observations with 116 DRG pairs (232 DRG codes) from more than 522 hospitals in six states from year 1998 to 2010. Table 2 shows the summary statistics of the key variables and Table 3 lists the number of hospitals by year and state in the final sample.

A small subset of observations have missing values for the adoption status of certain applications, so the samples in regressions for basic and advanced EMR applications are slightly different. When examining the role of upcoding benefits in the effect of EMR on *fraction*, I only include observations before year 2008 due to the fact that there is a major adjustment in DRG rules, and weights under the new system are no longer comparable to old weights.

5 Empirical Strategy and Results

I examine the effect of EMR adoption on hospital billing using a linear model controlling for DRG-pair fixed effects, hospital fixed effects, year fixed effects, and patient and hospital characteristics in an unbalanced panel of hospitals in the six states observed annually from 1998 to 2010. I proceed in three steps: First, I examine the overall effect of EMR adoption on the *fraction* of patients that are assigned the top code in each DRG pair. I also show the trend in the effect over time. Second, I examine heterogeneity in the effect of EMR among different types of hospitals, patient populations, and DRG pairs. Third, I explore whether providers increase the billing level via documenting more diagnoses or performing more procedures.

5.1 Overall effects of EMR adoption on revenue enhancement

I begin by examining the overall effect of adopting EMR on the *fraction* of patients in the top DRG code. Equation 5.1 shows the main specification I use:

$$fraction_{h,t,p} = \alpha + \beta EMR_{h,t} + \gamma \mathbb{X}_{h,t,p} + \theta \mathbb{Z}_{h,t} + \mu_t + \mu_h + \mu_p + \epsilon_{h,t,p}. \tag{5.1}$$

The unit of observation is the hospital-year-DRG pair. Here, h indexes hospitals, t indexes years, and p indexes DRG pairs. The dependent variable *fraction* is the share of admissions to DRG pair p in hospital h and year t assigned to the top code in that pair. $EMR_{h,t}$ is a dummy which equals 1 if hospital h has adopted EMR by year t and equals 0 otherwise. μ_t, μ_h, and μ_p are year, hospital and DRG fixed effects, which are differenced out in the estimation. I assume that $\epsilon_{h,t,p}$ is a normal i.i.d. variable and calculate heteroskedasticity-robust standard errors clustered by hospital. The primary coefficient of interest is β, which captures the marginal effect of EMR adoption on hospitals' revenue-enhancing practice. $\beta > 0$ signifies that hospitals increase their revenue-enhancing practice after adopting EMR and the magnitude is the percentage point change in $fraction$ that is associated with the adoption.

I include two sets of controls: First, $\mathbb{X}_{h,t,p}$ is a vector of controls for the characteristics of patients in DRG pair p, hospital h and year t: age and gender. Older patients are in general sicker and thus more likely to be assigned the top DRG code. A similar difference exist between men and women. The second set of controls, $\mathbb{Z}_{h,t}$, includes hospital characteristics, which include the number of beds, outpatient visits, inpatient admissions, full-time physicians, the percentage of Medicare discharges and Medicaid discharges, whether the hospital is a for-profit, nonprofit or government hospital, a teaching hospital, and a resident hospital. Since I control for hospital fixed effects in the model and many of these variables do not vary sufficiently over time, they will drop out if I use contemporaneous values. I also worry that EMR adoption may drive changes in these characteristics. Therefore, similarly to Dranove et al. (2013), I use their value in the baseline year and interact them with a linear time trend. However, results are not affected if these are replaced with contemporaneous values. In addition, I control for hospital fixed effects, DRG fixed effects, and year fixed effects in order to control for time-invariant unobservable heterogeneity in these dimensions. There is substantial heterogeneity in patient composition across different diagnoses since some conditions are more likely to have complications than others. There is also heterogeneity across hospitals due to reasons such as variations in physicians' practice across regions, variations in patient profiles (e.g., tertiary hospitals or trauma centers treat patients who are sicker than those seen at other hospitals), or variation in access to resources (e.g., some hospitals have resources to hiring professional coders to optimize their coding and maximize revenue, while others do not). *Fraction* could also vary across years due to the fluctuation in patient characteristics as well as financially induced changes in coding behavior due to annual adjustment in DRG weights (Dafny, 2005). Controlling for various fixed effects allows me to account for various unobservable heterogeneity.

This identification relies on the assumption that any systematic change in the fraction of patients who are assigned the top DRG code after EMR adoption is captured by hospital-level, DRG-pair-level and year-dummy controls, so any time-variant unobservable factors that affect *fraction* are uncorrelated with EMR adoption.

Table 4 shows the results of applying model 5.1 to the full sample. Columns (1) to (3) use each of the three EMR applications which together I label "basic EMR." Columns (4) to (5) use the two "advanced EMR" applications. The purpose of the first five columns is to show that the basic EMR applications all have similar effects and the same is true for advanced EMR applications. Therefore, it is logical to aggregate them into one measure for "basic EMR" and one measure for "advanced EMR," respectively.

The results suggest that adopting each individual EMR application is all associated with a significant increase in the fraction of patients coded as "with complications." The effects of applications in the same category are similar in magnitude. Clinical Decision Support (CDS) has the biggest and most significant effect, while Clinical Data Repository CDR has the smallest effect. This is expected because CDS is the application that directly assists physicians with decision making by providing treatment suggestions and reminders about patients' medical history; hence, it is more likely to directly facilitate revenue-enhancing coding behavior, while CDR, which is a data repository that stores patients' information in the background, is expected to have a smaller effect. The effect of Order Entry is somewhere in between. In general, the effects of adopting the three basic EMR applications are similar. The coefficients of advanced EMR, CPOE and physician documentation are both smaller in magnitude and less significant.[5],[6]

In column (6), I include two dummy variables—one is "basic EMR only," which equals one if the hospital has at least one basic EMR application but no advanced EMR, and the other is "advanced EMR," which equals one if the hospital has at least one advanced EMR

[5]Note that in regressions (4) and (5), the comparison group consists of a mixture of hospitals with no EMR and hospitals with basic EMR, so the coefficients are smaller than those in the first three columns.

[6]The sample size for columns (1) to (3) is slightly different from that for columns (4) and (5) because a small portion of the hospitals have missing information regarding their status on advanced EMR or basic EMR.

application (and if it has some advanced EMR, it must also have basic EMR). Both dummy variables equal 0 if the hospital does not have any EMR applications. The coefficients on the two dummy variables reflect the effect of adopting "basic EMR" and "both basic and advanced EMR" respectively compared to "having no EMR." The results indicate that the effect of "having basic EMR" and that of "having both basic and advanced EMR" are very close, although the effect of the latter is a bit larger and more significant. A t-test of the two coefficients yields a p-value of .6, indicating that, all else equal, there is no significant difference between the effect of adopting basic EMR only and adopting both levels of applications. If a hospitals already has basic EMR, then the additional effect due to the adoption of advanced applications is not statistically significant.

The absence of an additional effect after adopting advanced EMR may suggest that hospitals may not require the advanced functionality of EMR in order to enhance revenue. This is consistent with many anecdotal stories, since the potential mechanism that is mentioned most often is "cloning," a basic copy-and-paste functionality that is available in basic EMR systems.

To simplify my analysis, I combine the two measures and generate a single dummy for "having any EMR." Columns (7) and (8) show the results of this regression on slightly different samples. The sample in column (7) only includes observations with nonmissing measures of both basic EMR and advanced EMR. Since hospitals with advanced EMR all have basic EMR, the definition of this aggregated measure does not require information about the adoption status of advanced EMR; therefore, column (8) includes all observations with nonmissing data for the adoption of basic EMR (even though a small portion of them have missing data for advanced EMR). The results of columns (7) and (8) are very similar in all dimensions, so hereafter, I include all observations with a nonmissing value in the status of basic EMR for later analysis regardless of the availability of information about the advanced EMR, i.e., the sample in column (8).

In summary, the results in these regressions suggest that adopting EMR makes hospitals more likely to assign patients higher paying DRG codes. On average, adopting EMR leads to a 1.1 percentage point increase in the fraction of patients who are assigned the top code in a DRG pair. This moves an average hospital (*fraction*=0.624) from the 50th to 56th percentile in the distribution of *fraction*.

