The Impact of Health Information Technology on Hospital Demand

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Abstract

This paper tests whether hospital health information technology (IT) investment during the years 1999-2006 resulted in changes in hospital inpatient admissions. This demand analysis complements the existing health IT supply-side research, allowing for a more complete understanding of the impact of health IT on health care markets. The data include 100% of Medicare's fee-for-service inpatient admissions for beneficiaries aged 65 and over from 1999-2006 from the MedPAR file. Hospital characteristics were obtained from the 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 impacts of three technologies are evaluated: 1) Picture Archive and Communication System 2) Computerized Physician Order Entry and 3) Electronic Medical Records. Discrete choice analyses are used to model patients' choices. A market share model provides mean effects of health IT on admissions at a national level. 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 hospital health IT adoption decisions. The health IT interaction terms are jointly significant for most applications but only PACS adoption increased market share. The expected change in consumer surplus from no adoption to the 2006 PACS adoption levels is $91.5 million.

Key Words: Health Information Technology, Hospital Demand, Consumer Surplus

1. Introduction

The implementation of health IT in the U.S. health care system is expected to produce substantial benefits for patients. The Office of the National Coordinator of Health IT has stated that health IT will reduce costs and improve the efficiency health care delivery while 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. In fact, more investments in integrated and interoperable systems are expected to produce greater benefits. Some have estimated billions of dollars in potential savings (Hillestad et al., 2005). Because the impact of health IT is expected to be so large policy makers are troubled by the lethargic adoption rates. In an effort to increase adoption rates of health IT, the Federal government plans to subsidize $19 billion of certified electronic health record systems such that every American will benefit from EHRs by 2014 (Blumenthal, 2009). 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.

The majority of health IT benefits are expected to accrue to patients but the majority of the investment costs are incurred by hospitals and physician practices; and physicians and nurses are the ones who actually use the technology. As health IT advocates push for public policy promoting adoption hospitals and providers are merely seeking a means to capture a return on the investment. Returns on health IT investments in the form of higher revenues are possible through either reduce costs or increases the number of patients. However, many of the cost implications and, obviously, the quality effects will only be achieved if patients are treated in facilities with health IT systems. The body of supply-side (adoption, cost and quality) health IT

literature is constantly growing yet the demand-side literature is almost non-existent. This paper addresses this gap by testing whether hospital health IT investment from 1999-2006 resulted in changes in demand for hospitals. If health IT does make significant changes to the delivery and outcomes of care it is reasonable to expect that health IT will also change the demand for care. We expect patient perceptions of health IT as well as physicians' influences based on their knowledge of health IT will affect patient hospital decisions. Improved quality and efficient delivery of care should prompt patients and physicians to choose hospitals with health IT. An understanding of demand-side effects of health IT is vital for informing health IT policy and infrastructure development.

Our paper evaluates the impact of health IT on hospital demand by estimating the effect of health IT on a hospital's inpatient admissions. Empirically we test for changes in hospitals' zip code level shares of admissions related to the adoption of three types of health IT systems: electronic medical records (EMRs), computerized physician order entry (CPOE) and picture archiving systems (PACS); from the empirical models we calculate the magnitude of the impact as well as the welfare implications. The analysis uses zip code level hospital share information to estimate the parameters of patient utility function over inpatient hospital choice using the methods as outlined in Berry (1994). The data used to perform the analysis comes mainly from the combination of three datasets. Hospital health IT data from the HIMSS/Dorenfest database was merged with hospital characteristics from the American Hospital Association (AHA) and was linked with Medicare inpatient claims data, which provides patient level hospital choices and characteristics such as age, gender, and race. A panel data structure including hospital fixed effects is used to identify the impact of health IT on demand. Hospital fixed effects are included to control for endogeneity in hospitals' adoption of health IT and patient choices.

The significant coefficients of the hospital characteristics in out model are consistent with previous hospital choice literature. We find we cannot reject the null hypothesis that the health IT interaction terms are zero in PACS model, although the coefficient on the PACS dummy variable is not statistically significant. Tests for joint significance of the health IT interactions in the CPOE regression and the regression including the combination of EMR and CPOE also reject the null hypothesis at the 99% level. In both models, the health IT variable is also negative and statistically significant, suggesting health IT alone is not enough to increase patients utility for a hospital. A joint significance test does not reject the null hypothesis for the EMR model. The opportunity cost of travel to a hospital is used as a proxy for the cost of a hospital choice, allowing welfare estimates to be made in dollars. We find that in the year 2006 the expected change in consumer surplus from PACS adoption $91.5 million.

