HUID: 90855972 , 70592576

Access to Electronic Image Results and Physicians' ordering of Tests: A Follow-up Examination

Section 1: Introduction

The Patient Protection and Affordable Care Act jump started a widespread movement towards a nationwide, interoperable electronic health information system. With the passage of the Health Information Technology for Economic and Clinical Health, billions of dollars have been appropriated through the Department of Health and Human Services Office of the National Coordination for Health Information Technology (ONC) towards the adaptation of electronic medical records throughout the health care system and meaningful use of this technology.(1) The overarching objective of these investments is to improve the health of Americans through increased care coordination, quality of care monitoring, but imbedded in this effort is the notion of increased efficiency and resultant cost savings that may be realized through the reduction of duplicate diagnostic tests. In 2002, expenditures for imaging studies absorbed 14% of Medicare part B spending.(2) Projected savings from avoiding duplicative and excessive testing with the use of EMR range from $77.8 to $81 billion annually.(3-4) A limited number of studies performed in academic centers with highly interoperable EMR systems demonstrated a reduction in testing.(5-6) However, external validity of these evaluations towards ambulatory, private practices with non-interoperable EMR systems is likely very low.

One obstacle faced by the ONC is overcoming provider resistance to the adoption of new technologies. Studies have shown that early adopters of technologies differ from late or non-adopters. As recently as 2009, only 1.5% of US hospitals had a comprehensive EMR, with larger teaching hospitals in urban centers more likely to have EMR .(7) Only 4% of office-based physicians reported having a fully functional EMR in 2008.(2) Barriers to adoption include high capital requirements and maintenance costs. Individual providers may lack technical expertise to choose, implement and use an EMR system.(8) Early adoption of EMR by individual providers appears to be concentrated in primary care, large practices, in hospitals or medical centers and in the western region of the US.(6) However, the majority of ambulatory physician practices tend to be small (44%) and not attached to a hospital or a medical center (63%).(8) The impact of adoption of an EMR system in an ambulatory setting on health care utilization has not been evaluated until the study by McCormick, et al.(9)

Section 2: Replication using original methods

McCormick, et al. set out to determine whether the computerized availability of imaging results or image viewing, or the use of a full EMR, is associated with reductions in imaging test ordering in office-based physician practices. The authors conjectured that it was plausible that the electronic convenience of accessing results may in fact lead to an increase of test ordering.

The authors analyzed data from the 2008 National Ambulatory Medical Care Survey (NAMCS) of 28,741 patient visits to a nationally representative sample of offices. They used two indicators of physician access to imaging results: first, whether the practice had "a computerized system for viewing imaging results"; second, whether the practice had "electronic image viewing capability". The researchers used multivariate logistic regression models to separately model several outcomes of interest: ordering of any

imaging test, ordering of advanced imaging tests (CAT scan, MRI, or PET scan), and each of the advanced tests separately. They controlled for a number of patient and physician characteristics (see our replicated results in Tables 1-3). All analyses were weighted based on weights from the multistage probability sampling design of the survey. The authors found no evidence that office-based physicians with EMR access to imaging test results order fewer imaging tests. In fact, physicians' access to computerized imaging results was associated with a 40-70% greater likelihood of an imaging test being ordered, ceteris paribus.

In our subsequent analysis, outlined below, we addressed several limitations of that paper:

1. Selection bias – as outlined in the introduction, providers who are adopters of EMRs systematically differ from those who are not. While the authors controlled for some observable physician and practice characteristics, there may be other factors that may play a role in the usage of EMR. Thus, the assumption of a zero conditional mean and random sampling of their modeling approach may be violated. We identified additional physician/practice indicators which were available in the NAMCS dataset that were associated with EMR availability. We proceeded to match the EMR vs. no EMR groups based on physician and practice attributes, factors that precede the exposure of interest (see Section 3 for more details).
2. Missing data – the authors used a list-wise deletion method in their multivariate analyses, yet, we noted a substantial proportion of missing values for a number of covariates. For example, the availability of a computerized system for viewing imaging results indicator had 13% of missing observations. Since list-wise deletion may bias the estimates and inferences, especially if the missingness pattern is non-ignorable, we proceeded to multiple imputation (see Section 3 for details).
3. Confounding – while the authors purport to have conducted sensitivity analyses using a limited number of potential confounders, which appear not to have changed the association of interest (data not reported), there were potential confounders that were not controlled for, such as indicators of chronic illness, acute problems, number of prior visits, major reason for visit, and receipt of orthopedic care and physiotherapy.

