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

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Dedication

This dissertation is dedicated to my parents, Greg and Ann, for their love and encouragement every day I was in school; since the very first day over a quarter century ago.

Abstract

Health Information Technology (IT) research has been focused on health IT adoption and the supply-side effects such as the quality and efficiency of health care. This demand analysis complements the existing supply-side analyses, allowing for a more complete understanding of the impact of health IT on health care markets. The impact of health IT on demand for hospital inpatient services is estimated using Medicare beneficiary inpatient hospital admissions as a measure of patient choices. Two complementary discrete choice models are used to model patients' choices with the underlying assumption that patients are making a utility maximizing decision. Berry's specification of a linear market share model provides mean effects of health IT on hospital market share at a national level. A patient-level conditional logit model which includes interactions of patient characteristics and health IT is also estimated for a subset of hospitals and diagnoses. Hospital inpatient admission data from 1999-2006 was obtained from the MedPAR file. The data for this study includes 100% of Medicare fee-for-service (FFS) beneficiaries over age 65. 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 (PACS), 2) Computerized Physician Order Entry (CPOE) and 3) Electronic Medical Records (EMR). Combinations of these technologies are also studies. A panel data structure including hospital fixed effects is used to identify

the impact of health IT on demand. The hospital fixed effects are included to control for endogeneity in hospitals' adoption of health IT and patient choices. The health IT variable and interaction terms were jointly significant in market level and individual choice models for CPOE but did not result in significant impacts on hospital demand. Patient-level conditional logit model results are used to calculate consumer surplus welfare measures for hospitals with both EMR and CPOE systems. In 2006 approximately 10% of the analysis sample of hospitals had adopted EMR and CPOE. The change from no adoption to the 2006 adoption level produces a $228,000 increase in consumer surplus ($100/patient) for joint replacement patients and a $139,000 ($78/patient) increase for heart failure patients.

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1. Introduction

The nation's largest Health Information Technology 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 all of this 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. I address this gap in research 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); then, for technologies which results in changes in demand, I calculate the magnitude and welfare implications.

Potentially significant health and monetary benefits have made the development of health IT infrastructure a priority in the United States. Federal agencies have announced numerous health IT- focused policy initiatives and are funding a variety of research projects related to development, implementation, and use of health IT[1]. The Agency for Healthcare Research and Quality (AHRQ), the Centers for Medicare and Medicaid Services (CMS), and the U.S. Department of Health and Human Services Office of the National Coordinator of Health IT (ONC) are all supporting numerous projects financially as well as advising various aspects of health IT infrastructure development throughout the country.

[1] AHRQ has also funded at least one project researching the demand for HIT through a dissertation grant for my research. However, my grant was funded through the R36 dissertation grant funding announcement not and HIT funding announcement.

Health IT development has be a priority for the last two Presidential administrations. President Bush expressed interest in the development of America's health IT infrastructure (HIMSS, 2005). By 2008 AHRQ was funding $160 million in research projects related to health IT implementation and development. The Centers for Medicare and Medicaid Services (CMS) were funding a massive 5 year demonstration project to evaluate the effect of Electronic Health Records (EHRs) on the reduction in medical errors and improvements in the quality of care for Medicare beneficiaries (HHS, 2008). President Obama's FY 2010 budget allocated nearly $61 million for the ONC. The Federal budget proposed for FY 2011 requested $78 million for the ONC with an additional $2 million for the ONC from American Recovery and Reinvestment Act and $32 million for AHRQ to enhance patient safety (AAMC, 2010**)**. Although a FY 2011 budget was never approved, the agencies have continued to operate close to 2010 levels though continuing resolutions. The proposed 2012 budget has requested $57 million for the ONC with additional funding through the Public Health Service Act totaling $78.4 million (Government Health IT, 2011). In addition to the ONC budget funding the federal government is beginning to subsidize electronic health record adoption for providers and hospitals through 2016. Beginning in 2015 they also plan to institute financial penalties for providers not using EHRs that meet meaningful use standards (Blumenthal, 2009).

Federally funded research projects along with a variety of other sources of health IT research are producing a rapidly growing body of health IT literature. Some researchers are investigating adoption rates including predictive factors and barriers to adoption (Des Roches, 2008; Bower, 2005; Fonkych and Taylor, 2005; Gans et al., 2005). Others are studying the mechanisms and magnitude of potential cost savings through improved outcomes, reduced errors (Goldzweig et al., 2009; Chaudry et al., 2006) and increased efficiency (Borzekowski, 2009; Poissant et al., 2005; Furukawa, 2011). The economic health IT research has mainly focused on two areas, adoption and supply-side effects but there is also research on the design, implementation and standardization of health IT systems. Medical informatics engineers, decision and computer scientists, physicians, and other researchers are contributing an assortment of research. In all of this research there has been little to no mention of the effect health IT may have on the demand for services.

Hospital choice literature has consistently found that technology investment, hospital competition, and the role of quality are important factors in hospital choice. Health IT investments may have effects on all of three of these determinants of hospital choice, possibly more. Because of the relatively recent role of health IT, the hospital choice literature has not yet focused on the role of health IT and neither has health services research. The growing role of health IT in the delivery of health care along with greater availability of data, and recent advances in discrete choice modeling imply that the effect of health IT on hospital choice is an interesting, accessible and extremely relevant research area. If health IT does indeed improve quality of care for patients and make health care delivery more efficient for physicians, then there should be empirically observable increases in the number of patients using hospitals with health IT.

As health IT becomes more prevalent in the delivery of health care there should be little doubt that health IT will also increasingly affect patients' decisions. Even though hospitals may not directly advertise a new health IT system, patients do acquire information about hospitals through previous experiences there, family, friends and neighbors as well as their physician. Physicians, who are well informed of hospital health IT systems are a potentially major influence on a patient's hospital choice hospital. It is commonly assumed physicians act as patients' agents, acting in patients' best interests; however, in the case of health IT, physicians may also have their own interests at stake when recommending hospitals with health IT.

The main reasons to be concerned with the demand side effects of health IT are the potential changes in health care market structures and the implications for the business case for health IT systems. The ONC's mission includes the statement "promoting a more effective market place" (ONC, 2011). As CMS begins to subsidize EHR adoption there is a potential that changes in market structures will also result. No one has tested for changes in market structures and no one has shown to what extent any changes will affect the delivery of care. Changes in demand will also have an effect on the evaluation of health IT systems. Without accounting for changes in patient demand it is possible that cost and quality effects attributed to health IT may be misinterpreted. For example, a hospital which implements a new health IT system unaware that it will draw more patients may be unprepared to handle the influx of patients and the health IT system will appear to decrease quality or increase costs. Alternatively, if the health IT system results in fewer patients using a hospital any subsequent health IT value calculations cannot assume that the patient flow will remain constant and must account for lower future revenues. Without knowing how health IT impacts demand it is impossible to know the true effects of health IT.

I estimate the impact of health IT on demand for hospital inpatient services using Medicare beneficiary inpatient hospital admissions to identify patient choices. Two complementary discrete choice models are used to model patients' choices: 1) Berry's specification of a linear market share model provides mean effects of health IT and 2) a patient-level conditional logit model which includes interactions of patient characteristics and health IT. A panel data structure is used to identify the impact of health IT on demand and the inclusion of hospital fixed effects controls for endogeneity in hospitals' adoption of health IT and patient choices. Although the health IT variable and interaction terms were jointly significant in multiple specifications health IT was not found to have a significant marginal effect on hospital demand. Even without demand implications health IT adoption does create societal benefits. A consumer surplus welfare measure for adoption of EMR and CPOE was calculated using results from the conditional logit models. A change from no adoption to the 2006 level produces a total increase of $367,000 in consumer surplus, approximately $30,000 per hospital with EMR and CPOE.

There are very good reasons to believe health IT will affect health care markets either directly or indirectly. Without know if health IT affects where patients receive care any changes in the total amount of health care services could be attributed to either supply or demand factors. My research contributes to the growing body of health IT literature and supports current health policy debates by analyzing demand side effects of health IT. The remaining chapters are organized as follows: Chapter 2 provides a review of the relevant health IT literature and summarizes the hospital choice literature which underlies the econometric models in this paper; Chapter 3 outlines a conceptual economic model of patient demand for health IT and Chapter 4 explains the econometric approaches used in the analyses; Chapter 5 describes the data. In Chapter 6 I present my results; Chapter 7 is a brief discussion of my findings as well as the implications and limitations of my research. Chapter 8 offers some concluding remarks.

2. Literature Review

2.1 Health Information Technology Literature

Continuously evolving health IT policies and the subsequent research and evaluation make it impossible to briefly review all health IT literature. For the purpose of this paper I am only concerned with the aspects of health IT which directly affect demand; therefore, I focus my review on the findings of the two areas of health IT research most relevant to health IT demand: adoption and patient outcomes. A hospital must adopt a health IT system before experiencing an increased demand for health IT.[2] Understanding the current state of health IT adoption will provide context for the demand

[2] I am intentionally ignoring externalities.

effects. I assume quality improvements, reduced costs and improved efficiency are the mechanisms encouraging patients and doctors to use hospitals with health IT.

The state of the health IT infrastructure is still considered inadequate by many observers but adoption is increasing[3] and health IT research is keeping pace evaluating adoption and implementation. 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 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) estimate national adoption levels and examine the factors influencing adoption as well as the barriers to adoption. They find that as of 2005 the rate of adoption was increasing but the overall level was still very 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. Small physician groups were slower adopters. Managed care patient concentration was correlated with an increased the probability of adoption (Fonkych and Taylor, 2005).

A more recent survey of physicians from 2007-2008 found physicians in large group practices and those practicing in hospitals are still more likely to have EHR systems in their outpatient offices. Only 4% reported having a fully functioning system but 13% reported having a basic system (DesRoches, 2008). Wang et al. (2005)

[3] For example, in my data, only 16% of hospitals had a CPOE system in 2006 but that is nearly a 50% increase from 2005.

performed an analysis of factors influencing health IT adoption and came to similar conclusions as the researchers from RAND. Hospital market, financial, and organizational factors are all related to the adoption of health IT. For-profit hospitals are more likely to adopt information management systems. Although, Cutler et al., (2005) found for-profit hospitals were much less likely to adopt CPOE.

Parente and Van Horn (2006) addressed for-profit vs. not-for-profit hospital adoption behavior in more detail. They concluded these 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, not all studies identify the same adoption influences. 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). Though the adoption process is better understood today than it was even a few years ago research in this area will continue as health IT adoption continues.

Another body of literature evaluating cost, quality, and efficiency of health IT systems 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 EHRs were the three systems most often evaluated in the literature. Although interoperability is the feature of health IT systems 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).

Not all research has found positive quality effects. Using panel data containing EMR and CPOE adoption information from 2004 to 2007 McCullough et al. (2010) found 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. In a study of EHRs in ambulatory care, no significant quality improvement was found in 14 of 17 quality indicators (Linder et al. 2007). Furukawa (2006) also 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.

Other systematic reviews confirm most researchers have mixed conclusions regarding outcomes and costs. Garg et al. found CDS systems improve physician performance but the effect on patient outcomes was unclear (2005). A review of EHR and CPOE effecton physician and nurse efficiency found EHR decreased documentation times when systems were evaluated shortly after implementation but the longer the period between the implementation and evaluation the smaller the effect. CPOE with central station desktops was more efficient for nurses but for physicians resulted in increases in documentation time of 98% to 328% per working shift (Poissant et al. 2005). Goldzweig et al. updated Chaudry et al., (2006) in 2009 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 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.

