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Journal
Health Services Research, 53(2)

ISSN
0017-9124

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Publication Date
2018-04-01

DOI
10.1111/1475-6773.12695

Peer reviewed

HSR Health Services Research

DOI: 10.1111/1475-6773.12695
RESEARCH ARTICLE

The Effect of Access to Electronic Health Records on Throughput Efficiency and Imaging Utilization in the Emergency Department

Matthew M. Knepper, Edward M. Castillo, Theodore C. Chan, and David A. Guss

Study Objective. To evaluate whether the availability of Electronic Health Records (EHRs) reduces throughput time and utilization of advanced imaging for patients in an academic ED.

Data Sources. All patients arriving at an academic Emergency Department (ED) via ambulance between June 1, 2011, and June 4, 2012, were included in the study. This accounted for 9,970 unique ambulance patient visits.

Study Design. Retrospective noninterventional analysis of patients in an academic ED. The primary independent variable was whether the patient had a prior EHR at the study hospital. Main outcomes were throughput time, number of advanced diagnostic imaging studies (CT, MRI, ultrasound), and the associated cost of these imaging studies. A set of controls, including age, gender, ICD9 codes, acuity measures, and NYU ED algorithm case severity classifications, was used in an ordinary least-squares (OLS) regression framework to estimate the association between EHR availability and the outcome measures.

Principal Findings. A patient with a prior EHR experienced a mean reduction in CT scans of 13.9 percent ([4.9, 23.0]). There was no material change in throughput time for patients with a prior EHR and no difference in utilization of other imaging studies across patients with a prior EHR and those without. Cost savings associated with prior EHRs are $22.52 per patient visit.

Conclusion. EHR availability for ED patients is associated with a reduction in CT scans and cost savings but had no impact on throughput time or order frequency of other imaging studies.

Key Words. Electronic Health Records, health IT, throughput time, advanced imaging

The Health Information Technology for Economic and Clinical Health (HITECH) Act passed in 2009, authorizing the use of $19.2 billion in incentives for providers who adopt health information technology (HIT) that satisfies "meaningful use" criteria (Steinbrook 2009; Blumenthal 2010). This act accelerated the deployment of Electronic Health Record (EHR) systems in hospitals and medical practices. It also financed the development of Health Information Exchanges (HIEs) to facilitate the connectivity of individual EHRs (Williams et al. 2012). Nationally, EHR adoption rates among independent hospitals have since flourished, growing from 48 percent in 2008 to 77 percent in 2011 (Dranove et al. 2015).

Considering the high cost of HIT deployment, its impact on practice patterns, and the recent surge of adoption, there is relatively limited evidence of how this technology impacts patient care, health care costs, and productivity (Borzekowski 2009; Lee et al. 2013; Dranove et al. 2014). In an Emergency Department (ED) setting, the efficiency of information transmission should impact the speed with which physicians are able to diagnose and treat patients. Prompt availability of prior diagnoses, current medications, prior treatments, and test results should accordingly improve the efficiency of care (McCullough, Parente, and Town 2016). The ability to query prior diagnostic test results should also lead to reductions in repeat testing, including expensive imaging studies (Chaudhry et al. 2006; Tzeel, Lawnicki, and Pemble 2011; Frisse et al. 2012; Bailey et al. 2013; Lammers, Adler-Milstein, and Kocher 2014; Ross et al. 2013). However, many studies of EHRs have indicated an association with increased cost and reduced efficiency (Sidorov 2006; McCormick et al. 2012). A study by Furukawa, Raghu, and Shao (2010) revealed that EHR adoption was associated with an increase in costs per discharge of roughly 6 to 10 percent (Furukawa, Raghu, and Shao 2010). A study by Agha (2014), which included a panel of 3,900 hospitals between 1998 and 2005, found that Health IT increased billable charges by 1.3 percent without any evidence of cost savings, reductions in patient mortality, adverse drug reactions, or reductions in readmission rates (Agha 2014).

Moreover, deploying an EHR is expensive and has a major impact on established workflow. These factors are of particular importance in an ED. Analyzing the impact of the availability of an EHR on throughput and costs is essential to fostering ongoing adoption and justifying the expenditure of such systems. An analysis of the impact of the availability of a prior EHR on a

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patient seen in the ED can potentially serve as a surrogate for the impact of a Health Information Exchange (HIE) in a community.

