THE EFFECT OF ELECTRONIC HEALTH RECORDS ADOPTION ON PATIENT-SPECIFIC HEALTH EDUCATION PRESCRIPTION, TIME UTILIZATION, AND RETURNED APPOINTMENTS: A PROPENSITY SCORE WEIGHTED ANALYSIS

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INTRODUCTION

Background

- The United States spent 17.9% of GDP on health expenditure in 2012
- Medicare and Medicaid provide financial incentive for the adoption and use of the EHR system.
- “more than half of eligible providers have qualified for and received incentive payments for adoption of certified electronic health records.” – The White House

Research question

Will the adoption of Electronic Health Records system affect patient-specific health education prescription, time utilization, and returned appointments?

LITERATURE REVIEW

Industril 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).
- In order to receive the EHR stimulus money, the HITECH act (ARRA) requires eligible physicians to show “meaningful use” of an EHR system.
- In order to demonstrate meaningful use in 2014 Stage 1, eligible professionals must meet 13 required core objectives and 5 menu objectives from a list of 9.

Prior researches

- Mixed effect on health expenditure
- Very limited literature evaluated the effect of EHR on the utilization of patient-specific education resources.
- The effect of EHR system adoption on time efficiency is mixed and varies among different institutions.
- Evaluations of the effect of EHR on patient follow-up rates are limited.
- On the micro level, EHR has a mixed effect on cost-saving in physician practices.

Contributions

This paper contributes to the literature with a national-level perspective, empirically evaluating the outcome of EHR adoption on patient-specific health education prescription rates, patient interaction time, and returned appointment rates.

ANALYSIS PLAN

Analysis Plan

1. Data
2. Estimating treatment effect with observational data
3. Assumption of causal inference
4. Propensity score estimation
5. Propensity score weighted regression model
6. Sensitivity tests

Data

National Ambulatory Medical Care Survey (NAMCS) public use micro-data files:

- National probability sample survey of visits to office-based physicians.
- NAMCS data can be used to make physician estimates as well as visit estimates.
- NAMCS has information includes whether the physician practice has EHR system.

Estimating treatment effect with observational data

- Ideally, we would observe a 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.
- However, people in ”treatment 1”, ”treatment 2”, and ”control” groups likely different in both observed and unobserved ways.

Assumption of causal inference

Assumptions in causal analysis:

- Stable unit treatment value assumption (SUTVA)
- Unconfoundedness assumption.

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

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

Propensity score estimation

- Propensity score methods attempt to replicate two features of randomized experiments.
    - Propensity score methodologies can create groups that look only randomly different from one another (at least on observed variables).
    - Propensity score methods do not use outcome variables when setting up the design.
- Generalized Boosted Machine models (GBM) outperform simple logistic regression models in terms of bias reduction and mean squared error.
- We can check balance statistics after propensity score weighting (or matching).

Propensity score weighted regression model

Let $p_W(\mathsf{X}_i)$ denotes propensity score for physician i with treatment W, the weights satisfy

$$\omega_i[t] = \frac{1}{p_W(\mathsf{X}_i)}$$

Propensity score weighting has two advantages.

- Propensity score weighting permits most types of multivariate outcome analysis and does not require an outcome variable that is continuous or normally distributed.
- Unlike matching techniques, the weighting method maintains sample size.

Sensitivity tests

- First, we tested the robustness of the result with different covariate controls in multinomial propensity score weighted regression models.
- Second, we examined whether the results are robust to different multinomial propensity score weighted generalized regression models.
- Third, we checked whether the results are robust to propensity score weighted binary treatment assignments.
- Fourth, we tested the robustness of the result with a propensity score matching approach.

DESCRIPTIVE STATISTICS

Nominal and ordinal variables

- The adoption rate of the EHR system is grew rapidly after the implementation of the EHR incentive program.
- Health Maintenance Organizations (80.51%) are the most likely to fully adopt the EHR system among all health care practice owners.
- The full adoption rate of MSA areas (32.93%) and non-MSA areas (33.08%) is close to the national average (32.94%)
- In general, practices with higher numbers of managed care contracts tend to have higher adoption rates of the EHR system.
- Among all physician specialties, general and family practices are the most likely to fully adopt the EHR system. Ophthalmologists are least likely to adopt the EHR system.

