Heterogeneous Treatment Effect of Electronic Medical Records on Hospital Efficiency

Ruirui Sun

Graduate Center of City University of New York
rsun1@gradcenter.cuny.edu

Abstract

This paper empirically analyzes the potential disparities of the IT benefit on patients, since focusing on only average treatment effect may lead to "IT Paradox". The study sample is extracted from seven-year long nationally representative US inpatient data. I use variation in hospital competitors' IT adoption rates to identify the effect of Electronic Medical Records (EMRs) on Length of Stay (LOS) two years after for the focal hospital. The model is estimated using two-sample non-linear instrumental variable, which allows me to obtain the consistent causal effect of IT system. I utilize the Finite Mixture Model, which yields great flexibility in estimating the heterogeneous effect without manually stratifying the sample. The results illustrate that EMRs can lead to decrease in LOS, and IT benefit disparity exists based not only on patients of different diagnostic categories, but also on medical severity conditions.

Keywords: Hospital, Electronic Medical Records, Length of Stay, Finite Mixture Model

JEL Classification: I12

1 Introduction

Health care market is highly information intensive since care providers make medical decisions and provide services based on patients' available medical information, and thus would benefit from good information management technologies. Economists view technology innovation as a way to increase production (Solow, 1957) and improve efficiency (Bresnahan et al., 1999). Health Information Technology (Health IT) has been suggested greatly to reduce medical errors and so that to lower cost and improve efficiency. While the concept and expectation of the IT system has been accepted widely across the health care sector, existing literature has provided little empirical evidence nationwide. Moreover, the scope and disparities of how the Health IT system would be beneficial to patients has been rarely empirically examined.

Lack of empirical evidence does not necessarily mean a shortfall of the IT system. This might be merely an indication that Health IT study may easily fall into the "IT Paradox" trap (discussed more in section 2). This paper studies on of the foundation of Health IT system, the Electronic Medical Records (EMRs), and finds definite evidence of its impact on reducing inpatient Length of Stay (LOS). I use variation in hospital competitors' IT adoption rates to identify the effect of EMRs on Length of Stay (LOS) two years after for the focal hospital. The model is estimated using two-sample non-linear instrumental variable, which allows me to obtain the consistent causal effect of IT system. The study sample covers 23 millions of patients discharge information nationwide, which is extracted from National Inpatient Sample from 2002 to 2008. The sample covers patients of various age group, geographic areas, gender and races, disease types and severity level, while allowing for enough variation in adoption behaviors. Results show that CPOE along with Enterprise EMRs can reduce Length of Stay by as much as 16% for the total study population.

I propose that there are two levels of heterogeneous treatment effect. The first level is based on patients' observable patients heterogeneity, while the second level is identified by exploring the variation left in residuals from mean estimates. I observed that the first level of heterogeneity happens at patients diagnostic categories. To estimate the second level of heterogeneous treatment effect I introduced the Finite Mixture Model (FMM) method, which has been widely used in medical literature to examine mixtures among average treatment effect, in order to estimate the potential heterogeneity. The model identifies two types of EMRs effect on patients' Length of Stay, and it is further able to link the observable patients and hospitals characteristics to the heterogeneous effect identified. I also show that there is mixed IT effect among inpatient population, where 20% - 30% of the patients experience greater reduction in LOS due to EMRs than the rest of the patients. The model predicts that these 20% - 30% patients are the ones with more severe medical conditions, with longer LOS to start with, and their hospital characteristics are not shown to be significantly different to those that are not affected greatly by EMRs.

This study relates to both the economics literature of IT implementation and Health IT literature that studies the effectiveness of information system on population health care quality. In relation to economics literature, this paper takes advantage of the rich patient discharge level data and addresses the importance of heterogeneous effect, which has been argued in literature both theoretically and empirically as a way to tackle the IT paradox. In theory, researchers may have failed to identify information system due to *redistribution* of output. It is possible that the effect linked with information system can sometimes be positive and sometimes negative, with an overall sum of zero effect. Empirically, aggregated statistics may have overlooked any potential benefit of IT system because it fails to identify heterogeneity in the effect. In relation to the Health IT literature, my analysis result support the theoretical understanding of EMRs' working mechanisms. By design, with treatment guidelines embedded within the system, EMRs may inform care providers with alerts regarding testing, monitoring and interventions. This feature may result in the patients' disparities in receiving EMRs benefit, based on diagnoses, patients' medical complexity or the complementary of doctors' interactions with the system. Therefore it is expected that EMRs has more potential under complex cases than under moderate cases, and my empirical analysis supports this hypothesis.

The Finite Mixture Model gives special property when analyzing heterogeneity by avoiding the sharp dichotomy between the "moderate condition" and the "severe medical complexity", or between different hospital types. In understanding of the EMRs mechanism, the underlying unobserved heterogeneity which splits the inpatient population into latent classes is assumed to be based the person's latent degree of medical severity. The observed health conditions and hospital types etc. may be combined together to reflect the true heterogeneity, therefore simply stratifying the sample may fail to interpret this combination. On the other hand, the Finite Mixture Model consists of two-step estimation that captures this combination and therefore gives more flexibility than traditional methods.

The next section of this paper will discuss more information of "IT Paradox" from both theoretical and empirical perspectives, and then establish three main hypotheses tested in this study. Then followed by data description, statistical models and empirical estimation results.

2 The Paradox and Heterogeneity Hypotheses

2.1 The "IT Paradox"

Nobel Laureate economist Robert Solow first brought up the notion of information system paradox on the nation level productivity back in 1987, stating that "You can see the computer age everywhere but in the productivity statistics". This is referring to the problem that researchers have failed to find empirical evidence to support the realization of IT benefit on the economy as a whole. And such difficulty exists regardless of industries that researchers have been focusing on. Brynjolfsson (1993) reviews a handful of studies at the time to summarize this empirical challenge and raises four theoretical explanations: Measurement error of outputs and inputs; Mismanagement of the technology by managers; Time lags in the pay-offs to IT; and Redistribution, which may result in heterogeneous output levels or benefit among firms without adding to the total outcome. In particular, Brynjoflsson explains the hypothesis of redistribution as "rearranges the shares of pie without making it any bigger". Therefore, the redistribution hypothesis is essentially stating the possible heterogeneous effect of IT system among firms or products.

The theory of redistribution brings up two points that need to be considered when conducting empirical analysis. First, The identification of such heterogeneous effect variations requires usage of disaggregated level data. Brynjolfsson and Hitt (1996) conduct empirical analysis that find IT system yields strong positive output (a marginal return of $2.62 with every dollar spent). Their research takes into account of time lag of IT adoption, and utilizes detailed firm level information rather than industry level data, which they argue reveals the variations of output among firms. Secondly, redistribution gives a theoretical foundation for the existence of heterogeneous IT treatment effect. According to this theory, it is reasonable to believe that IT system contribute to firms differently: some firms are better adapted to the computerized work environment with improvements in work flow or procedures, while others may not be able to corporate with the new change. Therefore, an estimation of mean response of everyone can be misleading because the average effect is a mixture of substantial benefit for some, little or no benefit (or even harm) for others.

While the "IT Paradox" existed in studies of many other industries, Lapointe et al. (2011) summarize how theoretical foundations of this problem particularly fits into health care services. Lapointe et al. emphasize that currently in Health IT research area the issue of redistribution is given little consideration, that maybe Health IT fosters quality care in some sectors while not in others. However this paper focus more on the perspective of institutions where task redistribution happens rather than patient outcome, therefore there is a lack of discussion on EMRs impact on patients themselves. While this theoretical study did not provide more analysis about where the heterogeneous IT effect on patient outcome would take place, empirical researchers from other papers have made their assumptions according to observable characteristics available in data. McCullough et al. (2013) explore the heterogeneous effect of Health IT on Medicare inpatient mortality based on patient types and severity, while Miller and Tucker (2011) examine the heterogeneity of Health IT effect on neonatal outcome based on mothers' observable demographic difference, such as education and race.

2.2 Hypotheses and Heterogeneous Treatment Effect

Health IT is designed to store patients records safely and clearly, to reduce input errors and missing records, and to make communications more efficiently. Among various categories of Health IT, the basic and widely discussed ones include the Electronic Medical Records[1]. It contains digital format of patients' medical information, for example medical history, medication, laboratory test results and other clinical data. EMRs is to replace traditional paper-based handwritten medical records, to make it easier to read and keep track of patients' history information. Moreover, digital records can be transferred between care providers

[1] Another related concept is the Electronic Health Records (EHRs). EMRs contains the standard data gathered in one provider's office, whereas EHRs includes more comprehensive medical and clinical history that goes behind the information collected within the provider's office.

more convenient and faster under certain conditions.

The computerized storage of patients' information can lower the communication cost within the hospital (for example, IT allows physicians and nurses to access patients' record faster, without going through piles of paper-based files). This can lead to improvement in timeliness and precision (for example no unclear handwritten, or missing files etc.). Therefore it is expected to see that Length of Stay (LOS) will be shortened due to IT's impact.

One might argue that with an expensive investment as IT system, a hospital is encouraged with the incentive to provide more services (such as induced demand) that may result in longer LOS to cover the financial cost. However regardless of whether such inefficiency exists, the payment system in the US discourages the behavior of prolong LOS, since more private insurance as well as Medicare is changing to prospective payment according to diagnosis-related-groups (DRGs). Under such reimbursement strategy to hospital, hospitals are not payed based on the days the patients stayed, but rather their severity. Therefore there is often no financial incentive to keep patients for long period of time.

Yet there is limited evidence in literature that shows such benefit of EMRs. Parente and Van Horn (2006) finds no effect of Clinical IT (including EMRs) on LOS for Not-for-Profit hospitals, and a marginally significant 1% drop in LOS (at 10% significant level) for For-profit hospitals. However this study is based on hospital level average LOS analysis, which cannot capture the long tailed distribution of LOS found on individual level data. Aggregated analysis of technology improvement may get stuck into the "IT productivity paradox", which refers to the situation in empirical studies where the benefit of information system cannot be found in aggregate output statistics. This can be again attributed to the problem of "IT Paradox", as Brynjolfsson has argued about the aggregated level data missing the variation on disaggregated level issue. In this paper I analyze discharge level data, which provides details across patient types and characteristics and their outcome.

Hypothesis 1. *EMRs lead to faster discharge of patients from hospitals, as empirically, individual-level data set with rich demographic and medical information allows for identification and yields enough variation for analysis.*

Hypothesis 1 discusses the potential average benefit of EMRs on patients. However, understanding of potential heterogeneous EMRs effect helps evaluating the adoption of the IT system in health care sector. Patients not only differ on their observable characteristics, but also may response variously to technology improvement. EMRs treatment effect may vary according to individual's observed characteristics such as demographic information and admission reasons. Furthermore, heterogeneous effect should be expected if redistribution of benefit from Health IT indeed exist. The question is, where does heterogeneous effect happen. There has been lack of formal discussion in literature about the source of heterogeneity of EMRs impact. In this paper I investigate this issue from two levels.

The first level of heterogeneous effect is based on observable patient characteristics. I propose two aspects here: the admission type and diagnostics. Admission types (Emergency Room admission or not) and primary diagnosis can result in different procedures and care processes, and thus lead to receiving different level of IT benefit. For example, Emergency Room (ER) admissions are generally under more acute situations and would benefit from more comprehensive medical background of the patients. One such case is that an ER admission with stroke requires physicians' identification of the stroke types: clotting or bleeding, which call for distinct treatment procedures. These treatments can be counterproductive or even fatal if used interchangeably (Bhattacharya et al., 2013). Under this emergent circumstances, a hospital that can pull up the patient's past medical history faster and more accurate will help with the diagnosis and time to save live. However, this scenario would only work provided that the patient has been admitted to the hospital before and has his/her medical background information electronically stored. On the other hand, patient medical conditions can be identified into various Major Diagnostic Categories, with biologically driven responsiveness to treatment. Therefore it is reasonable to believe that EMRs can benefit patients differently based on their diagnoses. Athey and Stern (2002) find IT adoption for emergency response system improves individuals health status through improvement in timeliness, using panel data set of Pennsylvania counties during 1994-1996. McCullough et al. (2013) use medicare data on patient level with Diff-in-Diff analysis setup and show that IT's effect on Medicare patient outcome vary across four types of disease:

pneumonia(PN), congestive heart failure (CHF), coronary atherosclerosis(CA) and acute myocardial infarction(AMI). In this paper, I take consideration of all possible diagnostic categories.

Hypothesis 2. *Individuals admission types and main diagnosis may lead to different treatment procedures and care processes, and thus patients end up receiving different levels of EMRs benefit, which in this study refers to shorter Length of Stay.*

On top of Hypothesis 2, there are still reasons to believe that heterogeneous effect of EMRs exists within each subgroup of patients defined by their admission types and diagnosis, hence the second level of heterogeneous effect. Statistically, the mean estimates within each sub-population of patients express only the average magnitude of EMRs effect, while there is still variation left in residual.

First, EMRs treatment effect may vary according to individual's medical conditions. The role of EMRs includes not only storing information electronically, but also organizing such data to improve treatment decisions. For conditions that require constant monitoring and taking tests, EMRs can help monitor by generating large volume of data to be evaluated by providers. Patients with more severe medical conditions such as diabetes, hypertension or other high comorbidity measure can therefore be benefited more from the IT utilization. Also, patients that require services from multiple clinical specialists can have their physicians exchange information and communicate with each other faster with the help of EMRs and CPOE. Such benefits will be less obvious among patients with less medical complexity (McCullough et al., 2013). So the average treatment effect within each subsample by disease types can still be mixture of substantial benefits for some, little or no benefit (or even harm) for other patients.

Secondly, the potential heterogeneous treatment effect of EMRs adoption may happen to different types of hospitals. For example, it is reasonable to believe that for-profit hospitals will try to reduce LOS after EMRs adoption, due to cost minimizing concern, whereas such issue is less of concern to non-profit hospitals. Or teaching hospitals may have better trained physicians and nurses who are more adaptable to new technology implementation, than those non-teaching hospitals, therefore more reduction in LOS is expected. Moreover, IT complementary labor input and process adaption within an institute also plays an important part in the utilization of a IT system, hence the potential heterogeneity on hospital level.

Thirdly, heterogeneity may appear as distributional treatment effect. As mentioned above that IT system lead to improvement in timeliness by reducing communication cost, therefore it is reasonable to assume that individuals end up on different position of LOS distribution may experience EMRs effect differently. An individual who is admitted to hospital with two overnights stay may be discharged from hospital a few hours faster with EMRs shortening paperwork time. At the same time, an individual who is on the longer end of inpatient stay may be experiencing much faster discharge, because he/she has a longer LOS to begin with to receive improvement. Any improvement for short LOS will be minimal compared to those with long LOS. Yet again, one can argue that the distribution-based variations in treatment effect can be just reflecting the variations caused by patients' health condition. Those who has longer LOS are often the ones with more severe medical conditions than those who stay for a short time.

For the first two reasons of heterogeneous effect, one can conduct analysis on sub-samples based on observable medical conditions or hospital types. Yet there are two flaws to such study design. On one hand, observed medical conditions measure may not fully represent the true complexity and severity. On the other hand, observed medical conditions measure can be correlated with demographic background or hospital types, therefore it is hard to interpret the result as based on medical conditions or other factors. For example, being admitted to a large teaching hospital in a metropolitan area can be seen as indicating that the patient is in a substantially severe condition.

