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The Effect of Electronic Medical Records on Patient Satisfaction

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Introduction

Health information technology (HIT) has to the potential to reduce health care costs by tens of billions of dollars per year while improving care and patient satisfaction. One use of HIT is an electronic medical record (EMR) system which records patient data and provides data instantaneously to physicians during patient visits. Because of its potential, EMR implementation is an important focus of United States healthcare policy. As part of the American Recovery and Reinvestment Act, the Health Information Technology for Economic and Clinical Health Act (HITECH Act) provides $25.9 billion to incentivize effective adoption of EMR in clinicians and hospitals. Starting in 2015, the HITECH Act also punishes providers which have not yet adopted a meaningful EMR system.

Despite its large potential, implementing EMR does not guarantee productivity improvements. There are several problems which limit the effectiveness of EMR. Providers may have limited access to IT human capital in their region, which limits cost-effective EMR implementation (Dranove et. al. 2012). Independent physicians are reluctant to link their EMR systems to a hospital’s system. Incomplete data and poorly designed interfaces can introduce errors (Ash et. al. 2004).

Previous studies find limited average effects on costs and productivity from EMR implementation (Wu et. al. 2006 and Agha 2010). The debate over EMR effectiveness is a return of the “Productivity Paradox” argument which Robert Solow stated as “You can see the computer age everywhere but in the productivity statistics” (1987).

Lehigh Valley Health Network (LVHN) has implemented an EMR system in its outpatient OB/GYN offices and its Labor and Delivery Unit at its main hospital, Lehigh Valley Hospital-Cedar Crest (LVH-CC). LVHN used a customized commercial EMR system. Early EMR adopters, such as Duke, Johns Hopkins, UPMC, and Yale, developed systems in-house, which developed IT experience before eventual implementation of a commercial package (Dranove et. al 2012).

We collected data completeness surveys at LVHN’s Inpatient Labor & Delivery Triage Unit (Triage) and at outpatient OB/GYN offices. The surveys ask staff to indicate whether the most recent documentation is available to view on the EMR system for several specific measures relevant to pregnancy. Because we control for patient health using risk scores, these surveys allow us to measure the effectiveness of EMR data on patient satisfaction and quality of care.

There are several advantages to studying EMR adoption at LVHN’s Triage Unit and outpatient offices. First, LVHN used a commercial system. Previous research has studied EMR systems developed in-house. These systems are typically developed in leading academic hospitals in high-tech areas, which often lead to larger cost reductions (Dranove et. al. 2012). Furthermore, measuring the effect of a popular commercial system will have greater external validity. Second, LVHN’s system is integrated between office and hospital in a large system with 3,000 births per year. Communication errors are more frequent and transportation costs are larger between sites, which mean that the instantaneous availability of data in EMR systems should lead to greater productivity improvements when linked between sites versus as a stand-alone system. Data availability is also a signal of competence and is therefore an input into patient satisfaction. Third, pregnant patients interact with LVHN's system within a defined nine month period. This allows us to collect rich data during a defined but high-risk period.

Literature Review

As we will show, the effect of EMR on productivity and costs has been studied more rigorously than its effect on patient satisfaction. Productivity and costs affect the supply of healthcare but EMR also affects demand for healthcare. We also focus on patient satisfaction because patients cannot directly observe quality of care.

There are several factors which may limit the effect of health information technology on patient satisfaction. Many exogenous demographic characteristics also affect patient satisfaction, including age, ethnicity, socioeconomic status, and preexisting health conditions (Thiedke 2007). Doyle and Ware (1977) find that, among factors impacting care, physician conduct has the largest effect on patient satisfaction. Chang et. al. (2006) find that physician communication has a much larger effect than physician's technical skill on patient satisfaction. Dansky and Miles (1997) find that patient waiting time has a large effect on patient satisfaction. Previous studies (Lelievre and Schultz 2010 and Solomon and Dechter 1995) have found no effect of physician computer use on physician distraction. However, the surveys used in these studies specifically mentioned the physician's use of computers. For these reasons, we use almost all of these factors as control variables in our analysis of patient satisfaction.

We also collected patient satisfaction data over several years and several stages of implementation. Deily et. al. (2012) and Dranove et. al. (2012) both find that the beneficial impact of EMR increases of time since implementation. Since sharing information affects patient trust, we specifically look at what happens when patient data is linked between the LVHN triage unit and outpatient offices.

