Do Electronic Medical Records Improve Quality of Care?

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Abstract

This paper uses a unique dataset of patients suffering from chronic heart failure to investigate the effect of the electronic patient records system (EMR) on doctors' and patients' behavior and health outcomes. To analyze the impact of EMR on the behavior of doctors and patients, we present a model of patient compliance, where non-compliance is a result of the patient's uncertainty about the effectiveness of the treatment. Patients differ in their communication style, by which we mean their ability to exchange information with the doctor. We show that the introduction of electronic medical records system (EMR) is beneficial for low communication types' medication adherence; at the same time, higher communication type patients can actually decrease their compliance. The model's predictions are tested using the differential timing of EMR implementation in medical centers. Standard panel-data techniques using medical center, patient, and patient-physician pair fixed effects are utilized. A number of robustness checks confirm the stability of the main results.

1 Introduction

Advances in medical technology have been credited with drastic improvements in longevity in the past half century. However, while innovations in clinical treatment of medical conditions are pervasive and the adoption rate is high, little has been done to improve the organization of health care delivery and the ease of interaction between physicians and patients. This paper investigates the effects of introducing electronic patient medical records on the quality the physician-patient interaction and on patients' health behavior.

The interaction between physicians and patients is a complex process that is treated as a "black box" by most of the health economics literature. Here we model this interaction as a communication game between an agent (the physician) and a principal (the patient), and consider the patient's decision to adhere to the treatment offered by the physician as an outcome of this

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game. Then we introduce electronic medical records and hypothesize how they will affect the patient's decision in the context of the communication model. We proceed to empirically test the predictions of the theory using detailed data on physician-patient interactions and the subsequent compliance decisions taken by the patients.

The only integrated health care system in the US where computerized patient records have been fully introduced is the Veterans Health Administration (VHA). To test the empirical predictions of the effects of electronic medical records into clinical practice we use a unique nationally representative dataset including all patient-provider interactions between patients diagnosed with Chronic Heart Failure (CHF) and their doctors between 1998 and 2005. These data offer several significant advantages in addition to covering periods before and after the computerized records system went into use. First, access to care in the VHA is equalized, significantly reducing potential bias coming from under-insurance or patient-level financial considerations. The VHA also implements a fixed salary scheme for their medical personnel which limits physicians' financial incentives to over- or under-provide treatment. Second, the same panel of patients are followed through outpatient and pharmacy encounters for up to six years. Directly observing the pharmacological therapy prescribed to patients allows the construction of measures of both patient adherence to physician recommendations and the types of treatment strategies adopted by doctors for different patients.

The VHA organizes health care for US veterans around regional medical centers that supervise a number of satellite outpatient clinics. We use the variation in the timing of introduction of electronic medical records (EMRs) across different medical centers to identify the effects of EMRs on physician performance and patient outcomes. This paper shows that new technologies designed to improve the efficiency and coordination of care positively impact patients from disadvantaged backgrounds, while the effect on patients with higher socioeconomic status could even be negative.

The rest of this paper is organized as follows. Section 2 provides background on the VHA and the nature of the computerized system and discusses the relevant literature. Sections 3 and 4 introduces the theoretical model and discuss the model predictions. In section 5 we present the empirical model, specifications and robustness analysis. Section 6 is devoted to the data, and a description of the VHA's electronic medical records. We also offer a brief background on chronic heart failure as a medical condition. Section 7 presents the results from the empirical estimations. Section 8 concludes.

1.1 Relevant economics literature

This study relates to the economics literature analyzing the effects of adoption of information technology in organizations. The idea that information sharing could result in productivity gains has been tested in several areas of economic research (e.g. Hubbard, 2003) and evidence on the effects of IT diffusion on economic activity abounds (see Brynjolffson and Yan (1996) and Brynjolffson and Hitt (2000) for surveys). However, there has been little empirical or theoretical analysis of the effects of computerization and information-sharing in a health care setting. The closest study to this one is by Athey and Stern (2002), who consider the adoption of superior emergency-response systems (911) centers and its effect on patient outcomes in Pennsylvania. In this study, we concentrate on the effects on regular interactions between physicians, patients, and the pharmacy system.

We offer a simple model of physician-patient interaction where we view the physician and the patient as a team that is trying to accomplish a task - maintaining the patient's health. The model yields predictions on the effect of introduction of electronic medical records on the behavior of doctors and patients, depending on the quality of interaction between them. In the existing health economics literature, the predominant approach is consider the physician as an agent, who has more information than the patient (the principal) and who decides how to use this information to his advantage. The patient has only a passive role, she always follows the prescription. In our model, we recognize that the patient is also an active participant in the recovery process. One of the most important decisions is the compliance decision: whether or not to follow the treatment. We model the non-compliance as an outcome of a decision-making process on behalf of the patient. While our approach is similar to models of communication (e.g. Dewatripont and Tirole, 2005) and authority (Aghion and Tirole, 1997), we are not aware of any other existing research following this approach in the health economics literature.

Balsa and McGuire (2003) refer to communication and clinical uncertainty when modeling potential sources of differential treatment of whites and minorities. They make a number of assumptions about physician prejudice and uncertainty and show that their model can produce unequal outcomes under these assumptions. In their model, however, the physician effort is exogenous. Moreover, while Balsa and McGuire concentrate on modeling physician behavior under different assumptions (stereotyping, discrimination, clinical uncertainty), we focus on the patient as the main decision-maker in the treatment process.

We are able to empirically examine some of the model predictions on different channels through which EMR adoption influences patient outcomes, namely physician productivity, continuity of care, the incidence of pharmacy mistakes (duplicated prescriptions), and the effect on patient medication adherence, which is crucial to any therapeutic process.

2 Doctor-patient relationship: a game-theoretic approach

The traditional view on the doctor-patient relationship is this: the doctor prescribes the treatment, and the patient passively follows it. Imperfect compliance follows because patients sometimes behave irrationally: they do not understand their own benefits from the treatment, they forget to take their pills on time, etc. In such framework, there is no scope for altering the behavior of the patients - improving compliance - through the introduction of information technology. Our empirical results contradict this conclusions: the introduction of EMR in the VA setting not only affected patient's compliance, it did so in a differential way.

To understand these results, it is necessary to expand the above view and include the patient as an active participant in the recovery process.While such participation may take many forms, arguably the most important one is the decision to comply with the therapy. Since the patient is not a doctor herself, the compliance decision is typically made in the face of uncertainty about possible effects of the treatment. Notably, this uncertainty has two sources: one is the patient's inability to evaluate the adequatness of the prescription; another is the patient's understanding that there is a scope for doctor error. A rational patient weighs the costs of compliance - possible side effects as well as costs of doctor's mistake - against the benefit of improvement in health status.

The introduction of EMR has direct effect on this trade-off: doctors are supplied with an exogenous source of clinical information, which makes them better able to prescribe an adequate treatment. Even if the patient herself does not have an access[1] to that information, she trusts the prescription made by a better informed doctor more.

This simple theory provides for a good starting point. It does not explain, however, why EMR apparently had differential impact on patient compliance, even after conditioning on the same disease, age, co-morbidities. We hypothesize that the quality of communication that prevailed within these doctor-patient pairs was uneven. In particular, we assume that patients differ in their communication type - the ability to explain their condition to the doctor, and to answer doctor's questions clearly. Age, education level, language skills, cultural or languag differences with the doctor - all these factors may affect the quality of communication.

According to sociological and medical studies, the ability to communicate with the doctory is one of the most important determinants of patient satisfaction with care process (see e.g., Williams and Calnan, 1991; Vick and Scott, 1998). These attributes of the relationship have also been shown to affect health outcomes and patient compliance with medication therapy (Kaplan et al, 1989). In one study, Vick and Scott (1998) analyze responses from patient surveys and show that patients with higher socio-economic status patients prefer to make their own decisions about therapy over a joint decision with the physician, while older or lower-income patients prefer the physician to make the choice for them. In that survey, the ability to communicate with the physician was ranked highest among the different attributes of the doctor-patient interaction.

While the quality of communication may have independent effect on patient's trust and compliance, we focus on the communication as an information channel. With complicated conditions such as chronic heart failure, even the most experienced doctor needs to spend time with the patient in order to understand her individual condition. The effectiveness of his effort depends on the quality of communication with the patient, or the patient's communication type.

Thus we have identified both the quality of communication and the access to electronic medical records as channels in which health sensitive information can be transmitted from the patient to

[1] Recently, hospitals that introduce EMR have started offering online access to medical records to patients themselves. During the period of study, this feature was not available in the VA system.

the doctor. It is clear that an improvement in either of these dimensions will help the doctor make better informed choices and improve compliance, according to the theory outlined above. Ceteris paribus, patients with higher communication type and/or with access to EMR should exhibit better compliance rates. What is less clear is the interaction between these two channels. On the one hand, EMR is a substitute for some part of the communication, because it readily provides some "hard" clinical information. On the other hand, EMR is a complement to communication, as only the latter can provide "soft" information - patient's reaction to drugs, emotional state, choice of lifestyle. The soft is not recorded formally, but is important for the recovery and, moreover, patients value their ability to communicate this information to the doctor (REFERENCE?). To the extent that EMR crowds out the communication of "hard" information, it may also harm the process of receiving "soft" information, so the net effect on compliance may be negative.

In what follows, we employ game theoretic tools to examine how the introduction of information technology may alter the doctor-patient relationship, focusing on the quality of communication and compliance. This approach is relatively novel in health economics. Recently, it has been successfully employed by Balsa and McGuire (2001,2003) to discuss various sources of racial disparities in the treatment. However, we are not aware of any attempts to model compliance as an outcome of doctor-patient relationship.