Even if health IT is shown to improve the quality of medical care in the U.S. the quality improvements will eventually be evaluated in relation to the costs. Cost savings need to be realized through higher quality care to offset the costly new health IT systems. Some researchers have begun to address the issue using the limited available data. Astudy of the impact of health IT on hospital costs using data from 1987 - 1994 found clinical health IT systems do reduce hospital operating costs 3-5% but there is a substantial lag time before those costs are realized, 5 years, and those savings are only achieved if there is a large enough installed base of clinical systems within the hospital (Borzekowski 2009). A cost-benefit analysis of a CPOE system at Brigham and Women's Hospital found the system saved the hospital $28.5 million dollars over 11 years. The cost to develop, implement and operate the system however, was $11.8 million (Kaushal et al. 2006). A pharmacy bar code system at the same hospital resulted in a $3.49 million net benefit after 5 years (Mavigilia et al. 2007). These studies prove that it is possible to achieve a positive return on investment; but, it is worth noting that Brigham and Women's Hospital is one of the 4 leading health IT evaluation academic institutions mentioned by Chaudhry et al. (2006) with the funding and capability to design and implement its own health IT systems.

A 2005 RAND Health Information Technology Project cost-benefit simulation of EHR system adoption predicted over $1 billion in savings nationally due to decreased drug errors if interoperable systems were installed in all hospitals throughout the U.S. (Hillestad et al. 2005).Realistically, the 90% adoption rate of an interoperable EHR system assumed in Hillstad et al. is not likely to occur soon. At this point it is not even clear if stand alone hospital health IT systems hospitals reduce cost savings or improve quality. While the improvement in medical care is a major factor in the health IT decisions the business case for health IT cannot be made without cost savings. I argue any cost calculations are incomplete without accounting for the change in hospital demand.

2.2 Hospital Choice Literature

I address the need for more research to bridge the demand side gap in the health IT literature using a model 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. A review of the literature from several years ago identified three general types of hospital choice models. Gravity models based on the spatial interaction of patients and hospitals were the first type of hospital choice models used. These models were limited by an inability include hospital choices outside a patient's community. Aggregate measures use a proportion of patients from a given community who are admitted to a given hospital. The third type of model, conditional (multinomial) logit models, have become more common as better data has become available and computing capabilities have improved allowing for more complicated models and estimation techniques (Porell and Adams, 1995).

The logit models are all based on discrete choice models of consumer behavior (McFadden, 1973). Multinomial logit models are characterized by incorporating the consumer's characteristics as well as the characteristics of all of the consumers' potential choices into the model. As logit models became the common method of analysis and the models became more complex some researchers began to evaluate this method in more detail. Maximum likelihood estimation (MLE) was shown to be superior to linear estimation techniques when models involved many hospitals or hospitals which were not chosen by any patients (Garnick et al., 1990). Even though MLE is more difficult to implement than linear estimation it is important to know that linear estimates may be biased when policy and administrative decisions are based on the results.

More recent advances in the area of discrete choice models of differentiated product markets have also been applied to hospital choice research. By the assumptions of these methods each hospital in a market can be considered a product different from each other hospital in a market. Alternatively, hospitals could be considered multiproduct firms where each procedure a hospital offers could be considered a product slightly different from the same procedure at every other hospital. More flexible and detailed analysis of hospital choice has many policy implications including policy simulation and policy evaluation. Although gravity models have given way to these more advanced techniques the results from these new modeling techniques are consistent with early results, mainly hospital choice is driven largely by location. The proximity of patients to hospitals is a significant predictor of hospital choice in conditional multinomial logit choice models (Porell and Adams, 1995). Methods of hospital choice analysis other than discrete choice models have also concluded that location is a major factor in the choice of a hospital. An analysis of patient survey data using an analytic hierarchy process to determine the relative preferences of patients over hospital characteristics found that patients ranked the location of a hospital as the most important factor relative to all others when choosing a hospital. Technology was the 4th most important factor (Javalgi et al., 1991).

Researchers have also investigated the effect of factors other than distance that could feasibly affect the choice of a hospital. Hospital charges and quality of care are some of the hospital characteristics 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).

In addition to studying the hospital choice decisions at the patient level, patient hospital choices have been used 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. The competition measures are constructed from estimates of hospital demand based on discrete choice models. Using hospital characteristics, hospital-patient distance measures and patient demographics Kessler and McClellan (2000) estimate the probability that a patient would choose a certain hospital. These predictions are used to construct measures of hospital market competition and then estimate the welfare implications of that competition. In another study of the effect of changes in HMO hospital networks estimates of hospital demand are used in simulations of HMO reorganizations of hospital networks (Town and Vistnes, 2001). Gaynor and Vogt examine hospital competition in California and simulate the effect of hospital mergers based on estimates obtained from discrete choice models (2003). A study of the implications of managed care plans' hospital choice restrictions indicate that consumers do consider hospital availability when choosing health plans (Ho, 2006). My analysis uses methods similar to those in the papers mentioned above to identify the effect of health IT on hospital demand at a market and individual level.

3. Conceptual Model

Health IT systems in hospitals are obviously relevant to the quality, efficiency and productivity of hospitals, even if the size of the impact is debatable. I argue that stopping the analysis of health IT systems at the supply-side is a short sighted view of the health care system and economics. Health IT systems are not distinctly supply-side technologies. Assuming health IT does improve the quality of service and/or reduces production costs a simple graphical demand-supply analysis would show the supply curve for the hospital adopting this technology shifting to the right. The resulting equilibrium would be a lower price and a higher quantity of services sold. Even under the very unique health care market conditions the equilibrium quantity would be higher if prices were fixed by exogenous factors such as insurers or the government. The same result, increased quantity, is obtained when considering any effect health IT may have on demand directly. In that case, however, the resulting change in price is an increase, all else held constant. Given this elementary economic analysis, the impact of health IT on health care costs is ambiguous but the increase in demand for hospital services result is consistent. Whether health IT has an impact on a patient's hospital choice then becomes an empirical question.

There are two main mechanisms by which health IT will affect patient choices. Patients develop perceptions of hospital quality based on news reports, advertisements and past experiences regarding health IT systems. A 2009 survey of patient 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). I assume patient knowledge of health IT systems results in a belief that the quality of care is improved and medication errors are reduced[4]. Whether the reduction in medical errors is actually a result of the EMR is not as important to the decision maker as if they believe it does. It is also possible for health IT to create excess capacity for patients seeking faster access to certain procedures. If a patient is looking to schedule an elective surgery and health IT has led to productive efficiencies a hospital may have the capacity to perform more surgeries following the implementation of health IT. Thus, more patients choose the hospital with health IT for

[4] 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.

elective surgeries. In this case the actual effect of health IT on production does matter. In this area the evidence is just as mixed as the quality research (Furukawa, 2011; Poissant et al. 2005). So far there is some evidence of efficiency gains under certain circumstances but not broad effects. This may have an effect on some physicians in some hospitals but it is not likely the major driver of increased demand.

An interesting phenomenon of health care is that the decisions are not strictly made by the patients, as they are by consumers in a grocery store. The second way health IT affects patient choices is through significant influence by the patients' physicians. In some cases the physician actually makes the decisions. It is commonly assumed that the physician acts as the patient's agent and decides in the best interest of the patient. There is some evidence of physician influence over hospital choices; although, the research is limited by data availability. One study by Burns and Wholey (1992) that used a unique dataset including physician characteristics found that these characteristics explain a large amount of the variation in hospital choice. Contrary to this finding the analytical hierarchy process analysis found that a doctor's recommendation was only 7^{th} in relative importance below hospital location, reputation, technology, and cost of care (Javalgi et al., 1991).

In this case, the assumption that the physician acts as the patient's agent is not a necessary condition. I only need to assume that a patient prefers health IT based on recommendations from a physician. A benevolent physician will direct patients to hospitals with health IT if she believes health IT will facilitate higher quality/lower cost care for the patient. Alternatively, if a physician is less than benevolent and believes that health IT does not improve the quality of care but does make documentation and administrative responsibilities easier the physician can recommend patients choose a hospital with health IT. Patients who put any value on their physician's work environment will still prefer health IT in this situation. Although these scenarios have significantly different implications for patient care and the effect of health IT on quality my analysis is of demand for hospitals, measured by the number inpatient admissions, not hospital quality or physician acceptance of health IT.

It is possible that health IT systems will reduce the probability that a patient chooses a hospital if the health IT system does not exhibit positive supply-side effects. For example, if it is difficult for physicians to learn to use the new health IT system or if the system disrupts the care process physicians may direct patients away from hospitals with health IT systems. Currently the evidence of the actual effect of health IT is mixed but there are still strong beliefs that health IT improves the delivery of health care. I assume that physicians and patients generally believe in the often touted benefits of higher quality and/or more efficient care. From these assumptions about patients and physicians attitudes toward hospital choice and the small possibility that health IT has positive productivity effects I expect to find empirical evidence of increased demand for hospitals with health IT.

It is likely, that physicians who use health IT in their practice will encourage patients to go to hospitals with similar or complementary health IT systems. Efficiency gains are available to the physician at a minimum through knowing how the system works if not through being able to access patient records more easily. There is evidence that more physicians are starting to adopt health IT in their offices even though the cost and quality benefits of health IT in the literature are not overwhelming. A 2005 survey of medical group practices by Gans et al. (2005) highlighted the slow rate of adoption of EHRs, especially among smaller practices. However, physicians are adopting. The rate of practices with 21 or more physicians that had fully adopted a system was found to be near 20 percent. Adoption by small practices with five or fewer physicians was lower with only about 12 or 13 percent having fully adopted. Although, the survey found that 60 percent of those smaller practices planned to implement a system within two years. Similar results from 2001-2003 survey regarding the use and adoption gap between large and small physician groups were found by Burt and Sisk (2005). Recent initiatives and education programs by organizations such as the American Academy of Family Physicians and the Medical Group Management Association are encouraging health IT adoption and use by physicians. This research suggests that physicians are not all avoiding health IT, they may just be adopting office based systems more slowly than expected.

It is important to remember that the 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 the decision 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 words, part of the decision process remains in a "black box" (Luft et al. 1991). Thus, in the following proposed discrete choice analysis I assume that some factors influence a patient's hospital choice but the exact mechanism of this influence is not specified.

4. Empirical Models

Based on my conceptual model I am testing for an empirically observable increase of probability of a patient choosing a hospital after the hospital has implemented health IT. I assume patients use their own knowledge and preferences as well as physicians' recommendations to choose the hospital which they believe will provide the best medical care. The presence of an health IT system leads patients and physicians to believe the hospital is able to deliver better quality care and subsequently results in a higher probability of a patient choosing the hospitals with health IT.

4.1 Discrete choice models

Formally, I model an individual patient's decision 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). I am able to observe the patient's choice, *j*, and I assume that this choice is the one which maximized patient *i*'s utility. Patient *i*'s utilities of all the choices other than *j* are not observable. By assuming that the observed choice is the one which gave patient *i* the greatest utility patient *i*'s choice can be represented by an indicator function equal to 1 when $U_j > U_k$ and equal to 0 when $U_j \leq U_k$, where $j \neq k$. The parameters of this utility function can be estimated using a discrete-choice model of consumer behavior where Y_i is a random variable indicator for patient *i*'s choice. McFadden (1974) showed that when (if and only if) the J error terms are independent and identically distributed type I extreme value then

$$\Pr(Y_i = j) = \frac{\exp[\mathbf{X}_{k\mathbf{i}}\,\boldsymbol{\beta}]}{\sum_{k=0}^{J} \exp[\mathbf{X}_{k\mathbf{i}}\,\boldsymbol{\beta}]} \qquad (1)$$

This is often referred to as a (McFadden's) conditional logit model. This model is flexible enough such that the vector **x** can include both characteristics of individuals and choices (Greene 2003). The characteristics I include in my models are based on the specifications of the patient's utility functions. The patient's utility functions are based on my conceptual model of patient hospital choice as well as the available data.