Our main findings indicate that while the availability of EHRs has no effect on total throughput time, it does reduce the use of CT scans by nearly 14 percent. These findings are important in the light of the absence of evidence of cost savings in the literature. Moreover, a reduction in exposure to ionizing radiation in the form of CT scans may yield significant long-term health benefits for patients.

Institutional Setting

We perform a retrospective multicenter study of encounters at two EDs from June 2011 to June 2012. One hospital is an urban, academic teaching hospital (level 1 trauma center) with an annual census of approximately 37,000 visits. The other hospital is a suburban community hospital with an annual census of approximately 23,000 visits. This period was selected because it coincided with the period of interaction between the specialized ED EHR (WEBCHARTS) and the Health System EHR (EPIC). Study approval was obtained through the Human Research Protections Program (HRPP).

The study institution has had a robust EHR in place for over 5 years and the EDs had initially utilized a specialized EHR that connected to the institutional EHR. Prior study of the ED system supported improved operational efficiency of the electronic order entry component of the EHR, but no objective analysis has been conducted to assess the utility of the system on other parameters of performance.

The primary study sample limits patient enrollment to those arriving by ambulance for two important reasons. First, ambulance patient visits tend to be less discretionary, assuring a combination of patients with prior encounters and thereby likely to have some entry into the system's EHR along with those without prior contact at the study institution and no health information in the EHR. Additionally, ambulances generally go to the facility closest to the patient's pickup location, irrespective of the patient's preference. This feature adds an element of random assignment of patients to the study institution (Doyle et al. 2015). In the broader sample, in contrast, patients who choose to visit the study institution may do so based on factors related to the perceived quality of care or when they think the wait times will be the shortest, which are mechanically related to the outcome measures of interest. Therefore, including nonparamedic patients in the study sample would introduce a confounding selection bias to our estimates. Nonetheless, because walk-in patients account for over two-thirds of all visits, we redo all of our analysis on the full sample as a check on the external validity of our more trusted estimates.

Moreover, we only included patients with disposition admitted or discharged, excluding those that were transferred to another facility in order to avoid patients whose evaluation was not yet complete. Patients with clearly erroneous data entry into the system such as wrong day of arrival, which could result in negative length of stay or exceptionally long lengths of stay at odds with the documentation in the record, were also omitted from the study sample.

We further omit patients without a primary care physician. The majority of these patients are uninsured, and a substantial fraction is homeless. Thus, these patients have limited access to preventative care and disproportionately suffer from chronic and otherwise difficult-to-treat illnesses.

When all of the aforementioned patient groups are omitted, 9,970 paramedic patient encounters remain, 6,734 (68.5 percent) of which are in the treated [or EHR(+)] group to go along with 3,236 (31.5 percent) control [or EHR (−)] patients. The secondary sample of all patients includes 44,373 subjects, which can be further decomposed into 31,993 (72.1 percent) EHR(+) patients and 12,380 (27.9 percent) EHR (−) patients.

METHODS

The primary objective of this study is to compare EHR (+) patients to EHR (−) patients in order to determine the impact of EHR access on ED patient care. Data collected include population demographics of age and gender, time of arrival and time the patient left the ED, all imaging studies obtained, chief complaint, and discharge diagnosis (ICD9 codes). The primary outcomes variables were throughput time (arrival to left the ED), advanced imaging studies obtained (CT, MRI, ultrasound), and charges for imaging studies. Patients were categorized as EHR (+) provided that there was evidence of prior visits to either the study institution or a health provider affiliated with the study institution in the preceding 3 years. All others were categorized as EHR (−).

Our empirical strategy is to estimate the association between EHR (+) and length of stay (LOS) in an ordinary least-squares (OLS) regression, while controlling flexibly for a comprehensive set of patient and encounter-specific covariates that independently affect the outcome of interest. We use an identical strategy to separately estimate the association between EHR (+) and the use of specific advanced imaging examinations, such as CT scans, MRIs, ultrasounds, and all advanced imaging examinations.