2.1 Model

The purpose of the doctor-patient interaction is the recovery of the patient. The doctor needs to apply effort in order to understand the patient's condition and assign the best therapy. Although the effort is costly, the benevolent doctor will internalize the benefit from patient's recovery, which motivates him to apply effort[2].

A variety of factors may affect patient's beliefs, or her level of trust to the doctor. Some factors precede the patient's visit - experience from past interactions, doctor's credentials, reviews from other patients. Other factors occur during the visit itself: doctor's behavior (effort) and quality of his interaction with the patient. These are likely to be important, because the patient's experience during the visit directly precedes her decision to comply. Indeed, even though the patient cannot directly evaluate the quality of the prescription, she does observe doctor's effort. Everyone can read such signs as doctor's attitude, attention to detail, the total time spent on the visit. To the extent that doctor's effort is related to the gathering of information about her condition, the patient can make an inference about the likelihood that the prescribed treatment will be beneficial. As a result, the doctor's effort has a dual purpose: it both brings clinical information about the patient and determines the level of trust, and, eventually, compliance.

On both levels, the effectiveness of doctor's effort depends on the quality of interaction with

[2]By postulating a benevolent doctor, we abstract from possible financial incentives that may alter the choice of therapy. This is an adequate assumption in the VA hospital system, where pay is equalized. In private sector, financial incentives are important. Studying their effects is the subject of future research.

the patient. Within a given time frame, a doctor can get much less relevant information from an immigrant worker who speaks poor English, than from a native speaker. If the condition is complicated enough, this affects the doctor's ability to prescribe an adequate treatment. What is important from the compliance perspective, is that the patient understands this mechanism. Due to their different communication abilities, an immigrant worker and a native speaker would make different inferences from the same observed doctor effort.

The game between a patient and a doctor occurs in two periods. In the first period, the patient meets with the doctor and communication takes place, during which the doctor attempts to learn the patient's condition, or type, θ. The patient's type is her private information, and for simplicity we assume that she knows θ perfectly. The doctor applies a costly effort e and receives a noisy signal $\tilde{\theta}$. Patients differ in their communication style, represented by parameter ζ. Language skills, education, prior experience with the doctor - all these factors affect ζ, which can be interpreted as the ability of the patient to explain her condition to the doctor[3]. We assume the following communication technology:

$$\begin{aligned} P(\theta = \tilde{\theta}) &= 1 - p(e, \zeta) \\ p(e, \zeta) &= 1 - e\zeta,\ \zeta \geq 0 \end{aligned}$$

With probability $1 - p(e, \zeta) = e\zeta$ the doctor learns θ perfectly. On the other hand, he can make a mistake with probability $p(e, \zeta) = 1 - e\zeta$. The probability of mistake decreases both with the doctor's effort and with the patient's communication type: higher type patients enjoy better informed doctors at any given level of effort. We assume that the parameter ζ is observed by both parties. Based on the received signal, the doctor recommends a therapy.

In the second period, the patient decides whether or not to follow the recommended therapy, based on the cost-benefit analysis. Although the patient observes the treatment, we assume she cannot infer whether the doctor's signal was correct. This assumption reflects the ignorance of the patient about the treatment function. The patient also does not observe the doctor's signal, which creates a source of uncertainty about benefits of the treatment. The patient expects that with a fully informed doctor, when $\tilde{\theta} = \theta$, her benefit of following the therapy is $\tilde{B}$; when the doctor is misinformed, $\tilde{\theta} \neq \theta$, the benefit is $\tilde{B} - C$. That is, the doctor's misinformation is costly for the patient: for example, he may prescribe a pill without taking into account some condition, such as allergy. The parameter C characterizes the complexity of the patient's condition, as well as severity of the disease. For simple conditions, such as sore throat, little communication is needed:

[3]The communication parameter can also be interpreted as the quality of a match along a certain dimension (or several dimensions) between a physician and a patient that is pertinent to the curative process. For example, there is plenty of evidence that Hispanic doctors have proportionately more Hispanic patients (Stinson and Thurston, 2002) and that the racial profile of the patient population is a good predictor of the race of the phyisician (Komaromi et al, 1996). Patients express higher satisfaction if treated by a doctor of similar ethnicity or race, are likely to get more preventive care, and to maintain treatment for longer periods of time (Saha et al, 1999; Takeuchi et al, 1995; Cooper-Patrick et al, 1999).

even $e = 0$ guarantees an adequate prescription.

The patient is complying with the therapy if the expected net benefit is positive:

$$U_P = \tilde{B} - (1 - e\zeta)\, C > 0 \tag{1}$$

- where the value of non-compliance is normalized to zero.

During the visit, the doctor needs to form a belief about likelihood of compliance, because that affects his incentives to apply effort. We assume that the doctor knows the cost of mismatch C. This implies that the expected cost of compliance $(1 - e\zeta)\, C$ is common knowledge to both parties. However, the doctor is uncertain about the patient's perception of benefits of the treatment, $\tilde{B}$. For tractability, we assume that the doctor's belief about $\tilde{B}$ is:

$$\begin{aligned} \tilde{B} &= B + \eta \\ \eta &\sim U[-B; 0] \end{aligned} \tag{2}$$

The doctor knows B - the objective (actual) benefit of treatment, but not η - an idiosyncratic shock to the patients's perception of the treatment. In general, this shock may have two sources: one is the patient's private information about the effect of the treatment, or about the value of non-compliance; another is irrational noise in the decision making: patient's uncertainty about the treatment, prior (erroneous) beliefs about the condition, or simply forgetting. While both reasons for non-compliance can be important, here we focus on the latter one[4]. For simplicity (to avoid analyzing all corner solutions), we assume a wide support for η, so that at its lowest realization, $\eta = -B$, the patient does not comply; at the highest realization, $\eta = 0$, she complies with certainty, thanks to the following assumption:

Assumption 1 $B > C$

This assumption basically ensures that compliance happens only because of low realizations of patient beliefs, and not because of the incompetence of the doctor. Indeed, if the doctor knew in advance that $B - (1 - e\zeta)\, C < 0$, it would seem irrational to prescribe the pill in the first place.

In our model, the doctor is a benevolent one in the sense that he internalizes the patient's benefit from the treatment (excluding η, which we assume to be a result of patient's ignorance, not her private information, as discussed above). The optimal doctor's effort is determined from

[4] In this model, the assumption has no qualitative effect on the results. The distinction will appear in a richer model, where for example the patient is learning from the choice of the treatment.

the following program:

$$U_D = P\left(U_P\left(e\right) > 0\right)\left(B - \left(1 - e\zeta\right) C\right) - c(e) \to \max_e \tag{3}$$
$$e \geq 0$$
$$(1 - e\zeta) \geq 0$$

In reality, the doctor would also choose a therapy, based on his signal $\tilde{\theta}$ and the likelihood of compliance. For example, a doctor may choose a drug with slower curative but softer symptomatic effects, in order to induce compliance. In this model, we assume that the treatment function is given to him. In fact, in our setup there are no incentives for a strategic choice of treatment, because the patient does not update her beliefs from that choice.

To proceed, we need a technical assumption that guarantees an internal solution to the program (3).

Assumption 2 $\zeta^2 \leq \frac{1}{2C}$

The cost function is $c(e) = e^2/2$. It has desirable properties: it is equal to zero at $e = 0$ and its first derivative is positive, i.e. the marginal cost curve is increasing.

Lemma 1 *With assumptions (1) and (2), the optimal doctor's effort is:*

$$e^* = 2\zeta C \frac{B - C}{B - 2\zeta^2 C^2} \tag{4}$$

- which increases with ζ. If the cost of mistake is not too high, $C < B/2$, then doctor's effort increases with C. For higher cost levels, $B/2 < C < B$, there exists a threshold $\bar{\zeta}_1$, such that the doctor's increases with C for patients with $\zeta > \bar{\zeta}_1$, and decreases for others. As $\bar{\zeta}_1^2 < \frac{1}{2C}$, the latter set of (ζ, C) combinations is non-empty.
Proof. *See Appendix.* ■

We find that the optimal effort is increasing with the patient's communication style, which makes sense, because the productivity of doctor's effort increases with ζ. The effects of the cost of mistake C on the doctor's effort are non-linear: among patients with mild conditions, $C < B/2$, we find the doctor applying more effort to avoid mistake. However, once the condition becomes more complicated, the doctor responds to higher cost only if the patient is sufficiently communicative, $\zeta > \bar{\zeta}_1$. For other patients the probability of compliance is so low that the doctor becomes discouraged from applying more effort. Such effect is not obtained in a model with perfect compliance: when $P\left(U_P\left(e\right) > 0\right) = 1$, the solution to (3) is $e^* = \zeta C$ - which always increases with C.

2.2 The effect of EMR

When EMR is introduced, it raises the information set of the doctor, at any given level of effort. That is, the doctor becomes more informed regardless the signal $\tilde{\theta}$ he receives from the patient. Accordingly, he is able to adjust the treatment function in a way that minimizes the cost of a mistake, C. We do not explicitly model this change of treatment: instead, we assume that an introduction of EMR decreases C for all patients. To study the effect of EMR on compliance, we perform a comparative statics exercise of the expected cost of compliance, $(1 - e^{*}\zeta)\,C$, at various levels of ζ. According to (1), the expected cost of compliance determines the compliance rate, $P\left(U_P\left(e\right) > 0\right)$. Previously, in Lemma (1) we have established the reaction of the optimal effort to changes in C for various types of patients. We found that for many patients, lower C means lower effort; to translate this into changes in compliance, we need to find if the effort drops faster than C for some patients.