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Table 1. Frequency of Physicians' Image Test Ordering During Office Visits, By Patient and Practice Characteristics (weighted)

	% of visits in which physician ordered:			
Characteristic	Any Image	Any advanced image	MRI	CAT scan
Sex				
Female (n=16751)	16.89	3.29	1.58	1.57
Male (n=11990)	12.97	3.37	1.68	1.63
Age				
< 18 Yrs (n=5180)	5.77	0.59	0.39	0.23
18-45 (n=7945)	14.94	2.98	1.72	1.21
46-64 (n=8405)	20.06	4.82	2.40	2.30
>64 (n=7211)	17.06	3.90	1.52	2.15
Race				
Black (n=3384)	14.14	3.74	1.88	1.66
Non-Black (n=25357)	15.46	3.27	1.59	1.59
Ethnicity				
Hispanic (n=3891)	12.68	2.46	1.40	1.20
Non-Hispanic (n=24850)	15.69	3.44	1.65	1.65
Income				
Live in >Median Poverty Zip code (n=12395)	14.66	3.30	1.69	1.53
Live in other Zip code (n=16346)	15.77	3.33	1.57	1.64
Location				
Urban (n=26105)	15.43	3.37	1.62	1.63
Non-Urban (n=2636)	14.08	2.83	1.61	1.18
Type of Insurance				
Private (n=14507)	15.49	3.17	1.70	1.37
Medicare (n=6689)	17.38	4.11	1.54	2.35
Medicaid (n=3617)	9.47	1.85	1.00	0.91
Other (n=1057)	23.73	5.87	3.90	1.97
None (n=1697)	10.05	2.47	1.21	1.25
Physician Specialty				
Primary Care (n=14701)	13.37	2.19	1.05	1.07
Surgical (n=6996)	20.72	5.09	2.64	2.42
Medical (n=7044)	15.61	5.03	2.32	2.37
Seen previously by this physician				
Yes (n=24535)	14.18	2.98	1.43	1.42
No (n=4206)	23.68	5.84	3.04	2.85
Practice Setting				
Private (n=23669)	15.64	3.33	1.58	1.64
Community Center (n=3345)	10.78	2.58	1.27	1.25
HMO (n=645)	12.56	4.49	2.73	1.76
Free standing (n=842)	10.31	1.98	1.56	0.42
Other (n=240)	21.52	7.37	5.89	1.49
Physician owns practice				
Yes (n=17921)	14.98	3.18	1.55	1.54
No (n=10697)	16.05	3.65	1.79	1.72
Physician has computerized system for:				
Accessing imaging results				
Yes (n=13401)	18.04	4.47	2.22	1.05
No (n=14848)	12.90	2.23	1.07	2.15
Viewing actual images				
Yes (n=18543)	18.85	5.12	2.29	2.64
No (n=6458)	13.36	2.44	1.23	1.12

Table 2. Adjusted Odds of Ordering Any Imaging Test, by Patient and Practice Characteristics.

