

*Grant Final Report*

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**The Impact of Health Information Technology on  
Demand for Inpatient Services**

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# Abstract

**Purpose:** This health information technology (IT) demand analysis complements the existing supply-side research, allowing for a more complete understanding of the impact of health IT on health care markets.

**Scope:** The data for this study includes 100% of Medicare's fee-for-service inpatient admissions for beneficiaries over age 65 from 1999-2006 from the MedPAR file. Hospital characteristics were obtained from American Hospital Association Annual Hospital Survey. Hospital health IT system information is from the HIMSS/Dorenfest Integrated HEALTH CARE DELIVERY SYSTEM PLUS (IHDS+) DATABASE™. The impact of three technologies is evaluated: 1) Picture Archive and Communication System 2) Computerized Physician Order Entry and 3) Electronic Medical Records.

**Methods:** Discrete choice analyses are used to model patients' choices with the underlying assumption that patients are making a utility maximizing decision. A linear market share model provides mean effects of health IT at a national level. Patient-level models which include interactions of patient characteristics and health IT are estimated for a subset of hospitals and diagnoses in the mid-western U.S. A panel data structure including hospital fixed effects is used to identify the impact of health IT on demand while controlling for the endogeneity of hospitals health IT adoption decisions.

**Results:** The health IT variable and interaction terms are jointly significant in some specifications, in both the market level and individual choice models, and expected consumer surplus is positive but health IT is not found to have a large impact on overall hospital demand.

**Key Words:** health information technology, discrete choice models, hospital demand

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# Final Report

## Purpose

The nation's largest Health Information Technology (IT) advocate, the Office of the National Coordinator of Health IT, has stated that health IT will build a healthier future for our nation through cost reductions, efficiency improvements in the delivery of health care and most importantly by saving lives (ONC, 2011). Many proponents of health IT believe that overwhelming supply-side cost reductions from increased quality of care and improvements in the efficiency of health care delivery will more than make up for the costs of health IT investment. Indeed, the more integrated and interoperable the systems are the greater the expected benefits. Some have estimated billions of dollars in potential savings (Hillestad et al., 2005); others' estimates are more modest but predict cost savings none the less. All of this support for health IT investment has resulted in a flurry of activity to evaluate the diffusion process, develop standards for the integration of systems, fund demonstration projects and measure quality improvements. A vital element of health IT implementation which has been overlooked in the rush to evaluate health IT is the demand-side effect. Many of the cost implications and obviously the quality effects will only be achieved if patients are treated where there are health IT systems. Knowledge of patient demand for health IT is vital for informing health IT infrastructure development. We address this gap in the literature by empirically testing for changes in the demand for hospital inpatient services related to the adoption of three types of health IT systems: electronic medical records (EMRs), computerized physician order entry (CPEO) and picture archiving systems (PACS); from the empirical models we are able to calculate the magnitude of the impact as well as the welfare implications.

## Scope

### Background

Very little research exists regarding health IT demand while the body of research on health IT adoption and quality is growing rapidly. The factors influencing adoption and the barriers to adoption are a major research focus as health IT proponents look for ways to increase adoption. Research to date includes case studies of specific health IT systems within hospitals as well as broad overviews of the state of health IT in the U.S. Two studies by the RAND Corporation (Fonkych and Taylor, 2005; Bower, 2005) found that as of 2005 the rate of adoption was increasing but the overall level was still low; hospital adoption of electronic medical record systems was between 20 and 30 percent. There was also large variation in adoption rates related to size, not-for-profit status, and patient mix. Not-for profit hospitals with higher shares of Medicare and Medicaid patients had lower adoption rates. Managed care patient concentration was correlated with an increased probability of adoption (Fonkych and Taylor, 2005). Parente and Van Horn (2006) concluded organizations behave in ways consistent with the organization's

motives. For-profit hospitals adopt IT to reduce a patient's length of stay while not-for-profit hospitals adopt health IT to increase the quantity of services provide. However, McCullough (2007) did not find an effect of for-profit status on the probability of adoption. McCullough (2007) also identifies a decreasing effect of hospital scale on the probability of adoption throughout the 1990's unlike Wang et al. (2005) and Fonkych and Taylor (2005).

Another body of literature evaluating the effects of health IT on quality has found limited, positive effects of health IT but, the generalizability of these studies is unclear. A 2006 systematic review of health IT studies found that approximately 25% of studies included in the review were from 4 academic institutions. Of the remaining studies very few evaluated commercially available systems. Clinical decision support (CDS), CPOE, and electronic health records (EHRs) were the three systems most often evaluated in the literature. Although interoperability is the feature often cited as the key to improving quality and reducing costs, only 1% of the systems out of 257 articles had interoperable capabilities. In general the review found three major benefits of health IT on quality: increased adherence to guideline-based care, enhanced disease surveillance and monitoring, and fewer medication errors (Chaudhry et al., 2006). In 2009 Goldzweig et al. published an update to a 2006 literature review using publications from 2004-2007 and found some trends in health IT studies have changed; the proportion of studies from health IT leaders had decreased, studies of commercial (off the shelf systems) had increased, and in general the publication rate of health IT studies had increased to 179 from 2004-2007 compared to the 256 in the previous 10 year period. Even though the number of publications greatly increased, they found no more substantial research in the area of the cost-benefit analysis of health IT. Some other recent studies highlight the mixed quality findings. Furukawa (2006) found mixed effects of EMRs in emergency departments. Sophisticated EMRs were found to decrease length of stay and reduce treatment times depending on the types of services being delivered but emergency departments with no system were just as efficient as those with a with an EMR with minimal functionality. McCullough et al. (2010) found adoption of EMR and CPOE led to improvements in 2 of the 6 process quality indicators they evaluated. The positive results were larger in academic institutions. McCullough and Parente (2009) found small but positive effects of EMR on patient safety but there was no effect for nurse charting systems or PACS.