Proposition 1 *Suppose assumptions (1) and (2) hold. Then the introduction of EMR has the following effects, depending on the communication style, ζ.*
There exists a threshold $\bar{\zeta}_2$, $\frac{1}{2C} > \bar{\zeta}_2 > \bar{\zeta}_1$, such that the expected cost of compliance, $(1 - e^{*}\zeta)\,C$, decreases for patients with $\zeta < \bar{\zeta}_2$ and increases for patients with $\zeta > \bar{\zeta}_2$. Among patients with $\zeta < \bar{\zeta}_2$, those with $\zeta < \bar{\zeta}_1$ actually experience an increase in the doctor's effort.
Proof. *See Appendix.* ■

The results of this Proposition are illustrated on Figure (1).

We can interpret them by changing one of the parameters ζ, C fixed and changing the other. For many patients with a given ζ, the introduction of EMR (lower C) decreases doctor's effort. However, there is a category of patients - low communication type and high cost of mistake - for whom the doctor's effort actually increases. For patients with high enough value of ζ, the doctor's effort drops faster than C, leading to a higher expected cost of compliance and, consequently, to a lower compliance rate. On the other hand, patients with low value of ξ exhibit higher compliance rates after the EMR is introduced.

To get some intuition for this result, suppose that cost has changed by $\Delta C = C_1 - C_0$, inducing a change in effort $\Delta e = e_1 - e_0$. The corresponding change in the cost of compliance is:

$$(1 - e_1\zeta)\,C_1 - (1 - e_0\zeta)\,C_0 = \Delta C(1 - \zeta e_0) - \zeta \Delta e C_1$$

This expression has two parts, whose relative weight depends on ζ. For patients with low ζ, the first part dominates: they care more about the actual decrease in the cost of mistake than about changes in doctor's effort. In a sense, these patients are interested in "avoiding disaster": they understand that doctor may be misinformed because of their low communication skills, and put more weight the on external sources of doctor's information - such as EMR. For higher type patients, the second part dominates: changes in doctor's effort are more important that "avoiding

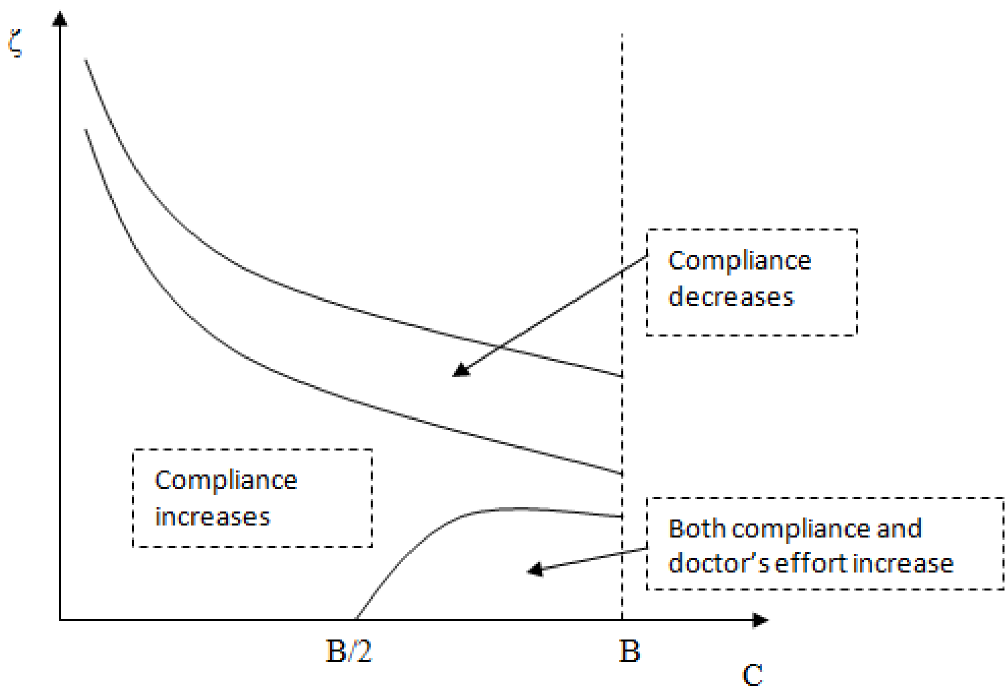

Figure 1: Effects of the introduction of EMR on various types patients, depending on parameters (ζ, C).

disaster", because the probability of misinformation is already low. We could say that these patients are seeking "customization of care" - they value the extra time the doctor spends with them. Some of that time is replaced by EMR, hence we see a decrease in the rates of compliance among these patients.

It is important to emphasize here that the effect of EMR on doctor's effort does not mean doctors become negligent. Also, our model does not say anything about other roles of doctor's effort. Instead, we observe that the information received through EMR crowds out the information gathering component of the doctor's effort. For example, doctors who have access to EMR may adopt a more active approach to treatment. This can manifest in (1) the physician spending less time listening to the patient; (2) the physician opting for an authoritative instead of a joint decision on the course of treatment; or (3) a more active approach to treatment management on behalf of the physician. These changes may decrease the quality of communication, as perceived by the patient. In a way, while it is important that doctor's are well-informed, it is also important that patients know about it.

The aggregate welfare effect of EMR is difficult to evaluate, as it depends on the relative weight of patients to each side of the communication threshold, $\bar{\zeta}_2$. Yet we expect that for the majority of patients the quality of care should increase, owing not only to information effects, but also better coordination of care, chronic disease management, etc. In other words, we expect that changes in doctor's effort, although important for a subset of patients, are not likely to outweigh benefits from the technology. By supplying doctors with information in an independent way, EMR serves as an equalizer among patients, reducing the variation in quality of care due to communication problems.

2.3 Model predictions

Our model of doctor-patient interaction yields several testable implications of the effect of introduction of EMR on various types of patients. In this framework, patients differ by ζ - communication type and by C - cost of mistake. Depending the combination of these parameters, the doctor may increase or decrease his effort, and the patient may decrease or increase her compliance, as shown on Figure (1). An empirical test of these predictions requires proxies for ζ and C, as well as a measure of doctor's effort. A real-world counterparts of the parameter C include indicators of the complexity and acuteness of the condition, severity of the disease, co-morbidities - factors that require an active interaction between the patient and the doctor. We should observe higher sensitivity of compliance to doctor's effort among patients with higher values of these factors. The communication parameter ζ can be broadly interpreted as a quality of match between a doctor and a patient, which includes all factors that facilitate interaction. Let i - index of the patient, and j - index of the doctor, and t - time of the interaction. Then ζ_{ijt} will have components: $\zeta_{ijt} = \zeta_i + \zeta_{ij} + \tilde{\zeta}_{ijt}$, where ζ_i - characteristics of the patient (such as language skills), ζ_{ij} - time-invariant factors that characterize the doctor-patient pair (such as common race), and $\tilde{\zeta}_{ijt}$ -

transitive factors pertaining to a particular interaction.

3 Empirical model

The base estimations utilize the panel structure of the data. Difference-in-differences in time of adoption by medical center and triple difference (time by medical center by proxy for patient type) estimators are used in models of the type:

$$Outcome_{igt} = \alpha + \beta EMR_{gt} + \theta * \zeta_i * EMR_{gt} + \delta X_{it} + \mu_g + \tau + \varepsilon_{igt}$$

Where $Outcome_{igt}$ is one of our measures of patient compliance with medication therapy. The medical center fixed effect is pinned down by μ_g which is common across all patients and all years, τ is a year fixed effect, X_{it} is a vector of patient characteristics, including income, race, marital status and coexisting medical conditions, and ε_{igt} is an unobserved patient level shock. Under ζwe group all observable variables that could be used as proxies for the communicative ability or the match value of the patient with the average physician working in the outpatient clinic. The coefficient θ estimates the differential effect of EMR adoption on patients of different types. All specifications include cohort fixed effects which absorb differences between patients diagnosed at different times. As a robustness check we also include a medical center*year time trend, to account for unobserved linear trends that may affect outcomes across medical centers.

3.1 The effect of EMR on physicians' treatment strategies

One of the predictions of the model is that the EMR will reduce physician uncertainty about a patient's θ and that may result in changes in treatment strategies employed by the doctor. The data allow the construction of two measures of treatment intensity. The first is the total number of different medications a doctor prescribes to a patient in a given year[5]. Controlling for patient demographic and health status, more medications that were attempted as part of the therapy indicate a more active treatment approach by the physician. An increase in the number of medications prescribed conditional on the patient's health state can be interpreted in two ways. First, we can think of it as stepping up the effort exerted by the physician in designing the optimal therapy. Second, a change in treatment strategy can be interpreted as a response to a falling cost of non-compliance for the patient. As the model predicts, EMRs reduce the cost of non-compliance for all patients, but the reduction is relatively larger for patients with low levels of ζ and high Cs. We expect intensity to pick up for patients endowed with ζ and C illustrated in region C on figure 1

[5]Here we mean the total number of distinct therapeutic agents, rather than the total number of drugs. We base the measure on the number of chemical formulas, rather than the formulary name of the drug. For example, packages of the same chemical formula coming in different doses are considered the same therapeutic strategy.

The second measure is the total days supply if a given pharmaceutical prescribed by the physician to the patient in a given year. We construct this measure as the sum of all days supply for a distinct active pharmaceutical agent across all prescriptions written by the physician for the patient. It can be thought of as an extension of a complement to the first measure described above. A more active therapy approach requires that different types of medications would be tried, and they would be changed more often. A more engaged physician would prescribe more diverse therapies, and necessarily ask for supplies that last shorter periods of time. If the number of attempted medications increases without a corresponding drop in the days' supply measure, we may be capturing a deteriorating health condition instead of a change in strategies by the doctor.