A major challenge to our analysis is the fact that the availability of EHRs is contingent upon whether a patient has had a prior encounter with the academic institution's health care system within the 3 years prior to the beginning of the sample. Thus, the treated group contains the subset of patients who may be chronic users of inpatient, outpatient, or ED facilities. All else equal, we would expect that the types of patients with a record available are of *worse* initial health and hence have inferior measured outcomes. Absent a source of identifying variation, we estimate the relationship between our outcome variables and the EHR treatment while flexibly controlling for patient characteristics, such as age, sex, insurance provider type, triage acuity, patient disposition, and patient ICD9 codes, that are likely correlated with health status. To the extent that these patient characteristics proxy for health status, adding them as controls should purge the association between EHR (+) and throughput time of the "adverse selection" effect.

Additionally, we control for novel sources of variation in the outcome measures, such as unique identifiers for the attending physician, the time of day during which the visit took place, and the patient caseload upon arrival. Physician identifiers, for example, help reduce biases that may result from unobserved idiosyncratic differences in treatment practices that can influence treatment times and the level of testing. Time of day and patient caseload controls capture volume and flow patterns, which may independently affect both throughput time and the allocation of advanced imaging resources across patients.

Finally, we perform sensitivity checks that alter both the way in which diagnostic codes are grouped and the study sample used and then re-estimate the relationship between EHR (+) and our outcome measures. First, we re-estimate the relationship between EHR (+) and throughput time (imaging examinations) after having replaced ICD9 codes with a more coarse diagnosis classification system. This alternative diagnosis classification system is the NYU ED algorithm, which maps diagnostic discharge codes (ICD9 codes) associated with each patient visit to seven easily interpretable classifications on the basis of whether care was required within 12 hours, whether the ailment was primary care treatable, and whether the condition was preventable or avoidable (Billings, Parikh, and Mijanovich 2000a, b). The algorithm was created by a panel of primary care and ED physicians who had analyzed the full records of nearly 6,000 patients. Based on the initial ailment, demographic factors, and treatment procedures provided in the record, the algorithm weights the probability that the patient visit falls into one of the following seven categories: injuries, psychiatric, substance abuse, non-emergent, emergent but primary care treatable, ED care needed but preventable or avoidable, and ED care needed and the condition was unavoidable.

Next, we replace primary ICD9 codes with secondary ICD9 codes (when available). This modification results in reassigned diagnostic codes for nearly 20 percent of the study sample but should not alter our estimated relationship if the baseline estimates are valid. Also, one might think that patients who come in for psychiatric or substance abuse issues are quite different from the typical patient and that the availability of an EHR should have less influence over throughput time in these cases. Furthermore, the EHR (–) group does contain a slightly larger fraction of these types of patients. Thus, we might worry that if it takes longer to treat psychiatric and substance abuse patients, we would spuriously attribute part of the throughput reduction to the availability of EHRs. To address this concern, we rerun our estimating equation on the subsample that excludes patient visits that are motivated by mental illness. Lastly, the subset of patients suffering from injuries is expected to be the "most random" of all types of ED visits. Thus, we assess the relationship between EHR (+) and our outcomes as a further check on the credibility of our main results.

In accordance with current best practice, we cluster our OLS standard errors at the day-site level to allow for arbitrary correlation in unobserved staffing patterns across each ED site in the sample.

RESULTS

Table 1 reports the means and standard deviations for the full set of observable characteristics across EHR (+) and EHR (–) patients. The EHR (+) patients are more than 10 years older. EHR (+) patients are also more likely to be admitted to the hospital than EHR (–) patients.