Next, I examine the effect of EMR adoption over time. The main purpose of this step is (1) to check and rule out the existence of any pre-adoption trend that could complicate the interpretation of my results, and (2) to examine the trend in the effect of EMR in the post-adoption period. After including all the control variables and differencing out all fixed effects, I expect to see no pre-adoption trend in *fraction*. I also expect the effect of EMR on *fraction* to be increasing over several years following adoption as the EMR system is rolling out. Equation 5.2 shows the specification.

$$fraction_{h,t,p} = \alpha + \Sigma_{L=i}\beta_L EMR_{h,t+L} + \gamma \mathbb{X}_{h,t,p} + \theta \mathbb{Z}_{h,t} + \mu_t + \mu_h + \mu_p + \epsilon_{h,t,p}$$
$$i \in \{\leq -4, -3, -2, 0, 1, 2, \geq 3\} \tag{5.2}$$

The only difference between 5.2 and 5.1 is that I replace the single dummy for post-EMR adoption with a set of dummy variables indicating each year from four years before adoption to three years after. For example, $EMR_{h,t}$ equals 1 in the year of adoption, $EMR_{h,t+2}$ equals 1 two years after the adoption, etc. The omitted category is "1 year before adoption." The sample excludes hospitals that have not adopted any EMR by the end of my sample period. Figure 3 plots the coefficients on the set of dummy variables indicating the years relative to the adoption time. (Regression results are also listed in column (1) of Table 6). There is no pre-adoption trend in *fraction*, and there is a slight delay in the effect of EMR and that effect keeps rising over several years following adoption.

5.2 Heterogeneous effect across different types of hospitals and patient populations

In this section, I examine whether the impact of EMR adoption on hospitals' billing levels varies across different subsamples of hospitals and patient populations. If the observed effect on coding is purely due to technological changes brought on by EMR, and if hospitals are only passively coping with such changes instead of actively and sophisticatedly using EMR as a tool to enhance revenue, we should expect a relatively homogeneous effect across different hospitals and patient types. Otherwise, we should see heterogeneity in such effect that is corresponding to hospitals' various incentives of boosting billing.

I first run separate regressions using the model in equation 5.1 on the subsamples of for-profit, nonprofit and government hospitals. Results in columns (2) to (4) of Table 5 show that the effect of EMR on *fraction* at for-profit hospitals is twice as large as that at nonprofit hospitals. The effect at government hospitals, although similar in magnitude to that at nonprofit hospitals, is not statistically significant. This is consistent with previous findings by Dafny (2005) and Silverman and Skinner (2004). Figure 4 shows the differential trend of effect over time. The effect on for-profit hospitals starts exceeding that on nonprofit hospitals two years after the adoption year. By the third year after adoption, the upcoding level of for-profit hospitals has increased by 3.6 percentage points, compared with 1.6 percentage points at nonprofit hospitals. There is also a slight pre-adoption upward trend at for-profit hospitals. One potential explanation is that adopting EMR is only part of what those hospitals do in order to boost revenue. During the years leading up to the adoption, hospitals may have been hiring external coding consultants to optimize their billing or building up other complementary resources while looking for the right EMR vendor. The adoption of EMR accelerates the whole process of revenue enhancement.

Financially distressed hospitals should be more willing to assign patients higher-paying DRG codes in order to boost revenue or improve risk-adjusted quality measures. In columns (5) and (6) of Table 5, I run separate regressions on financially distressed and non-distressed hospitals and find that the effect of EMR adoption on *fraction* is a lot larger at financially distressed hospitals than non-distressed hospitals. Figure 5 shows the effect over time.

I also examine whether the effect of EMR on hospitals' revenue-enhancing practice varies by patient population. Columns (7) and (8) in Table 5 show results of separate regressions for the sample generated from Medicare patients only and non-Medicare patients only. Consistent with my hypothesis, *fraction* increases in both Medicare and non-Medicare patient populations after adoption but the magnitude is larger in Medicare population. Figure 6 plots the trend of effect over time.[7]

5.3 Heterogeneous effects across DRG pairs

In this section, I examine heterogeneity in the effect of EMR on *fraction* across DRG pairs with different financial incentives of upcoding. DRG pairs with a larger difference between the reimbursement amount of the top and bottom codes give hospitals more incentives to switch patients into the top code. At the same time, however, the potential for upcoding within these DRG pairs is more likely to have been fully exploited even without EMR. I use a measure called "spread" to quantify the financial incentive for upcoding a specific DRG pair. *spread* is defined as follows:

$$spread_{p,t} = DRG\ weight\ in\ top\ code_{p,t} - DRG\ weight\ in\ bottom\ code_{p,t}. \tag{5.3}$$

This measure varies across years and DRG pairs. All else equal, the larger this value is, the more additional profit a hospital can generate by moving patients from the bottom code to the top code. I interact this measure with the dummy indicator of EMR adoption status to examine the heterogeneous effects of EMR on upcoding across pairs with different *spreads*.

[7]Columns (2) to (5) in Table 5 show the complete results of these regressions.

The specification of the model is as follows:

$$fraction_{h,t,p} = \alpha+\beta EMR_{h,t}+\delta spread_{p,t}+\kappa EMR_{h,t}\times spread_{p,t}+\gamma\mathbb{X}_{h,t,p}+\theta\mathbb{Z}_{h,t}+\mu_t+\mu_h+\mu_p+\epsilon_{h,t,p}. \tag{5.4}$$

In this model, I include *spread* as an explanatory variable and interact it with the dummy variable for EMR adoption. The other specifications are the same as in equation 5.1. The coefficient I am primarily interested in is β_3. It signifies how financial incentives relate to the effect of EMR on upcoding. Column (1) of Table 7 reports the key coefficients from this regression. The coefficient on EMR adoption is positive and significant as expected. The coefficient of *spread* signifies that DRG pairs with a larger *spread* have a significantly higher coding level before EMR adoption. One standard deviation change (SD=0.48) in spread is associated with a 1.7 percentage point increase in the fraction of patients assigned the top code. The coefficient of the interaction term of spread and EMR adoption indicates that the the effect of EMR on *fraction* significantly decreases as *spread* increases. The effect of EMR on a DRG pair with an average spread (mean=0.63) is 0.018, and 1 standard deviation change of spread (0.48) is associated with a reduction of 0.053 in the effect of EMR, which is a 28% reduction.

These coefficients suggest that before EMR adoption, patients in DRG pairs with larger upcoding incentives are more likely to be assigned the top code, but the additional increase in such probability due to EMR adoption is smaller compared with those with smaller upcoding incentives. In other words, the effect of EMR on *fraction* diminishes as *spread* increases. In order to demonstrate this pattern in a clearer way, I break down the continuous *spread*' measure into quartiles. The specification is shown below:

$$\begin{aligned} fraction_{h,t,p} = \alpha + \beta EMR_{h,t} + \Sigma_i\delta_i spreadQi_{p,t} + \Sigma_i\kappa_i EMR_{h,t} \times spreadQi_{p,t} \\ +\gamma\mathbb{X}_{h,t,p} + \theta\mathbb{Z}_{h,t} + \mu_t + \mu_h + \mu_p + \epsilon_{h,t,p}, \qquad i \in \{1,2,3\}. \end{aligned} \tag{5.5}$$

$spreadQ1_{p,t}$ to $spreadQ3_{p,t}$ are dummy variables indicating whether the spread of DRG pair p falls into the first, second or third quartile of the distribution of all DRG pairs' weights in year t. All three equal 0 if it falls into the fourth quartile. I expect the pre-adoption *fraction* to be positively correlated with the size of *spread*; hence the omitted category, which has the largest *spread*, should have the highest baseline coding level, and δ_i $i = 1, 2, 3$ should all be negative, with δ_3 being the least negative and δ_1 being the most negative. At the same time, the effect of EMR on *fraction* should be negatively correlated with the size of *spread*; therefore the omitted category should be the least affected by EMR and κ_i $i = 1, 2, 3$ should all be positive, with κ_3 being the smallest and κ_1 being the largest.

Column (2) of Table 7 shows the result of estimating model 5.5. The signs of the coefficients are as expected. The results are better shown in a figure. Figure 7 shows the average *fraction* of DRG pairs in each *spread* quartile before and after EMR adoption based on the calculation using the estimated coefficients.[8] This figure indicates that EMR adoption leads to an increase in *fraction* for DRG pairs in all quartiles, but the *fraction* of DRG pairs with a large *spread* already reached a relatively high level before EMR adoption; hence the additional increase due to EMR adoption is much smaller than that of DRG pairs with a smaller *spread*. This pattern is consistent across DRG pairs in all *spread* quartiles. The range in *fraction* after EMR adoption is also much smaller than that before EMR adoption, with a range of 0.026 pre-adoption and 0.012 post-adoption, which constitutes a reduction of 54%.

