THE IMPACT OF INFORMATION TECHNOLOGY ON TREATMENT VARIATION IN HEALTHCARE

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ABSTRACT

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Rising healthcare costs and the delivery of reliable and effective patient care are arguably one of the greatest problems facing society today. Information technology investment is widely cited as a potential solution to this problem. At the core of healthcare is a tension. On the one hand you want healthcare providers to develop standardized procedures for treatment of disease while looking for better treatments. Other the other hand the delivery of care occurs through knowledge, skills, and judgment of physicians. There is likely to be variation in how physicians apply this knowledge in practice. In an effort to reduce cost and enhance reliability providers seek to disseminate these procedures with greater speed than in the past. Research suggests that by reducing treatment inconsistency, healthcare costs in the United States alone could be reduced by nearly 700 billion dollars without impacting patient outcome. Theory suggests information technology, in the form of electronic medical records (EMR), should reduce treatment inconsistency by reducing search costs, increasing the speed of information diffusion, reducing monitoring costs, and facilitating a more aggregate study of outcomes. Data for this study was gathered from over 700,000 patient admissions from multiple archival sources. Using a

cross-classified hierarchical model results demonstrate that information technology does increase consistency of treatment patterns, for diagnoses with a high number of potential treatments, when EMR is: a) present for a sufficient amount of time or b) in larger hospitals or c) used in an integrated delivery system or d) there is an increased ratio of salaried physicians to total physicians. Implications for future research suggest that the effectiveness EMR are contextually dependent upon both the clinical setting and the disease to which EMR is applied. Implications for practice suggest that impacts from EMR adoption are likely to vary between practice areas, require a substantial amount of time to yield positive results, and are more likely to yield positive results in larger hospitals and in those hospitals where more physicians using the system are employed directly by the hospital.

I dedicate this dissertation to my family. First, I would like to thank my beautiful wife for her support and patience through this long process. Thank You. I would also like to thank my parents for many years of loving support. Much appreciation is due to my brother, sister, and brother-in-law for keeping me grounded during this process. To my niece and nephew, Zoe and Evan, thank you for reminding me life should be fun. Finally, I would like to thank my cat, Rain, more making me laugh.

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Chapter I: Introduction

Rising healthcare costs, particularly in the United States, have become a key concern for both public policy makers and researchers for several reasons. Healthcare spending in the United States accounts for nearly 16% of GDP and has been rising more rapidly for decades. Healthcare costs for retirees, which rose much faster than initial projections, are commonly cited as major contributing factors in recent corporate bankruptcies. Impacts of rising healthcare costs are not limited to corporate bankruptcies. A 2007 study found that for 62% of all personal bankruptcies were the result of medical problems, despite the fact that 78% of those had medical insurance when their illness began (Himmelstein, et. al., 2007). In contrast, in 1981 only 8% of those filing for bankruptcy cited medical problems. Rising healthcare costs have also contributed a growing share of government expenditures, at both the federal and state level, and are commonly cited as among the most intractable problems facing public finance.

Going forward, the demographic realities of a rapidly growing aged population make the problem of rising healthcare costs especially salient. The most common observation is that the United States spends substantially more than other industrialized countries, but gets no better outcomes. In a nutshell, healthcare in the United States in very expensive. It is generally believed that the US system is inefficient, with several possible problems resulting in inefficiency. Possible causes for the inefficiency in healthcare range for the high information asymmetry between consumer and supplier to moral hazard and adverse selection problems to medical malpractice laws (Folland, et. al., 2004). One of these problems is the issue of geographically inconsistent treatment patterns. Treatment inconsistency is both a problem and a cause of other problems in healthcare. Some estimates rate treatment inconsistency as the single largest source of variation in healthcare today. Treatment inconsistency is generally thought to arise as a result of informational asymmetries *between* physicians (Phelps, 1992). In the health economics literature, treatment inconsistency is also known as the “small area variation” problem or SAV.

> “'Small areas variations’ in medical care use present a phenomenon that many economists find disquieting. In the most simple form, the large literature on this topic has shown that a person's chances of receiving a particular medical intervention depend heavily on geographic location, even after holding constant factors normally considered as affecting demand for medical treatment.”-Phelps, 1995

Current estimates are that by increasing consistency of treatment patterns healthcare costs could be reduced by 30%, both within the U.S. and worldwide without impacting outcome (Phelps and Parente, 1990; Wennberg, et. al., 2002). A reduction in cost of this magnitude equates to nearly 700 billion dollars in the United States and over 1.5 trillion dollars worldwide.

Among the most commonly cited solutions to contain rising healthcare costs is healthcare information technology. The key observation is that healthcare in the U.S. lags other countries by several years in terms of information technology usage and that the lack of IT in the U.S. healthcare system creates inefficiencies. Investment in information technology (IT) is often viewed as an important ingredient in addressing the problem of rapidly rising healthcare costs. Healthcare has also traditionally lagged other industries in IT investment. Recently, large investments, both public and private, have been made in healthcare IT.

The market for healthcare has also long been understood to be dominated with issues of information and uncertainty (Arrow, 1963). Because of the information issues in healthcare a form of capital investment which addresses those informational issues would seem likely to improve efficiency, but to date empirical findings as to the impact of IT in healthcare have been mixed (Garg, et. al., 2005; Chaudhry, et. al. 2006). Research on the impact of IT in healthcare has been generally conducted on two fronts, by those who research IT impacts and by those who study healthcare. Research by those who study IT has, generally, not fully accounted for the unique organizational context of healthcare, which leads to phenomena highly specific to healthcare. For example, since many hospitals are explicitly non-profit and most revenue in healthcare involves third party payment, there is general agreement among healthcare researchers that financial-based performance measures which are fine in most contexts, such as revenue, are, at best, insufficient in a healthcare context. A hospital is not a manufacturing plant. Research by those who study healthcare has generally taken an over simplified view of IT. For example, implementing a complex IT system will not yield value the same way faster lab equipment would. IT is a general purpose technology, which often requires complementary investment and particular organizational conditions to yield value (Bresnahan and Trajtenberg, 1995). Yet, in many studies of IT in the healthcare literature IT is treated precisely that way. An IT system is not a stamping press. This dissertation focuses on how, given proper conditions, IT provides lower monitoring costs, easier information aggregation, and faster information diffusion to reduce SAV. Specifically, this dissertation will address the following research questions:

Do electronic medical records enhance consistency in healthcare treatment patterns?

If so, under what conditions do electronic medical records enhance the consistency in healthcare treatment patterns?

Theories from health economics and information systems, as well as archival data and relevant literature and analysis will be presented to address these questions.

Chapter II: Literature Review

The theoretical foundation for this study is found in two separate disciplines. First, health economics has devoted considerable attention to the causes and implications of treatment inconsistency. However, since our interest is in whether and how the use of IT contributes to the enhancement of treatment consistency, existing research on performance effects of IT usage is relevant and forms the basis for this study. First, this study will present research related to the healthcare context, paying careful attention to inhibitors which likely contribute to the phenomena of treatment inconsistency. Second, a review of the literature relevant to this study looks at the evidence and causes of treatment variation through the lens of health economics. Thirdly, we review the theory as to why IT should result in positive outcomes in this context and evidence is presented of the returns to IT investment and the role of complements to IT investments. Because this study looks the phenomena of treatment inconsistency through the lens of health economics, the review of theory as it relates to IT is presented in economic terms to help us understand how IT relates to treatment inconsistency, which has been studied in economic terms. Finally, after reviewing IT from an economic perspective, this study will review the literature on effects of IT usage in healthcare.

Healthcare Context

The purpose of this section is to explore the nature of the healthcare context using the lens of health economics. Healthcare is a unique context. Issues of information and uncertainty dominate the market for medical care (Arrow, 1963). Many of the normal market and organizational assumptions do not hold in healthcare. In a normal market context inferior products will be driven out of the market by consumers seeking a superior product, in healthcare there are many reasons why this may not happen. I will highlight five of these reasons. First, the demand for healthcare is a derived demand. People do not want healthcare *per se*, they want health. Health generally behaves like a capital stock, in that in generally declines over time. But, health can be both produced, though exercise and dietary habits, and consumed by the consumer (Grossman, 1972). In healthcare, the end product is unique and demand for the product is unlike other goods.

Second, there exists a high degree of information asymmetry between consumer and producer in healthcare. Producers are much better informed than consumers. The information asymmetry rises to the point that supplier induced demand is possible (Wennberg, 1985; Iversen and Luras, 2000). The degree of information asymmetry in healthcare is unique (Arrow, 1963). While the agency problems created from this information asymmetry could normally be resolved though a proper incentive structure, in healthcare even ex-post analysis is difficult. Healthcare consumers are often times unable to access the quality of service even after the service is rendered (Weisbrod, 1978). In healthcare, customers often do not even know they want the product until the person selling them the product tells them so.

Third, insurance of one form another plays a large role as the primary payment mechanism in healthcare (Gibson and Waldo, 1981). Healthcare consumers are usually spending someone else's money. The presence of insurance naturally gives rise to issues of both moral hazard and adverse selection. Moral hazard issues manifest as people consuming more healthcare than they otherwise would since they do not directly bear the costs of the service provided and as a result do weigh costs and benefits as in a normal market. Consumer behavior changes as a result of the insurance. Adverse selection is the problem whereby people are more likely to seek insurance when they know the insurance is more likely to be used, thereby increasing the cost of insurance for others in the insurance pool. The payment mechanism creates unique problems in healthcare (Manning, et. al, 1987). In healthcare, people are often spending other people's money.

Fourth, physicians play a unique role in healthcare markets. Physicians have a great deal of autonomy. Private practice physicians often have privileges at hospitals, which give them a great deal of control over hospital resources. These private practice physicians are often not part of the organization hierarchy (Harris, 1977). In healthcare, those that control supply resources are often not part of the organization which owns the supply resources.

Finally, hospitals often have multiple objectives beyond profit maximization (Arnould and DeBrock, 1986). Many hospitals are expressly non-profit. For those hospitals which are for-profit it, the nature of the business makes it difficult from a public relations standpoint to achieve substantial profit. In healthcare, suppliers have stated objectives beyond profit maximization and in practice it is problematic to make large profits off sick people.

To summarize, the organization arrangement in healthcare is unique. Healthcare is filled with information problems, payment issues, unique issues of control over organizational resources, and providers often have multiple objectives beyond profit maximization. A summary of these differences is shown in table 1.

Table 1. Healthcare as an Organizational Context

How Healthcare is Different	Citation
The marketplace for medicine is characterized by uncertainty… its functioning essentially represents an exchange of information.	Arrow, 1963.
Healthcare is derived demand. Consumers want are healthy days, not healthcare per se. Health capital is both consumed and produced.	Grossman, M., 1972
Physicians control resources of an organization which they are often not a member of. Harris models this as a duopoly with hospital and physician in competition.	Harris, 1977
Information asymmetry so high it is difficult for buyers to judge the quality of product, even after purchase.	Weisbrod, 1978
High majority of healthcare expenditures are paid by third parties.	Gibson and Waldo, 1981
Potential for supplier-induced demand	Wennberg, 1985
Hospitals do not have profit-maximization as the primary objective	Arnould and DeBrock, 1986
Issues with third-party payment: Moral Hazard & Adverse Selection	Manning, et. al., 1987
Potential for supplier induced demand: physicians with a shortage of patients have higher income, order more tests, and have longer consultations.	Iversen and Luras, 2000

We have looked at the factors which make healthcare a unique context. We have also illustrated many of the normal assumptions do not hold and often result in phenomena unique to healthcare. Next, we will examine one such phenomenon, the subject of this study, treatment variation.

Evidence of Inconsistency

The focus of this section is to examine the nature of treatment consistency and its implications for performance outcomes in healthcare. Healthcare organizations balance competing goals in the delivery of healthcare. On the one hand, they seek to manage total outcomes in terms of cost and quality of care. However, the delivery of care itself occurs through the skills, knowledge, and judgment of physicians. Physicians are analogous to knowledge workers because they apply knowledge and skill to diagnosing disease and choosing appropriate treatment. There is likely to be variation in how physicians choose treatment across patients often for the same illness. Healthcare economists refer to this as the SAV problem.

