The Effect of the Electronic Healthcare Record on Physician Behavior: A Propensity Score Weighted Analysis

A Thesis
submitted to the Faculty of the
Graduate School of Arts and Sciences
of Georgetown University
in partial fulfillment of the requirements for the
degree of
Master of Public Policy
in Public Policy

By

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Washington, DC
April 11, 2015

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Abstract

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Acknowledgments

In a real thesis, this section would contain acknowledgments such as, "This work was funded by National Science Foundation Grant Number AAA-00-00000 (Benjamin Franklin, Principal Investigator)," and "I would like to thank John Doe for helping me proofread my thesis and Mary Roe for drawing my graphs."

The acknowledgments are included in the table of contents but do not have a chapter number. To achieve that, we declare them to be a `\pseudochapter` (which is defined only in `guthesis.sty`).

I (Mark Maloof) would like to thank Michael Covington for developing this LaTeX style sheet for the University of Georgia. Zachary Hunter deserves special thanks for revising the UGA style file to work with the new version of LaTeX (2e) as well as the previous version (2.09). The revisions in Version 3.0 of `guthesis.sty` are largely the work of Isidor Ruderfer. Other credits appear in the style sheet itself.

Preface

If your thesis has a preface, this is where it goes. A preface is not an introduction, and most theses do not need them.

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Chapter 1

Introduction (working)

The US spend 17.9% of GDP on health expenditure in 2013, according to the World Bank, and it is continuing to growth. Some scholars proposed that one way to reduce health care spending and improve health care efficiency is to adopt the Electronic Healthcare Record (EHR). The Obama Administration has prioritized the improvement of quality and efficiency of the health care system. President Obama signed the American Recovery and Reinvestment Act of 2009 which provides financial incentive for adoption and meaningful use of electronic health records. The adoption of EHR increased rapidly [CITATION NEEDED].

Given the increasing adoption of EHR, and the implementation of EHR incentive programs, the effect of electronic health care record on health outcomes are of interest. Empirically measured effect of adopting EHR on cost is still very limited, and the results are mixed.

Chapter 2

Literature review

2.1 Background

In 2009, the US Congress passed the American Recovery and Reinvestment Act (ARRA), which appropriates funds to promote the adoption and use of health information technology (HIT). The American Recovery and Reinvestment Act has set aside $2 billion which will go towards programs developed by the National Coordinator and Secretary to help health care providers implement HIT and provide technical assistance through various regional centers (HHS, 2013).

The Centers for Medicare & Medicaid Services launched the Medicare and Medicaid Electronic Health Care Record (EHR) Incentive Programs after the passage of ARRA of 2009. These programs provide incentive payments to eligible professionals, eligible hospitals, and critical access hospitals (CAHs) as they adopt, implement, upgrade or demonstrate meaningful use of certified EHR technology. In order to receive the EHR stimulus money, the HITECH act (ARRA) requires eligible physicians to show "meaningful use" of an EHR system.

Take Medicare EHR incentive program as an example. Eligible physicians must attest yearly to demonstrating meaningful use to receive the EHR incentive and avoid a Medicare payment adjustment. In order to demonstrate meaningful use of 2014 Stage 1, eligible professionals must meet 13 required core objectives and five menu objectives from a list of 9. The core objectives includes recording selected patient demographics, maintaining active medication list, protecting electronic health information, etc.. The menu objectives includes using certified EHR technology to identify patient-specific education resources, sending patient reminders, and implementing drug formulary checks, etc. (CMS, 2014c).

2.2 Effect of EHR on health expenditure

Limited empirical studies estimated the potential net benefits that could arise from adopting health information technologies (HITs), including the EHR at the national level. The RAND Corporation estimated annual net savings to the health care sector from efficiency alone could be $77 billion or more based surveys, publications, interviews, and an expert panel review. (RAND, 2005). Hillestad et, al. claimed that effective EHR implementation and networking could eventually save more than $81 billion annually by improving health care efficiency and safety. Savings could be doubled by using health information technology to preventive care and chronic disease management (Hillestad et al., 2005). However, some other researchers do not find the positive cost-saving effect of EHR adoption on national health expenditure. For example, Adler-Milstein et al. found that ambulatory EHR adoption did not impact total cost, although it slowed ambulatory cost growth (Adler-Milstein et al., 2013b). Sidorov claimed that much of the literature on EHRs fails to support the primary rationales for using them, and it is unlikely that the U.S. health care bill will decline as a result of the EHR alone (Sidorov, 2006). There are also researchers suggest the adoption of EHR has a negative effect on cost-reduction (Teufel et al., 2012).

EHR also provides a platform for predictive analysis, saving health care spending by allocating medical resources efficiently. Bates et al. proposed there are unprecedented opportunities to use big data, acquired from EHR, to reduce the costs of health care in the United States (Bates et al., 2014). Roski et al. also pointed out big data has the potential to create significant value in health care by improving outcomes while lower cost (Roski et al., 2014). However, the integration of EHR into predictive analytics is still challenging. Roski et al. also claimed that big data's success in creating value in the health care sector may require changes in current policies to balance the potential societal benefits of big-data approaches and the protection of patients' confidentiality (Roski et al., 2014).

2.3 Effect of EHR on healthcare efficiency and quality

The effect of EHR on efficiency is mixed. A systematical literature review suggested that 92 percent of the recent articles on health information technology show measurable benefits emerging from the adoption of health information technology (Buntin et al., 2011). For example, a study found that hospital with more-advanced health IT had fewer complications, lower mortality, and lower costs than their counterparts(Amarasingham et al., 2009). Other suggest that simply adopting electronic health records is likely to be insufficient to drive substantial gains in quality or efficiency (DesRoches et al., 2010).

Time efficiency is one of the possible outcomes of EHR adoption. Physicians spent time on patients-interactions and documentation of clinical information. Clinicians hope that an EHR could increase the patient interaction time, which improves the quality of health care, while reducing documentation time (Leung et al., 2003). However, EHR is unlikely to reduce documentation time (Poissant et al., 2005) and the effect of EHR system adoption on time efficiency is mixed and varying among different institutions (Chaudhry et al., 2006).