These regression results are consistent with the existence of a "ceiling effect" in hospitals' revenue-enhancing practice. Providers tend to exploit the revenue-enhancing potential and are most incentivized to do so where the payoff is the highest. Hospitals have been doing more "upcoding" on patients in DRG pairs with a larger *spread* even without the assistance of EMR; therefore, there is less additional benefit EMR can provide in terms of inflating billing codes, since there is a "ceiling" on how much upcoding can be done. For those DRG pairs with smaller financial incentives for upcoding, providers are not able to exploit as much of the potential without EMR; therefore, adopting EMR is especially beneficial in terms of expanding their capacity to exploit the potential of elevating bills among these codes.

5.4 More diagnosis codes or higher treatment intensity?

Medical records document what diseases patients have and what procedures providers perform. Such information is translated into corresponding diagnosis codes and procedure codes. In this section, I explore the mechanism of hospital revenue enhancement by examine changes in diagnosis codes and procedure codes.

In order to study changes in diagnosis codes, I run the same model as 5.1 but replace the dependent variable with the fraction of patients with 2 plus, 3 plus, 4 plus, or 5 plus diagnosis codes. Table 8 shows the regression results. The coefficients of EMR adoption in all regressions are positive and significant, indicating that the whole distribution of the number of recorded diagnosis codes shifts towards the right (i.e., more codes) after EMR adoption. The effect is especially strong in internal medicine (see Table A4 for regression results on a sample restricted to a set of DRG codes in internal medicine).

[8] The average levels of *fraction* are obtained by replacing the actual values of the EMR- adoption dummy and spread-quartile dummies with hypothetical values and generating a predicted *fraction* using estimated coefficients. For example, the pre-adoption *fraction* of spreadQ4 is obtained by replacing $spreadQi_{p,t}$ with 0 and replacing $EMR_{h,t}$ with 0 for all observations. Note that the differences between average *fraction*s are equal to the corresponding estimated coefficients in the regression model.

I run the same regression using measures of treatment intensity as dependent variables. The results are shown in Table 9. Columns (1) to (3) use the fraction of patients with 1 plus, 2 plus, and 3 plus procedures. Column (4) and (5) use the total charges. None of the measures show any evidence of changes in treatment intensity after EMR adoption. I am concerned that the null results might be attributed to the fact that a measure counting all procedures is too coarse, so I also examine changes in several common procedures, including MRI, ultrasound, CT scan, and blood tests, by regressing the mean and median of the number of each test in a hospital year on EMR adoption and find no evidence that there is any change after EMR adoption (see Table A3 for results).

These results together indicate that hospitals generate additional revenue via documenting more diagnoses and there is no evidence that they increase care intensity. Put another way, although patients look sicker, providers do not actually provide more treatment. This is consistent with my hypothesis, as hospitals have an incentive to document more diagnosis codes in order to trigger higher-paying DRG codes but have no incentive to increase care intensities since payments are a flat rate conditional on DRG.

5.5 How much money is at stake?

In this section, I calculate the amount of extra reimbursements hospitals can obtain due to the specific type of revenue-enhancing practice I study in this paper after EMR adoption. Based on the estimation results in the last column of Table 4, the fraction of patients in the top code of each DRG pair increases by 1.1 percentage point after EMR adoption. In year 2011, the total reimbursement for Medicare inpatient short stay was $128 billion. About 47% of Medicare patients are assigned a DRG code among those in pairs. The average weight for these patients is 1.12 and the average *spread* is 0.52. Therefore, a change of 1.1 percentage point in the fraction of patients that are assigned the top DRG code leads to an annual increase of $307 million (95% confidence interval: $224 million – $390 million) in Medicare reimbursements.[9] As shown in my results, similar revenue-enhancing practice also exists in non Medicare patients. Since Medicare accounted for 28% of spending on hospital care in 2010 (Commission et al., 2007), the additional annual reimbursement for the whole population due to this particular type of revenue enhancement is around $ 1.2 billion.

[9] Another way of calculating this is as follows: The total number of Medicare discharges from short stay hospitals in 2011 was 12.34 million. 47% of all discharges were in paired DRG codes, and 1.1% of those are switched to the top code after EMR adoption, adding an additional 0.52 DRG weight per patient. As mentioned in Silverman and Skinner (2004), reimbursement per 1.0 DRG weight was equal to roughly US$4000 during the mid-1990s, while the Medicare payment per capita for inpatient services roughly was doubled from the mid-1990s to 2011 (Medicare and Medicaid Statistical Supplement, 2012 version). By multiplying these number together, the additional Medicare payment due to EMR adoption is about $270 million.

The actual amount of money at stake is likely to be a lot larger than $ 1.2 billion. Unlike the upcoding phenomenon documented in the previous literature,[10] such revenue-enhancing practice using EMR is applicable to other are settings and payment rules. For example, "Cloning" and other revenue-enhancing practice are found to be most prevalent in outpatient and ambulatory settings (Abelson et al., 2012). Under the fee-for-service payment, providers' have incentives to document more procedures since the reimbursement is often based on that. Although it is hard to give an estimate of the impact of EMR outside of the empirical setting I study in this paper, this particular type of revenue enhancement is likely to be a tip of the iceberg.

6 Robustness Test

6.1 Are patients sicker?

My identification is based on the assumption that patient composition, particularly in terms of the extent of sickness, does not change before and after EMR adoption. It is possible though that the adoption of EMR improves the quality and efficiency of care overall so that the provider can treat sicker patients, or that EMR becomes a competitive advantage of hospitals so that they attract more sicker patients. In order to test this, I examine changes in the patients' Charlson index and ages after EMR adoption.

The Charlson index was developed to predict one-year patient mortality using comorbidity data obtained from diagnosis codes in hospital charts and is often used to measure patients overall health conditions (see, for example, Silverman and Skinner (2004)). It assigns each of the 22 comorbid conditions (such as diabetes, liver disease, tumor, leukemia, congestive heart failure, etc.) a score of 1,2,3, or 6, depending on the risk of dying and then sums up the scores to provide a total score that predicts mortality (Charlson et al., 1987). Many studies have validated the Charlson index in a wide variety of diseases for numerous clinical outcomes (de Groot et al., 2003). I generate the Charlson index for each patient using the diagnosis codes in HCUP data and generate average the sum of Charlson weights by hospital-year DRG pair. I run the same regression as in column (10) of Table 4 but replace the dependent variable with the average sum of the Charlson weights.

Columns (1) and (2) of Table 10 show the results from this regression. The dependent variable in column (1) is the sum of the Charlson weights, so it ranges from 0 to about 15. Since the distribution of the Charlson index is quite skewed, in column (2) I categorize observations with the sum of the Charlson weights equal to or larger than 2 into one group

[10]See, for example, Dafny (2005), in which the upcoding behavior is induced by changes in the reimbursement amount of a subset of inpatient billing codes, so the effect is localized to those codes.

and run the same regression. Both columns show similar results that there is no change in patients' general health status measured by Charlson index after EMR adoption. In column (3) I use the average age of patients in each hospital-year DRG pair as the dependent variable and find that there is no change in the patients' age after EMR adoption.

As another falsification test, I examine the changes in diagnosis codes for DRG codes that are not in pairs. If the observed increase in the number of diagnoses is all due to changes in patient health, we would see similar effects in non-paired DRG codes. I run the same regression on the non-paired DRG codes and find that the coefficients on EMR adoption are not significant and are smaller in magnitude (see Table A5).[11]

It is still possible that patients' health conditions change in a more subtle way and these measures can not capture, but at least I do not find the evidence for any compositional change at an aggregated level. At the same time, it is unlikely that hospitals are able to attract sicker patients in all DRGs. In addition, the fact that hospitals do not perform more procedures after EMR adoption makes it even more unlikely that the patients are actually sicker. Together, these results imply that the effect of EMR adoption on coding changes is unlikely to be due to the fact that hospitals are treating sicker patients after adopting EMR. Rather it is likely due to the fact that hospitals actively use EMR to boost billing.

6.2 Other robustness tests

I also conduct additional tests to address other concerns regarding the specification. Some of the observations are collapsed using a small number of patient-visit-level data. I am concerned that those observations can bias my results. In column (2) of Table 11, I drop the observations collapsed from 5 or fewer patient-visit-level observations. The coefficient on the key variable barely changes.