2. Literature Review

The proponents of health IT often cite improved health care quality as the reason that health IT adoption levels should be higher. Simply, without access to health IT patients can not benefit from improved quality. 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. A more recent survey by Jha and colleagues (2010) found that the share of hospitals that had adopted either basic or comprehensive electronic health records[1] is still very low but had risen modestly, from 8.7 percent in 2008 to 11.9 percent in 2009. Only 2% of those would meet the federal meaningful use standards.

[1] Although the terms are often used interchangeably the ONC has defined an EMR as a patient's legal record created in a facility and the data source for the EHR. The EHR is the system that gives patients, physicians, insurers and others access to the patients record across facitlities (Habib, 2010).

With the goal of increasing adoption the factors influencing adoption are a major research focus. Research has found that there is large variation in adoption rates related to hospital characteristics such as size, not-for-profit status, and patient mix. Not-for profit hospitals with higher shares of Medicare and Medicaid patients have been found to have lower EMR 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 provided. This is consistent with Cutler et al. (2005) who found CPOE was being adopted by teaching hospitals but not by for-profit hospitals. 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).

Even though health IT adoption is often promoted on the basis the quality benefits, the literature evaluating the effects of health IT on quality has found only limited, positive outcomes. The generalizability of many of these studies is also 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. 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 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.

3. Model

A. Conceptual Model

Our analysis applies discrete choice methods to identify the effect of health IT on hospital demand at a market level. We make two assumptions about the role of health IT in a patient's hospital choice. First we assume patients develop perceptions of hospital quality regarding health IT systems based on news reports, advertisements and past experiences. Patient knowledge of health IT systems does result in a belief that the quality of care is improved and medication

errors are reduced[2]. A 2009 survey of patients' perceptions of health IT found 78% 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. When asked if they would be more likely to use a doctor with health IT in the practice 32% of respondents said yes, 57% said it would make no difference (Gaylin et al., 2009). These beliefs 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 influential in our models as patients' perceptions of quality.

The reality of the health care system is that decisions are not strictly made by the patients. Our second assumption is that health IT affects patient choices significantly through physicians influence too. A physician acting as a patient's agent will choose the hospital with health IT when it improves the quality of care the patient will receive. However, if a physician is a selfish actor the physician may still choose to recommend the hospital with health IT if reductions in the administrative burden allow the physician to provide care more efficiently. Although these scenarios have significantly different implications for patients, the analysis is of demand for hospitals, measured by the number inpatient admissions, not patient satisfaction or physician acceptance of 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. Some of these factors such as patient and hospital characteristics are observable. Other factors such as patients' perceptions of

[2] 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.

hospital quality and physicians' recommendations are not observable to researchers. Because of the difficulty in measuring the magnitude and influence of factors such as a physician's preferences on a patient's choice, it is common to model observed patient choices while leaving some details of the decision pathway vague. In other 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 health IT influences a patient's hospital choice through patient and physician preferences but the exact mechanism of this influence is not specified. Based on the empirical evidence of some improvements in the delivery and quality of health care; patients beliefs that health IT does improve care, and slowly increasing adoption rates we expect to find empirical evidence of increased demand for hospitals with health IT.

B. Econometric Model

Hospital choice research consistently finds patient choices are driven largely by hospital location; but, hospital charges and quality of care (Luft et al., 1990; Luft et al., 1991); patient level characteristics such as disease severity and socio-economic status (Tai et al., 2004) and hospital amenities (Goldman and Romley, 2010) have also been found to affect choices. We know of no models of hospital choice evaluating the effect of health IT. This paper addresses the demand-side gap in the health IT literature using a model of patient hospital choice based in consumer choice theory similar to the methods used by Kessler and McClellan (2000); Town and Vistnes (2001); Gaynor and Vogt (2003); Ho (2006); and Dranove et al. (2008).

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 by discrete choice methods (Green 2003). The analysis uses hospital admission data aggregated at a zip code market level. In this specification, patients within a zip

code are assumed to be homogenous and market shares are interpreted as measures of patient preferences. All hospitals within a 100 mile radius of a zip code center are considered market participants and subsequently 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.