For the third reason illustrated above, quantile regression for treatment effect estimation may be applicable for distribution-based heterogeneous effect. Yet the correlation across different quantiles that each individual test statistics at different quantile relies on, makes it difficult to understand the treatment estimates. Moreover, Fink et al. (2014) finds that analysis using either interactions or quantile regressions for heterogeneous effect analysis suffer from the problem of over-rejecting the null hypothesis using traditional standard errors and p-values for testings. They argue that after all, each interaction term represents a separate hypothesis beyond the original experimental design and results in a substantially increased type I error, and individual test result for each percentile groups suffer from the issue of reusing the same data, as argued by White (2000).

Therefore, not only the true underlying mechanism that causes variability of EMRs effect is unknown (I listed three possibilities of the sources above), but it is also difficult to incorporate a traditional estimation strategy for heterogeneous effect. I propose a new way to think about the origination of heterogeneous treatment effect, which is the Finite Mixture Model that consists of two steps. On the first step, the model identifies the presence of unobserved heterogeneity and on the second step, I take account of all known characteristics to explain the heterogeneous effect, if found any. This contributes to my third hypothesis, which is that there is a second level of heterogeneous effect. What differentiate this paper from previous Health IT studies is that, in this analysis all of patients' and hospitals' characteristics are taken into account without having to make presumptions of how to divide up the study sample. In fact, there is no need to stratify the sample and I utilize all available information. The strategy to test for this hypothesis is illustrated in section 4.

Hypothesis 3. *Within each admission types and major diagnosis group, it is expected to see that EMRs heterogeneous effect still exist. And such variation can be explained by linking the observables to the differences found by the model.*

3 Data Description

There are two main sources of data used for analysis. The first one is obtained from the 2008 Healthcare Information and Management Systems Society (HIMSS) Analytics. The HIMSS Foundation conducts annual survey questions to over 3000 hospitals in the US about information on Health IT adoption. Hospitals included in this database are those that are part of certain integrated health delivery systems. This database contains detailed information on Health IT adoption on hospital level, including the type of applications, adoption date, operating status, and adoption plans.

The second source of data comes from the 2002 to 2008 National Inpatient Sample (NIS), which is part of the Healthcare Cost and Utilization Project conducted by Agency for Healthcare Research and Quality (AHRQ). NIS is the largest inpatient health care database in the United States, yielding national estimates of hospital inpatient stays. It is a repeated cross-sectional dataset that resample every year to represent about 20% of the US hospitals each year. It contains discharge level medical information, and demographic information. Medical information includes admission time, length of stay, up to 25 diagnosis records and up to 15 procedure records for each patient. It also includes patients' insurance or Medicare/Medicaid status, and total out-of-pocket charges. These discharge variables allow me to generate patients' Charlson Comorbidity Index, which is a measure of medical severity[2].

Hospital Referral Region data set from Dartmouth Atlas, and one year AHA data set are also used to capture industry market structure hospital characteristics.

There are some potential sample selection issues to this study. First, to make usage of the two major data sets, I need to use AHA ID to link them. However in the NIS data, some states prohibit the identification of hospitals and therefore information from such states are not available for analysis. Secondly, HIMSS only survey the hospitals that belong to integrated systems, thus small and independent stand-alone hospitals are not in this analysis. Considering these problems that may cause bias in the analysis, I restrict my study sample only to hospitals from states that are available to analyze in all years.

On the patient side, it is important to notice that there are fundamental differences in patients background. First of all, patients who are transferred into a hospital from other health care facility may indicate that such patients are of even more severe health situation, who needed more intensive care. Secondly, child birth as the primary reason for a hospital stay should not be viewed as the same as those who were admitted due to disease. Therefore I drop discharges that are transferred from other care providers or of birth giving to make sure the final sample consists of patients who are comparable to each other. I also exclude

[2]Charlson Comorbidity Index, developed by Charlson et al. (1987), is a adjusted-risk weighted sum of 17 comorbidity conditions; the higher the score the more likely the predicted outcome will result in mortality or higher resource use.

deaths during inpatient stay. The final sample consists of 23,852,189 discharges over the seven years. There are in total 1271 hospitals from 21 states. Figure 1 shows the geographic coverage of hospitals studied. As shown in the graph, the final sample consists mostly states with high population density. About one third of the hospitals (450) appear only once in all seven years, another one third appear twice (414), and the rest appear more than three times during the study period.

The variable of interest is patients' Length of Stay, measured in days. Same-day discharge is coded as having LOS equals to zero. The final controlled variables are categorized into three groups (plus year and state fixed effect). The first group is demographic information, including age, gender, race, zip code income level, and patients' payer types. The second part is health status, which includes two variables: total Charlson Comorbidity Index and an indicator of Emergency Room Admission. The third part is hospital characteristics, including hospital size, ownership types and other indicators. Summary statistics are shown in table 1). On average, LOS is longer in hospitals with IT adoptions (4.540 versus 4.459 for Enterprise EMRs and 4.56 versus 4.474 for EMRs + CPOE), and patients in IT implemented hospitals tend to have higher Charlson Comorbidity Index (1.046 versus 1.018 for Enterprise EMRs and 1.042 versus 1.028 for EMRs + CPOE). On hospital level, hospitals with EMRs implemented tend to be the ones that are larger (in terms of bed size), with various affiliations, belonging to health care delivery systems, and teaching hospitals.

3.1 Definition of EMRs

The definition of EMRs was unclear during the past few years, so it results in inconsistent measure in literature. For example, Fonkych and Taylor (2005) define two stages of EMRs adoption in their analysis: a basic EMRs system that contains Computerized Patient Records, Clinical Data Repository and Clinical Decision Support; whereas a advanced EMRs is the basic EMRs plus Computerized Physician Order Entry. Miller and Tucker (2011) defined their basic EMRs as having adopted "Enterprise EMR" together with other clinical support. [3]

I adapt two measure of EMRs in my analysis, one is the "Enterprise EMR" as basic EMRs, and the other one is "basic EMRs plus Computerized Physician Order Entry (CPOE)". Due to the structure of HIMSS questionnaire[4], the EMRs is coded in a similar fashion to the one used in the work by Miller and Tucker (2011). Hospitals are coded as having an EMRs system one year after their initial "Enterprise EMRs" contract year, and the system is reported as "Live and Operational". Similar method applies to the coding of "EMRs plus CPOE". There are two reasons to add the CPOE into EMRs definition. First, in theory, CPOE can help shorten Length of Stay since it is designed to reduced medical errors, and records and transfer information faster. This means fewer potential hospital stays for patients, so that they don't have to stay for a longer period waiting for further corrections and communications from care providers. Second, CPOE utilization has been assigned as the goal of Stage I of the Meaningful Use by HITECH. Therefore it has essential policy implication to understand the magnitude of CPOE's impact.

4 Identification Strategy

4.1 Basic Model

The basic model is trying to find whether last year's EMRs adoption has any effect on current year's Length of Stay, after controlling for hospital characteristics (membership, teaching status, bed size, ownership etc), patient demographics (age, gender, race, zip code income level, payer type etc), and patient severity (measured by Charlson Index). Model is estimated using the negative binomial distribution due to the long tail distribution of LOS. Therefore the estimation specification is

$$E(y_{ikt}) = f(\beta_0 + \beta_1 \mathrm{EMRs}_{k,t-1} + X_i\beta_2 + S_i\beta_3 + H_k\beta_4 + \lambda + \phi), \tag{1}$$

[3]Starting 2009, HIMSS Analytics changes the IT components' definition in their questionnaire. EMRs in HIMSS database is now a categorical variable that includes six types of applications, where "Enterprise EMR" is dropped.

[4]Since the HIMSS data set is a survey questionnaire, there are inevitable measurement errors in recording the information. Researchers have indicated that the status of hospitals IT adoption can be inconsistent across years, due to the error made by respondents who were filling out the survey.

where i indicate each discharge unit, and k indicates hospitals at each t period, X_i stands for demographic characteristic of the discharge, S_i is the observable severity of the discharge, H_k is the observable hospital characteristic, and λ and ϕ indicate state and year fixed effect, respectively. Particularly, β_1 is the estimator of interest in this analysis. Function f follows negative binomial distribution.

One of the biggest challenge is that EMRs adoption decision is endogenously made. If hospitals decided to implement EMRs at the same time practicing more on treatments for patients that acquire longer LOS and services, then the naive estimates β_1 in equation 1 should not be interpreted as causal. As pointed out in Elnahal et al. (2011), high quality adopters acquire more and faster Health IT. In literature, most studies on detecting EMRs effect on hospital quality of care were conducted within a certain hospital(e.g. Bates et al. (1999), Dexter et al. (2004)). In a few studies that are to capture national results, researchers tend to use panel data to control for hospital fixed effect (e.g.McCullough et al. (2010)). Miller and Tucker (2011) use privacy laws in each state as an instrument for EMRs adoption, because hospitals in states where patients record were under restrict sharing permissions, were more resistant to adopt this information sharing based technology. However, this instrument is invalid to use in my study because none of the states in my sample except for NC had a strict privacy law during the study period, hence the low variation in state legislation for identification of first stage regression.

4.2 Two Sample Instrumental Variable Model

In this study, I adapt the usage of a different instrument for the EMRs adoption, which is the one-year lagged EMRs adoption rate of a hospitals' competitors. Suppose hospital i is facing the decision whether to implement EMRs or not. If it sees more of its competitors in the market installing the system, then it will be more inclined to adopt the technology too. This is the same rationale as described in the paper of banking market, where banks decide to implement information system just to keep up with its competitors(Prasad and Harker, 1997). The assumption implies that the IT adoption decision is closely correlated with competitors' behavior, yet competitors don't affect the outcome of focal hospital directly.

The idea of using competitors relationship in an industry as an instrument is not a completely new idea in IO literature. For example, Evans et al. (1993) use this idea in airline industries, where they combine instrumental variable method in a fixed-effect model to eliminate bias. Their instrumental variable is a one-year lagged firm indicator (Route Herfindahl, to indicator a firm's ranking position in the industry). Davis (2005) utilizes this method for movie theater industry, where he uses two-quarter lagged values of market structure to instrument for current market structure (variations come from the movement in competitor's ranking among movie theaters). In health economics research, Dafny et al. (2009) study if the competitiveness in health care market causes changes in insurance premiums. In this study, they used market-specific shocks induced by a large national merger to instrument for changes in market concentration. The results show unbiased estimates that the mean increase in local market HHI during 1998-2006 raised premiums by roughly 7 percent.

The exogeneity assumption of IV methods states that the instrumental variables only affect the outcome variable indirectly through the endogenous variable. For competing hospitals' adoption rate to work as a proper instrument, I am imposing the assumption that competitors' EMRs adoption does not directly improve the focal hospital's patients benefit. There are several reasons to believe that such assumption on the EMRs network externalities is valid. First, hospitals adopt different plans from numerous IT providers, which makes the inter-hospital health information exchange difficult. The EMRs are primarily installed for enhance communications within the hospital to system itself, instead of transferring usage. Secondly, very few hospitals exchange patients' health records with competitors. Besides, under state privacy law and the HIPPA regulation, inter-hospital information sharing is strongly restricted (Miller and Tucker, 2009). Furthermore, in my analysis I excludes transferred patients from the sample. Therefore competitor's EMRs adoption should not directly affect focal hospital's service. Evidently, Lee et al. (2013) conducted production function estimation of Health IT adoption and found no evidence of network externalities on hospitals' productivity. McCullough et al. (2013) tested the hypothesis of EMRs spillover effect the in Diff-and-Diff setting. Results show that neighboring EMRs and CPOE adoption does not influence the focal hospital's magnitude of IT impact.

Due to sample selection and my restrictions on the states to be included, the merged dataset (discharge level) is only showing a subsample of the hospital population. Yet it is to be believed that the correlation of EMRs adoption and previous years' competitors' adoption rate is happening across the entire hospital population. Therefore I am adopting the two sample IV (TSIV) method brought up by Angrist and Krueger (1992), which illustrate that TSIV can still yield consistent estimates. The first stage regression is based on HIMSS dataset only, which contains the entire system-related hospitals for each year (hospital level). Therefore the first stage logit regression model is as follows:

$$P(\text{EMRs adoption}_t|H, w) = \frac{1}{1 + exp(-(w_0 + w_1 \text{Competitors' EMRs rate}_{t-1} + Hw_2 + \phi + \epsilon_t))}, \quad (2)$$

where the significance of w_1 estimator is of interest. Since the second stage regression is parameterized into the non-linear negative binomial distribution, traditional two-stage IV method yields inconsistency (for comprehensive illustration of such inconsistency, please review Terza et al. (2008)). As a result I adopt the residual included control function method, where both the variable of interest (in this case, the last year EMRs adoption decision) and the residuals from first stage regression are inserted into second stage regression, instead of the predicted value of last year EMRs decision.

$$E(y_{ikt}) = f(\beta_0 + \beta_1 \text{EMRs}_{k,t-1} + \gamma \text{F.S.residual}_{k,t-1} + X_i\beta_2 + S_i\beta_3 + H_k\beta_4 + \lambda + \phi), \quad (3)$$

The residual inclusion idea was first suggested by Hausman (1978) in linear models to test for endogeneity. Similarly in non-linear set up, if the residual coefficient is significant in the second stage regression, then it suggests the existence of endogeneity.

4.3 Heterogeneous Effect Models

It is important for economists to identify the heterogeneous effect of any intervention, to understand how different population are impacted. As mentioned in Hypotheses, there are two levels of heterogeneous treatment effect of EMRs. On the first level, EMRs can affect patients within different disease types differently. On the second level, even within each subsample of patients grouped according to the diagnoses, patients are still expected to affected by heterogeneously based on their health status, which is indicated by a latent variable.

For analysis on the first level of EMRs heterogeneous treatment effect, I split the full sample into subsamples based on the admission types and patients' major diagnostic category. Then the model is estimated using Two Sample Instrumental Variables to obtain consistent estimates.

To establish the estimation second level of heterogeneous effect, I conduct Finite Mixture Model (FMM). FMM is a suitable way to integrate all observed differences in variables, using all available information in the sample, without manually split the sample into different categories. The theoretical derivation of mixture of densities has been established in the statistics literature for decades (e.g. see McLachlan and Basford (1988)), and Lindsay (1995) has provided more in-depth discussions of the utilization of FMM. The mixture model is also widely used in medical research studies. For example in the book of Schlattmann (2009), he discussed numerous applications of the FMM method, including analysis of gene expression data, pharmacokinetics, toxicology, and meta-analysis of published work. In econometrics, Heckman and Singer (1984) demonstrated the mixture model analysis for duration data, and estimated the distribution function of the unobservables. Deb and Trivedi (1997) publish the first work of utilizing FMM analysis on binomial count model in health economics field, where they estimate the demand for medical care based on unobserved health status of the elderly.

According to my proposed hypothesis, I begin with the assumption that there are at least two different groups in the population, the more severe patients and the less severe ones. To show this in the mixture model concept, it means there are two sub-populations in the whole population. The identification of these two components is based on the latent variable that indicating health conditions. I do not put any constraint on how to separate these two populations based on observed characteristics. I'm letting the model to do this separation for me, through maximizing likelihood method.