In column (3), I show that weighting observations using the number of patient visits in each hospital-year DRG pair does not change the conclusion. As expected, the magnitude of effect slightly decreases, since the effect of EMR on revenue-enhancing practice is more prominent in smaller hospitals (see the results in Table A2), which are likely to have limited resources for optimizing their coding before EMR adoption and therefore benefit more from EMR adoption.

There were major changes of the DRG rules in 2008. Although similar upcode incentives still remain and my data provide consistent DRG categorization till 2010, I drop observations in year 2008 or later as another robustness test. The result is shown in column (4). EMR

[11] Note that, although it is much more difficult, it is still possible to switch patients across non-paired DRG codes, so hospitals may still want to record more diagnoses for those patient. Therefore the coefficient on EMR adoption may not be zero.

decisions sometimes are made at hospital system level instead of individual hospital level, hence in column (5), I cluster standard error at health system level, and the results still hold.

I also compare my results with the previous literature on upcoding. In particular, Silverman and Skinner (2004) examines upcoding in two specific DRG pairs (4 DRG codes), pneumonia and respiratory infections. All four DRGs are common respiratory ailments, which carry inherent uncertainty and potential to for upcoding. I run my model on these DRG pairs only and find that the coefficient is similar to that when running the model on the full sample. At the same time, the difference in the effects of EMR on these two pairs is also consistent with the "ceiling effect": DRGs 79 and 80 (respiratory infections with/without CC) have a *spread* of 0.73, while DRGs 89 and 90 (pneumonia with/without CC) have a *spread* of 0.41. The average pre-adoption fraction of patients assigned the top code in the former pair is higher than that in the latter (0.92 vs. 0.87), but the effect of EMR adoption on the former is smaller than that on the latter (0.007 vs. 0.012). The results in the Silverman and Skinner (2004) study also suggest the possibility of switching patients across DRG pairs. In my data though, the share of patients in the "respiratory infection" pair out of all the patients in these two pairs is positively correlated with EMR adoption, but the coefficient is not significant (p=0.22), indicating that switching across DRG pairs may not be of first-order importance in this scenario.

7 Discussion and Conclusion

Adopting Electronic Medical Records is not simply a process of replacing paper-based records with electronic ones, but rather an unprecedented way of transforming the practice in the entire health care industry. As the government continues to make investments to aggressively push providers to adopt EMR, it is critical to understand how providers truly respond to the adoption of such technology. Are providers taking advantage of the potential efficiency gains brought on by the technology to control costs and improve quality or are they using it as a tool to ease their way to gaming the system and enhancing revenue? The answers to these questions are particularly important from a policy standpoint as such revenue-enhancing practice by hospitals have extensive impact on health costs, patient safety, and the accuracy of quality measures.

As the first study that uses a large-scale dataset to directly examine the effect of EMR adoption on providers' coding practice, this paper draws on a variety of data sources on EMR, patient coding, hospital characteristics, and patient characteristics. It demonstrates the effect of EMR adoption on hospital revenue enhancement with a focus on changes in medical and billing codes. The adoption of EMR leads to a significant increase in the fraction of patients who are assigned higher-paying DRG codes. There is a slight delay in this effect, which is consistent with a phased rollout of EMR in the hospital and a phased adaptation to local circumstances documented in the previous literature. The effect of this particular type of revenue enhancement using EMR translates into an annual increase $1.2 billion in reimbursement. However, this estimated amount is likely to be a tip of the iceberg— Considering the fact that the revenue enhancement using EMR also exists in other forms and is likely to be more prominent in outpatient and emergency care, the actual amount of money at stake is much larger.

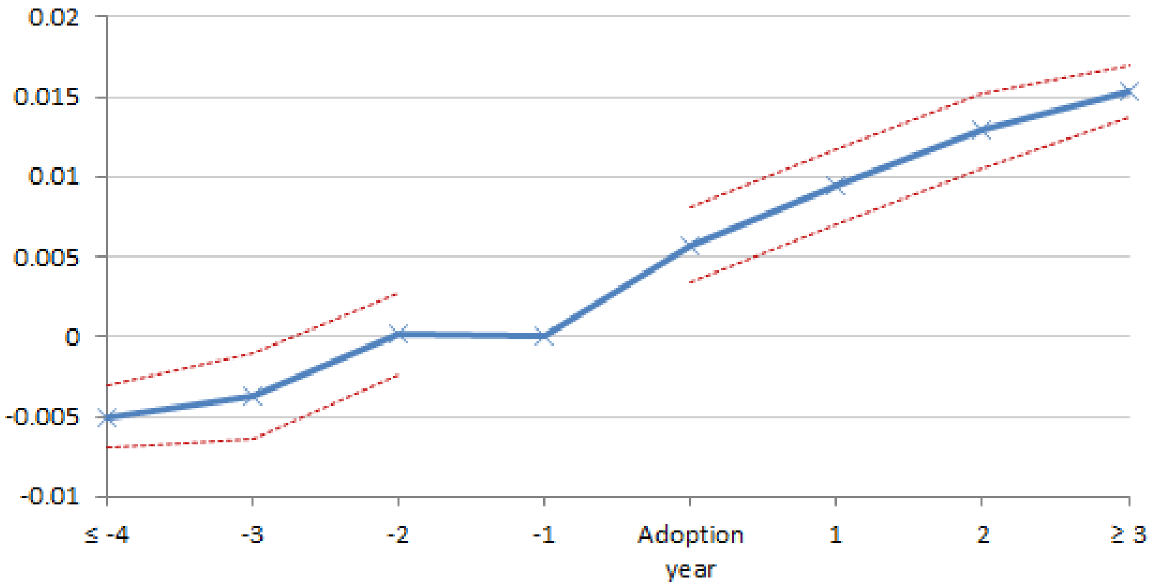
More importantly, my results indicate that hospitals demonstrate a substantial level of sophistication in using EMR to escalate their billing: under the DRG payment system, which pays more for sicker patients but not for performing more procedures, providers increase the number of documented diagnoses but do not perform more procedures; those who give more weight to financial gains, such as for-profit hospitals and financially distressed hospitals, tend to make greater use of EMR to boost billing; they also tend to exploit more of the upcoding potential among the Medicare population, where the monitoring from the payer is likely to be the less, the use of prospective payment rules is more stable, and patients are in general sicker. Lastly, the pattern of "ceiling effects" suggests that EMR might be helping hospitals, which previously focused limited resources on areas where the return on inflating billing is the largest, expand their capacity to exploit the rest of the billing codes. Such heterogeneity is worrying because it potentially punishes the providers that do not engage in such revenue-enhancing behavior and lead to inaccurate risk-adjusted quality measures.

As is true for any empirical work, this study has a number of limitations. First, I observe a subset of medical providers and can only measure certain forms of revenue-enhancing practice. Providers in outpatient and ER settings face different reimbursement rules and could have different incentives and strategies for coding. Although I believe that many of the potential mechanisms of EMR leading to revenue-enhancing practice are also applicable to other care settings, I cannot quantify the exact magnitude of the effect. Second, my main measure of revenue enhancement can only capture the changes within the same DRG pair. It is also possible for hospitals to switch patients across DRG pairs, although such effect may not be of the first-order importance as shown in robustness test, so the magnitude of the effect I find is likely to be a lower-bound even in the setting of inpatient Medicare patients. Third, the data I use only covers six state. Although they spread out across the whole country, there may still be concerns about the external validity of my results if these states are not representative enough.

The study also leaves open questions. For example, how much of the observed effect on billing reflects an efficiency or quality improvement such as EMR capturing important medical information that was previously missed and how much is due to a higher level of sophistication in maximizing billing but generates no clinical benefits or even undermines care quality. Another question is why I do not observe any changes in the number of procedure codes. Under the DRG payment system, hospitals are not incentivized to perform more procedures, but from the perspective of some physicians, especially those who are not affiliated with hospitals, there may be incentives to perform and/or document more procedures, since that is what these physicians' pay largely depends on. It may be that the changes in procedure codes happen in a more subtle way and require more sophisticated measures to be detected.