Characteristic	Odds ratios, results model	Odds ratios, images model
Sex		
Female (n=16751)	1.43***	1.42***
Male (n=11990)	Baseline	Baseline
Age		
< 18 Yrs (n=5180)	Baseline	Baseline
18-45 (n=7945)	2.72***	2.88***
46-64 (n=8405)	3.95***	4.28***
>64 (n=7211)	3.26***	3.28***
Race		
Black (n=3384)	0.86	0.85
Non-Black (n=25357)	Baseline	Baseline
Ethnicity		
Hispanic (n=3891)	0.90	0.89
Non-Hispanic (n=24850)	Baseline	Baseline
Income		
Live in >Median Poverty Zip code (n=12395)	0.93	0.94
Live in other Zip code (n=16346)	Baseline	Baseline
Location		
Urban (n=26105)	1.06	1.04
Non-Urban (n=2636)	Baseline	Baseline
Type of Insurance		
Private (n=14507)	Baseline	Baseline
Medicare (n=6689)	0.98	0.97
Medicaid (n=3617)	0.92	0.92
Other (n=1057)	1.60**	1.69**
None (n=1697)	0.58**	0.50***
Physician Specialty		
Primary Care Specialty (n=14701)	0.83	0.85
Surgical Specialty (n=6996)	Baseline	Baseline
Medical Specialty (n=7044)	0.78	0.75
Seen previously by this physician		
Yes (n=24535)	0.53***	0.55***
No (n=4206)	Baseline	Baseline
Practice Setting		
Private (n=23669)	Baseline	Baseline
Community Center (n=3345)	0.52***	0.61*
HMO (n=645)	0.42**	0.41*
Free standing (n=842)	0.57	0.81
Other (n=240)	2.44	0.93
Solo practitioner		
Yes	0.64***	0.64***
No	Baseline	Baseline
Physician owns practice		
Yes (n=17921)	0.77	0.82
No (n=10697)	Baseline	Baseline
Practice mostly prepaid		
Yes	1.02	1.00
No	Baseline	Baseline
Hospital-owned practice		
Yes	0.71	0.87
No	Baseline	Baseline
Physician compensation base on cost profiling		
Yes	0.96	0.98
No	Baseline	Baseline
Physician has computerized system for:		
Accessing imaging results		
Yes (n=13401)	1.44***	-
No (n=14848)	Baseline	-
Viewing actual images		
Yes (n=18543)	-	1.47***
No (n=6458)	-	Baseline

*p<0.05 **p<0.01 ***p<0.001

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Table 3. Adjusted Odds of Ordering Any Advanced Imaging Test, by Patient and Practice Characteristics.

Characteristic	**Odds ratios, results model**	**Odds ratios, images model**
Sex		
Female (n=16751)	0.94	0.92
Male (n=11990)	Baseline	Baseline
Age		
< 18 Yrs (n=5180)	Baseline	Baseline
18-45 (n=7945)	3.81***	3.46***
46-64 (n=8405)	5.88***	5.93***
>64 (n=7211)	4.65***	4.61***
Race		
Black (n=3384)	0.98	0.95
Non-Black (n=25357)	Baseline	Baseline
Ethnicity		
Hispanic (n=3891)	0.83	0.86
Non-Hispanic (n=24850)	Baseline	Baseline
Income		
Live in >Median Poverty Zip code (n=12395)	0.92	1.01
Live in other Zip code (n=16346)	Baseline	Baseline
Location		
Urban (n=26105)	1.05	0.95
Non-Urban (n=2636)	Baseline	Baseline
Type of Insurance		
Private (n=14507)	Baseline	Baseline
Medicare (n=6689)	1.19	1.15
Medicaid (n=3617)	1.38	1.41
Other (n=1057)	2.10***	2.36***
None (n=1697)	0.86	0.88
Physician Specialty		
Primary Care Specialty (n=14701)	0.66*	0.67
Surgical Specialty (n=6996)	Baseline	Baseline
Medical Specialty (n=7044)	1.05	1.00
Seen previously by this physician		
Yes (n=24535)	0.53***	0.55***
No (n=4206)	Baseline	Baseline
Practice Setting		
Private (n=23669)	Baseline	Baseline
Community Center (n=3345)	0.96	1.06
HMO (n=645)	1.23	1.17
Free standing (n=842)		0.92
Other (n=240)	3.84	0.30
Solo practitioner		
Yes	0.63**	0.63**
No	Baseline	Baseline
Physician owns practice		
Yes (n=17921)	1.37*	1.50*
No (n=10697)	Baseline	Baseline
Practice mostly prepaid		
Yes	0.90	0.97
No	Baseline	Baseline
Hospital-owned practice		
Yes	1.48	1.68
No	Baseline	Baseline
Physician compensation base on cost profiling		
Yes	1.19	1.24