Table 2 reports the distribution across the NYU ED categories within the two samples. EHR (–) patients are 3 to 5 percent more likely to visit for complications associated with drug or alcohol abuse. While this could be concerning, these cases account for fewer than 9 percent of all visits among paramedic transport patients and we later show that our estimation results are robust to the exclusion of these patient types. Furthermore, EHR (+) patients

Table 1: Table of Means

	EHR (−)	*EHR (+)*	*p-Value*
Acuity	1.933	1.932	.948
	[0.497]	[0.446]	
Age	48.808	57.395	.000
	[20.859]	[18.227]	
Male	0.538	0.517	.051
	[0.499]	[0.500]	
Fraction discharged	0.727	0.603	.000
	[0.446]	[0.489]	
Total no. of ICD9s	1.296	1.349	.000
	[0.621]	[0.663]	
Length of stay (minutes)	358.14	399.18	.000
	[229.2]	[225.18]	
Total imaging studies	1.802	1.650	.000
	[2.169]	[1.804]	
Total CT scans	0.615	0.498	.000
	[1.019]	[0.845]	
Total ultrasound scans	0.091	0.085	.333
	[0.316]	[0.304]	
Total MRI scans	0.045	0.048	.668
	[0.315]	[0.310]	
N	3,236	6,734	

Note: Acuity measure is on a descending scale so that 1 = most severe and 3 = least severe. SD in brackets.

are 12 to 15 percent less likely to be visiting for an injury, 6 percent more likely to be visiting for a nonemergent reason, and roughly 6 percent more likely to be visiting for unavoidable emergencies. The latter group of patients are victims of the most severe types of emergencies, such as strokes and heart attacks, and experience average treatment times significantly above the mean (418 vs. 386 minutes) and receive nearly 0.6 more imaging examinations than the average patient (2.26 vs. 1.66). However, patients with nonemergent conditions are less likely to require intensive care. This disparity in the composition of EHR (+) and EHR (−) patients across these categories is a reflection of their differences in age and presenting conditions. Lastly, the EHR (+) group experiences an average length of stay roughly 11 percent higher than that of the EHR (−) group (399 vs. 358 minutes). On the contrary, the EHR (+) group receives 19 percent fewer CT scans (.50 scans per person vs. .62 scans per person).

Table 3 shows the main results for the association between EHR (+) and throughput time. When we control only for time and location effects, EHR (+)

Table 2: Classification by NYU ED Categories

	EHR (−)	*EHR (+)*	*p-Value*
Psychiatric	0.041 [0.199]	0.036 [0.186]	.157
Drugs/alcohol	0.077 [0.267]	0.044 [0.206]	.000
Injury	0.257 [0.437]	0.102 [0.303]	.000
Non-emergent	0.156 [0.298]	0.204 [0.323]	.000
Emergent, pc treatable	0.155 [0.204]	0.218 [0.218]	.000
ED care needed, avoidable	0.043 [0.171]	0.063 [0.205]	.000
ED care needed, unavoidable	0.223 [0.322]	0.277 [0.324]	.000
N	3,236	6,734	

predicts an *increase* in total throughput time of 50 minutes. However, once we control for patient demographics, other predetermined characteristics, and encounter-specific variables, the association falls to a positive 23 minutes. Lastly, when we include current measures of patient conditions and acuity, the relationship between EHR (+) and throughput time vanishes to a statistical 0 percent ([−0.7, 6.0]). We interpret this as evidence that EHR (+) patients are more chronically ill than EHR (−) patients since controlling for characteristics that proxy for health status erases the positive relationship between access to EHRs and total throughput time. We then interpret the coefficient on EHR status in the most comprehensive specification—0 minutes—as an upper bound for the treatment effect. Analysis of the full sample of patients exhibits a similar pattern across specifications with the upper bound for treatment only slightly higher at 13 minutes.

In Table 4, we further assess if our estimate is insensitive to the way in which the diagnostic codes are grouped. When replacing ICD9 codes with NYU categories or replacing primary ICD9 codes with secondary ICD9 codes, the relationship between EHR (+) and throughput time hovered around a statistically insignificant positive 2 percent. When the subsample was further restricted to injured patients or excluded psychiatric or substance abuse patients from the sample, the association between EHR (+) and throughput time is similarly indistinguishable from 0. These consistently null results corroborate the estimates in the main sample, which suggest that the

Table 3: Association between EHR (+) and ED Length of Stay (LOS)