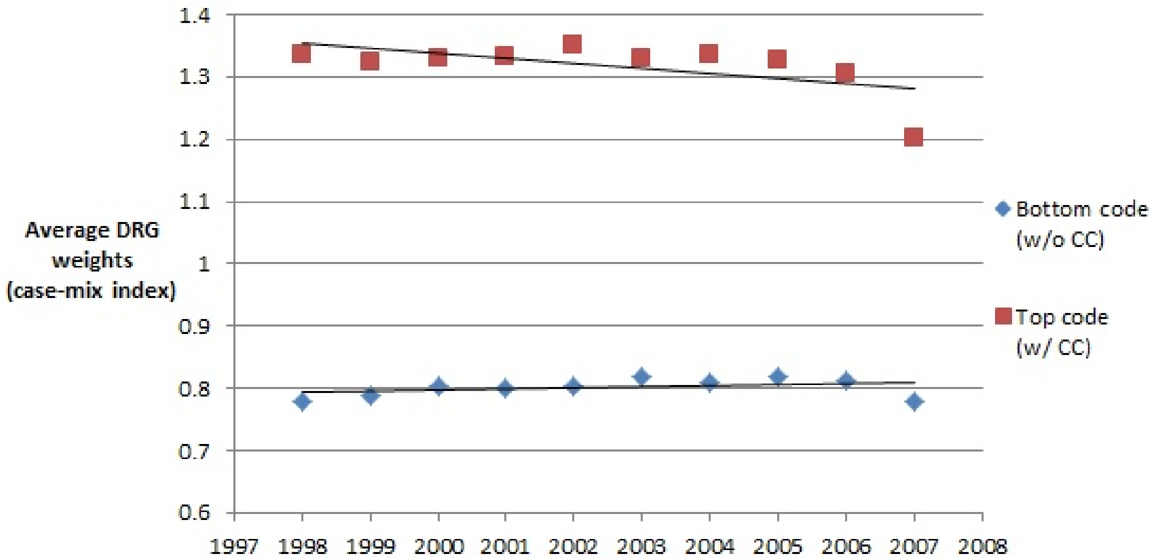
Despite the limitations, I believe that my results have important policy implications. The evidence of hospitals using EMR to boost revenue provides a potential explanation for the puzzle why EMR does not generate cost reduction and quality improvements as expected. HIT incentives are aggressively pushing the whole US health care industry to move into the IT era, while the guidelines for coding practice and the way of monitoring, which were designed to handle paper-based records, still lag behind. Ambiguity and incompleteness in coding rules, as well as the lack of proper oversight, generate incentives for providers to game the system. In order to address this problem, payers should increase the level of auditing, and more importantly, devote efforts to innovate new audit tools and algorithms that can detect problematic electronic claims. As suggested by my results, providers have a substantial level of sophistication and respond to various "upcoding" incentives. Policy makers should take these reactions into account when developing coding guidelines and looking for audit targets.

Figure 1: Effect of EMR on *fraction* by years relative to adoption (raw data)



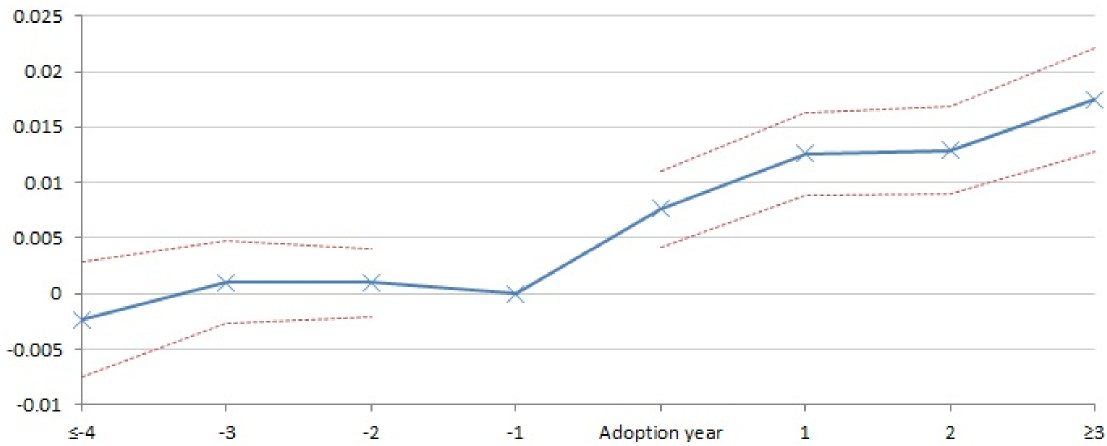
Note: This figure shows the relative level of hospitals' revenue-enhancing practice over time in raw data. It is generated by regressing the fraction of patients assigned the higher-paying code within each DRG pair only on a set of dummy variables indicating the years relative to the adoption year and plotting the coefficients. The omitted category is "1 year before adoption." The dashed lines show 95% confidence intervals.

Figure 2: Trend in average DRG weights over time



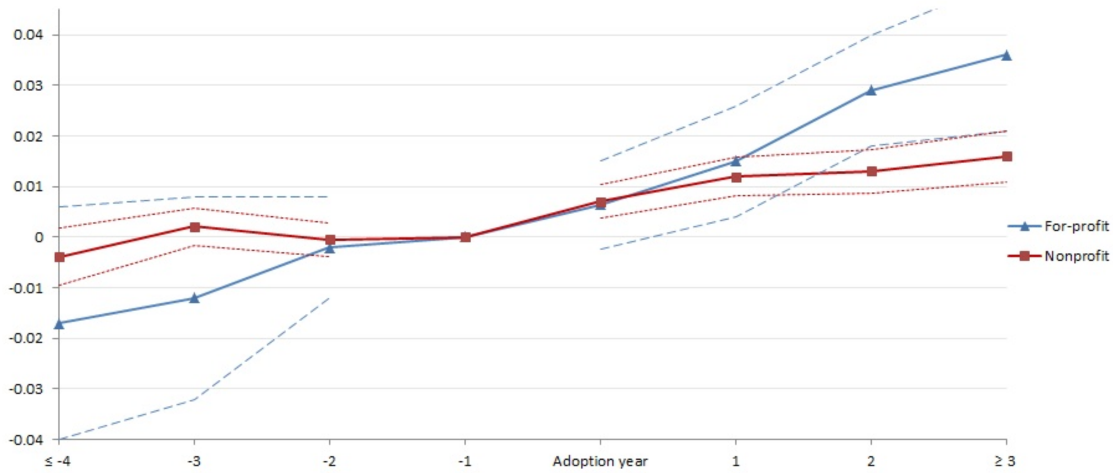
Note: This figure shows the trend in average weights of patients (i.e., case-mix index) in the top (with CC) and bottom (without CC) codes over time. The difference between the weights (and, hence, health expenditure) of the top and bottom codes becomes smaller over time. This is consistent with the hypothesis that more patients who should be in the bottom code are upcoded into the top code, leading to a smaller difference in the level of sickness between these two groups of patients. Comparable DRG weights after year 2007 are not available due to adjustments in DRG rules in 2008.

Figure 3: Effect of EMR on *fraction* by years relative to adoption (main model)



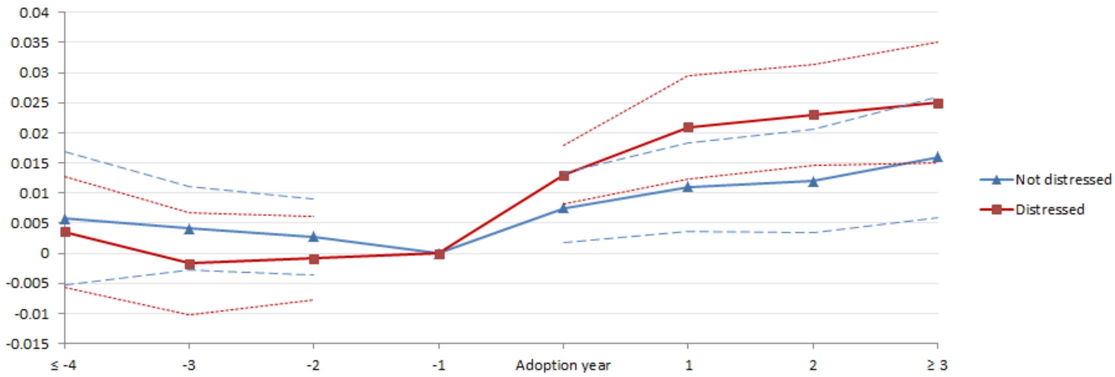
Note: This figure shows the relative level of hospitals' revenue-enhancing practice over time based on the estimation results of equation 5.2. The dependent variable is the *fraction* of patients in the higher-paying code of each DRG pair. I plot the coefficients on the dummy variables indicating years relative to adoption. The regression includes all controls (as shown in table A1), hospital fixed effects, year fixed effects and DRG-pair fixed effects. The omitted category is "1 year before adoption." The dashed lines show 95% confidence intervals. The unit of observation is hospital-year DRG pair. Sample size is is 344,495. See Table 5 for the detailed regression results.