Besides the underlying utility function which allows an economic interpretation of logit parameters the logit probabilities include several advantages. First, the probabilities are necessarily between 0 and 1 which is not true of linear probability models. Second, these probabilities are also assured to sum to 1 by the denominator term for each decision maker. This is useful when interpreting the results and not necessarily true with other models such as probits which do not contain a similar denominator. Third, the shape of the logit probability has implications for the interpretation of results and the policy implications. The greatest impact of a change in representative utility is around the area where the probability of being chosen is 50% a consequence of the S-shaped probability. This means that small increases in representative utility for hospitals with approximately 50% chance of being chosen will result in greater probabilities of being chosen than larger increases in relative utility for hospitals with small or large probabilities of being chosen (Train 2003). This is relevant to my analysis because it means for a large enough population even a small impact of health IT on the relative utility of a patient can have large impact on a hospital's demand if a hospital's probability of being chosen is near 50%.

4.1.1 Identification

The size of the data set is prohibitively large to estimate a single discrete choice model at the patient level for every Medicare patient admitted to the hospital through the period 1999-2006. However, the 8 year panel of hospitals provides the identification strategy for the models I can estimate. By using hospital panel data which has observations pre and post health IT implementation difference-in-differences (DID) identification is possible. The DID estimates are the equivalent of taking the difference of the average outcomes of the treated and untreated groups. In my models I am comparing the change in patient hospital choices over hospitals adopting health IT and hospitals which do not adopt. A second piece 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. I employ two complementary discrete choice models of consumer choice in differentiated product markets by exploiting the availability of DID and hospital fixed effects in my data to identify the effect of health IT on patient choices.

In my models the indicator variables representing health IT systems are the variables of interest. I am 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 as I have just described. I construct choice sets for each model in an intuitive and theoretically consistent ways which I describe below. Even without complete knowledge of a patient's decision making process I am able to model a patient's decision in such a way that I can inform my model with the information I do have and account for variations resulting from the information I do not have.

4.1.2 Berry model

My first approach 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 measures of patient preferences. All hospitals within 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 market level data. To begin, I propose a patient utility function can be represented as:

$$u_{ijzt} = \beta_1 \mathrm{HIT}_{jzt} + \beta_2 \mathrm{X}_{jzt} + \xi_j + \varepsilon_{jzt} + \beta_3 \mathrm{T}_t + \upsilon_{ijzt} \quad (2)$$

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*. HIT_{jzt} is a dummy variable indicating whether or not hospital *j* has a health IT system in period *t*. A 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*. Some of these characteristics are constant across zip codes: teaching status, hospital size (natural log of number of beds), for-profit status and hospital system status. The vector X also contains a variable which 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.

Based on the exposition in 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 T_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. Based on the transformation in Berry (1994), I estimate the parameters in (1) using a linear, share equation given by:

$$(\ln S_{jzt} - \ln S_{0zt}) = \beta_1 HIT_{jzt} + \beta_2 X_{jzt} + \bar{\xi}_j + \bar{\tau}_t + \varepsilon_{jzt} \qquad (3)$$

This noteworthy feature of this transformation is that the model retains the properties of the conditional logit market share model.

A common identification assumption made for this type of model is that the hospitals do not observe the shocks to mean hospital quality when deciding whether or not to adopt health IT. In this specification the average hospital quality, ξ_j, maybe correlated with health IT adoption decisions but ε_{jzt} is not. Similar identification assumptions are made by Berry, Levinsohn and Pakes (1995), Nevo (2001), Petrin

(2002), and Town and Liu (2003). Besides this identification assumption the inclusion of hospital fixed effects and DIDs contribute to the identification of the models' parameters.

The shares, S_{jzt}, for hospital *j* in year *t*, are defined at the market level, *z*, by zip codes. A market choice set is defined as every hospital within 100 miles of the zip code center. The outside good hospital choice, S_{0zt}, is defined as all hospitals outside of the 100 mile radius. 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). One consequence of this market definition to note is that many hospitals are included in more than one market; however, market size is based on patients' billing zip codes so patients are only counted in one market.

4.1.2 Conditional logit model:

The second type of model I employ, 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:

$$U_{jit} = \beta_1 X_{jt} + \beta_3 X_{it} * W_{jt} + \beta_4 d_{ij} + \beta_4 d_{ij} * W_{it} + T_t + \xi_j + \varepsilon_{ijt} \quad (4)$$

This is similar to the utility function given by equation (2) with a few significant differences. First, this equation will be estimated at the patient level rather than the market level. The X_{jt} is a vector of hospital specific characteristics which vary by time period. These include hospital size measured by the natural log of the number of beds and indicator variables for teaching status, for profit status and hospital system status which equal 1 if true and zero otherwise. Besides these hospital characteristics the X_{jt} vector will include an health IT dummy variable for each technology of the 3 technologies of interest in my study: EMR, CPOE, PACS. These health IT variables will equal 1 if hospital *j* has that system in period *t*, otherwise the variable will equal 0.

In this model specification 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. On average, older patients may choose hospitals differently than female patients. I am able to identify the effect of patient characteristics 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, admission type (elective admission = 1).

Previous examples of hospital choice models such as Kessler and McClellan (2000), Town and Vistnes (2001) and others find that besides patient and hospital characteristics the travel distance to the hospital is a significant predictor of hospital choice. Therefore, 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 will vary across hospitals by patient zip code so the coefficient is identified. Distance is also interacted with patient characteristics in the d_{ij}* W_{it} term in equation (4). Trends in time which may affect patient decisions but which are not observable are controlled for using a set of polynomial time trend variables $\delta_{t.}$ These trends account for unobservable time shocks which vary over time but not between hospitals. As in the Berry model a hospital-specific fixed effect, ξ_j, will be included to account for mean differences across patients' preferences of hospitals such as perceptions of hospital quality.

I define a hospital choice set for each patient as the set of all hospitals within 50 miles of a patient's zip code of residence which had at least 75 admissions for that DRG group within a year. Any hospitals outside of the 50 mile radius or with fewer than 75 admissions are considered part of the outside option. By limiting the sample to hospitals with at least 75 admissions all of the hospitals with only one or two admissions are eliminated from the choice set. This also allows for a significantly smaller number of fixed effects and for the maximum likelihood estimates to converge[5]. The 50 mile radius was also set for this reason. The exclusion criteria results in approximately 25% of patients choosing the outside option.

This outside option allows for situations where a patient who lives in Minnesota but went to a hospital in Florida during the winter to be included in the model which does add some information. Additionally, the inclusion of an outside option allows me normalize the utility of one choice common to all patients to zero. This essentially sets

[5] A minimum of 25 admissions resulted in estimation problems. A minimum of 50 admissions resulted in no models with jointly significant HIT variables and HIT interactions. Approximately 5% more admissions are part of the outside good when a minimum of 75 admissions is used rather than 50.

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 (4) are parameters to be estimated and the error term, ε_{ijt}, is assumed to be i.i.d. Type I extreme value. With this distribution of the error term the choice probabilities for hospitals by patients at time t can be shown using equation (1) with the addition of a *t* subscript where $\beta_1$is applicable:

$$P_{ijt} = \frac{\exp[\beta_1 X_{jt} + \beta_2 X_{jt} * W_{it} + \beta_3 d_{it} + \beta_4 d_{it} * W_{it} + T_t + \xi_j]}{\sum_{k=0}^{J} \exp[\beta_1 X_{kt} + \beta_2 X_{kt} * W_{it} + \beta_3 d_{it} + \beta_4 d_{it} * W_{it} + T_t + \xi_k]} \quad (5)$$

4.2 Estimation:

Both the linear, share model and the conditional logit model can be estimated using maximum likelihood estimation. The parameters of interest are those associated with the health IT dummy variables but the other parameters will also be informative. The log-likelihood function for the conditional logit is: Y_i

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{J} d_{ij} \log \text{Prob}(Y_i = j) \qquad (6)$$

where $d_{ij} = 1$ if $Y_i = j$ and 0 otherwise. This log-likelihood is the same for a market share model when d_{ij} is defined as the proportion of the market share (Greene 2003).

The advantage of the linear share model I specify in (3) is that the transformation derived by Berry (1994) results in a linear specification. There are multiple benefits of a linear model but for my analysis the major advantage is the reduction in computation power and time. I estimate the linear share model for a sample of all Medicare inpatient admissions in 2,600+ hospitals per year for all patients over the age of 65 for 8 years.

It is not feasible to estimate the conditional logit model using the full sample of patients because the sample is so large. Instead I estimate the conditional logit model using a sub-sample from three Midwestern states MN, WI, and IA and two clinical subsets of the data from those states. These three states were selected because they are contiguous and include a wide range of hospital types, small rural hospitals, urban trauma centers, national referral center, etc. Health IT adoption rates in these states are similar to the national average and it can be reasonably assumed patients in parts of these states have some information about health IT[6]. One DRG subset contains patients admitted for a procedure that is generally elective, joint replacement, and the other contains patients who are most often admitted through the emergency room, heart failure. Models of these two DRG subsets are estimated separately for each type of health IT. Given that I am investigating three technologies the specifications result in 3 estimations of the linear share model and 6 estimations from the conditional logit model. Additional estimations were also performed with all three data sets using combinations of health IT systems within hospitals. All of the estimations are performed in Stata 11-MP on a Minnesota Supercomputing Institute server.

4.3 Parameter Estimates

Traditionally, interpreting the results from linear share models and conditional logit models requires some caution. The resulting parameter estimates need to be

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[6] Wisconsin is home the national HIT vendor Epic Systems. The headquarters for UnitedHealth Group (UHG) is in Minnesota and UHG is has been involved with HIT through numerous subsidiaries. Additionally, each of the three states has a top tier research university with a school of public health as well as numerous medical schools.

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 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). For example, I expect the distance measure to be negative which implies that the further away a hospital is the less likely a patient is to choose that hospital relative to the other hospitals and the outside good which was normalized to a utility of zero. A magnitude of -.25 does not mean that a patient is 25% less likely to choose a hospital which is one mile further away.

By incorporating the outside option in each choice set of both models I have implicitly set the utility of one choice to zero. This normalization allows for a somewhat more direct interpretation of the parameters; essentially, the parameter estimates may be interpreted as binary logit relative risks. By normalizing the coefficient values of the outside hospital choice o to 0 the relative risk of choosing alternative j compared to the outside option is:

$$\frac{\Pr Y_j}{\Pr Y_o} = e^{xb} \quad (7)$$

(Cameron and Trivedi, 2003). Although, this is somewhat more informative than the parameter estimates alone I am still interested in finding the magnitude of the impact of certain variables, specifically those for health IT.

Although the parameter estimates do not tell me everything I would like to know they are informative. Beginning with the parameters estimates and the standard deviations I will be able to determine if and how certain variables influence a patient's hospital choice. Further calculations can be made to estimate the magnitude of the effect of statistically significant variables. In both the linear share models and the conditional logit models I expect the health IT coefficients to be positive and statistically significant. This will imply that health IT has a positive impact on a patient's hospital choice.

I expect the distance measure to be negative as increased travel time and distance are expected to reduce the probability of a patient choosing a hospital. The interaction term between a rural indicator variable and the distance traveled should also be negative. Patients living in a rural area are more likely to have to travel further to go to a hospital than patient living in an urban area where there are more hospital choices. A negative coefficient implies the impact of travel distance is lower for rural patients compared to urban patients when choosing a hospital. Assuming larger hospitals and teaching hospitals have more resources and provided better quality I expect the coefficients on ln(beds) and teaching variables to be positive and significant. This is consistent with the theory that patients and physicians are choosing provide better care or are presumed to provide better care.

Patients with time to consider their hospital choice are assumed to be more likely to choose hospitals with health IT. More time allows them to gather information and decide which hospital will provide the best care. Patients making decisions in emergency situations are more likely to choose the most convenient hospital. I do not observe the time patients take to consider their hospital choice but I do observe the type of hospital admission which serves as a decision type proxy. I assume a patient who chooses a hospital for an elective procedure has time to consult their physician and investigate hospitals and a patient who is admitted through the emergency room or urgent care is less likely to have spent time any time investigating hospitals. The coefficient of the interaction between elective admission and health IT is expected to be positive and significant. This can be interpreted as the impact of health IT on a patient's utility is greater for elective admissions than it is for patients without elective admissions. Another way to express this is there is higher probability of patients choosing hospitals with health IT when their admissions are for elective procedures.