We propose a patient utility function represented by:

$$u_{ijzt} = \beta_1 \mathrm{HIT}_{jzt} + \beta_2 \mathrm{X}_{jzt} + \bar{\bar{\xi}}_j + \bar{\tau}_\mathrm{t} + \varepsilon_{jzt} + \upsilon_{ijzt} \quad (1)$$

In this specification u_{ijzt} is the indirect utility of patient *i* who lives in zip code *z* of choosing hospital *j* in time *t*. A one year lagged health IT adoption variable, HIT_{jzt} is a dummy variable indicating whether or not hospital *j* has a health IT system in period *t* based on adoption in *t-1*. The lagged indicator allows for more consistent estimates of health IT adoption due to possible reporting errors in the data. If health IT is adopted in period *t-1* but not until a week before the survey it is very unlikely the effects of health IT will be captured in period *t-1*'s data. Additionally, health IT may be purchased on one date and rolled out in the hospital over time. Again, the following period survey is less likely to include misreporting bias. The *z* subscript is included in the specification for consistency in notation, but health IT does not vary according to a patient's zip code. The X is a vector of hospital characteristics for each hospital 1 to *J* in the market, for each period *t*. The characteristics are constant across zip codes: hospital size (natural log of number of beds), for-profit status and hospital system status. The vector X also contains variables that vary by market: a distance measure equal to the straight line distance from the hospital to the zip code center and an indicator variable which takes the value of 1 if the zip code is a rural area and is equal to 0 otherwise. Rural status is based on RUCA v2.0 codes with the

standard assumption that any value greater than 4.0 is a rural area (Gowrisankaran et al. 2010). The data set is restricted to markets with 10 or more hospital admissions in a given year.

Based on Berry (1994), ξ_j is an unobserved, time invariant mean valuation of hospital j which includes patients' and physicians' perceptions of hospital quality and reputation; ε_{jzt} is a market-time level shock to the mean valuation. Similarly τ_t is an unobserved, time-varying constant which includes changes common to all markets and hospitals, but which vary over time. The time invariant hospital effects and the time varying effects are represented by a set of hospital fixed effects and time dummy variables (or time trend variables), respectively. An individual error term υ_{ijzt} is assumed to be distributed i.i.d., Type I Extreme Value. Finally, for each market an outside good is defined as all hospitals beyond the 100 mile market radius. The utility of the outside good is normalized to zero.

Berry (1994) showed that the results of 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:

$$(\ln S_{jzt} - \ln S_{0zt}) = \beta_1 HIT_{jzt} + \beta_2 X_{jzt} + \bar{\bar{\xi}}_j + \bar{\tau}_t + \varepsilon_{jzt} \quad (2)$$

where the dependent variable is the difference in the natural log of the market share of hospital j 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, the 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 impact of health IT is measured in separate models for each technology (EMR, CPOE, PACS) and one combination of technologies (EMR plus CPOE). The health IT indicator variable equals 1 if hospital *j* has the application 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(hospital beds) and indicator variables for for-profit status and hospital system status which respectively equal 1 if the hospital is for-profit or part of a hospital system, and 0 otherwise[3]. The model specified in (2) includes the time invariant hospital effects and the hospital-market constants time varying effects are through a set of hospital fixed effects and year dummy variables.

C. 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. In the models, we are comparing the change in patient hospital choices between hospitals adopting and not adopting health IT; the DID estimates are the equivalent of taking the difference between the change in admissions at hospitals with health IT and the change in admission at hospitals without 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. The indicator variables representing health IT systems

[3] Teaching status was not included in the final specifications with hospital fixed effects due to the high correlation between the fixed effect and the teaching status dummy variable.

are the variables of interest. We are able to control for observable hospital characteristics 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.

4. Data

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 underrepresented 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, latitude and longitude), teaching status, number of beds, for-profit or not-for-profit status, and whether the hospital belongs to a hospital system. The match rate between the hospitals in the AHA data and the HIMSS data was approximately 92% for the 8 year period, an average of 2,619 hospitals per year.

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 combination of AHA/HIMSS data; the resulting data set retained approximately 80% of the total MedPAR claims. 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 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 zip code file included the latitude and longitude of each zip code center as of the 1999 census. 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 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.