Figure 4: Effect of EMR on *fraction* by years relative to adoption: For-profit vs. nonprofit hopsitals



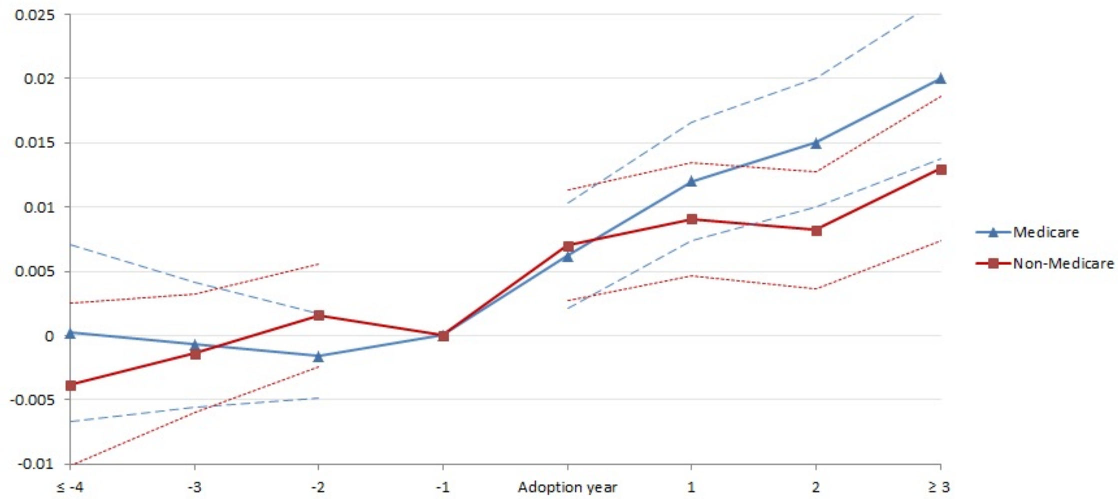
Note: This figure shows the relative level of revenue-enhancing practice for hospitals with different profit status over time. I run separate regressions on the two types of hospitals using model 5.2. The dependent variable is the *fraction* of patients in the higher-paying code of each DRG pair. I plot coefficients on the dummy variables indicating years relative to the adoption year. The blue solid line (with triangle markers) represents for-profit hospitals and the red solid line (with square markers) represents nonprofit hospitals. The blue dashed line and the red dotted line indicate their 95% confidence intervals, respectively. The unit of observation is hospital-year DRG pair. Samples exclude hospitals that have not adopted any EMR by the end of the sample period. Sample size is 41,798 for for-profit hospitals and 245,416 for nonprofit hospitals. See Table 5 for the detailed regression results.

Figure 5: Effect of EMR on *fraction* by years relative to adoption: financially distressed vs. not distressed hospitals



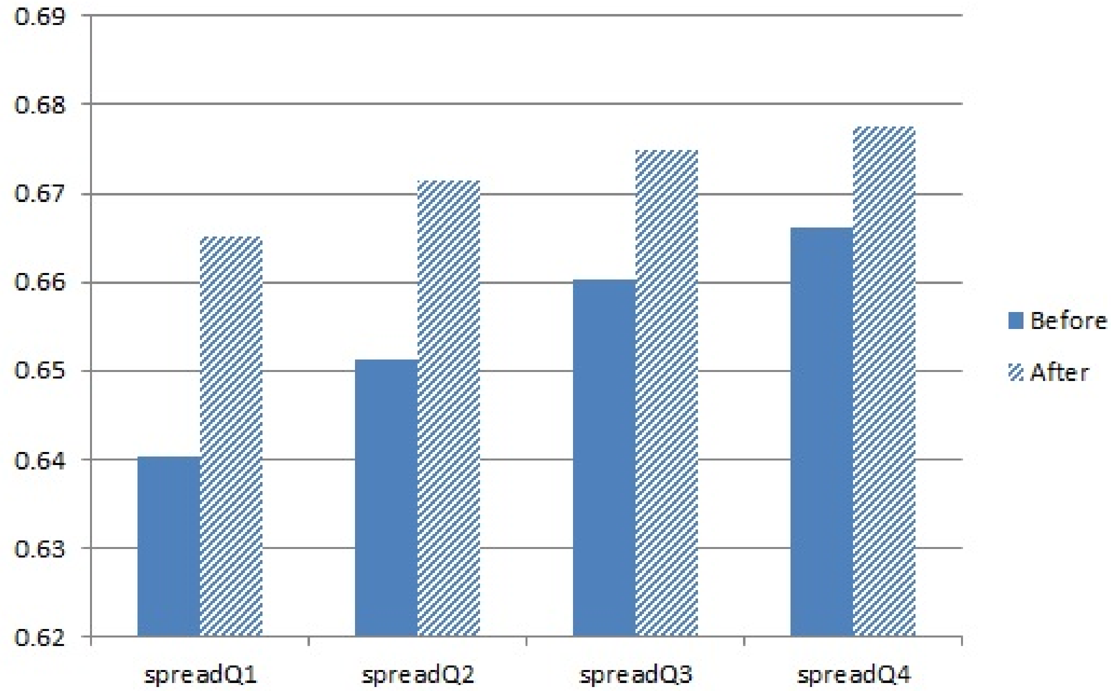
Note: This figure shows the relative level of revenue-enhancing practice for hospitals with different financial status over time. I run separate regressions on the two types of hospitals using model 5.2. The dependent variable is the *fraction* of patients in the higher-paying code of each DRG pair. I plot coefficients on the dummy variables indicating years relative to the adoption year. The blue solid line (with triangle markers) represents hospitals that are not financially distressed and the red solid line (with square markers) represents those that are financially distressed. The blue dashed line and the red dotted line indicate their 95% confidence intervals, respectively. The unit of observation is hospital-year DRG pair. Samples exclude hospitals that have not adopted any EMR by the end of the sample period. Sample size is 45,340 for financially distressed hospitals and 47,694 for those that are not financially distressed. See Table 5 for the detailed regression results.

Figure 6: Effect of EMR on *fraction* by years relative to adoption: Medicare vs. non-Medicare patients



Note: This figure shows the relative level of hospitals' revenue-enhancing practice on Medicare and non-Medicare patients over time. I run model 5.2 on samples generated using Medicare patients only and non-Medicare patients only. The dependent variable is the *fraction* of patients in the higher-paying code of each DRG pair. I plot the coefficients on the dummy variables indicating years relative to the adoption year. The blue solid line (with triangle markers) represents the Medicare sample and the red solid line (with square markers) represents the non-Medicare sample. The blue dashed line and the red dotted line indicate their 95% confidence intervals, respectively. The unit of observation is hospital-year DRG pair. Samples exclude hospitals that have not adopted any EMR by the end of the sample period. Sample size is 250,472 for the Medicare sample and 264,057 for the non-Medicare sample. See Table 5 for the detailed regression results.

Figure 7: Average *fraction* pre- and post-adoption by quartiles of *spread*: "Ceiling Effect"



Note: This figure shows the average *fraction* of patients assigned the higher-paying DRG code by quartile of *spread* and adoption status. *spread* is a measure of the upcoding incentives in a DRG pair. SpreadQ1 to spreadQ4 are indicators for the quartiles of *spread* within which each observation falls. *spread* increases from Q1 to Q4. The pre-adoption *fraction* is positively correlated with *spread*, but the effect of EMR is negatively correlated with *spread*. This shows evidence that is consistent with "ceiling effects." The average *fractions* are obtained based on the estimation results of equation 5.5 (output shown in Table 7). The sample includes observations from 1998 to 2007.