No	Baseline	Baseline
Physician has computerized system for:		
Accessing imaging results		
Yes (n=13401)	1.72**	-
No (n=14848)	Baseline	-
Viewing actual images		
Yes (n=18543)	-	1.72**
No (n=6458)	-	Baseline

*p<0.05 **p<0.01 ***p<0.001

Section 3 – Modification of original methods

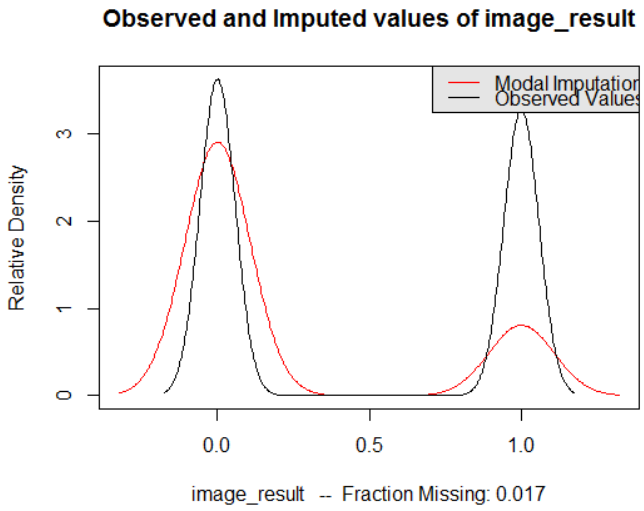
We sought to evaluate whether access to a computerized system for viewing imaging results is independently associated with a provider proclivity to order imaging tests.

The original model used ignores the problem of missing data, which is quite prevalent . For instance if we ran a model using all the covariates and outcome variables, we would only have 18632 observations. Using multiple imputation however leaves us with all 28741 observations. (10-11)

With access to the image result as the treatment variable, the global imbalance measure (L1) is 0.977 for the original data set. After imputation, the balance improves slightly, for each imputation, the imbalance measures (L1) are 0.968, 0.967, 0.968, 0.967, 0.968. In addition, multiple imputation does not change any of the odds ratios significantly, but improves the standard error of almost every coefficient(11).

Figure 1 gives us the relative densities of the imputed and observed values for electronic access to image result. Thus the missing values were more likely to lack an access to an image result than to have access.

Figure 1:



Further, we seek to determine the causal effect of health IT, as defined by electronic access to past image results by using coarsened exact matching to match observations based on practice characteristics. (12) Matching on the practice characteristics allows us to compare the effect of adding electronic access to image results for similar practices. In addition these characteristics are unlikely to change as a result of adding this access. Further, some literature suggests that Practice characteristics may be more predictive of the use of Health IT and electronic medical records.(13) Matching in this way greatly improves the balance of the data to 0.314 for each imputation, and still leaves us with at least 27163 observations (from the imputation with the lowest number of observations).

In addition, we sought to control more precisely for patient health by including dummies for chronic conditions, number of medications, whether preventative care was accounted for in physician compensation and whether physiotherapy and/or osteoporosis care was ordered into our model. The significance of the coefficients for chronic conditions and physiotherapy and osteoporosis care and these variables suggests that patient's health significantly contributes to the probability of tests being ordered. Table 4 shows the frequency of practices/patients with given characteristics that have electronic access to Image results for both the original and matched and imputed datasets. Since we matched on Practice Characteristics the differences in the frequencies seems to be more pronounced based on these characteristics. Overall, however, the matching and imputation steps do not alter these frequencies in a noticeably significant way