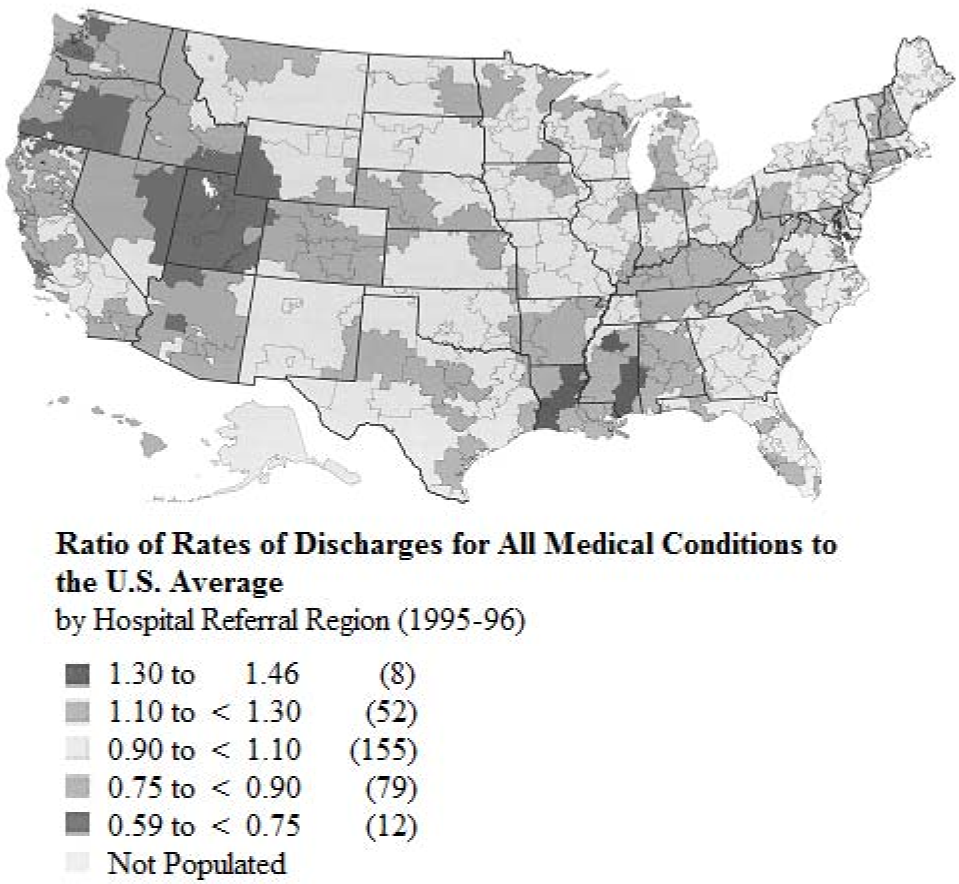
A major source of uncertainty in healthcare is uncertainty on the part of the physician as to the best course of treatment for a given disease. Research shows significant inconsistency among medical professionals in rates of treatment types for various conditions, which is geographically correlated (Wennberg, and Gittelsohn, 1973). This inconsistency between physicians is known as the SAV problem. More specifically:

> SAV is defined as "the large differences in the rates of use of medical services (e.g., hospital admissions and surgical or diagnostic procedures) between geographic regions."-Health Service Research Group

This geographic correlation is believed to be an artifact of inadequate diffusion of treatment innovations, among other reasons. In information systems terms, information on what treatment is best for what condition moves slowly between physicians. Prior studies have estimated that the magnitude of consumer welfare loss due top treatment inconsistency could exceed losses due to moral hazard and could be the largest source of inefficiency in healthcare (Phelps and Parente, 1990). Treatment inconsistency is typically empirically investigated on a treatment rate basis, but demonstrated on both a cost and treatment rate basis. For example, researchers on treatment inconsistency often look differences between areas in the proportion of people receiving a particular treatment for a given disease. An example, from Wennberg (1999) is shown in figure

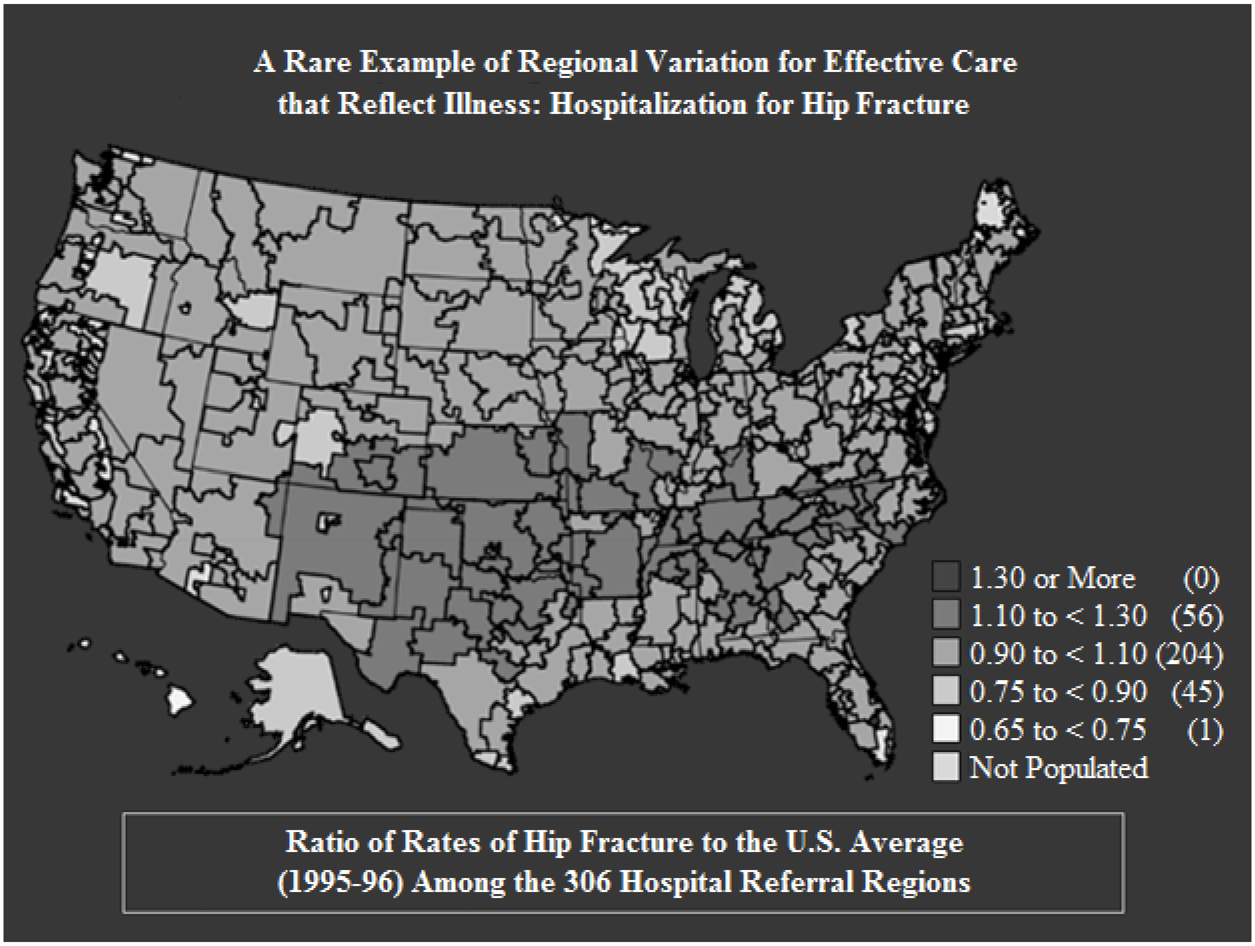
1. This shows variation in overall discharge rate between different geographic areas, a relatively high variation example.

Figure 1. Variations in discharge rates, a high variation example



Some conditions have low uncertainty and a low number of treatment options. As a result, they exhibit relatively low variation. For example, the choice of a physician to hospitalize a patient who has a hip fracture is a low variation example. This is shown in figure two.

Figure 2. An example of low variation condition.



It is important to understand how treatment inconsistency is measured. Treatment inconsistency is most commonly measured using coefficient of variation (COV), which is the standard deviation of a rate of a given treatment over the mean rate of the treatment in question. The principle advantage of using COV is that it allows for comparison across multiple procedures where the underlying rate of illness varies. Treatment inconsistency researchers also use the extremal quotient ratio, which is the ratio of highest to lowest observed rates. A rough rule of thumb is the extremal ratio is ten times the COV. A number of studies control for other factors using some sort of multiple regression before calculating the COV. Given how widely observed the phenomena, and inability of control factors to explain substantial amount of variation in prior studies, many modern studies lack of controls via multiple regressions.

Treatment inconsistency has been shown to hold in a wide range of medical care markets around the world (McPherson, et. al., 1982). Most of the work on treatment inconsistency has focused upon surgical procedures, although the analysis has been done on a spending or admission rate basis. The first study on treatment inconsistency was by Glover (1938) which looked at tonsillectomies. Tonsillectomy rates are still studied today in modern treatment inconsistency studies (Wennberg, 1990). Lewis (1969) looked at multiple treatment types such as tonsillectomies, hernia repair, and hemorrhoid injection. Research on treatment inconsistency began to receive major attention with Wennberg and Gittelsohn's (1973) study was published in *Science*. The study was the first to look at treatment inconsistency from multiple lenses looking at not only treatment rates, but also variations in resources, utilizations, and expenditures. Another study looked at multiple treatments including prostate surgery, tonsillectomy, appendectomy, gall bladder removal, and hysterectomy (Wennberg, et. al., 1975). Phelps and Parente (1990) looked at 63 different procedures. More recent studies have looked at the variation in office visit length, labs test ordered, and expense between physicians by diagnostic class, such as digestive problems, cardiac issues, or skin disorders (Grytten and Sorensen, 2003). Studies have generally found that for some procedures uncertainty is low because both diagnosis is fairly definitive, there are few alternate treatments, and the consequences to not treating the illness are clear. For these procedures, such as hernia repair or appendectomy, COV is low, in the range of 0.10 to 0.20. For other procedures, such as tonsillectomies, diagnosis is difficult, there are multiple treatment options, and efficacy is unclear. For these procedures COV is in the range of 0.40 to 0.7.

Treatment inconsistency has also been studied in many different contexts and at many different levels of aggregation. Glover's (1938) study was a county-level study in Britain. Lewis (1969) also studied at the county-level in Kansas. The Wennberg et. al. (1973, 1975) studies which started the modern treatment inconsistency studies were most conducted at the hospital service area (HSA) level in the Northeast United States. Additional studies have compared HSAs across countries. McPherson, et. al. (1982) conducted a study of 7 procedure types using 46 HSAs in Norway, Britain, and New England. Since much of the reasoning for treatment inconsistency revolves around how well physicians are informed, researchers have also investigated treatment inconsistency across communities with medical schools (Wennberg, 1990). More recently researchers have investigated the variation in treatment pattern between individual physicians (Grytten and Sorensen, 2003) and between hospitals (Lougheed, et. al., 2006). An overview of these studies is presented in table 2. The main two takeaways from this table are 1) that treatment inconsistency has been found to be a problem in locations worldwide and 2) the degree of inconsistency varies by disease.

Table 2. Evidence of treatment inconsistency

Where Studied	**Findings**	**Citation**
Cross-county in Britain	COV = 0.66 (tonsillectomy)	Glover, Allison, 1938
Kansas, county-level	COV = 0.29 (tonsillectomy), 0.52 (appendix), 0.22 (hernia), 0.40 (hemorrhoids)	Lewis, C., 1969
Vermont, 13 service areas	Multiple per person measures used: resources, expenditures, utilization and procedures.	Wennberg and Gittelsohn, 1973
Maine, 42 Hospital Service Areas (HSA)	COV = 0.24 (prostate), 0.43 (tonsil), 0.18 (appendix), 0.14 (hernia), 0.55 (hemorrhoids), 0.23 (gall bladder), 0.25 (hysterectomy)	Wennberg and Gittelsohn, 1975
7 procedures studied, 46 HSAs in Norway, Britain, and New England.	COV (sample) = 0.48 (tonsil-Norway), 0.31 (tonsil-Britain), 0.36 (tonsil-New England)	McPherson, et. al., 1982,
U.S., 13 large regions (states or parts of large states),	30 procedures, COV (sample) = 0.79 (injection of hemorrhoids) to .10 (hernia repair)	Chassin, et al., 1986
New York counties, 63 procedures	COV (samples of the 63) = 0.42(tonsillectomy), 0.28 (hysterectomy), 0.36 (coronary bypass)	Phelps and Parente, 1990
16 Medical School Cities, 30 procedures	COV = 0.116 (Colectomy), 0.142 (small intestine resection), 0.152 (hernia repair) to 0.520 (spinal fuson), 0.525 (total knee replacement), and 0.825 (carotid endarterectomy)	Wennberg, 1990
Norway: 2336 physician practices	By diagnosis: COV = 0.64 (digestive), 0.88 (cardiac), 0.57 (skin)	Grytten and Sorensen, 2003
16 Ontario Hospitals	Hospitalization rates for asthma, COV = 0.309 (children) & 0.529 (adults)	Lougheed, et. al., 2006

We have shown that healthcare is a unique context, often giving rise to unique phenomena. Evidence was presented that one such phenomenon, treatment variation, is both important and widely occurring. Next, we will explore likely reasons why treatment variation occurs.

Causes of Treatment Inconsistency

Treatment inconsistency does not result from a single cause. Research shows six key reasons for treatment inconsistency: localized schools of thought, property rights issues, problems of inference from a small sample size, slow information diffusion, high search costs, and difficulty in monitoring (Phelps, 1992). First, schools of thought become established in a given area. The market for healthcare is local in nature. Once a school of thought becomes established at a particular location it becomes quite costly to alter local opinion (Westert and Groenewegen, 1999; Grytten and Sorensen, 2003). In the markets for manufactured goods inefficient production methods are forced out of business at faster rate by more efficient methods of production because the goods can be produced and transported across wider geographic range.

Second, treatment inconsistency is partially a result of a free-rider problem. Unlike medical devices and drugs, no property rights exist for producers of new treatments. Producers do not gain temporary monopoly rights to the treatment. Producers are also not liable for the result new treatment, except on a single case-by-case with individual patients they treat (Phelps, 1992; McClellan, 1995). As a result of this, those who devise new treatments do not have the same incentives to test treatment effectiveness with large sample double-blind studies as drug and medical device manufacturers do.

Third, physicians are left with a substantial inference problem as to the effectiveness of a particular treatment. In contrast with procedures, medical devices and drugs are tested using large scale statistical studies. In general, medical procedures are not tested this way (McClellan, 1995). Research literature for procedures consists of mostly case studies or small sample case studies (Phelps, 1992). Because of the large number of possible diseases, each individual physician will see a relatively small number of patients. As a result, practitioners are left on their own to decide what works best (Luft, et. al., 1979; Wennberg and Gittelsohn, 1982). A high degree of uncertainty as to the optimal course of treatment results because the research literature does not provide definitive statistical evidence.

Fourth, the rate of diffusion for advances in medical procedures is slower than for traditional innovations. In traditional markets a superior technological innovation will, over time, eventually come to dominate the market. Yet, in many cases there is no converge of opinion over time. For example, variations in tonsillectomy rates across regions have changed slightly since 1938 (Folland and Stano, 1990). Diffusion of new knowledge about medical procedures is believed to be quite slow (Phelps, 1992; Grytten and Sorensen., 2003).

Fifth, search costs in medicine are quite high. The rate of publication in biological sciences coupled with the large range of treatments that a typical physician administers creates a search space so large that becoming aware of alternative treatments is a legitimate concern (Phelps, 1992; McClellan, 1995).