Three technologies from in the HIMSS data are 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 variety of aspects of patient care they affect. CPOE systems are most likely implemented as a means of improving patient safety. 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. Given the current empirical literature CPOE and EMR systems have ambiguous empirical quality effects. Patients and physicians who believe these systems provide more efficient, higher quality care are expected to choose hospitals with these systems[4]. Both of these systems increase physician effort in that orders and records now must be entered digitally. 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. There is no evidence that the diagnoses from electronic images are of a better quality than from films.

Table 1 shows the number of hospitals included in the sample each year, and the percentage of those hospitals that had adopted health IT. CPOE adoption does not begin until later in the observation period, but the rate after five years is similar to the rates of EMR and PACS after the first five years. PACS were the most widely adopted health IT systems in 2006, with nearly half of the hospitals in the sample reporting PACS systems. EMR systems were only operational in about a third of the hospitals in the sample by 2006 and only 15.8% of hospitals had adopted CPOE. The percentage of adopters of PACS and CPOE approximately doubles

[4] A physician is assumed to choose hospitals as a patient's agent as described in section 3 part A.

every year from 2002 through 2006. The increase in adoption is slower for EMR during this period.

Not all of the hospitals from the first year are observed in subsequent years. Some leave the sample because they merged or closed, other hospitals enter the industry after 1999. This produces an unbalanced panel of hospitals. A noticeable feature of the data is the decrease in the number of hospitals in the years 2003 and 2004. By 2006 the number of hospitals was back to the level from the beginning of the sample period. In the AHA sample there is a noticeable downward trend in total hospitals beginning in 2001. A similar drop in hospitals is observable in the HIMSS data between 2002 and 2004. There are an average of 2,620 unique hospitals per year with a maximum of 2,771 in 2000 and a low of 2,483 in 2004. The characteristics of the aggregate hospital choice data are shown in Table 2. The annual average hospital share per market is 8.73% and the average percent of patients choosing a hospital outside of the market is 4.87%. The average number of hospital choices per market is approximately 17, with an average within-market travel distance of about 35 miles. There are a total of 2,363,541 hospital-zip code-year combinations in the eight year panel.

Examining the characteristics of hospitals with health IT over time, it is apparent that for some technologies adopters differed from non-adopters. Table 3 shows that early adopters were more likely to be teaching hospitals, less likely to be for-profit and were generally larger in terms of number of beds. Compared to 2003, the CPOE adoption rate was still low in for-profit hospitals at 8.55% and higher in teaching hospitals, with a 53% adoption in 2006. Compared to the total sample of hospitals, for-profit hospitals made up 21% of all hospitals and 37% of all hospitals were teaching hospitals. By 2006 all technologies were being adopted by hospitals with

fewer beds. Throughout the observation period, health IT adoption rates for all technologies were consistent with the proportion of hospitals that were members of a system.

5. Results

A. Coefficient Estimates

The regression results we present are informative as to the mean effects of health IT within hospital markets, but this model is not able to identify the effects of individual patient characteristics on hospital decisions[5]. Additionally, the parameter estimates must be considered in terms of the underlying utility model; which is to say, they should be considered estimates of utility function parameters. The regression results are shown in Tables 4 and 5 and are reasonable and generally consistent with previous hospital choice models; for-profit and system membership are associated with lower utility levels while patients prefer closer hospitals that are larger in size (i.e. more beds). The coefficients on the rural market indicators are positive and significant in all models and are 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; patients do not want to travel outside the rural market.

The EMR and PACS regression results from the 1999-2006 panel are presented in Table 4. A test for joint significance rejects the null hypothesis at the 99% level that the health IT interaction terms are zero in PACS model, although the coefficient on the PACS dummy variable is not statistically significant. The joint significance test does not reject the null hypothesis for the EMR model. In the PACS model the only health IT interaction variable that is statistically significant is the PACS*Rural interaction. The positive coefficient suggests that in rural markets

[5] The impact of health IT on hospital choice at the patient level is discussed in "The Impact of Health Information Technology and demand for inpatient hospital services (Barrette, 2011) and is being addressed in more detail in Barrette (2011)

there is an increase in patient's utility at hospitals with PACS. This is consistent with the theory that PACS make the delivery of care more efficient. In rural areas easier access to imaging results would benefit patients and physicians.