Another important factor of healthcare efficiency and quality is the likelihood of follow-up health care appointments. Low "kept appointment" rates adversely affected continuity of care and led to inefficient clinic scheduling processes (Myers and Heffner, 2001). Although the CMS listed “Send reminders to patients per patient preference for preventive/follow-up care” as an objective in measuring meaningful use of EHR system (CMS, 2014a), the evaluation of the effect of EHR on patient follow-up rate is limited.

Patient-centered education, which provided by EHR-based system, allows patients to understand their health better and make informed lifestyle adjustments. CMS requires eligible physicians to provide patient-specific education resources to more than 10 percent of all unique patients in order to obtain the EHR incentive program funding (CMS, 2014b). Very limited literature evaluated effect of EHR on patient-specific education resources utilization.

2.3.1 Physicians’ financial incentives on EHR

On the micro level, EHR has a mixed effect on cost-saving of physician practices.

Some scholars claimed that the long-term return on adoption of EHR is positive. For example, Wang et al. estimated that a provider could gain $86,400 net benefits from using an electronic medical record for a 5-year period, resulting in a positive financial return on investment to the health care organization (Wang et al., 2003). Bell and Thornton claimed that based on the size of a health system and the scope of implementation, benefits of HITs for large hospitals can range from $37M to $59M over a five-year period in addition to incentive payments (Bell and Thornton, 2011).

However, more researchers argued that physicians have insufficient financial incentive to implement EHR in the first place. Gans et al. surveyed a nationally representative sample of medical group practices and suggested that adoption of EHR is progressing slowly, at least in smaller practices (Gans et al., 2005). Jha et al. found a similar result that on the basis of responses from 63.1% of hospitals surveyed, only 1.5% of U.S. hospitals have a comprehensive electronic-records system (Jha et al., 2009). Adler-Milstein et al. found electronic health records will yield revenue gains for some practices and losses for many by using survey data from 49 community practices. Practices are encountering greater-than-expected barriers to adopting an EHR system (Adler-Milstein et al., 2013a).

2.4 Contribution to literature

Giving the increasing participation in the Medicare and Medicaid Electronic Health Records (EHR) Incentive Programs, and the increased policy interest in controlling health expenditures, the evaluation of the effect of EHR on physician behavior are of interest.

Although the number of health information technology evaluation studies is rapidly increasing, empirically measured behavior data are limited and inconclusive. Some research projected the potential benefit of adoption of EHR with data from surveys, publications, interviews, and expert panel reviews. However, there are limited research focus on empirical analysis of national wide data. Literature on outcome of adopting EHR, especially the effect of EHR on patient-specific health education prescription, is limited. This paper could contribute to the literature with a national-level perspective and evaluate the outcome of EHR adoption on health education, time spent with MD, and returned appointment rate.

Another major limitation of the literature is its generalization. Insufficient reporting of contextual and implementation factors makes it impossible to determine why most health IT implementations are successful but some are not. This paper will consider which factors may contribute to a better outcome of EHR adoption. It could help making government incentive programs more efficient by selecting proper physician practices.

Chapter 3

Data source

The data source for this study was National Ambulatory Medical Care Survey (NAMCS) public use micro-data files. NAMCS is a national probability sample survey of visits to office-based physicians conducted by the National Center for Health Statistics, Centers for Disease Control and Prevention. NAMCS has information at visit level, including whether the physician practice has Electronic Medical Record (EMR) system, health education prescription, the breakdown of patients by different payment type, time spent with physician for each visit, and whether the visit is a returned appointment, etc. The sample size for 2008, 2009, and 2010 public use micro-data files, which includes information about adopting EMR, are 28,741, 32,281, and 31,229, respectively.

I used information on adoption of EMR system to identify the treatment groups and potential comparison groups. The survey question was described as "Does your practice use an electronic medical record or health record (EMR/HER) system? (Not including billing records system)." (Nat, 2010). Three possible groups in this treatment variable including "Yes, all electronic", "Yes, part paper and part electronic", and "No". The other characteristics were used as covariates in the propensity score estimation and models.

The sampling of NAMCS is a multistage process. The first-stage sample includes 112 primary sampling units (PSUs) by geological distribution. The second stage stratified physicians into 15 groups and select physicians within each PSU. The final stage is the selection of patient visits within the annual practices of sample physicians. The basic sampling unit for the NAMCS is the physician-patient encounter or visit.

Start from 2005, NAMCS includes provider weight that allow researchers to produce aggregated visit statistics at the physician level. In this analysis, I summarized visits level data to physician level data based on recommendation provided by Ambulatory Statistics Branch of Centers for Disease Control and Prevention (Amb, 2012). There are 3,777 physicians' information available after the aggregation. 157 cases were dropped afterward due to incompleteness and 1 case were ignored due to negative physician weight. 3619 observations were available for further analysis.

Chapter 4

Analysis Plan

4.1 Estimating treatment effect with observational data

Ideally, we would observe physician in three possible conditions: one in which she has fully adopted the EHR system, one in which she has partially adopted the EHR system, and one in which she has not. We can express our evaluation problem as follows: Let $W_i = 1$ for physician i who has fully adopted the EHR system, let $W_i = 2$ for physician i who has partially adopted the EHR system, and let $W_i = 0$ for physician i who has not yet adopted the ENR system. Let $Y_i(1)$ refer to the time efficiency for physician i who has fully adopted the EHR system, let $Y_i(2)$ refer to the time efficiency for physician i who has partially adopted the EHR system, and let $Y_i(0)$ refer to the patient interaction time for physician i who has not adopted the EHR system. Although all outcomes are possible in theory, we cannot observe all possible outcome $Y_i(0)$, $Y_i(1)$, and $Y_i(2)$ for physician i while holding all other conditions constant. We only observe $Y_i(0)$ if $W_i = 0$, $Y_i(1)$ if $W_i = 1$, and $Y_i(2)$ if $W_i = 2$ with our data (Imbens and Wooldridge, 2008). People in "treatments" and "control" groups likely different in both observed and unobserved ways.