Continuous variables

- The adoption status of the EHR system has potential influence on outcome variables.
- There is no significant age difference between the fully treated group and the control group.
- Fewer patients patient with complex chronological conditions visited practices without an EHR system.
- Practices with full EHR adoption tended to have a higher percentage of privately insured patients.

PROPENSITY SCORE BALANCE

Measuring propensity score balance (1)

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.

Measuring propensity score balance (2)

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 these two groups

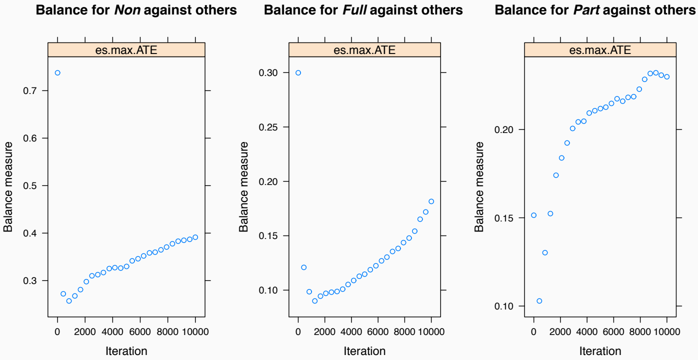
$$d_x = \frac{|\Delta M_x|}{S_x}$$

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

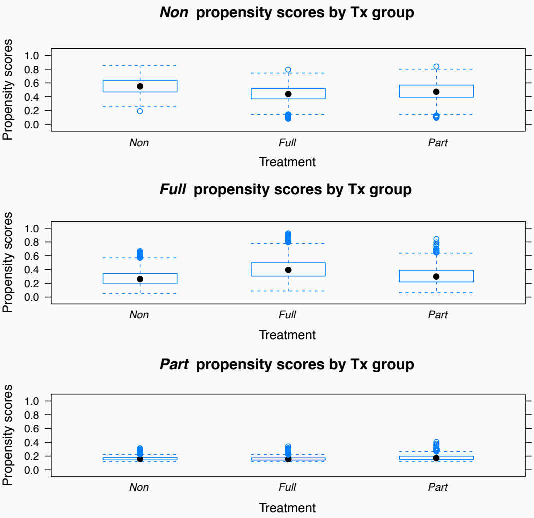
$$S_x = \sqrt{\frac{S_{xt}^2 + S_{xp}^2}{2}}$$

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

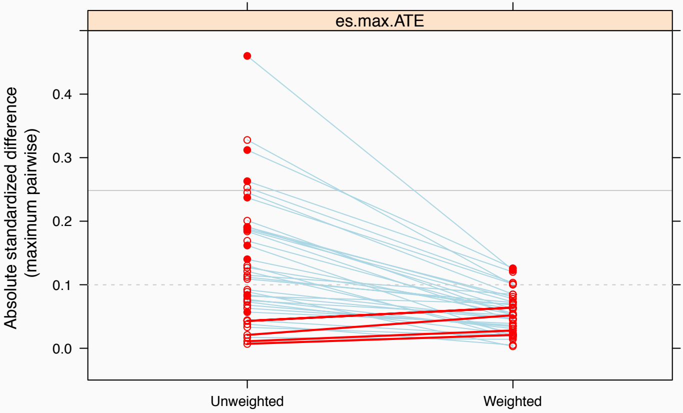
Sufficient iterations of GBM model



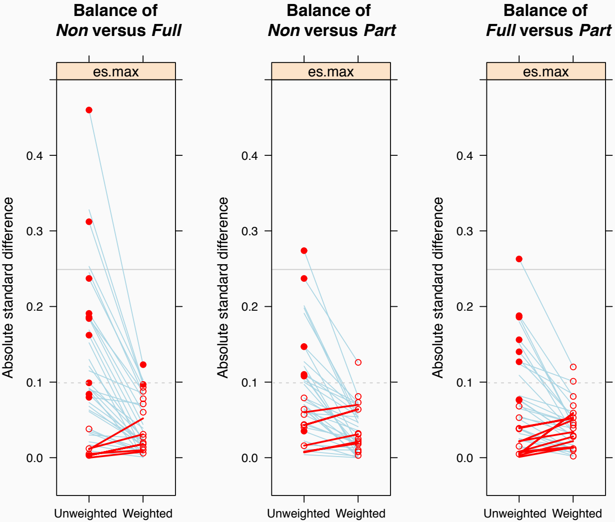
Overlapping assumption satisfied



Propensity score balance achieved (overall)