Several studies use panel data to exploit variation in hospital adoption of EMR. Dranove et. al. (2012) focuses on cost reductions from EMR adoption. They find that cost reductions are heterogeneous and depend on complementary human capital, i.e. IT workers. Furthermore, they find that cost reduction from EMR adoption takes several years and may take an indefinite period of time in regions with sparse IT industry.

Agha (2011) uses Medicare claims data to measure costs and quality of care. EMR adoption is associated with an initial 1.3% increase in costs and there is no decrease in costs five years after EMR adoption. In addition, using patient mortality, medical complications, adverse drug events, and readmission data, she finds no improvement in quality of care from EMR.

Miller and Tucker (2010) find that state privacy laws reduce the effectiveness of EMR adoption because they reduce communication between offices. After controlling for privacy laws using an instrumental variables approach, they find that EMR adoption leads to a significant drop in infant mortality. They find that the reduction in deaths is driven by situations where previous data is most significant and no reduction in deaths in other situations. Rough calculations show an increase of $531,000 in costs per life saved.

Wu et. al. (2006) review the literature on EMR adoption. They find that quality improvement is most effective in preventive care but they also find inconclusive evidence on changes in efficiency and cost improvements. Unlike with other medical treatments, EMR effectiveness depends crucially on implementation and generalizability from specific systems is difficult.

Studies of patient satisfaction used much smaller samples on a much smaller scale. Furthermore, they use pre-post analyses as opposed to instrumental variables approaches. Some studies such as Hsu et. al. (2005) and Rethans et. al. (1988) find improvements in patient perception of care. However, the survey questions bring specific attention to the doctor's of EMR, which biases results. Other surveys which bring attention to the use of EMR typically do not find any significant improvements in care. Nagy and Kanter (2007) find no significant improvements in patient satisfaction after EMR adoption in a Kaiser Permanente medical center in southern California. One specific limitation of this study is that only measured patient satisfaction up to 6 months after EMR adoption. Also, the Kaiser Permanente system is based in Oakland, California, near Silicon Valley, and developed its EMR system in-house.

Data

LVHN is a nonprofit health network with three hospital campuses and approximately 3,000 births per year. We collected survey data from one hospital campus and eight outpatient OB/GYN campuses. LVHN implemented a customized, commercial EMR system at the triage section of its Labor & Delivery unit in August 2009. It implemented an EMR system produced by the same company in its outpatient OB/GYN offices beginning in June 2009. In June 2011, information began flowing between the Triage unit and outpatient offices.

The dependent variables in the models are Press Ganey patient satisfaction surveys. The Press Ganey surveys are mailed to patients a short period after visits to the Triage unit and outpatient offices. There are separate surveys for hospital visits and office visits with different questions. The surveys ask for ratings of care along several dimensions such as staff friendliness, office cleanliness, overall rating of care, and patients' confidence in care provider. Patients respond on a scale from 1 (very poor) to 5 (very good).

We use information availability surveys to measure the effect of EMR on care providers' awareness of patient data. We implemented separate surveys for the Triage units and outpatient offices. The Triage surveys were first implemented in June 2009. After patient visits, we gave the care provider a survey asking whether the care provider had access to the most recent documentation from the outpatient offices for the following items: cervical exam, blood pressure measurement, up-to-date antenatal problem list, non-stress test result, prior uterine incision type, Group B strep results, and Medicaid patient request for tubal sterilization. For the cervical exam, blood pressure measurement, up-to-date antenatal problem list, the possible responses are Yes or No. For the other questions, the possible responses are Yes, No, or N/A.

For pre/post analyses, we included dummy variables indicating whether the patient visited after a certain of EMR implementation. In the inpatient model, we include a dummy variable indicating whether the date is after August 1, 2009, the date that the EMR was upgraded in Triage. In the outpatient office model, we include two dummy variables indicating whether the patient visited after EMR was implemented in that office. These dates ranged from June 1, 2009 to October 20, 2009. We also include a dummy variable indicating whether the patient visited after information began flowing the Triage unit to the outpatient offices. This date was either June 2, 2011 or July 7, 2011 depending on the office.