4.4 Marginal Effects

A common method 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. In other words it is possible to determine the impact of a 1 unit change in characteristic x on the share or probability of being chosen. 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 with respect to x_j:

$$\frac{dP_j}{dx_j} = [P_j (1 - P_j)]\, \beta \qquad (8)$$

The marginal effects in the linear, share model are similar with hospital j and k 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 varaiables can be approximated by equations (7) and (8) but are not necessarily accurate. These derivatives is merely provides an approximation for discrete variables. Technically, the marginal effect of discrete variables those should be calculated as:

$$\Delta \mathrm{P}_j = \left[\frac{\exp[X_j \beta]}{\sum_{k=0}^{J} \exp[X_k \beta]} \right]^{x=1} - \left[\frac{\exp[X_j \beta]}{\sum_{k=0}^{J} \exp[X_k \beta]} \right]^{x=0} \qquad (9)$$

Where again, shares may replace probabilities.

I also calculate the marginal effects for two continuous variables from the models, distance and ln(beds) to present a basis for comparing the marginal effects of health IT to other factors which impact demand. For analyses with small choice sets these are simple calculations which can be performed for any or all of the regressors and for each alternative. In my analysis it is not feasible to report marginal effects for each variable and every hospital but it is also not necessary to report the all of the results. Instead, I calculate the marginal effects for each hospital within each choice or market then find a patient- or market-weighted average. From the market level marginal effects I am also able to calculate a weighted average marginal effect for a hospital. The marginal effects of from either the Berry model or the conditional logit model can also be interpreted numbers of patients rather than percentages.

A slightly different calculation is needed to find the marginal effect of discrete variables such as health IT. Using the estimated utility parameters I estimated new hospital share and choice probabilities simulating a change from no- health IT to health IT for each hospital in the data set. It is necessary to simulate this change one hospital at a time, holding all other hospitals constant in order to allow shares or probabilities to shift within choice sets. If I were to switch all hospitals to health IT adopters at one time I would not be able to distinguish changes in patient choices. The change in shares or probabilities from switching is found by taking the difference between the estimates from the two simulations for each hospital. After I have simulated both probabilities for each hospital I again average each hospital's shares and probabilities over patients. After this final step I am left with a set of changes in probabilities (or shares) similar to those from a continuous variables. I can also aggregate these marginal effects from market level to hospital level and find the average marginal effect in terms of a number of patients. Utility parameters and marginal effects are both valuable measures of the impact of health IT or other variables on the demand for inpatient services but a more tangible measure is numbers of patients. As a final step in my analysis I convert the marginal effects to patient admissions using an average hospital's characteristics.

5. Data

The data used to perform the analysis comes from the combination of three main datasets. Hospital characteristics data were 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.

This hospital database was linked with 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 information technology 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.

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. Additional data, such as zip code level geographic information was used to supplement the hospital and claims data. 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 longitudinal feature of this dataset is what I rely upon for identification of the effect of health IT. In addition to including a large number of observations of patient choices the hospitals' IT investments are observed over time which allows more analysis than a one period, cross section of hospital IT data or a time series of aggregate health IT data. The dataset used for this analysis include observations on three health information technologies over 8 years of the Medicare inpatient claims data (1999-2006). These years of data and technologies are a subset of the data used by McCullough, Parente and Town in a series of working papers measuring the impact of health IT on inpatient quality and hospital charges (2011). This data was restricted to inpatient facility admissions; it does not include skilled nursing facilities and it excludes critical access hospitals admissions[7].

5.1 Health Information Technologies

Not all information technology in a hospital is equal; for example, some technologies are related to record keeping while others provide clinical support functions. Because of the differences in the types of health IT used in hospitals it is necessary to identify specific types of technologies to analyze. Three technologies or applications were 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. Some systems like CPOE may be implemented as a means of improving patient safety. These systems which directly affect the delivery of care therefore directly affect patients as well as physicians. CPOE systems allow physicians to enter medical orders directly

[7] I benefited greatly in using this data as well. I would like to thank professors McCullough, Parente and Town for permission to use of this data set and add a special thank you to Dr. McCullough and Hawre Jalal for the exceptional work they performed in cleaning and merging the HIMSS data and the MedPAR files.

into a computer. It is expected to decrease the time it takes to complete the order and reduce the ambiguity of handwritten orders. Some CPOE systems for medication may also reduce the number of medication errors by monitoring orders and alerting physicians of incorrect doses or frequencies, adverse drug interactions, and drug allergies (Gartee, 2007). A PACS application stores and automates cardiology and radiology images used for diagnosis. The systems allow a user to digitally retrieve, route and display images (HIMSS, 2004). PACS allow physicians to more easily access and review images resulting in faster more efficient treatments. PACS have less of a direct clinical impact on patients because images are not involved in administering care; PACS are used in determining what care to administer. However, there still may be benefits to patients or doctors through quick and efficient access to images resulting in faster treatments. I expect PACS to have the same effect on patients and physicians as CPOE and EMRs.

There is constant reference to EMRs and EHRs in the popular press and peer-reviewed literature. Unfortunately, the definition of an EMR and EHR is not always made explicit and not everyone defines them in the same way. One way to define an EMR or EHR system is by the system's capabilities. Fonkych and Taylor (2005) used this approach to measure EMR system adoption in hospitals. They defined a basic EMR system to include a computerized patient record (CPR), clinical decision support (CDS), and clinical data repository (CDR). Their definition also required that these components and any additional quality or outcomes related applications work together within one system.

The definition of EMR in this data set is based on the EMR variable which is available in the most recent release of HIMSS data. In the years of data prior to the inclusion of an EMR variable an hospital is considered to have an EMR if it has implemented CPR, CDS and CDR. These applications, and eventually the EMR replaces paper medical records. The goal of these databases is to eliminate redundant records and concisely store health care data entered by providers or produced by various other applications for the lifetime of a patient. The systems are required to adhere to the same clinical, legal, and administrative requirements as paper records (HIMSS, 2004).

The health IT indicator variables are included in every model with a 1 year lag. For example the year 1999 includes a measure of health IT from 1998. This allows for a more consistent estimate of health IT due to possible reporting errors in the data. If health IT is adopted in 1999 but not until a week before the survey it is very unlikely the effects of health IT will be captured in the 1999 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 bias from misreporting.

5.2 Study Population

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.

Both sets of models include Medicare beneficiaries residing in urban and rural areas. It is possible that rural patients experience different benefits from health IT than urban patients through possible continuity of care or other health care delivery efficiency gains. To account for this possibility a rural/urban indicator variable was included in the data set based on the University of Washington's Rural Urban Commuting Area (RUCA) Codes, version 2.0 (WWAMI, 2005). All patients with zip codes in a Metropolitan area were assumed to reside in urban areas. Patients residing in Micropolitan areas (large rural areas), small towns, and rural areas were considered rural. The indicator variable equals 1 if the patient resided in a rural zip code and 0 if the residence was assumed to be urban. In the final linear share data set 32.7% of the zip codes were coded as rural areas.

5.2.1 Berry Model Data

The linear share 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. This is an extremely large number of hospital admissions that was limited in some degree by the use of the HIMSS/Dorenfest and AHA data sets. The match rate between the hospitals in the AHA data and the HIMSS data was approximately 92% for the 8 year period. Since the HIMSS data is not collected for every hospital there is not a perfect match rate between the claims data the HIMSS-AHA data. Depending on the year the match rate with hospitals from the claims data was between 74% and 83%. This is still representative of approximately 80% of the total claims. Additionally a small percentage of claims (<1%) were excluded because of zip code mismatches between the 1999 zip location file and the claims data. The zip code file included the latitude and longitude of each zip code center as of the 1999 census zip codes; consequently some zip codes from later years did not match the zip codes from 1999. The resulting data set included an average of 8,531,771 observations per year from an average of 2,619 hospitals per year.

Table 1 depicts the number of hospitals included in the sample each year and the percentage of the sample that adopted health IT. CPOE adoption does not begin until half-way through the observation period but after 4 years the adoption rate of 16% was about twice that of EMR (9%) or PACS (7%) after 4 years. PACS are the most widely adopted health IT systems in 2006 with almost half of the hospitals in the sample reporting they use a PACS system. EMR systems were only operational in about a third of the hospitals in the sample by 2006. Another noticeable feature of the data is the sharp 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. An imperfect crosswalk between those two data sets may also contribute to the decrease in hospitals in my data. Not all of the hospitals from the first year are observed in subsequent years. Some leave the sample because they merged or closed. Obviously, other hospitals enter the industry after 1999. This produces an unbalanced panel of hospitals.

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%

Examining data from 2006 when adoption rates were the highest and the number of hospitals was close to the 8 year average[8] it is apparent that health IT adopters differed from non-adopters. Table 2 shows that health IT adopters were more likely to be teaching hospitals, less likely to be for-profit and were generally larger, in terms of number of beds. CPOE was the least likely to be adopted by for-profit hospitals at a rate of 9% but most likely to be adopted by teaching hospitals 53% of the time. Compared to the total population for-profit hospitals made up 21% of all hospitals and 37% of all hospitals

[8] The average number of hospitals per year = 2620.

were teaching hospitals. This is consistent with the results of Cutler et al. (2005) who found CPOE was being adopted by teaching hospitals and not for-profit hospitals.

Table 2: Hospital Characteristics by Health IT in 2006

	Total Hospitals	**Percent Teaching**	**For Profit**	**System Member**	**Number of Beds**
All Hospitals	2649	37%	21%	62%	210.6 (171.5)
EMR	905	43%	16%	56%	237.5 (185.2)
CPOE	421	53%	9%	60%	267.9 (196.3)
PACS	1297	45%	12%	62%	259.3 (193.6)

Standard Deviations in parentheses

5.2.2 Conditional Logit Model Data

In order for the model to be estimated the conditional logit data set needed to be significantly smaller than the linear share data set. 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. The results of the conditional logit model estimations may not be generalizable to all areas of the country especially if other areas have significantly different population or hospital characteristics. However, these models do explicitly include patient characteristics which the linear share model does not. Estimates from these models can be used to determine the extent the demand for hospitals is influenced by health IT through patient characteristics. Further investigation into the influence of patient characteristics in other geographic areas and DRGs is left for future research.

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 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). In the Medicare population DRGs are used in the calculation of hospital inpatient reimbursement rates by grouping diagnoses and procedures with similar clinical characteristics and resource utilization. Using the DRG codes that are assigned to patients in the Medicare claims data the demand effect of health IT can be studied for groups of similar procedures and conditions.

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. A patient planning to undergo cosmetic surgery may spend months researching which hospital to choose. To test for an impact of health IT in both types of patient populations I choose the two DRG codes listed by CMS as the most common "elective" and "other" admissions in 2006. DRG code 544[9] 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. By not restricting the samples to only one type of admission an elective admission dummy variable can be created and interacted with health IT in the conditional logit models. An interaction of the elective admits dummy variable and health IT will show the

[9] 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.

effect health IT has on patient choice by type of admission. The number of admissions for both DRG codes and the percentage of which were elective admissions is shown in Table 2. The difference between the two groups in the number of elective versus non-elective admissions is obvious. By not restricting the data to only one type of admission I am able to control for the variation within the groups include variables to test for interactions between admission type and other choice characteristics.

The CMS claims data includes measures of patient age, gender, race besides type of inpatient admission. An elective admission variable equals 1 if the admission was coded as an elective and 0 otherwise. Age is included as the patients age recorded for each inpatient admission. A gender indicator variable is included where Gender = 1 if a patient is female and 0 otherwise. From the categorical race variable I constructed an indicator variable to be used in the regression model which equals 1 if a patient's race is not listed as white/Caucasian and 0 otherwise.