4.2 Assumption of causal inference

There are two assumptions associate with estimating treatment effect. The first assumption is the stable unit treatment value assumption (SUTVA). The SUTVA requires that there is no interference between units, that is, treatment assignment of one unit does not affect potential outcomes of another unit. We cannot test this statistically with our data. This is a strong assumption in our analysis since (1) there are possibility communication between different physician practice about the adoption of EHR system, which could possible affect the outcome; (2) there are different version of the EHR system within different practices.

The second assumption is no unmeasured confounders. An estimate of the EHR's effect on doctors' behavior relies on an assumption of no unmeasured confounders of treatment assignment, that is,

$$W_i \perp (Y_i(0), Y_i(1), Y_i(2)$$

(Imbens and Wooldridge, 2008). In other words, the assignment of study participants to treatment conditions (i.e. fully adopted EHR, partially adopted EHR, and no adoption) is independent of the outcome of these three groups. In experimental settings, treatment groups (in this case, physicians who partially or fully adopted the EHR system) and control group were random assigned, which ensure that both observed and unobserved factors of treatment and control group have similar distribution. If the assignment to adopt the EHR system is based on randomization, this assumption is easy to statisfy and the causal inference would be straightforward. However, this assumption often violates in non-experimental setting. This is a strong assumption with the evaluation of EHR effect since a national level experiment on the effectiveness of the EHR adoption is expensive and infeasible. Violation of unconfoundedness could bias result because of omitted variable bias.

To estimate the effect of the EHR adoption on physician behavior, we can obtain the following model:

$$Y_i = \beta_0 + \beta_1 W_i + \Sigma_{i=2}^{k} \beta_k X_{ik} + \epsilon_i$$

In this model, Y_i is the outcome of interest for physician i, including percentage rate of patient-specific education resource prescribed, time spent with the physician, and percentage rate of returned patients. W_i is the EHR adoption status for physician i, including fully adopted EHR, partially adopted EHR, and no EHR adoption. X_{ik} are k observable characteristics for physician i, including MSA status, physician specialty, Solo status, etc. We will describe more details in descriptive statistics section. Coefficient β_1 estimate the treatment effect of the EHR adoption on three outcome variables if the model is correct and satisfies the assumption of unconfoundedness.

This condition is unlikely with NAMCS data. For example, physicians in the treatment group A, which they fully adopted the EHR systems, may systematically different than physicians in the control group. This difference could in both observed and unobserved ways. With large number of covariates that has unknown functional relationship with treatment and outcome, it is hard to specify regression adjustment model. Without appropriate instrumental variable or regression discontinuity cutoff available, the propensity score matching method is one of few available techniques that can be used to access the treatment effect of the EHR system on physician behavior.

4.3 Propensity score estimation

As described above, estimating causal effects with observational data is challenging since it involves estimating the unobserved potential outcomes. Propensity score methods attempt to replicate two features of randomized experiments. On the one hand, propensity score methodologies can create groups that look only randomly different from one another (at least on observed variables). On the other hand, propensity score methods do not use outcome variables when setting up the design. With these two features, treatment assignment and the observed covariates are conditionally independent given the propensity score (Guo and Fraser, 2014):

$$\boldsymbol{X_i} \perp W_i \mid e(X_i)$$

Conditional on the propensity score, each physician has the same probability of assignment to treatment, as in a randomized experiment setting. After propensity score estimation, physicians in the control group who have not adopted the EHR system are comparable with those who in treatment groups with similar propensity scores, at least on observable characteristics.

Hirano et al. claimed that the resulting estimate is asymptotically efficient if the propensity score is estimated non-parametrically using a series estimator (Hirano et al., 2003). McCaffrey et al. summarized that recent studies of propensity score estimation in binary case of two treatment show that, in terms of bias reduction and mean squared error (MSE), machine learning methods outperform simple logistic regression models with iterative variable selection (McCaffrey et al., 2013). One application of using machine learning algorithms to estimate propensity score is the use of Generalized Boosted Machine models (GBM).

GBM is a general, automated, data-adaptive algorithm that fits several models by way of a regression tree, and then merges the predictions produced by each model. In other words, GBM estimation captures complex and nonlinear relationships using nonparametric estimation, which means the complexity of the fitted model depends on sample size. GBM aims to minimize sample prediction error; that is, the algorithm stops iterations when the sample prediction error is minimized (Guo and Fraser, 2014). Comparing with traditional methods, "the GBM model's iterative estimation procedure can be tuned to find the propensity score model leading to the best balance between treated and control groups, where balance refers to the similarity between different groups on their propensity score weighted distributions of pretreatment covariates" (McCaffrey et al., 2013). GBM model can also use all available covariates and is not subject to the particular modeling choices made by the analyst (Hillm et al., 2015).

Two common boost algorithms for propensity score estimation is Stata's *boost* program and R's *gbm* program. These two different packages do not lead to different results on covariate control and estimates of treatment effects (Guo and Fraser, 2014). In this analysis, we used GBM model, developed by (McCaffrey et al., 2004), to estimate the propensity score of each physician. Our boosted model uses the default setting of twang package (McCaffrey et al., 2013) with R (R Core Team, 2014), which has 10,000 GBM interactions, three interactions, a bagging fraction of 1.0, and a shrinkage parameter of 0.01, based on McCaffrey's (2013) recommendation. We use physician weight as sample weight in multinomial propensity score estimation procedure.

To assess the quality of propensity score estimation, we use diagnostics to check the balance after propensity score weighting. The goal of propensity score estimation and weighting is to have similar covariate distributions in the matched treated, and control groups. We use both numerical summaries of balance and graphic summaries of balance to evaluate the quality of propensity score weighting. We relied primarily on the absolute standardized difference (ASD, also referred to as the Effect Size or the absolute standardized mean difference) to assess the balance after weighting.

4.4 Propensity score weighted regression model

The essential feature of propensity score weighting model is the treatment of estimated propensity scores as sampling weights to perform a weighted outcome analysis. Propensity score weighting has two advantages. On the one hand, propensity score weighing permits most types of multivariate outcome analysis and does not require an outcome variable that is continuous or normally distributed. On the other hand, unlike matching techniques, weighting method maintains sample size (Guo and Fraser, 2014).