	(1)	*(2)*	*(3)*
Ambulance pts. (n = 9,933)			
EHR (+)	50.2***	23.3***	10.2
	(5.3)	(6.7)	(6.9)
	[39.7, 60.6]	[10.1, 36.6]	[−2.7, 23.1]
R^2	.0437	.1424	.2846
Full sample (n = 43,914)			
EHR(+)	50.2***	29.7***	13.1***
	(2.4)	(2.8)	(2.3)
	[45.5, 54.9]	[24.2, 35.2]	[8.5, 17.7]
R^2	.0869	.1888	.4019
Day, month, hour	Yes	Yes	Yes
Location	Yes	Yes	Yes
Age	No	Yes	Yes
Sex	No	Yes	Yes
Caseload	No	Yes	Yes
Insurance codes	No	Yes	Yes
Primary care zip codes	No	Yes	Yes
Attending physician	No	Yes	Yes
ICD9 codes	No	No	Yes
Acuity	No	No	Yes
Procedure	No	No	Yes
Admission status	No	No	Yes

Note: Each model is adjusted for patient covariates as indicated. The units of the estimated effects are in minutes. Standard errors, clustered at the day-site level, are in parentheses.
*p < .05, **p < .01, ***p < .001. 95% CIs are in brackets.

availability of EHRs has no effect on throughput time for the study sample. Estimates on the full sample of patient visits hover around a positive 3 percent.

Table 5 presents analogous results for the association between EHR (+) and the use of advanced imaging examinations. The OLS estimates indicate that EHR(+) patients experience a reduction in CT scans of .075 per patient, a decline of 13.9 percent ([4.9, 23.0], $p < .01$) of the mean. We do not observe any statistically significant relationship between EHR status and ultrasounds or MRIs. However, EHR(+) patients also experience a suggestive decrease in total imaging examinations by .076, which suggests that all the imaging examination reductions are driven by reduced use of CT scans. CT scans are run most frequently in the ED. To the extent that "bottlenecking" occurs, this finding is consistent with the hypothesis that physicians are more likely to ration the use of CTs according to whether they can access prior test results. When walk-in patients are included, the estimates are nearly identical for all forms of

Table 4: Sensitivity Analysis: Association between EHR (+) and ED Length of Stay (LOS)

	(1)	(2)	(3)	(4)
Ambulance pts.	(n = 9,933)	(n = 9,933)	(n = 1,513)	(n = 9,015)
EHR (+)	13.0*	9.7	2.2	10.9
	(6.3)	(6.6)	(16.9)	(6.8)
	[0.5, 25.4]	[−3.2, 22.6]	[−29.8, 36.7]	[−2.5, 24.2]
R^2	.2385	.2833	.4789	.2953
Full sample	(n = 43,914)	(n = 43,914)	(n = 5,650)	(n = 42,106)
EHR (+)	13.3***	13.2***	5.6	12.6***
	(2.3)	(2.3)	(5.8)	(2.3)
	[8.7, 17.9]	[8.6, 17.8]	[−5.8, 16.9]	[8.2, 17]
R^2	.3682	.3997	.4999	.4099
NYU ED algorithm	Yes	No	No	No
Secondary ICD9 codes	No	Yes	No	No
Injuries only	No	No	Yes	No
Psych/substance abuse pts.	Yes	Yes	No	No

Note: Subsample used for each model is indicated above. All models are adjusted for time of visit, location, age, sex, caseload, ICD9 codes, case complexity, insurance codes, zip codes of primary care physicians, attending physician, acuity, procedures, and admission status. The units of the estimated effects are in minutes. Standard errors, clustered at the day-site level, are in parentheses. *p < .05, **p < .01, ***p < .001. 95% CIs are in brackets.

imaging other than for CT scans, where the estimated reduction falls to 5.4 percent ([1.9, 9.3], $p < .001$) of the mean.

Lastly, Table 6 provides a sensitivity analysis for the use of CT scans. We find that the estimated reduction in CT scans is similarly invariant to the use of the NYU ED algorithm, secondary ICD9 codes, restrictions to injured patients only, and the exclusion of psychiatric and substance abuse patients from the study sample. The estimated reduction in CT scans for EHR(+) patients is bounded between 8.8 and 18.4 percent for all of these specifications and samples. In the full sample, the estimated reduction in CT scans is bounded between 4.3 and 10.3 percent for EHR (+) patients.