The patient characteristics for each DRG sample are shown in Table 3. The percent of female patients is higher in the joint replacement group but similar across technologies for both DRGs. Rural patients appear to have been admitted to hospitals with EMR much more frequently than to hospitals with other technologies. The low rate of rural patient admissions to hospitals with CPOE is probably due to the low rate of CPOE adoption. There is not an obvious reason why rural patients have lower admission rates to hospitals with PACS. One explanation is that PACS is being adopted in primarily urban areas compared to EMRs which are being adopted across a wider variety of hospital locations. An interesting aspect of the average distance traveled to hospitals with

CPOE is how much smaller it is than other hospitals. I expected higher average distances to hospitals with CPOE because fewer hospitals have CPOE so the distance to that hospital from any given zip code would be higher. It is possible that since so few hospitals have adopted CPOE that there are also very few patients who chose hospitals with CPOE. If some of the patients who did choose hospitals with CPOE had very short travel distances their travel may be driving the average down.

Table 3: Patient Characteristics by Health IT

	Patient Admissions	Percent Female	Percent Rural	Percent Non-White	Average Age	Average Miles Traveled
Joint Replacement						
Total	**183,544**	**64.38%**	**44.45%**	**2.18%**	**76.5 (7.1)**	**14.0 (12.8)**
EMR	12.44%	64.73%	40.01%	2.07%	76.5 (7.2)	14.8 (12.8)
CPOE	3.68%	65.67%	21.01%	2.70%	76.4 (7.2)	11.9 (11.6)
PACS	16.43%	63.88%	27.67%	2.25%	76.3 (7.2)	14.1 (12.8)
Heart Failure						
Total	**147,549**	**56.14%**	**34.51%**	**5.07%**	**80.8 (8.1)**	**9.6 (10.0)**
EMR	12.15%	56.36%	37.72%	2.79%	81.6 (8.1)	10.2 (10.0)
CPOE	3.46%	56.49%	21.30%	4.74%	81.6 (8.3)	9.2 (9.4)
PACS	15.38%	55.86%	19.28%	4.56%	81.3 (8.4)	10.8 (10.9)

Standard Deviations in parentheses

I also included a Charlson Co-Morbidity Index as a severity measure for each patient based on the diagnosis codes recorded for an admission. The Charlson index is a common severity measure in health services research which predicts a patient's 1-year probability of mortality on a scale of 0-17. I expected the severity measures to differ by DRG assuming patients who choose to have a hip or knee replacement are more likely healthier than patients being admitted to an emergency room for heart failure. The rate of patients discharged deceased is much higher for patients with CHF than those patients receiving a joint replacement. There was not significant variation in the Charlson Index between DRGs although there was some variation among patients within each DRG population. In both populations the Charlson Score has a similar distribution across patients, approximately 28%, 30% and 42% for scores of 0, 1 and 2, respectively. Severity enters the model through interactions with health IT, ln(Beds) and distance. If the interaction of severity and these hospital characteristics has a major influence on a patient's hospital choice the result will be estimates which are biased downward but these are not the variables of interest and the Charlson index is a sufficient control for severity within the logit model populations. The mean admission and severity indices are reported in Table 4.

Table 4: Mean Patient Severity by Health IT

	Patients	**Elective Admissions**	**Average Charlson Index**	**Discharged Deceased**
Joint Replacement				
Total	**183,544**	**78.73%**	**1.13 (.83)**	**0.69%**
EMR	12.44%	80.89%	1.13 (.83)	0.57%
CPOE	3.68%	82.61%	1.12 (.84)	0.59%
PACS	16.43%	82.59%	1.13 (.83)	0.65%
Heart Failure				
Total	**147,549**	**10.73%**	**1.13 (.83)**	**4.56%**
EMR	12.15%	13.60%	1.13 (.83)	4.39%
CPOE	3.46%	8.06%	1.13 (.83)	3.03%
PACS	15.38%	8.13%	1.13 (.82)	3.75%

Standard Deviations in parentheses

5.3 Descriptive Statistics

Before employing the detailed discrete choice models simple aggregate level analysis can be used to identify trends in the data. Specifically, do hospitals which adopted health IT have more inpatient admissions than non-adopters? I have already shown that adopters tend to have more beds and are likely to be teaching hospitals which may influence the number of admissions regardless of health IT. Table 5 shows the total number of admissions per year from the full data set and the distribution of those admissions by type of health IT. From 1999 through 2006 the total number of admissions increased each year. Admissions increased even in years 2003 and 2004 when there was a drop in the number of hospitals. At the same time the number of admissions to hospitals with health IT steadily rose. By 2006 over half of inpatient admissions were to hospitals with PACS while only slightly more than a third of admissions were to hospitals with EMR. Comparing the 2006 hospital health IT adoption rates to the 2006 admission rates it appears that the number of admissions was proportionate to the level of adoption.

Table 5: Admission Rates by Year and Type of Health IT

	Admissions	EMR	CPOE	PACS
1999	7,961,501	4%	-	-
2000	8,281,176	6%	-	4%
2001	8,410,233	9%	-	8%
2002	8,420,541	11%	-	11%
2003	8,688,403	18%	1%	19%
2004	8,716,052	23%	5%	32%
2005	8,850,943	29%	11%	47%
2006	8,925,319	38%	18%	60%

Table 6 shows adoption rates for both DRG data sets. Again the 2006 admission rates for both groups are proportional to the rate of health IT adoption. The total admissions did not increase each year in these samples though. There were drops in total admissions in both groups in 2003 and 2004 with increases in 2005 and decreases again in 2006. In this population total admissions are generally decreasing during the period when adoption is increasing.

Table 6: Admission Rates by DRG, Year and Type of Health IT

	Admissions	**EMR**	**CPOE**	**PACS**
Joint Replacement				
1999	20,726	1.51%	-	-
2000	21,756	2.98%	-	2.95%
2001	22,396	4.83%	-	4.66%
2002	23,206	4.54%	-	7.17%
2003	22,560	14.36%	0.54%	10.59%
2004	23,818	20.07%	2.46%	21.66%
2005	25,609	21.15%	9.32%	33.22%
2006	23,483	26.87%	15.55%	45.79%
Heart Failure				
1999	19,346	3.02%	-	-
2000	20,145	3.01%	-	2.53%
2001	19,265	4.66%	-	4.25%
2002	19,267	4.41%	-	6.35%
2003	17,141	15.20%	0.61%	10.25%
2004	17,266	19.05%	2.14%	23.07%
2005	18,044	20.89%	8.69%	34.68%
2006	17,075	31.21%	17.97%	47.71%

Another approach to describing trends in the data is available through the unique structure of the data. The hospital level panel dataset with repeated observations of hospitals over time provides pre- and post observations for adopters of health IT and data for non-adopters over time. This data format (along with some strong assumptions) lends itself to a special case of the first-differences estimator for a fixed effects model commonly known as a difference-in-differences (DID) estimator (Cameron & Trivedi 2006). This estimator is a convenient descriptive statistic because it is intuitively simple and easy to calculate.

The DID model can be estimated using ordinary least squares (OLS) regression and binary dummy variables but a two period model can be simplified further. In the general 2-period DID model the OLS estimate is equivalent to taking differences of the average outcomes of the treated and untreated groups. First, the difference between the average outcome for the treated and untreated group is taken for each period

$$\bar{A}_t = (\bar{A}_t^{HIT} - \bar{A}_t), \text{ where } t = 1999 \text{ or } 2006 \qquad (10)$$

Then the difference between the two period differences is calculated as:

$$\bar{A}_{DID} = (\bar{A}_{2006} - \bar{A}_{1999}) \qquad (11)$$

The variables $\bar{A}_t^{HIT}$ and $\bar{A}_t$ are respectively the average hospital admissions in period *t* for hospitals which adopted health IT and those which did not. One DID estimator can be estimated for any two years using this approach. Extension to multiple years using a regression approach is possible but unnecessary for descriptive purposes.

Using average admissions from 1999 and 2006 I estimate a DID estimator for each technology. In all categories the average number of admissions increased from 1999 to 2006, as expected. Also, for all three technologies the average number of admissions was greater for hospitals with health IT. The DID estimator in the bottom right hand corner of each health IT matrix in Table 7 is the statistic of interest. For both CPOE and EMR the DID estimator is negative. The average number of admissions at hospitals who adopted either of these technologies decreased with the adoption of health IT. Average admissions did increase over time at hospitals that adopted PACS.

Table 7: Average Admissions Difference-in-Differences by Type of Health IT

	1999	2006	Difference
EMR	3,399	3,538	139
No EMR	2,695	3,005	310
Difference	703	533	*-170*
CPOE	3,488	3,728	241
No CPOE	2,806	3,085	279
Difference	682	644	*-38*
PACS	3,699	3,918	219
No PACS	2,301	2,415	114
Difference	1,398	1,503	*105*

A trade off for the simplicity of this estimator is that the estimator does not account for any differences between hospitals other than the treatment effect. Additionally, the DID estimator rests on some strong assumptions. In order for the DID estimator to be unbiased, the implementation of health IT system cannot be systematically related to unobserved factors which also affect hospital admissions (Wooldridge, 2002). Two obvious unobservable factors which may affect both hospital admissions and health IT system adoption are unobserved hospital quality and physician influence. The DID estimator assumes the distribution of hospital quality and physician preferences for health IT are the same across adopters and non-adopters. Hospital quality leads to biased results if higher quality hospitals are more likely to implement health IT and patients are more likely to go to the higher quality hospitals. Physician influence will be problematic if physicians direct patients to hospitals with health IT and physicians influenced the adoption of health IT at those hospitals. Both of these issues lead to an unclear causal pathway. Did hospitals adopt health IT because higher demand was expected or did higher demand occur because of the health IT? I assume it is unlikely one physician has enough control over patients' and hospitals' decisions to result in a substantial bias. In the discrete choice models I will employ hospital fixed effects to control for hospital specific unobservables such average perceptions of quality. To some extent I can also test for the influence of quality on hospital choice in the Berry models. I discuss this in more detail in the next chapter.

Consistent DID estimation also relies on the assumption that time specific effects are common across all hospitals (Cameron & Trivedi 2006). This assumes that hospitals that adopted health IT are subject to the same time shocks as non-adopters. If hospitals' admissions between these two groups would have been different for reasons, other than health IT, the DID estimator will attribute all of those differences to the health IT. I include time dummy variables or time trend variables in my discrete choice models to control for this.

The econometric problems associated with the DID approach, causation and endogeneity, are important because similar problems can arise in discrete choice models. I attempt to correct for this in the discrete choice models I described in chapter 4. The summary statistics in tables 1-6 also highlight the need to control for patient and hospital characteristics which vary by health IT system. As a descriptive statistic the DID estimator showed EMR and CPOE adopters experience a decrease in demand. The aggregate measure indicates health IT likely has an overall impact. A deeper understanding of the impact of health IT is possible by asking, does health IT affect individual patient decisions? If it does affect patients, what is the magnitude of this effect? These two questions are best addressed with a discrete choice analysis utilizing the individual patient level data in the dataset. The discrete choice models incorporate more information by representing a patient's utility function and predicting decisions based on characteristics of the patient and characteristics of the choices. The physician influence in this decision is implicitly assumed in the model. The results of these models are presented in the next section.

6. Results

The econometric methods proposed in chapter 4 involve estimating a demand for hospital inpatient services using patient characteristics, hospital characteristics and observed patient choices. A hospital's decision to implement health IT is considered a treatment or policy intervention and the change in the total number of patients choosing a hospital is the outcome of interest. The discrete choice models use market level and patient level hospital choice data to estimate the probabilities of patients choosing a hospital from a choice set. The parameter estimates from these models illustrate whether or not health IT affects a patient's hospital choice and marginal effects are calculated to find the magnitude of the effect. My results indicate that the adoption of CPOE has a positive impact on demand for a hospital for some types of patients.