Propensity score balance achieved (by treatments)



REGRESSION RESULTS

Patient-specific health education prescription rates

Table 6.1: Estimated effect of EHR adoption on patient-specific health education prescription rates

	Dependent variable: patient-specific health education prescription rates							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Full EHR	0.034*	0.143*	0.037**	0.034**	0.043**		0.039***	
	(0.018)	(0.074)	(0.018)	(0.017)	(0.019)		(0.015)	
Part EHR	0.033	0.135	0.034*	0.034*		0.028		0.006
	(0.020)	(0.084)	(0.020)	(0.019)		(0.021)		(0.020)
Constant	0.411***	−0.363***	0.401***	0.334***	0.405***	0.363***	0.401***	0.344***
	(0.031)	(0.128)	(0.010)	(0.064)	(0.035)	(0.034)	(0.027)	(0.035)
Treatment	*Multiple*	*Multiple*	*Multiple*	*Multiple*	*Binary*	*Binary*	*Binary*	*Binary*
PS	*Weighting*	*Weighting*	*Weighting*	*Weighting*	*Weighting*	*Weighting*	*Matching*	*Matching*
Controlled ASMD >0.1	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Controlled ASMD <0.1	*No*	*No*	*No*	*Yes*	*No*	*No*	*No*	*No*
Error dist.	*Normal*	*Binomial*	*Normal*	*Normal*	*Normal*	*Normal*	*Normal*	*Normal*
Observations	3,619	3,619	3,619	3,619	2,999	2,473	2,292	1,240
R^2							0.017	0.028
Adjusted R^2							0.011	0.017
Log Likelihood	-2,048.801		-2,072.498	-1,853.567	-1,613.901	-1,385.733		
Akaike Inf. Crit.	4,127.603		4,150.996	3,787.134	3,255.802	2,799.466		
Residual Std. Error							0.340 (df = 2278)	0.347 (df = 1226)
F Statistic							2.942*** (df = 13; 2278)	2.675*** (df = 13; 1226)

Note:Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

Time utilization

Table 6.2: Estimated effect of EHR adoption on patient-physician interaction time

	Dependent variable: patient-physician interaction time							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Full EHR	0.222	0.010	−0.038	0.353	0.319		0.475	
	(0.532)	(0.024)	(0.538)	(0.472)	(0.568)		(0.403)	
Part EHR	0.189	0.007	0.054	0.213		0.122		−0.125
	(0.574)	(0.026)	(0.593)	(0.519)		(0.605)		(0.554)
Constant	25.074***	3.213***	21.821***	20.295***	25.938***	25.420***	23.439***	24.723***
	(1.102)	(0.044)	(0.345)	(2.247)	(1.297)	(1.383)	(0.743)	(0.964)
Treatment	*Multiple*	*Multiple*	*Multiple*	*Multiple*	*Binary*	*Binary*	*Binary*	*Binary*
PS	*Weighting*	*Weighting*	*Weighting*	*Weighting*	*Weighting*	*Weighting*	*Matching*	*Matching*
Controlled ASMD >0.1	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Controlled ASMD <0.1	*No*	*No*	*No*	*Yes*	*No*	*No*	*No*	*No*
Error dist.	*Normal*	*Poisson*	*Normal*	*Normal*	*Normal*	*Normal*	*Normal*	*Normal*
Observations	3,619	3,619	3,619	3,619	2,999	2,473	2,292	1,240
R^2							0.053	0.078
Adjusted R^2							0.048	0.068
Log Likelihood	-14,216.760		-14,331.300	-13,858.460	-11,843.320	-9,902.171		
Akaike Inf. Crit.	28,463.530		28,668.600	27,796.920	23,714.630	19,832.340		
Residual Std. Error							9.203 (df = 2278)	9.468 (df = 1226)
F Statistic							9.895*** (df = 13; 2278)	8.006*** (df = 13; 1226)