The office surveys were first implemented in June 2009 in eight outpatient OB/GYN offices. These surveys similarly asked about the care provider's access to patient information. First, it asks whether the patient has visited the Triage unit before. If so, then the survey continues and asks how many times the patient has visited Triage. It also whether the care provider had access to the most recent documentation from Triage for the following items: new diagnoses, cervical exam, non-stress test result, and laboratory work. For these questions, the possible responses are Yes, No, or N/A.

Demographic controls for the inpatient model include ethnicity, insurance type, age, and prior patient health risk. Ethnicity is a binary variable with 1 indicating nonwhite and 0 indicating white. For insurance type, we separate Medicaid and non-Medicaid patients. Age is a binary variable with 1 indicating the patient is at least 35 years of age. Prior patient health risk is calculated using a risk scoring model which maps various health risk factors to a real number. Depending on the model, we also control for time. In some models we use dummy variables separating month and in other models we use dummy variable separating years. We used a larger number of dummy variables in models with a larger sample size.

The demographic controls for outpatient model are ethnicity, insurance type, age and prior patient health risk. For the insurance type, we separate Medicaid, managed care, and other types of insurance using dummy variables. Age is modeled using two dummy variables indicating whether the patient is at least 35 years of age, between 18 and 34 years of age, or less than 18 years of age. Ethnicity and prior patient health risk are both calculated in the same way as the inpatient model. In addition we also control for whether the patient is rating her first visit to the office, wait time in the exam room, and wait time in the waiting room. We use dummy variables to separate to the two outpatient office organizations, College Heights and OB/GYN Associates. There are also dummy variables indicating the degree of the care provider, which is either Medical Doctor, Doctor of Osteopathy, Certified Registered Nurse Practitioner, Physician's Assistant, or other.

Empirical Approach

We use three types of empirical approaches to measure the effect of EMR implementation on patient satisfaction. In the first approach, we regress patient satisfaction scores on data completeness dummy variables and control variables. The limitation of this approach is small sample size because only a small number of patients were included in our surveys and filled out a patient satisfaction survey. In the second approach, we pool data completeness measures over each two week period. So, each patient's data availability score is the average of the data completeness scores recorded during the time period of the patient's visit. We can then use every patient that filled out a patient satisfaction survey in our analysis. For both of these first two approaches, we use the ordered probit and linear regression. These two approaches allow us to estimate the impact of availability of each datum on patient satisfaction. Finally, we use a pre-post regression analysis which measures how patient satisfaction scores change at each stage of EMR implementation. This method has the largest sample size but suffers from omitted variable bias if another factor is driving changes in patient satisfaction.

First approach

To isolate the effect of the availability of specific patient data, we used the data completeness surveys administered in the Triage unit and at the outpatient offices. We use LVHN's Press-Ganey surveys collected after Triage and outpatient office visits as measures of patient satisfaction. Because the responses are ordinal measures on a Very Poor to Very Good Likert scale, we estimate the following ordered probit model of patient satisfaction for each Press-Ganey survey question:

$$L_k^* = \beta_0 + \beta_1 P_k + \beta_2 C_k + \varepsilon_k$$

where L^*_{kt} is unobserved but we observe:

$$L_k = 0 \; if \; L^*_k \leq 0$$

$$L_k = 1 \; if \; 0 < L^*_k \leq \mu$$

$$L_k = 2 \; if \; \mu < L^*_k.$$

K indexes patient and L_k represents one of the Press-Ganey survey responses. Although each patients chooses from one of five responses from Very Poor to Very Good on each question, few patients (around 10 percent) report Very Poor to Fair for each response so we combine Very Poor, Poor, and Fair into one category, which responds to $L_k = 0$. P_k includes patient demographic dummy variables for race, age, managed care, Medicaid, and year of observation as well as the individual patient risk scores we measured. C_k includes the average level of data completeness reported by the staff members for each of the individual data elements. That is, C_k is the proportion of visits in which a survey was administered such that the data element was reported available. We estimate a model in which C_k is defined as the average level of data completeness over all applicable data elements. In this case C_k is a univariate measure of data completeness so that we can estimate the overall effect of the level of data completeness.

We also estimate the family of models

$$L_k = \beta_0 + \beta_1 P_k + \beta_2 C_k + \varepsilon_k$$

using Ordinary Least Squares where P_k is defined as before and C_k is defined in all ways described above. L_k is a binary 0/1 variable with 1 defined as a Very Good response on the Press-Ganey survey and 0 defined as Very Poor to Good.