6.1 Berry model Results

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. Alternatively, by aggregating hospital-market effects across markets allows for a hospital level interpretation. The mean effects of health IT may be used to inform or evaluate policy decisions. Financial penalties imposed on late adopters coupled with decreases in demand may have significant business implications for those hospitals operating at the margin. This model is not able to identify the effects of individual patient characteristics on hospital decisions. Patient level characteristics effects, which also have policy implications, are included in the conditional logit models presented in section 6.2.

6.1.1 Berry Model: Fixed Effects Excluded

Before estimating the full specification of the Berry model I estimated a separate model for each technology excluding hospital fixed effects. Selected coefficients estimates and standard errors (clustered by hospital) are shown in Table 8. The models do control for mean changes over time that are constant across all hospitals through the time dummy variables, T, but do not control for mean characteristics of the hospital that might affect patient choice. The time dummy variables are not reported in the table but are statistically significant for every year and negative for years 2003 and 2004. The coefficients for dummy variables are interpreted relative to the outside good. A negative

Table 8: Berry Model - Selected Results: Excluding Hospital Fixed Effects

Technology:	EMR	CPOE	PACS
HIT	.327	-1.13*	-.470
	(.446)	(.655)	(.324)
HIT*For Profit	-.203*	.195	.214**
	(.120)	(.191)	(.088)
HIT*System	-.106	.178	-.055
	(.097)	(.147)	(.083)
HIT*Teaching	.071	-.337*	-.106
	(.111)	(.178)	(.083)
HIT*ln(Beds)	-.032	.141	.118*
	(.087)	(.132)	(.063)
HIT*Distance	-.001	.005***	.000
	(.001)	(.002)	(.001)
HIT*Rural	.029	-.077	-.020
	(.070)	(.083)	(.050)
For-Profit	-.125	-.165*	-.160*
	(.086)	(.085)	(.086)
System	.079	.048	.080
	(.077)	(.075)	(.075)
Teaching	-.485***	-.453***	-.462***
	(.080)	(.078)	(.080)
Ln(Beds)	.424*	.428*	.394*
	(.066)	(.064)	(.065)
Distance	-.088***	-.087***	-.087***
	(.005)	(.005)	(.005)
Distance Squared	.001***	.001*	.001*
	(.000)	(.000)	(.000)
Rural	1.75***	1.73***	1.72***
	(.261)	(.260)	(.260)
HIT Variables Joint Significance Test Pr>F(7, 3025)	.2486	.0006	.0265

Standard Errors in parentheses
*** Statistically significant at the 1% level
** Statistically significant at the 5% level
* Statistically significant at the 10% level

coefficient on a time dummy variable implies patients had lower utility in those two years relative to the choice of an hospital outside of the market. Since those two years had the lowest number of hospital choices the result may suggest a general decrease in patient utility due to fewer hospital choices.

The health IT variable and health IT interactions were jointly statistically significantly different from zero in only the CPOE ($Pr > F = .0006$) and PACS models ($Pr > F=.0265$). The coefficient estimates from these specifications imply that health IT is a significant factor in a patient's hospital decision. EMRs do not have any effect on patient decisions. The health IT coefficient in the CPOE model was the only statistically significant health IT variable. It was also negative which implies that CPOE adoption has a negative impact on market level demand for the hospital. Of the other CPOE variables only the HIT*Teaching interaction term is significant and it is also negative. The summary statistics show teaching hospitals are also the most likely to have adopted CPOE. These results imply CPOE systems at teaching hospitals decreases demand relative to other hospitals within a market. It is possible health IT in teaching hospitals results in inefficiencies in care because of a large learning curve for health IT. Without fixed effects the model only accounts for the hospital characteristics that are included. It is possible on average teaching with health IT have a negative effect on demand but that some teaching hospitals use health IT very well and have a higher demand. This model just does not able to account for unobservable hospital characteristics. The PACS model has two statistically significant health IT interactions with ln(Beds) and for-profit status. In both cases the sign is positive. Patients' utilities for larger hospitals and for for-profit hospitals with PACS are higher relative to other hospitals in the market and the outside market choice.

These signs on the CPOE and PACS variables and interactions are consistent with the DID estimates but are subject to the same criticism. This specification does not control for endogeneity in hospital health IT adoption and patient choice. It is still possible that hospitals with health IT and more patients are different on average than those without health IT and with fewer patients. Another way to put this is that hospitals that adopt health IT may be hospitals which patients prefer for reasons other than the health IT. They may have characteristics such as being higher quality, having lower cost or having more technology which makes them more likely to adopt health IT and be preferred by more patients. Fixed effects are included in the following estimations to account for hospital specific effects. These hospital fixed effects do affect the hospital characteristic and health IT and coefficient estimates.

6.1.2 Berry Model Results Including Fixed Effects

The most obvious difference in the results of the Berry model regressions presented in Table 9 compared to those in Table 8 are the negative and insignificant health IT parameter estimates for all three technologies. A test for joint significance rejects the null hypothesis that the health IT-hospital characteristic interaction terms are zero in the CPOE model at the 95% level. The interaction terms which are different from zero in this model is informative as to the effect of health IT on demand. The difference between this model and the previous models is the inclusion of individual hospital fixed effects which are not individually reported in the Table 9. The constant term produced by the estimation equation used by the Stata xtreg command is also not included in Table 9. The constant can be interpreted as the mean of the fixed effects (Stata, 2001). In all models this constant is positive and significant. The difference in the parameter estimates and significance level suggests there is endogeneity in hospital health IT and hospital choice – the hospitals people tend to choose are the same hospitals which tend to adopt health IT. This endogeneity was evidenced to some degree in the total number of admissions in hospitals with health IT compared to non-adopters. The changes in the parameter estimates and significant fixed effects constant are further proof. The relationship between hospital choice and health IT 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 time trend variable 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 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 does account for the fact that patients are not choosing hospitals based on health IT alone. The inclusion of multiple interactions of CPOE adoption with hospital characteristics are also measures of factors influencing a patient’s decision.

Table 9: Berry Model – Selected Results: Including Hospital Fixed Effects

Technology:	EMR	CPOE	PACS	EMR & CPOE
HIT	0.02009	-0.40176	-0.04526	-0.63835
	(0.20301)	(0.40965)	(0.18238)	(0.50206)
HIT*Trend	0.00511	0.09637**	0.00997	0.06355
	(0.00748)	(0.04169)	(0.00953)	(0.05530)
HIT*Forprofit	-0.07096	-0.17508	0.07179	0.12422
	(0.05764)	(0.14264)	(0.05614)	(0.30841)
HIT*System	-0.04180	0.07731	-0.00262	0.18921*
	(0.04320)	(0.09521)	(0.03744)	(0.10816)
HIT*ln(Beds)	0.00298	-0.03321	-0.01133	0.03748
	(0.03518)	(0.06677)	(0.02918)	(0.08879)
HIT*Miles	-0.00157	0.00541*	0.00102	0.00412*
	(0.00126)	(0.00179)	(0.00104)	(0.00243)
HIT*Rural	0.01405	-0.09151*	-0.01832	-0.03834
	(0.04642)	(0.05513)	(0.03429)	(0.07395)
For-profit	-0.20209***	-0.11490	-0.19980**	-0.11843
	(0.07670)	(0.11661)	(0.07805)	(0.12052)
System	-0.09091**	-0.18559**	-0.09147**	-0.17997***
	(0.04574)	(0.08438)	(0.04626)	(0.08045)
Ln(beds)	0.14521***	0.15158	0.14749***	0.14248
	(0.05191)	(0.10865)	(0.05255)	(0.10874)
Miles	-0.13169***	-0.31389***	-0.13053***	-0.13307***
	(0.00419)	(0.00454)	(0.00437)	(0.00449)
Miles Squared	0.00084***	0.000835***	0.00084***	0.00083***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Rural	0.67129***	1.19623***	0.65001***	1.21876***
	(0.12819)	(0.13851)	(0.13017)	(0.13751)
Trend	1.45818***	-1.30608***	1.46034***	-1.30662***
	(0.03574)	(0.11634)	(0.03583)	(0.11431)
Trend-Squared	-0.41246***	0.63326***	-0.41188***	0.63415***
	(0.00811)	(0.04324)	(0.00809)	(0.00589)
Trend-Cubed	0.03182***	-0.06629***	0.03174***	-0.06609***
	(0.00062)	(0.00594)	(0.00063)	(0.59433)
HIT Variables Joint Significance Test: Pr>F(7, 3025)	0.52960	0.00660	0.66920	0.3573

Standard Errors in parentheses
*** Statistically significant at the 1% level
** Statistically significant at the 5% level
* Statistically significant at the 10% level

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 results 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 of the health IT variable alone is negative, meaning as distance from a hospital increases a patient’s utility for that hospital decreases. Patients are less willing to travel further for a hospital unless there is some reason to travel the extra distance that is worth the travel costs. This result is opposite of what was shown in the DID estimator and the Berry model without fixed effects but neither of those models account for endogeneity of health IT adoption.

Some evidence to support the hypothesis that patients’ travel distance increases for CPOE can be found in the DRG specific data samples. From 2004 to 2006, as CPOE systems were beginning to be adopted at an increasing rate the average distance traveled to hospitals with CPOE was also increasing. In 2004 the average distance traveled by patients admitted to a hospital with CPOE for joint replacement procedures was 8.94 miles. Two years later in 2006 the average distance traveled to a hospital with CPOE was 12.81 miles. While patients were traveling farther to hospitals with health IT in 2006 more hospitals also had CPOE systems in 2006 than 2004, 15% compared to 4%. This supports the hypothesis that patients choose hospitals with CPOE even if the travel distance to the hospital is further than they would have otherwise traveled; but the average distances in both of these years were much lower than the 2003 average distance however suggesting other factors were also influencing distance traveled.

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. Only in the CPOE model are for-profit status and hospital size not statistically significant. Possibly because of a lack of variation in the hospitals which adopted CPOE early.

The teaching status dummy variable was excluded from the model when the fixed effects were included because that variable was likely to be poorly estimated due to the high correlation with the fixed effect. The coefficient on rural market is also positive. This can be interpreted as patients in rural markets prefering hospitals within those markets relative to an outside hospital. This is consistent with the effect of travel distance. Distance is always negative implying the further a patient has to travel the bigger the decrease in utility. Patients in rural areas do not want to travel very far and prefer hospitals within the market area of their residences. In my model this is 100 miles.

For-profit status and system status are negative in all models. Relative to the outside hospital choice and other markets within a market patients have lower utilities for these types of hospitals. These result leads to some interesting questions about the role of subsidies for health IT. If for-profit hospitals become more appealing with following the adoption of health IT policy makers may question whether it is appropriate to subsidize health IT if it will increase the revenues of for-profit hospitals. The effect of CPOE on the distance patients will travel also has policy implications. If the effect is large enough CPOE or other health IT systems may affect market sizes and heavy subsidies in one market area may inadvertently affect hospital demand in other markets.

The possible presence of endogeneity suggests some factor which influences health IT adoption is also influencing demand. A worrisome possible factor is hospital quality. If higher quality hospitals are adopting health IT and those hospitals have a higher demand there may be endogeneity in hospital choices influencing the results even with the inclusion of the fixed effects. I am able to test for this for this to some extent by including a two year lead health IT variable and re-estimating the fixed effects models. If future health IT adoption is a significant predictor of hospital choice then there is likely an institutional factor such as hospital quality affecting hospital adoption as well as patient choice that is not controlled for by the fixed effects. Neither the health IT lagged variable nor the health IT lead variable is statistically significant when I re-estimate the models. When the fixed effects are excluded both the health IT lag and health IT lead variables are negative and statistically significant. I am confident that endogeneity is mitigated to the extent it is possible to do so by the inclusion of the fixed effects.