3.2 Patients' response

The data allow us to follow patients across interactions with different physicians over time. Throughout the rest of the text, the index i indexes the patient, j indexes the doctor, and t is the year in which the interaction took place. The patient-specific parameter ζ is not observed directly in the data. We think of the parameter ζ as having two parts – a patient-specific part, and a patient-doctor specific part. The patient-specific part of ζ_i is common across all physicians and affects each patient-physician interaction in a similar way. For example, if a patient has had negative previous experiences with the VA medical care system, he will be more distrustful of all health care providers and a lower ζ_i. We assume that the patient-specific ζ_i does not change over time. The patient-provider specific part of $\zeta- \zeta_{ij}$,is particular to the doctor-patient pair. We think of ζ_{ij} as the match-specific portion of the parameter, which captures the level of trust between a patient and a physician inspired by factors exogenous to the physician's efforts. For example, one such factor is common ethnicity or race. We assume that ζ_{ij}does not change with time.

The main patient-level empirical model is

$$Outcome_{ijt} = \zeta_i * EMR_t + \zeta_{jt} * EMR_t + EMR_t + \zeta_t + \zeta_{ij} + X_{it}\beta + \varepsilon_{ijt}$$

Where EMR_t is an indicator equal to one if the electronic medical records system has been fully implemented in the outpatient clinic visited by the patient and X is a vector of patient characteristics such as age, demographics, socioeconomic status and health. We omit the coefficients to avoid confusion with the parameter terms. The analysis is conducted using doctor-patient-year-level variation in outcomes. The outcome variable is the doctor-patient-year specific medication adherence rate or the sum of unpicked prescriptions written by doctor j for patient i in year t.

Patients vary along multiple dimensions that are not necessarily captured by controls for socioeconomic status and health offered by the data. Including patient-level fixed effects in the models accounts for unobserved patient characteristics that affect a patient's medication adherence and do not change over time. In the main patient-level model the patient fixed effect will absorb ζ_i and the mean of the ζ_{ij}. A within regression will yield a coefficient on the interaction term EMR*patient type that will capture both the EMR-specific effects of ζ_i and of all the $\zeta'_{ij}s$.

One of the predictions of the model is that the EMR would alter the relationships of a given patient with different doctors differently depending on the intensity of the interaction between them. A patient-doctor pair that has a lot of match-specific knowledge capital will have higher initial levels of ζ_{ij}. The model predicts that such pairs may experience a drop in the patient's medication adherence as a consequence of the EMR, depending on C. To test this hypothesis, we interact the EMR with the number of doctor-specific patient visits within the year, assuming that doctors who are visited more often by the patient maintain a higher level of ζ_{ij}. If our predictions are correct, physicians who receive more visits from the patient will experience a drop in the adherence level relative to physicians who are visited less often. This can be tested by lookoing at the interacton term between EMR and the measure of match intensity. A negative coefficient on the interaction term between visits and EMR in a patient fixed-effect regression will lend empirical evidence to the hypothesis.

Including provider-patient match fixed effects would absorb both patient-specific (common across physicians) and patient-doctor-match specific (within physician-patient pair) unobservables that are not changing over time. Both ζ_i and ζ_{ij} will be captured by the physician-patient pair fixed effect. The coefficient on patient-provider specific interaction term will capture the match-specific within-pair effect of the introduction of the EMR. The difference between the interaction coefficient estimates from the patient fixed effects model and from the patient-doctor match fixed effects model indicate how much of the differential effect of the EMR is due to assortative matching between physicians and patients induced by the EMR.

The two best proxies for ζ available in the data are the patient's race and his annual income. We assume that black race is a proxy for the level of compatibility in the provider-patient pair as well as for the general familiarity and trust of the patient in the health care system. Black patients with cardiac conditions are less satisfied with the health care they receive and more likely to mistrust the system overall (LaVeist et al., 2000). Even though we do not have data on physicians' race, it is safe to assume that the majority of physicians practicing in the veterans health system are not African American. There may be differences in satisfaction with care and physician-patient cooperation based on racial matching. For example, Saha et al. (1999) find that minority patients who see minority physicians are more likely to rate physicians highly and to report receiving preventive care. Patients holding negative stereotypes about their physicians are less likely to be satisfied with the care they receive and less likely to adhere to physician therapy recommendations (Bogart et al., 2004). Black race is commonly assumed to proxy for lower socioeconomic status and educational attainment. Thus, we expect that on average black patients would exhibit lower levels of ζ higher levels of C. Income is a direct measure of socioeconomic status and a good proxy for educational attainment. Medical sociology studies have shown that patients of higher SES are more active in seeking and supplying information about their condition (Pendleton and Bochner, 1980; Boulton et al, 1986) and prefer to be more directly involved in decision-making. We expect that higher income is associated with higher levels of ζ. In the empirical analysis we use the vector Z(income, black race) to proxy for different levels of ζ.

3.3 Robustness analysis

A first robustness check includes medical-center*time trends that control for any unobserved linear trends in outcomes in a given medical center over time. Second, we estimate an instrumental variables (IV) specification as a robustness check. An IV is warranted for several reasons. First, conditional on starting the EMR implementation in the same year, the time of final (full) implementation could differ due to unobserved factors which change with time and are not picked up by the medical center fixed effect (or the patient- or doctor-patient fixed effects). Second, it is not a priori clear what part of the EMR system is most responsible for changes in outpatient care outcomes. This introduces a measurement error in the treatment variable that is likely to bias the estimation results downwards. Finally, selection of patients into outpatient clinics that have already implemented the EMR is unlikely, but still possible.

An instrumental variable is needed which correlates with the probability of full EMR implementation conditional on the start of implementation but not with omitted variables which change with time and are potentially correlated with the outcomes. Here we utilize the regional organization of the Veterans Health Organization and the fact that budgets are decided at the regional, rather than the local level. The VHA is divided into 23 regional networks (VISNs) which are responsible for regional coordination of care, supervision of the medical centers, budgeting and other administrative duties. The set of instruments includes the number of medical centers in the regional network that have already fully implemented the EMR system in the first clinic where the patient was seen, a dummy indicating whether the EMR implementation has started in that clinic, and an interaction between the two variables. The focus is on the VISN of first visit to avoid any selection bias arising from differential sorting of patients across VISNs. The number of medical centers per VISN varies from 3 to 11. From the data it appears that medical centers belonging to the same VISN started adopting the EMRs at the same time, with an average of 8 months delay between the first and the last adopters.

The validity of the instrument hinges on the assumption that the total number of medical centers in the first VISN does not affect patient outcomes net of the patient/provider/patient-provider pair and year fixed effects. There is no variation in the number of medical centers per VISN over the time period, however there is variation in the number of medical centers with completed EMR systems. The first stage of the 2SLS is as follows:

$$EMR_{igt} = \alpha_i + \beta NMC_{0t} * EMR\_began_{0t} + \psi EMR\_began_{0t} + \xi NMC_{0t} + \upsilon_{igt}$$

Where EMR_began_{0t} is set equal to 1 if the EMR implementation was started in the first medical center that the patient ever visited in year t and 0 otherwise; α_i is a patient or a doctor-patient pair fixed effect depending on the specification. NMCs is the number of medical centers in the VISN that the patient visited first that had completed the EMR implementation by year t. All medical centers which finished the implementation necessarily started it, but not all who started finished by the end of the period under observation. Figure 2 shows a scatter plot of the year EMR was first started in the center vs the year of full implementation . Significant variation in the time to full implementation exists between different medical centers.

4 Data

The data come from the VHA Medical SAS inpatient and outpatient datasets, the Beneficiary Identification Records Locator Subsystem (BIRLS) death files, the VHA Enrollment files, and the Veterans Service Support Administration (VSSA) clinic performance measures database. The data cover all outpatients who were diagnosed with chronic heart failure in the VHA between October 1998 and October 2004 .

Between 1998 and 2004, the majority of veterans belonged to the age cohorts who served in World War II, the Korean War, and the Vietnam War. The median age of all veterans is 55, with veterans comprising the majority of all males older than 65. The proportion varies by race. The sample is restricted to patients who utilized community based outpatient clinics at least twice in the first year after CHF diagnosis. These people could be credibly identified as outpatients served by the Veterans Health Administration. Individuals whose race could be verified either across visits and/or by using the inpatient datasets and Medicare data were excluded from the analysis.

The sample consists of male veterans only. Female veterans comprise less than 2 per cent of the veterans who served in these wars. The final sample consists of 83800 VHA patients. CHF disproportionately affects elderly people and the military had restrictions on enrolling African Americans until the Korean War. This means that blacks are underrepresented in this sample compared to the overall veteran population and to the US population in general. Black patients comprise about 6.3 per cent of the sample .

The month and year of full implementation of the EMR system are available for 104 medical centers and their satellite outpatient clinics. The distribution of the timing of implementation is recorded in table 1. The sample covers the period from October 1998 to January 2005. Patients join the sample throughout this period. The largest numbers of new patients enter in years 2001 and 2002. This coincides with the period of largest expansion of the VHA health care system. The years 1998 are 2005 are incomplete, since 1998 includes data from the last three months of the year and 2005 only contains data from January. A potential concern is that the patients joining the VHA health system after 1998 could have an advanced stage of CHF at the time of observed first diagnosis within the VHA. This bias should be alleviated by including cohort dummies. Most of the new patients who joined the VHA after 1998 are white patients with higher income. Therefore, any discrepancy in severity at first diagnosis would work against finding racial differences in survival and would bias the coefficient on black race in the survival regressions downwards.