This research addresses the need for more research to bridge the demand-side gap in the health IT literature using models of patient hospital choice based in consumer choice theory. There is a large literature spanning health services, marketing, economics, and medical journals related to hospital choice research. Conditional and multinomial logit models have become more common as better data has become available and computing capabilities have improved (Porell and Adams, 1995). These models are characterized by the ability to incorporate the consumer's characteristics as well as the characteristics of all of the consumers' potential choices into the model. More recent econometric advances in the area of discrete choice models of differentiated product markets have also been applied to hospital choice research to study hospital behavior. Multiple research papers have used hospital choice analysis in studies of hospital competition and analysis of the welfare effects of hospital competition (Kessler and McClellan, 2000; Town and Vistnes, 2001; Gaynor and Vogt, 2003; Ho, 2006).

The results of discrete choice modeling techniques are consistent with early hospital choice results; mainly that hospital choice is driven largely by location. Researchers have also investigated the effect of factors other than distance to the hospital that could feasibly affect the choice of a hospital. Hospital charges and quality of care are some of the hospital characteristics

specified also includes  $\xi_j$ , an unobserved, time invariant mean valuation of hospital  $j$  which includes patients and physicians perceptions of hospital quality and reputation;  $\tau_t$  is an unobserved time varying constant which capture changes common to all markets and hospitals but which vary over time;  $\varepsilon_{jzt}$  is a market-time level shock to the mean valuation. The time invariant hospital effects and the time varying effects are represented by a set of hospital fixed effects and polynomial time trend variables, respectively.

**Patient Level Analysis.** The second model, again based on a random utility model, is a traditional conditional logit model. This model is estimated at the patient level and contains characteristics of the hospital choices and, through interaction terms, characteristics of patients. An indirect random utility function of patient  $i$  for hospital  $j$  in period  $t$  is given by:

$$U_{jit} = \beta_1 X_{jt} + \beta_3 X_{it} * W_{jt} + \beta_4 d_{ij} + \beta_4 d_{ij} * W_{it} + \tau_t + \xi_j + \varepsilon_{ijt} \quad (2)$$

The  $X_{jt}$  is a vector of hospital specific characteristics which vary by time period. These include hospital size measured by  $\ln(\text{hospital beds})$  and indicator variables for for-profit status and hospital system status which equal 1 if they are true and zero otherwise. Besides these hospital characteristics the  $X_{jt}$  vector will include a health IT dummy variable for one of the three technologies of interest in our study: EMR, CPOE, PACS. These health IT variables will equal 1 if hospital  $j$  has an IT system in period  $t$  and 0 otherwise.

A patient characteristics vector  $W_{it}$ , which does not vary across hospitals within a patient's choice set, would not be identified but patient characteristics might affect a patient's hospital decision. It is possible to identify the effect of patient characteristics if they are interacted with hospital characteristics, which do vary across hospitals. The interaction term  $X_{it} * W_{jt}$  includes the interaction of patient characteristics age, gender (female = 1), race (non-white = 1), severity measured by the Charlson Index, and admission type (elective admission = 1). The distance variable  $d_{ij}$  calculated as the straight line distance from the center point of a patient's zip code of residence to hospital  $j$  is also included. Distances vary across hospitals by patient zip code so the coefficient is identified as the hospital characteristics are but distance is also interacted with patient characteristics. As in the Berry model a hospital-specific fixed effect,  $\xi_j$ , will be included to account for mean differences across patients' preferences of hospitals such as perceptions of hospital quality and trends in time which vary over time but not between hospitals and may affect patient decisions are controlled for using a set of polynomial time trend variables  $\delta_t$ .

A hospital choice set for each patient is defined as the set of all hospitals within 50 miles of a patient's zip code of residence which had at least 35 admissions for that DRG group within a year. Any hospitals outside of the 50 mile radius or with fewer than 35 admissions are considered part of the outside option. The inclusion of an outside option allows for the normalization of a utility common to all patients to zero. This essentially sets the baseline for the utility parameters which can then be said to lead to increases or decreases in utility relative to the outside option. The betas in (2) are parameters to be estimated and the error term,  $\varepsilon_{ijt}$ , is assumed to be i.i.d. Type I extreme value.

that have been shown to affect hospital choice (Luft et al., 1990; Luft et al., 1991). A study of the influence of hospital and patient characteristics on rural Medicare beneficiary hospital choices found distance to a hospital was a significant factor in decisions for older patients who were more likely to choose the closest rural hospital. Complex acute medical conditions and higher socio-economic status were associated with lower use of the closest rural hospital (Tai et al., 2004). Another study found a one standard deviation increase in hospital amenities increased hospital demand by 38.5% (Goldman and Romley, 2010). Our analysis applies discrete choice methods to identify the effect of health IT on hospital demand at a market and individual level.