Because each of these models requires a separate equation for each survey question, we use a principal component analysis (PCA) to find a univariate measure of patient satisfaction. The PCA converts a set of possibly correlated variables to a set of uncorrelated variables. The first principal component is the linear combination of all variables with the highest variance. Therefore, instead of simply taking the arithmetic mean of all survey responses we use the first principal component for a better measure of patient satisfaction. We estimated all models above except with L_k defined as the first principal component of the Press-Ganey survey variables.

Second approach

Because we have a small sample from the inpatient Triage unit for which a staff member was administered one of our data completeness surveys and the patient completed a Press-Ganey, we estimated a larger sample model in which C_k is defined differently. We averaged the data completeness responses for all patients over two week periods in which we collected surveys. We calculate the median number of days from Triage visit to admission for all patients which we administered a data completeness survey to. For each patient in the Press-Ganey database, we estimate the date that the patient visited Triage by subtracting the median delay from Triage to admission from the date of hospital admission for that patient. We then define C_k to be the average proportion of data completeness for each measure over all patients in the approximate time period that the patient visited triage. For example suppose that we find a patient admitted on June 20 and the average delay from Triage visit to admission is 20 days. We estimate the patient visited Triage on May 31 and define C_k to be the average level of data completeness over the two week time period which includes May 31. We also estimate a model in which C_k is defined as the average level of data completeness over all measures over all patients in each time period so that C_k is a univariate measure of data completeness over each time period.

Third approach

To use an even larger sample size, we estimate the same class of samples using a different approach of defining C_k. We define C_k to be a set of time variables. We include two pre-post dummy variables. The first dummy variable is defined to be 1 if the patient visited after EMR was implemented in the patient's outpatient office and 0 other wise. The second dummy variable is defined to be 1 if the patient visited after the EMR systems in the offices were linked to the LVHN's triage unit. We also include a set of dummy variables for each month of our sample. Using this approach, we can include patients who visited before EMR implementation to get a pre-post analysis of the effectiveness of EMR implementation.

Results

Due to a small sample size, the information availability survey models do not present any statistically significant results. The descriptive statistics for the Triage information availability data are presented in Table 1. The sample size was N=83. That is, 83 patients completed a Press Ganey survey and had an information availability survey filled out by their care provider after the visit. For some data, the information was available in only 2 percent of patients. Similarly, the descriptive statistics for the office information availability data are presented in Table 3. The sample size was N=167, where 167 patients had both the Press Ganey and information availability surveys filled out.

The pre/post analyses provide more interesting results. For most questions, there were statistically significant changes in patient satisfaction at different points of EMR implementation. For the outpatient data, we present the results in table 5 of changes in responses to two questions. I3 is "our concern for patients' privacy". O3 is "care received during visit". Note that in the results, we do not present the coefficients for our monthly dummy data but they were included in the ordered probit regression. These data show that patient satisfaction decreased with wait time and for Medicaid and managed care patients. We see a statistically significant drop in patient satisfaction immediately after EMR is implemented in the offices. There is a statistically significant rise in patient satisfaction immediately after information begins flowing from the Triage unit to the offices. Using estimations of marginal effects, we find that EMR implementation led to a 10 to 26 percentage point in the probability of a patient rating care given as "very good." Linking Triage and offices led to a 6 to 28 percentage point increase in the probability of a patient rating care given as "very good."

For the inpatient Triage data, we present the ordered probit pre/post analysis in Table 6. I3 asks the patients "how well the physician kept you informed" and L4 asks the patients to rate "care received during visit to hospital". As in the outpatient case, we do not present the monthly dummy variables but they were included in the regressions. These data show that EMR implementation led to statistically significant changes in patient satisfaction. However, the directions of changes were different for the two different questions. Patients reported lower satisfaction in the physicians keeping patients informed. On the other hand, overall patients rated their level of care higher.

Limitations

For the information first and second approaches, the main limitation is a small sample size. For the inpatient data, the sample size was only 150. For the outpatient data, the sample size was only 85. The reason is that from the information availability surveys that we offered, only a proportion were offered Press Ganey survey and only a proportion responded to the surveys.

With a larger sample size, we would be able to multiply the effect of each piece of information on patient satisfaction by the total change in information availability after EMR implementation to get an estimate of the aggregate effect EMR implementation on patient satisfaction.