With propensity score weighting, the control of selection biases is achieved through weighting and counterfactuals are estimated through a regression model. When dimension of pre-treatment variables $\mathbf{X}$ is large, it is difficult to ensure both the regression model is correct, and a consistent estimator will be obtained (Rubin, 1997). Also, the estimated modeling leads to extrapolation if the distribution of some confounders do not overlap with each other, since the effect is primarily determined by treated subjects in one region of $\mathbf{X}$ space and by control subjects in another. In contrast, the regression model with propensity score weighting largely circumvents this since pretreatment variables $\mathbf{X}$ and treatment group variable W should be approximately independent after propensity score estimation. By adding covariates into the regression adjustment, we will obtain "double robustness" that further improve the precision of estimators (Lunceford and Davidian, 2004). We used an estimate of the propensity score as weights, and uses these weights in a weighted regression of the potential outcome on treatment and observed covariates.

We estimate a separate propensity score weighted regression model for each outcome. We include covariates that have maximum ASD greater than 0.1.

4.5 Sensitivity tests

Finally, we conduct sensitivity tests of the following four cases.

First, we test the robustness of the result to different covariate controls with multinomial propensity score weighted regression models. We test this in two cases: (1) including only treatment variable with no covariates; (2) including all possible covariates and treatment assignment variable.

Second, we test whether the results are robust to different multinomial propensity score weighted generalized regression model. Based on the distribution of dependent variables, we use Binomial regression for the EHR adoption status on health education prescription rate, Poisson regression for the EHR adoption status on time spent with MD, and Binomial regression for the EHR adoption status on returned appointment rate.

Third, we test whether the results are robust to propensity score weighted binary treatment assignment. We create two separated datasets. One with only physicians who have fully adopted EHR and control group. Another with only physicians who have partially adopted EHR system and control group. We estimated propensity score with binary treatment and estimate the effect of full EHR adoption and partial EHR adoption on outcome variables.

Fourth, we test the robustness of the result with propensity score matching approach. We use nearest neighbor matching for binary treatment cases and assess the treatment effect of the EHR adoption.

Chapter 5

Descriptive Statistics

5.1 Nominal and Ordinal Variables

As shown in Table 5.1, more physician practice fully adopted the EHR system since 2008. While 54.21% of physicians reported that they have no EHR system adoption in 2008, 5.75% percentage points less physician report they have no EHR adoption in 2010, reducing 10.6% percent comparing to year 2008. Meanwhile, 38.8% physicians reported they have full EHR system adoption on 2010, while only 27.49% physicians reported then have fully adopted the EHR system in 2008. Comparing with year 2008 (18.3%), fewer physicians partially adopt the EHR system in 2010 (12.73%). The result suggests the adoption rate of the EHR system is growing rapidly after the implementation of the EHR incentive program.

The adoption of EHR has statistically significant difference between different practice ownerships ($p < 0.0001$). Physicians or physician group has lower likelihood to adopt EHR system. In our sample, 53.95% respondents who are physicians or physician groups reported they have no EHR adoption. Health Maintenance Organization (80.51%) has the highest likelihood to fully adopt the EHR system, among all health care practice ownerships. There is no substantial difference of partially adopt the EHR system between different practice ownership types. The full adoption rate among other hospital (35.26%), other health care corporations (47.59%), or all others (44.14%) are also variance.

There are no statistically significant relationship between adoption of the EHR system and whether the practice is in metropolitan statistical areas ($\chi^2 = 1.4319$). The full adoption rate of MSA area (32.93%) and non-MSA area (33.08%) is close to the national average (32.94%). However, geographic regions have statistically significant relationship with the adoption of the EHR system ($\chi^2 = 16.41$). Physicians that are in West region has higher likelihood to adopt EHR system, while physicians in Northeast or South region have less likelihood to adopt it, comparing with physicians who are in Midwest region.

Another physician practice's characteristics of interest are the number of managed care contracts. The contract between a physician and a managed care organization can affect payment, office organization, practices and procedures, and confidential records as well as clinical decision-making (DeBlasio, 2008). In general, practice with higher number of managed care contracts tends to have higher adoption rate of the EHR system. 38.08% physician practice with more than ten managed contracts has fully adopted the EHR system while only 20.92% physician practice with no managed contracts fully adopted the EHR system. There are no statistically or substantially difference of partially adoption rate among difference managed care contracts.

Physician specialty has statistically significant relationship with the adoption of the EHR system ($p < 0.0001$). Among all physician specialties, general and family practice have the highest likelihood to fully adopt the EHR system. 43.17% physicians who are general or family practice reported they had fully adopted the EHR system. Ophthalmologists have the lowest likelihood to adopt the EHR system. More than half of ophthalmologists reported they have no EHR adoption. Among all other physician specialities, oncology (38.36%), internal medicine (37.76%), urology (37.57%), and orthopedic surgery (37.09%) also have higher likelihood of fully EHR adoption.

Comparing with the group practice, solo practice has less likelihood to fully adopt the EHR system. Over half of group practice fully or partially adopted the EHR system, while less than 40% solo practices adopted the EHR system.

Table 5.1: Descriptive Statistics (Nominal and Ordinal Variables)

Variable	P_{No}	P_{Full}	P_{Part}
Year of Visit			
2008	0.5421	0.2749	0.1830
2009	0.4859	0.3252	0.1889
2010	0.4846	0.3881	0.1273
$\chi^2_4 = 44.95$			
Ownership Type			
Physician or physician group	0.5395	0.2989	0.1616
Health Maintenance Organization (HMO)	0.0647	0.8051	0.1302
Community health center	0.4293	0.3522	0.2185
Medical/academic health center	0.4714	0.3627	0.1659
Other hospital	0.4305	0.3526	0.2169
Other health care corporation	0.3434	0.4759	0.1807
Other	0.3436	0.4414	0.2150
$\chi^2_{12} = 146.29$			
Metropolitan Statistical Area			
MSA	0.5064	0.3293	0.1644

Descriptive Statistics (Nominal and Ordinal Variables, Cont'd)