## Context

Patients develop perceptions of hospital quality based on news reports, advertisements and past experiences regarding health IT systems. A 2009 survey of patients' perceptions of health IT, conducted jointly by NPR, the Kaiser Family Foundation and the Harvard School of Public Health, found 67% of respondents believe that greater adoption of EMRs would improve the overall quality of care in the U.S.; 53% percent believed EMRs would reduce medical errors (Monegain, 2009). We assume patient knowledge of health IT systems results in a belief that the quality of care is improved and medication errors are reduced<sup>1</sup>. This belief should result in more patients choosing hospitals with health IT. Whether improvements in quality and reductions in medical errors actually occur is the subject of the supply-side analyses and is not as important to the decision maker in the models as the perceptions of changes in quality.

In health care decisions are not strictly made by the patients; thus, health IT affects patient choices significantly through physicians' influence too. If health IT does have quality or efficiency effects physicians should also choose hospitals with health IT for their patients. If a physician is acting as a patient's agent the physician would choose the hospital with health IT because it improves the quality of care the patient will receive. If a physician is a selfish actor the physician would choose the hospital with health IT if it reduces the administrative burden and allows the physician to provide care more efficient. Although these scenarios have significantly different implications for a patient our analysis is of demand for hospitals, measured by the number inpatient admissions, not patient satisfaction or physician acceptance of health IT. Currently the evidence of the actual effect of health IT is mixed but there are strong beliefs that health IT improves the delivery of health care. From the assumptions about patients and physicians attitudes toward health IT and hospital choice we expect to find empirical evidence of increased demand for hospitals with health IT.

In the analysis, patients' observed choices are being used to make inferences about the role of health IT on the patient's hospital choice. The patient-physician-technology interaction is implied in the decision process but is not explicit in the model. Many factors influence where a patient chooses to receive care. Some of these factors such as patient and hospital characteristics are observable. Other factors such as patients' perceptions of hospital quality and physicians' recommendations are not observable to researchers. Because of the difficulty in measuring the magnitude of factors such as a physician's influence on a patient's choice it is common to model observed patient choices while leaving the some details of the decision pathway vague. In other

<sup>1</sup> Anecdotal evidence supports this claim as well: in March 2011 The Fairview University of Minnesota Medical Center placed signs and brochures around the hospital announcing its new electronic health record system. The brochure highlighted faster access to test and lab results, new medication dispensing safe guards and patient safety features.

words, part of the decision process remains in a “black box” (Luft, et al. 1991). Thus, in the following discrete choice analysis it is assumed that some factors influence a patient’s hospital choice but the exact mechanism of this influence is not specified.

## Methods

### Study Design

**Market Level Analysis.** Formally, an individual patient’s decision is modeled as a utility maximization problem where patient  $i$  faces a choice of  $J$  hospitals. This decision can be represented by a random utility model and estimated utilizing discrete choice methods (Green 2003). In this specification patients within a zip code are assumed to be homogenous and market shares are measures of patient preferences. The analysis uses hospital admission data aggregated at a zip code market level. All hospitals within a 100 mile radius of a zip code center are considered market participants and subsequently they are potential hospital choices for patients in that zip code. By using a zip code as a market the model contains the smallest level of distinct markets available in the data and does not require aggregating markets. Aggregating to larger market areas would place unnecessary restrictions on the assumptions regarding patient preferences.

Berry (1994) showed that a linear regression analogous to a conditional logit model can be derived using a patient’s indirect utility function and estimated using market level data. Based on that transformation, the parameters in (1) can be estimated using a linear, share equation given by:

$$(\ln S_{jzt} - \ln S_{0zt}) = \beta_1 HIT_{jzt} + \beta_2 X_{jzt} + \xi_j + \bar{\epsilon}_t + \epsilon_{jzt} \quad (1)$$

The dependent variable is the difference in the natural log of the market share of each hospital and the share of the outside option. A hospital’s market share is calculated as the number of hospital market admissions divided by the total number of market admissions. This market definition results in a large number of markets with numerous observations within each market. Additionally, markets are clearly defined geographically and there is significant variation between hospitals within markets as well as across markets over time. These features make the data particularly well suited for this methodological approach (Town and Liu, 2003). For each market an outside option is defined as all hospitals beyond the 100 mile market radius and the utility of the outside option is normalized to zero. The health IT effects are measured by separate dummy variables for each of the three technologies of interest in our study: EHR, CPOE, PACS. These health IT variables will equal 1 if hospital  $j$  has that system in period  $t$  and 0 otherwise. The  $X_{jt}$  vector includes hospital specific characteristics which vary by time period. These include hospital size measured by  $\ln(\text{hospital beds})$  and indicator variables for for-profit status and hospital system status which equal 1 if they are true and zero otherwise<sup>2</sup>. The model

<sup>2</sup> Teaching status was not included in specifications with hospital fixed effects due to the high correlation between the fixed effect and the teaching status dummy variable.