6.2 Conditional Logit Model Results

According to the Berry model results there is evidence that at the market level a health IT system, CPOE, does impact a patient's hospital decision. What is also seen from this model is that not accounting for endogeneity will bias the results toward finding an effect of health IT which does truly exits. In the conditional logit models I again control for endogeneity through hospital fixed effects. I expect the estimates from the conditional logit models without controlling for hospital fixed effects to be biased upward. With more detail and in patient level observations I expect small but significant coefficients on health IT and its interactions in at least the CPOE models. The results of the conditional logit model presented in this section have important implications for hospitals as well as policy makers. 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. Policy makers should also be concerned with whether health IT adoption will lead to changes in patient mix. If health IT adoption increases the illness burden at a hospital without sufficiently improving quality, cost, and efficiency of care there could be significant health effects for patients and operational effects for hospitals. It is important for hospitals to know if patients with certain conditions are more likely to respond to health IT than others in order for the hospitals to fully estimate the cost and benefits of health IT.

6.2.1 Conditional Logit Results for Individual Health IT Systems

Prior to estimating the conditional logit models specified in (4) I again initially estimated the model without the hospital fixed effects. Compared to the fixed effects estimates these results confirm the presence of endogeneity in the DRG samples as well. The fixed effects conditional logit model was estimated for 8 different specifications, once for each of the three technologies and a combination of technologies for the two DRG groups. The individual hospital fixed effect coefficients are not reported but the majority of the hospital fixed effects are statistically significant in the heart failure 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 it is likely that a hospital's patients choose for heart failure treatment 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.

In only one model for the joint replacement sample were the coefficients on the health IT variables and the health IT interactions jointly statistically different from 0. A Wald test (d.f. 10) of the joint significance of EMR & CPOE combination and its interactions was equal to .000. The CPOE, PACS and EMR & CPOE models had jointly significant health IT variables and interactions in the heart failure sample. It is not a surprising that the EMR models coefficients were not found to be different than zero since those coefficients were not jointly significant in the Berry model either. EMRs may influence physicians' behavior and may affect quality but at this point it appears none of those effects correspond with changes in patient decisions. EMR is never a significant predictor of hospital choice. Based on the results of the Berry model, it appears some health IT does not influence decisions on average but for certain populations health IT does influence patient choice. PACS are not significant on average but they are significant in the heart failure population used for the conditional logit analysis. There are several potential reasons. 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.

Table 10: Conditional Logit – Selected Results: Joint Replacement Sample

	EMR	**CPOE**	**PACS**	**EMR & CPOE**
HIT	-1.62213*	0.43598	0.90724	0.14355
	(0.952875)	(0.708967)	(0.59926)	(0.88575)
HIT*Trend	0.03009	0.10877**	0.01408	0.04470
	(0.022249)	(0.043304)	(0.02420)	(0.03040)
HIT*Miles	0.01022	0.00007	0.00105	-0.01001
	(0.008704)	(0.010379)	(0.00636)	(0.01430)
HIT*Beds	0.26983**	-0.03493	-0.06019	-0.00861
	(0.107002)	(0.079813)	(0.07645)	(0.13776)
HIT*Age	-0.00011	-0.00466	-0.00764**	0.00180
	(0.007291)	(0.005732)	(0.00374)	(0.00476)
HIT*Female	-0.01315	-0.02747	-0.05238	0.00313
	(0.033602)	(0.033943)	(0.03321)	(0.04190)

HIT*Non-white	-0.08365	0.12565	0.03187	-0.18387
	(0.168855)	(0.18818)	(0.17205)	(0.19404)
HIT*Chalson Score	-0.00330	-0.01300	-0.00721	-0.03952**
	(0.014311)	(0.020073)	(0.01221)	(0.01535)
HIT*Elective	-0.36313	-0.13616	-0.04881	-0.19499*
	(0.324349)	(0.146159)	(0.21734)	(0.11343)
HIT*Rural	0.08607	-0.21629	-0.04744	0.05751
	(0.216695)	(0.271183)	(0.15086)	(0.34447)
For-profit	0.07820	0.07357	0.11925*	0.06213
	(0.083913)	(0.048736)	(0.07111)	(0.04803)
ln(Beds)	0.18429	0.07357	0.15999	0.91319
	(0.448761)	(0.597093)	(0.44580)	(0.59786)
System	-0.08534	0.38488***	-0.09185	0.34796***
	(0.201439)	(0.035784)	(0.20831)	(0.03054)
Miles	-0.18278***	-0.20976***	-0.18367***	-0.20986***
	(0.031798)	(0.027254)	(0.03275)	(0.02782)
Miles squared	0.00152***	0.00150***	0.00150***	0.00150***
	(0.000323)	(0.000329)	(0.00033)	(0.00033)
Rural*Miles	0.06175***	0.06174***	0.06294***	0.06129***
	(0.010267)	(0.001101)	(0.01099)	(0.01094)
Trend	-0.00025	-0.51730	-0.13159	-0.54124
	(0.393279)	(0.916915)	(0.38519)	(0.92581)
Trend Squared	0.01782	0.27914	0.02149	0.27210
	(0.08075)	(0.397043)	(0.07720)	(0.39888)
Trend Cubed	-0.00140	-0.04020	-0.00167	-0.03887
	(0.005473)	(0.05173)	(0.00525)	(0.05177)
Health IT Variables Joint Significance Test $Pr > \chi^2_{(9\ d.f)}$ =	0.1246	0.1704	0.4132	0.0000

Standard errors are in parentheses
* **Statisically signifcant at the 1% level
** Statisically signifcant at the 5% level
* Statisically significant at the 10% level

The conditional logit results from CPOE models including fixed effects for both DRGs are presented in Tables 10 and 11. The individual fixed effect coefficients are not reported. The joint significance of CPOE and CPOE interactions establishes CPOE influences a patient’s hospital choice; however, there is only one interaction term that is individually statistically significant. I conclude there are not significant interactions between patient characteristics and health IT which affect their choices. I do not find older or sicker patients more or less likely to choose hospitals with CPOE. In both patient cohorts the CPOE dummy variable and most of the CPOE interactions are not significant even though they are jointly not equal to zero. The CPOE*Trend interaction is positive and significant in both populations. This is consistent with the results from the Berry model. Over time hospitals with CPOE are more likely to be chosen by patients with than hospitals without CPOE or the outside good. The outside good being any hospital outside of a 50 mile radius of a patient's zip code and all hospitals within 50 miles with less than 75 admits per year.

Table 11: Conditional Logit – Selected Results: Heart Failure Sample

	EMR	**CPOE**	**PACS**	**EMR & CPOE**
HIT	-1.30908**	0.70373	0.95821**	-0.48000
	0.65338	0.60133	0.44169	0.63991
HIT*Trend	0.03072	0.07539*	0.03668***	0.06233***
	0.02907	0.04202	0.01361	0.03582
HIT*Miles	0.01007	-0.01390	0.00414	-0.04087**
	0.01014	0.01232	0.00692	0.01659
HIT*Beds	0.03625	-0.03810	-0.01953	0.11716
	0.10063	0.07784	0.06132	0.12348
HIT*Age	0.00963**	-0.00530	-0.01280***	0.00179
	0.00412	0.00697	0.00428	0.00509
HIT*Female	0.00074	-0.04511	-0.06081	0.02766
	0.03855	0.08265	0.04178	0.08807
HIT*Non-white	-0.44050	0.05054	0.11771	-0.67864***
	0.44781	0.39715	0.30925	0.22036
HIT*Chalson Score	-0.01386	-0.03821	0.02929*	-0.02660
	0.01767	0.02765	0.01636	0.04673

HIT*Elective	0.26788	-0.13838	-0.44066	-0.25465
	0.23822	0.33220	0.30320	0.36162
HIT*Rural	0.11435	0.12316	-0.07291	0.52962*
	0.29130	0.25120	0.16154	0.34215
For-profit	0.11442*	0.06050	0.12514***	0.05253
	0.06097	0.06982	0.04685	0.07031
ln(Beds)	-0.03322	-0.01507	-0.06094	-0.01877
	0.39041	0.42933	0.38753	0.42727
System	0.00742	0.32118**	0.01867	0.30753**
	0.05641	0.14953	0.05251	0.14857
Miles	-0.27025***	-0.27159***	-0.27357***	-0.27176***
	0.03949	0.03923	0.03915	0.03976
Miles squared	0.00247***	0.00235***	0.00245***	0.00234***
	0.00042	0.00044	0.00042	0.00044
Rural*Miles	0.06980***	0.07242***	.07169***	.07230***
	0.01096	0.01262	0.01161	0.01260
Trend	-0.09784	-0.19622	-0.08131	-0.19851
	0.32611	1.59494	0.34932	1.61186
Trend Squared	0.03779	0.01435	0.03896	0.00685
	0.08574	0.71798	0.08991	0.72337
Trend Cubed	-0.00369	-0.00268	-0.00380	-0.00121
	0.00650	0.09682	0.00679	0.09737
Health IT Variables Joint Significance Test $Pr > \chi^2_{(9\ d.f)}$ =	0.241	0.001	0.009	0.000

Standard errors are in parentheses
* **Statisically signifcant at the 1% level
** Statisically signifcant at the 5% level
* Statisically significant at the 10% level

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. There is not a significant effect in the heart failure sample though. 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 which included 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. This is consistent with previous research that finds distance is one of the largest determinants of hospital choice. Distance is negative in both models; 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. I 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.

6.2.2 Conditional Logit Results for Combined Health IT Systems

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. The results of two additional estimations of combined health IT measures are also shown in Tables 10 and 11. The measure EMR and CPOE is a dummy variable equal to one when a hospital's EMR lag and CPOE lag variables both equal one.

In both DRG samples the health IT combination variable and interactions are jointly significantly different from 0. The Wald test is significant at the 99% level for both tests. In the heart failure sample the health IT combination variable coefficients is negative while in the joint replacement sample it is positive. They are not significant in either model. If health IT systems within hospitals with multiple systems are interoperable there should be health IT capabilities available in those at hospitals which are not at hospitals without out multiple systems. Physicians and patients would prefer hospitals where interoperability improves care. If health IT systems individually lead to efficiencies but the use of multiple systems creates inefficiencies patients and physicians are expected to avoid those hospitals. These quality gains may not be achieved as the combination of EMR and CPOE has a significant negative interaction coefficient in the heart failure sample. A negative but not significant effect was found in the joint replacement 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.

6.3 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. These estimates can be interpreted as marginal effects from any linear model 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 at a hospital is 3370 in 2006 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(Beds) would be equivalent to 148 beds and result in 98 more admissions on average. 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 can be calculated in the same way. 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 my results show health IT does have an effect on the marginal patients a hospital admits.

7. DISCUSSION

A 16% adoption rate of CPOE in 2006 among 2649 hospitals is relatively low compared to PACS or EMRs but CPOE seems to be the system with the greatest impact on hospital demand, albeit a very small impact. The costs of CPOE systems, like any health IT system are difficult for researchers to obtain. Generally the costs of health IT investments differ greatly among institutions and vendors so even cost estimates vary widely. Based on a 2005 AHRQ presentation of CPOE investment costs and assuming the representative hospital is an average size (300 beds) the cost of implementing CPOE in 2003 was between $7 and $9 million dollars. Half of which half is assumed to be invested in the first year. The estimated life span of the average CPOE system is 7 years (Culler, 2005). If Borzekowski's estimates are correct and clinical health IT systems reduce operating costs by 3-5% but not until the 5th year of having an health IT system the average hospital does not have much time to benefit from reduced costs. From my estimates the impact of health IT systems on the demand for hospitals is negligible. The only remaining means for a hospital to achieve a return on health IT investments is through supply-side cost savings. As the literature review above points out there is still disagreement as to the magnitude of quality and efficiency gains from health IT.