Table 4. Patient and Practice Characteristics by Access to Imaging Results

Characteristic	**Access to image results**			
	Original data (N=28249)		Matched, Imputed data*	
	No (N=14848)	Yes (N=13401)	No*	Yes*
	Patient Characteristics			
Gender				
Female	60.00%	56.25%	59.88%	56.44%
Age				
<18	17.94%	18.72%	17.88%	18.39%
18-45	29.86%	24.81%	29.92%	25%
45-64	28.79%	29.51%	28.88%	29.55%
>64	23.41%	26.96%	23.32%	27.07%
Race				
Black	12.99%	10.85%	12.92%	10.53%
Ethnicity				
Hispanic	14.82%	11.65%	15.07%	12.05%
Income				
Lives in zip code > Median poverty	42.08%	43.38%	42.73%	43.55%
Type of Insurance				
Private	63.68%	64.56%	51.17%	54.06%
Medicare	22.28%	24.47%	23.12%	25.59%
Medicaid	14.04%	10.97%	14.60%	11.56%
Other	3.24%	3.41%	3.79%	3.87%
None	7.10%	4.78%	7.32%	4.92%
Number of Chronic Conditions				
0 Chronic Conditions	50.26%	46.01%	46.82%	43.12%
1 Chronic Conditions	24.88%	24.50%	24.99%	24.54%
2 Chronic Conditions	12.85%	13.83%	12.83%	13.99%
3 Chronic Conditions	6.94%	8.96%	6.92%	9.08%
4 Chronic Conditions	5.07%	6.70%	4.95%	6.76%
Diagnosis				
Asthma	5.29%	5.96%	5.22%	6.01%
Cancer	5.60%	5.86%	5.39%	5.87%
Cerebrovascular disease	1.62%	2.23%	1.62%	2.32%
CHF	1.44%	1.80%	1.41%	1.84%
COPD	3.15%	3.21%	3.15%	3.24%

Depression	10.38%	7.94%	10.54%	8.20%
Diabetes	9.55%	11.07%	9.48%	11.17%
Hyperlipidemia	12.28%	15.43%	12.24%	15.67%
Hypertension	22.53%	26.65%	22.37%	26.82%
Ischemic Heart Disease	3.87%	5.60%	3.89%	5.41%
Osteoporosis	1.80%	2.29%	1.79%	2.40%
Obesity	5.83%	6.72%	5.77%	6.84%
Number of Medications				
0 medications	27.23%	26.96%	27.58%	26.89%
1 medications	24.43%	20.79%	24.23%	20.54%
2 medications	15.73%	14.83%	15.77%	14.78%
3 medications	10.26%	9.23%	10.20%	9.21%
4+ medications	22.35%	28.19%	22.23%	28.57%
Location				
Urban	91.92%	89.82%	91.73%	90.14%
Region				
Northeast	20.99%	22.66%	21.48%	21.89%
Midwest	21.03%	23.55%	19.95%	22.32%
South	34.59%	30.43%	34.77%	29.92%
West	23.39%	23.36%	23.80%	25.87%
Physiotherapy ordered	1.68%	2.62%	1.74%	2.69%
Orthopedic care ordered	1.31%	2.48%	1.31%	2.56%
Major reason for visit				
New problem	33.39%	33.42%	32.92%	33.24%
Chronic-routine	32.13%	29.64%	31.76%	29.61%
Chronic-flare up	7.55%	9.32%	7.27%	9.18%
Pre/post surgery	6.45%	9.00%	6.12%	8.69%
Preventative Care	20.48%	18.62%	19.70%	17.60%
Physician/Practice Characteristics				
Physician specialty				
Surgical specialty	54.27%	49.56%	53.59%	48.49%
Primary Care specialty	19.41%	30.48%	19.21%	29.94%
Medical specialty	26.32%	19.96%	27.20%	21.57%
Seen Previously by Physician	86.69%	84.70%	86.66%	83.98%
Factors taken into account for compensation				
Quality of care - Preventative Care	23.02%	33.24%	18.80%	30.42%
Practice setting				
Private	85.57%	84.74%	83.96%	80.40%
Community Center	12.89%	10.63%	12.88%	10.46%
HMO	0.21%	2.16%	0.22%	4.46%
Free Standing clinic	1.10%	2.23%	2.06%	4%
Other	0.23%	0.24%	0.89%	0.68%
Physician owns practice	67.87%	60.73%	66.77%	58.08%
Solo physician	35.67%	23.02%	36.52%	23.09%
Practice mostly prepaid	5.74%	7.19%	5.77%	10.17%
Physician compensation based on cost-profiling	8.37%	15.12%	6.93%	15.07%
Hospital owned practice	7.66%	14.19%	7.95%	17.70%