## Data Sources

The data used to perform the analysis comes from a combination of three main datasets. Hospitals' health IT information is from the HIMSS/Dorenfest Integrated HEALTH CARE DELIVERY SYSTEM PLUS (IHDS+) DATABASE™. The HIMSS dataset is constructed from a near census of acute, non-federal, U.S. hospitals. Although this represents a majority of U.S. hospitals small hospitals (less than 100 beds) are still under represented in the data. For the hospitals in the dataset detailed historical information regarding the health IT software, hardware, and infrastructure installed in the hospitals is available as well as data regarding plans for future technology investment at those hospitals. HIMSS data is probably the most often cited health IT adoption data in the literature and it is also currently the most comprehensive and accessible data. This health IT database was linked with hospital characteristics data obtained from the American Hospital Association annual survey database. This database contains information regarding hospitals' physical and organizational characteristics such as location (hospital zip code and latitude and longitude), teaching status, number of beds, profit or not for profit status, and whether the hospital belongs to a hospital system. Medicare inpatient claims data is the third source of data providing patient level choices and characteristics such as age, gender, and race. The Medicare inpatient claims for all Medicare beneficiaries from the period of 1999 to 2006 were linked to the AHA survey and HIMSS data. The unit of observation is an individual hospital stay. The Medicare claims were obtained from the Medicare Provider Analysis and Review (MedPAR) file. MedPAR aggregates all of the claims that occur during a stay into single observation in the file. The inpatient data is identified by a unique patient ID at the hospital level so it is possible to link a patient's observed hospital choice with the hospital and IT characteristics. The Medicare fee-for-service (FFS) population is not a representative sample of patients across the U.S. but it does constitute a large insured population with consistent national coverage. Even though the patients in Medicare FFS are older and sicker, on average, than patients in Medicare Advantage program or a private, commercially insured population private insurer data is difficult to obtain and would not necessarily constitute a national sample. The Medicare reimbursement system allows patients to use almost any hospital thus making specification of the choice set clear. The Medicare sample is also useful for the purposes of this study because this population is more likely to use inpatient hospital services. Sample sizes that are too small are not a concern given the size of the population and the types of conditions chosen for analysis. Since Medicare patients are also generally sicker than private commercially insured patients the benefits of health IT are likely to be greater. Additional data, such as zip code level geographic information was used to calculate distances. This data was matched by zip code to patients and does not vary over all observations but does vary among hospitals by zip code.

The Berry model data set includes all Medicare FFS patients age 65 and older who were admitted to the hospital between January 1, 1999 and December 31, 2006. The conditional logit data set needed to be significantly smaller than the Berry model data set in order for the model to be estimated. A sub-sample of the claims data from the Berry model data set which included all of the claims from MN, IA and WI was used to estimate the conditional logit models. Since the type of health care services a patient receives can vary greatly by the condition being treated it is possible that health IT will affect patients' choices more for certain types of services than others. One method previously used in the literature for identifying and grouping patients to include in the hospital choice analysis is to use the Medicare medical and surgical Diagnostic Related

Groups (DRGs) (Town and Vistnes 2001; Burns and Wholey, 1992). A patient’s ability to choose a hospital is expected to be greater in non-emergency situations. A patient suffering from a life threatening condition is assumed to be more likely to choose the nearest hospital. To test for an impact of health IT in both types of patient populations we choose the two DRG codes listed by CMS as the most common “elective” and “other” admissions in 2006. DRG code 544<sup>3</sup> is the code for total hip and knee joint replacement therapy (CMS 2007) and is usually an elective admission. The most common “other” (non-elective) DRG code in 2006 was for Heart Failure & Shock, DRG code 127.

**Table 1. Adoption rates by year and type of health IT**

|      | Hospitals | EMR | CPOE | PACS |
|------|-----------|-----|------|------|
| 1999 | 2608      | 3%  | -    | 0.1% |
| 2000 | 2771      | 5%  | -    | 2%   |
| 2001 | 2734      | 7%  | -    | 5%   |
| 2002 | 2681      | 9%  | -    | 7%   |
| 2003 | 2504      | 17% | 1%   | 13%  |
| 2004 | 2483      | 21% | 4%   | 24%  |
| 2005 | 2529      | 26% | 8%   | 36%  |
| 2006 | 2649      | 34% | 16%  | 49%  |

Three technologies<sup>4</sup> are identified in the HIMSS data to be included in this analysis: 1) Picture Archive and Communication System (PACS), 2) Computerized Physician Order Entry (CPOE), and 3) Electronic Medical Records (EMR). Technologies were chosen based on the various aspects of patient care they affect. CPOE systems are most likely implemented as a means of improving patient safety. Other systems such as PACS are designed to increase the efficiency of delivery of care. PACS allow physicians to more easily access and review images resulting in faster more efficient treatments. EMRs are assumed to improve quality through better care management and efficiency by eliminating redundant records and concisely storing health care data entered by providers or produced by various other applications for the lifetime of a patient. Table 1 shows the percentage of hospitals with each type of health IT systems by year.