Little is known about physicians beyond their clinical decisions regarding different patients. The data contain a unique physician identifier which helps link all patient visits to the same provider. Every physician has an ID within the medical center where she or he practices. If a physician changes Medical Centers, she gets a new id. In the data such cases are coded as a new physician ID within the new medical center and it is impossible to link the same doctor across Medical Centers. However, since Medical Centers are geographically far apart, it is unlikely that such cases as common. The identifier is also present on the prescription, linking different therapy decisions to the same doctor. Physicians' demographic or educational data are not released by the VHA.

Every patient has a primary care provider. Even if several providers practice in the same outpatient clinic, the first course of action for a nurse receiving a scheduling call from a patient is to attempt a visit with the primary provider. Patients are allowed to change primary providers, but the changes are binding, i.e. once a new provider has been chosen as the primary, she retains this role until the patients requests a change. If the primary provider is not available for a visit, a patient could be assigned to a substitute or another physician practicing in the same clinic. The institutional set-up of outpatient care is not conducive to "shopping around" for the best matching physician in the practice. A physician-patient pair is defined as a match between a patient and a doctor who have more than two interactions in the data. The indicator of an interaction is a new prescription written by the doctor for the patient. Patients see a number of doctors over the course of treatment. African Americans see more doctors, but they get fewer prescriptions per doctor, implying that the intensity of their relationship with any given physician is lower.

4.1 The electronic medical records system

The computerized patient records system was introduced between 1995 and 2004 in different VHA medical centers and their satellite outpatient clinics. The electronic record contains information on all patient medical conditions, the outpatient visits and inpatient episodes, as well as the past and current medication therapy. It also records the identity of the providers whom the patient has encountered and their recommendations. Hence, if the patient met two different doctors in consecutive meetings, the second physician has a complete record of the medication therapy prescribed by the first physician, as well as all vitals, lab results, and previous adverse health events.

The electronic medical records system examined in this study is part of a much larger electronic patient data infrastructure (VISTA) which has been in use in the VHA since the late 1970s (Brown at al, 2003). The new elements of VISTA, which were implemented around the period of interest, were the Bar Code Medication Administration (BCMA), used in inpatient services, and the Computerized Patient Record System (CPRS), recording patient information across inpatient and outpatient encounters and pharmacy data. CPRS includes provider order entry and provider-entered electronic progress notes. It was releasedas a separate IT product initially in 1996, and its implementation was mandated in the VHA nationally in 1999. Among other applications, CPRS contains patient-specific records of pharmacy order, lab reports, progress notes, vital signs, inpatient and outpatient encounters. In September 2002, providers entered over 90% of medication orders electronically (Brown et al, 2003). Other features of CPRS include a notification system that immediately alerts clinicians about clinically significant events such as abnormal test results, a strategy that helps prevent errors by requiring an active response for critical information. A patient posting system, displayed on every CPRS screen, alerts clinicians to issues related to the patient, including crisis notes, special warnings, adverse reactions, and advance directives. Figure 2 shows a screen-shot of a cover page of an electronic patient record available through CPRS.

BCMA is a bed-side application which allows nurses to validate medication against a patient barcode. It was implemented nationwide in 1999-2000. It has been linked to significant reductions in adverse incidents due to medical errors. The data in this study are from outpatient records, making the CPRS implementation an interesting case study. A priori it is not clear whether electronic records would affect patient compliance at all, or even how new technologies would affect patients of different SES. On the one hand, it has been argued that adoption of new technologies could be slower for patients of lower SES (Goldman and Smith, 2005). n the other hand, IT might serve to close the gap in health knowledge capital between patients of different SES. If improved coordination serves to close the communication effectiveness gap, one would find changes in both physician actions and the coordination of care.

4.2 Chronic Heart Failure

The paper focuses on patients who have received a diagnosis of chronic heart failure (CHF). There are several reasons to focus on this condition. First, heart disease is the leading cause of death in the elderly and is the most costly single condition in Medicare in recent years (33.2 billion dollars in 2007)[6] . Second, heart disease is an Ambulatory Case Sensitive Condition, which makes it particularly susceptible to policy interventions in an outpatient setting. It has been shown that expensive hospitalizations and re-hospitalizations can be avoided with adequate preventive care and disease management. Finally, heart failure is rarely misdiagnosed, and there are clear guidelines for pharmacologic outpatient-based treatment. This study relies on the clinical guidelines to construct a measure of doctor clinical quality and test whether doctors provide the optimal therapy to both racial groups.

Congestive heart failure is a progressive health disorder with fatal outcomes. Mortality rates in the first year after diagnosis are about 10 per cent. However, if care is managed well, patients' chances of living longer and their quality of life can be improved significantly. The recommended medical therapy is well publicized. Once the first year of treatment has passed successfully, chances of longer-term survival increasingly depend on the patients' and doctors' ability to adapt the treatment and lifestyles to counter the progression of the disease. Short-term (one-year) mortality

[6]According to the AHA statistical abstract, 2007 (http://www.americanheart.org/downloadable/heart/1166711577754HS_StatsInsideT

is more likely to be influenced by the patient's initial physical condition at diagnosis, while longer-term survival would be more sensitive to medical therapy and the ability of the patient and the doctor to effectively coordinate the management of the disease. Appendix A in Simeonova (2008) discusses the medical condition and treatment options in more detail.

4.3 Patient adherence measures

If there is little substitutability between doctor and patient effort, no therapy would work without the patient's active participation. While health studies evaluate the effect of doctor inputs, they rarely account for the effect of patients' response to physicians' efforts. Leonard and Zivin (2005) provide one of the few models of health production that explicitly accounts for patient input. Patient response could be especially important for chronic conditions such as chronic heart failure that are managed on an outpatient basis, and that require an investment of daily effort by the patient.

This study uses data on prescription refills to define two measures of patient adherence to therapy. The first is the medication adherence ratio, which we also call patient compliance. The VHA pharmacy data contain a "days supply" variable attached to each prescription, as well as the time when the first dose was dispensed and the time of subsequent refills. Using the "days supply" variable one can determine whether the prescription was refilled on time. A refill is defined as "compliant" if it was picked up within 3 days of the expiration of the previous days' supply . The adherence measure is defined as the number of prescriptions which were not re-filled on time over the total number of prescriptions. According to the most comprehensive study of adherence measures, the one defined here is ranked the best in the context of an integrated pharmacy system[7] (Ostenberg and Blaschke, 2005).The same technique is used to formulate aggregate patient adherence per year and individual patient adherence for every patient-doctor pair.

$$\text{Medication adherence ratio} = ((\text{N prescriptions filled on time})/(\text{Total N prescriptions}))$$

Note that this measure is defined over prescriptions that were picked up by the patient, and does not include prescriptions written by the provider, but ignored or forgotten by the patient.

A second measure of the coordination between a physician and a patient available from the data is the number of prescriptions ordered by the physician but never picked up by the patient. A prescription which was never picked is an indication of an action which the physician wanted to take (she could call the pharmacy and cancel the Rx, or cancel electronically through the EMR if she made an error), but was not accepted by the patient. For example, a patient wouldn't pick up an Rx for a compound they know they are allergic to. Thus, we consider fewer unpicked

[7] The VA pharmacy only fills prescriptions that were ordered by a physician within the VA health care system. The pharmacy keeps electronic records for all transactions which is independent of the EMR system. Pharmacy records cover the entire medication history of the patient and are exhaustive within the VA health care system.

prescriptions as an indicator of improved coordination of care between physicians and patients, as well as a marker for patient adherence to recommended therapy.

5 Results

We start by testing whether our proxies for ζ exhibit the expected correlations with patient adherence in a sample of observations before the introduction of the EMR. Table 3 contains results from regressions controlling for all demographic and medical characteristics of the patients, cohort- and year-dummies, and clinic fixed effects for the sample of clinics and years before the implementation of the EMR. African American patients are less likely to adhere to medication therapy pre-EMR and they are more likely to leave prescriptions unpicked. Income does not seem to have an important role for medication adherence once other controls are included, however better-off individuals are more likely to pick up all of their prescriptions. We interpret these results as supporting evidence that black race and lower income are suitable proxies for lower levels of ζ, while higher income conditional on non-African American race is a proxy for higher levels of ζ.

5.1 The effect of EMR on treatment strategies

We briefly comment on the results obtained from empirical models testing for changes in physicians' treatment strategies induced by the EMR. The first set of results is presented in Table 4 Panel A. The results support the empirical predictions of the model. Post-EMR physicians adopt a different therapy strategy for African American patients. The total number of distinct pharmaceutical agents prescribed increases and the average days supply decreases. The coefficients are reduced by about 1/4th in models controlling for physician-patient pair fixed effects in columns (3) and (4). About 25% of the change in treatment intensity may be attributable to patient matching to more actively prescribing providers as a result of the EMR. Still, 75% of the effect is due to changes within physician-patient pairs. The corresponding reduction in the interaction coefficient on EMR and black race in the day's supply regression from (2) to (4) in Panel B is much smaller. The coefficient on the interaction between income and EMR has the opposite sign, but does not significantly affect the first outcome. The analysis shows an increase in the average days' supply post-EMR for better-off patients. However, this increase in much smaller than the reduction experienced by African American patients. These findings suggest that African American race is a good proxy for the group of patients with low ζ and high costs of compliance, corresponding to region C on figure 1. As these patients' medication adherence is most favorably affected by the EMR, we expect that the improvement in compliance among African Americans will be large compared to the expected decrease in compliance among high ζ-low C (higher income) patients.