Table 1: Types of EMR and hospital adoption rates

EMR application name	Adoption rates (%) 1998	2010
Basic EMR		
Clinical Decision Support (CDS)	20.8	81.9
Clinical Data Repository (CDR)	21.9	86.3
Order Entry	26.3	88.6
Any of the three	27.5	89.6
Advanced EMR		
Computerized Provider Order Entry (CPOE)	0.68	58.9
Physician Documentation (PD)	3.1	49.9
Either of the two	2.9	61.4

Table 2: Summary statistics

	Mean	SD	min	max
EMR Adoption Rate (2010 value)				
Clinical Decision Support (CDS)	0.82	0.39	0	1
Clinical Data Repository (CDR)	0.86	0.34	0	1
Order Entry	0.89	0.32	0	1
Any of the three	0.90	0.31	0	1
Computerized Provider Order Entry (CPOE)	0.59	0.49	0	1
Physician Documentation (PD)	0.50	0.50	0	1
Either of the two	0.61	0.49	0	1
Measure of Revenue-Enhancing Practice (2010 value)				
fraction	0.70	0.26	0	1
patients with $\geq$ 2 diagnoses	0.97	0.092	0	1
patients with $\geq$3 diagnoses	0.93	0.15	0	1
patients with $\geq$1 procedure	0.68	0.35	0	1
patients with $\geq$2 procedures	0.41	0.34	0	1
average total charges	34732.5	33232.7	160	805115
Patient Demographics (2010 value)				
Average age	56.5	21.6	0	124
Female	59.00%			
Medicare patients	40.01%			
Charlson index	1.48	1.40	0	15
Hospital Characteristics (2010 value)				
% Teaching hospitals	11.2			
% Resident hospitals	32.4			
% For profit hospitals	14.9			
% Nonprofit hospitals	69			
% Government hospitals	16.1			
# of beds	245.4	168.9	6	993
# patient visits per hospital year	4453.1	3652.3	1	21620
Total outpatient visits (000s)	185.1	244.3	0	2990.0
Total inpatient days (000s)	63.7	49	35	308.5
Total admission (000s)	13.9	9.86	32	71.1
Births	1755.2	1618.8	0	8049
Full-time physicians and dentists equivalent	28.5	82.6	0	906
Medicare discharges(000s)	4.9	3.6	0	21.05
Medicaid discharges(000s)	2.6	2.9	0	19
Number of patient visits per hospital-year DRG pair	50.2	107.4	1	3814
Spread	0.63	0.48	0.082	3.065
Debt:asset ratio:	0.63	0.47	0	3.76

Table 3: Number of hospitals in the sample by state and year

Year	AZ	CA	CO	MD	NJ	WA	Total
1998	23	0	27	32	33	27	142
1999	22	0	26	32	33	27	140
2000	25	0	27	32	35	27	146
2001	25	0	27	32	35	27	146
2002	25	0	27	32	35	27	146
2003	25	161	27	32	35	27	307
2004	29	175	44	32	37	44	361
2005	29	174	44	32	37	44	360
2006	33	186	47	32	39	45	382
2007	33	186	47	32	39	44	381
2008	32	189	48	32	39	44	384
2009	32	187	48	32	40	44	383
2010	32	181	48	31	40	44	376
Total	365	1,439	487	415	477	471	3,654

Table 4: Overall effect of EMR on *fraction* by application

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mean (*fraction*) =	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67
Clinical Decision Support	0.013***							
	(0.0030)							
Clinical Data Repository		0.0097***						
		(0.0031)						
Order Entry			0.011***					
			(0.0032)					
CPOE				0.0076**				
				(0.0033)				
Physician Documentation					0.0055*			
					(0.0033)			
Basic EMR only						0.011**		
						(0.0048)		
Advanced EMR						0.012***		
						(0.0039)		
Any EMR							0.012***	0.011***
							(0.0036)	(0.0033)
Observations	344495	344495	344495	359010	359010	268208	268208	344495
Adjusted R^2	0.458	0.458	0.458	0.443	0.443	0.460	0.460	0.458

Notes: Unit of observation is hospital-year DRG pair. Sample includes data from 1998 to 2010. The dependent variable is the fraction of patients that are assigned the higher-paying code (with complications). All regressions include controls, hospital fixed effects, DRG-pair fixed effects, and year fixed effects. See equation 5.1 for the model specification. See Table A1 for a full list of controls.
Robust standard errors are clustered by hospital and are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of EMR on *fraction* by hospital characteristics and patient population

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	By ownership type			By financial status		By patient population	
	For-profit	Not-for-profit	Government	Distressed	Not distressed	Medicare	non-Medicare
mean(fraction) =	0.68	0.68	0.65	0.66	0.67	0.67	0.61
Any EMR	0.023*	0.011***	0.0095	0.018***	0.0071	0.011***	0.0082**
	(0.013)	(0.0034)	(0.010)	(0.0063)	(0.0059)	(0.0040)	(0.0039)
Observations	46851	249365	48279	45340	47694	258494	271412
Adjusted R^2	0.432	0.486	0.375	0.450	0.459	0.262	0.377

Notes: Unit of observation is hospital-year DRG pair. Sample includes data from 1998 to 2010. All regressions include hospital fixed effects, DRG-pair fixed effects, and year fixed effects, as well as patient and hospital characteristics. See Table A1 for a full list of controls. Robust standard errors are clustered by hospital and are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effect of EMR on *fraction* over time by hospital characteristics and patient population

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	By ownership type			By financial status		By patient population	
		For-profit	Not-for-profit	Government	Distressed	Not distressed	Medicare	Non-Medicare
mean(fraction) =	0.67	0.68	0.68	0.65	0.66	0.67	0.67	0.61
$\leq$ 4 years before adoption	-0.0044	-0.017	-0.0039	0.016	0.0036	0.0058	0.00021	-0.0038
	(0.0052)	(0.023)	(0.0057)	(0.014)	(0.0092)	(0.011)	(0.0069)	(0.0063)
3 years before adoption	0.00100	-0.012	0.0021	0.010	-0.0017	0.0041	-0.00071	-0.0014
	(0.0037)	(0.020)	(0.0037)	(0.015)	(0.0085)	(0.0069)	(0.0049)	(0.0046)
2 years before adoption	0.00096	-0.0020	-0.00046	0.010	-0.00081	0.0028	-0.0016	0.0016
	(0.0030)	(0.010)	(0.0033)	(0.0087)	(0.0069)	(0.0063)	(0.0033)	(0.0040)
year of adoption	0.0079**	0.0064	0.0070**	0.019	0.013**	0.0075	0.0062	0.0070
	(0.0034)	(0.0088)	(0.0033)	(0.015)	(0.0049)	(0.0058)	(0.0041)	(0.0043)
1 year after adoption	0.012***	0.015	0.012***	0.018	0.021**	0.011	0.012**	0.0091**
	(0.0038)	(0.011)	(0.0038)	(0.016)	(0.0086)	(0.0074)	(0.0046)	(0.0044)
2 years after adoption	0.013***	0.029**	0.013***	0.0035	0.023***	0.012	0.015***	0.0082*
	(0.0040)	(0.011)	(0.0043)	(0.015)	(0.0084)	(0.0086)	(0.0050)	(0.0046)
3 years after adoption	0.017***	0.036**	0.016***	0.0091	0.025**	0.016	0.020***	0.013***
	(0.0047)	(0.015)	(0.0051)	(0.016)	(0.010)	(0.010)	(0.0062)	(0.0056)
Observations	331462	41798	245416	44248	45340	47694	250472	264057
Adjusted R^2	0.467	0.443	0.487	0.405	0.450	0.456	0.268	0.382

Notes: Unit of observation is hospital-year DRG pair. Sample includes data from 1998 to 2010. All regressions include hospital fixed effects, DRG-pair fixed effects, and year fixed effects, as well as patient and hospital characteristics. See Table A1 for a full list of controls. Robust standard errors are clustered by hospital and are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effect of EMR on *fraction* by *spread*

	(1)	(2)
	fraction	*fraction*
mean(*fraction*) =	0.67	0.67
Any EMR	0.025***	0.012**
	(0.0047)	(0.0047)
Spread	0.035***	
	(0.0099)	
Spread× any EMR	-0.011***	
	(0.0035)	
Spread Q3		-0.0058
		(0.0040)
Spread Q2		-0.015***
		(0.0052)
Spread Q1		-0.026***
		(0.0061)
Spread Q3× anyEMR		0.0031
		(0.0034)
Spread Q2× anyEMR		0.0087**
		(0.0039)
Spread Q1× anyEMR		0.013***
		(0.0047)
Observations	239918	239918
Adjusted R^2	0.463	0.463

Notes: Unit of observation is hospital-year DRG pair. Sample includes annual data from 1998 to 2007. *spread* is defined as the difference between the weights of the top code and the bottom code of each DRG pair. SpreadQ1 is a dummy indicating that the DRG pair has a *spread* below the 25th percentile among all observations of that year. Similarly, Q2 and Q3 correspond to the 25th to 50th and the 50th to 75th quartiles. The top quartile is omitted. Regressions include controls, hospital fixed effects, DRG-pair fixed effects, and year fixed effects. See Table A1 for a full list of controls. Robust standard errors are clustered at the hospital level and are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Effect of EMR on diagnosis codes