Variable	P_{No}	P_{Full}	P_{Part}
Non-MSA	0.4823	0.3308	0.1869
$\chi^2_2 = 1.43$			
Managed Care Contracts			
None	0.6234	0.2092	0.1674
Less than 3	0.4939	0.3419	0.1642
3-10	0.5318	0.2994	0.1688
Greater than 10	0.4537	0.3808	0.1655
$\chi^2_6 = 56.82$			
Physician specialties			
General/family practice	0.4238	0.4317	0.1445
Internal medicine	0.4761	0.3776	0.1464
Pediatrics	0.5243	0.3107	0.1650
General surgery	0.5905	0.2494	0.1601
Obstetrics and gynecology	0.5065	0.3218	0.1718
Orthopedic surgery	0.4356	0.3709	0.1935
Cardiovascular diseases	0.4246	0.3037	0.2717
Dermatology	0.6625	0.2297	0.1079
Urology	0.4559	0.3757	0.1684
Psychiatry	0.7140	0.1424	0.1436
Neurology	0.5539	0.2771	0.1690

Descriptive Statistics (Nominal and Ordinal Variables, Cont'd)

Variable	P_{No}	P_{Full}	P_{Part}
Ophthalmology	0.6344	0.1504	0.2152
Otolaryngology	0.5055	0.3483	0.1462
Other specialties	0.5122	0.3148	0.1730
Oncology	0.3444	0.3836	0.2721
$\chi^2_{28} = 132.67$			
Region			
Northeast	0.5091	0.3080	0.1829
Midwest	0.5204	0.3227	0.1568
South	0.5232	0.3110	0.1658
West	0.4560	0.3814	0.1626
$\chi^2_{6} = 16.41$			
Solo			
Yes	0.4386	0.3910	0.1704
No	0.6367	0.2041	0.1592
$\chi^2_{2} = 147.56$			
Total	0.5039	0.3294	0.1667
Obs.	1,853	1,146	620

Descriptive Statistics (Nominal and Ordinal Variables, Cont'd)

Variable	P_{No}	P_{Full}	P_{Part}
Weighted Counts	480,645	314,233	159,030

5.2 Continuous variables

As shown in the Table 5.2, the adoption status of the EHR system has potential influence on outcome variables. Physicians who have fully or partially adopted the EHR system have higher likelihood to prescribe patient-specific education resource. While 39.7% patients have received education resources during their visit at practice without the EHR system, more than 44% patients received education resource during their visit at practice with the EHR system adoption. As for patient-physician interaction time, there is no systematical difference between the practice with the EHR adoption or not. On average, patients spend 22 minutes with their medical doctor, and there is no substantial difference among different EHR adoption status. For returned appointment rate, physician practice who have fully adopted the EHR system has lower returned appointment rate (66.16%), comparing with the other groups whose returned appointment rate is higher than 71 percent.

As for the characteristic of patients, there is no significant age difference between the fully treated group and the control group. Practice with the EHR system partially adopted has higher average patient age. This is constant with patients insurance status since practices with partially adopted EHR system has higher likelihood to accept Medicare patients. There is significant difference between the average number of chronological disease between the fully treated group and the control group.

Less patient with complex chronological conditions visited practice without the EHR system.

Physician practices with difference EHR adoption status tend to have different payment structure. Practice with fully EHR adoption tends to have higher percentage of privately insured patients. On average, 60.85% visits are privately insured patients at a practice without the EHR system adoption while 64.75% visits are privately insured patients at the practice with the EHR system fully adopted. There is slight difference among Medicare, Medicaid, or self-paid patients between different EHR adoption status. Practice with the EHR system fully adopted has slightly less likelihood to accept Medicare, Medicaid, or self-paid patient, comparing with the control group. Practices with fully adopted EHR system have higher likelihood to accept work compensation patients.

Table 5.2: Descriptive Statistics (Continuous Variables)

Variable	$Mean_{No}$	$Mean_{Full}$	$Mean_{Part}$
Outcomes			
Patient education prescription rate	0.3970	0.4418	0.4419
Time spent with MD	22.3401	21.6737	21.8993
Retured appointment rate	0.7245	0.6616	0.7187
Patient insurance type			
Private insurance	0.6086	0.6475	0.6041
Medicare	0.2474	0.2301	0.2827
Medicaid	0.1372	0.1117	0.1417
Self-pay	0.0843	0.0426	0.0602
Workers Compensation	0.0137	0.0155	0.0112
Avg. patient age	46.2783	46.4305	48.0636
Avg. chron cond.	1.1214	1.2606	1.2617
Obs.	1,853	1,146	620
Weighted Counts	480,645	314,233	159,030

Chapter 6

Propensity score balance

The goal of propensity score weighting is to have similar covariate distribution (or "balance") in the weighted treated and control groups. We relied on the absolute standardized mean difference (ASMD, also referred to as the absolute standardized bias or the Effect Size) to assess the balance. The ASMD d_x was calculated as the absolute difference in means between two different groups, divided by the square root of the average sample variances for this two groups using the following formula (Haviland et al., 2007):

$$d_x = \frac{|\Delta M_x|}{S_x}$$

where ΔM_x is the difference of means between two groups, S_x is calculated by:

$$S_x = \sqrt{\frac{S_{xt}^2 + S_{xp}^2}{2}}$$

where S_{xt}^2 and S_{xp}^2 denotes the standard deviations of variable x in group t and group p.

In our analysis, each character has three ASMD statistics, including the difference between non-adopter and fully adaptor, the difference between non-adopter and partially adopted and the difference between partially adopted and fully adopted. We collapse these three statistics to covariate level for comparison propose. Hill et al. summarised that ASMDs less than 0.25 were considered acceptable, with values below 0.10 representing a more stringent standard (Hillm et al., 2015).

To optimize the balance statistics of interest, ASMD, we need to make sure the propensity score estimation models run for a sufficiently large number of iterations. We do this by evaluating whether the maximum ASMD appears to be decreasing after 10,000 iterations. Figure **??** shows the relationship between number of iteration and balance measurement, maximum ASMD. In this analysis, it appears that each of the maximum ASMD is optimized with substantially fewer than 10,000 iterations.