Table 5 presents the results of the regressions with CPOE and EMR with CPOE. Because CPOE adoption data does not begin until after 2002, the CPOE and the EMR plus CPOE models are only estimated for 2003- 2006. A test for joint significance of the health IT interactions rejects the null hypothesis at the 99% level in both models. In both models, the health IT variable is also negative and statistically significant, suggesting health IT alone is not enough to increase patients utility for a hospital. In fact, the results imply that CPOE and EMR with CPOE decrease the probability a patient would choose a hospital. An EMR model is also estimated for this period as a source of comparison. A test for joint significance rejects the null hypothesis at the 95% level in the short panel EMR model. The health IT variable is, in this model, positive but not significant.

The sign on the distance coefficient is negative and statistically significant in all models, meaning as distance from a hospital increases, a patient's utility for that hospital decreases. This is consistent with previous hospital choice literature. The HIT*Miles coefficient in the CPOE model is positive and statistically significant. The CPOE*Rural variable in the model also has a coefficient, but is not significant. CPOE increases utility for patients as the distance from the hospital increases. There is a benefit to patients who travel longer distances to hospitals with CPOE. Since CPOE is more likely to be available at larger teaching hospitals, this coefficient may be capturing the average effect of severely ill patients who are traveling to distant referral centers. A positive coefficient on the EMR with CPOE interaction with hospital beds is possibly evidence of economies of scale. Both of these results are consistent with the theory that patients

and physicians choose a hospital with the greatest benefit, and in these situations CPOE increases the total benefit.

The differences in the characteristics of hospitals with health IT from those without health IT suggest there are hospital characteristics affecting health IT adoption which may also affect patient choices. Hospital fixed effects are included in all of the models to control for potential endogeneity in a hospital's decision to adopt health IT and hospital choices. As expected, in specifications without hospital fixed effects, both the EMR and PACS variables joint tests are significant at the 95% level. In the PACS model the coefficient on the PACS indicator is negative and significant but the interactions with for profit status, size, and rural are all positive and significant. In the shorter panel for the CPOE systems all of the interactions are jointly significant but only the IT*miles interactions are significant. The joint significance in the EMR model, and the large number of significant interactions in the PACS model, is evidence that the health IT is likely related to unobservable hospital characteristics that are controlled for by the fixed effects are necessary.

We further investigate the presence of endogeneity in the model by re-estimating the PACS model with a two year lead health IT variable. If future health IT adoption is a significant predictor of hospital choice, there is likely an institutional factor, such as hospital quality, affecting adoption, as well as patient choices that is not controlled for by the fixed effects. In the PACS model without interactions the coefficient on the PACS adoption indicator is positive and significant. When the model is re-estimated without health IT interactions the health IT lead variable is not statistically significant but the coefficient on PACS adoption remains postitive and significant. When the interactions are included both the health IT and health IT lead variables are negative but neither is significant at the 95% level. The PACS*Rural interaction is

still positive and significant in this specification. From the results of these tests we are confident in the estimates and significance of our results.

B. Marginal Effects

While the coefficient estimates are informative as to overall effects on utilities, it is also helpful to know how those utilities translate into patient admissions at hospitals. We demonstrate the impact of health IT on hospital patient volumes in 2006 by simulating changes in market shares due to changes in health IT. The average effect of health IT on hospital's patient volumes is shown in Table 6. Market shares for the entire sample were predicted simulating a change from health IT to no health IT adoption for one hospital while holding all other characteristics and hospitals constant. Patient volumes were found by multiplying market shares by the market population then summing market volumes by hospital. The average simulated volumes were then compared to actual predicted volumes to find the difference in patients. This process was repeated for each hospital with health IT in 2006, then hospital volumes were averaged over all simulations. This method is similar to the one used Gowriskakran et al. (2010) to find the effect of CAH conversion of rural hospitals.

We find that PACS adoption increased patient volume in 2006 by an average of 57 patients. The adoption of CPOE and EMR with CPOE was associated with decreases in average hospital volumes. For all three technologies, the effects on patient volumes were less than ±2% of the total hospital volume. As a baseline measure we also simulated the effect of a 20 bed increase rather than PACS; meaning, in addition to simulating no health IT, we simulated the addition of 20 beds. Although overall admissions increase from the addition of hospital beds, the addition of beds in place of PACS resulted in an average hospital volume of 21 fewer admissions than the 2006 adoption PACS adoption levels.

C. Consumer Welfare

The ability to estimate 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 are used to calculate the marginal effects, 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.