5.2 Patients' response

We first consider the effects of EMR on the aggregate (medical center) level. Table 5 presents results from difference-in-differences models of average patient compliance indicators before and after the EMR. The analysis is at the level of physician-patient-year cell means and the outcomes are our two measures of patient compliance - the ratio of compliant refills (patient compliance) and the number of unpicked prescriptions. The main effect of EMRs is small, negative and statistically insignificant. The coefficients on black race in specifications (1) and (5) show a lower average compliance rate associated with African American race. Specifications (2) and (6) include an interaction term between black race and EMR which obtains, as predicted, a positive coefficient for the first outcome. After controlling for the interaction between EMR and African American race, pre-EMR difference in medication adherence between blacks and whites increases to 6.1 percentage points, which is more than a ten percent gap relative to the mean. The coefficient on the interaction term in the models using the number of unpicked prescriptions is negative as predicted, although not that strong statistically.

The income variable has a negative coefficient across both outcomes in (1) and (5), which appears contradictory at first. But the income coefficient in specifications (1) and (5) captures the average effects of higher income both before and after the EMR. As we show in columns (3) and (7), the association between income and medication adherence changes from positive before the EMR to slightly negative after the EMR. Finally, specifications (4) and (8) offer robustness checks including a medical-center specific linear time trend. On average, EMRs increased compliance among African American patients relative to whites and decreased compliance among higher-income patients relative to lower-income ones.

One of the empirical predictions of the model is that the EMR will reduce the cost of a patient's compliance the most with physicians with whom he has a high level of provider-patient specific ζ. We hypothesize that more frequent interactions increase a physician's patient-specific knowledge and these pairs carry a relatively higher ζ. The number of visits that resulted in a new prescription is used a proxy for the familiarity between a physician and a patient in model specifications reported in in Table 6. Column (1) has medication adherence as an outcome of interest, and column (2) has the sum of unpicked prescriptions in the year. As the amount of interaction increases, so does patient compliance. The EMR causes a reduction in medication adherence, which is relatively higher with physicians whom the patient knows better.

The second column in table 6 shows the differential effects of EMR on the number of unpicked prescriptions in a year. If a patient sees a physician more often, he is more likely to skip picking up a prescription written by that physician. The effect of the EMR clearly depends on the average number of prescriptions written. Post-EMR, patients are more likely to ignore the treatment choices of physicians whom they see less often. At first sight these results appear to contradict the findings on compliance reported in column (1). However, ignoring a physician's recommendation altogether is a much stronger signal of lack of trust than having imperfect compliance with the therapy *conditional on having picked up the medication*. Picking up medications can be viewed as the extensive margin of compliance, with medication adherence as the intensive margin. The main effect of the EMR could be an increase in coordination with the main provider, even if the secondary (intensive-margin) effect on compliance is negative.

Table 7 reports results from our main specification showing the effect of EMR on individual patients (panel A) and doctor-patient pairs (panel B). The first two columns show the results from OLS regressions including patient (Panel A) or physician-patient pair (Panel B) fixed effects. The third specification allows for different linear trends across medical centers. The fourth and fifth columns report results from a fixed-effects IV estimation used as a robustness check. Appendix table 1 shows the results from the first stage regressions used in the IV estimations. The coefficients on the instruments are large and the joint F-test of significance for the excluded instruments is well above the commonly accepted threshold for weak instruments (generally considered to be around 10). The probability that the medical center has fully implemented EMRs is very strongly positively correlated with whether the implementation has started in the first VISN visited by the patient, with a coefficient close to 0.5. The more medical centers in the first VISN, the more likely it is that the implementation has completed, but conditional on having started, a medical center is less likely to have completed the implementation if there are more neighboring medical centers that have already finished the implementation. We interpret these results both as evidence of positive spill-overs between different medical centers in the same regional network and as competition for resources once the implementation has commenced.

We control for annual income in all specifications reported in table 7. It changes little over time for the same patient, and the mean of the income variable is absorbed by the patient fixed effect. However, even small changes in income may have effects on compliance. For example, as income increases medications become more affordable, even if they were always cheaper than on the private market[8]. Columns (1) and (2) show results from specifications including interactions of black race and income with the EMR indicator. The coefficients capture the joint effects of the patient-specific and the mean of the patient-doctor-specific parts of ζ. The interaction between black race and EMR is positive and significant. The interaction between income and EMR is negative. Including this interaction term in the regression reduces the magnitude of the black*EMR coefficient by about 1/6, suggesting that some of the effect associated with black race is in fact due to the lower average socio-economic status of black patients. Still, the differential effect on African American patients remains positive and significant, implying that the race indicator captures characteristics of the physician-patient interaction and the patient that are not controlled by income or health status.

As a robustness check we include a medical-center*time linear trend in column (3). The interaction coefficient with black race is reduced, but still positive, and there is very little change in the income interaction terms. In columns (4) and (5) we show the results from the IV specification.

[8]The charge for a refill of any medication included in the VHA formulary in 2007 was 8 dollars

The interaction coefficients are slightly larger, with larger standard errors. This is consistent with the expectation of measurement error in the treatment (EMR) variable and the interaction terms. The coefficient on black race loses the statistical significance, but the interaction term with income is still negative and significant. Since we don't explicitly control for the interaction black*EMR in (5) the income interaction term picks up some of the effects associated with black race. Overall the results from the IV specifications confirm the OLS results.

Comparing the OLS results from Panel A and Panel B in table 7 reveals more evidence about the level at which the effects of the EMR operate. The level of variation in all specifications in panel B is the physician-patient pair, and the identifying variation comes from doctor-patient pairs who existed both before and after the introduction of the EMR. This ensures that any selection of providers that may have been influenced by the EMR is not biasing the results. The coefficients in Panel B are remarkably similar to those in Panel A. First, the interaction terms black*EMR and income*EMR have the same magnitude across the models including only patient fixed effects and patient-physician fixed effects. The contribution of the doctor-specific part of the patient's ζ is not so significant and the main effect of the EMR across different patient types is patient- rather than patient-physician specific. Second, the IV and the OLS specifications yield similar results. Overall, the estimates reported in table 7 indicate that the EMR had differential effects for different patient types and those effects are not driven by provider-patient matching or other unobservable confounders.

In table 8 we report results from equivalent specifications using the sum of upicked prescriptions as an outcome. The coefficient estimates confirm the predictions of the model and the signs are in the direction we would expect given the results in table 7.

6 Conclusions

We develop a simple model of physician-patient interaction to place the introduction of electronic medical records in a conceptual framework that yields testable predictions. In this framework, differential patient compliance with medication therapy is influenced by the physician-patient interaction and the result of an optimization process by the patient. A unique dataset of physician-patient interactions and the resulting therapy prescriptions in used to test the empirical hypotheses. Implementing electronic medical records has significant impact on physician and patient behavior and the outcomes of the physician-patient interaction. The effects differ depending on the type of patient. Patients who were in a disadvantaged position in terms of their interaction with the medical care system prior to the EMR gain the most from the new technology. However, some of the patients who were more actively involved in the treatment process and had higher compliance pre-EMR could reduce their compliance after the EMR implementation. We interpret this as a preference for care customization among higher SES patients. The empirical results confirm these predictions.

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7 Appendix 1: Theory

Proof of Lemma (1) We solve the unconstrained version of (3) and then verify that in the optimum both constraints are satisfied. After differentiating, the first order condition is:

$$2\zeta CB - 2\zeta C^2 (1 - e\zeta) = Be \tag{5}$$

- from which (4) is readily obtained. Since $B > C$, the restriction $e^* > 0$ implies: $B - 2\zeta^2 C^2 > 0$, or $\zeta^2 < B/\left(2C^2\right)$. Since $1/(2C) < B/\left(2C^2\right)$, this condition is satisfied by assumption (2). We also need to verify that $(1 - e^*\zeta) \geq 0$. From the first order condition,

$$\begin{aligned}
(1 - e^*\zeta) &= 1 - 2\zeta^2 C \frac{B - C}{B - 2\zeta^2 C^2} \\
&= \frac{B - 2\zeta^2 C^2 - 2\zeta^2 CB + 2\zeta^2 C^2}{B - 2\zeta^2 C^2} \\
&= \frac{B\left(1 - 2\zeta^2 C\right)}{B - 2\zeta^2 C^2} \geq 0
\end{aligned}$$

Since $B - 2\zeta^2 C^2$, we need $\left(1 - 2\zeta^2 C\right)$, which is again implied by assumption (2). The effort is always monotonically increasing with ζ. The derivative of the optimal effort with respect to C is:

$$\begin{aligned}
\frac{\partial e^*}{\partial C} &= 2\zeta \frac{(B - 2C)\left(B - 2\zeta^2 C^2\right) - C(B - C)(-4\zeta^2 C)}{\left(B - 2\zeta^2 C^2\right)^2} \\
&= 2\zeta B \frac{B + 2\zeta^2 C^2 - 2C}{\left(B - 2\zeta^2 C^2\right)^2}
\end{aligned}$$

- whose sign is determined by $\left(B + 2\zeta^2 C^2 - 2C\right)$. Solving $B + 2\zeta^2 C^2 - 2C = 0$, we obtain the first threshold $\bar{\zeta}_1^2 = \frac{1}{2C}\frac{2C - B}{C} < \frac{1}{2C}$. If $\zeta > \bar{\zeta}_1$ we have $\partial e^*/\partial C > 0$ - the effort increases with cost of mistake. Since $\zeta > 0$, this constraint matters only if $\bar{\zeta}_1 > 0$, or $B > C > B/2$; for lower costs, $C < B/2$, we have $\partial e^*/\partial C > 0$ for all $\xi > 0$. QED.