Another limitation is that this is not a randomized, controlled trial. Ideally, we would be able to randomly shut off EMR for half of visits. This trial would generate a larger sample size because it would not require paper surveys to be offered after visits. Nevertheless, the information availability model attempts to mimic this type of randomized, controlled trial.

Response rates also present a possible bias to our results. Care provider response rates were higher when a research assistant was physically present at the Triage unit to offer surveys. Since the surveys were voluntary, care providers may have been less likely to complete surveys during busy time periods, which is precisely when EMR are most effective in improving information availability. Response rates were also low for patients in filling out Press Ganey forms.

For the pre/post analysis, it is more difficult to demonstrate causality. Any number of simultaneous events could have effected patient satisfaction without changing information availability. With a larger sample size, however, we were able to get a more precise estimate of the effect of EMR implementation. Furthermore, previous results in studies which measure cost reductions such as Dranove et. al. (2012), not patient satisfaction, confirm our same qualitative results on the effect of EMR.

Conclusion

These results show that initial EMR implementation leads to an initial reduction in patient satisfaction. This result is likely due that the fact that EMR initially disrupts workflow and reduces care provider-patient communication. Once information began flowing from the Triage unit to outpatient offices, patient satisfaction rose. Depending on the question, patient satisfaction rose above its initial levels before EMR implementation. These results confirm previous studies on EMR which find that the effectiveness of EMR increases over time since implementation. Since, we controlled for any time trends, this study measures the discrete effects of implementation. One theory which explains these results is that EMR is most effective when information flows over a distance. When the paper records are physically present at the location that a patient is visiting, we should expect a smaller effect from EMR implementation. However, using EMR still disrupts workflow. So, this theory explains the initial drop in patient satisfaction. Once the Triage and office EMR systems were linked, we then saw improved patient satisfaction due to improved information availability.

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Table 1: Descriptive Statistics – Outpatient Information Availability Model

Variable	N	Mean	SD	Min	Max
Care received during visit	83	2.71	0.48	1	3
Was this your first visit here?	82	1.9	0.3	1	2
Minutes wait for exam room	80	9.72	14.53	0	110
Minutes wait in exam room to see care provider	81	11.43	16.2	0	110
Risk Score	83	1.03	0.61	0.02	4.54
Age 18-34	83	0.87	0.34	0	1
Age 35+	83	0.12	0.33	0	1
College Heights	83	0.47	0.5	0	1
Medicaid	83	0.04	0.19	0	1
Managed Care	83	0.14	0.35	0	1
Nonwhite	83	0.1	0.3	0	1
CRNP	83	0.19	0.4	0	1
DO	83	0.06	0.24	0	1
MD	83	0.69	0.47	0	1
(mean) visittotriageyes	83	0.05	0.2	0	1
(mean) visittotriageno	83	0.57	0.47	0	1
(mean) newdiagnosesyes	83	0	0	0	0
(mean) newdiagnosesno	83	0.04	0.19	0	1
(mean) cervialexamyes	83	0.01	0.05	0	0.5
(mean) cervialexamno	83	0.04	0.19	0	1
(mean) nonstresstestyes	83	0.02	0.12	0	1
(mean) nonstresstestno	83	0.02	0.15	0	1
(mean) labworkyes	83	0.02	0.15	0	1
(mean) labworkno	83	0.02	0.12	0	1

Table 2: Descriptive Statistics – Outpatient Pre/Post Analysis

Variable	N	Mean	SD	Min	Max
Care provider explanations of prob/condition	4905	2.73	0.54	1	3
Care received during visit	5027	2.7	0.54	1	3
Was this your first visit here?	4978	1.85	0.36	1	2
Minutes wait for exam room	4877	10.38	24.66	0	830
Minutes wait in exam room to see care provider	4880	9.62	23.75	0	715
Risk Score	5080	0.57	0.64	-0.95	7.97
Age 18-34	5080	0.39	0.49	0	1
Age 35+	5080	0.61	0.49	0	1
Medicaid	5080	0.02	0.14	0	1
Managed Care	5080	0.05	0.22	0	1
Nonwhite	5080	0.09	0.28	0	1
CRNP	5080	0.21	0.41	0	1
DO	5080	0.15	0.36	0	1
MD	5080	0.56	0.5	0	1
PA	5080	0.05	0.23	0	1
Post EMR	5080	0.4	0.49	0	1
Post Information Linkage	5080	0.06	0.24	0	1