A typical FMM contains two stages of analysis. The first stage model with C components (in my study here with the assumption mentioned above, $C = 2$) looks like this:

$$f(y|\boldsymbol{x}, \{\theta_j\}\{\pi_j\}, j = 1, ..., C) = \sum_{j=1}^{C} \pi_j f_j(y|\boldsymbol{x}; \theta_j) \tag{4}$$

where $0 < \pi_j < 1$ and $\sum_{j=1}^{C} \pi_j = 1$, θ_j is parameter of $\boldsymbol{x}$, j indicates different components in the model, and π_j is the predicted share/percentage of component j among the entire population. In other words, the log-likelihood is the sum of each component's log-likelihood, weighted by the probability. More specifically, LOS is modeled by Negative Binomial distribution. Thus for the Negative Binomial density for each observation i

$$f(y_i|\boldsymbol{x}\{\theta_j\}\{\pi_j\}, j = 1, ..., C) = \sum_{j=1}^{C} \pi_j \frac{\Gamma(y_i + \alpha_j^{-1})}{\Gamma(\alpha_j^{-1}) y_i!} \left(\frac{\alpha_j(\boldsymbol{x}\theta_j)}{1 + \alpha_j(\boldsymbol{x}\theta_j)}\right)^{y_i} \left(\frac{1}{1 + \alpha_j(\boldsymbol{x}\theta_j)}\right)^{\alpha_j^{-1}}, \tag{5}$$

where $\alpha_j \geq 0$ is referred to as the index or dispersion parameter. When $\alpha_j \to 0$, the distribution converges to Poisson distribution. The subscript j of α_j indicates that each component of the mixture follows its own distribution density. At this stage, the model predicts C types of heterogeneous effects (again, in this paper, $C = 2$) of EMRs on LOS. At the same time, the model will predict π_j, the predicted share of the components. Notice that all shares of the components should have sum of one. That is,

$$\sum_{j=1}^{C} \pi_j = 1 \tag{6}$$

$$0 < \pi_j < 1 \tag{7}$$

Parameters of the finite mixture distributions for LOS are estimated by maximum likelihood.

The second stage of FMM relates the predicted heterogeneous groups to each observation. Although the class probabilities, π_j are not informative for individual-level assignment of observations into classes, Bayes' theorem can be used to estimate the posterior probability that observation y_i belongs to component c:

$$Pr(y_i \in \text{population} \quad c|\boldsymbol{x}_i, y_i, \{\theta_k\}) = \frac{\pi_c f_c(y_i|\boldsymbol{x}_i, \theta_c)}{\sum_{j=1}^{C} \pi_j f_j(y_i|\boldsymbol{x}_i \theta_j)}. \tag{8}$$

After the two-stage FMM analysis, the model hasn't related the predicted heterogeneity to the observable characteristics of each inpatient record to understand how the estimated sub groups differ. I use the estimates of the posterior probabilities of class-membership to assign individuals in the sample to a unique class and use these classifications to explore the determinants and correlates of class membership. This process is estimated using OLS regression.

5 Results

5.1 Basic Model and First Level Heterogeneous Treatment Effect

Figure 2 shows the adoption of Enterprise EMRs and EMRs + CPOE over years. The adoption of Enterprise hits above 40% by 2008, whereas the adoption of CPOE is much lower, with slightly more than 20%. The adoption rates are consistent with the information provided in Dranove et al. (2012), which shows the implementation of CPOE is about 22% in 2008.

Table 2 reports the first stage of IV regression. The instrument (one-year lagged EMRs adoption rate from competitors in the same HRR area as focal hospitals) shows strong correlation with the EMRs adoption of each focal hospital. This is true for both Enterprise EMRs and EMRs + CPOE adopters, which supports the correlation requirement of the instrument to the endogenous variable. Hospital ownership type shows significant correlation to adoption decisions. Compared to For-profit hospitals, government owned or non-profit hospitals are shown to be more likely to invest in the IT technology, probably because the financial pressure at the beginning of the adoption process is too heavy and does not meet profit-maximization criteria for a for-profit hospital. Belonging to a health care delivery system is significantly associated with IT adoption, which may be explained by the incentive gained from IT for easier inner system communication, or by the larger bargaining power in negotiating prices. At the same time, accredited by or affiliated to other organizations almost do not show significant associations to the EMRs adoption behavior.

First two columns of table 3 (a) and 3 (b) show both the Enterprise EMRs and EMRs + CPOE adoption effect on LOS respectively, under Negative Binomial regressions. Notice the model also controls for patients' Major Diagnosis Category (MDCs) that is not reported in the tables. The rest four columns study the heterogeneous effect of EMRs based on discharges' admission types. All of the estimated coefficients show negative sign, which corresponds to *Hypothesis 1* that EMRs shows benefit in timeliness and thus reduce LOS. Across the two sub-tables, coefficients in table 3(b) are bigger than the ones in table 3(a), indicating that LOS is reduced more with added CPOE to EMRs than Enterprise EMRs alone.

Furthermore, results also show a consistent pattern in the size of effect within each sub-table. The point estimates of IV estimators are all larger than the naive estimators, and under the CPOE + EMRs implementation, IT's effect is all statistically significant. When ignoring endogeneity under naive regression (column 1, 3, and 5), the one-year lagged EMRs adoption shows to drop LOS by about 1.4% to 2%. When controlling for endogeneity (column 2, 4, and 6) using Two Sample IV, LOS are shown to be reduced by 11% caused by Enterprise EMRs and by 16% by using EMRs + CPOE. In other words, while the residuals from first stage regression pull away any unobserved factors in EMRs adoption decision making, the coefficient on lagged EMRs variable is expected to be showing the true treatment effect. Along with this result, we see that patients' demographic information and their severity (Charlson Index) are showing significant correlation to the hospital staying length, along with several hospital characteristics. LOS increases with the increase of age; black patients tend to have longer LOS compared to white non-Hispanic patients while Hispanic patients how the opposite coefficient signs; Female patients stay for fewer days compared to male patients; higher Charlson Index is correlated with longer LOS while patients admitted through ER are staying with longer LOS than those that are not ER admissions.

In response to *Hypothesis 2*, results show that the first level of heterogeneous treatment effect that based on patients admission types is not significant. Under Enterprise EMRs setting, neither sub-sample based on ER/Non-ER admission shows significant impact from the IT system. Also The effect on Non-ER admitted sample shows smaller EMRs effect than the ER admitted sample, and the significance drops for Non-ER patients under in naive estimation. Under EMRs + CPOE setting however, Non-ER admitted patients receive significant 15.8% drop in LOS, whereas ER admitted patients receive significant 10.2% drop. Moreover, table 3(a) shows that residual from first stage is insignificant, whereas in table **??**(b) they are significant except for ER admissions. This suggests that for ER discharges under EMRs + CPOE setting, there is little to no endogeneity detected. The point estimates on ER admission has been lower than Non-ER in both Health IT settings, although not statistically significant. In theory, it is plausible to assume that patients with ER admission may expect to benefit more from IT system than those who are not, because ER admissions in general reflects more complicated situations that require constant monitoring and immediate response. Yet the lack of empirical results to support this theory may be due to the fact that in some emergent cases, IT system can use up to its potential only if the patient has been admitted to this same hospital before or there is patient records on file already to be extracted from. Since I cannot identify the readmission using this particular data set I was not able to further investigate on this possibility.

There are eight sub-tables in table 6 reporting results from eight Major Diagnoses Categories. The IV estimation showing consistent causal effect is reported on column 1 and 3 in all sub-tables. The drop of LOS due to Enterprise EMRs implementation ranges from 6.4% (Digestive, Hepatobiliary, and Pancreas disease, table 6(c)) to 45.4% (Injuries, Poison, Burns, Toxic and Trauma, tablemdc(h)). This confirms *Hypothesis 2* that heterogeneous EMRs effect can be found across different diagnostic types. And once more the combination of EMRs + CPOE is showing greater effect than the Enterprise EMRs setting.

EMRs with CPOE adopted shows greater effect than Enterprise EMRs alone. This should not be a surprise for CPOE allows providers to interact with patients' medical data stored through EMRs, make decisions in real time and may use it to place medical orders. Therefore it is expected to see EMRs and CPOE show greater effect when combined together. Besides, the definition of Enterprise EMRs in HIMSS database is not very clear of its measurement. Survey respondents may be answering to this IT system referring to other types of IT system they have implemented, since the word "Enterprise EMRs" seems to cover a range of IT system instead of just one application. CPOE is also the first stage requirement of HITECH Meaningful Use regulation, which once more emphasize its importance.

5.2 Second Level Heterogeneous Treatment Effect

Sub-tables (a) and (b) of table 4 are showing the results from FMM first stage regressions for consistent estimation, where the FMM model is automatically identifying two types of observations that are receiving different EMRs effect based on unobserved latent class [5]. According to the result, there are about 77% "component 1" ("C 1" as in the column title) observations and 23% "component 2" ("C 2" as in the column title) observations. For Enterprise EMRs, patients in component 1 experience an insignificant drop of LOS by 3.3%, 3.9% and 0.5% (all discharges, ER admissions and Non-ER admissions, respectively), whereas the component 2 patients are significantly affected by EMRs adoption, with the magnitude of effect much higher that of component 1: 18.2%, 12% and 18.3% drop in LOS under EMRs adoption (all discharges, ER admissions and Non-ER admissions, respectively).

For Enterprise EMRs plus CPOE, patients in component 1 experience insignificant drop of LOS by 3.1%, 2.0% and 7.1%, whereas the component 2 patients also are significantly affected by CPOE added EMRs, with the magnitude of effect much larger than that of component 1: 20.5%, 17.4% and 19.8% drop in LOS under EMRs adoption (all discharges, ER admissions and Non-ER admissions, respectively). Once more, added CPOE cause greater reduction in LOS than Enterprise EMRs alone. And notice the significance power increased in the analysis of EMRs + CPOE setting, which again emphasize the importance of CPOE added to EMRs. All together, component 2 patients received much larger impact by EMRs than component 1 did.

So far the results only distinguish the two heterogeneous groups. But who are those

[5] Just a reminder that the second stage of FMM analysis is to estimate the probabilities of each observation belonging to different heterogeneous component, therefore the result is not reported in tables here.

component 1 and 2 patients? To which degree are they being different? To answer these questions, I first check the distributions of LOS in each component. The densities are shown in figure 3. All four graphs tell a similar story: that patients belong to component 1 have on average shorter LOS while those in component 2 on average have longer LOS with longer right tails in the distribution. To summarize, those who on average staying in hospitals for a longer period see a larger drop in LOS with the implementation of EMRs.

I then impose the model to regress the posterior probability of being in "component 1" on demographic and hospital characteristics, time and state fixed effect, and on patient severity. Results are shown in table 5. Age, gender and race have some significant effects on assigning patients into each component: older patients and black patients are more likely to be assigned to component 2, the group that has longer average LOS and experiences larger effect by IT as component 1 patients does. Female patients are more likely to belong in component 1.

Patients' observable health indicators also plays important role in these regressions, that those who were admitted through ER are more likely to be in component 1, and patients with more severe medical conditions are more likely to be component 2. More specifically, graph 4 shows the composition of comorbidity in each component. This graph gives a nice visual explanation of how these two components of patients differ in medical severity.

In general, an image can be drawn from the significant variables, which shows that component 2 patients are of worse health conditions than component 1 patients. Not only the comorbidity disparities send a clear signal, but also the demographic characteristics is showing the consistent information: Older patients are generally less healthier than younger one; female patients tend to be healthier than males of the same age; black patients in general suffers from more severe health conditions than the other races.

However, hospital characteristics almost show no significant correlations in separating the patients into two components. In other words, when controlled for other patient level information, patients who are affected by EMRs differently have no significant variations in the types of hospitals that they are staying. Therefore, this result is implicating that it is not the observed hospital level characters except for "Critical Access Hospitals (CAHs)", but rather the patients demographic and Comorbidity differences that are the reasons of heterogeneous EMRs impact. At the same time, it is reasonable to believe that "Critical Access Hospitals" can be largely improved by EMRs due to the nature of CAHs, since they are required to maintain an annual average LOS of no more than 96 hours for acute inpatient care.

In summary, the Finite Mixture Model is in support of *Hypothesis 3*, that there is unobservable latent variable that assigns patients as either the "less severe ones" or "more severe ones", and they are affected by EMRs differently. The model identifies two types of EMRs effect on Length of Stay for all patients in study sample: Component 1 patients have lower comorbidity index, are more likely to be younger patients who stay in hospitals for relatively shorter days and on average experience a drop of 2 - 7% in LOS; Component 2 patients are in relatively worse medical conditions (high comorbidity index), more likely to be of older age, staying in hospitals for a longer period and on average experience a drop of 12-21% in LOS after one year of EMRs implementation. The reason for this result could be that component 1 patients start with short Length of Stay, and any effort to shorten the days would have minimal effect. At the same time, for component 2 patients, longer LOS may give them more space to improve (in terms of shortening stays) through EMRs help. It can be done either through faster process of paperwork, or making fewer medical errors during procedures, or help the decision making for physicians easier and faster. However these factors are not identifiable in this study.

5.3 More evidence on the Two Level Heterogeneous Treatment Effect

In this section I review more evidence of the two levels of the heterogeneous treatment effect. Sample is first divided into sub-samples based on each patient's Major Diagnosis Category (MDCs). The MDCs are formed by dividing all possible principle diagnoses (coded in ICD-9-CM) into 25 mutually exclusive diagnosis areas[6]. Due to extremely low frequencies (less

[6]MDCs is one of the most common ways of categorizing patients, although it has its limitations in representing the disease type. For example, MDCs are coded with respond to organ systems or etiology, so that there is no explicit category for neoplasms.

than 1%) in some categories, I grouped similar categories in my analysis (e.g. Female and Male Reproductive System are grouped together as the Reproductive System). Table 6 and its sub-tables show both the IV and FMM regressions results for each category. Only eight out of 20 disease groups that are of large sample size are shown here and together they cover 64% of the total sample. These are the disease that affect the majority of the population.

As is discussed above, from Table 6, Negative Binomial regressions show that LOS drops by 6.4% (Table 6(c).) to 45.4% (Table 6(h).) for each of these diagnoses, with EMRs + CPOE showing higher impact. Such variations in the magnitude of EMRs impact is again consistent with the hypothesis of the existence of the first level heterogeneous EMRs treatment effect, based on observable disease types. At the same time, the FMM results show consistent patterns as in the analysis of patients with all diagnosis categories, which is in accordance to the hypothesis on the existence of second level heterogeneous treatment effect. Within each of the diagnosis group, component 2 patients are always shown to be impacted more than component 1. And the component 2 in each category is consistently referring to the more severe patients within the diagnosis category, only with the distribution of component 1 and 2 differs slightly across MDCs.

6 Conclusion

This paper examines how EMRs improves efficiency in timeliness by reducing LOS. By using a seven-year period sample with detailed discharge level medical information I am able to identify the EMRs effect which may take years to appear, and at the same time to generate and control for patients' medical conditions. The results show that on average, for patients with all diagnoses LOS is reduced by 11% to 16% under consistent estimation due to the implementation of EMRs. Added CPOE can reduce LOS more than Enterprise EMRs alone. One need to notice that the consistent estimates of EMRs treatment effect should be interpreted as the Local Average Treatment Effect (LATE) as discussed in Imbens and Angrist (1994). Although there are hospitals in sample did not adopt any IT system at all during the study period, it is not sufficient to believe they are the never-takers since their future adoption behavior could change with more hospitals turning towards Information System management.

Results also support the existence of two levels of heterogeneous treatment effect. The source of first level comes from patients' admission types and diagnostic groups. Within each sub-group of patients lies the second level of heterogeneous effect based on health conditions of the patients. FMM results further show that this second level of heterogeneous effect does not come from the variations in hospital types that patients are admitted to. In other words, regardless of the observable hospital types, more severe patients benefit more from the EMRs than those who are relatively less severe, in terms of shortening the time spent in side the institute. By utilizing the FMM method, patients' characteristics and medical conditions together identify the underlying heterogeneity even among each stratified inpatient sample based on diagnoses, without putting dichotomy restrictions on the sample prior to the analysis.