Note:Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

Returned appointment rates

Table 6.3: Estimated effect of EHR adoption on returned appointment rates

	Dependent variable: returned appointment rates							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Full EHR	-0.031^{**}	-0.150^{**}	-0.035^{**}	-0.020	-0.030^{**}		-0.011	
	(0.015)	(0.070)	(0.014)	(0.013)	(0.015)		(0.012)	
Part EHR	-0.008	-0.038	-0.011	-0.012		-0.002		0.020
	(0.018)	(0.086)	(0.018)	(0.016)		(0.017)		(0.016)
Constant	0.679^{***}	0.747^{***}	0.719^{***}	0.392^{***}	0.696^{***}	0.694^{***}	0.678^{***}	0.683^{***}
	(0.026)	(0.125)	(0.009)	(0.055)	(0.027)	(0.028)	(0.023)	(0.028)
Treatment	*Multiple*	*Multiple*	*Multiple*	*Multiple*	*Binary*	*Binary*	*Binary*	*Binary*
PS	*Weighting*	*Weighting*	*Weighting*	*Weighting*	*Weighting*	*Weighting*	*Matching*	*Matching*
Controlled ASMD >0.1	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Controlled ASMD <0.1	*No*	*No*	*No*	*Yes*	*No*	*No*	*No*	*No*
Error dist.	*Normal*	*Binomial*	*Normal*	*Normal*	*Normal*	*Normal*	*Normal*	*Normal*
Observations	3,619	3,619	3,619	3,619	2,999	2,473	2,292	1,240
R^2							0.018	0.017
Adjusted R^2							0.013	0.007
Log Likelihood	-1,394.416		-1,423.651	-1,011.757	-1,101.507	-911.617		
Akaike Inf. Crit.	2,818.832		2,853.302	2,103.514	2,231.015	1,851.235		
Residual Std. Error							0.284	0.277
							(df = 2278)	(df = 1226)
F Statistic							3.251^{***}	1.649^{*}
F Statistic							(df = 13; 2278)	(df = 13; 1226)

Note:Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

DISCUSSION

Patient-specific health education prescription rates

There are multiple plausible reasons that can explain the EHR's positive effect on patient-specific health education prescription rates.

- First, patient-specific education resources are easy to prescribe with the EHR system.
- Second, the EHR incentive program has set patient-specific education as a menu objective.
- Third, physicians may intentionally use the EHR for shared decision-making and education to improve patient engagement.

Time utilization

Several factors contributed to a mixed-time utilization outcome after EHR adoption.

- On the one hand, time efficiency could have improved as physicians became familiar with EHR systems.
- On the other hand, certain EHR systems have poor usability.
- Additionally, physicians could have continued to perform certain tasks using paper-based methods, even though the computer automatically performed these tasks for them.

Returned appointment rates

EHR adoption has a negative (although not robust) effect on returned appointment rates. There are a few hypothetical explanations.

- First, the EHR system may improve the quality of treatment, and thus, there would be no need to revisit the physician.
- Second, the patient may disregard the automatic reminder generated by the EHR system.
- Third is alert fatigue experienced by physicians; they routinely ignore alerts due to the high volume generated by the EHR system.

Limitations

- A specific patient who has multiple encounters at the survey site in a certain year has a heavier weight than a counterfactual patient who used health care less frequently.
- Our casual inference method is based on strong assumptions due to the limitation of observational data.
- The effect of EHR system adoption on time efficiency is mixed and varies among different institutions.
- Evaluations of the effect of EHR on patient follow-up rates are limited.
- Empirical research on the casual relationship between studied outcomes and health quality is still limited.

Policy implications

- The first is linking patient education with quality improvement efforts.
- Second, the CMS should work with physicians and vendors to improve the usability of EHR systems.

Questions?