Proof of Proposition (1). The expression for the expected cost comes from the first-order condition (5):

$$(1 - e\xi)\, C = B - \frac{B}{2\xi}\frac{e}{C}$$

- from which we see that expected cost increases with introduction of EMR only if the effort falls faster than C, i.e., $\partial(e/C)/\partial C > 0$. Differentiating e/C,

$$\begin{aligned}
\frac{\partial(e/C)}{\partial C} &= 2\zeta\frac{-\left(B - 2\zeta^2 C^2\right) - (B - C)(-4\zeta^2 C)}{\left(B - 2\zeta^2 C^2\right)^2} \\
&= 2\zeta\frac{-B - 2\zeta^2 C^2 + 4\zeta^2 CB}{\left(B - 2\zeta^2 C^2\right)^2} \\
&= 2\zeta\frac{-B + 2\zeta^2 C(2B - C)}{\left(B - 2\zeta^2 C^2\right)^2} > 0
\end{aligned}$$

This inequality holds if $\xi^2 > \frac{1}{2C}\frac{B}{2B-C}$, which gives the second threshold, $\tilde{\zeta}_2$. We should have $\tilde{\zeta}_2 > \tilde{\zeta}_1$, because $\partial e^*/\partial C > 0$ is a necessary condition for $\partial(e/C)/\partial C > 0$, but not a sufficient one. Indeed,

$$\begin{aligned}
\frac{1}{2C}\frac{B}{2B - C} &> \frac{1}{2C}\frac{2C - B}{2C} \\
2BC &> (2B - C)(2C - B) \\
2BC &> 5BC - 2C^2 - 2B^2 \\
(B - C)^2 &> 0
\end{aligned}$$

We also need to verify that the threshold is binding $\tilde{\zeta}_2$, i.e. $\tilde{\zeta}_2 < \frac{1}{2C}$, which is an upper limit on ξ, by assumption (2) - which ensures an interior solution in this model.

$$\begin{aligned}
\frac{1}{2C}\frac{B}{2B - C} &< \frac{1}{2C} \\
B &< 2B - C \\
0 &< B - C
\end{aligned}$$

QED.

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Table 1: Timing of EMR implementation in the VHA

Year of full implementation and N centers	Beginning of implementation is N centers
1995 (2)	1989 (1)
1996 (1)	1994 (2)
1997 (2)	1995 (1)
1998 (16)	1996 (5)
1999 (32)	1997 (5)
2000 (15)	1998 (40)
2001 (13)	1999 (37)
2002 (14)	2000 (6)
2003 (6)	2001 (5)
2004 (2)	2002 (2)
Still in progress in 2004 (4)	

Figure 2: A screenshot of the CPRS user interface

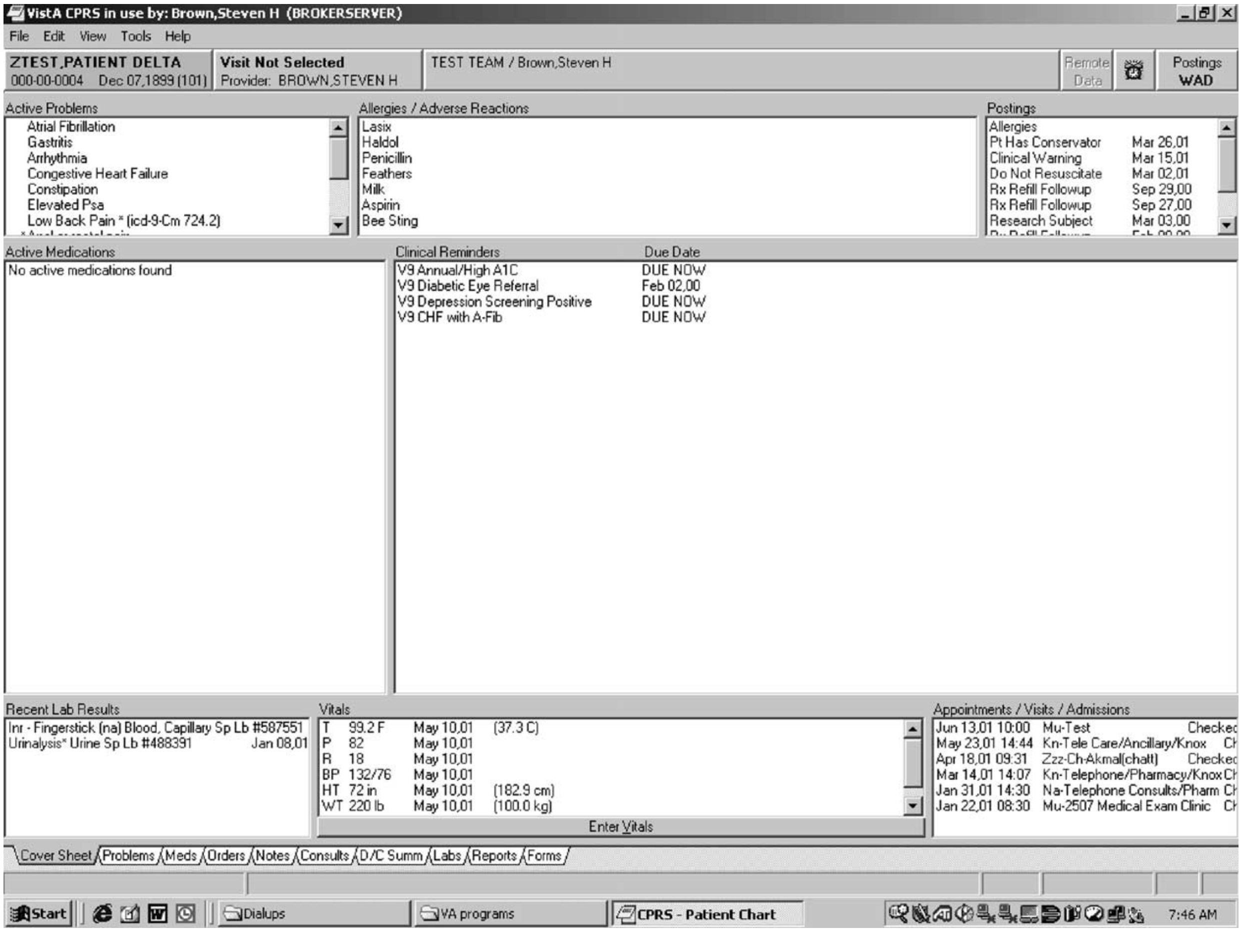

Table 2: Means of key variables by EMR status; Standard deviations in parentheses

	No EMR			
	whites		blacks	
	N	Mean	N	Mean
age	23835	70.560	2205	65.616
		[9.413]		[11.843]
income/10K	23835	2.771	2205	1.501
		[5.815]		[1.557]
Married (%)	23835	66.5		52
Surv 1 year (%)	23835	0.975	2205	0.981
Surv 2 year (%)	23249	0.951	2164	0.955
Surv 3 year (%)	22122	0.926	2067	0.933
Surv 4 year (%)	20436	0.908	1929	0.925
	With EMR			
	whites		blacks	
age	28341	72.821	1283	65.501
		[9.130]		[12.067]
income/10K	28341	3.373	1283	1.651
		[7.267]		[2.234]
Married (%)	28341	70	1283	50
Surv 1 year (%)	28341	0.946	1283	0.948
Surv 2 year (%)	26446	0.925	1197	0.949
Surv 3 year (%)	23043	0.915	1036	0.930
Surv 4 year (%)	18335	0.906	795	0.931

Coordination of care

	No EMR			
All measures are per calendar year	whites		blacks	
	N	Mean	N	Mean
N docs/patient	72869	2.114	8708	2.478
		[1.372]		[1.694]
Ratio compliant	72869	0.590	8708	0.532
		[0.348]		[0.352]
N not picked	72869	0.227	8708	0.254
		[0.754]		[0.803]
N scripts/doctor	72869	4.036	8708	4.001
		[3.544]		[3.655]
N meds/provider	72869	3.3	8708	3.3
Total days supply/medication	72869	228	8708	226
	With EMR			
	whites		blacks	
N docs/patient	266071	2.074	18915	2.390
		[1.305]		[1.526]
Ratio compliant	266071	0.552	18915	0.514
		[0.339]		[0.350]
N not picked	266071	0.092	18915	0.103
		[0.521]		[0.540]
N scripts/doctor	266071	4.452	18915	4.496
		[3.716]		[3.952]
N meds/provider	266071	3.4	18915	3.6
Total days supply/medication	266071	257	18915	242

Table 3: Pre-EMR period. The analysis is at the level of the physician-patient-year cell.

	(1)	(2)
	Medication adherence	N unpicked Rxs
Income	-0.000	-0.001**
	(0.000)	(0.000)
Age	0.000	0.001
	(0.000)	(0.000)
Married	0.000	-0.001
	(0.005)	(0.008)
Black	-0.049***	0.023
	(0.015)	(0.015)
MC fixed effects	YES	YES
Constant	0.843***	-0.010
	(0.025)	(0.042)
Observations	67333	67333
R-squared	0.038	0.045

Included are cohort- and year-dummies, controls for co-morbidities. Standard errors are clustered at the level of the medical center.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: The effects of EMR on physicians' therapy decisions. Fixed effects OLS regressions. The observations are physician-patient-year cell averages.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A				*Panel B*			
	N medications prescribed				Mean medication supply			
	FE	FE	FE	FE	FE	FE	FE	FE
EMR	0.013	0.019	-0.061	-0.060	-0.752	-1.520	-4.230	-3.616
	(0.037)	(0.039)	(0.047)	(0.048)	(3.036)	(3.070)	(4.449)	(4.434)
EMR*black	0.128**	0.126**	0.090	0.090	-7.091**	-6.772**	-6.427	-6.705*
	(0.053)	(0.054)	(0.073)	(0.073)	(2.812)	(2.813)	(3.956)	(4.015)
Income	-0.002	-0.000	-0.004	-0.004	-0.236	-0.510***	-0.518	-0.311
	(0.003)	(0.004)	(0.006)	(0.004)	(0.170)	(0.172)	(0.371)	(0.270)
EMR*income		-0.002	0.000			0.293*	0.217	
		(0.002)	(0.003)			(0.169)	(0.308)	
Age	0.107*	0.107*	0.086	0.086	-4.720	-4.733	0.446	0.453
	(0.061)	(0.061)	(0.077)	(0.077)	(2.967)	(2.967)	(5.675)	(5.676)
Patient FE	X	X	-	-	X	X	-	-
Provider-patient FE	-	-	X	X	-	-	X	X
Observations	327686	327686	327686	327686	327686	327686	327686	327686
R-squared	0.350	0.350	0.811	0.811	0.274	0.274	0.617	0.617

All specifications include cohort- and year-dummies, as well as controls for co-morbidities. Standard errors are clustered at the level of the medical center.