This study can shed light on the policy that encourages Health IT adoption and intends to reduce health care cost across country, and especially address the potential benefit from Stage I of Meaningful Use. The result shows that CPOE and other EMRs system can bring benefit to hospitals by improving efficiency. Even though this study does not contain cost information, the benefit of reducing LOS may be associated with reducing waste of medical care. It may justify the large amount of Federal Health IT subsidies in the attempt to bring down total health care expenditures.

References

J. D. Angrist and A. B. Krueger. The effect of age at school entry on educational attainment: an application of instrumental variables with moments from two samples. *Journal of the American Statistical Association*, 87(418):328–336, 1992.

S. Athey and S. Stern. The impact of information technology on emergency health care outcomes. *Rand journal of economics*, 33(3):399–432, 2002.

D. W. Bates, G. J. Kuperman, E. Rittenberg, J. M. Teich, J. Fiskio, N. Ma'Luf, A. Onderdonk, D. Wybenga, J. Winkelman, and T. A. Brennan. A randomized trial of a computer-based intervention to reduce utilization of redundant laboratory tests. *The American journal of medicine*, 106(2):144, 1999.

J. Bhattacharya, P. Tu, and T. Hyde. *Health Economics*. The labor market for physicians. Palgrave Macmillan, 2013. ISBN 9781137029966.

T. F. Bresnahan, E. Brynjolfsson, and L. M. Hitt. Information technology, workplace organization and the demand for skilled labor: Firm-level evidence. *No. w7136 National Bureau of Economic Research*, 1999.

E. Brynjolfsson. The productivity paradox of information technology. *Communications of the ACM*, 36(12):66–77, 1993.

E. Brynjolfsson and L. Hitt. Paradox lost? firm-level evidence on the returns to information systems spending. *Management Science*, 42(4):541–558, 1996.

M. E. Charlson, P. Pompei, K. L. Ales, and C. R. MacKenzie. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *Journal of chronic diseases*, 40(5):373–383, 1987.

L. Dafny, M. Duggan, and S. Ramanarayanan. Paying a premium on your premium? consolidation in the US health insurance industry. Technical report, National Bureau of Economic Research, 2009.

P. Davis. The effect of local competition on admission prices in the us motion picture exhibition market*. *Journal of Law and Economics*, 48(2):677–707, 2005.

P. Deb and P. K. Trivedi. Demand for medical care by the elderly: a finite mixture approach. *Journal of applied Econometrics*, 12(3):313–336, 1997.

P. R. Dexter, S. M. Perkins, K. S. Maharry, K. Jones, and C. J. McDonald. Inpatient computer-based standing orders vs physician reminders to increase influenza and pneumococcal vaccination rates. *JAMA: the journal of the American Medical Association*, 292 (19):23662371, 2004.

D. Dranove, C. Forman, A. Goldfarb, and S. Greenstein. The trillion dollar conundrum: Complementarities and health information technology. *No. w18281 National Bureau of Economic Research*, 2012.

S. Elnahal, K. Joynt, S. Bristol, and A. Jha. Electronic health record functions differ between best and worst hospitals. *American Journal of Managed Care*, 17(4):e121–47, Apr. 2011. ISSN 1088-0224.

W. N. Evans, L. M. Froeb, and G. J. Werden. Endogeneity in the concentration–price relationship: Causes, consequences, and cures. *The Journal of Industrial Economics*, pages 431–438, 1993.

G. Fink, M. McConnell, and S. Vollmer. Testing for heterogeneous treatment effects in experimental data: false discovery risks and correction procedures. *Journal of Development Effectiveness*, 6(1):44–57, 2014.

K. Fonkych and R. Taylor. *The state and pattern of health information technology adoption*, volume 409. Rand Corporation, 2005.

J. A. Hausman. Specification tests in econometrics. *Econometrica: Journal of the Econometric Society*, pages 1251–1271, 1978.

J. Heckman and B. Singer. A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica: Journal of the Econometric Society*, pages 271–320, 1984.

G. W. Imbens and J. D. Angrist. Identification and estimation of local average treatment effects. *Econometrica: Journal of the Econometric Society*, pages 467–475, 1994.

L. Lapointe, M. Mignerat, and I. Vedel. The it productivity paradox in health: A stakeholder's perspective. *International journal of medical informatics*, 80(2):102–115, 2011.

J. Lee, J. S. McCullough, and R. J. Town. The impact of health information technology on hospital productivity. *The RAND Journal of Economics*, 44(3):545–568, 2013.

B. G. Lindsay. Mixture models: theory, geometry and applications. In *NSF-CBMS regional conference series in probability and statistics*, pages i–163. JSTOR, 1995.

J. S. McCullough, M. Casey, I. Moscovice, and S. Prasad. The effect of health information technology on quality in us hospitals. *Health Affairs*, 29(4):647654, 2010.

J. S. McCullough, S. Parente, and R. Town. Health information technology and patient outcomes: The role of organizational and informational complementarities. *No. w18684 National Bureau of Economic Research*, 2013.

G. J. McLachlan and K. E. Basford. Mixture models: Inference and applications to clustering. *Applied Statistics*, 1988.

A. Miller and C. Tucker. Can healthcare IT save babies? *The Journal of Political Economy*, 119(2):289–324, 2011.

A. R. Miller and C. Tucker. Privacy protection and technology diffusion: The case of electronic medical records. *Management Science*, 55(7):1077–1093, July 2009. ISSN 0025-1909, 1526-5501. doi: 10.1287/mnsc.1090.1014.

S. T. Parente and R. L. Van Horn. Valuing hospital investment in information technology: Does governance make a difference? *Health care financing review*, 28 (2):31, 2006. URL `http://www.cms.gov/Research-Statistics-Data-and-Systems/Research/HealthCareFinancingReview/Downloads/06-07Winpg31.pdf`.

B. Prasad and P. T. Harker. Examining the contribution of information technology toward productivity and profitability in us retail banking. *The Wharton Financial Institutions Center Working Papers*, 97(9), 1997.

P. Schlattmann. *Medical applications of finite mixture models*. Springer Science & Business Media, 2009.

R. M. Solow. Technical change and the aggregate production function. *The review of Economics and Statistics*, pages 312–320, 1957.

J. V. Terza, A. Basu, and P. J. Rathouz. Two-stage residual inclusion estimation: addressing endogeneity in health econometric modeling. *Journal of health economics*, 27(3):531–543, 2008.

H. White. A reality check for data snooping. *Econometrica*, 68(5):1097–1126, 2000.

Table 1: Summary Statistics

	Enterprise EMRs	No EMRs Adopted	EMRs + CPOE	No CPOE Adopted
Length of stay (cleaned)	4.540	4.459	4.560	4.474
Demographic				
Age	51.936	52.007	51.614	52.114
Black	0.104	0.082	0.098	0.091
Hispanic	0.093	0.109	0.095	0.104
Asian and other race	0.311	0.321	0.323	0.314
Female	0.599	0.601	0.600	0.600
Low Income	0.208	0.215	0.204	0.215
Missing Income	0.031	0.023	0.036	0.023
Lower to Medium Income	0.237	0.240	0.243	0.237
Medium Income	0.245	0.239	0.250	0.239
Medicare	0.382	0.398	0.375	0.397
Medicaid	0.172	0.175	0.177	0.173
Other Insurance	0.085	0.091	0.089	0.088
Health Status				
Charlson Score	1.046	1.018	1.042	1.028
Admitted through ER	0.422	0.444	0.410	0.443
N (Discharge $\times$ Year)	11,693,287	12,192,068	6,757,555	17,127,800
Hospital Characteristics				
Ownership: Gov.	0.173	0.201	0.192	0.191
Ownership: Non Profit	0.757	0.637	0.776	0.657
Critical Access Hospital	0.063	0.244	0.055	0.208
System	0.631	0.570	0.653	0.577
Cancer program approved by ACS†	0.548	0.352	0.589	0.382
Residency training approved by GME†	0.341	0.166	0.401	0.188
AMA† Medical school affiliation	0.424	0.231	0.467	0.261
Accreditation by CARF†	0.180	0.086	0.185	0.104
Teaching	0.133	0.060	0.164	0.068
Rural Referral Center	0.098	0.067	0.087	0.076
Bed Size: less than 100	0.191	0.438	0.203	0.383
Bed Size: less than 300	0.491	0.381	0.444	0.415
Bed Size: less than 500	0.183	0.133	0.196	0.140
Bed Size: more than 500	0.136	0.048	0.156	0.061
N (Hospital $\times$ Year)	980	1,708	531	2,157

† Abbreviations:
ACS: American College of Surgeons
AMA: American Medical Association
CARF: Commission on Accreditation of Rehabilitation Facilities

Table 2: First Stage Regressions

	Enterprise EMRs	Enterprise EMRs + CPOE
Lagged Competitors IT adoption	1.200 (0.201)***	1.664 (0.264)***
Ownership: Gov.	1.155 (0.160)***	1.359 (0.202)***
Ownership: Non Profit	1.176 (0.140)***	1.341 (0.172)***
Critical Access Hospital	-0.763 (0.173)***	-1.222 (0.227)***
System	0.242 (0.085)***	0.529 (0.105)***
Cancer program approved by ACS†	-0.042 (0.100)	0.141 (0.120)
Residency training approved by GME†	-0.013 (0.155)	0.263 (0.194)
AMA† Medical school affiliation	0.284 (0.142)**	0.157 (0.176)
Accreditation by CARF†	0.232 (0.119)*	0.036 (0.141)
Teaching	0.199 (0.156)	0.275 (0.181)
Rural Referral Center	0.390 (0.125)***	-0.003 (0.170)
N Hospital × Year	23,031	23,031

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes hospital size, year and state fixed effect.
Standard error clustered at hospital level.
† Abbreviations:
ACS: American College of Surgeons
AMA: American Medical Association
CARF: Commision on Accreditation of Rehabilitation Facilities

Table 3: Effect of EMRs on LOS

(a). Effect of Enterprise EMRs on LOS

	All Patients		ER Admissions		Non ER Admissions	
	(1)	(2)	(3)	(4)	(5)	(6)
Enterprise EMRs	-0.014*	-0.112*	-0.017*	-0.089	-0.010	-0.096
	(0.007)	(0.061)	(0.009)	(0.078)	(0.009)	(0.075)
Residual from First Stage		0.101		0.073		0.089
		(0.062)		(0.081)		(0.074)
Age	0.005***	0.005***	0.006***	0.006***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.083***	0.084***	0.076***	0.076***	0.098***	0.099***
	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)
Hispanic	-0.018**	-0.017**	-0.012	-0.012	-0.016**	-0.015*
	(0.008)	(0.008)	(0.011)	(0.011)	(0.008)	(0.008)
Asian and other race	0.002	0.002	-0.001	-0.001	0.007	0.007
	(0.007)	(0.007)	(0.009)	(0.009)	(0.008)	(0.008)
Female	-0.023***	-0.023***	-0.038***	-0.038***	-0.005**	-0.005**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Low Income	0.027***	0.028***	0.034***	0.035***	0.020**	0.020**
	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.008)
Lower to Medium Income	0.017***	0.017***	0.022***	0.022***	0.011*	0.011*
	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)
Medium Income	0.013***	0.013***	0.017***	0.017***	0.009*	0.009*
	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
Charlson Score	0.076***	0.076***	0.082***	0.082***	0.072***	0.072***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Admitted through ER	0.036***	0.036***				
	(0.006)	(0.006)				
Medicare	0.129***	0.129***	0.146***	0.146***	0.120***	0.120***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Medicaid	0.135***	0.135***	0.208***	0.208***	0.076***	0.076***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
Other Insurance	0.021***	0.020***	0.047***	0.046***	0.002	0.002
	(0.008)	(0.007)	(0.008)	(0.008)	(0.012)	(0.012)
ownership: Gov.	0.027*	0.048**	0.040**	0.055**	0.016	0.034
	(0.015)	(0.020)	(0.018)	(0.025)	(0.018)	(0.023)
ownership: non profit	-0.017	0.004	-0.021*	-0.006	-0.011	0.007
	(0.011)	(0.018)	(0.013)	(0.022)	(0.013)	(0.021)
critical access hospital	-0.059***	-0.070***	-0.139***	-0.146***	-0.019	-0.029
	(0.022)	(0.023)	(0.022)	(0.023)	(0.030)	(0.032)
system	0.000	0.005	0.010	0.013	-0.013	-0.008
	(0.008)	(0.009)	(0.010)	(0.012)	(0.010)	(0.010)
Cancer program approved by ACS	-0.003	-0.005	-0.009	-0.010	0.005	0.004
	(0.009)	(0.009)	(0.012)	(0.011)	(0.010)	(0.010)
Residency training approved by GME	0.035**	0.035**	0.019	0.019	0.044**	0.044**
	(0.014)	(0.014)	(0.013)	(0.013)	(0.021)	(0.021)
AMA Medical school affiliation	-0.005	0.001	-0.001	0.004	-0.000	0.005
	(0.013)	(0.014)	(0.012)	(0.013)	(0.020)	(0.022)
Accreditation by CARF	0.011	0.016	0.010	0.013	0.013	0.017
	(0.012)	(0.012)	(0.015)	(0.016)	(0.012)	(0.012)
Teaching Hospital	0.056***	0.062***	0.042**	0.046**	0.072***	0.077***
	(0.015)	(0.015)	(0.019)	(0.018)	(0.017)	(0.017)
Rural Referral Center	-0.045***	-0.037***	-0.046***	-0.040***	-0.041***	-0.034**
	(0.011)	(0.012)	(0.014)	(0.015)	(0.012)	(0.014)
N	23,852,189	23,852,189	11,282,328	11,282,328	12,569,861	12,569,861

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes Major Diagnostic Category, hospital size, year and state fixed effect.
Standard error clustered at hospital level.
† Abbreviations:
ACS: American College of Surgeons
GME: Graduate Medical Education
AMA: American Medical Association
CARF: Commission on Accreditation of Rehabilitation Facilities