CONCLUSIONS

As is the case with many studies that are without a source of randomly assigned variation in treatment, we cannot conclude that the relationship between the availability of EHRs and our outcome measures is causal. Though we control for other patient-level covariates and comorbidities that

Table 5: Association between EHR (+) and Number of Advanced Imaging Examinations

	(1) *Total Imaging*	(2) *CT Scans*	(3) *Ultrasound*	(4) *MRI Scans*
Ambulance pts. (n = 9,933)				
EHR (+)	−0.0764	−0.0747**	−0.0130	0.0019
	(0.0478)	(0.0248)	(0.00937)	(0.00943)
	[−0.17, 0.02]	[−0.12, −0.03]	[−0.03, 0.01]	[−0.02, 0.02]
R^2	.3670	.3376	.2035	.1514
Full sample (n = 43,914)				
EHR (+)	−0.0760***	−0.0292***	−0.0100*	0.0018
	(0.0168)	(0.0080)	(0.0045)	(0.0036)
	[−0.04, −0.10]	[−0.01, −0.05]	[−0.001, −0.019]	[−0.005, 0.009]
R^2	.3690	.2793	.1953	.1169

Note: All models are adjusted for time of visit, location, age, sex, caseload, ICD9 codes, case complexity, insurance codes, zip codes of primary care physicians, attending physician, acuity, procedures, and admission status. Standard errors, clustered at the day-site level, are in parentheses. *p < .05, **p < .01, ***p < .001. 95% CIs are in brackets.

Table 6: Sensitivity Analysis: Association between EHR (+) and Number of CT Scans

	(1)	(2)	(3)	(4)
Ambulance pts.	(n = 9,933)	(n = 9,933)	(n = 1,513)	(n = 9,015)
EHR (+)	−0.0986***	−0.0797***	−0.0475	−0.0858***
	(0.0251)	(0.0244)	(0.0864)	(0.0268)
	[−0.15, −0.05]	[−0.13, −0.03]	[−0.22, 0.12]	[−0.14, −0.03]
R^2	.2107	.3465	.5149	.3585
Full sample	(n = 43,914)	(n = 43,914)	(n = 5,650)	(n = 42,106)
EHR (+)	−0.0556***	−0.0365***	−0.0232	−0.0379***
	(0.0085)	(0.0080)	(0.0293)	(0.0081)
	[−0.07, −0.04]	[−0.05, −0.02]	[−0.08, 0.03]	[−0.05, −0.02]
R^2	.1727	.2884	.4707	.2976
NYU ED algorithm	Yes	No	No	No
Secondary ICD9 codes	No	Yes	No	No
Injuries only	No	No	Yes	No
Psych/substance abuse pts.	Yes	Yes	No	No

Note: Subsample used for each model is indicated above. All models are adjusted for time of visit, location, age, sex, caseload, ICD9 codes, case complexity, insurance codes, zip codes of primary care physicians, attending physician, acuity, procedures, and admission status. Standard errors, clustered at the day-site level, are in parentheses.
*p < .05, **p < .01, ***p < .001. 95% CIs are in brackets.

can plausibly influence throughput times and number of imaging examinations administered, we are still merely making a cross-sectional comparison. A more convincing study design would be a before-and-after study that introduces EHR and compares change in outcomes for those before and after the change. However, even this approach can be hampered by other changes that may occur in the before and after time frame.

Another limitation of the study is that EHR (+) patients tend to be less healthy than EHR (−) patients: Since an EHR could have only been generated provided that the patient had a prior encounter at one of the clinics or EDs affiliated with the study institution, we expect that the EHR (+) group is more chronically ill than is the EHR (−) group. However, this biases our results toward finding a positive association between EHR availability and throughput time. We do partially correct for this confound by controlling for case severity and diagnostic codes, but the residual variation in treatment efficiency may not be entirely purged of this bias. Another bias that works in the same direction is that all patients with at least one prior encounter are assigned to the EHR (+) group, even if the depth of information provided in the record is minimal and of little utility. Because these biases work against our finding a reduction in throughput time and imaging examinations among EHR (+) patients, we interpret our results as a conservative estimate of the true effect.