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Pre- and Post-EMR, effects on the clinic level. OLS regressions. The analysis is at the level of the physician-patient-year cell

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	*(8)*
	Medication adherence				Sum unpicked RX			
EMR	-0.005	-0.007	-0.005	-0.011	0.037	0.037	0.035	-0.011
	(0.012)	(0.012)	(0.012)	(0.009)	(0.026)	(0.026)	(0.026)	(0.009)
EMR*black		0.019**	0.018**	0.007		-0.009	-0.008	0.007
		(0.008)	(0.008)	(0.011)		(0.016)	(0.016)	(0.011)
Income	-0.001***	-0.001***	0.000	-0.000	-0.000	-0.000**	-0.001**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EMR*income			-0.001**	-0.001*			0.001*	-0.001*
			(0.000)	(0.000)			(0.001)	(0.000)
Age	0.000	0.000	0.000	0.000	0.000	0.000*	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.002	-0.002	-0.002	-0.002	-0.004	-0.005*	-0.005*	-0.005**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Black	-0.048***	-0.061***	-0.061***	-0.052***	0.014*	0.024	0.023	0.026*
	(0.011)	(0.014)	(0.014)	(0.014)	(0.008)	(0.016)	(0.016)	(0.014)
MC FE	X	X	X	X	X	X	X	X
MC*time trends	-	-	-	X	-	-	-	X
Obs	327686	327686	327686	327686	327686	327686	327686	327686
R-sq	0.029	0.029	0.029	0.032	0.079	0.078	0.078	0.081

All models include cohort- and year-dummies, controls for co-morbidities. Standard errors are clustered at the level of the medical center.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Differential effects of EMR depending on the intensity of physician patient interaction. Fixed effects OLS regressions. The analysis is at the level of the physician-patient-year cell

	(1)	(2)
	Medication adherence	Sum unpicked RX
	FE	FE
EMR	0.003	0.220***
	(0.012)	(0.042)
EMR*N Rx	-0.001**	-0.042***
	(0.001)	(0.010)
N Rx	0.001***	0.071***
	(0.001)	(0.010)
Income	-0.000	-0.000
	(0.001)	(0.001)
Age	0.002	0.019
	(0.010)	(0.014)
Patient FE	YES	YES
Constant	0.354	-0.011
	(0.625)	(0.741)
Observations	327686	327686
R-squared	0.370	0.304

All models include year-dummies, and controls for co-morbidities. The standard errors are clustered at the level of the medical center.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Patient medication adherence

	(1)	(2)	(3)	(4)	(5)
	Panel A - Patient				
	FE	FE	FE	IV-FE	IV-FE
EMR	-0.004	0.002	-0.007	-0.026	-0.015
	(0.011)	(0.011)	(0.009)	(0.023)	(0.026)
EMR*black	0.018***	0.015**	0.002	0.027	
	(0.006)	(0.006)	(0.008)	(0.021)	
Income	-0.000	0.002**	0.001**	-0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EMR*income		-0.002***	-0.002***		-0.003***
		(0.000)	(0.000)		(0.001)
Age	0.003	0.003	0.004	0.007	0.007
	(0.010)	(0.010)	(0.007)	(0.010)	(0.009)
Patient FE	X	X	X	X	X
MC*time	-	-	X	-	-
R-squared	0.370	0.370	0.371		

	Panel B – provider-patient pairs				
	FE	FE	FE	IV-FE	IV-FE
EMR	-0.003	0.003	-0.010	-0.030	-0.022
	(0.019)	(0.020)	(0.015)	(0.030)	(0.031)
EMR*black	0.018**	0.016*	-0.001	0.016	
	(0.009)	(0.009)	(0.012)	(0.016)	
Income	-0.000	0.002	-0.002*	-0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EMR*income		-0.002**	0.001		-0.003***
		(0.001)	(0.001)		(0.001)
Age	0.009	0.010	0.011	0.010	0.010
	(0.011)	(0.011)	(0.009)	(0.010)	(0.011)
Prov-pat FE	X	X	X	X	X
MC*time	-	-	X	-	-
Obs	327686	327686	327686	327686	327686
R-squared	0.688		0.689		

All models include year-dummies, and controls for co-morbidities. The standard errors are clustered at the level of the medical center. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: Sum unpicked prescriptions – patient fixed effects

	Panel A - Patient				
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	IV-FE	IV-FE
EMR	0.031	0.027	-0.006	0.016	-0.006
	(0.023)	(0.023)	(0.023)	(0.132)	(0.118)
EMR*black	-0.002	-0.000	-0.006	-0.070	
	(0.020)	(0.020)	(0.016)	(0.057)	
Income	-0.001	-0.002**	-0.002**	-0.001	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EMR*income		0.002***	0.002***		0.005***
		(0.001)	(0.001)		(0.001)
Age	0.033*	0.033*	0.031*	0.022	0.024
	(0.017)	(0.017)	(0.016)	(0.015)	(0.017)
Patient FE	X	X	X	x	x
MC*time			X		
R-sq	0.249	0.249	0.256		

	Panel B – provider-patient pairs				
	FE	FE	FE	IV-FE	IV-FE
EMR	0.019	0.023	0.014	-0.048	-0.071
	(0.033)	(0.032)	(0.030)	(0.147)	(0.134)
EMR*black	-0.031	-0.033	-0.036*	-0.093*	
	(0.030)	(0.031)	(0.022)	(0.052)	
Income	-0.003*	-0.001	-0.003**	-0.001	-0.004**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
EMR*income	0.002		0.001		0.004*
	(0.001)		(0.001)		(0.002)
Age	0.036	0.036	0.036	0.031	0.031
	(0.039)	(0.039)	(0.033)	(0.030)	(0.028)
Prov_patient FE	X	X	X	X	X
MC*time	-	-	X	-	-
Obs	327686	327686	327686	327686	327686
R-squared	0.580	0.580	0.548		

All models include year-dummies, and controls for co-morbidities. The standard errors are clustered at the level of the medical center. Robust standard errors in parentheses

Appendix 2: Additional Tables

Figure 1A: Year CPRS began vs year of full implementation

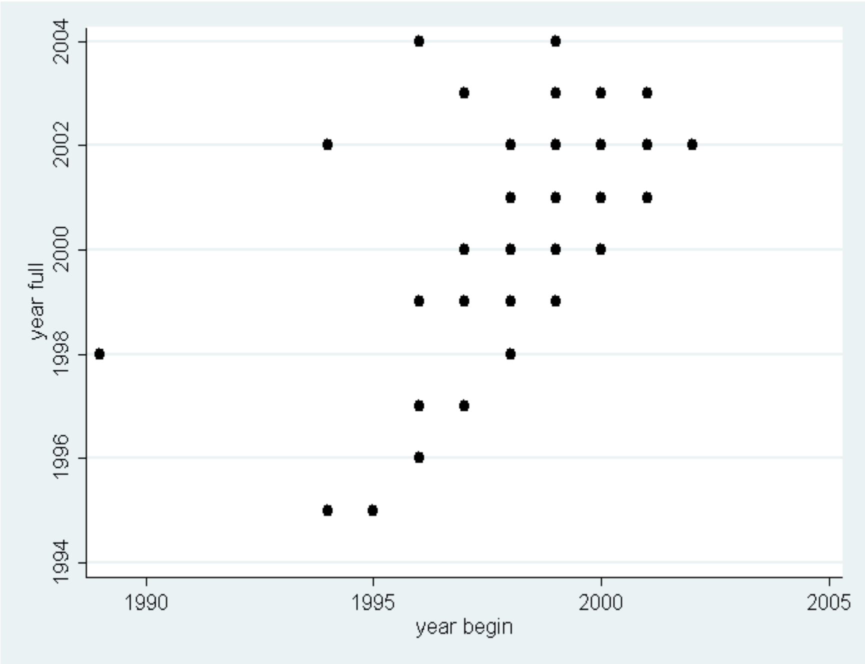

Table 1A: First stage regression coefficients and standard errors used in the 2SLS estimation reported in table 7 columns (4) and (5) and table 8 columns (4) and (5)

Outcome: full EMR implementation	(1)	(2)
NMCs*EMR_begin	-0.103***	-0.103***
	(0.001)	(0.002)
EMR_begin	0.448***	0.409***
	(0.004)	(0.005)
NMCs	0.142***	0.146***
	(0.001)	(0.002)
Income	-0.000	0.000
	(0.000)	(0.000)
Age	0.000	-0.004
	(0.006)	(0.008)
Patient FE	X	-
Physician-Patient FE	-	X
Constant	-0.039	0.285
	(0.435)	(0.530)
Observations	327686	327686
R-squared	0.696	0.838

All models include year-dummies, and controls for co-morbidities. The standard errors are clustered at the level of the medical center. Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%