As the federal government is beginning to spend billions of dollars subsidizing health IT adoption it is only appropriate to evaluate the societal value of health IT. 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 based on diagnosis related groups and beneficiaries' contributions are minimal. Although payments are adjusted by hospital, there is not enough variation in prices across hospitals to provide reliable CS 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 travel costs will provide a proxy for the cost of a hospital choice, allowing for welfare estimates in dollars.

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 (Langer; 2005). Because the data includes mostly elderly and retired individuals, calculating costs using hourly wages is not applicable. A median income level is applicable and is easily available. Using the median U.S. 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 calculated to be $.70 plus the $.522 travel cost which produces a one way time-travel cost of per mile $1.22 for one person. The distance variable in the data is one way (from the patient to the hospital) but most people return from the hospital so the travel cost is doubled. Assuming that a sick and 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. Finally, the cost is rounded to $7 for incidental costs which are difficult or impossible to quantify, such costs as for people that are traveling from rural areas with poor infrastructure, travel 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 $12. From these "market based" travel cost comparisons, an estimate between $6 and $10 appears 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 for a single year can be stated as:

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

Where

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

The expected CS of a change in health IT is calculated in a manner similar to the marginal effect. The total expected change in CS is the weighted average of the difference in the CS with and without health IT across all markets. For the year 2006 the expected change in consumer surplus between the PACS adoption levels and no systems is $91.5 million.

6. Discussion

There is evidence that from 1999 through 2006, at the market level, some health IT systems do affect patient's hospital decisions. For PACS, there is a small but positive marginal impact on hospital market share, and subsequently patient volumes, while for CPOE and EMR with CPOE there is a negative impact. Additionally, the expected consumer surplus value of PACS is found to be positive. These results are consistent with a theory that health IT influences demand through an effect on physician effort rather than through quality. PACS lead to marginal increases in demand yet have no obvious quality benefit. As the empirical literature shows, quality effects of CPOE are minimal; however, CPOE does increases in effort for physicians. Our results are consistent with this evidence and find CPOE and EMR with CPOE result in marginal decreases in demand. There is also scant evidence of quality benefits from EMRs but it is possible that EMRs increase nurse effort rather than physician effect which is why we find no effect of EMRs on demand. Nurses do not have the same level of involvement in patient hospital choice as physicians.

Panel data with fixed effects in the context of this analysis does appear to estimate an accurate impact of health IT in a discrete choice model. However our results do demonstrate caution is necessary when evaluating health IT due to endogeneity. This is a problem that

currently plagues health IT research and has important implications for research. The possibility of endogeneity implies case studies, small samples, or even cross sectional approaches will produce upwardly biased estimates of the impact of health IT.

As the federal government is beginning to subsidize billions of dollars of health IT investments over the next few years additional research on the market implications health IT is important. 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 or in all markets. In fact, some of our results imply patient severity may influence the demand for hospitals with CPOE. Further research in this area has significant policy and health care administration implications. If health IT leads to changes in a hospital's patient demographics and patient mix, hospitals, insurers and policy makers should be particularly interested in the effects of health IT and the relationship with patient characteristics.

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 involve the generalizability of our results. The dataset is extremely large and choice sets vary by zip code, resulting in parameter estimates based on similarities of patients within zip codes. Analysis at a patient level or other sub-samples of the data is necessary to fully understand the impact of health IT on hospital choice. 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 managed care or commercially insured populations who face different prices, co-pays and deductibles than the Medicare population.

7. Conclusion

Health IT adoption and the implications for patient choices are crucial to the ongoing health policy debate; however prior to this paper, the topics had yet to be researched together in detail. The growing body of health IT literature and continued interest in health IT adoption provide a relevant framework for applying the results. This research contributes to the health IT literature by providing estimates of the impact of health IT on hospital demand, as well as estimates of the welfare effects of these choices.

There is a strong belief that health IT will result in significant improvements in patients' health as well as the health care system; however, returns on health IT investment for hospitals are also necessary in order to facilitate adoption. Previous supply-side analyses that estimate health IT value from cost reductions and improved outcomes do not include the effect of changes in patient flows or hospital revenues. Furthermore, the supply-side estimates do not account for

broader social welfare as a consumer surplus measure does. We find that for some technologies such as PACS adoption does result in increased patient volumes. Systems such as these that produce returns on investment that accrue to the hospital can be expected to be adopted more than others. In our data from 1999-2006 PACS does have the highest level of adoption. 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 returns in health care markets to both patients and health care providers.