(b). Effect of Enterprise EMRs + CPOE on LOS

	All Patients		ER Admissions		Non ER Admissions	
	(1)	(2)	(3)	(4)	(5)	(6)
EMRs + CPOE	-0.019*	-0.138***	-0.030**	-0.102**	-0.013	-0.158***
	(0.010)	(0.038)	(0.013)	(0.046)	(0.011)	(0.047)
Residual from First Stage		0.124***		0.075		0.152***
		(0.039)		(0.046)		(0.048)
Age	0.005***	0.005***	0.006***	0.006***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.083***	0.085***	0.075***	0.076***	0.098***	0.100***
	(0.007)	(0.006)	(0.008)	(0.008)	(0.007)	(0.007)
Hispanic	-0.017**	-0.015**	-0.012	-0.011	-0.016*	-0.013*
	(0.008)	(0.008)	(0.011)	(0.011)	(0.008)	(0.008)
Asian and other race	0.001	0.003	-0.001	-0.001	0.007	0.009
	(0.007)	(0.007)	(0.009)	(0.009)	(0.008)	(0.008)
Female	-0.023***	-0.023***	-0.037***	-0.037***	-0.005**	-0.005**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Low Income	0.027***	0.027***	0.034***	0.034***	0.020**	0.020**
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Lower to Medium Income	0.017***	0.017***	0.022***	0.022***	0.011*	0.011*
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Medium Income	0.013***	0.013***	0.017***	0.017***	0.009*	0.009*
	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
Charlson Score	0.076***	0.076***	0.082***	0.082***	0.072***	0.072***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Admitted through ER	0.036***	0.036***				
	(0.006)	(0.006)				
Medicare	0.129***	0.129***	0.146***	0.146***	0.120***	0.120***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Medicaid	0.135***	0.135***	0.208***	0.208***	0.077***	0.077***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
Other Insurance	0.021***	0.021***	0.047***	0.047***	0.003	0.002
	(0.007)	(0.007)	(0.008)	(0.008)	(0.012)	(0.012)
ownership: Gov.	0.027*	0.042***	0.040**	0.049***	0.015	0.033*
	(0.015)	(0.015)	(0.017)	(0.019)	(0.017)	(0.018)
ownership: non profit	-0.016	0.000	-0.020*	-0.010	-0.010	0.009
	(0.010)	(0.011)	(0.012)	(0.013)	(0.013)	(0.015)
critical access hospital	-0.060***	-0.072***	-0.140***	-0.146***	-0.020	-0.035
	(0.022)	(0.022)	(0.022)	(0.023)	(0.030)	(0.031)
system	0.001	0.009	0.011	0.016	-0.013	-0.002
	(0.008)	(0.009)	(0.010)	(0.011)	(0.010)	(0.010)
Cancer program approved by ACS	-0.003	-0.002	-0.009	-0.008	0.005	0.007
	(0.009)	(0.009)	(0.012)	(0.012)	(0.010)	(0.010)
Residency training approved by GME	0.036**	0.042***	0.020	0.024*	0.045**	0.051**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.021)	(0.021)
AMA Medical school affiliation	-0.006	-0.004	-0.001	-0.001	-0.000	0.002
	(0.013)	(0.013)	(0.012)	(0.012)	(0.020)	(0.019)
Accreditation by CARF	0.012	0.012	0.011	0.011	0.013	0.014
	(0.012)	(0.011)	(0.014)	(0.014)	(0.012)	(0.011)
Teaching Hospital	0.057***	0.065***	0.043**	0.048***	0.073***	0.082***
	(0.015)	(0.015)	(0.018)	(0.017)	(0.017)	(0.017)
Rural Referral Center	-0.045***	-0.045***	-0.046***	-0.046***	-0.041***	-0.041***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)	(0.012)
N	23,852,189	23,852,189	11,282,328	11,282,328	12,569,861	12,569,861

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Model also includes Major Diagnostic Category, hospital size, year and state fixed effect.

Standard error clustered at hospital level.

† Abbreviations:

ACS: American College of Surgeons

GME: Graduate Medical Education

AMA: American Medical Association

CARF: Commission on Accreditation of Rehabilitation Facilities

Table 4: Heterogeneous Effect of EMRs Adoption on LOS

(a).Enterprise EMRs Adoption

	All Discharges		through ER Admissions		through Non-ER Admissions	
	C 1	C 2	C 1	C 2	C 1	C 2
Enterprise EMRs	-0.033	-0.182**	-0.039	-0.120	-0.005	-0.183*
	(0.049)	(0.090)	(0.057)	(0.101)	(0.072)	(0.109)
Residual from Fisrt Stage	0.018	0.172*	0.020	0.107	-0.004	0.172
	(0.049)	(0.093)	(0.058)	(0.106)	(0.072)	(0.108)
Age	0.006***	0.004***	0.007***	0.004***	0.005***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.067***	0.098***	0.054***	0.084***	0.078***	0.132***
	(0.005)	(0.009)	(0.006)	(0.009)	(0.005)	(0.011)
Hispanic	0.007	-0.037***	0.001	-0.023*	0.017***	-0.046***
	(0.006)	(0.011)	(0.007)	(0.013)	(0.007)	(0.012)
Asian and other race	-0.005	0.006	-0.018**	0.009	0.008	0.009
	(0.005)	(0.010)	(0.008)	(0.012)	(0.005)	(0.012)
Female	0.034***	-0.065***	0.032***	-0.080***	0.037***	-0.037***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Low Income	0.032***	0.025***	0.049***	0.027***	0.016***	0.029**
	(0.005)	(0.009)	(0.007)	(0.010)	(0.006)	(0.012)
Missing Income	0.010	0.087***	0.015	0.094***	0.011*	0.084***
	(0.007)	(0.012)	(0.011)	(0.016)	(0.006)	(0.014)
Lower to Medium Income	0.019***	0.014**	0.034***	0.015*	0.007	0.015*
	(0.004)	(0.007)	(0.006)	(0.008)	(0.005)	(0.009)
Medium Income	0.014***	0.012*	0.025***	0.013*	0.006	0.011
	(0.003)	(0.006)	(0.005)	(0.007)	(0.004)	(0.007)
Charlson Score	0.061***	0.073***	0.063***	0.079***	0.057***	0.074***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Admitted through ER	0.047***	0.043***				
	(0.007)	(0.007)				
Medicare	0.096***	0.144***	0.135***	0.148***	0.070***	0.144***
	(0.004)	(0.005)	(0.004)	(0.006)	(0.004)	(0.006)
Medicaid	0.057***	0.202***	0.127***	0.267***	0.014***	0.140***
	(0.003)	(0.008)	(0.004)	(0.009)	(0.004)	(0.011)
Other Insurance	-0.031***	0.074***	0.014**	0.069***	-0.064***	0.076***
	(0.005)	(0.011)	(0.007)	(0.010)	(0.007)	(0.015)
ownership: Gov.	-0.003	0.082***	-0.013	0.093***	0.001	0.061*
	(0.015)	(0.030)	(0.017)	(0.033)	(0.020)	(0.035)
ownership: non profit	-0.004	0.018	-0.004	0.004	-0.010	0.023
	(0.014)	(0.027)	(0.016)	(0.029)	(0.019)	(0.031)
critical access hospital	-0.057***	-0.043	-0.069***	-0.254***	-0.040**	0.095
	(0.015)	(0.056)	(0.017)	(0.043)	(0.020)	(0.081)
system	-0.000	0.010	-0.000	0.020	-0.004	-0.004
	(0.007)	(0.013)	(0.008)	(0.016)	(0.008)	(0.015)
Cancer program approved by ACS	-0.005	-0.000	-0.010	-0.005	0.001	0.011
	(0.006)	(0.013)	(0.008)	(0.015)	(0.007)	(0.015)
Residency training approved by GME	0.016	0.054***	-0.016	0.041**	0.037*	0.060**
	(0.015)	(0.018)	(0.013)	(0.018)	(0.019)	(0.025)
AMA Medical school affiliation	-0.021	0.026	-0.004	0.013	-0.030	0.052**
	(0.015)	(0.018)	(0.013)	(0.017)	(0.021)	(0.026)
Accreditation by CARF	0.002	0.029	0.018*	0.014	-0.007	0.039**
	(0.008)	(0.019)	(0.010)	(0.022)	(0.009)	(0.018)
Teaching Hospital	-0.021**	0.124***	-0.040***	0.093***	-0.007	0.142***
	(0.010)	(0.021)	(0.013)	(0.025)	(0.012)	(0.025)
Rural Referral Center	-0.017*	-0.057***	-0.016	-0.056***	-0.014	-0.056**
	(0.010)	(0.019)	(0.012)	(0.020)	(0.011)	(0.023)
Constant	0.786***	1.839***	0.534***	1.427***	0.937***	1.879***
	(0.035)	(0.087)	(0.063)	(0.104)	(0.035)	(0.113)
N	23,852,189	23,852,189	11,282,328	11,282,328	12,569,861	12,569,861
π (predicted share)	0.77	0.23	0.69	0.31	0.82	0.18

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes Major Diagnostic Category, hospital size, year and state fixed effect.
Standard error clustered at hospital level.
† Abbreviations:
ACS: American College of Surgeons
GME: Graduate Medical Education
AMA: American Medical Association
CARF: Commission on Accreditation of Rehabilitation Facilities

(b). EMRs + CPOE Adoption

	All Discharges		through ER Admissions		through Non-ER Admissions	
	C 1	C 2	C 1	C 2	C 1	C 2
EMRs + CPOE	-0.031	-0.205***	0.020	-0.174***	-0.071*	-0.198***
	(0.030)	(0.054)	(0.042)	(0.063)	(0.039)	(0.064)
Residual from First Stage	0.010	0.197***	-0.050	0.152**	0.058	0.202***
	(0.031)	(0.053)	(0.043)	(0.061)	(0.039)	(0.065)
Age	0.006***	0.004***	0.007***	0.004***	0.005***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.067***	0.099***	0.058***	0.087***	0.079***	0.134***
	(0.005)	(0.009)	(0.006)	(0.009)	(0.005)	(0.011)
Hispanic	0.007	-0.035***	-0.000	-0.023	0.018***	-0.044***
	(0.006)	(0.011)	(0.008)	(0.014)	(0.007)	(0.012)
Asian and other race	-0.005	0.008	-0.015*	0.010	0.008	0.012
	(0.005)	(0.010)	(0.008)	(0.012)	(0.005)	(0.012)
Female	0.034***	-0.065***	0.023***	-0.088***	0.037***	-0.037***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Low Income	0.032***	0.025***	0.047***	0.027**	0.016***	0.029**
	(0.005)	(0.009)	(0.007)	(0.011)	(0.006)	(0.012)
Missing Income	0.011*	0.090***	0.020*	0.103***	0.012**	0.085***
	(0.007)	(0.012)	(0.011)	(0.016)	(0.006)	(0.014)
Lower to Medium Income	0.019***	0.014**	0.031***	0.015*	0.007	0.016*
	(0.004)	(0.007)	(0.006)	(0.008)	(0.005)	(0.009)
Medium Income	0.014***	0.012**	0.023***	0.014*	0.006*	0.012*
	(0.003)	(0.006)	(0.005)	(0.007)	(0.004)	(0.007)
Charlson Score	0.061***	0.073***	0.069***	0.079***	0.057***	0.074***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Admitted through ER	0.047***	0.043***				
	(0.007)	(0.007)				
Medicare	0.096***	0.144***	0.140***	0.148***	0.070***	0.144***
	(0.004)	(0.005)	(0.004)	(0.006)	(0.004)	(0.006)
Medicaid	0.057***	0.202***	0.136***	0.279***	0.014***	0.140***
	(0.004)	(0.008)	(0.004)	(0.010)	(0.004)	(0.011)
Other Insurance	-0.031***	0.074***	0.021***	0.073***	-0.064***	0.076***
	(0.005)	(0.011)	(0.007)	(0.010)	(0.007)	(0.015)
ownership: Gov.	-0.006	0.070***	-0.021	0.093***	0.009	0.047*
	(0.011)	(0.023)	(0.013)	(0.027)	(0.014)	(0.027)
ownership: non profit	-0.006	0.008	-0.018	0.006	-0.000	0.011
	(0.010)	(0.018)	(0.011)	(0.019)	(0.012)	(0.023)
critical access hospital	-0.057***	-0.045	-0.077***	-0.283***	-0.047***	0.095
	(0.014)	(0.056)	(0.016)	(0.050)	(0.018)	(0.081)
system	0.000	0.015	-0.003	0.026*	0.001	0.001
	(0.007)	(0.012)	(0.008)	(0.015)	(0.008)	(0.015)
Cancer program approved by ACS	-0.004	0.004	-0.010	-0.001	0.001	0.016
	(0.006)	(0.013)	(0.008)	(0.016)	(0.007)	(0.015)
Residency training approved by GME	0.017	0.064***	-0.013	0.053***	0.040**	0.069***
	(0.015)	(0.018)	(0.013)	(0.019)	(0.019)	(0.025)
AMA Medical school affiliation	-0.022*	0.016	-0.006	0.008	-0.029*	0.043*
	(0.013)	(0.017)	(0.012)	(0.017)	(0.018)	(0.024)
Accreditation by CARF	0.001	0.021	0.018*	0.011	-0.006	0.030*
	(0.007)	(0.017)	(0.009)	(0.021)	(0.008)	(0.018)
Teaching Hospital	-0.021**	0.129***	-0.034***	0.103***	-0.002	0.147***
	(0.010)	(0.021)	(0.013)	(0.025)	(0.012)	(0.025)
Rural Referral Center	-0.019**	-0.071***	-0.020*	-0.071***	-0.014	-0.071***
	(0.008)	(0.017)	(0.011)	(0.020)	(0.009)	(0.020)
Constant	0.785***	1.821***	0.591***	1.540***	0.917***	1.862***
	(0.035)	(0.084)	(0.058)	(0.103)	(0.034)	(0.111)
N	23,852,189	23,852,189	11,282,328	11,282,328	12,569,861	12,569,861
π (predicted share)	0.77	0.23	0.69	0.31	0.82	0.18

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes Major Diagnostic Category, hospital size, year and state fixed effect.
Standard error clustered at hospital level.
† Abbreviations:
ACS: American College of Surgeons
GME: Graduate Medical Education
AMA: American Medical Association
CARF: Commission on Accreditation of Rehabilitation Facilities

Table 5: Posterior Probability of being Component 1

	Enterprise EMRs	EMRs + CPOE
Age	-0.000***	-0.000***
	(0.000)	(0.000)
Black	-0.003**	-0.003*
	(0.001)	(0.001)
Hispanic	0.001	0.001
	(0.002)	(0.002)
Asian and other race	0.000	0.001
	(0.001)	(0.001)
Female	0.006***	0.006***
	(0.001)	(0.001)
Low Income	-0.001	-0.001
	(0.001)	(0.001)
Missing Income	-0.003	-0.003
	(0.002)	(0.002)
Lower to Medium Income	-0.001	-0.001
	(0.001)	(0.001)
Medium Income	-0.001	-0.001
	(0.001)	(0.001)
Charlson Score	-0.007***	-0.007***
	(0.000)	(0.000)
Admitted through ER	0.002	0.002
	(0.001)	(0.001)
ownership: Gov.	0.000	0.000
	(0.003)	(0.003)
ownership: non profit	0.003	0.003
	(0.002)	(0.002)
critical access hospital	0.017***	0.017***
	(0.004)	(0.004)
system	0.000	0.000
	(0.002)	(0.002)
Cancer program approved by ACS	0.001	0.001
	(0.002)	(0.002)
Residency training approved by GME	-0.001	-0.001
	(0.003)	(0.003)
AMA Medical school affiliation	0.000	-0.000
	(0.003)	(0.002)
Accreditation by CARF	-0.002	-0.002
	(0.003)	(0.002)
Teaching Hospital	-0.005	-0.005
	(0.003)	(0.003)
Rural Referral Center	0.001	0.001
	(0.002)	(0.002)
Medicare	-0.011***	-0.011***
	(0.001)	(0.001)
Medicaid	-0.007***	-0.007***
	(0.001)	(0.001)
Other Insurance	-0.005***	-0.005***
	(0.002)	(0.002)
Constant	0.746***	0.746***
	(0.014)	(0.014)
R^2	0.02	0.02
N	23,852,189	23,852,189

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes hospital size, year and state fixed effect.
Standard error clustered at hospital level.