Finally, because of the professional nature of healthcare and the idiosyncratic nature of illness, monitoring is difficult in medicine. Because of the idiosyncratic nature of the production activity even basic monitoring requires a quite complicated adjustment for case-mix (McClellan, 1995). Also, most physicians are not part of an organizational hierarchy and operate with a great deal autonomy.

A summary of these causes is shown in table 3. The main takeaways from this table are that treatment inconsistency is multi-causal and that it can be linked to: 1) inferring treatment effectiveness from a small sample size, 2) uncertainty, 3) the influence of local schools of thought, 4) high search costs, and 5) slow diffusion of innovations.

Table 3. Causes of treatment inconsistency

Cause	**Citation**
Small sample inference	Luft, et. al. 1979
Small sample size and uncertainty of treatment	Wennberg and Gittelsohn, 1973
Localized schools of thought, high search costs, professional nature of the activity makes monitoring difficult, and free-rider problem due to property rights	Phelps, 1992
Slow rate of diffusion.	Folland and Stano, 1990
Small sample size inference, localized schools of thought, professional nature of the activity, and search costs	McClellan, 1995
Local schools of thought	Westert and Groenewegen, 1999
Localized schools of thought and slow diffusion of innovation.	Grytten and Sorensen 2003

Critique of Healthcare Literature

The healthcare industry is a unique organizational context in several ways. First, healthcare is characterized by a high degree of informational uncertainty. In healthcare, a high degree of information asymmetry exists between buyer and supplier. Because of this information asymmetry the reinforcing market forces are altered. In a normal market, producers of inferior goods are driven out of the market by competition as buyers learn about product quality. In healthcare markets are local in nature and the information asymmetry is so high that patients are unable to evaluate the quality of services, even after purchase. The second way healthcare is unique is that the demand for healthcare is a derived demand. Consumers do not want healthcare per se, what they want is health. As such, health is both consumer and produced by the consumer. The consumer actively plays a role in the build-up of “health capital” though diet and exercise. Finally, healthcare is a unique organizational context because of the role of physicians. Physicians enjoy a great deal of autonomy. Often physicians often exert substantial control over the resources of an organization even though they may not be a part of that organization. As a result of many of these differences, healthcare results in phenomena particular to healthcare.

One phenomena particular to healthcare is treatment inconsistency. Treatment inconsistency is the idea that a patient’s odds of obtaining a particular treatment for a given illness are highly dependent upon location. This geographic dependence is a form of inefficiency. Treatment inconsistency is thought to be one of the largest forms of inefficiency in healthcare. Treatment inconsistency is generally thought to arise from informational issues between physicians. Treatment inconsistency has been studies in multiple contexts using multiple procedures. Treatment inconsistency exists all over the world.

Treatment inconsistency is thought to arise from multiple causes, most of which deal with informational issues between physicians. In healthcare, those who develop new procedures lack the intellectual property rights granted to those to develop new drugs or medical devices. Because of this difference in intellectual property rights, as well as the expense involved in clinical trials, research on the effectiveness of particular treatments often involves sample sizes which are too small to detect differences in treatment effectiveness between treatment modes. As a result much of the literature on new procedures involves either case studies or small sample sizes statistical analysis. Physicians are somewhat left on their own to infer the effectiveness of a given treatment. Healthcare markets are local in nature and often time local schools of thought as to how to treat a particular illness arise, which could result in treatment inconsistency. Healthcare has been shown to exhibit a slow rate of diffusion for new procedural innovations. The literature on healthcare is vast and keeping informed by keeping up with the literature represents a substantial challenge to treatment providers. Finally, the role of physicians and the professional nature of activities make monitoring in the classic organizational sense difficult in healthcare.

So far, we have demonstrated with evidence from prior literature that healthcare is a unique context which often gives rise to unique phenomena. Treatment variation is one such phenomena, which is both important and widespread. Likely causes of treatment variation include several information-related factors. Since many of the likely causes of treatment variation are thought to be information-related, it would seem logical that technology which handles information could impact treatment variation. As a result, in this next section we will examine both theory and evidence of the likely impacts of information technology.

Theory and Evidence of Returns to Information Technology

The purpose of this section is to describe the theoretic arguments as to why IT should have positive impacts on organizational performance and to outline the empirical evidence to support these arguments. First, this section attempts to bridge the gap between the literature of health economics and information systems by expressing IS theories in economic terms. While the terminology presented in this section might be well known to some IS researchers, given the broad theory bases IS research draws from, it is likely unfamiliar to some. The concepts presented in this section should be relatively well-known to IS researchers, albeit using somewhat different terms. This is necessary because the phenomenon which is the focus of this study, treatment inconsistency, has been most deeply studied through the lens of health economics. After discussing the theoretic arguments will be an examination of the empirical evidence of returns to information technology.

Literature has provided theoretic arguments as to why IT is likely to impact performance. Later it this review, when I discuss the healthcare context and causes of treatment inconsistency as studied by health economists, the value of framing IT in terms of economic theory will become more apparent. Since much, if not all, of the uniqueness of the healthcare context and causes of treatment inconsistency identified by health economists are the result from information issues framing some common IS ideas in economic terms greatly aids translation between the two literatures.

From an economic theory perspective IT has a number of interesting features. This review will first look at the capital forming effects of IT and then at the cost impacts of IT. It as a capital stock has three key points relevant to this study: the role of complementary investment in IT, IT as a form of memory capital, and the role of the network as a capital stock. The cost impacts of IT also have three interesting features: IT lowers search costs, IT reduces monitoring costs, and IT lowers the cost of information diffusion.

First, IT is a general purpose technology (David, 1990). As a general purpose technology most of the benefits comes from the fact that IT facilitates the formation of other forms of capital. A parallel is often drawn by researchers between IT and another general purpose technology, electricity (David, 1990; Atkeson and Kehoe, 2007). IT is like electricity in that the main benefit come not directly from the good itself, but rather from all of the new products and services it facilitates. With IT this can take the form of physical goods or new organizational forms. Mainly what this suggests is that IT investment needs complementary investment. One form of complementary investment, which is not new, is the complement between capital goods and training. Research recognized a long time ago that with complex capital goods training and worker skills are complementary to capital investment (Griliches, 1969). This complementarity can also be an impediment to adoption. As firms consider investing in new technology, they must also consider the investment needed to retrain a workforce which has built of a stock of human capital which is complementary to the existing capital base. The more experience a workforce has with an old technology, the greater the benefits of the new technology must be to trigger adoption of the new replacement technology (Atkeson and Kehoe, 2007). The main point here is that complementary investments play a significant role in IT investment. IT is not simply a faster machine. Second, IT is a form of organizational memory (Simon, 1973). This memory can be viewed as a capital stock. Because it is a memory, the capital stock builds over time.

The third capital forming impact of IT relates to network externalities. Research on networks has shown that the value of certain goods grows as a positive function of the number of users (Katz and Shapiro, 1985). Many IT goods produce network effects. Networks effects can be first-order or second-order. First-order network effects are where the direct value is a positive function of the amount of adoption of a product. An example of this is the telephone. The value a telephone has is directly a function of the number of people one could call with the telephone. A second-order network effect is when an indirect benefit increases as the number of adopters rises for a given product. For example, there are often more software titles available for more popular computing platforms. From the standpoint of this study, network effects are impact the size of the knowledge pool from which to discern the best course of treatment. Researchers have primarily focused upon the impact network effects have upon competition, pricing, and adoption rates (Katz and Shapiro, 1986). The implication for this study is that more users of a healthcare IT system, which aids in information diffusion, the greater the benefits to the group as a whole. The network becomes a form of capital available to the organization. A larger information network results in a larger pool from which to sample treatment efficacy from, so organizational factors which contribute to a larger information sharing network should provide greater informational value.

IT has three principle cost impacts: reducing search costs, reducing monitoring costs, and reducing the cost of information diffusion. First, IT reduces search costs (Bakos, 1997). The implication for this study can be drawn from theory on search costs. A reduction in search costs implies lower variance in outcome (Stigler, 1961). While Stigler (1961) modeled the outcome of search as price paid by consumers, the implication is that some variance comes about because the marginal benefits of additional search are outweighed by the marginal costs of additional search. The residual uncertainty results in variance in outcome. IT reduces this residual uncertainty by shifting the search cost curve. Second, IT reduces monitoring costs (Malone, Yates, and Benjamin, 1987). By reducing monitoring costs IT should help to change organizational forms (Simon, 1973). A reduction in monitoring cost should reducing hierarchy by increasing span-of-control and allow for level-skipping (Radner, 1992). IT should also impact the make versus buy decision because active monitoring could at least some degree substitute for costly contracting (Malone, Yates, and Benjamin, 1987). Finally, IT speeds or lowers the cost of information diffusion (Huber, 1990).

In summary, the theoretic implications of IT can be roughly divided into the capital forming effects and cost implications. IT both facilitates and requires additional forms of capital. IT helps build information capital over time by acting as a form of memory. Networks are formed by IT, which act as a form of capital for the organization. Search costs are reduced by IT, which lower outcome variance. Monitoring costs are lowered by IT, which allow for new organizational forms. Finally, IT lowers the cost of information diffusion. The literature for this is summarized in table 4.

Table 4. IT Theory

Theory	**Citation**
Reducing search costs results in lower variance	Stigler, 1961
Capital investment and human capital are complementary	Griliches, 1969
IT is a form of organizational memory and provides access to external information to the organization.	Simon, 1973
Network effects form a barrier to entry	Katz and Shapiro, 1985
Technology adoption takes longer initially with network effects	Katz and Shapiro, 1986
IT reduces transaction costs, search costs, and monitoring costs.	Malone, Yates, and Benjamin, 1987
IT is a general-purpose technology, it facilitates other investments	David, 1990
IT speeds information diffusion, increases participation in decision making, more consistent division of decision making authority	Huber, 1990
Lower monitoring costs lead to changes in organizational structure	Radner, 1992
IT requires a time to build up a stock of data capital.	Brynjolfsson, and Yang, 1996
IT reduces search costs	Bakos, 1997
New technology can take a long time to be adopted because firms build up a skill base which is complementary to old technology	Atkeson and Kehoe, 2007

Empirical evidence of the returns to IT investment has primarily focused upon four areas: 1) the connection between IT investment and production outcomes, 2) intermediate production impacts of IT, 3) secondary effects of IT investment, and 4) lagged effects of IT investment.

Interest in the impact of IT investment on production outcomes is most often traced to Robert Solow, who coined the term "productivity paradox" (Solow, 1987). Solow's observation was that empirically increased investment in IT appeared to have no impact on productivity. Since that time, Brynjolfsson and Hitt (1996) found positive returns to IT, it terms of output, using firm-level data using a Cobb-Douglas production function. Key to the issue was that industry-level data, which had been used to estimate returns to IT up until that point, often did not have sufficient granularity to capture productivity impacts and that the price deflators used to calculate IT capital levels were not properly calculated. The issue surrounding the price deflators was based upon Gordon's (1989) research which showed that commonly accepted price deflators for IT capital did not capture the rapid advances in computing power. This research was extended to look at the impact on labor productivity. Again using firm-level data IT was found to have positive impact on labor productivity (Hitt and Brynjolfsson, 1996). Another study found a positive relationship between IT spending and firm market value using the Tobin's q measure (Bharadwaj, et. al., 1999).

Prior to the work on IT and end-outcome measures, such as labor productivity or output, a research looked at the impact of IT on intermediate measures of business value. Research showed that IT had positive impacts on intermediate measures of business value, such as inventory turnover (Barua, et. al., 1995). Later, empirical research showed process-level improvements in cycle times and error rate reduction (Mukhopadhyay, et. al., 1997).

Secondary impacts from IT investment manifest in terms of substitution effects in the production process, consumer surplus, and spillover effects. IT is a substitute for both ordinary capital and labor (Dewan and Min, 1997). IT investment also has been shown to increase consumer surplus (Hitt and Brynjolfsson, 1996). The idea is that IT results in higher quality goods, better service, and other consumer benefits which are intangible and difficult to measure in a classic economic sense. Open source production models are facilitated by IT. What is different about open source production models is in several instances the "free" product is of higher quality that the commercial product (Lerner and Tirole, 2002). The lack of property rights in open source markets seems to be offset by the additional rents to be gained from the reputational effects of being a key player in a successful open source project. Finally, IT investment has shown to have positive spillover impacts on productivity on both buy and suppliers. The idea is that IT investment exhibits positive externalities in that it facilitates coordination between transacting parties (Cheng and Nault, 2007).

Research shows that both users and firms require a period of time to become productive at using IT, given that the investments are often complex (Curley and Pyburn, 1982). Empirical research has also demonstrated that IT investment at the firm-level takes several years to manifest in positive returns (Brynjolfsson and Hitt, 2003). The general rationale for lagged impacts from IT is that computers are a general-purpose technology with primary purpose of making other complementary investments, such as process redesign, possible. Brynjolfsson and Yang (2000) offer a simpler of how lagged returns to IT investment might occur. They state that server installation must come before database software installation, which must also come before data acquisition. They point out that it might takes years for a stock of data to build up to a sufficient level that better decisions are made as a result of the initial IT purchase.

In summary, empirical evidence of the returns to IT investment point to several benefits. IT improves productivity, output, and market value. Consumers and supply chain partners also benefit from IT investment. Process-level evidence also points to positive impacts of IT investment. Evidence also suggest that IT investments often require a significant amount of time to show substantial returns, as they are often complex and require time to learn how to use. A summary is presented in table 5.

