Health Information Technology and Patient Safety: Evidence from Panel Data

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Health information technology (IT) will likely play a prominent role in upcoming policy initiatives. While health IT value is well documented in leading academic institutions, its national value remains indeterminate. We studied this issue by estimating the effect of health IT on key patient safety measures with national data. Using four years of Medicare inpatient data we find that EMR has a positive but small effect on patient safety; although, the effect does grow with time. While these results are encouraging, we suggest that health IT spending be accompanied by investment in the evidence base needed to evaluate this technology.
Introduction and Background

Health information technology (IT) investment has emerged as an early Obama administration priority. The proposed economic stimulus package includes $20 billion of 2009 health IT spending. During President Obama’s 2008 presidential election campaign, a $50 billion health IT spending program was proposed. These policy prescriptions build on nearly ten years of advocacy from policymakers, purchasers, medical providers. The Institute of Medicine (IOM) issued an early call for increased health IT utilization to improve patient safety. The IOM further argued that health IT may reduce costs by improving care delivery efficiency.\(^1\) Similarly, Hillestad and colleagues estimate that health IT may yield savings in excess of $142 billion per year.\(^2\)

For all of the acknowledged impact of electronic medical records (EMR), there is limited evidence linking such technology to specific improvements in health outcomes at a national level. Studies have repeatedly demonstrated the correlation between health IT and clinical quality. Notable reviews include: Kuperman and Gibson, Kaushal and colleagues, Garg and colleagues, and Chaudhry and colleagues.\(^3\) Overall, these studies conclude that health IT is a promising technology that can improve quality and reduce costs. Despite its potential, health IT’s true value remains uncertain. Countervailing forces may
also reduce and potentially reverse health IT’s social value. Health IT may, for example, undermine patient care through poor interface design that could increase the probability of errors, disruptions to workflow, and significant labor requirements that don’t directly contribute to patient care.\textsuperscript{4} Other studies found empirical evidence suggesting that health IT may endanger clinical quality.\textsuperscript{5}

While the literature to date provides a crucial foundation for understanding health IT and its clinical value, these studies largely constitute single-site studies at technologically and clinically advanced academic medical centers and integrated delivery systems that do not constitute the mainstream of the medical care in the United States.\textsuperscript{6}

**Empirical Approach**

Our goal was to build on the empirical literature by linking health IT implementations to clinical outcomes using a large, nationally representative source of Medicare patient data. We also observe four years of data (1999 to 2002) for each hospital. This allows us to employ a difference-in-differences approach to measure changes in patient safety with changes in health IT investments and increases our ability to make causal inferences regarding health IT and patient safety for all types
of medical intuitions, not only industry leaders. The empirical approach is further described in Appendix 1.

We analyze three health IT applications: EMR, nurse charts, and PACS. These technologies were selected because they diffused rapidly during our study period and likely affected patient safety. We characterize an EMR as a computerized patient record supported by a clinical data repository and providing clinical decision support capabilities. EMRs are designed to replace traditional paper records and serve as a basic repository of medical information. Nurse chart applications facilitate the creation, modification, and evaluation of patient care plans. Finally, PACS applications automate imaging for multimedia review and provide image retrieval, routing, display, and archiving capabilities. Our data source tracks EMR components independently (and separately from clinical notes, nurse charting, etc.), thus facilitating a more standardized definition of EMR than is typically available from secondary data.

Patient safety indicators (PSIs) are our outcome measures. We focus on three PSIs: infection due to medical care, postoperative hemorrhage or hematoma, and postoperative pulmonary embolism or deep vein thrombosis (DVT). PSI selection was based on two criteria. First, we consulted with clinical experts to
identify outcomes that health IT was likely to influence. Second, we selected relatively frequent events.

We also control for patient characteristics, including age at admission, gender, race, and a risk score. Higher risk scores indicate more complicated cases.