Table 6: Impact of EMRs on Major Diagnosis Category

(a).Respiratory System

	Enterprise EMRs			EMRs + CPOE		
	Negative Binomial	Component 1	Component 2	Negative Binomial	Component 1	Component 2
Health IT	-0.135**	-0.079	-0.141	-0.102**	-0.006	-0.164**
	(0.063)	(0.053)	(0.109)	(0.046)	(0.040)	(0.072)
Residual from First Stage	0.126*	0.075	0.128	0.089*	-0.007	0.163**
	(0.066)	(0.053)	(0.113)	(0.047)	(0.043)	(0.072)
Age	0.007***	0.007***	0.006***	0.007***	0.007***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	-0.009	-0.013*	0.022*	-0.009	-0.013**	0.023*
	(0.009)	(0.007)	(0.012)	(0.009)	(0.007)	(0.013)
Hispanic	-0.046***	-0.023**	-0.045**	-0.046***	-0.024**	-0.043**
	(0.012)	(0.009)	(0.017)	(0.012)	(0.010)	(0.017)
Asian and other race	-0.007	-0.013	0.012	-0.006	-0.014	0.013
	(0.010)	(0.009)	(0.014)	(0.010)	(0.009)	(0.014)
Female	-0.021***	0.038***	-0.088***	-0.021***	0.038***	-0.088***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)
Low Income	0.002	0.011	0.001	0.002	0.010	0.002
	(0.009)	(0.008)	(0.012)	(0.009)	(0.008)	(0.013)
Lower to Medium Income	0.004	0.008	-0.001	0.004	0.008	-0.001
	(0.007)	(0.006)	(0.010)	(0.007)	(0.006)	(0.010)
Medium Income	0.004	0.008	0.001	0.004	0.008	0.001
	(0.006)	(0.005)	(0.009)	(0.006)	(0.005)	(0.009)
Charlson Score	0.043***	0.045***	0.030***	0.043***	0.045***	0.030***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Admitted through ER	-0.017**	-0.019***	-0.006	-0.017**	-0.019***	-0.006
	(0.007)	(0.005)	(0.011)	(0.007)	(0.005)	(0.011)
Medicare	0.083***	0.090***	0.072***	0.083***	0.090***	0.072***
	(0.005)	(0.004)	(0.007)	(0.005)	(0.005)	(0.007)
Medicaid	0.124***	0.060***	0.203***	0.124***	0.059***	0.202***
	(0.007)	(0.005)	(0.011)	(0.007)	(0.005)	(0.011)
Other Insurance	0.016**	-0.030***	0.071***	0.016**	-0.030***	0.071***
	(0.008)	(0.006)	(0.013)	(0.008)	(0.006)	(0.013)
ownership: Gov.	0.006	-0.032*	0.051	-0.009	-0.047***	0.041
	(0.021)	(0.018)	(0.036)	(0.018)	(0.015)	(0.027)
ownership: non profit	-0.002	-0.010	0.012	-0.016	-0.025**	0.004
	(0.019)	(0.015)	(0.033)	(0.013)	(0.012)	(0.022)
critical access hospital	-0.137***	-0.087***	-0.233***	-0.132***	-0.078***	-0.235***
	(0.021)	(0.016)	(0.054)	(0.020)	(0.015)	(0.054)
system	-0.003	-0.000	-0.002	-0.003	-0.004	0.002
	(0.011)	(0.008)	(0.016)	(0.010)	(0.009)	(0.015)
Cancer program approved by ACS	-0.005	0.001	-0.011	-0.002	0.002	-0.008
	(0.011)	(0.009)	(0.016)	(0.011)	(0.009)	(0.016)
Residency training approved by GME	0.012	-0.021	0.058***	0.017	-0.021	0.065***
	(0.016)	(0.018)	(0.020)	(0.016)	(0.018)	(0.020)
AMA Medical school affiliation	0.001	-0.009	0.001	-0.006	-0.013	-0.007
	(0.016)	(0.016)	(0.020)	(0.015)	(0.016)	(0.019)
Accreditation by CARF	0.013	0.011	0.015	0.008	0.008	0.009
	(0.014)	(0.011)	(0.021)	(0.013)	(0.010)	(0.020)
Teaching Hospital	0.027	-0.073***	0.114***	0.027	-0.077***	0.119***
	(0.018)	(0.015)	(0.028)	(0.018)	(0.015)	(0.027)
Rural Referral Center	-0.008	0.017	-0.044*	-0.018	0.011	-0.055**
	(0.016)	(0.014)	(0.027)	(0.015)	(0.013)	(0.025)
N	2,362,632	2,362,632	2,362,632	2,362,632	2,362,632	2,362,632
π (predicted share)		0.81	0.19		0.81	0.19

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes local income level, payer type, hospital size, year and state fixed effect.
Standard error clustered at hospital level.

(b).Circulatory System

	Enterprise EMRs			EMRs + CPOE		
	Negative Binomial	Component 1	Component 2	Negative Binomial	Component 1	Component 2
Health IT	-0.128	-0.015	-0.172	-0.139**	-0.036	-0.161**
	(0.086)	(0.079)	(0.119)	(0.055)	(0.051)	(0.069)
Residual from First Stage	0.093	-0.011	0.141	-0.139**	-0.036	-0.161**
	(0.088)	(0.079)	(0.122)	(0.055)	(0.051)	(0.069)
Age	0.004***	0.009***	0.001***	0.004***	0.009***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.050***	0.072***	0.049***	0.050***	0.072***	0.050***
	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)
Hispanic	-0.002	0.010	-0.003	-0.001	0.010	-0.001
	(0.013)	(0.013)	(0.016)	(0.013)	(0.013)	(0.016)
Asian and other race	-0.008	-0.035***	0.017	-0.008	-0.035***	0.018
	(0.010)	(0.011)	(0.012)	(0.010)	(0.011)	(0.012)
Female	0.005*	0.040***	-0.019***	0.005*	0.040***	-0.019***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Low Income	0.039***	0.074***	0.023**	0.039***	0.074***	0.023**
	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)	(0.011)
Lower to Medium Income	0.026***	0.054***	0.010	0.027***	0.054***	0.010
	(0.008)	(0.007)	(0.010)	(0.008)	(0.007)	(0.010)
Medium Income	0.023***	0.041***	0.013	0.023***	0.041***	0.013
	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)	(0.009)
Charlson Score	0.154***	0.123***	0.156***	0.154***	0.123***	0.156***
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)
Admitted through ER	-0.038***	0.101***	-0.110***	-0.038***	0.101***	-0.110***
	(0.009)	(0.017)	(0.008)	(0.009)	(0.017)	(0.008)
Medicare	0.195***	0.091***	0.248***	0.195***	0.092***	0.249***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
Medicaid	0.256***	0.147***	0.345***	0.257***	0.148***	0.346***
	(0.009)	(0.008)	(0.012)	(0.009)	(0.008)	(0.013)
Other Insurance	0.066***	0.042***	0.099***	0.067***	0.042***	0.100***
	(0.010)	(0.008)	(0.013)	(0.010)	(0.008)	(0.013)
ownership: Gov.	0.021	-0.017	0.043	0.011	-0.016	0.027
	(0.026)	(0.025)	(0.035)	(0.020)	(0.019)	(0.026)
ownership: non profit	0.022	0.008	0.027	0.017	0.011	0.015
	(0.023)	(0.022)	(0.033)	(0.015)	(0.015)	(0.020)
critical access hospital	-0.070**	-0.037	-0.085	-0.070**	-0.039*	-0.082
	(0.034)	(0.023)	(0.076)	(0.033)	(0.021)	(0.075)
system	0.013	0.004	0.025	0.015	0.005	0.028*
	(0.012)	(0.012)	(0.015)	(0.012)	(0.011)	(0.015)
Cancer program approved by ACS	-0.025**	-0.012	-0.032*	-0.023*	-0.012	-0.029
	(0.013)	(0.012)	(0.017)	(0.013)	(0.012)	(0.017)
Residency training approved by GME	0.025	0.002	0.050**	0.031	0.004	0.058**
	(0.021)	(0.023)	(0.024)	(0.021)	(0.023)	(0.024)
AMA Medical school affiliation	0.013	-0.016	0.025	0.006	-0.016	0.014
	(0.020)	(0.023)	(0.023)	(0.019)	(0.021)	(0.022)
Accreditation by CARF	0.027**	0.006	0.049***	0.022	0.007	0.040**
	(0.014)	(0.016)	(0.018)	(0.013)	(0.015)	(0.017)
Teaching Hospital	0.042**	-0.075***	0.107***	0.047**	-0.072***	0.111***
	(0.019)	(0.019)	(0.023)	(0.019)	(0.020)	(0.023)
Rural Referral Center	-0.031*	-0.014	-0.053**	-0.039***	-0.013	-0.065***
	(0.017)	(0.015)	(0.024)	(0.015)	(0.013)	(0.022)
N	4,120,364	4,120,364	4,120,364	4,120,364	4,120,364	4,120,364
π (predicted share)		0.71	0.29		0.71	0.29

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes local income level, payer type, hospital size, year and state fixed effect.
Standard error clustered at hospital level.

(c).Digestive, Hepatobiliary, Pancreas

	Enterprise EMRs			EMRs + CPOE		
	Negative Binomial	Component 1	Component 2	Negative Binomial	Component 1	Component 2
Health IT	-0.064 (0.091)	-0.035 (0.112)	-0.089 (0.090)	-0.136*** (0.047)	-0.083* (0.045)	-0.169*** (0.063)
Residual from First Stage	0.040 (0.089)	0.015 (0.108)	0.060 (0.091)	0.098** (0.044)	0.040 (0.040)	0.142** (0.062)
Age	0.007*** (0.000)	0.007*** (0.000)	0.006*** (0.000)	0.007*** (0.000)	0.007*** (0.000)	0.006*** (0.000)
Black	0.055*** (0.006)	0.044*** (0.006)	0.063*** (0.008)	0.055*** (0.006)	0.043*** (0.006)	0.064*** (0.008)
Hispanic	-0.050*** (0.008)	-0.021*** (0.007)	-0.077*** (0.013)	-0.048*** (0.008)	-0.020*** (0.007)	-0.074*** (0.013)
Asian and other race	-0.042*** (0.008)	-0.038*** (0.007)	-0.039*** (0.013)	-0.042*** (0.008)	-0.039*** (0.007)	-0.038*** (0.013)
Female	-0.014*** (0.002)	0.029*** (0.002)	-0.064*** (0.004)	-0.014*** (0.002)	0.029*** (0.002)	-0.064*** (0.004)
Low Income	0.033*** (0.009)	0.044*** (0.009)	0.021* (0.012)	0.033*** (0.009)	0.043*** (0.009)	0.021* (0.012)
Lower to Medium Income	0.031*** (0.008)	0.040*** (0.009)	0.022** (0.009)	0.031*** (0.008)	0.040*** (0.009)	0.022** (0.009)
Medium Income	0.023*** (0.007)	0.030*** (0.007)	0.017** (0.008)	0.024*** (0.007)	0.030*** (0.007)	0.017** (0.008)
Charlson Score	0.077*** (0.001)	0.074*** (0.002)	0.068*** (0.001)	0.077*** (0.001)	0.074*** (0.002)	0.068*** (0.001)
Admitted through ER	-0.031** (0.012)	-0.039*** (0.015)	-0.014 (0.010)	-0.031** (0.012)	-0.039*** (0.015)	-0.014 (0.010)
Medicare	0.093*** (0.006)	0.048*** (0.006)	0.138*** (0.008)	0.093*** (0.006)	0.049*** (0.006)	0.139*** (0.008)
Medicaid	0.143*** (0.006)	0.077*** (0.005)	0.223*** (0.010)	0.143*** (0.006)	0.077*** (0.005)	0.223*** (0.010)
Other Insurance	0.029*** (0.007)	0.021*** (0.006)	0.034*** (0.009)	0.029*** (0.007)	0.022*** (0.007)	0.034*** (0.009)
ownership: Gov.	0.035 (0.025)	0.005 (0.026)	0.068** (0.030)	0.038** (0.017)	0.009 (0.013)	0.070*** (0.026)
ownership: non profit	0.003 (0.025)	-0.005 (0.027)	0.021 (0.028)	0.010 (0.013)	0.001 (0.012)	0.025 (0.019)
critical access hospital	-0.185*** (0.024)	-0.130*** (0.022)	-0.274*** (0.043)	-0.191*** (0.022)	-0.134*** (0.017)	-0.281*** (0.043)
system	0.010 (0.012)	0.018 (0.012)	0.008 (0.015)	0.015 (0.012)	0.021* (0.012)	0.014 (0.015)
Cancer program approved by ACS	-0.002 (0.010)	-0.001 (0.008)	0.003 (0.014)	-0.001 (0.010)	-0.000 (0.008)	0.006 (0.014)
Residency training approved by GME	0.054 (0.033)	0.034 (0.042)	0.081*** (0.026)	0.060* (0.033)	0.038 (0.042)	0.090*** (0.026)
AMA Medical school affiliation	-0.031 (0.033)	-0.049 (0.041)	-0.014 (0.024)	-0.033 (0.029)	-0.049 (0.036)	-0.018 (0.022)
Accreditation by CARF	0.009 (0.014)	0.005 (0.011)	0.014 (0.021)	0.009 (0.012)	0.007 (0.009)	0.011 (0.020)
Teaching Hospital	0.050*** (0.018)	-0.017 (0.015)	0.120*** (0.028)	0.056*** (0.018)	-0.013 (0.014)	0.127*** (0.027)
Rural Referral Center	-0.051*** (0.016)	-0.033* (0.017)	-0.078*** (0.020)	-0.054*** (0.013)	-0.033*** (0.012)	-0.084*** (0.018)
N	3,099,182	3,099,182	3,099,182	3,099,182	3,099,182	3,099,182
π (predicted share)		0.80	0.20		0.80	0.20

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes local income level, payer type, hospital size, year and state fixed effect.
Standard error clustered at hospital level.