Table 3: Descriptive Statistics – Inpatient Information Availability Model

Variable	N	Mean	SD	Min	Max
skill of the physician	148	2.41	0.7	1	3
overall rating of care given at hospital	136	2.7	0.51	1	3
Nonwhite	166	0.19	0.39	0	1
Managed Care	167	0.1	0.3	0	1
Medicaid	167	0.11	0.31	0	1
Age 35+	167	0.2	0.4	0	1
2010	167	0.19	0.39	0	1
2011	167	0.41	0.49	0	1
Risk Score	167	1.14	0.45	0.41	2.53
Survey average	164	0.76	0.32	0	1
(mean) Cervical_Exam_Yes	167	0.69	0.46	0	1
(mean) Cervical_Exam_No	167	0.29	0.44	0	1
(mean) Blood_Pressure_Yes	167	0.78	0.4	0	1
(mean) Blood_Pressure_No	167	0.19	0.39	0	1
(mean) Antenatal_Prob_List_Yes	167	0.8	0.39	0	1
(mean) Antenatal_Prob_List_No	167	0.17	0.37	0	1
(mean) Non_Stress_Test_Yes	167	0.08	0.26	0	1
(mean) Non_Stress_Test_No	167	0.25	0.41	0	1
(mean) Prior_Uterine_Incision_Yes	167	0.07	0.24	0	1
(mean) Prior_Uterine_Incision_No	167	0.04	0.2	0	1
(mean) Group_B_Strep_Yes	167	0.62	0.48	0	1
(mean) Group_B_Strep_No	167	0.1	0.3	0	1
(mean) Tubal_Steril_Yes	167	0	0.04	0	0.5
(mean) Tubal_Steril_No	167	0.12	0.31	0	1

Table 4: Descriptive Statistics – Inpatient Pre/Post Analysis

Variable	N	Mean	SD	Min	Max
How well the physician kept you informed	36957	2.49	0.64	1	3
Overall rating of care given at hospital	3040	2.68	0.54	1	3
Risk score	42765	2.3	1.72	-1.19	15.87
Nonwhite	42752	0.11	0.31	0	1
Age 35+	42765	0.89	0.31	0	1
Managed care	42765	0.16	0.37	0	1
Medicaid	42765	0.03	0.18	0	1
Post implementation	42765	0.44	0.5	0	1

Table 5: Results from Ordered Probit – Outpatient Pre/Post Analysis

	(1)	(2)
VARIABLES	I3	O3
Post EMR Implementation	-0.174	-0.563***
	(0.142)	(0.138)
Post Integration with Triage	0.112	0.663**
	(0.289)	(0.310)
Was this your first visit here?	0.021	0.025
	(0.057)	(0.055)
Minutes wait for exam room	-0.003***	-0.004***
	(0.001)	(0.001)
Minutes wait in exam room to see care provider	-0.002**	-0.003***
	(0.001)	(0.001)
Age 18-34	0.064	-0.270
	(0.235)	(0.251)
Age 35+	0.357	0.000
	(0.235)	(0.251)
Survey Delay	-0.003***	-0.002*
	(0.001)	(0.001)
Risk Score	-0.009	-0.019
	(0.034)	(0.032)
Nonwhite	-0.082	-0.008
	(0.070)	(0.069)
Medicaid	-0.394***	-0.204
	(0.135)	(0.138)
Managed Care	-0.108	-0.182**
	(0.088)	(0.084)
College Heights	0.765	0.053
	(1.117)	(0.042)
cut1		
Constant	-0.848	-1.125
	(0.916)	(0.901)
cut2		
Constant	0.147	0.080

	(0.916)	(0.901)
Observations	4,586	4,690
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

Table 6: Results of Ordered Probit – Inpatient Pre/Post Analysis

	(1)	(2)
VARIABLES	I3	L4
Post EMR Implementation	-1.079**	0.423*
	(0.444)	(0.234)
Nonwhite	0.089***	-0.123**
	(0.020)	(0.059)
Medicaid	-0.017	0.054
	(0.034)	(0.083)
Age 35+	0.089***	-0.006
	(0.020)	(0.056)
Risk Score	-0.020***	-0.038
	(0.004)	(0.052)
cut1		
Constant	-1.355***	-1.694***
	(0.046)	(0.162)
cut2		
Constant	-0.111**	-0.470***
	(0.045)	(0.158)
Observations	36,945	3,037
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		