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Table 1: Health IT Adoption Rates by Year

Hospitals	n	w/ EMR	w/ PACS	w/ CPOE	w/ EMR & CPOE
1999	2,608	0.0253	0.0012	0.0000	0.0000
2000	2,771	0.0502	0.0242	0.0000	0.0000
2001	2,734	0.0711	0.0545	0.0000	0.0000
2002	2,681	0.0867	0.0720	0.0000	0.0000
2003	2,504	0.1656	0.1338	0.0096	0.0028
2004	2,483	0.2161	0.2400	0.0407	0.0177
2005	2,530	0.2622	0.3549	0.0838	0.0451
2006	2,649	0.3427	0.4896	0.1589	0.0932

Table 2: Hospital Market Descriptive Statistics

	1999	2000	2001	2002	2003	2004	2005	2006
Average Market Share	0.0887	0.0883	0.0874	0.0869	0.0866	0.0862	0.0868	0.0871
	(0.1660)	(0.1662)	(0.1654)	(0.1651)	(0.1647)	(0.1642)	(0.1648)	(0.1647)
Average Out of Market Share	0.0497	0.0501	0.0495	0.0433	0.0490	0.0486	0.0501	0.0495
	(0.0648)	(0.0660)	(0.0650)	(0.0649)	(0.0647)	(0.0640)	(0.0655)	(0.0647)
Average Within Market Distance	34.56	34.58	34.81	34.95	34.88	35.03	35.40	35.32
	(25.78)	(25.72)	(25.74)	(25.71)	(25.60)	(25.68)	(25.76)	(25.70)
Average Choices per Market	16.57	17.36	17.49	17.59	16.53	16.39	16.43	16.95
	(13.57)	(13.90)	(14.04)	(14.00)	(13.17)	(13.02)	(12.40)	(12.77)
Percent Rural Markets	0.3121	0.3229	0.3224	0.3196	0.3194	0.3204	0.3230	0.3228
Unique Zip Codes	36,498	36,681	36,762	36,699	36,412	36,392	36,635	36,706
Unique Hospital-Zip Code-Year Combinations	283,273	300,079	304,131	305,616	285,004	282,960	295,612	306,866

Standard deviations in parentheses

Table 3: Hospital Characteristics by Health IT Application

	All Hospitals		w/ EMR		w/ PACS		w/ CPOE		w/ EMR & CPOE	
	1999	**2006**	**1999**	**2006**	**1999**	**2006**	**2003**	**2006**	**2003**	**2006**
For-profit	0.1737	0.2140	0.0152	0.1571	0.3333	0.1218	0.0000	0.0855	0.0000	0.0445
System	0.6262	0.6516	0.6667	0.6416	0.6667	0.6245	0.5833	0.6010	0.2857	0.6113
Teaching	0.3819	0.3658	0.5758	0.4071	1.0000	0.4526	0.4583	0.5297	0.5714	0.5628
Average Beds	209.86	210.58	314.85	237.38	417.67	259.31	338.38	267.85	449.71	266.10
	(164.22)	(151.73)	(246.28)	(185.24)	(166.26)	(193.61)	(284.23)	(196.27)	(247.68)	(184.28)

Standard deviations in parentheses

Table 4 - Regression Results: 1999-2006 Panel

	EMR		PACS	
	Coefficient	S. E.	Coefficient	S. E.
Health IT	-0.04982	0.05951	-0.04979	0.03674
Health IT*For-profit	-0.00775	0.01539	0.00018	0.01495
Health IT*System	-0.01541	0.01145	-0.01172	0.00863
Health IT*ln(Beds)	0.01731	0.01067	0.01018	0.00684
Health IT*Miles	-0.00135	0.00081	0.00004	0.00057
Health IT*Rural	0.01588*	0.02419	0.06542***	0.0141
For-profit	-0.06296*	0.03519	-0.06692*	0.03511
System	-0.07731***	0.02711	-0.07749***	0.02704
ln(Beds)	0.0996***	0.02521	0.09932***	0.02555
Rural	1.51613***	0.03035	1.50487***	0.03068
Miles	-0.12096***	0.00317	-0.12077***	0.00322
Miles^2	0.00072***	0.00001	0.00072***	0.00001
Miles*For-profit	0.00121	0.00090	0.00137	0.00091
Miles*System	0.0024***	0.00078	0.00242***	0.00078
Miles*ln(Beds)	0.00182***	0.00061	0.00174***	0.00062
Miles*Rural	-0.01039***	0.00056	-0.0105***	0.00056
Year 2000	-0.00149	0.00344	-0.00288	0.00345
Year 2001	-0.00763**	0.00376	-0.00974**	0.00379
Year 2002	-0.01374***	0.00429	-0.01732***	0.00431
Year 2003	-0.01238***	0.00452	-0.01961***	0.00464
Year 2004	-0.00371	0.00490	-0.01467***	0.00515
Year 2005	-0.01424**	0.00569	-0.02833***	0.00613
Year 2006	0.01298**	0.00564	-0.00258	0.00626
Constant	0.98595***	0.13452	1.00078***	0.13571
Unique Observations	2,363,541		2,363,541	
Unique Hospitals	3,026		3,026	
Test for Joint Significance of Health IT Interactions	F(6, 3025) = 1.58 Prob > F = .1496		F(6, 3025) = 5.40 Prob > F = .0000	