## Measures

**Identification.** By using a panel of hospital data from 1999-2006 which has observations both pre and post health IT implementation a difference-in-differences (DID) identification of the effect of health IT is possible. The DID estimates are the equivalent of taking the difference

<sup>3</sup> Prior to October 2005 DRG 544 was coded as DRG 209. Both DRG codes are for joint replacement and are included in the data without distinguishing between codes other than through the year dummy variable. For simplicity I shall refer to this sample by DRG 544 or Joint Replacement.

<sup>4</sup> Hospital pharmacy bar coding system implementation data is available in the HIMSS data set beginning in 2004. By measuring health IT implementation with a 1 year lag only 2 years of data were available for the analysis which did not leave enough of a longitudinal sample for reliable estimation. Especially since during the first few years of data collection the percent of hospitals reporting bar coding systems was extremely small.

of the average outcomes of the treated and untreated groups. In our models we are comparing the change in patient hospital choices between hospitals adopting and not adopting health IT. A second element of the identification strategy is the use of hospital fixed effects to account for unique unobserved hospital characteristics. The inclusion of hospital fixed effects is intended to eliminate endogeneity from time invariant factors, such as hospitals with higher propensity to adopt health IT. Health IT adoption is not likely to be associated with demand shocks because of the considerable planning and capital required for implementation. We employ two complementary discrete choice models of consumer choice in differentiated product markets by exploiting the availability of DID and hospital fixed effects in the data to identify the effect of health IT on patient choices. The indicator variables representing health IT systems are the variables of interest. We are able to control for the observable characteristics of hospitals as well as observable characteristics of the patients but some factors involved in the decision are unobservable. Two of the most important unobservable factors are perceived quality and the actual set of hospitals a patient chooses from. The hospital fixed effect variables serve as controls for mean level quality. The large radius for the hospital choice sets is designed to include as many hospitals as possible while allowing for the model to still be estimated.

**Parameter Estimates.** Traditionally, interpreting the results from any type of conditional logit models requires some caution. The resulting parameter estimates need to be considered in terms of the underlying utility model; which is to say, they should be considered utility function parameters. This is an important distinction because it means the magnitude of the parameters cannot be interpreted directly. The sign of the parameter estimates alone can be used to judge the relative importance of a variable but not the magnitude (Cameron and Trivedi, 2002). The parameters estimates (and standard deviations) can be used to determine if variables influence a patient's hospital choice but further calculations are necessary to estimate the magnitude of the effect.

**Marginal Effect.** A common method for estimating the magnitude of the impact of a variable of interest is the calculation of the marginal effect. This calculation shows the effect of a change in a regressor on an outcome probability. For a conditional logit model the marginal effect of  $x_j$  on the probability of choosing  $x_j$  for person  $i$  can be found by differentiating the estimated probability with respect to the variable of interest,  $x_j$ : The marginal effects in the linear share models are similar with hospital market shares replacing choice probabilities. Since these marginal effects are found by taking the derivative of the logit probability function with respect to  $x$  the marginal effects of discrete variables must be calculated as the difference in the function evaluated with the variable of interest set to one and zero, holding all other variables constant.

## Limitations

Two study limitations are immediately imposed by the use of logit models. First, the preceding models allow variables to vary over time or across choices and patients but there is only one parameter estimate. It is possible that these variables may have different effects on different patients or hospitals and parameter estimates should be allowed to vary accordingly. Second, the pattern of substitutions among choices has important implications in a logit model and can impose too strict of a structure on individuals' choices. In the logit model the probability

ratio of any two alternatives depends only on those two alternatives. This property is referred to as independence from irrelevant alternatives (IIA). This study assumes there are many distinguishing characteristics among hospitals and the probability of choosing one hospital over another depends only on the characteristics of those two hospitals. Both of these limitations can be addressed by the use of more complicated models but the models used in this analysis are valid and reasonable considering this was the first analysis of this type to address the issues of demand for hospitals and health IT. More complex models may be used in future research to refine the estimates of the impact of health IT on hospital demand.

Other limitations of the analysis result from the data. The dataset is extremely large and choice sets vary by zip code resulting in a large number of parameter estimates. The use of DRGs to select patients or limiting patients was only one way the study population can be reduced to a more manageable size. Other sub-samples of the data are necessary to fully understand the impact of health IT on hospital choice. A second limitation involves the generalizability. Medicare data is commonly used because of its availability. However, it may not accurately represent the rest of the insured population in the U.S. The results may not approximate choice probabilities or the welfare implications for a managed care or commercially insured populations who face different prices, co-pays and deductibles than the Medicare population. Third, the logit model with panel data and fixed effects does estimate a more accurate model of patient choice than a cross sectional model or time series model but the possibility of biased estimates remains. The largest possible source of that bias is the result of health IT adoption being an endogenous decision. This is a problem that plagues all health IT studies.

## Results

### Principal Findings

**Market Level (Berry) Model.** The results of the first set of estimations, from the Berry model, are informative as to the mean effects of health IT within hospital markets. The mean effects of health IT may be used to inform or evaluate policy decisions. This model is not able to identify the effects of individual patient characteristics on hospital decisions. Patient level characteristic effects, which also have policy implications, are included in the conditional logit models. Both types of models are estimated using maximum likelihood estimation in Stata 11 on the Minnesota Supercomputing Institute servers.