Table 5. Evidence of Returns to IT Investment

Findings	Context	Citation
It require time to learn how to use, expect lags for returns to manifest	Case studies of 33 organizations plus surveys of 33 firms. Ranged in size from $55M to $2.5B	Curley and Pyburn,1982
IT improves intermediate measures, such as inventory turnover, but not final output	60 business units in 20 US companies	Barua, et. al., 1995
IT positively impacts output.	367 Large US firms, Firm-level, output, Cobb-Douglas	Brynjolfsson and Hitt, 1996
IT has positive impacts on labor productivity and consumer surplus, but not on profitability	367 Large US firms, labor productivity, profitability, and consumer surplus	Hitt and Brynjolfsson, 1996
IT is a net substitute for both labor and ordinary capital	330 large US firms, substitution	Dewan and Min, 1997
IT improves cycle time and quality	46 mail processing centers	Mukhopadhyay, et. al., 1997
IT investment positively impacts market value	631 firms over 5 years, market value	Bharadwaj, et. al., 1999
IT can impacts can be difficult to measure: open source software shows that high quality goods can be produced without property rights	Review article with case studies: Apache, Linux, Perl, Sendmail	Lerner and Tirole 2002
The long-term (5-7 years) returns to IT greatly exceed the short-term returns to IT, in terms of productivity and output	Firm-level, productivity and output	Brynjolfsson and Hitt, 2003
Productivity returns to IT spillover to downstream purchasers	Industry-level, IT spill-over impact on productivity	Cheng and Nault, 2007

To review, there are multiple theoretic arguments as to why one should expect positive returns to IT. The arguments most salient to this study, on treatment variation in healthcare, are that IT a) facilitates information aggregation, b) speeds information diffusion, c) reduction in search costs, and d) lowering of monitoring costs. This is important because treatment variation is thought to arise due to a) poor information aggregation, b) slow information diffusion, c) high search costs, and d) high monitoring costs. Furthermore, empirical evidence supports the notion that IT adds value. Theory also suggests that IT is a general purpose technology and as such should require complimentary conditions to yield value and there is empirical evidence to support this theory. The next section will examine these complimentary conditions. The role of compliments should be especially important in studying treatment variation, since the phenomena occurs in a healthcare context. We know that context in healthcare is quite unique and important.

Role of IT Complements

The purpose of this section is to examine the role of factors which compliment IT and help give rise to value. Information technology is a general-purpose technology (David, 1990). Much of the value of IT comes from the complementary investment it facilitates, not the direct impact of automation (Bresnahan and Trajtenberg, 1995). IT can directly impact productivity though automating manual processes, but IT also has a second role as a mechanism for coordination (Brynjolfsson, et. al., 2000). Research suggests that the impact of IT as a coordination mechanism is much larger than the direct productivity impacts of automation (Gurbaxani and Whang 1991; Malone et al. 1989). As a result, IT investments often require investment in complementary organizational capital to yield expected returns. Organizational capital can include items such as process redesign, training, hiring a more skilled workforce, and new organizational designs. In order for investments in these complementary assets to be successful, it is highly likely to that they need to be customized to the firm in question (Powell and Dent-Micallef, 1997). Examples would be a including both formal training and cross-training specifically designed to address new IT capital and form IT skills.

Other work on IT investment has shown that organizational structure plays a critical role in obtaining value from IT investments (Orlikowski, 1992). Research has shown that system use is a critical mediator for success of IT investments. While this principle may sound simple, mush research has shown that often times users use very few of the features contained within an IT system (Burton-Jones and Gallivan, 2007). Organizational factors, such as peer influences and top-management involvement, have been shown to have a large impact upon IT system users (Weill, 1992).

Finally, institutions are structures which help to maintain order between people. According to institutional theory there are three types of structures which impact individual thought and behavior: structures of signification, structures of legitimization, and structures domination (Scott, 2001). Structures of signification are organizational rules which define interaction and inform. Structures of legitimization show that things such as rituals and tradition help maintain social order. Structures of domination show that there is an inherent asymmetry of authority and resources in social interaction. Orlikowski (1992) showed that organizations use these institutional structures to make sense of technology, in a process called structuration. It was further argued that managers can influence the assimilation and use of technology by manipulating these structures, in a process called metastructuring. Metastructuration can either enforce or change the existing social environment. For example, managers can institute incentives for people to use a given technology. Research has also shown that the more closely aligned the individuals are with a given institution, the more readily their behaviors can be influenced by that institution (Chatterjee, et. al., 2002). The implication is that given the unique nature of healthcare organizations, institutional factors should play an especially prominent role in influencing technology impacts.

A summary of this literature is shown in table 6. The main take away from this literature is that IT investment often requires particular organization conditions and complimentary investments to yield value.

Table 6. Complements to IT investment

Complementary Factor	**Citation**
Need management commitment to IT firm-wide, prior experience with IT	Weill, 1992
Need for organizational support	Orlikowski, 1992
Need process redesign, decentralized authority	Brynjolfsson, 1996
Need training, Management commitment, and new organizational practices	Powell and Dent-Micallef, 1997
Employee Mix/Human Capital	Francalanci and Galal, 1998
IT enables new processes and organizational designs	Brynjolfsson, et. al., 2000
Human Capital/education	Dewan and Kraemer, 2000
Management and Organizational practices	Cooper, et. al., 2000
Management and Organizational practices: skilled labor & process redesign	Bresnahan, et. al., 2002
Institutional factors influence outcome of IT investment	Chatterjee, et. al., 2002
System use is an important mediator of IT value	Burton-Jones and Gallivan, 2007

Critique of IT Literature

Evidence of the return to investments in IT supports the notion that IT investments have positive business value. Empirical studies have shown IT to have positive impacts final outcome measures such as productivity, output, market value, as well as positive impacts on intermediate outcome measures such as inventory turnover and process cycle time. Evidence also supports the notion that IT investments exhibit significant lag effects and are a net substitute for both ordinary capital and labor. The general idea that IT investments are general purpose technologies, which require significant complementary investment, has empirical support. In terms of economic theory, IT investments should exhibit particular capital forming effects and particular cost impacts. First, in terms of capital formation, IT is a general-purpose technology. As a general-purpose technology often times IT investments require other complementary investments to yield value. As complex technologies, IT investments often require time for people to learn how to use them. Time is also required for IT investments to build up a stock of data capital or memory. IT investments also function as communication tool. As communications tool, IT investments often exhibit network externalities. The value of IT investments often rises as a function of the number of users of a given technology or system. From a cost standpoint, IT investments lower search costs, monitoring costs, and the cost of information diffusion. Lowering monitoring costs reduces outcome variance over time. Reducing monitoring costs allows for new organizational arrangements, such as greater span-of-control or increased outsourcing. By reducing the cost of information diffusion, IT investments should speed information diffusion rates. As a general-purpose technology, IT investments require complementary investments in training, process redesign, and management and institutional support to yield expected returns.

In the next section, we will review the current literature on the impacts healthcare information technology. This is important because this shows how this study fits into the existing literature, as well as were the deficiencies exist in the literature.

Healthcare IT

The purpose of this section is to review the literature on the impacts of IT in healthcare. Evidence on the impact of IT in healthcare is mixed. Literature on IT impacts in healthcare have looked at both final outcome measures, such as productivity or output or mortality , as well as intermediate performance measures such as error rates, cycle times, utilization, and complications (Menon, Lee, and Eldenberg, 2000; Chaudhry, et. al., 2006). A recurring theme among studies on IT and healthcare is the role of time lags, the empirical evidence generally supports the notion that IT investments require a substantial time period for users to learn how to use the technology (Devaraj and Kohli, 2000; Amarasingham, et. al., 2009). Studies drawing from IT literature base, consistent with the literature on IT investment, appeared more likely to include complementary investment factors such as business process reengineering (BPR) and training (Devaraj, S. and Kohli, R., 2000; Bhattacherjee, et. al., 2007; Athey, S. and Stern, S., 2002). These studies find positive impacts to IT and often included (Devaraj, S. and Kohli, R., 2000; Menon, N., Lee, B., Eldenburg, L., 2000; Athey, S. and Stern, S., 2002). Studies based in the medical literature painted a more mixed view of outcomes IT investment (Garg, A., et. al., 2005; Poissant, et. al., 2005; Chaudhry B, et. al., 2006). These studies generally did not include complementary investments and generally took a "tool view" of IT investments. The studies based in the medical literature used a more nuanced choice of outcomes, consistent with the idea that healthcare is a unique context, including outcome measures such as error rate, differential mortality, utilization rates, and complication rates (Watson, et. al., 2005; Chaudhry, et. al., 2006; Amarasingham, et. al., 2009). What is missing from this literature is a study that takes into account the unique nature of IT investment, as well as the unique context of healthcare. A summary of these studies in presented in table 7. The main takeaway from table 7 is the evidence as to the impact of IT is, to date, mixed.

Table 7. Studies of Impact of IT in Healthcare

Findings	**Type**	**Citation**
Positive, after time lags.	Information Systems	Devaraj and Kohli, 2000
Positive. IT contributes to output and productivity.	Information Systems	Menon, et. al., 2000
Positive. Savings in drug costs, better utilization, and less accounting errors.	Medical	Wang, et. al., 2003
Mixed. Some IT improves performance, but many don't. Finds bias in studies.	Medical	Garg, et. al., 2005
Negative. IT system facilitated medication error.	Medical	Koppel, et. al., 2005
Negative. Increased mortality and medication error rates.	Medical	Watson, et. al., 2005
Mixed. Helped nurses, slowed down physicians.	Medical	Poissant, et. al., 2005
Mixed. Quality impacts are positive, but cost and utilization impacts are inconclusive.	Medical	Chaudhry, et. al., 2006
Mixed. Only clinical IT impacted performance.	Information Systems	Bhattacherjee, et. al., 2007
Positive. Fewer complications, lower mortality and cost.	Medical	Amarasingham, et. al., 2009

Theory and evidence about the impacts of IT investment suggest that IT: a) is a general-purpose technology which often requires complementary investments to yield positive returns, b) lowers search costs, which lower the variance of outcomes, c) facilities the accumulation of "memory capital" over time, d) lowers monitoring costs, e) speeds information diffusion, and f) exhibits network effects. While many of the potential impact of IT would seem to result in positive returns in healthcare, findings on the impact of IT in healthcare to date are mixed. Most studies on the impacts of IT in healthcare have either: a) used a rich understanding of IT investments focused upon the impact of IT on traditional outcome measures such as profitability or response time, or b) used a simplified view of IT investment with a rich understand of the particular phenomena which arise out of the unique context of healthcare. What is needed in this literature is a study which takes into account the particular impacts of IT investments on phenomena which are unique to healthcare, such as treatment inconsistency.

Summary

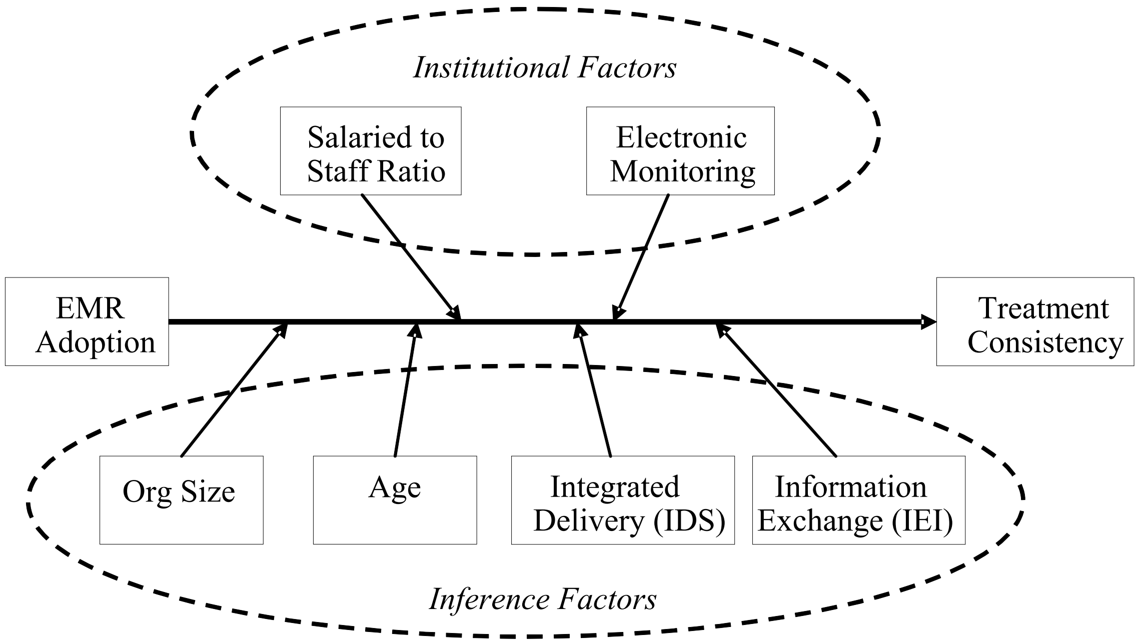
In summary, healthcare is a unique context which violates many commonly held assumptions of how both organizations and markets work. The unique nature of healthcare gives rise to phenomena which are particular to healthcare. One of these phenomena is treatment inconsistency. Empirical evidence for treatment inconsistency has been found in many contexts, at many different levels of aggregation, and across many procedures. Estimates of the efficiency loss due to treatment inconsistency suggest that it is one of the leading, if not the leading, sources of inefficiency in healthcare. Treatment inconsistency is thought to arise from multiple causes, most of which are related to information issues. Possible causes for treatment inconsistency are: a) formation of localized schools of thought, b) inferring the treatment effectiveness of medical procedures from small samples, c) slow diffusion of information, d) high-search costs, and e) difficulty in monitoring.

Prior literature from information systems suggest that under the proper conditions information technology can aid in information diffusion, facilitate data aggregation, reduce search costs, and reduce monitoring costs. Prior literature also suggests that complementary factors play a substantial role in outcomes derived from IT. IT requires time to learn how to use and institutional support to promote proper system use.

Chapter III: Theory Development and Research Hypotheses

Prior research has shown that treatment inconsistency can result from difficulty of institutions in monitoring of physician activities, inference from a small sample size, high search costs, slow information diffusion, and localized schools of thought. Prior research has also shown that IT can reduce search costs, decrease monitoring costs, speed information diffusion, connect people across distance, require use, and often particular organizational conditions to yield value. Figure 1 presents the research model. The model proposes that IT will improve consistency in treatment patterns and, consistent with prior research, provides for several organizations conditions which are likely to facilitate IT impacts on treatment consistency. Those conditions are roughly divided into those conditions which are likely to result in the IT system building up more data to combat small size inference problems. In the model these are labeled *inference factors*. Also, the model identifies organizational conditions which are like to facilitate use of the IT system or be complementary to it. These factors are labeled, *institutional factors*.