We measured the effect of health IT on patient safety using multivariate regression. In particular, we measured the relationship between each PSI and a set of patient controls, health IT indicators, and interactions between health IT applications and time; this allowed the affect of health IT to change with time. We also included a full set of hospital and time fixed effects; consequently, we estimated the change in outcomes that followed health IT adoption. We separately estimated models for each PSI at the admission level.

Results

Our results show that EMRs are the only health IT applications to have a clear and statistically significant effect on patient safety (marginal effects of health IT are shown in Table 1 of the appendix). Specifically, EMR utilization is associated with reduced infections due to medical care. We observe that EMR became more effective with each passing year, suggesting that hospitals were either improving their EMR implementation (e.g., care guidelines, training, improved interface, etc.) or that EMR technology itself was improving.
While this result is promising, it is small, constituting only about 2 averted infections per year at an average hospital. Furthermore, EMR affected neither the deep vein thrombosis PSI nor the hemorrhage PSI. Neither PACS nor nurse chart applications had a systematic relationship with any PSI. The EMR and nurse chart applications each had one positive and significant health IT-by-year interaction effect. In the absence of a significant baseline effect, these coefficients simply describe deviations from the baseline health IT effect which is not significantly different from zero.

**Discussion and Policy Implications**

This analysis advances the understanding of health IT value by estimating an average benefit of health IT using a national inpatient sample. We find little evidence that health IT improved quality. While EMR was associated with reduced infection rates, the effect was small and no effect was found for other applications and outcomes. There was, however, evidence that EMR’s value grew with time. Although these results are interesting, they face important limitations further discussed below and in the appendix. It remains to be seen whether newer technologies such as CPOE have substantially improved outcomes. Below we discuss the context of our findings with respect to previous related research, explanations for some
of the non-effects of health IT, limitations of our approach and policy implications.

Previous research developed health IT value estimates largely based on extrapolation from single-site studies. This approach has many desirable features as it is based on detailed studies with specific knowledge of health IT applications and patient characteristics. Our research suggests that early adopters (i.e., leading academic medical centers) are high quality and likely have better than average outcomes. Consequently, we propose health IT value measures based on actual experiences from a national sample of hospitals and patients. While our approach provides the foundation for improved health IT valuation we do not purport to refute or replace previous studies. This study provides tentative evidence of a positive causal relationship between health IT and clinical quality. This methodological approach builds on Parente and Vanhorn’s study demonstrating the potential for use of Medicare claims data to assess health IT’s effect on costs.¹⁰

Our finding that EMR reduces infections due to medical care seems reasonable. Typically, EMR systems allow healthcare providers to better track patient care – a crucial tool when so many disparate providers must be coordinated to provide high quality medical care. EMR also integrates different clinical
data feeds for later analysis to identify how medical care processes prevent or cause medical errors.

Our lack of significant relationships for other technologies and PSIs are harder to interpret. They may reflect a poorer match between intervention and outcomes or even suggest that these technologies have little value. There is also a statistical explanation for these non-findings. The sample size associated with infections during medical care is much greater than those of the other PSIs. Across all four years, 10,157,940 admissions were analyzed to identify the effect of health IT. For post-operative pulmonary embolism there were only 1,751,094 admissions eligible for analysis and the frequency of post-operative hemorrhages was far less, with only 682 events identified in the Medicare population in 2000.

One of the most notable limitation our study faces is difficulty in addressing time-varying, unobserved heterogeneity correlated with health IT adoption. Inasmuch as hospitals make other, unobserved, quality improving initiatives when they adopt health IT, we will overestimate health IT value. This concern is, however, mitigated by several factors. First, many hospitals implemented health IT to forestall Y2K problems. Second, health IT adoption was spurred by the first IOM report, To Err is Human.\textsuperscript{11} This report emphasized health IT’s potential to improve clinical quality. Third, adoption was spurred by HIPAA-
compliance preparations, although, these laws were not in full effect until 2003. These three events constitute an exogenous shock to health IT adoption, suggesting that this period is a particularly appropriate time to implement a difference-in-differences identification strategy (see Athey and Stern, for a more detailed discussion of the relevant technology diffusion and econometric identification issues).12