	(1)	(2)	(3)	(4)
		Fraction of patients with		
	$\geq$ 2 diagnosis codes	$\geq$ 3 diagnosis codes	$\geq$ 4 diagnosis codes	$\geq$ 5 diagnosis codes
mean=	0.96	0.89	0.81	0.72
Any EMR	0.0039*	0.0071**	0.010**	0.011**
	(0.0020)	(0.0030)	(0.0044)	(0.0052)
Observations	344495	344495	344495	344495
Adjusted R^2	0.388	0.455	0.505	0.536

Notes: Unit of observation is hospital-year DRG pair. Sample includes data from 1998 to 2010. All regressions include hospital fixed effects, DRG-pair fixed effects, and year fixed effects, as well as patient and hospital characteristics. See Table A1 for a full list of controls. Robust standard errors are clustered by hospital and are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effect of EMR on treatment intensity

	(1)	(2)	(3)	(4)	(5)
	Fraction of patients with			Charges	
	$\geq$ 1 procedure code	$\geq$ 2 procedure codes	$\geq$ 3 procedure codes	Total Charges	ln(Total Charges)
mean=	0.70	0.43	0.25	31227	9.8
Any EMR	0.0041	0.0032	0.0038	-320.5	0.013
	(0.0048)	(0.0059)	(0.0055)	(796.2)	(0.017)
Observations	344495	344495	344495	344495	34495
Adjusted R^2	0.758	0.680	0.591	0.555	0.820

Notes: Unit of observation is hospital-year DRG pair. Sample includes data from 1998 to 2010. All regressions include hospital fixed effects, DRG-pair fixed effects, and year fixed effects, as well as patient and hospital characteristics. See Table A1 for a full list of controls. Robust standard errors are clustered by hospital and are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Changes in patients' health condition

	(1)	(2)	(3)
	Charlson index	Charlson index (truncated)	Age
mean=	1.48	0.92	58.3
Any EMR	-0.0011	0.0012	-0.18
	(0.010)	(0.0043)	(0.12)
Observations	344495	344495	344495
Adjusted R^2	0.716	0.689	0.627

Notes: Unit of observation is hospital-year DRG pair. Sample includes data from 1998 to 2010. All regressions include hospital fixed effects, DRG-pair fixed effects, and year fixed effects, as well as patient and hospital characteristics. See Table A1 for a full list of controls. Robust standard errors are clustered by hospital and are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Robustness check

	(1)	(2)	(3)	(4)
	Drop cell observations<6	Weighted Least Squares	Drop year>2008	Cluster SE at health system
Any EMR	0.010***	0.0089***	0.017***	0.011***
	(0.0031)	(0.0034)	(0.0039)	(0.0038)
Observations	252764	344495	242872	344495
Adjusted R^2	0.688	0.838	0.462	0.458

Notes: Unit of observation is hospital-year DRG pair. Sample includes data from 1998 to 2010. All regressions include hospital fixed effects, DRG-pair fixed effects, and year fixed effects, as well as patient and hospital characteristics. See Table A1 for a full list of controls. Robust standard errors are clustered by hospital and are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Table A1: Overall effect of EMR on *fraction* with coefficients of controls

	(1)	(2)	(3)
	fraction	fraction	fraction
	0.67	0.67	0.67
Basic EMR only	0.011**		
	(0.0048)		
Advanced EMR	0.012***		
	(0.0039)		
Any EMR		0.012***	0.011***
		(0.0036)	(0.0033)
Age $<$ 20	-0.29***	-0.29***	-0.29***
	(0.012)	(0.012)	(0.010)
20$\leq$ Age $<$40	-0.14***	-0.14***	-0.14***
	(0.0057)	(0.0057)	(0.0050)
Age$\geq$65	0.13***	0.13***	0.13***
	(0.0045)	(0.0045)	(0.0040)
% female	-0.026***	-0.026***	-0.025***
	(0.0032)	(0.0032)	(0.0029)
Beds(000s)	0.051***	0.051***	0.064***
	(0.019)	(0.019)	(0.019)
log(outpatient visits)	-0.0011	-0.0011	-0.0017
	(0.0014)	(0.0014)	(0.0015)
log(admissions)	-0.012	-0.012	-0.011*
	(0.0075)	(0.0075)	(0.0065)
log(fulltime MD)	0.0000056	-0.0000073	-0.00056
	(0.00097)	(0.00097)	(0.00092)
Nonprofit$\times$ year	0.0013	0.0013	0.0018*
	(0.0012)	(0.0012)	(0.00094)
For-profit$\times$ year	0.0018	0.0018	0.0041***
	(0.0018)	(0.0018)	(0.0014)
Residency hospital$\times$ year	-0.0028***	-0.0028***	-0.0019**
	(0.00093)	(0.00094)	(0.00084)
Academic hospital$\times$ year	0.00052	0.00053	0.00018
	(0.0010)	(0.0010)	(0.00100)
% Medicare discharge $\times$ year	-0.0065*	-0.0066*	-0.0061*
	(0.0036)	(0.0036)	(0.0031)
% Medicaid discharge $\times$ year	0.00034	0.00025	-0.0020
	(0.0048)	(0.0047)	(0.0037)

Observations	268208	268208	344495
Adjusted R^2	0.460	0.460	0.458

Notes: Unit of observation is hospital-year DRG pair. Sample includes data from 1998 to 2010. All regressions include hospital fixed effects, DRG-pair fixed effects, and year fixed effects, as well as patient and hospital characteristics. Robust standard errors are clustered by hospital and are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Effect of EMR on *fraction* by hospital size

	(1)	(2)
	Beds<200	Beds$\geq$ 200
mean(fraction) =	0.679	0.671
Any EMR	0.015***	0.008**
	(0.0055)	(0.0038)
Observations	166648	177847
Adjusted R^2	0.401	0.538

Notes: Unit of observation is hospital-year DRG pair. Sample includes data from 1998 to 2010. All regressions include hospital fixed effects, DRG-pair fixed effects, and year fixed effects, as well as patient and hospital characteristics. See Table A1 for a full list of controls. Robust standard errors are clustered by hospital and are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Effect of EMR on average number of common procedures

	(1)	(2)	(3)	(4)
	MRI	Ultrasound	CT scan	Lab tests
mean=	0.0073	0.0328	0.0293	0.0009
Any EMR	0.00057	0.0024	0.0014	0.00038*
	(0.0011)	(0.0050)	(0.0056)	(0.00023)
Observations	3628	3628	3628	3628
Adjusted R^2	0.753	0.749	0.675	0.521

Notes: Unit of observation is hospital year. Sample includes data from 1998 to 2010. All regressions include hospital fixed effects and year fixed effects, as well as patient and hospital characteristics. See Table A1 for a full list of controls. Robust standard errors are clustered by hospital and are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effect of EMR on common diagnosis codes in internal medicine

	(1)	(2)	(3)	(4)
	Fraction with $\geq$ 2 diagnosis	Fraction with $\geq$ 3 diagnosis	Fraction with $\geq$ 4 diagnosis	Fraction with $\geq$ 5 diagnosis
mean=	0.98	0.94	0.89	0.81
Any EMR	0.0057**	0.0070**	0.014***	0.016***
	(0.0025)	(0.0033)	(0.0050)	(0.0059)
Observations	45141	45141	45141	45141
Adjusted R^2	0.278	0.425	0.530	0.598

Notes: Unit of observation is hospital-year DRG pair. Sample includes annual data from 1998 to 2010. All regressions include year fixed effects, DRG-pair fixed effects, and year fixed effects. Robust standard errors are clustered at the hospital level and are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Effect of EMR on diagnosis codes (nonpaired DRG)

	(1)	(2)	(3)	(4)
	Fraction of patients with			
	$\geq$ 2 diagnosis codes	$\geq$ 3 diagnosis codes	$\geq$ 4 diagnosis codes	$\geq$ 5 diagnosis codes
mean=	0.96	0.89	0.81	0.72
either	0.0030	0.0054	0.0073	0.0075
	(0.0022)	(0.0035)	(0.0046)	(0.0050)
Observations	536651	536651	536651	536651
Adjusted R^2	0.363	0.477	0.550	0.584

Notes: Unit of observation is hospital-year DRG. Sample includes the data of DRG codes that are not in pairs from 1998 to 2010. All regressions include hospital fixed effects, DRG fixed effects, and year fixed effects, as well as patient and hospital characteristics. See Table A1 for a full list of controls. Robust standard errors are clustered by hospital and are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$