(d).Musculoskeletal

	Enterprise EMRs			EMRs + CPOE		
	Negative Binomial	Component 1	Component 2	Negative Binomial	Component 1	Component 2
Health IT	-0.092	-0.084*	-0.155	-0.096*	-0.024	-0.169*
	(0.076)	(0.051)	(0.133)	(0.058)	(0.041)	(0.094)
Residual from First Stage	0.073	0.078	0.122	0.078	0.014	0.151
	(0.077)	(0.051)	(0.135)	(0.060)	(0.044)	(0.095)
Age	0.006***	0.009***	0.002***	0.006***	0.009***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.122***	0.077***	0.131***	0.122***	0.077***	0.132***
	(0.009)	(0.006)	(0.013)	(0.009)	(0.006)	(0.013)
Hispanic	0.052***	0.036***	0.039**	0.053***	0.036***	0.042***
	(0.012)	(0.008)	(0.016)	(0.012)	(0.008)	(0.016)
Asian and other race	0.003	0.003	0.007	0.003	0.002	0.007
	(0.010)	(0.008)	(0.020)	(0.010)	(0.008)	(0.020)
Female	-0.002	0.054***	-0.085***	-0.002	0.054***	-0.085***
	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.005)
Low Income	0.055***	0.023***	0.098***	0.055***	0.023***	0.098***
	(0.009)	(0.006)	(0.016)	(0.009)	(0.006)	(0.016)
Lower to Medium Income	0.020***	0.006	0.041***	0.020***	0.006	0.041***
	(0.007)	(0.005)	(0.012)	(0.007)	(0.005)	(0.012)
Medium Income	0.015***	0.008**	0.026***	0.015***	0.008**	0.026***
	(0.005)	(0.004)	(0.009)	(0.005)	(0.004)	(0.009)
Charlson Score	0.098***	0.062***	0.122***	0.098***	0.062***	0.122***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Admitted through ER	0.272***	0.161***	0.366***	0.272***	0.161***	0.366***
	(0.008)	(0.006)	(0.012)	(0.008)	(0.006)	(0.012)
Medicare	0.097***	0.053***	0.170***	0.097***	0.053***	0.170***
	(0.005)	(0.004)	(0.010)	(0.005)	(0.004)	(0.010)
Medicaid	0.262***	0.120***	0.418***	0.263***	0.120***	0.419***
	(0.009)	(0.006)	(0.015)	(0.009)	(0.006)	(0.016)
Other Insurance	0.058***	-0.011	0.168***	0.059***	-0.011	0.169***
	(0.008)	(0.007)	(0.013)	(0.008)	(0.007)	(0.013)
ownership: Gov.	0.056*	0.011	0.080*	0.049**	-0.004	0.068*
	(0.029)	(0.019)	(0.045)	(0.024)	(0.017)	(0.036)
ownership: non profit	0.019	0.023	0.022	0.014	0.009	0.015
	(0.022)	(0.015)	(0.040)	(0.016)	(0.012)	(0.028)
critical access hospital	0.005	-0.090***	0.307***	0.005	-0.083***	0.302***
	(0.028)	(0.020)	(0.083)	(0.028)	(0.021)	(0.082)
system	-0.021	-0.014	-0.024	-0.019	-0.017*	-0.020
	(0.013)	(0.009)	(0.020)	(0.013)	(0.009)	(0.019)
Cancer program approved by ACS	-0.006	-0.003	-0.021	-0.004	-0.002	-0.017
	(0.013)	(0.009)	(0.020)	(0.013)	(0.009)	(0.020)
Residency training approved by GME	0.026	0.008	0.061**	0.031*	0.009	0.068**
	(0.017)	(0.012)	(0.028)	(0.017)	(0.012)	(0.028)
AMA Medical school affiliation	0.011	-0.004	0.027	0.006	-0.009	0.019
	(0.016)	(0.012)	(0.028)	(0.016)	(0.011)	(0.027)
Accreditation by CARF	-0.010	-0.014	0.013	-0.014	-0.018*	0.006
	(0.016)	(0.010)	(0.025)	(0.015)	(0.010)	(0.024)
Teaching Hospital	0.081***	0.020	0.148***	0.083***	0.018	0.153***
	(0.022)	(0.015)	(0.035)	(0.022)	(0.015)	(0.035)
Rural Referral Center	-0.023	0.012	-0.080***	-0.029*	0.006	-0.090***
	(0.017)	(0.015)	(0.028)	(0.016)	(0.014)	(0.027)
N	2,175,878	2,177,042	2,177,042	2,175,878	2,177,042	2,177,042
π (predicted share)		0.84	0.16		0.84	0.16

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes local income level, payer type, hospital size, year and state fixed effect.
Standard error clustered at hospital level.

(e).Skin, Breast

	Enterprise EMRs			EMRs + CPOE		
	Negative Binomial	Component 1	Component 2	Negative Binomial	Component 1	Component 2
Health IT	-0.189**	-0.041	-0.382**	-0.162***	-0.010	-0.284***
	(0.092)	(0.077)	(0.172)	(0.061)	(0.052)	(0.103)
Residual from First Stage	0.178*	0.023	0.377**	0.161**	-0.008	0.319***
	(0.096)	(0.078)	(0.176)	(0.065)	(0.053)	(0.108)
Age	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.098***	0.051***	0.142***	0.099***	0.051***	0.143***
	(0.011)	(0.009)	(0.020)	(0.011)	(0.009)	(0.020)
Hispanic	-0.036***	-0.018	-0.059***	-0.034***	-0.018	-0.056***
	(0.011)	(0.012)	(0.021)	(0.011)	(0.012)	(0.021)
Asian and other race	-0.055***	-0.067***	-0.023	-0.054***	-0.068***	-0.022
	(0.016)	(0.010)	(0.032)	(0.016)	(0.009)	(0.031)
Female	-0.144***	-0.117***	-0.140***	-0.143***	-0.117***	-0.140***
	(0.005)	(0.004)	(0.010)	(0.005)	(0.004)	(0.010)
Low Income	0.087***	0.072***	0.102***	0.087***	0.072***	0.102***
	(0.010)	(0.010)	(0.018)	(0.010)	(0.010)	(0.018)
Lower to Medium Income	0.073***	0.057***	0.083***	0.073***	0.057***	0.083***
	(0.009)	(0.008)	(0.016)	(0.009)	(0.008)	(0.016)
Medium Income	0.057***	0.040***	0.085***	0.057***	0.040***	0.086***
	(0.008)	(0.006)	(0.015)	(0.008)	(0.006)	(0.015)
Charlson Score	0.029***	0.008***	0.063***	0.029***	0.008***	0.063***
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)
Admitted through ER	0.127***	0.182***	0.004	0.127***	0.182***	0.005
	(0.011)	(0.010)	(0.017)	(0.011)	(0.009)	(0.017)
Medicare	0.238***	0.167***	0.301***	0.238***	0.167***	0.301***
	(0.008)	(0.006)	(0.015)	(0.008)	(0.006)	(0.015)
Medicaid	0.270***	0.156***	0.413***	0.270***	0.156***	0.413***
	(0.009)	(0.007)	(0.018)	(0.009)	(0.007)	(0.018)
Other Insurance	0.028**	-0.039***	0.128***	0.028**	-0.038***	0.129***
	(0.011)	(0.012)	(0.017)	(0.011)	(0.012)	(0.017)
ownership: Gov.	-0.003	-0.062**	0.091*	-0.022	-0.069***	0.049
	(0.030)	(0.025)	(0.051)	(0.022)	(0.020)	(0.035)
ownership: non profit	0.023	-0.013	0.082*	0.006	-0.020	0.041
	(0.024)	(0.022)	(0.044)	(0.017)	(0.016)	(0.028)
critical access hospital	-0.067**	-0.025	-0.119*	-0.063**	-0.022	-0.105
	(0.027)	(0.022)	(0.072)	(0.026)	(0.021)	(0.071)
system	0.006	-0.001	0.013	0.007	-0.003	0.013
	(0.013)	(0.011)	(0.022)	(0.013)	(0.011)	(0.022)
Cancer program approved by ACS	-0.009	-0.006	-0.012	-0.004	-0.006	-0.002
	(0.014)	(0.012)	(0.021)	(0.014)	(0.012)	(0.021)
Residency training approved by GME	-0.023	-0.013	-0.028	-0.015	-0.013	-0.013
	(0.019)	(0.021)	(0.029)	(0.019)	(0.021)	(0.029)
AMA Medical school affiliation	0.010	-0.027	0.061**	0.000	-0.029	0.039
	(0.020)	(0.019)	(0.031)	(0.019)	(0.019)	(0.028)
Accreditation by CARF	0.032**	0.018	0.055*	0.024	0.016	0.035
	(0.016)	(0.015)	(0.028)	(0.015)	(0.015)	(0.026)
Teaching Hospital	-0.053**	-0.101***	0.007	-0.052**	-0.102***	0.008
	(0.021)	(0.020)	(0.039)	(0.021)	(0.019)	(0.039)
Rural Referral Center	0.011	-0.003	0.042	-0.005	-0.006	0.010
	(0.022)	(0.018)	(0.039)	(0.020)	(0.017)	(0.036)
N	615,856	615,856	615,856	615,856	615,856	615,856
π (predicted share)		0.82	0.18		0.82	0.18

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes local income level, payer type, hospital size, year and state fixed effect.
Standard error clustered at hospital level.

(f).Endocrine, Nutritional, Metabolic

	Enterprise EMRs			EMRs + CPOE		
	Negative Binomial	Component 1	Component 2	Negative Binomial	Component 1	Component 2
Health IT	-0.191**	-0.111*	-0.294**	-0.123**	-0.018	-0.287***
	(0.086)	(0.065)	(0.139)	(0.056)	(0.046)	(0.090)
Residual from First Stage	0.178**	0.106	0.270*	0.106*	0.001	0.281***
	(0.089)	(0.064)	(0.145)	(0.058)	(0.048)	(0.092)
Age	0.007***	0.006***	0.006***	0.007***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.062***	0.049***	0.068***	0.062***	0.048***	0.070***
	(0.008)	(0.007)	(0.016)	(0.008)	(0.007)	(0.016)
Hispanic	0.005	0.007	-0.003	0.005	0.006	-0.001
	(0.011)	(0.008)	(0.019)	(0.011)	(0.008)	(0.019)
Asian and other race	-0.010	-0.021**	0.012	-0.010	-0.021**	0.014
	(0.014)	(0.009)	(0.025)	(0.014)	(0.009)	(0.025)
Female	-0.071***	-0.008***	-0.124***	-0.070***	-0.008***	-0.123***
	(0.004)	(0.003)	(0.008)	(0.004)	(0.003)	(0.008)
Low Income	0.077***	0.080***	0.071***	0.077***	0.079***	0.072***
	(0.009)	(0.008)	(0.016)	(0.010)	(0.008)	(0.016)
Lower to Medium Income	0.055***	0.061***	0.047***	0.055***	0.061***	0.048***
	(0.008)	(0.007)	(0.014)	(0.008)	(0.007)	(0.014)
Medium Income	0.041***	0.045***	0.043***	0.041***	0.045***	0.043***
	(0.007)	(0.006)	(0.013)	(0.007)	(0.006)	(0.013)
Charlson Score	0.061***	0.044***	0.066***	0.061***	0.044***	0.066***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Admitted through ER	0.060***	0.076***	0.016	0.060***	0.076***	0.017
	(0.010)	(0.009)	(0.014)	(0.010)	(0.009)	(0.014)
Medicare	0.185***	0.129***	0.210***	0.185***	0.129***	0.210***
	(0.009)	(0.006)	(0.014)	(0.009)	(0.006)	(0.014)
Medicaid	0.266***	0.139***	0.401***	0.266***	0.138***	0.402***
	(0.010)	(0.007)	(0.017)	(0.010)	(0.007)	(0.017)
Other Insurance	0.093***	0.035***	0.171***	0.093***	0.035***	0.172***
	(0.010)	(0.007)	(0.018)	(0.010)	(0.007)	(0.018)
ownership: Gov.	0.049*	-0.011	0.112***	0.024	-0.032*	0.086***
	(0.027)	(0.020)	(0.043)	(0.021)	(0.016)	(0.033)
ownership: non profit	0.021	0.007	0.051	-0.002	-0.014	0.028
	(0.022)	(0.017)	(0.037)	(0.014)	(0.013)	(0.024)
critical access hospital	-0.065	-0.058***	-0.004	-0.056	-0.048***	-0.000
	(0.043)	(0.018)	(0.151)	(0.042)	(0.017)	(0.151)
system	0.020	0.009	0.033*	0.018	0.004	0.037**
	(0.014)	(0.011)	(0.020)	(0.013)	(0.011)	(0.019)
Cancer program approved by ACS	0.010	-0.000	0.015	0.013	0.001	0.021
	(0.013)	(0.011)	(0.019)	(0.013)	(0.011)	(0.020)
Residency training approved by GME	0.046**	0.033	0.062**	0.051**	0.034	0.075***
	(0.021)	(0.025)	(0.024)	(0.021)	(0.025)	(0.024)
AMA Medical school affiliation	-0.019	-0.044**	0.009	-0.030	-0.051**	-0.008
	(0.019)	(0.020)	(0.025)	(0.018)	(0.020)	(0.023)
Accreditation by CARF	0.012	0.010	0.029	0.005	0.006	0.017
	(0.016)	(0.011)	(0.026)	(0.015)	(0.010)	(0.024)
Teaching Hospital	0.007	-0.047***	0.097***	0.006	-0.052***	0.103***
	(0.021)	(0.016)	(0.033)	(0.021)	(0.017)	(0.032)
Rural Referral Center	0.001	0.012	-0.024	-0.014	0.004	-0.049*
	(0.016)	(0.013)	(0.030)	(0.015)	(0.012)	(0.026)
N	850,731	850,988	850,988	850,731	850,988	850,988
π (predicted share)		0.82	0.18		0.82	0.18

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes local income level, payer type, hospital size, year and state fixed effect.
Standard error clustered at hospital level.

(g).Kidney and Urinary Tract

	Enterprise EMRs			EMRs + CPOE		
	Negative Binomial	Component 1	Component 2	Negative Binomial	Component 1	Component 2
Health IT	-0.078	-0.075	-0.048	-0.118***	-0.065	-0.137*
	(0.071)	(0.060)	(0.116)	(0.045)	(0.041)	(0.071)
Residual from First Stage	0.064	0.065	0.030	0.106**	0.046	0.143**
	(0.074)	(0.060)	(0.121)	(0.048)	(0.042)	(0.072)
Age	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.130***	0.084***	0.165***	0.130***	0.084***	0.167***
	(0.009)	(0.007)	(0.016)	(0.009)	(0.007)	(0.017)
Hispanic	0.018	0.030***	0.002	0.020*	0.031***	0.005
	(0.012)	(0.011)	(0.017)	(0.012)	(0.011)	(0.017)
Asian and other race	0.012	-0.001	0.029**	0.012	-0.001	0.031**
	(0.010)	(0.010)	(0.015)	(0.010)	(0.010)	(0.015)
Female	0.012***	0.076***	-0.059***	0.012***	0.076***	-0.059***
	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)
Low Income	0.045***	0.040***	0.059***	0.045***	0.039***	0.060***
	(0.009)	(0.008)	(0.014)	(0.009)	(0.008)	(0.014)
Lower to Medium Income	0.031***	0.028***	0.038***	0.032***	0.028***	0.038***
	(0.008)	(0.007)	(0.011)	(0.008)	(0.007)	(0.011)
Medium Income	0.024***	0.025***	0.027***	0.024***	0.025***	0.028***
	(0.006)	(0.005)	(0.010)	(0.006)	(0.005)	(0.011)
Charlson Score	0.087***	0.073***	0.091***	0.087***	0.073***	0.091***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Admitted through ER	0.062***	0.083***	0.034***	0.062***	0.083***	0.034***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
Medicare	0.211***	0.185***	0.224***	0.211***	0.185***	0.224***
	(0.006)	(0.006)	(0.010)	(0.007)	(0.006)	(0.010)
Medicaid	0.241***	0.156***	0.352***	0.241***	0.156***	0.352***
	(0.009)	(0.007)	(0.017)	(0.009)	(0.007)	(0.017)
Other Insurance	0.062***	0.011	0.140***	0.062***	0.011	0.140***
	(0.012)	(0.010)	(0.021)	(0.012)	(0.010)	(0.021)
ownership: Gov.	0.037	0.019	0.043	0.035*	0.012	0.051*
	(0.025)	(0.021)	(0.038)	(0.020)	(0.017)	(0.030)
ownership: non profit	0.003	0.008	-0.004	0.003	0.002	0.005
	(0.021)	(0.018)	(0.034)	(0.015)	(0.014)	(0.022)
critical access hospital	-0.071***	-0.043**	-0.109	-0.074***	-0.042**	-0.117
	(0.025)	(0.019)	(0.077)	(0.024)	(0.019)	(0.077)
system	0.003	0.006	0.002	0.007	0.006	0.009
	(0.012)	(0.009)	(0.018)	(0.011)	(0.009)	(0.016)
Cancer program approved by ACS	0.007	0.003	0.012	0.009	0.005	0.014
	(0.012)	(0.010)	(0.018)	(0.012)	(0.010)	(0.018)
Residency training approved by GME	0.015	0.012	0.027	0.021	0.015	0.034
	(0.016)	(0.014)	(0.025)	(0.016)	(0.014)	(0.025)
AMA Medical school affiliation	-0.014	-0.023*	-0.010	-0.018	-0.027**	-0.012
	(0.015)	(0.014)	(0.025)	(0.014)	(0.013)	(0.023)
Accreditation by CARF	0.002	0.005	-0.004	-0.001	0.003	-0.006
	(0.013)	(0.011)	(0.021)	(0.013)	(0.011)	(0.020)
Teaching Hospital	0.024	-0.019	0.082***	0.028*	-0.018	0.090***
	(0.016)	(0.014)	(0.025)	(0.016)	(0.014)	(0.025)
Rural Referral Center	-0.027	-0.013	-0.051*	-0.033*	-0.018	-0.056**
	(0.018)	(0.016)	(0.027)	(0.017)	(0.015)	(0.025)
N	970,319	970,319	970,319	970,319	970,319	970,319
π (predicted share)		0.79	0.21		0.79	0.21

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes local income level, payer type, hospital size, year and state fixed effect.
Standard error clustered at hospital level.