Lastly, the findings in this study may only be applicable to this single Health System ED, ambulance patients, and to this particular EHR.

DISCUSSION

Our estimates of the effect of availability of EHRs on throughput time remained small and positive or null across all specifications. We have also found that the availability of EHRs is associated with a reduction in CT scans by 13.9 percent [resulting in charge cost savings of $22.52 per patient encountered], but it has no relationship with the number of MRI scans, ultrasounds, or other forms of imaging examinations. This finding makes sense in light of the fact that CT scans are among the most common type of advanced imaging technology used in EDs.

These results are consistent with a study by Tzeel et al. (2011), which found that access to patient EHRs through a Health Information Exchange system led to reductions in CT scans. Weiner et al. (2003) and Carr et al. (2014) similarly demonstrate that access to prior test results can reduce future orders of such tests. Our primary contribution is to show that these results are also present when including a thorough set of patient-level controls and alternate groupings of such controls, which reduces concerns that the relationship is purely associational. For example, unlike other studies evaluating the utility of health information technology, we were fortunate enough to have detailed enough data to control for physician-specific effects and the severity of the presenting conditions.

Moreover, our treatment variable does not consider whether a physician actually queries the EHRs but instead only considers whether such a record is available. However, this is a more conservative approach as compared to other studies since physicians are more likely to query an EHR whenever they think it would be helpful. Thus, our results provide an estimate of the average per-patient value of having an EHR, which may be of more policy relevance than prior estimates found in the literature.

Beyond the cost savings associated with reduced utilization of CT scans, there is the potential added benefit of reduced exposure to ionizing radiation (Brenner et al. 2003; Brenner and Hall 2007; Tubiana, Nagataki, and Feinendegen 2008). Hence, the 13.9 percent reduction in CT scans highlights a potential long-term health benefit attributable to EHR availability.

Despite broad deployment of EHR systems, there is only limited evidence of its utility. In this article, we add to that evidence by highlighting the possible time savings and demonstrated imaging examination reductions associated with the availability of Electronic Health Records. Integrated EHR systems, such as Health Information Exchange (HIE), will allow for independent providers to exchange patient information at the point of care. While this study provides a glimpse into the potential benefits that can arise from an integrated EHR system, future studies of the impact of a fully integrated system on costs and outcomes are certainly merited as the American Reinvestment and Recovery Acts and Affordable Care Acts continue to provide large sums of money to finance the establishment of such systems.

ACKNOWLEDGMENTS

This is an unfunded study to which all authors volunteered their own time.

The authors would like to sincerely thank Julie Cullen, Eli Berman, and Jeffrey Clemens for their continued feedback and support.

Joint Acknowledgment/Disclosure Statement: Each author declares that he has no relevant or material financial interests that represent a conflict of interest with respect to the results of the research described in the manuscript. All co-authors were employed by the University of California, San Diego, who paid our salaries while we conducted the research. David Guss, Theodore Chan, and Edward Castillo were directly employed by the UCSD Emergency

Department while Matthew Knepper was employed as a Teaching Assistant in UCSD's Department of Economics. Additionally, the corresponding author, Matthew Knepper, switched employers in August of 2015 when he began working for the Bureau of Economic Analysis (BEA) upon graduating from his PhD program. Thus, the BEA also paid him a salary while he worked on the project, though the lion's share of the work had been completed prior to the job transition.

As an employee of the Bureau of Economic Analysis, the corresponding author has provided a copy of the manuscript to his Associate Director, who may vet the paper to ensure that no particular policy stance has been supported by its employees. However, this policy is in place in order to protect the perceived objectivity of the Bureau of Economic Analysis as an extension of the federal government. Results are never withheld, only normative policy opinions that might compromise the objectivity of the Bureau of Economic Analysis. Below I list all other relevant disclosures.

Prior Dissemination: Conference Presentation: 2014 Society of Academic Emergency Medicine Meeting, Date: May 16, 2014, Location: Dallas, TX.

Disclosures: None.

Disclaimers: The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Bureau of Economic Analysis (BEA).

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Supporting Information

Additional supporting information may be found online in the supporting information tab for this article:

Appendix SA1: Author Matrix.