While we find some value in large scale health IT investment, our results are tempered by limitations in patient safety metrics observable from administrative data. Infections and hemorrhages are examples of important patient safety measures, but so are many other outcomes such as adverse drug events. This illustrates a serious problem with the existing evidence base; namely, that nationally available patient safety metrics are less than comprehensive. Thus researchers are left with a choice of potentially detailed data with limited samples (e.g., single-site studies) or incomplete outcome measures with large samples. In either case, the evidence base is not yet sufficient to draw definitive conclusions about the value of health IT in improving health care quality and outcomes. This should strongly suggest to health IT enthusiasts that any new investment should be accompanied by rigorous evaluation and investment in the evidence base needed for further evaluation. This conclusion supports the role of a comparative effectiveness
institute to examine the value to society of future public-sector health IT investment.

Administrative data may form the basis for part of this evaluation infrastructure. The PSIs created by AHRQ were an important initial investment, but this issue demands far greater attention. One solution could be to use the federal investment to develop an IT infrastructure that supplements administrative data with clinical information.
Notes


4. J.S. Ash, M. Berg, and E. Coira. “Some Unintended Consequences of Information Technology in Health Care: The
Nature of Patient Care Information System-Related Errors, ”
Journal of the American Medical Informatics Association 11,
no. 2 (2004): 104-112; R.G. Berger, and J.P. Kichak,
“Computerized Physician Order Entry: Helpful or Harmful?”
Journal of the American Medical Informatics Association 11,
no. 2 (2004): 100-103 and R. Koppel, et al., “Role of
Computerized Physician Order Entry Systems in Facilitating
Medication Errors,” Journal of the American Medical

Consequences Related to Computerized Provider Order Entry,
” Journal of the American Medical Informatics Association
of Adverse Drug Events in a Highly Computerized Hospital,”
Archives of Internal Medicine 165, no. 10 (2005): 1111-
1116.

6. Note that a few studies examined multihospital settings.
For example, S. Devaraj and R. Kohli, “Information
Technology Payoff in the Health-Care Industry: A
Longitudinal Study,” Journal of Management Information
Systems 16, no. 4 (2000): 41-67, investigated the effect of
health IT on 30-day post-operative mortality using patient-
specific information. They employed data from an eight-
hospital system over 36 months. K. Lee and T.T. Wan.

7. As a practical matter, we can only generate precise measures of health IT value for applications that diffuse rapidly during our study period. While applications like computerized physician order entry (CPOE) are interesting, they are rare and diffuse slowly during; thus, we cannot measure their value.

8. K. Fonkych and R. Taylor, The State and Pattern of Health Information Technology Adoption (Santa Monica, Calif.: RAND Corporation, 2005). Clinical decision support in HIMSS refers to ex post clinical data analysis capabilities rather than real time decision support features associated with computerized physician order entry (CPOE) applications.

9. Application definitions are based on the 2001 HIMSS data documentation published by Dorenfest, S.I. “The Third Dorenfest Complete Integrated Healthcare Delivery System+


Appendix – Empirical Approach

Data

We measure health IT value by combining hospital- and patient-level data during 1999-2002. Our primary clinical data source, the 100% MedPAR inpatient Medicare claims data file, provides patient-specific outcomes and severity adjustment measures for all Medicare inpatient admissions in our study period. The Healthcare Information and Management Systems Society (HIMSS) Analytics Database provides detailed hospital IT adoption data for a variety of applications including electronic medical records (EMR), nurse charts, and picture archiving communications systems (PACS). HIMSS Analytics comprises a near census of acute care, urban, nonfederal US hospitals.¹ These data are further combined with the American Hospital Association’s (AHA’s) annual survey which describes hospital characteristics. These data form a balanced panel of 2,707 hospitals serving over 80 million patients during 1999-2002.