The Berry model regressions produce negative and statistically insignificant health IT parameter estimates for all three technologies – EMR, CPOE and PACS. A test for joint significance rejects the null hypothesis that the health IT interaction terms are zero in the CPOE model at the 95% level, but does not reject the null in the other two models. The interaction terms from the CPOE model are informative as to the effect of health IT on demand. Drawing conclusions from the other two models is tenuous. Compared to parameter estimates from specification without hospital fixed effects, which are positive and significant in all models, it is apparent the relationship between hospital health IT adoption and hospital demand is endogenous. This has important implications for research; the existence of endogeneity implies case studies,

small samples, or even cross sectional approaches will produce upwardly biased estimates of the impact of health IT.

In the CPOE specification the health IT coefficient estimates is negative which implies health IT reduces a patient's utility for a hospital but the coefficient estimates of the health IT dummy variable is not individually statistically significant. The model accounts for the fact that patients are not choosing hospitals based on health IT alone through the inclusion of multiple interactions of the health IT variable with hospital characteristics which are jointly significant in the CPOE model. The HIT\* Miles coefficient in the CPOE model is a positive and statistically significant interaction term in the model. The positive sign on the coefficient means CPOE leads to an increase in utility for patients as their distance from the hospital increases. The result that patients are willing to travel further to a hospital with health IT is consistent with the theory that patients will choose a hospital with the greatest benefit and they believe health IT will increase these benefits. The sign on the distance coefficient is negative, meaning as distance from a hospital increases a patient's utility for that hospital decreases, which is consistent with previous hospital choice literature.

The time trend variable in the CPOE model is negative and significant while the trend squared is positive and significant. This implies a decreasing trend in admissions which is slowing over time. The health IT\* Trend interaction is also positive and significant which implies health IT had a positive effect on hospital choice over time. The CPOE\* Rural variable in the Berry model has a negative and significant effect on hospital choice. Hospitals with CPOE in rural markets are less likely to be chosen than hospitals without CPOE in those markets. This may be indicative of differences between rural and urban hospitals. Other results of the CPOE and other regressions are the statistically significant hospital characteristic variables. In almost every model for-profit status, system status, hospital size (ln(beds)), rural location and distance from the hospital are significant predictors of a hospital choice. The coefficient on rural market is positive. This can be interpreted as patients in rural markets preferring hospitals within those markets relative to an outside hospital. This is consistent with the effect of travel distance. Only in the CPOE model are for-profit status and hospital size not statistically significant. Possibly because of a lack of variation among the hospitals which adopted CPOE early.

**Patient Level (Conditional Logit) Model.** The fixed effects conditional logit model is estimated for 8 different specifications; a model is estimated for the two patient populations—joint replacement and heart failure, once for each of the three technologies individually plus for a combination of EMR and CPOE. As in the market level models comparison of the fixed effect and no-fixed effect specification suggest endogeneity is present. The majority of the hospital fixed effects are statistically significant in the heart failure models. This was not true of the joint replacement models. This suggests hospitals that patients choose for treatment of heart failure have significant unobservable characteristics which influence the patients' choices. Since most heart failure admits in the data occur through the emergency room or urgent care it is likely that the hospitals patients choose for heart failure treatments are known by patients to provide heart failure treatment or easily accessible emergency rooms. The shorter average travel distance to a hospital in the heart failure sample compared to the joint replacement sample supports this hypothesis. Contrary to the hypothesis that health IT would not play a role in the heart failure sample which is typically an emergency admission, the CPOE and PACS models had jointly significant health IT interaction coefficients. The EMR coefficient is negative and significant but the test for joint significance of the health IT interactions is not significant.

There are several potential reasons the health IT coefficient in the PACS model is positive and significant in the heart failure population. Possibly, PACS do matter in some admissions but not for the all DRGs. It is not obvious which conditions are influenced or how since cardiology and radiology imaging is likely to be used in CHF and joint replacement populations but PACS interactions were jointly significant in only the heart failure population. Additionally, the sample of patients and hospitals might be too small to find an effect or joint replacement patients in the sample states (MN, WI and IA) are not influenced by PACS as much as they are in other parts of the country.

The conditional logit results imply CPOE interactions with hospital characteristics also have very little impacts on patients' hospital choices. Hospital characteristics also seem to have a minimal impact on individual choices in these models. In the joint replacement sample for-profit status has a positive effect on the probability of a hospital being chosen. Although, there is not a significant effect in the heart failure sample. A for-profit dummy variable was not interacted with CPOE in either model and can also be considered part of the outside good. The small number of hospitals which had adopted CPOE in the study period resulted in no for-profit hospitals with CPOE explicitly in the choice sets. Teaching status is also omitted from the conditional logit estimations because it is highly correlated with the hospital fixed effects.