There are many reasons an increase in demand from health IT would be valuable to the evaluation of a health IT systems Return on Investment (ROI). For example, if health IT did increase demand, the resulting increase in revenues may potentially produce a net revenue gain after the costs of the system have been recovered. If health IT did lead to large changes in demand one might assume hospitals would have noticed and adoption rates would be higher. The results of my analysis suggest health IT does not have a significant impact on demand for a hospital. The number of CPOE adopters in 2011 is undoubtedly higher than it was 5 years ago and that adoption rate will likely increase drastically in the next 5 years as subsidies and penalties are imposed. For policy makers intent on spurring adoption these subsidies and penalties may be the only way to facilitate adoption. Whether the adoption which results is beneficial to patients, hospitals and society is another question policy makers should be concerned with. The cost savings from reductions in medical errors and increased efficiencies is beyond the scope of this paper but the discrete choice models I use are valuable for estimating measures of consumer welfare.

7.1 Consumer Welfare

The regression results showed CPOE does have a small positive effect on hospital demand although many proponents of health IT claims the biggest benefits will occur through system interactions and interoperable systems. In 2006 only about 10% of hospitals in the sample had adopted both an EMR and CPOE system. Estimating the value of these inter-related systems is a benefit of the conditional logitdel based on a random utility model is the ability to conveniently perform welfare calculations using the parameter estimates. 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. An example of this is a welfare analysis of computed tomography (CT) scanners used to compute the social rate of return of R&D. The value of the CT scanners was calculated using hedonic price model and discrete choice model parameters (Trajtenberg 1989).

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 a hospital there is not enough variation in prices across hospitals. An alternative approach to using prices is to assign a dollar value to the distance traveled from a patient's residence to a hospital. The price to the patient is then represented by the travel cost. Travel could also be calculated by time and then travel-time costs could be calculated by the average hourly wage. Neither method is preferred to price data but 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.

Since the majority of the people in my sample are elderly and retired calculating costs using hourly wages is not the most intuitive measure even though the median income measure is an easily available figure. 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 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. Using the median US income in 2006 of $52,000 the median cost per minute is $.40, assuming a 40 hour week. The median cost per mile of travel time is then $.70 plus the $.52 travel cost produces a one way time/travel cost of per mile \$1.22 for one person. I measure distance in my 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 distance from the hospital. I finally round this to \$7 for incidental costs I cannot quantify particularly cost for people that are traveling from rural areas, 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:

$$\mathrm{E}(\mathrm{CS}_{\mathrm{zj}}) = \frac{1}{\alpha_{jz}} \ln\left(1 + \sum_{j=1}^{J} e^{(\beta_1 HIT_j + \beta_2 X_{zj} + \xi_j)}\right) \quad (13)$$

Where

$$\frac{1}{\alpha_{jz}} = \left(-\frac{1}{\frac{\partial Utility}{\partial Distance}}\right)\left(\frac{\$7}{1\ mile}\right) \qquad (14)$$

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 EMR with CPOE 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.

I hypothesized that health IT would have a positive impact on demand and result in an increase in consumer surplus. I found an effect on demand for one technology, CPOE, but in terms of patients the effect was negligible. For technologies which do not significantly affect patients' hospital choices, such as EMR and PACS, it not as relevant to calculate the consumer surplus but other welfare measures may eventually be used to estimate the value of health IT to consumers, hospitals, or society. One approach would be to focus on smaller sections of the population when looking for a demand effect. Certain age groups or regions of the country may be more responsive to demand than others. For instance, zip codes near cities where there is a health IT system company may know more about health IT because there is more information available to the public and thus it plays a bigger role in the hospital choice.

7.2 Limitations of Logit Models

The logit model is a useful method for analyzing individuals' decisions but it may impose unnecessary or unreasonable assumptions on the decision making process. The logit model is often criticized for restricting the substitution patterns of products and for assuming individuals' preferences for characteristics are homogeneous. There are some situations where this is not a problem but if there are doubts about individuals' tastes or choices a more flexible mixed logit model may be used. Besides allowing for random coefficients which take into account differences in individual taste the mixed logit can be used to deal with some of the other methodological problems associated with logit models including restricted substitution patterns and errors which are correlated over time (Train 2003).

7.2.1 Preference Variations

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 would have different effects on patients and parameter estimates should be allowed to vary accordingly. Another possibility is that parameters vary across hospitals. Health IT might affect different hospitals in different ways. Applying utility maximization theory, a mixed logit model can be derived which will allow for the possibility of random coefficients (Train 2003). The coefficients will vary over decision makers with some distribution which is specified by the researcher usually normal or log-normal. Estimation of the model can be performed with maximum simulated likelihood. The simulation procedure is used to estimate the mean and variance (or covariance) of the density function describing the random parameters. The parameterization of the utility maximization model is the same as (3) except the parameters β_1 which are no longer fixed will now be denoted by an *i* subscript indicating they vary by individual. If they were to vary by hospital β_2 would include a *j* subscript. It is hypothesized that in this model the coefficients on health IT will be random with respect to patients because patients have different physicians. Since different physicians have different opinions of health IT the coefficient of health IT could be different for each observed patient.

7.2.2 Independence of Irrelevant Alternatives

If the pattern of substitutions among choices has important implications or is the focus of the research a traditional logit model may impose too strict of a structure on individuals' choices. In the 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 is not always a prohibitive property. In the case of hospitals there are many distinguishing characteristics and it is reasonable to believe the probability of choosing hospital A over hospital B depends only on the characteristics of those two hospitals. However, if third hospital C entered the market with all the same characteristics as the first hospital except for its name the market shares predicted for each hospital by the logit model would be incorrect. The market would likely split evenly among the similar hospital with A and C each receiving ¼ of the patients and hospital B still receiving ½. The logit probabilities would predict the market shares of all of hospital to be 1/3 because the probability ratios are restricted to equal 1.

Town and Vistnes (2001) argue that there is enough variation in the hospital characteristics that IIA does not cause estimation problems. Kessler and McClellan (2000) claim that by including additional distance variables for likely and unlikely substitute hospitals the IIA property is not an econometric problem. Because the choice sets are so varied across patients in my models there is not one hospital which is the most obviously the closest substitute and there are relatively few patients with the exact same choice sets. I do not suspect IIA produces biased estimates in my models.

If future research suggests IIA is a concern there is recourse. Multiple tests are available to test for differences in the coefficients of two different model specifications. If the coefficients are significantly different when the closest and most similar hospitals are omitted from the choice set IIA may be a problem. If IIA was suspected the issue could be dealt with in various ways. A random coefficient model could be used to estimate the component of the error term which causes correlation among the utilities for different alternatives (Train, 2003). A different logit specification could also b used, either a nested logit or mixed logit model. Both of these models allow more flexibility in substitution patterns. The mixed logit incorporates the characteristics of all of the alternatives in the ratio of probabilities. As in a random coefficients model a distribution needs to be specified by the researcher relating how characteristics of the choices are related (Train 2003).

7.3 Study Limitations

Besides the limitations of the logit model already discussed there are several limitations of the analysis which will affect the interpretation of results. First, 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. Even by limiting the study population the dataset is extremely large. Other sub-samples of the data or other estimation techniques may applicable to estimate the models in order to validate these results.

A second limitation of the study 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. Even using an estimated travel cost to calculate welfare implications is questionable in the Medicare population which consists of mainly retirees. These results may or may not approximate choices probabilities or the welfare implications for a managed care or employer-funded insured population who face different prices, co-pays and deductibles than the Medicare population. This study is still an important first step in understanding the role health IT plays in patient's decisions and the ultimate effect this has on hospital markets. Further insight can be achieved by expanding the analysis to other insured populations.

Third, the logit model with panel data and fixed effects does estimate a more accurate model of patient choice than a cross sectional 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. I have shown some indications that this is a common scenario. Less likely are unobservable factors which affect the adoption of health IT and patient choices. The inclusion of hospital fixed effects reduces the bias due to omitted hospital level variables but endogeneity is still a concern, especially given the difference between the coefficient estimates in my models with and without fixed effects.

In the logit model health IT system choice is assumed to be exogenous, as are the rest of the hospitals characteristics. In reality hospitals are able to choose whether or not to adopt an health IT system and when to do so. The models estimated up to this point are applicable if hospitals adopt health IT and no other unobservable factors change over time between the high demand and low demand hospitals. It is possible to obtain estimates of the effect of health IT on hospital demand assuming that demand responds to the health IT. If hospitals have some reason to expect a higher demand in the future they may adopt health IT in preparation for that expected demand increase. Also, hospitals with higher demands may adopt health IT with the expectation that the health IT systems will increase efficiency. If health IT adoption is a function of demand and demand is a function of hospital health IT parameter estimates will be biased.

There are multiple ways for dealing with endogeneity in a linear model; the logit has fewer econometric solutions but some do exist. The simplest solution is the use of the linear share approach which allows for the use of instrumental variables because following the transformation the equation to be estimated has a linear form. This requires a set of instrumental variables (IV) or a vector of variables which is correlated with health IT adoption but uncorrelated with Medicare inpatient demand. The choice of IV is always difficult but several possibilities exist: characteristics of neighboring hospitals, Medicaid demand for the hospital, and the share of HMO patients at a hospital are three options. All three are arguably related to health IT demand but unrelated to a Medicare patient's hospital choice. Other IV may exist and may be tried in the model. All of these IV may be tried and the parameter estimates can be compared to determine which IV model is the most appropriate.

If endogeneity does lead to biased estimates corrections may need to be made to the welfare calculations. Given the size of the health IT effect that I found and the possibility of additional endogeneity it is possible that any IV or other corrected estimates will find no impact of health IT on demand. This could have significant policy implications in terms of investment decisions and subsidies for health IT. The IV approach is left as an endeavor for future research.

7.4 Extensions

The success of this analysis in finding some positive impact of CPOE on inpatient demand advocates extending the research in the future to other health IT systems, among more DRGs. With different claims data the analysis could also be extended to different populations such as HMOs or Medicaid. More interesting extensions of the research may include closer analysis of regional effects e.g. does health IT have more or less of an effect in certain areas or at certain hospitals and how does that compare to other medical resource use in that area? There is minimal evidence that health IT has an effect on the distance a patient is willing to travel to get to a hospital but I am studying an older population. There is also significant evidence that older patients do not travel as far. Future research may be necessary to investigate hospital markets and competition measures with a broader range of patients. Hospitals may be able to compete with hospitals further away and market size and structure should be re-evaluated. The framework proposed here also lends itself to further welfare analysis and policy simulations which will be useful as health IT becomes more prevalent.

8. Conclusion

The search for evidence in support of health IT has focused on studies of health IT adoption and the supply-side effects health IT such as quality and efficiency. The demand analysis in this paper complements the existing supply side analyses and allows for more complete and dynamic estimates of the effect of health IT on health care markets. An understanding of the role of health IT on the market for health care will allow policy makers and the health care industry to make more informed decisions regarding the adoption and use of health IT. 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 which that was 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.

As health IT development continues further analysis of the demand-side effects of health IT is needed for a complete understanding of the role health IT plays in health care markets including the impact on costs, competition, and future adoption of health IT. Understanding how health IT affects demand for care will allow for dynamic evaluations of health IT adoption and a clearer understanding of the role health IT plays in the delivery of care. I found not all health IT affects patient choices. I argue that these choices include physician influence, thus while physicians' acceptance of health IT may be growing however that acceptance may not have yet translated to the choices physicians make for their patients. Computerized order entry systems do have a small effect on patient choices but I found no significant effect on hospital demand at the market level or patient level.

If health IT systems, CPOE or others do not reduce operating costs or increase revenues it is difficult to construct the business case for health IT. However, the impact of CPOE on hospital demand does create a positive consumer welfare effect. Approximately a $30,000 per hospital increase in consumer surplus is found by comparing 2006 EMR&CPOE adoption rates to no adoption for joint replacement and heart failure patients. The lack of cost data and cost benefit studies as well as the focus of health IT literature on a subset of leading institutions limits researchers' ability to focus on health IT return on investment studies across the breadth of health IT infrastructure in the U.S. The results of this analysis do indicate a potential value to hospitals and patients from the adoption of CPOE.

My 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. In this research I 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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