We analyze three health IT applications: EMR, nurse charts, and PACS.² These technologies were selected because they diffused rapidly during our study period and likely affected patient safety. Following Fonkych and Taylor’s definition, we characterize an EMR as a computerized patient record supported by a clinical data repository and providing clinical decision
support capabilities. EMRs are designed to replace traditional paper records and serve as a basic repository of medical information. Nurse chart applications facilitate the creation, modification, and evaluation of patient care plans. Finally, PACS applications automate imaging for multimedia review and provide image retrieval, routing, display, and archiving capabilities. The HIMSS data track EMR components independently (and separately from clinical notes, nurse charting, etc.), thus facilitating a more standardized definition of EMR than is typically available from secondary data.

Patient safety indicators (PSIs) are our outcome measures. They are constructed from MedPAR data using Agency for Health Research and Quality’s (AHRQ’s) algorithms. These metrics were based on patient safety measures introduced by Zhan and Miller. We focus on three PSIs: infection due to medical care, postoperative hemorrhage or hematoma, and postoperative pulmonary embolism or deep vein thrombosis (DVT). PSI selection was based on two criteria. First, we consulted with clinical experts to identify outcomes that health IT was likely to influence. Second, we selected relatively frequent events.

We also control for patient characteristics. Each of the models estimated below include age at admission, gender, race, and a risk score. The risk score is computed from the average allowed cost weight by DRG and centered on one. For example, a
patient with a risk score of 2.57 would be a more complicated case than a patient with a score of 0.8.

**Analysis & Results**

We perform multivariate analyses to measure the effect of health IT on patient safety. We regress each PSI on a set of patient controls, health IT indicators, and interactions between health IT applications and time. This specification allows the affect of health IT to change with time. We also include a full set of hospital and time fixed effects; consequently, we estimate the change in outcomes that follows health IT adoption. We separately estimate linear probability models for each PSI at the admission level.

We perform both bivariate and multivariate analyses. Our main dependent measure is the status of a PSI. Each of the PSI dependent variables is a binary variable equal to 1 if an adverse event occurred and zero otherwise. Control variables include patient age, gender (female=1, else=0), race (non-white=1, else 0), risk score, and year of admission. Our primary health IT variables are a set of three binary indicators for the presence of EMR, nurse charting, and PACS applications respectively. These health IT variables were lagged by one year to reflect anecdotal evidence and expert interviews indicating that health IT value is realized one or more years subsequent to
adoption. We also recognize that health IT value may change with time through unobserved learning and innovation. Consequently, we include a set of nine health IT-by-year interaction terms allowing health IT to have a different affect in each year. These terms are interactions of the binary health IT application variables with binary indicators for the years 2000, 2001, and 2002 respectively.

Finally, we control for unobserved hospital attributes by including hospital-specific fixed effects. This creates over 2,700 binary variables, one for each hospital in the study. These fixed effects control for hospital attributes that are stable across time such as bed size and patient case load as well as idiosyncratic factors associated with each hospital. Most importantly, this design controls for unobserved time-invariant quality differences. Essentially, this specification controls for some types of selection in the health IT adoption process. If, for example, high quality hospitals are early adopters, our identification strategy provides causal estimates. If, on the other hand, health IT adopters make other, unobserved, quality-enhancing changes (i.e., hiring more nurses, staff training, etc.) when they adopt health IT, then we would overestimate health IT value. It is important to note that in the absence of fixed effects we find that health IT is strongly correlated with improved outcomes. Essentially, we find that
early adopters are otherwise high quality hospitals and that cross-sectional estimates suffer from selection bias.

As noted in the article, time varying unobserved heterogeneity is a potential problem when correlated with health IT adoption. This is not, however, a problem if such correlated patient safety initiatives were specifically designed to complement health IT. These would, in effect, be part of the policy-relevant outcome from increased health IT adoption.