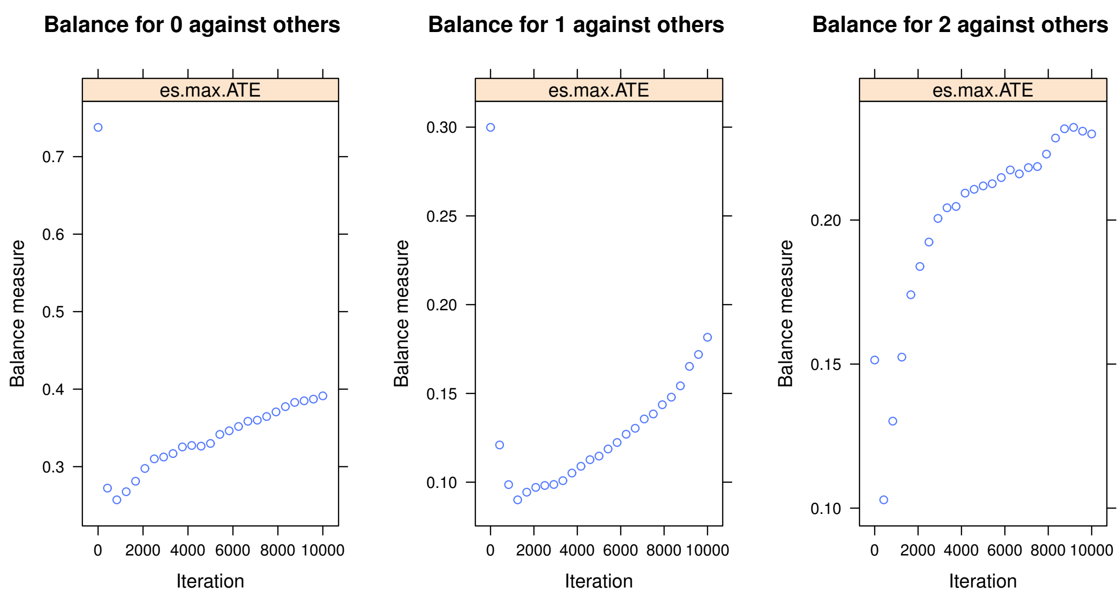

Figure 6.1: **GBM iterations and balance measure**

Propensity score analyses assume that each experiment unit has a non-zero probability of receiving each treatment (Burgette et al., 2015). We can examine the overlap of the empirical propensity score distribution in order to assess the plausibility of this assumption. As shown in the Figure **??**, the overlap assumption generally seems to be met.

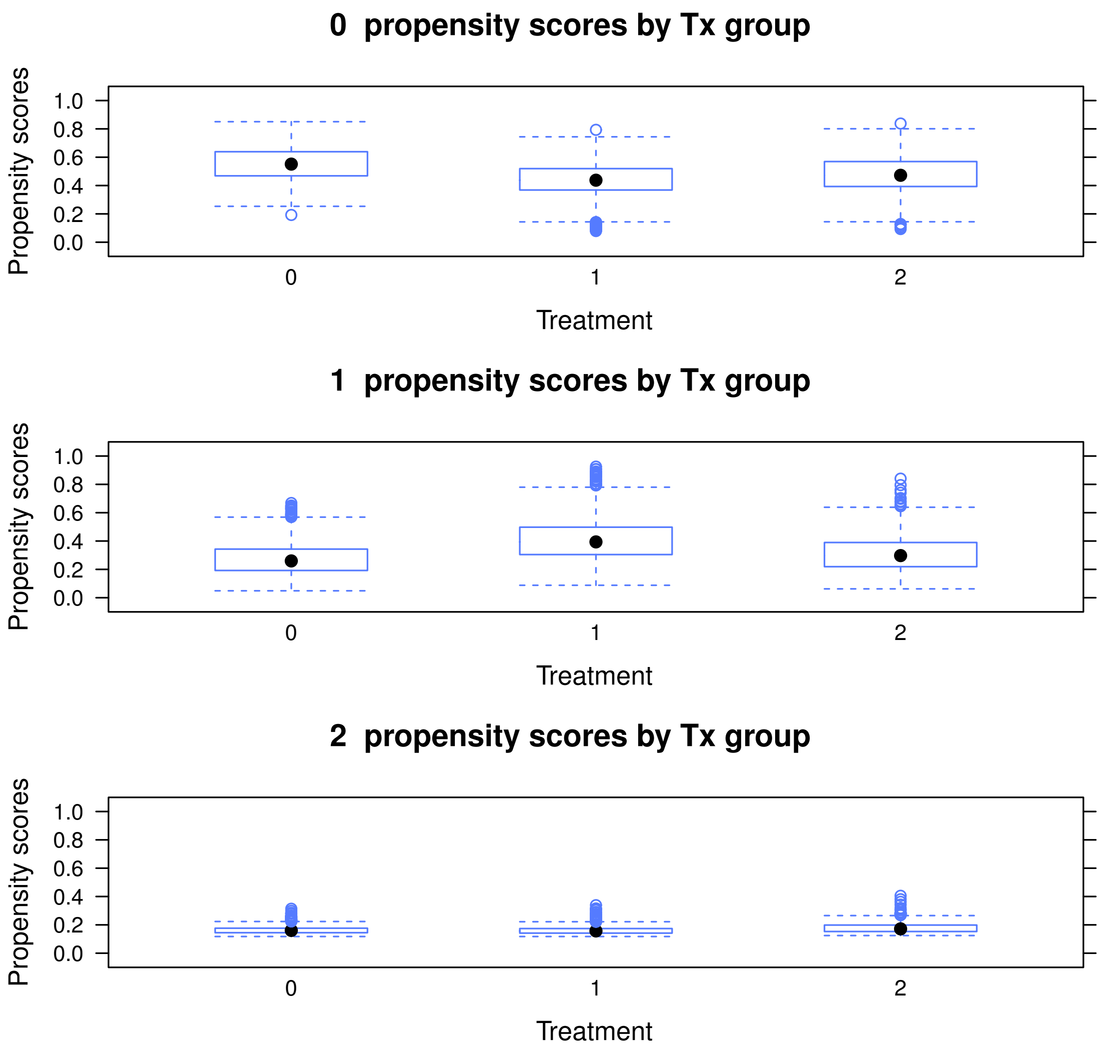

Figure 6.2: **Propensity score overlapping assumption**

Figure **??** and Table 6 summarizes balance statistics from propensity score estimation with GBM model. Figure **??** provides comparisons of the ASMD between each groups, before and after weighting. As shown in the Figure **??**, the $ASMDs < 0.25$ criterion is easily met for all pretreatment variables after propensity score weighting.