Figure 3. Research Model



The treatment inconsistency phenomenon is thought to arise from multiple causes. Prior research shows that many of these causes are related to information. Treatment inconsistency causes which information technology would possibly impact: 1) local schools of thought, 2) small sample size inference, 3) slow diffusion of innovations, 4) high search costs, and 5) difficulty in monitoring. The impacts of IT on these causes are in some cases direct and in other cases indirect. The direct impacts will first be reviewed and then the indirect impacts. This study will address the impact of IT on treatment consistency. The IT that is the object of study is electronic medical records (EMR). EMR is not one thing, but rather a bundle of features. The bundle of features which included the following: a) a clinical data repository, b) clinical decision support system (CDSS), c) computerized practitioner order entry (CPOE), d) physician documentation, e) a controlled medical vocabulary, and f) an order entry system.

The first direct impact is information technology connects people across distance. IT lowers the cost of transmitting patient information across distance, facilitating consultation with remote physicians. Consultation by local physicians with remote physicians is likely to raise the awareness of local physicians to medical practices in remote locations and make the remotely located physicians more aware of medical practice at the local location. This IT facilitated communication is likely to reduce the information asymmetry between locations, thereby reduces one of the suspected causes of treatment inconsistency.

The second direct impact is information technology allows physicians to pool records in a central repository. This information aggregation enables physicians have a higher degree of certainty when reflecting upon past cases to infer the effectiveness of various treatments.

The third, and final, direct impact is that IT speed information diffusion. For example, many EMR systems include a clinical decision support (CDSS) feature which, are designed to help physicians and other health professionals with decision making tasks. The CDSS contains a knowledgebase which is updated on an ongoing basis to reflect current medical thinking from literature. The CDSS feature in EMR should speed information diffusion.

It is also likely to have indirect impacts upon treatment inconsistency. For example, IT lowers search costs. While EMR does not explicitly search medical literature, the CDSS feature included in some EMR applications provides links to current literature on a given topic. Finally, by digitizing patient records IT facilitates monitoring by lowering monitoring costs for the organization.

In summary, many of the causes of treatment inconsistency relate to information issues which seem likely to be impacted by the implementation of EMR. Specifically, IT is likely to have a direct impact upon treatment inconsistency by connecting physicians across a wider geographic area, allowing physicians to infer effectiveness over a larger sample size, and impacting the speed of information diffusion through CDSS. IT is also likely to facilitate lowering of the cost of searching the medical literature and facilitating increased monitoring of physician actions by the healthcare organization. Given these issue it is argued that:

> *Hypothesis 1: EMR will be positively associated with increased treatment consistency.*

Institutional Factors

Studies on IT investment have shown that to obtain the desired impact from IT investment a number of other investments and actions, which complement IT investment, must occur. IT investment should not simply be purchasing of hardware or software, it should include investments in training, process redesign, and institutional support for the use of the IT investment in question. One of these complementary actions is the influence of institutions, through managerial acts of domination, upon individuals to use IT.

Institutions exert influence upon individual action. In the context of healthcare IT the individual action would be physician use of an EMR system. The role of the institution is particularly important in the context of this study because of the role of the physician. Physicians enjoy a great deal of autonomy. Physicians are often not part of the hospital hierarchy, despite the fact they exert a great deal of control over hospital resources. For EMR systems to impact treatment consistency, the IT systems must be used. System use is influenced by the institution, in this case the hospital organizational hierarchy. While it could be argued the physician autonomy is high regardless of whether they are a part of the formal hospital hierarchy or not, it seems more likely that physicians which are part of the formal hierarchy are more likely to use the EMR system. As such, hospitals where a greater share of practicing physicians are directly paid by the hospital, salaried physicians, and are part of a formal hierarchy should be more inclined to use an It system. This leads to the following:

Hypothesis 2: An increased ratio of salaried to total physicians will positively moderate the impact of EMR on treatment consistency.

Healthcare organizations have a difficult time monitoring physicians (Phelps, 1992). IT lowers monitoring costs. EMR systems can be used to provide input to applications, such as case mix management software, which are explicitly designed to monitor and review hospital activities. Case mix management is form of a monitoring application which provides integrated information from admission, discharge, transfer, utilization review, patient billing, and abstracting to monitor and understand the mix of patient types and patient services. It could be argued, given in idiosyncratic nature of healthcare, IT systems do not provide adequate detail to aid in monitoring and actually inhibit monitoring by masking necessary detail. However, I feel this is unlikely given the volume of patients and resource limitations a modern healthcare organization faces today. It would seem that IT enabled monitoring, such as case mix management software, would prove useful at identifying cases for further more detailed investigation. Therefore, this leads to the following hypotheses:

Hypothesis 3: The presence of monitoring applications will positively moderate the impact of EMR on treatment consistency.

Inference Factors

Due to the small sample case-study nature of medical research on procedures, physicians are often left on their own to infer which procedure is the best treatment for a given illness. In information systems terms, the medical research does not have enough data to yield a definitive recommendation as to the proper treatment for a given disease. Given that most physicians face a wide array of illness, this often means that a given physician must infer treatment effectiveness from a small sample size obtained from personal experience. The physician is left to base their decision of their own limited dataset. This problem of inferring from a small sample size can lead to problem with sampling error. IT offers a potential solution to this issue in that IT allows physicians to pool electronic records so that the inference as to treatment effectiveness is done using a larger sample size. In simple terms IT facilitates data aggregation for further analysis. The larger sample size should lead to less sampling error. More data should lead to better decisions. Hospital characteristics which lead to a larger base of outcomes from which to sample should enhance the impact of IT on treatment consistency. An integrated delivery model is where the hospital in question is part of a larger organization which contains multiple hospitals or healthcare facilities. This should lead to a larger outcome base from which to sample. Information Exchange Initiative is two or more independent healthcare organizations (HCOs) in a geographic area collaborating to share common patient information for the improvement in community health status, patient care, or viability of the HCOs. A common variety of information exchange initiatives is regional healthcare information networks (RHINs). This leads to the following hypotheses:

> *Hypothesis 4: Increased organizational size will positively moderate the impact of EMR on treatment consistency.*

Hypothesis 5: An integrated delivery system organizational model will positively moderate the impact of EMR on treatment consistency.

Hypothesis 6: An Information Exchange Initiative will positively moderate the impact of EMR on treatment consistency.

Given that imputing treatment effectiveness from insufficiently small sample sizes to gain adequate statistical power is believed to a key cause for treatment inconsistency, it is likely that electronic medical record systems need to be installed for a period of time to impact treatment consistency. Also, IT systems are complex and require time to learn how to use. These two reasons lead to the following hypothesis:

Hypothesis 7: The age of EMR installation will be positively moderate the impact of EMR on treatment consistency

Control Factors

Common control factors when studying hospitals primarily relate to the size of the hospital and the demand mix that the hospital receives. A number of factors often relate with the size of the hospital. Larger hospitals have greater resources, handle more case volume, and generally have a wider degree of labor specialization. This is typically measured using staffed bedsize, which is the current inpatient capacity of the hospital. Demand mix or case mix is also studied. Some hospitals handle more complex cases than others and as a result have higher mortality rates and higher cost. This is typically modeled using a case mix index, which is a weighted average of patients based upon severity of diagnoses of admitted patients. The import issue here is that the type of patient matters. Finally, while some researchers in the past have included for-profit/non-profit status, it has proven insignificant many times in the past and the general belief is the for-profit and non-profit hospitals behave in much the same way.

Chapter IV: Research Methodology

This study uses archival data from multiple sources. The data for treatment consistency comes from the Healthcare Cost and Utilization Project (HCUP) Nationwide Inpatient Sample (NIS). NIS is the largest all-payer inpatient care database in the United States. NIS contains data on more than eight million hospital stays covering over 1,000 hospitals. Data on the explanatory variables comes from the Healthcare Information and Management Systems Society (HIMSS) database and the The Dorenfest Institute for Health Information Technology Research and Education. HIMSS covers nearly 5,000 healthcare establishments and includes detailed IT profile for each healthcare establishment. The project covers the year 2007.

Treatment Variation

The purpose of this study is to look at the impact of IT on treatment consistency in healthcare. It is important to note a few key principles specific to this line of research. First, in keeping with prior literature, treatment consistency is measured in terms of coefficient of variation (COV). COV can be thought of as a measure of as treatment *inconsistency*. Second, each procedure can be associated with a diagnosis. A diagnosis is the physician's statement of what the clinical cause or disease is for a given medical problem. Rates for procedures are calculated as the frequency with which a given procedure is used when a given diagnosis is rendered. In the case of this study, I am interested in the inter-hospital consistency between physicians within a hospital for a given diagnosis/procedure combination.

First, from the NIS core file the primary diagnosis, primary procedure number, hospital identifiers, and synthetic physician number are extracted from the database. Second, I calculated the rate at which each physician uses a given procedure for each by diagnosis.

Finally, at the hospital-level I calculate a measure of treatment inconsistency (COV) for each hospital for diagnosis/procedure combination. This is done by calculating the standard deviation in treatment rate between physicians within the hospital and dividing by the mean treatment rate at that hospital. The list of procedures which this is calculated for was adopted from Wennberg (1990) and is shown in Appendix B. The dataset I use covers inpatient admissions only. Since the time Wennberg's study was published a number of procedures which used to be done on an inpatient basis are now done an outpatient basis and will not be included in my dataset. As a result of this trend in medical practice and the need to have adequate sample size at the lowest physician/diagnosis/procedure level, I limited my study to those procedures which contain at least 10,000 cases in the overall dataset. The result was that this study looks at 759,879 cases over 11 procedures. A decomposition case count is shown in table 8.

Table 8. Procedures used in this study

Procedure	Cases
Colectomy	21,071
Resection of small intestine	12,331
Cholecystectomy	77,837
Simple mastectomy	13,853
Hysterectomy	31,351
Appendectomy	61,885
Prostatectomy	31,532
Total hip replacement	52,072
Coronary bypass surgery	39,891
Total knee replacement	113,592
Cesarean section	304,464

Finally, the NIS database contains information on 1044 hospitals. Because of state-level differences in reporting, 422 hospitals do not contain hospital-level identifiers. An additional 255 hospitals did not contain necessary physician-level identifiers due to other state-level reporting differences. 23 hospitals did not have the necessary least two physicians conducting any of the studied procedures to calculate a consistency measure. Also the NIS database, which contains outcome information and the HIMSS database, which contains the explanatory factors, do not have a common hospital identifying code. They were merged though a combination of factors such as street address and hospital name. 21 hospitals were unable to be merged between the two datasets. Resulting sample was 309 hospitals matched between the two datasets.

EMR Adoption

First, EMR is not a single piece of equipment. EMR is a collection of software features. For the year of this study, there are seven possible features which are classified by HIMSS as EMR. Features include clinical data repository, clinical decision support, computerized practitioner order entry (CPOE), enterprise EMR, Medical Terminology/Controlled Medical Vocabulary, order entry, and physician documentation. The HIMSS system indicates if the system is "live and operational" or in other stages of installation. This study only considers features which are "live and operational". A more detailed definition of each of these features can be found in appendix C at the end of this document.

Secondly, this study measures, if it has an EMR system, how long the system has been in place. This is done by measuring the presence of EMR features in prior years of HIMSS. Measuring the age of EMR installation presents a few challenges. First, HIMSS does not measure the same features over time. Features are added over time to what is measured. For instance the oldest HIMSS database to cover EMR features is the 1998 database which measures three of the features: clinical data repository, clinical decision support, and order communications. The 1998 definition of order communications maps to the 2007 definition of order entry. As a result of this a method of measurement for EMR must be developed to provide consistency across years. Consistent with prior literature I define the hospital as having EMR if it reports having half of these features, inclusionary in cases where there are an odd number of possible features. For example, in 2007 if the hospital has three of the possible seven features it is deemed to have an EMR system in place. In cases such as 2006 which includes six possible features, the hospital is deemed to have EMR if it has three of the features “live and operational”. Note that for hospitals that do not have EMR installed in 2007, AGE is by definition zero. For 43 of 309 hospitals there was missing age data due to a change in hospital identified from year-to-year. In these cases the mean age for hospitals with EMR was substituted for the missing values for those hospitals with EMR. There was no missing data for EMR. 178 hospitals in the dataset had EMR.

Thirdly, this study measures the ratio of fulltime salaried physicians to total physicians with admitting privileges at the hospital. These measures come from the HIMSS database. For 171 of 309 hospitals, the value was incalculable since the database includes missing values for either total physicians or salaried physicians. For these values the mean value was substituted for the missing data.

Fourthly, the database includes indicators which show if the hospital is part of an information exchange (IE), operates as part of an integrated delivery system model (IDS), or uses monitoring software (MON). IE is defined as: “Attempts by two or more independent healthcare organizations (HCOs) in a geographic area to collaborate to share common patient information for the improvement in community health status, patient care, or viability of the HCOs. A common variety of information exchange initiatives is regional healthcare information networks (RHINs).” IDS is defined as “A healthcare organization (HCO) that owns at least two hospitals.” For monitoring software (MON), we looked at the use of case mix management software. Case mix management is defined as "An application that provides integrated information from admission, discharge, transfer, utilization review, patient billing, and abstracting to monitor and understand the mix of patient types and patient services." There was no missing data for IE, IDS, or MON. 239 hospitals had monitoring, 35 were part of an information exchange, and 22 were part of an integrated delivery organization.

Finally, we measure the size of the hospital using the number of staffed beds. Staffed beds is defined as "Number of Beds that can be operated at present staffing levels" and is generally considered a better measure of hospital size than bedsize which is the number of licensed beds at the hospital (Folland, 2004). There were no missing data elements for SIZE.