We also recognize that separate admissions within hospitals are not independent observations. Unobserved attributes (time varying and otherwise) will be correlated across patients at the same hospital. Consequently, we allow for correlation in errors by hospital both across observations and across time (Bertrand, Duflo, and Mullainathan discuss these issues for a similar situation). We also estimate robust standard errors to account for the use of a linear estimator on nonlinear data. Ultimately, these techniques overestimate our standard errors making our measures of significance conservative.

This approach and the size of our sample led to substantial computational burdens for the estimation of linear probability models. Our approach does, however, advance the literature and has attractive features such as the inclusion of a control sample, including patient characteristics such as severity of illness, allowing health IT value to have a lagged effect, and
allowing for vintage- or time-dependent health IT value. Finally, by using hospital fixed effects, the complaint that each hospital has a unique burden, mission, clinical caseload, culture, geography and financial position, could be taken into account.

Appendix Notes


2. As a practical matter, we can only generate precise measures of health IT value for applications that diffuse rapidly during our study period. While applications like computerized physician order entry (CPOE) are interesting, they are rare and diffuse slowly during; thus, we cannot measure their value.

3. K. Fonkych and R. Taylor, The State and Pattern of Health Information Technology Adoption (Santa Monica, Calif.:
RAND Corporation, 2005). Clinical decision support in HIMSS refers to ex post clinical data analysis capabilities rather than real time decision support features associated with computerized physician order entry (CPOE) applications.


7. Note that we explore Bonferroni and Holm-Bonferroni corrections to our significance tests as we estimate our model with three separate dependent variables. This proves to be relevant for the baseline effect of EMR on infections due to medical care which, under a direct application of these techniques exceeds the 0.05 significance threshold by 0.0079. While this may appear discouraging, we believe it is not the
appropriate comparison for two reasons. First, our standard errors are upward biased as discussed in this appendix. Second, these significance test corrections do not incorporate the pattern of parameter values across coefficients.

**Table 1**

Year-specific and system-specific effect of Health IT on patient safety indicator, adjusted by patient risk and hospital specific attributes (per 1,000 admission)

<table>
<thead>
<tr>
<th></th>
<th>IT in all Years</th>
<th>Year-specific IT Impact</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>2000</td>
</tr>
<tr>
<td>Infection due to Medical Care</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electronic Medical Records</td>
<td>-0.2912**</td>
<td>-0.0134**</td>
</tr>
<tr>
<td>PACS</td>
<td>-0.3056</td>
<td>-0.1010</td>
</tr>
<tr>
<td>Clinical/Nursing IT</td>
<td>-0.0053</td>
<td>-0.0331</td>
</tr>
<tr>
<td>Post-operative Hemorrhage or Hematoma</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electronic Medical Records</td>
<td>0.0503</td>
<td>0.0866</td>
</tr>
<tr>
<td>PACS</td>
<td>-2.2799</td>
<td>-0.0079</td>
</tr>
<tr>
<td>Clinical/Nursing IT</td>
<td>-0.0213</td>
<td>0.0717</td>
</tr>
<tr>
<td>Postoperative Pulmonary Embolism or DVT</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electronic Medical Records</td>
<td>0.0870</td>
<td>0.3299</td>
</tr>
<tr>
<td>PACS</td>
<td>2.3452</td>
<td>0.3784</td>
</tr>
<tr>
<td>Clinical/Nursing IT</td>
<td>0.1933</td>
<td>-0.2254</td>
</tr>
</tbody>
</table>

*denotes significance at alpha=0.10, ** at alpha=0.05, and *** at alpha=0.001

Note: Health IT effects are lagged one year.

**Notes to table 1:** The first column describes the baseline effect for each technology on its respective PSI. Subsequent columns present year-specific deviations in the effect of health IT on patient safety.
Acknowledgements

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