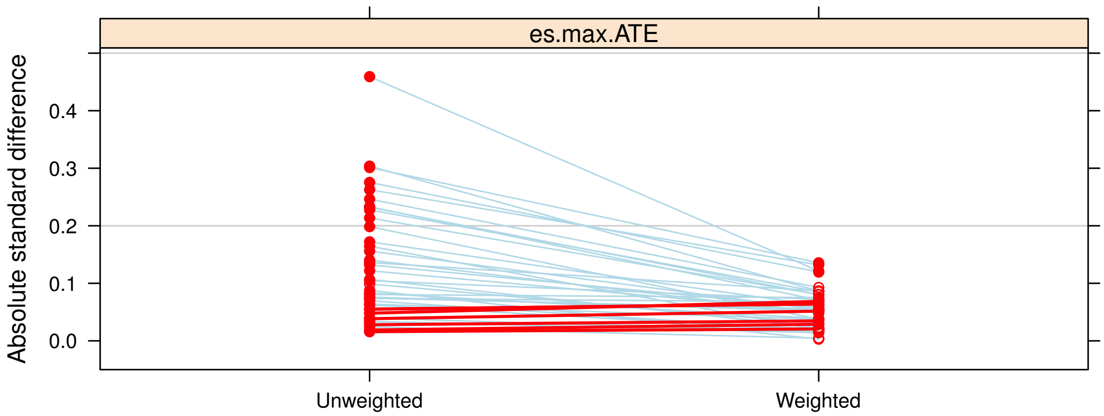

Figure 6.3: **Propensity score balancing**

Table 6 shows that few variables' ASMDs exceeds 0.10 threshold after weighting but non of them exceed 0.1260.

Although the observed covariates balanced relatively well, it is possible that unobserved differences between each two of three groups could still remain.

Table 6.1: Propensity Score Balance Statistics

Variable	Max Std. ES (UNW)	Max Std. ES (PSW)
Ownership Type		
Physician or physician group	0.3123*	0.1259*
Health Maintenance Organization (HMO)	0.2530*	0.1033*
Community health center	0.1089*	0.0725

Propensity Score Balance Statistics (Cont'd)

Variable	Max Std. ES (UNW)	Max Std. ES (PSW)
Medical/academic health center	0.0680	0.0337
Other hospital	0.0754	0.0524
Other health care corporation	0.1693*	0.0549
Other	0.0922	0.0470
Metropolitan Statistical Area		
MSA	0.0427	0.0643
Non-MSA	0.0427	0.0643
Managed Care Contracts		
None	0.2372*	0.1006*
Less than 3	0.0111	0.0285
3-10	0.1209*	0.0235
Greater than 10	0.2452*	0.0853
Physician specialties		
General/family practice	0.1913*	0.0776
Internal medicine	0.0818	0.0702
Pediatrics	0.0167	0.0145
General surgery	0.0893	0.0032
Obstetrics and gynecology	0.0070	0.0208
Orthopedic surgery	0.0632	0.0364
Cardiovascular diseases	0.2011*	0.0520

Propensity Score Balance Statistics (Cont'd)

Variable	Max Std. ES (UNW)	Max Std. ES (PSW)
Dermatology	0.1907*	0.0615
Urology	0.0730	0.0219
Psychiatry	0.3280*	0.0998
Neurology	0.1297*	0.0168
Ophthalmology	0.1840*	0.0435
Otolaryngology	0.0384	0.0048
Other specialties	0.0206	0.0516
Oncology	0.1266*	0.0624
SOLO	0.4605*	0.1233*
Region		
Northeast	0.0568	0.0395
Midwest	0.1122*	0.0680
South	0.0331	0.0191
West	0.1146*	0.0850
Avg. chron cond.	0.1618*	0.0199
Avg. patient age	0.0768	0.0306
Patient insurance type		
Private insurance	0.0837	0.0457
Medicare	0.1882*	0.0815

Propensity Score Balance Statistics (Cont'd)

Variable	Max Std. ES (UNW)	Max Std. ES (PSW)
Medicaid	0.1398*	0.0526
Workers Compensation	0.0440	0.0199
Self-pay	0.1860*	0.0727
Visit Year	0.2630*	0.1199*

Note: * Std. ES > 0.1000

Bibliography

Julia Adler-Milstein, Carol E. Green, and David W. Bates. A survey analysis suggests that electronic health records will yield revenue gains for some practices and losses for many. *Health Affairs*, 32(3):562–570, 2013a. doi: 10.1377/hlthaff.2012.0306. URL `http://content.healthaffairs.org/content/32/3/562.abstract`.

Julia Adler-Milstein, Claudia Salzberg, Calvin Franz, E. John Orav, and David Westfall Bates. The impact of electronic health records on ambulatory costs among medicaid beneficiaries. *Medicare & Medicaid Research Review*, 3(2), 2013b.

Ruben Amarasingham, Laura Plantinga, Marie Diener-West, Darrell J Gaskin, and Neil R Powe. Clinical information technologies and inpatient outcomes: a multiple hospital study. *Archives of Internal Medicine*, 169(2):108–114, 2009.

Code to Produce Aggregated Visit Statistics at the Physician or Facility Level. Ambulatory Statistics Branch, 2012.

David W. Bates, Suchi Saria, Lucila Ohno-Machado, Anand Shah, and Gabriel Escobar. Big data in health care: Using analytics to identify and manage high-risk and high-cost patients. *Health Affairs*, 33(7):1123–1131, 2014.

Beverly Bell and Kelly Thornton. From promise to reality achieving the value of an ehr. *Healthcare Financial Management*, 65(2):51–56, 2011.

Melinda Beeuwkes Buntin, Matthew F. Burke, Michael C. Hoaglin, and David Blumenthal. The benefits of health information technology: A review of the recent literature shows predominantly positive results. *Health Affairs*, 30(3): 464–471, 2011.

Lane Burgette, Beth Ann Griffin, and Dan McCaffrey. Propensity scores for multiple treatments: A tutorial for the mnps function in the twang package, 2015.