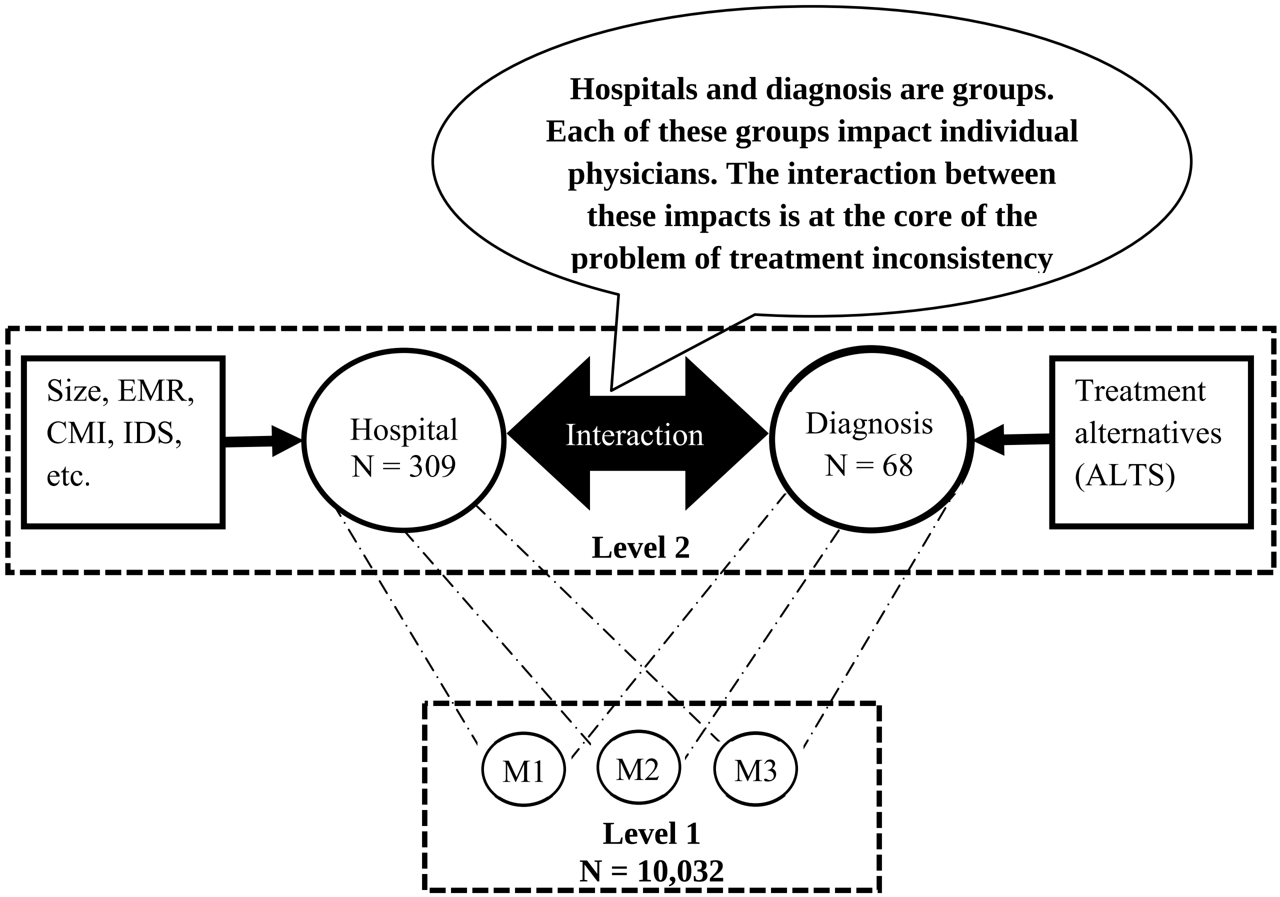
At the diagnosis-level I imputed, out of the NIS dataset, the number of treatment alternatives (ALTS) listed for a given diagnostic code. The study was limited to diagnoses which accounted to at least 2% of the diagnoses observed for the 11 procedures which were the focus for this study. 68 diagnoses were used in this study. There was not missing data.

Chapter V: Analysis and Results

Analytical Overview

The hypotheses proposed in this study were tested using a cross-classified hierarchical model (CCHLM). It is important to, at least briefly, discuss why this is an appropriate, both from a measurement and theory standpoint, method for testing the proposed hypothesis, before discussing standard measures of variables in question, such as summary statistics and correlations. For example, faculty belong to two groups: 1) a local group or hierarchy, the university, which has a set of characteristics such as size and social norms which influence individual behavior, and 2) a greater professional hierarchy or specialization by type of activity which also have characteristics, such as publication standards and group norms, which also influence individual behavior. Much of the behavior of individual faculty could potentially be explained by influence and interaction of influence between these two groups. The same holds in this case. Except that in the case of treatment consistency there is a rather explicit tension between local and global standards which is at the core of the problem being investigated. Surely local norms influence physician choices and surely these choices also vary by professional specialization and problem type. CCHLM tries to address this. First, in the case of this study the items being grouped are not people, but rather a measure of inconsistency at each hospital for each treatment/disease combination. The outcome measures used in this study are measured at the diagnosis/treatment/hospital level (level-1). Not every hospital contains a measure for every diagnosis/treatment combination. An illustration of CCHLM in this context is shown in figure 2.

Figure 4. Illustration of a cross classified hierarchical model



Another way to understand why CCHLM is necessary is to consider how the grouping impacts measurement. In order to calculate a level-1 consistency measure there need to be, at minimum, two physicians at the given hospital which have had the diagnosis in question. So, there are more measures for some diagnoses than others and some hospitals have more measures than others. When the correlations and means are calculated at the lowest level, the level 1, measures will be biased towards weighting those hospitals and diagnoses which are more frequently occurring. This problem can be observed by comparing correlations and means at hospital-level to correlations and means calculated at level-1. The summary statistics for level-1 and hospital-level measures are shown in tables 9 and 10, respectively. Note, that both the mean and standard deviation between the covariates are different depending upon whether they are measured at level-1 or hospital-level or diagnosis-level, because some groups or hospitals have more measures than others. This can be shown by observing the summary statistics for hospital size (SIZE) when measured at level-1 versus when measured at hospital-level. The mean when calculated at hospital level is 280.6, but when reported at hospital level is 197.2. Standard deviation and other measures also change. This highlighted in tables 9 and 10. The same effect can be seen for the measures of treatment alternatives (ALTS) for a diagnosis, the statistical measures change base upon level of aggregation. This is highlighted in tables 9 and 11.

This is because some groups have more “individuals” than other groups. In this case the “individuals” are not per se, but rather measurements of behavior. The fact that the groups have unequal number of members biases the measurement. For example, the same effect would be observed is one was measuring students in a classroom and teacher age all at one level. If all classrooms had the same number of students, the measure of average teacher age would be the same as if you lined up all the teachers and averaged their ages, but if some classrooms had more students than others the average age would be weighted more heavily in favor of the ages of the teachers with more students.

Table 9. Level 1 summary statistics (within hospital variation for disease/treatment combinations)

	Mean	Median	Mode	St. Dev.	Min	Max	Count
INCON	0.189	0	0	0.261	0	1.512	10032
FT	0.852	0.837	0.837	0.144	0.077	1	10032
SIZE	**280.624**	**253**	**25**	**197.759**	**15**	**1303**	**10032**
MON	0.849	1	1	0.358	0	1	8519
IE	0.139	0	0	0.346	0	1	1394
IDS	0.117	0	0	0.322	0	1	1177
AGE	5.637	8	0	4.360	0	10	10032
EMR	0.645	1	1	0.479	0	1	6469
ALTS	**76.864**	57	14	**97.285**	2	732	10032

Table 10. Hospital-level summary statistics

	Mean	Median	Mode	St. Dev	Min.	Max.	Count
FT	0.837	0.837	0.837	0.170	0.077	1	309
SIZE	**197.188**	**147**	**25**	**182.956**	**15**	**1303**	**309**
MON	0.773	1	1	0.419	0	1	239
IE	0.113	0	0	0.317	0	1	35
IDS	0.071	0	0	0.258	0	1	22
AGE	5.005	7	0	4.444	0	10	309
EMR	0.576	1	1	0.495	0	1	178

Table 11. Diagnoses-level summary statistics

	ALTS
Mean	**88.103**
Median	42.500
Mode	26
Standard Deviation	**131.335**
Minimum	2
Maximum	732
Count	68

This problem of aggregation is not simply limited to over or under weighting measures resulting in biased measures. Of greater concern to researchers trying to determine causation, this can result in changes in correlations when the level of aggregation changes. The change in correlation is not always simply a change in magnitude; it can change the direct of the correlation. Observe the correlations in tables 12 and 13. Note that the correlations not only are different between covariates when aggregated at different levels, in some cases they have a different sign altogether. For example, the correlation between FT and EMR is negative when measured at level-1, but positive when measured at hospital-level. When grouped at **level-1** a **negative correlation** is observed, but when grouped at **hospital-level** a **positive correlation** is observed. This is the same data for both calculations. This is highlighted in tables 12 and 13. This could lead to problems of ecological or atomistic fallacy, whereby a causal relationship is inferred which is simply a result the level of aggregation at which analysis is performed. A hierarchical modeling approach solves this measurement issue, in a way which other methods such as error clustering corrections cannot, by explicitly modeling the phenomena with separate error and intercept terms at both levels of aggregation.

Table 12. Level-1 correlations

	INCON	**FT**	**SIZE**	**MON**	**IE**	**IDS**	**AGE**	**EMR**	**ALTS**
INCON	1								
FT	0.000	1							
SIZE	0.080	0.029	1						
MON	0.017	0.064	0.171	1					
IE	0.019	-0.054	0.079	0.049	1				
IDS	0.045	-0.046	0.296	0.078	0.201	1			
AGE	0.014	0.009	0.114	0.315	-0.008	0.101	1		
EMR	0.017	**-0.031**	0.084	0.311	-0.033	0.069	0.959	1	
ALTS	0.305	0.003	0.063	0.022	0.011	0.039	0.009	0.009	1

Table 13. Hospital-level correlation

	FT	SIZE	MON	IE	IDS	AGE	EMR
FT	1						
SIZE	0.115	1					
MON	0.110	0.259	1				
IE	-0.009	0.091	0.047	1			
IDS	0.000	0.338	0.090	0.139	1		
AGE	0.026	0.219	0.385	-0.001	0.132	1	
EMR	**0.006**	0.192	0.396	-0.024	0.110	0.968	1

Analysis

In terms of theory, at the core of phenomena being investigated in this study is the fact that physicians, like academics, are professionals belonging to multiple groups. Physicians are part of a local group or hierarchy within a hospital, but are also part larger professional group or hierarchy which corresponds to their field of specialization. Physician specialization is generally done by body system, such as cardiologist or neurologist, in much the same way as diagnoses. Also, diagnoses are in effect a group which differ in terms of the degree of treatment uncertainty. All are important. The tension between impacts of these groups is at the core of the issue of inconsistent treatment patterns between physicians. In his study the outcome is measured at one level, level-1, the study at causal relationships at grouping level, hospital-level, and a third grouping, diagnosis-level is likely to play a large role. A modeling approach which directly confronts the issue of different and overlapping groups all impacting outcome, should provide both better measurement and closer alignment between theory and model. CCHLM does precisely this.

The modeling approach used to test the proposed hypotheses looks at precisely the issues discussed above. At level-1, separate between-cell error term is estimated for each level-1 equation (e_{ijk}) which results in a fixed effect for each diagnosis/hospital combination (π_{0jk}) as well as residual effect for each level-2 grouping, diagnosis (b_{00j}) and hospital (b_{00j}). These are shown in equations 1 and 2. This approach has several advantages. First, because this groups by diagnosis, this provides much better control for differences in case-mix than would be accounted for with a single case-mix number per hospital. This effectively decomposes the aggregated case mix into a disease-by-disease regression.

Equation 1. HLM Level-1

$$ICON_{ijk} = \pi_{0jk} + e_{ijk}$$

Equation 2. HLM Level-2

$$\pi_{0jk} = \theta_0 + b_{00j} + c_{00k} + \gamma_{01} FT_j + \gamma_{02} SIZE_j + \gamma_{03} MON_j + \gamma_{04} EMR_j + \gamma_{05} IE_j + \pi_{0jk} + \gamma_{06} IDS_j + \gamma_{07} EMR_j * IE_j + \gamma_{08} EMR_j * IDS_j + \gamma_{09} EMR_j * SIZE_j + \gamma_{010} EMR_j * MON_j + \gamma_{011} EMR_j * FT_j + \gamma_{012} EMR_j * AGE_j + \beta_{01} ALTS_k + \gamma_{014} FT_j * ALTS_k + \gamma_{016} SIZE_j * ALTS_k + \gamma_{018} MON_j * ALTS_k + \gamma_{020} EMR_j * ALTS_k + \gamma_{022} IE_j * ALTS_k + \gamma_{024} IDS_j * ALTS_k + \gamma_{026} EMR_j * IE_j * ALTS_k + \gamma_{028} EMR_j * IDS_j * ALTS_k + \gamma_{030} EMR_j * SIZE_j * ALTS_k + \gamma_{032} EMR_j * MON_j * ALTS_k + \gamma_{034} EMR_j * FT_j * ALTS_k + \gamma_{036} EMR_j * AGE_j * ALTS_k$$

Results

For all analysis, hypotheses will be tested at $\alpha = 0.05$. Results first show that inconsistency varies significantly hospital-to-hospital, table 14, and diagnosis-to-diagnosis, table 15.

Table 14. Hospital and level-1 variance

Final estimation of hospital and level-1 variance components:					
Random Effect	**ST. Dev.**	**Variance Component**	**d.f.**	**chi-2**	**p-value**
INTRCPT1/ ICPTROW ,b_{00j}	0.02137	0.00046	283	581.194	<0.001
level-1, e	0.16528	0.02732			

Table 15. Diagnosis-level variance

Final estimation of diagnosis level components:					
Random Effect	**ST. Dev.**	**Variance Component**	**d.f.**	**chi-2**	**p-value**
INTRCPT1/ ICPTCOL,c_{00k}	0.15936	0.02539	42	12829.8	<0.001

Also, the results also show that the impact of hypothesized hospital-level factors on inconsistency vary in most cases, significantly diagnosis by diagnosis. This is shown by the interaction parameters between the number if alternative treatments for a diagnosis (ALTS) and the hypothesized effects in table 16. All of the seven hypothesized effects will be tested with the diagnosis level (ALTS) interaction.