* matched on pre-treatment variables: previously seen, visit to a physician with a surgical specialty, seeing their doctor in a private office, in a practice owned by the provider, but not in a solo practice, practice not prepaid, or owned by the hospital or using cost profiling, practitioner

not compensated based on quality of care (e.g., preventive care); for each of the five imputations, the total N is 27163, 27205, 27202, 27204, 27176. With 14607, 14635, 14602,14621 and 14594 without access to image results, and 12556,12570,12600,12583, and 12582 with access.

After CEM, we conducted multivariate analyses using unweighted logistic models. Under the assumption that weights are non-informative conditional on covariates and since we were interested in estimating the average treatment effect on the treated (ATT), we assumed that the estimated probability of the outcome, conditional on treatment and the covariates is equal to the probability of the outcome, conditional on treatment, covariates and weights. Thus, the sampling weights were not included in our multivariate models. (15,16)

Our quantity of interest was the first difference in percent of tests ordered with electronic access to results. Models were run in three ways: univariate (unadjusted model), adjusting for covariates used in matching algorithm in order to account for remaining imbalance between the treatment and matched controls (partially adjusted model), adjusting for matching covariates and patient attributes in order to account for confounding by case-mix and to isolate the effect of electronic access to results on imaging test ordering (fully adjusted model). All multivariate models were conducted on the matched and imputed dataset.

The restricted model (unadjusted model) was compared to the unrestricted model (partially adjusted) was compared using the likelihood ratio test, p-value <0.001 (chi-sq, df=13). Similarly, the partially adjusted model was compared to the fully adjusted model using the likelihood ratio test, p-value <0.001 (chi-sq, df=30), confirming that the fully adjusted model fit performed significantly better. This was confirmed in a ROC analysis (fig. 2), in which the fully adjusted model dominated the other nested models.