***Statistically significant at the 1% level

** Statistically significant at the 5% level

* Statistically significant at the 10% level

Table 5 - Regression Results: 2003-2006 Panel

	EMR		CPOE		EMR & CPOE	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Health IT	0.0685	0.05376	-0.17038***	0.05868	-0.23102***	0.07212
Health IT*For-profit	-0.04133**	0.01595	-0.03023	0.02507	-0.05195	0.06332
Health IT*System	-0.01169	0.01292	-0.00224	0.01429	0.01017	0.01719
Health IT*ln(Beds)	-0.00336	0.00944	0.01736	0.01077	0.02859**	0.0133
Health IT*Miles	-0.00124	0.00082	0.00259**	0.00103	0.00215	0.00136
Health IT*Rural	0.02219	0.02715	0.00822	0.02808	-0.00461	0.04905
For-profit	-0.03594	0.03912	-0.04949	0.03874	-0.04744	0.03807
System	-0.0514	0.03124	-0.05832*	0.03099	-0.05517*	0.03097
ln(Beds)	0.05239	0.03388	0.05432	0.03356	0.05239	0.03343
Rural	1.52771***	0.03147	1.53198***	0.03131	1.53532***	0.03118
Miles	-0.12064***	0.00319	-0.1203***	0.00322	-0.12055***	0.0032
Miles^2	0.00073***	0.00001	0.00073***	0.00001	0.00073***	0.00001
Miles*For-profit	0.00111	0.00094	0.00135	0.00094	0.00133	0.00093
Miles*System	0.0019**	0.00088	0.00202**	0.00088	0.00195**	0.00088
Miles*ln(Beds)	0.00154**	0.00061	0.00134**	0.00061	0.00143**	0.00061
Miles*Rural	-0.01027***	0.00057	-0.01022***	0.00057	-0.01026***	0.00057
Year 2004	0.00726***	0.00276	0.00613**	0.00278	0.00695**	0.00274
Year 2005	-0.00295	0.00398	-0.00523	0.00402	-0.00366	0.00388
Year 2006	0.02296***	0.0041	0.01913***	0.00409	0.02118***	0.00393
Constant	1.23129***	0.1825	1.24787***	0.18063	1.24959***	0.18007
Unique Observations	1,170,442		1,166,836		1,170,442	
Unique Hospitals	2,082		2,797		2,802	
Test for Joint Significance of Health IT Interactions	F(6, 2081) = 2.17 Prob > F = 0.0429**		F(6, 2796) = 2.99 Prob > F = 0.0065***		F(6, 2081) = 2.86 Prob > F = 0.0088***	

***Statisically signifcant at the 1% level

** Statisically signifcant at the 5% level

* Statisically significant at the 10% level

Table 6 - 2006 Marginal Hospital Volume Effects

	N	Mean Change in Status Quo Average Hospital Volume (Standard Deviation)	Mean Percent Change in Hospital Volume
PACS	1297	56.99	1.46%
		(80.92)	
+20 Beds[1,2]	1297	21.17	0.54%
		(78.03)	
CPOE	421	-67.82	-1.82%
		(126.09)	
EMR & CPOE	247	-52.82	-1.54%
		(122.35)	

[1]Uses coefficient estimates from PACS model assuming a 20 bed increase instead of a PACS system.

[2]A 20 bed increase is a 7.71% increase in the average number of beds for hospitals with PACS.