The CPOE\* distance coefficient is not significant in either DRG cohort model. The distance and distance squared terms are significant as expected. Distance is negative in both models, consistent with the theory that patients are less likely to choose hospitals that are further away. The rural-distance interaction was positive in both models; patients in rural areas are more likely to choose hospitals further away, most likely because their choice of hospitals is limited. In the joint replacement sample the Age\*Distance interaction term which is not reported, was also negative and significant but is not significant for the heart failure sample. We hypothesize that older patients with joint problems are much less likely to want to travel further or are less able to travel further to a hospital. Patients with heart failure are much more likely to want to get to the closest hospital even if they are older. It is also possible that age is acting as a proxy for severity in addition to the Charlson index variable. Older patients tend to have more co-morbidities and require more health care services. Assuming older patients needing joint replacements are marginally healthier than older patients with heart failure the Age\* Distance coefficients are consistent with the theory that healthier patients are more discerning in their hospital choices. In the joint replacement sample distance is a significant factor in older patients' hospital choices only because they are not as sick as the heart failure patients.

Many hospitals that adopt one health IT system adopt more than one health IT system. If efficiency or quality gains accrue with more health IT systems as Borzekowski (2009) found, then there is a possibility that combinations of health IT systems also impact demand. If health IT systems within a hospital are interoperable or even compatible there should be benefits available in those hospitals which are not observed in hospitals without multiple systems. Physicians and patients should prefer hospitals where interoperable features improve care. If health IT systems individually lead to efficiencies but the use of multiple systems creates inefficiencies patients and physicians should avoid those hospitals. In both DRG samples the health IT combination variable (EMR & CPOE) and interactions are jointly significantly different from 0. The Wald test is significant at the 99% level for both populations. In the heart failure sample the health IT combination variable coefficients is negative while in the joint replacement sample it is positive, but they are not significant in either model. Also, in both samples the health IT\* distance interaction term was negative; it was only significant in the heart

failure sample. This suggests multiple systems do not improve the coordination of care to the point that patients will travel further for the hospital with those systems.

## Discussion

**Marginal Effects.** The coefficient estimates from the logit models do not give magnitudes of the effects of specific variables on patients' choices. The size of the effects can be found in the marginal effects of the variables. In Berry model the coefficients can be interpreted as the effect of a one unit increase in the variable of interest on the dependent variable. For the distance variable this can be explained as a one mile increase in the distance from a patient's zip code to the hospital. The market weighted average hospital effect of a 1 mile change in distance on the probability of a patient choosing a hospital is -13%, assuming the other variables are held constant. The distance term from the distance squared variable which remains in the derivative is held constant at the average distance to a hospital within each market. If the average number of admissions in 2006 at a hospital is 3370 patients the effect of a 1 mile change is equivalent to a decrease in 438 patients. The average hospital effect of a 1% change in bed size is 2.9%. The average bed size in 2006 was 210, a 1% increase in  $\ln(\text{Beds})$  would be equivalent to 148 beds and result in 98 more admissions on average. As previously mentioned the distance from a hospital has a negative marginal effect in both DRG populations as well. In the CPOE specifications a -1.44% change in the probability of choosing a hospital results from a 1 mile change in distance, away from the hospital, in the joint replacement sample and -1.67% change in the heart failure sample.

The marginal effect of CPOE adoption is calculated as the difference in expected patients between health IT and without – holding all other variables constant. The effect is small but for hospitals with large number of admissions the result is a measurable impact on demand for inpatient services. In the joint replacement and heart failure samples the average annual marginal effect of adopting CPOE is 5 patients and 7 patients respectively. A hospital's location and size are clearly much more relevant to the number of patients a hospital admits each year but the results show health IT does have an effect on the marginal patients a hospital admits.

**Consumer Welfare.** The ability to estimating the value of health IT systems is a benefit of the conditional logit framework based on a random utility model. Even though the parameter estimates can be used to calculate the marginal effects or elasticities of health IT, a welfare analysis provides a social value of health IT. The results of a welfare analysis can be used for future health IT implementation and policy making decisions. According to the random utility assumptions underlying the logit model a researcher observes a patient's indirect utility and the distribution of the remaining utilities. This allows the expected consumer surplus (CS) to be calculated (Train 2003). Policies such as the implementation of health IT may be evaluated by comparing expected CS measures between alternatives or over time.

Unfortunately, calculation of the expected CS measure requires an estimate of the marginal utility of income. In most settings this is easily found because prices or income variables are included in the dataset. However, this dataset does not include prices since Medicare reimburses hospitals through a prospective payment system with a fixed amount for a given DRG. Although some payments are adjusted by hospital there is not enough variation in prices across hospitals to provide reliable estimates. An alternative approach to using prices is to assign a dollar value to the time spent and distance traveled from a patient's residence to a hospital. The opportunity cost

of travel time combined with an average travel cost will provide an estimate of the cost of getting to the hospital. The price of a hospital to the patient is then represented by the total travel cost. In the absence of price data this method will allow estimates of changes in patients' welfare resulting from health IT. It is possible that health IT draws patients to a hospital further away than would otherwise be chosen resulting in a loss in their total welfare due to the extra travel time. The welfare effect on patients is important for future decisions made by policy makers, hospital decision makers, physicians, insurance companies, as well as patients themselves.