A Figure 2 B

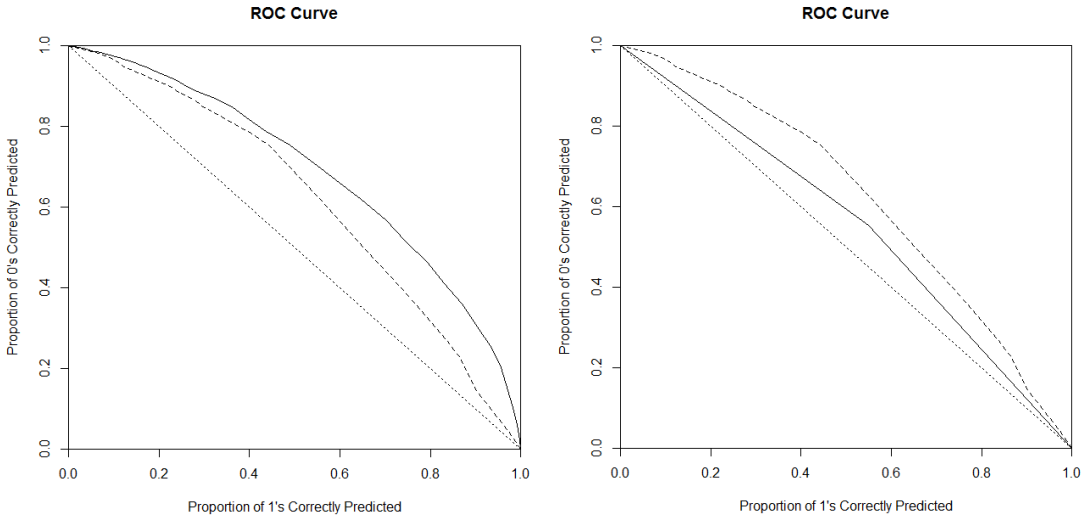


Figure 2.A. ROC curves of matched model controlled for physician/practice characteristics (dotted line) and matched model without controlling for other covariates (solid line). The matched controlled model dominates.
Figure 2.B: ROC curves of matched model controlled for physician/practice characteristics and patient characteristics (solid line) and matched model controlled for physician/practice characteristics (dotted line). The 'fully' controlled model dominates.

To calculate a more policy-relevant quantity of interest, we look to the first differences between practices without access to patient's image results and those with access. While the original article suggests that electronic access can increase the likelihood of ordering tests by 40%, we focus on calculating the first difference of tests ordered for the median survey participant.

Table 3:

First expected difference in percentage of orders for any imaging test by availability of a computerized system for accessing imaging results

Model	Expected value for ordering tests without access to results	95% Confidence interval	First difference for ordering tests with access to results	95% Confidence interval	Expected % increase
Matched/Unadjusted	12.6%	12.0%-13.1%	5.3%	4.5%-6.2%	42.2%
Matched/Adjusted for MD/practice characteristics*	18.3%	17.0%-19.5%	5.3%	4.2%-6.5%	29.2%
Matched/Adjusted for MD/practice and patient characteristics**	19.9%	16.3%-23.7%	5.1%	3.9%-6.6%	25.9%
Unmatched***	20.5%	16.7%-24.2%	7.0%	4.0%-10.2%	34.1%

*for median participant: previously seen, visit to a physician with a surgical specialty, seeing their doctor in a private office, in a practice owned by the provider, but not in a solo practice, practice not prepaid, or owned by the hospital or using cost profiling, practitioner not compensated based on quality of care (e.g., preventive care)

**for median participant: female, age 45-64, not black or Hispanic, living in an urban area above median poverty in South region of US, with private insurance, no chronic conditions, taking 2 medications, major reason for visit: routine, chronic problem, receiving orthopedic care but not physical therapy

***based on model by McCormick, et al.

Section 4: Discussion and Limitations

Our results confirm that access to electronic records can lead to an increased ordering of tests, however, they show that this effect may be less than previously suggested. The odds ratios from the model in McCormick et.al suggests a 40% increase in the likelihood of ordering any test, whereas the in sample results from our model suggest only a 25.9% increase in this likelihood for the median participant. Moreover, our results suggest that only about 5 percentage points of tests will be ordered in practices with electronic access to patients' past image results. This suggests that from a broad policy perspective that the effect of Health IT remains ambiguous, especially as our results are still limited by the data available. More information on the doctors ordering tests would likely improve any model, as health IT is most likely to be adopted by the practices that are more likely to order tests, given that a high volume of services is most likely needed to support the cost of investing in such technology. Personal

characteristics of physicians such as age, race, gender or year of graduation may also explain a proclivity towards electronic medical records. In addition, these findings could support the notion that competition to possess the newest technology may drive up healthcare costs. However, if additional tests prevent future procedures and illnesses, then the adoption of such technology may drive down healthcare costs in the long term. A longitudinal study could be useful in examining this theory. Unfortunately, it may be possible that the effect of this technology on the most important outcome variable, patient's health, may not be observable until long after the technology becomes outdated. Furthermore, the rapid pace of technological development may actually provide an incentive for providers to hold out on adopting new technologies, in anticipation of falling prices or improving quality (12). An interesting approach may be to compare sets of "early-adopters" who use the most updated Health information systems, to "late-comers" who are willing to wait to adopt. Despite these limitations, our results confirm that the cost-saving capability of electronic medical records should not be taken for granted, is quite nuanced, and that more rigorous analysis of the costs and benefits should be conducted on such a prevalent policy issue.

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