First, results did not support for hypothesis1, “EMR will be positively associated with increased treatment consistency.” EMR was significantly positively associated with treatment inconsistency.

Secondly, results supported for hypothesis 2, “An increased ratio of salaried to total physicians will positively moderate the impact of EMR on treatment consistency.” An increased ratio of salaried to total physicians, in the presence of an EMR system was significantly negatively associated with treatment inconsistency.

Thirdly, results did not supported for hypothesis 3, “The presence of monitoring applications will positively moderate the impact of EMR on treatment consistency.” The presence of monitoring applications, in the presence of an EMR system was significantly positively associated with treatment inconsistency.

Fourthly, results supported for hypothesis 4, “Increased organizational size will positively moderate the impact of EMR on treatment consistency.” Larger hospitals, in the presence of an EMR system was significantly negatively associated with treatment inconsistency.

Fifthly, results supported for hypothesis 5, “An integrated delivery system organizational model will positively moderate the impact of EMR on treatment consistency.” Hospitals with an integrated delivery model which have EMR systems were significantly negatively associated with treatment inconsistency.

Sixthly, results did not support for hypothesis 6, “An Information Exchange Initiative will positively moderate the impact of EMR on treatment consistency.” Hospitals which participated in an information exchange were not significantly negatively associated with treatment inconsistency.

Finally, results supported for hypothesis 7, “The age of EMR installation will be positively moderate the impact of EMR on treatment consistency.” Hospitals which had EMR systems longer were significantly negatively associated with treatment inconsistency. Results are shown in table 16 and a summary of hypotheses is shown in table 17.

Table 16. Model results

	Fixed Effect	coefficient	standard error	t-ratio	N	p-value
Direct Effects	INTERCEPT	0.110776	0.036003	3.077	9643	0.002
	FT	-0.032532	0.030786	-1.057	307	0.291
	BEDS	0.000019	0.000023	0.826	307	0.409
	CMI	0.009998	0.009594	1.042	307	0.298
	EMR	-0.020214	0.03743	-0.54	307	0.59
	IE	0.003637	0.012026	0.302	307	0.763
	IDS	0.027726	0.018656	1.486	307	0.138
Direct Moderated Effects	EMR*IE	-0.011381	0.015598	-0.73	307	0.466
	EMR*IDS	-0.013593	0.021157	-0.642	307	0.521
	EMR*SIZE	0.000057	0.00003	1.92	307	0.056
	EMR*MON	-0.03058	0.015871	-1.927	307	0.055
	EMR*FT	0.04178	0.037679	1.109	307	0.268
	EMR*AGE	0.000018	0.002134	0.009	307	0.993
Cross-classified Direct Effects	ALTS	-0.00001	0.000283	-0.037	66	0.971
	FT*ALTS	0.000511	0.000268	1.91	9643	0.056
	SIZE*ALTS	0.000001	0	5.105	9643	<0.001
	MON*ALTS	-0.000165	0.000075	-2.205	9643	0.027
	EMR*ALTS	0.001032	0.000299	3.455	9643	<0.001
	IE*ALTS,	0.000222	0.000081	2.742	9643	0.006
	IDS*ALTS	0.000237	0.000108	2.193	9643	0.028
Cross-classified Moderation Effects	EMR*IE*ALTS	-0.000143	0.000105	-1.363	9643	0.173
	EMR*IDS*ALTS	-0.000306	0.000124	-2.474	9643	0.013
	EMR*SIZE*ALTS,	-0.000001	0	-2.655	9643	0.008
	EMR*CMI*ALTS	0.000346	0.000122	2.827	9643	0.005
	EMR*FT*ALTS	-0.000775	0.000314	-2.469	9643	0.014
	EMR*AGE*ALTS	-0.00005	0.000014	-3.669	9643	<0.001

Tests of Robustness

Due to the relatively new nature of hierarchical models, established robustness tests are relatively limited. However, all commonly used tests showed good model fit. Overall model fit was good, explaining 59.4% of the variance of treatment inconsistency. As a comparison, the most closely designed study to this, which looked at physician-level treatment inconsistency and which used COV as an outcome measure, environmental factors explained 10-15% of variation in practice patterns (Grytten and Sorensen, 2003). I also compared the CCHLM results to the results of an OLS regression with the same explanatory factors. An OLS regression with the same covariates explains 10.13% of variance. Results for OLS did not result in significant improvement when error terms were clustered on both hospital ID and diagnosis. The CCHLM model explained 5.86 times the variance of OLS estimates for models containing the same explanatory factors. For purposes of comparison, OLS estimates can be viewed in table 17 and OLS model fit statistics in table 17.

Table 17. OLS with error clustering results

(Std. Err. adjusted for 309 clusters in hospid)				
		Robust		
	Coef.	Std. Err	t-ratio	p-value
ft	0.04999	0.03453	1.45	0.149
size	0.00007	0.00003	2.21	0.028
mon	-0.00348	0.01013	-0.34	0.732
ie	0.01756	0.01436	1.22	0.222
ids	0.02993	0.01574	1.9	0.058
emr	0.07277	0.03953	1.84	0.067
emr*ft	-0.04967	0.04336	-1.15	0.253
emr*size	0.00004	0.00004	1.05	0.294
emr*mon	-0.00878	0.01887	-0.47	0.642
emr*ie	-0.02749	0.01822	-1.51	0.132
emr*ids	-0.01166	0.01859	-0.63	0.531
emr*age	-0.00229	0.00248	-0.92	0.356
alts	0.00109	0.00036	3.04	0.003
ie*alts	-0.00005	0.00014	-0.36	0.718
ids*alts	0.00035	0.00022	1.6	0.111
size*alts	0.00000	0.00000	-0.17	0.863
ft*alts	-0.00029	0.00037	-0.77	0.44
emr*ft*alts	0.00015	0.00029	0.53	0.599
emr*size*alts	0.00000	0.00000	-1.35	0.179
emr*mon*alts	0.00008	0.00015	0.53	0.598
emr*ie*alts	0.00025	0.00018	1.34	0.18
emr*ids*alts	-0.00061	0.00025	-2.46	0.014
emr*age*alts	-0.00001	0.00002	-0.24	0.809
_cons	0.05594	0.03080	1.82	0.07

Table 18. OLS model fit results

Number of obs	10032
F (23,308)	44.44
Prob > F	0
R-squared	0.1013
Root MSE	0.24811

As a further robustness check I regressed the explanatory factors on the residuals and found nothing was significantly related to the residuals. Finally, and most compellingly, I examined the distribution of the residuals. The histogram and Q-Q plot of the residuals were normally distributed, but kurtotic. The kurtosis, or peakness towards the mean, indicates that the model is more efficient than a standard model. The histogram and Q-Q plot of the residuals are shown in figures 2 and 3, respectively. Also, for purposes of comparison figure 5 shows OLS residuals, which are not normally distributed. This provides further evidence of the superiority of CCHLM to OLS with error clustering.

Figure 5. Histogram of residuals.

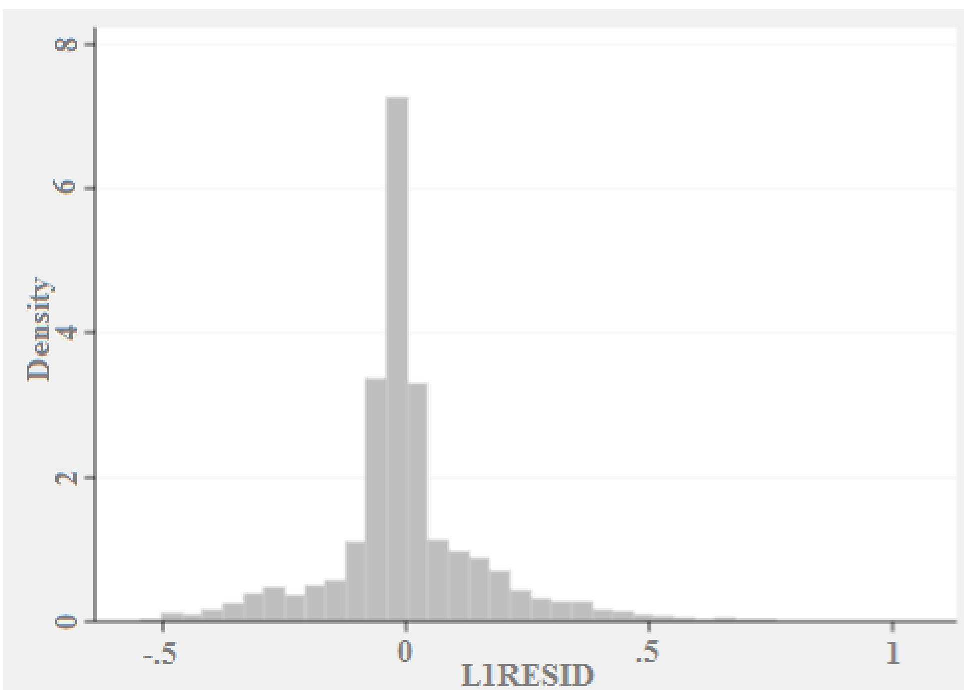


Figure 6. Q-Q Plot of residuals.

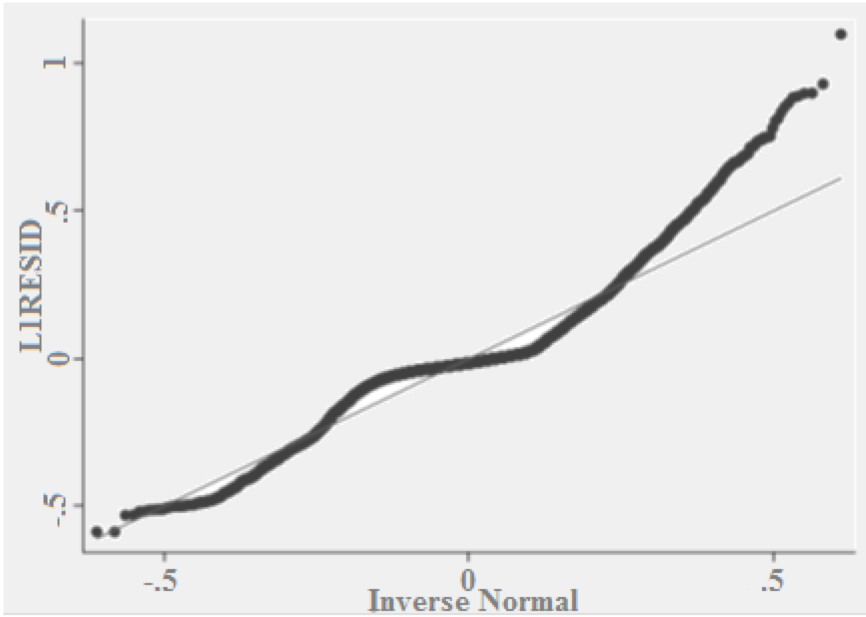
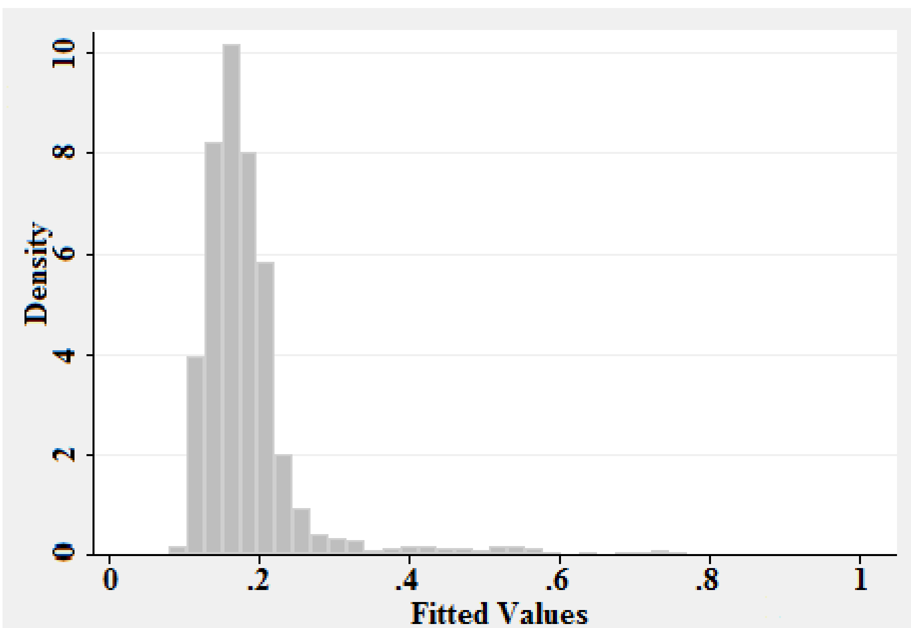


Figure 7. OLS residuals



Finally, a summary of overall results can be found in table 17 below.

Table 19. Summary of Results

Hypothesis	Result	Support
H1: EMR will be positively associated with increased treatment consistency.	Positive***	No
H2: An increased ratio of salaried to total physicians will positively moderate the impact of EMR on treatment consistency.	Negative*	Yes
H3: The presence of monitoring applications will positively moderate the impact of EMR on treatment consistency.	Positive**	No
H4: Increased organizational size will positively moderate the impact of EMR on treatment consistency.	Negative**	Yes
H5: An integrated delivery system organizational model will positively moderate the impact of EMR on treatment consistency.	Negative*	Yes
H6: An Information Exchange Initiative will positively moderate the impact of EMR on treatment consistency.	Not significant	No
H7: The age of EMR installation will be positively moderate the impact of EMR on treatment consistency.	Negative***	Yes
Note: *,**, and *** represent significance at $\alpha = 0.05$, 0.01, and 0.001 respectively.		