Basit Chaudhry, Jerome Wang, Shinyi Wu, Margaret Maglione, Walter Mojica, Elizabeth Roth, Sally C. Morton, and Paul G. Shekelle. Systematic review: Impact of health information technology on quality, efficiency, and costs of medical care. *Annals of Internal Medicine*, 144(10):742–752, 2006. doi: 10.7326/0003-4819-144-10-200605160-00125. URL +http://dx.doi.org/10.7326/0003-4819-144-10-200605160-00125.

CMS. Eligible professional meaningful use menu set measures measure 4 of 9, 2014a.

CMS. Eligible professional meaningful use menu set measures measure 5 of 9, 2014b. URL http://www.healthit.gov/providers-professionals/achieve-meaningful-use/menu-measures/patient-education-resources.

CMS. 2014 definition stage 1 of meaningful use, 2014c. URL http://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Meaningful_Use.html.

Susan Leach DeBlasio. Managed care contracts - key provisions for providers, 2008. URL http://corporate.findlaw.com/law-library/managed-care-contracts-key-provisions-for-providers.html.

Catherine M. DesRoches, Eric G. Campbell, Christine Vogeli, Jie Zheng, Sowmya R. Rao, Alexandra E. Shields, Karen Donelan, Sara Rosenbaum, Steffanie J. Bristol, and Ashish K. Jha. Electronic health records' limited successes suggest more targeted uses. *Health Affairs*, 29(4):639–646, 2010.

David Gans, John Kralewski, Terry Hammons, and Bryan Dowd. Medical groups' adoption of electronic health records and information systems. *Health Affairs*, 24(5):1323–1333, 2005.

Shenyang Guo and Mark W Fraser. *Propensity score analysis: Statistical methods and applications*, volume 11. Sage Publications, 2014.

Amelia Haviland, Daniel S Nagin, and Paul R Rosenbaum. Combining propensity score matching and group-based trajectory analysis in an observational study. *Psychological methods*, 12(3):247, 2007.

HHS. Recovery act-funded programs, 2013. URL `http://www.hhs.gov/recovery/programs/`.

Richard Hillestad, James Bigelow, Anthony Bower, Federico Girosi, Robin Meili, Richard Scoville, and Roger Taylor. Can electronic medical record systems transform health care? potential health benefits, savings, and costs. *Health Affairs*, 24(5):1103–1117, 2005.

Carolyn J Hillm, William T Gormley, and Shirley Adelstein. Do the short-term effects of a high-quality preschool program persist? *Early Childhood Research Quarterly*, 2015.

Keisuke Hirano, Guido W Imbens, and Geert Ridder. Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica*, 71(4):1161–1189, 2003.

Guido M Imbens and Jeffrey M Wooldridge. Recent developments in the econometrics of program evaluation. Technical report, National Bureau of Economic Research, 2008.

Ashish K. Jha, Catherine M. DesRoches, Eric G. Campbell, Karen Donelan, Sowmya R. Rao, Timothy G. Ferris, Alexandra Shields, Sara Rosenbaum, and David Blumenthal. Use of electronic health records in u.s. hospitals. *New England Journal of Medicine*, 360(16):1628–1638, 2009. doi: 10.1056/NEJMsa0900592. URL `http://www.nejm.org/doi/full/10.1056/NEJMsa0900592`. PMID: 19321858.

Gabriel M Leung, LH Philip, Irene OL Wong, Janice M Johnston, and Keith YK Tin. Incentives and barriers that influence clinical computerization in hong kong: a population-based physician survey. *Journal of the American Medical Informatics Association*, 10(2):201–212, 2003.

Jared K Lunceford and Marie Davidian. Stratification and weighting via the propensity score in estimation of causal treatment effects: a comparative study. *Statistics in medicine*, 23(19):2937–2960, 2004.

Daniel F McCaffrey, Greg Ridgeway, and Andrew R Morral. Propensity score estimation with boosted regression for evaluating causal effects in observational studies. *Psychological methods*, 9(4):403, 2004.

Daniel F McCaffrey, Beth Ann Griffin, Daniel Almirall, Mary Ellen Slaughter, Rajeev Ramchand, and Lane F Burgette. A tutorial on propensity score estimation for multiple treatments using generalized boosted models. *Statistics in medicine*, 32(19):3388–3414, 2013.

Esther F Myers and Sharon M Heffner. Strategies for improving follow-up client appointment-keeping compliance. *Journal of the American Dietetic Association*, 101(8):935–939, 2001.

2010 NAMCS Micro-Data File Documentation. National Center for Health Statistics, 2010.

Lise Poissant, Jennifer Pereira, Robyn Tamblyn, and Yuko Kawasumi. The impact of electronic health records on time efficiency of physicians and nurses: a systematic review. *Journal of the American Medical Informatics Association*, 12(5):505–516, 2005.

R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2014. URL `http://www.R-project.org/`.

RAND. *Health Information Technology Health Information Technology: Can HIT Lower Costs and Improve Quality?* RAND, 2005.

Joachim Roski, George W. Bo-Linn, and Timothy A. Andrews. Creating value in health care through big data: Opportunities and policy implications. *Health Affairs*, 33(7), 2014.

Donald B Rubin. Estimating causal effects from large data sets using propensity scores. *Annals of internal medicine*, 127(8_Part_2):757–763, 1997.

Jaan Sidorov. It ain't necessarily so: The electronic health record and the unlikely prospect of reducing health care costs. *Health Affairs*, 25(4):1079–1085, 2006.

Ronald J Teufel, Abby Swanson Kazley, Myla D Ebeling, and William T Basco. Hospital electronic medical record use and cost of inpatient pediatric care. *Academic pediatrics*, 12(5):429–435, 2012.

Samuel J. Wang, Blackford Middleton, Lisa A. Prosser, Christiana G. Bardon, Cynthia D. Spurr, Patricia J. Carchidi, Anne F. Kittler, Robert C. Goldszer, David G. Fairchild, Andrew J. Sussman, Gilad J. Kuperman, and David W. Bates. A cost-benefit analysis of electronic medical records in primary care. *The American Journal of Medicine*, 114(5):397–403, 2003.