The average cost per mile published by the national transportation agency AAA was estimated to be \$.522 per mile in 2006. An ABC survey of travel times found that the average travel time to work was 26 minutes for a distance of 16 miles resulting in an average travel time of 1.625 minutes per mile. Since the majority of the people in the sample are elderly and retired calculating costs using hourly wages is not applicable but the median income is an easily available figure. Using the median US income in 2006 of \$52,000 the median cost per minute is \$.40, assuming a 40 hour week. The average cost per mile of travel time is then \$.70 plus the \$.52 travel cost which produces a one way time-travel cost of per mile \$1.22 for one person. I measure distance in the data as one way (from the patient to the hospital) but most people return from the hospital so this cost should be doubled in order to account for the trip cost. Assuming that an elderly person does not drive themselves to the hospital an additional time cost can be included for the driver and the driver's two extra trips back home. The total trip cost then becomes \$6.30 per mile from the hospital. I finally round this to \$7 for incidental costs which are difficult or impossible to quantify, particularly cost for people that are traveling from rural areas with poor infrastructure, during inclement weather, etc. As a bench mark for the market cost of a driving trip the Metro Mobility transit service in Minneapolis, MN costs \$3 one way within the city and \$4 for trips during rush hour. The two-way cost would be \$6 - \$8 for a trip within the city. A taxi in Milwaukee, WI, Washington D.C. or New York, NY would cost approximate \$4 - \$6 per mile; the two-way trip cost would be between \$8 and \$10. From these "market based" travel cost comparisons an estimate between \$6 and \$10 seems reasonable. The \$7 cost per mile is used to convert the marginal utility of distance to a marginal utility of dollars.

The market level expected CS calculation can be stated as:

$$E(CS_{zj}) = \frac{1}{\alpha_{jz}} \ln \left( 1 + \sum_{j=1}^J e^{(\beta_1 HIT_j + \beta_2 X_{zj} + \xi_j)} \right) \quad (3)$$

Where

$$\frac{1}{\alpha_{jz}} = \left( - \frac{1}{\frac{\partial Utility}{\partial Distance}} \right) \left( \frac{\$7}{1 \text{ mile}} \right) \quad (4)$$

The expected CS of a change in health IT can be calculated in a manner similar to the marginal effect by finding the difference between the CS for hospital  $j$  with health IT and without. Averaging the difference in CS over all markets produces an average expected CS.

The expected change in consumer surplus change from no combination EMR - CPOE systems to the 2006 status quo adoption levels results in an increase of \$228,475 for the joint replacement population and \$139,327 for the heart failure population. This is approximately \$19,000 and \$11,000 per hospital with EMR and CPOE, respectively. Alternatively it is

equivalent to \$100 and \$80 per patient who choose a hospital with EMR and CPOE. The value per hospital is well below the millions it would cost for an average hospital to implement EMR and CPOE but the result is a net benefit to society beyond what accrues to each hospital in added revenue from any additional patients. Assuming these benefits are consistent across all 2649 hospitals the adoption of EMR and CPOE systems by all hospitals would result in a consumer surplus of over \$50 million for the joint replacement population alone.

## **Conclusions**

According to the Berry model results there is evidence that at the market level a health IT system, CPOE, does have a small but significant marginal impact a patient's hospital decision. While it is important to know average effects of health IT it is likely that health IT does not have the same effect for all types of patients. Hospitals may be particularly interested in effects due to patient characteristics if health IT leads to changes in a hospital's patient demographics and patient mix. The results of the conditional logit model are based on more detail and patient level observations and but also find small marginal effects of health IT in the heart failure population more than the joint replacement population. Currently, it does not appear as though health IT adoption has enough of an effect on demand to change market structures or hospital patient mix. The expected consumer surplus value is found to be positive. It is important to note that not accounting for endogeneity will bias the results toward finding an effect of health IT which very likely does not truly exist.

## **Significance**

The topics of this research, hospital choice and health IT adoption, are both very relevant in today's political and economic arenas; however prior to this the topics had yet to be researched together in detail. A large body of hospital choice literature and general discrete choice methods literature was used to support the specification and estimation of the econometric models. Additionally, the growing body of health IT literature and continued interest in health IT provide a relevant framework for applying the results. This research contributes to the hospital choice literature by including the effect of information technology and by controlling for endogeneity to the extent possible within the models. This research also contributes to the health IT literature by providing estimates of the effect of health IT on patient choice as well as estimates of the welfare effects of these choices.

## **Implications**

The results imply caution is necessary when evaluating the value of health IT. If endogeneity is not controlled for the effects of health IT will be inflated. Evidence from this and other health IT literature suggests the hospitals which have adopted health IT through 2006 were inherently different from those which had not. This research found patients would have been more likely to choose the hospitals which adopted health IT even if the hospitals hadn't adopted health IT. Without controlling for this effect health IT appeared to have a much greater impact on patient choice than it actually does.

Previous, supply-side analyses that find value through reduced costs and better outcomes do not include the value of potential increased revenue and consumer welfare. Without accounting for those benefits supply-side estimates of the value of health IT are biased downward. Investments in health IT are increasing as the role of health IT in health care is growing and there is a strong belief that this will lead to significant improvements in patients' health and the health care system. Hopefully, it will and research will follow suit and focus on the full scope of health IT effects, supply and demand, costs and quality. As adoption rates continue to increase it will be crucial to continue to evaluate the effect of health IT on demand and the consequences on market structures in order to ensure health IT is producing efficient and valuable effects in health care markets.

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