Chapter VI: Discussion and Conclusion

The purpose of this study was to examine the impact of information technology, mainly electronic medical records, on treatment consistency in healthcare. This is an important question because healthcare is increasingly consuming resources at unsustainable rate, there is general agreement that healthcare is quite inefficient, and by some estimates treatment inconsistency is the single largest source of inefficiency in healthcare today. Also, society has made massive investments in healthcare information technology, despite mixed evidence as to the impact of IT in healthcare. Most of the causes for inconsistency in treatment practices are widely thought to be related to information related, so it seems worthwhile to investigate the impact of information-related capital, such as electronic medical records systems, on treatment inconsistency. Using data from multiple archival sources, this study looked at the impact of EMR and associated environmental conditions on treatment consistency for 309 hospitals, 68 diagnoses, and over 700,000 procedures from 2007. The study looked at an outcome specific to the highly unique organizational and market conditions of healthcare. Consistent with prior findings from the Information Systems literature, the study found that IT is not a "silver bullet", but rather produces positive impacts when proper organizational conditions are present and requires time to yield benefits.

Limitations

Before discussing the implications of this study, it is important to understand the limitations. There are three primary limitations: lack of established robustness checks for cross-classified hierarchical models, missing data concerns, and interpretation of results. CCHLM models lack a number of established diagnostics for model fit available with other modeling techniques. This raises potential problems such as heteroskedasticity, could result in biased standard error estimates and thus biased inferences. Other potential problems include non-independent error terms. However, there are a few reasons to believe the model is sufficiently robust. First, the hierarchical structure of the CCHLM model inherently involves much more detailed decomposition of error clustering than corrections used in conventional regression forms. Second, by regressing level-1 residuals on the original covariates, this is effectively a Breush-Pagan Test for heteroskedasticity and the model indicates no problems. Third, the kurtotic, but normal, nature of the distribution of the residuals suggests a highly efficient model. Fourth, the model simply explains much more variance than other techniques. By cross-nesting to two hierarchies, diagnosis and hospital, the model explicitly address the notion from theory that treatment inconsistency is somewhat a result of tension between local standards of practice and global professional norms by modeling both. The diagnosis captures both differences in uncertainty between diagnoses and because diagnoses are organized the same way as professional specialization, diagnoses make an excellent proxy for the professional specialization of the physicians within a hospital.

Missing data is another potential concern. Due to differences between states in what level of granularity they report hospital identifiers and the use of synthetic physician identifiers, 677 of 1044 hospitals on the outcome dataset were unusable. This could result in a biased sample. However, the size of the 309 hospitals in the sample was 182.95 and the standard deviation was 197.19, with hospital sizes ranging from 8 beds to 1303 beds. Nationwide average, imputed from HIMSS over 5,000 hospitals shows the population average to be 148.94 and true standard deviation to be 158.78, ranging from 2 beds to 1303 beds. The sample in this, while slightly larger and with slightly more variance, appears quite representative. Other missing data elements include the ratio of fulltime to total physicians and the age of installation for EMR. For both of these covariates the mean was substituted for the missing values, which should, if anything, reduce variance and explanatory power. There is no reason to believe that these variables were missing due to nonresponse or other bias and therefore should not cause problems from inferring a statistically significant relationship between the covariates and the dependent variable.

The final potential limitation with this model has to do with the interpretation of the results. This is the first study to address within-hospital treatment consistency. Most studies on treatment consistency look at the ecological-level, such as county-level or hospital referral region, where data availability is much better. This makes comparing the results from this study somewhat difficult. However, the average level of inconsistency (INCON) reported in this study, 0.189 and standard deviation, 0.261, were consistent with prior studies at both the physician and ecological-level suggesting that conducting between physician within hospital consistency measures is feasible and consistent with prior studies.

Implications for Future Research

Before discussing interesting future directions for this research not included in this study, it is important to review the findings which were not supported and some of the reasons why the study might not have found support to provide interesting future directions within the existing framework of the research question this study addresses. There were three hypotheses which were not supported. First, hypothesis one, which looked at the direct impact of EMR on treatment consistency, not only was not supported, but showed statistically significant positive impact on inconsistency. While on this surface this seems problematic, this isn't necessarily surprising. Prior studies of IT investments have shown that there is a sufficient learning period with similarly complex IT investments, such ads enterprise resource planning systems, whereby performance decreases for a period of time while learning is occurring. The EMR variable simply measures whether or not the hospital has an EMR system, not how long they have had the system. The length of time the hospital has had the EMR system is especially important in the case of impacting treatment consistency. Since many of the theorized effects require time for the EMR system to build a stock of "data capital" from which physicians can extract meaningful imputations of impacts of various treatment practices, the time since adoption is especially important. The AGE moderator which measures time since adopting an EMR system supports this explanation. An interesting future direction could be a panel study to investigate the impacts of EMR system adoption on treatment consistency over time.

The second hypothesis which was not supported was hypothesis three, which dealt with the moderating impacts of monitoring systems on EMR impacts. In the case of hypothesis three, the impacts were also significantly positively associated with treatment inconsistency. In the case of monitoring software, I studied case mix management software, which helps hospital administrators understand the mix of patients and outcomes base upon billing information. Perhaps monitoring applications, since they do not work directly off the patient medical record, but rather the billing record, could be thought of as separate application. Therefore, monitoring would be more likely to have direct effects, rather than moderated effects. Also, unlike most of the other hypotheses moderators monitoring does not increase the amount of data physicians have to imputes treatment effectiveness for, but rather function primarily as a mechanism of institutional control. With this data monitoring shows statistically significant direct effects increasing treatment consistency for diagnoses with a high number of treatment alternatives. More research is needed to differentiate the impacts of monitoring applications on treatment consistency, perhaps monitoring deserves separate study.

The final non-supported hypothesis was hypothesis 6, which dealt with the moderating impact of information exchange on treatment consistency. This effect was directionally consistent with what was hypothesized, but had a p-value of 0.173. Information exchanges between hospitals are a relatively new phenomenon, so there were only 35 hospitals in the sample which participated in them. It is likely that the hypothesized moderating impact is there, but there is not sufficient sample size to detect this. With a new dataset, which contains more hospitals participating in information exchanges, it is quite possible the effect could be detected. More research needs to be done in this area.

In addition to examining this research within the context of the existing framework, there are a few more interesting areas for future research. These include studying the impacts at the ecological level, sequence-of-action consistency, and greater methodological use of cross-classified models. First, most of the research to date on treatment consistency in healthcare has been conducted at the ecological level, such as counties or hospital referral region. It would be helpful to researchers, practitioners, and policy makers to able to compare like studies. Furthermore, while at least some data points for IT investment are available for every hospital in the US, hospital-level data on practice patterns is more limited. Due to state-level differences in reporting, in healthcare much more data becomes available to researchers at higher levels of aggregation in healthcare. So, in contrast to what often happens in other industries, in healthcare using analysis at the ecological level is likely to result in greater sample size and more statistical power, as well as better generalizability of findings.

Second, the NIS dataset provides information on not only primary procedures, but also up to fifteen other procedures performed. NIS also provides a sequence, in terms of days, that the procedures were performed. This allows researchers to look at sequences of actions. It would be possible to develop not only a variance view to treatment consistency, but also a process view of treatment consistency.

Finally, empirical results suggest that cross-classified hierarchical models, while used for a while by education researchers, show great promise for not only healthcare researchers, but also more broadly for researcher doing economic/business research. Initial results indicate they can both greatly increase explained variance and provide a more nuanced view when subjects below to multiple groups. Possible examples include cross-country analysis where firms are nested in two groups: industries and countries. Both the industries and countries have distinct characteristics which are likely to impact firm performance and also likely to interact in interesting ways. Cross-classified hierarchical models seem to provide an excellent framework to tease out those interesting interactions.

Implications for Practice

This study contains several interesting findings, which have important implications for both practitioners and policymakers. First and foremost, IT is not a “silver bullet”. IT investment requires particular conditions to yield positive results. In the case of within-hospital treatment consistency, EMR investment requires specific organizational conditions. For example, this study provides evidence that positive impacts from EMR investment are likely when a greater portion of physicians practicing in the hospital to be part of the formal hospital hierarchy. This is thought to be result of the hierarchy being able to promote proper use of EMR, through greater institutional control, and better compliance developed local standards of care.

Secondly, EMR systems are likely to exhibit network effects and therefore yield greater benefits in conditions where there are more users, such as larger hospitals or hospitals which are linked with others through an integrated delivery model.

Thirdly, this study provides evidence that IT investment, under proper conditions, improves consistency of care. The problem of inconsistent practice patterns has been an important one, which has stumped researchers and policy experts for years. This study provides evidence, consistent with the idea that treatment inconsistency arises due to informational issues, that information technology can improve treatment consistency.

Finally, this study also provides evidence, consistent with research on IT investment in other industries, that IT investments require time to yield benefits. In the case of EMR's impact upon treatment consistency, it is unclear whether or not this time lag is due to the time require for the system to build up a stock of "data capital" or if this is organizational learning. What is clear is that modern IT systems are complex technologies. As complex technologies, they require time to learn how to use before they are likely to yield benefits.

Conclusion

Unsustainable increases in healthcare costs are widely recognized as one the largest problems facing society today. Information technology investment is widely cited as a potential solution to this problem, even though evidence to date is mixed as to its impact. Healthcare is a unique environment. Often, normal assumptions do not hold in healthcare. As a result, healthcare results in phenomena which is idiosyncratic to healthcare. This dissertation focused upon one such phenomenon, treatment inconsistency. Treatment inconsistency is significant variation in treatment rates, across different levels of aggregation, for various medical procedures and is believed to be one of the largest sources of inefficiency in healthcare. Treatment inconsistency is believed to result from information asymmetry between physicians as to the best course of treatment. Treatment inconsistency exists all over the world. Research suggests that by reducing treatment inconsistency, healthcare costs in the United States alone could be reduced by nearly 700 billion dollars without impacting patient outcome. Using data from 700,000 patient admissions and 309 hospitals, this dissertation provides evidence, consistent with theory, that information technology does increase consistency of treatment patterns, for diagnoses with a high number of potential treatments, when EMR is: a) present for a sufficient amount of time or b) used in larger hospitals or c) used in an integrated delivery system or d) there is an increased ratio of salaried physicians to total physicians.

APPENDICES

Appendix A: Procedures used in Wennberg (1990)

1. Colectomy 2. Resection of small intestine 3. Inguinal hernia repair 4. Pneumonectomy 5. Extended simple radical mastectomy 6. Cholecystectomy 7. Open heart surgery 8. Simple mastectomy 9. Proctectomy 10. Repair of retina 11. Hysterectomy 12. Pacemaker insertion 13. Appendectomy 14. Prostatectomy 15. Thyroidectomy 16. Total hip replacement	17. Peripheral artery bypass 18. Embolectomy, lower limb artery 19. Diaphragmatic hernia 20. Coronary bypass surgery 21. Aorto-iliac-femoral bypass 22. Graph replacement of aortic aneurysm 23. Excision of intravertebral disc 24. Mastoidectomy 25. Laparotomy 26. Spinal fusion with or without disc excision 27. Total knee replacement 28. Carotid endarterectomy 29. Cesarean section

Appendix B: Variables from HIMSS database

Clinical Data Repository*	"A centralized database that allows organizations to collect, store, access and report on clinical, administrative, and financial information collected from various applications within or across the healthcare organization that provides healthcare organizations an open environment for accessing/viewing, managing, and reporting enterprise information."
Clinical Decision Support*	"An application that uses pre-established rules and guidelines, that can be created and edited by the healthcare organization, and integrates clinical data from several sources to generate alerts and treatment suggestions. Example: All patients who have potassium below 2.5mg% should not have a cardiac glycoside. The physician would enter into the system the prescription for a cardiac glycoside and the system would pop up an alert to the fact that the patient should not be given this medicine due to the low level of potassium in their blood."
Computerized Practitioner Order Entry (CPOE)	"An order entry application specifically designed to assist clinical practitioners in creating and managing medical orders for patient services or medications. This application has special electronic signature, workflow, and rules engine functions that reduce or eliminate medical errors associated with practitioner ordering processes."
Enterprise EMR*	"An application environment that is composed of the clinical data repository, clinical decision support, controlled medical vocabulary, order entry, computerized practitioner order entry, and clinical documentation applications. This environment supports the patient's electronic medical record across inpatient and outpatient environments, and is used by healthcare practitioners to document, monitor, and manage health care delivery."
Medical Terminology/ Controlled Medical Vocabulary	"A vocabulary server application that normalizes various medication vocabularies used by system applications in a healthcare delivery environment."
Order Entry (Includes Order Communications)	"An application that allows for entry of orders from multiple sites including nursing stations, selected ancillary departments, and other service areas; allows viewing of single and composite results for each patient order. This function creates billing records as a by-product of the order entry function.
Physician Documentation	"This software documents notes that describe the care or service to a client. Health records may be paper documents or electronic documents, such as electronic medical records, faxes, emails, audio or video tapes and images. Through documentation, physicians

	communicate their observations, decisions, actions and outcomes of these actions for clients. Documentation software tracks what occurred and when it occurred.’
Case Mix Management	“An application that provides integrated information from admission, discharge, transfer, utilization review, patient billing, and abstracting to monitor and understand the mix of patient types and patient services.”
Information Exchange Initiative	“Attempts by two or more independent healthcare organizations (HCOs) in a geographic area to collaborate to share common patient information for the improvement in community health status, patient care, or viability of the HCOs. A common variety of information exchange initiatives is regional healthcare information networks (RHINs).”
Integrated Delivery System (IDS)	“A healthcare organization (HCO) that owns at least two hospitals.”
Full-time Salaried Physicians	“Physicians that are full-time salaried employees of the hospital or health care system, receiving a regular paycheck from the organization (i.e. residents, salaried physicians at clinics, hospitalists, and other full-time medical staff).”
Total Physicians	“Total number of physicians in the hospital.”
Staffed Beds	“Number of Beds that can be operated at present staffing levels.”

Note: Variables most likely to be used in this study are denote with a *.

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