(h).Injuries, Poison, Burns, Toxic, Trauma

	Enterprise EMRs			EMRs + CPOE		
	Negative Binomial	Component 1	Component 2	Negative Binomial	Component 1	Component 2
Health IT	-0.097	-0.156	0.001	-0.454***	-0.223***	-0.402***
	(0.187)	(0.104)	(0.197)	(0.119)	(0.076)	(0.138)
Residual from First Stage	0.043	0.125	-0.054	.369***	0.175**	0.332**
	(0.191)	(0.104)	(0.201)	(0.119)	(0.077)	(0.139)
Age	0.007***	0.008***	0.006***	0.007***	0.008***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.018	0.002	0.029	0.021	0.002	0.034*
	(0.018)	(0.012)	(0.020)	(0.018)	(0.011)	(0.020)
Hispanic	0.037	0.022	0.032	0.043*	0.024	0.040
	(0.027)	(0.015)	(0.027)	(0.026)	(0.015)	(0.026)
Asian and other race	0.029	-0.014	0.047	0.033	-0.013	0.053*
	(0.027)	(0.016)	(0.029)	(0.027)	(0.016)	(0.029)
Female	-0.145***	-0.018***	-0.166***	-0.144***	-0.018***	-0.164***
	(0.007)	(0.006)	(0.009)	(0.007)	(0.006)	(0.009)
Low Income	0.080***	0.065***	0.081***	0.078***	0.064***	0.079***
	(0.018)	(0.013)	(0.021)	(0.018)	(0.013)	(0.020)
Lower to Medium Income	0.082***	0.059***	0.083***	0.081***	0.059***	0.083***
	(0.014)	(0.010)	(0.016)	(0.014)	(0.010)	(0.016)
Medium Income	0.053***	0.039***	0.055***	0.054***	0.040***	0.056***
	(0.011)	(0.009)	(0.014)	(0.011)	(0.009)	(0.014)
Charlson Score	0.051***	0.059***	0.040***	0.051***	0.059***	0.040***
	(0.004)	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)
Admitted through ER	-0.054***	-0.096***	-0.047***	-0.057***	-0.096***	-0.051***
	(0.016)	(0.010)	(0.018)	(0.016)	(0.010)	(0.018)
Medicare	-0.016	0.027***	-0.022	-0.015	0.027***	-0.020
	(0.014)	(0.010)	(0.017)	(0.014)	(0.010)	(0.017)
Medicaid	0.087***	0.011	0.164***	0.089***	0.012	0.166***
	(0.017)	(0.012)	(0.021)	(0.016)	(0.012)	(0.021)
Other Insurance	-0.069***	-0.062***	-0.064***	-0.069***	-0.062***	-0.063***
	(0.016)	(0.015)	(0.018)	(0.016)	(0.015)	(0.018)
ownership: Gov.	0.173**	0.105***	0.166**	0.211***	0.103***	0.215***
	(0.067)	(0.035)	(0.073)	(0.053)	(0.029)	(0.060)
ownership: non profit	0.049	0.036	0.061	0.095**	0.037*	0.118**
	(0.058)	(0.029)	(0.062)	(0.041)	(0.021)	(0.047)
critical access hospital	-0.010	-0.101**	0.133	-0.048	-0.104***	0.085
	(0.119)	(0.039)	(0.241)	(0.115)	(0.038)	(0.236)
system	-0.021	0.000	-0.012	0.006	0.008	0.014
	(0.030)	(0.016)	(0.030)	(0.030)	(0.016)	(0.030)
Cancer program approved by ACS	0.007	0.033*	-0.006	0.012	0.036**	-0.001
	(0.033)	(0.018)	(0.034)	(0.032)	(0.018)	(0.033)
Residency training approved by GME	0.051	0.006	0.074*	0.072**	0.017	0.092**
	(0.035)	(0.027)	(0.044)	(0.035)	(0.028)	(0.044)
AMA Medical school affiliation	0.015	0.009	0.012	0.013	0.002	0.015
	(0.035)	(0.027)	(0.041)	(0.033)	(0.026)	(0.040)
Accreditation by CARF	0.060	0.004	0.081*	0.061	0.001	0.084**
	(0.043)	(0.020)	(0.043)	(0.039)	(0.018)	(0.041)
Teaching Hospital	0.252***	0.085***	0.271***	0.276***	0.092***	0.296***
	(0.043)	(0.027)	(0.044)	(0.040)	(0.026)	(0.042)
Rural Referral Center	-0.101***	-0.058**	-0.127***	-0.100***	-0.067***	-0.117***
	(0.036)	(0.023)	(0.042)	(0.034)	(0.022)	(0.040)
N	431,273	431,273	431,273	431,273	431,273	431,273
π (predicted share)		0.68	0.32		0.68	0.32

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Model also includes local income level, payer type, hospital size, year and state fixed effect.
Standard error clustered at hospital level.

Figure 1: States included in study sample

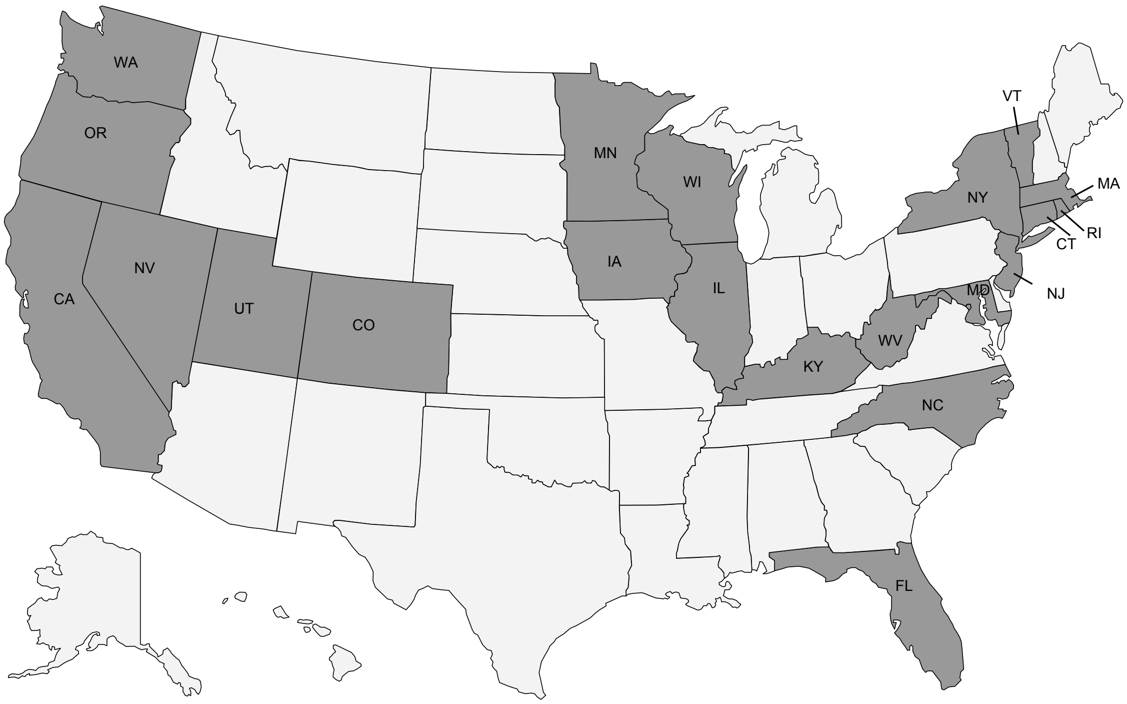

Figure 2: EMR adoption trend

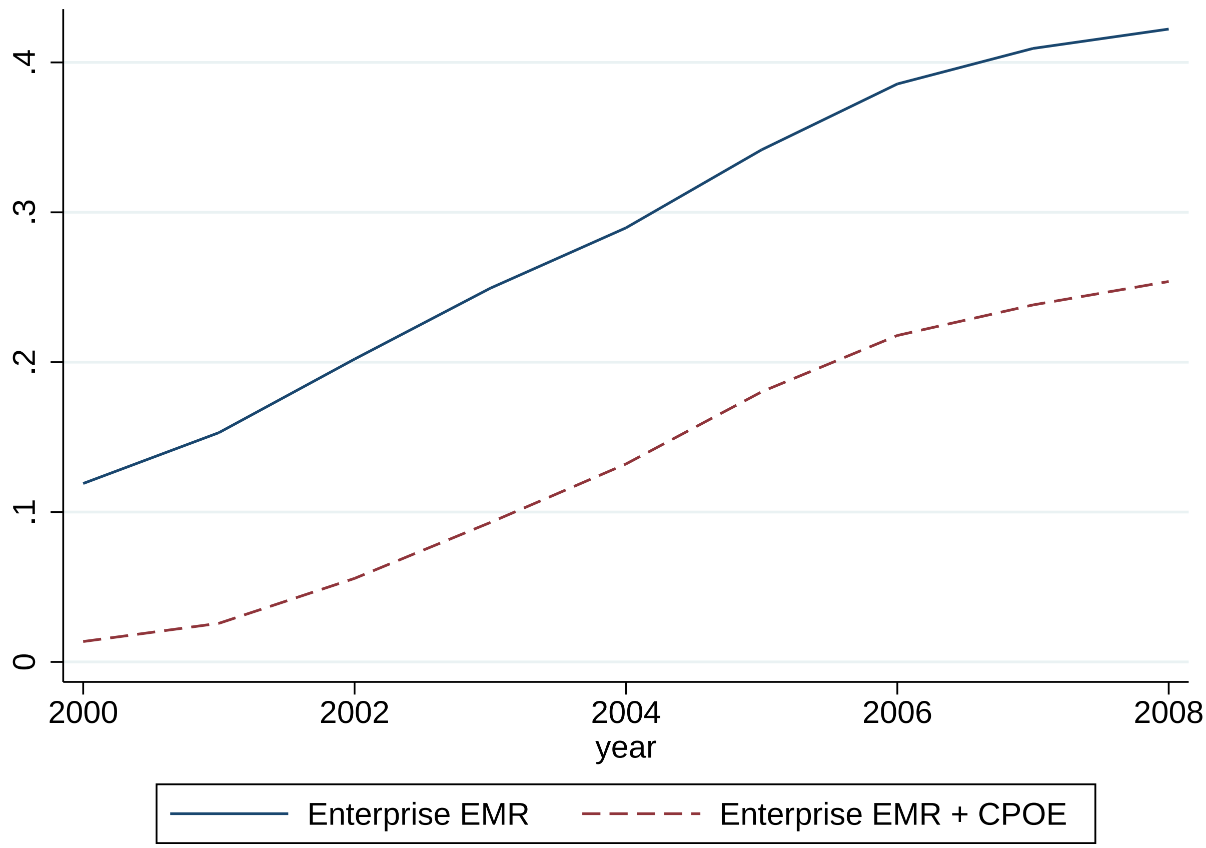

Figure 3: Heterogeneous densities by Patient Groups

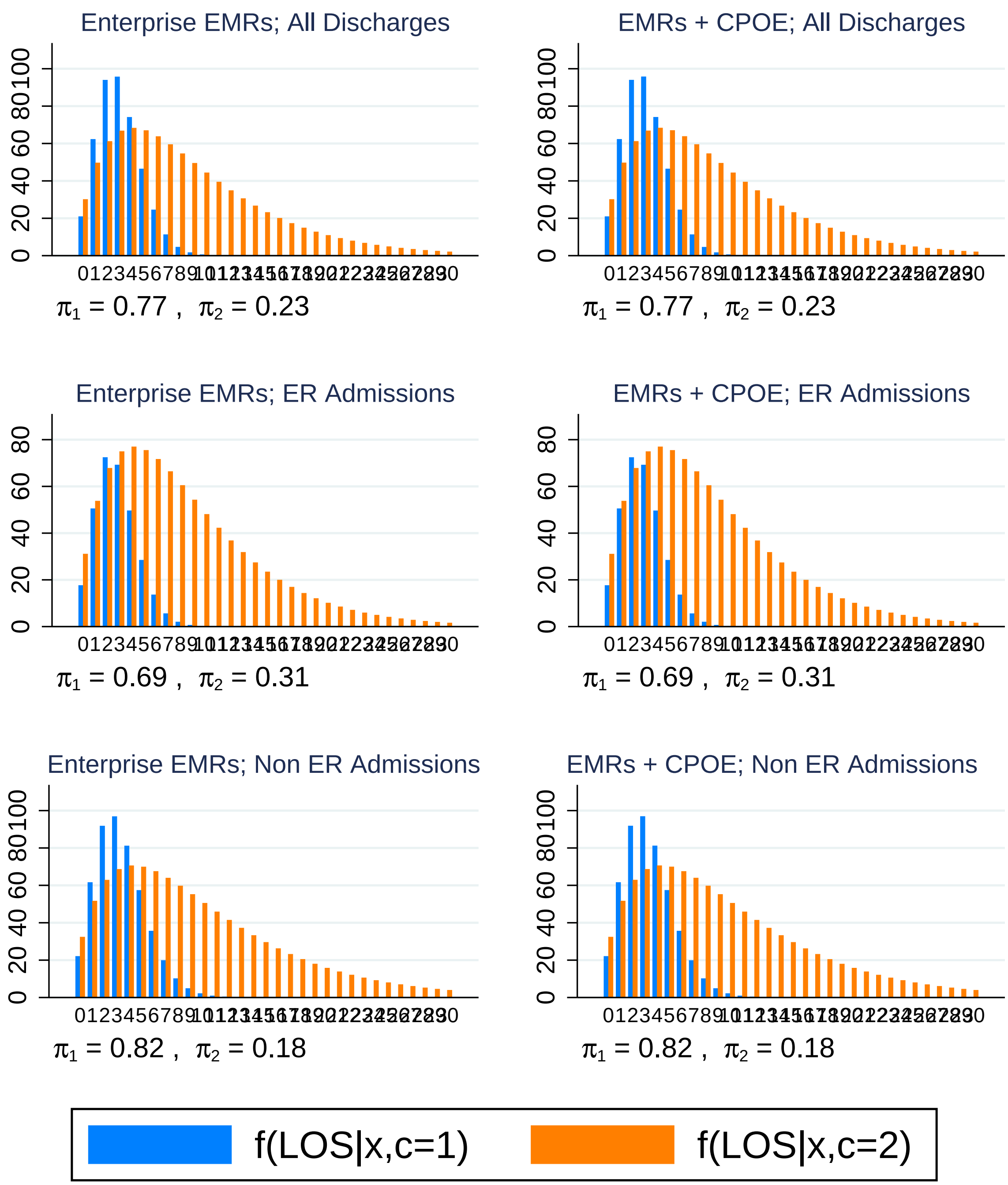

Figure 4: Distribution of Charlson Elements by Heterogeneous Patient Groups