Economic Analysis of the Hospitalist Program in the Saskatoon Health Region

A Thesis Submitted to the College of

Graduate Studies and Research

In Partial Fulfillment of the Requirements

For the Degree of Master of Science

In the Department of Finance and Management Science

University of Saskatchewan

Saskatoon, Saskatchewan, Canada

Timothy Kent

Supervisors

Keith Willoughby

George Tannous

PERMISSION TO USE

In presenting this thesis in partial fulfillment of the requirements for a Postgraduate degree from the University of Saskatchewan, I agree that the Libraries of this University may make it freely available for inspection. I further agree that permission for copying of this thesis in any manner, in whole or in part, for scholarly purposes may be granted by the professor or professors who supervised my thesis work or, in their absence, by the Head of the Department or the Dean of the College in which my thesis work was done. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to the University of Saskatchewan in any scholarly use which may be made of any material in my thesis.

Requests for permission to copy or to make other use of material in this thesis in whole or part should be addressed to:

Head of the Department of Finance and Management Science

Edwards School of Business

University of Saskatchewan

25 Campus Drive

Saskatoon, Saskatchewan S7N 5A7

ABSTRACT

The Saskatoon Health Region has initiated a review board to evaluate the effectiveness of its relatively new hospitalist program. Under the program, physicians do not keep regular office hours for which to see patients. Instead they work out of the hospital and primarily care for inpatients. Studies have found this program to increase efficiency in the delivery of care in other countries and regions without reducing the quality of the services provided, as measured by patient satisfaction, continuity of care, and readmission and mortality rates. This thesis examines the hospitalist program's effects on inpatient length of stay, readmissions, and rate of mortality. We find that the additional funding spent on the program does not significantly affect patient readmission or mortality rates. However there is evidence that the program has increased patient length of stay among those with atypically long hospital stays. Over the entire sample patient length of stay is however shown to decrease with time implying the physicians are becoming more efficient in diagnosis of illnesses and delivery of care, although this result cannot be attributed to the hospitalist program. We also identify a reduction in length of stay due to the change in physician payment structure, from fixed to fixed plus variable pay among patients with typical lengths of stay. Through this reduction in patient length of stay, patient throughput can be increased and more patients can receive care in the Saskatoon Health Region.

TABLE OF CONTENTS

CHAPTER 1:

Introduction and Motivation

Innovative medical procedures and programs have allowed hospitals to increase the effectiveness of the care provided to patients along with increasing the number of patients receiving care. One such program is the hospitalist model of physician lead inpatient care. The effectiveness of this program has not been evaluated in the Saskatoon Health Region (SHR), and thus a care group was initiated to review it. This thesis is part of a larger analysis of the hospitalist model. The research will determine if the hospitalist program is economically efficient and is providing a net benefit to the SHR.

A hospitalist is a care provider, most often a physician, who provides inpatient care during a hospitalization. This care provider becomes the patient's primary care provider during their hospital stay until they are discharged back into the community to the care of their family physician (Cammarata, 2005).

Literature suggests that hospitalists are excellent care providers, leaders, and highly effective resident teachers. More important, hospitalists have been shown to reduce costs, reduce the length of stay, increase patient satisfaction, and provide timely, evidence-based care. (Dynan et al 2009, Gregory et al 2003, Kuo et al 2010, Lindenauser et al 2007, Rifkin et al 2004, and Wachter et al 2002) However, most of the evidence is derived from data in the United States. In large part we do not know the effectiveness, efficiency, or cost-benefits of Canadian hospitalist programs.

The hospitalist program at 5th Medicine, St. Paul's Hospital (Saskatoon Health Region) was initially set up as a 'best practice' for providing inpatient care. Hospitalist programs have been undertaken with success in other regions around Canada and The United States. Previously, four general internal medicine (GIM) hospitalist services covered 100 patients on this unit in St. Paul's. Now, an evidence-based modification to include a fifth service of general practitioners (GP) or family physicians has occurred. The benefits of adding the GP group are twofold: 1) Appropriate patients can be delegated to the GP hospitalist service. This will free up specialist time in the GIM Group; Since GIM hospitalists divide their time between specialist services and hospitalist care, this shift will make that balance more manageable. 2) There is now an expanded base of the number of practitioners providing in-hospital services, therefore care should be timely, cost-effective, and indicators such as length of stay and mortality are hypothesized to be reduced. (Department of Medicine 2008).

This research thesis will analyze retrospective de-identified patient level data from St. Paul's (and Saskatoon City Hospital as the Intensive Care, Primary Care and the Medicine Units were consolidated to St. Paul's from October 2008 to January 2009), reporting the data such as length of stay, Resource Intensity Weight (resource usage), readmissions, raw in hospital mortality, Case Mix Groups (patient diagnosis and severity), patient characteristics (age and gender), and patient demographics, including income, socio-economic status, and neighbourhood/ residence. The time period ranges between January 2007 to November 2010, and includes data from St. Paul's and City Hospital. The purpose of this research is to identify the hospitalist program's impact on the delivery of inpatient care and to quantify its effects. Hospitalist efficiency will be measured by the length of stay and resource usage of each patient case, while the readmission and in-hospital mortality rates will measure the quality of care. It is hypothesized that this program has reduced length of stay, and the readmission and mortality rates. If this hypothesis is supported, funding the hospitalist program at Saskatoon Health Region will be shown to reduce direct costs and in combination with indirect benefits can result in a positive net benefit.

Multivariate regression analysis will be conducted on the data to identify these relationships, and economic analysis will be run to measure the program effects. The dependent variables include inpatient length of stay, the readmission rate, and in-hospital mortality. The independent or test variables will be the funding spent on the hospitalist program through the Saskatoon Health Region, the date of admission, and the change in payment structure. Several control variables will be included in the model such as patient characteristics, demographics, and severity of the admitted patients.

This thesis will support Saskatoon Health Region decision-making; by determining whether the benefit associated with the hospitalist program outweigh the costs. This will be based on evaluated benefits of the program and particularly patient-centered outcomes.

This research will build the body of literature as it will be the first Saskatchewan based study of a hospitalist program.

The thesis will continue as follows: Chapter 2 will provide a description of the hospitalist program in the Saskatoon Health Region, followed by literature on the process of economic evaluation and empirical studies of other hospitalist programs. Chapter 3 will address hypothesis development. Chapter 4 will discuss methodology and variable selection. Chapter 5 will report the results and findings of the research, and finally a conclusion is presented in Chapter 6.

CHAPTER 2

2.1 The Hospitalist Model

The Saskatoon Health Region (SHR) has established the Hospitalist Advisory Committee, a care group, to conduct a review of the hospitalist program as it stands today. This group's task is to assist the SHR in the decision to continue, alter, and/or discontinue the hospitalist program.

There are several established models of physician care that can be classified as hospitalist programs. The most general and widely accepted definition would be:

> *The hospitalist is a physician who specializes in supervising patient care during a hospital stay; he or she receives the patient from the general practitioner (GP), becomes that patient's primary care physician for the duration of hospitalization, and then returns the patient to the care of the general practitioner upon release*. (Cammarata, 2005)

This program is commonly recognized to have begun in the United States around 1996, when Robert Wachter first coined the name, and it has grown tremendously over the years to be a common health care strategy in most large cities. A recent study has shown that hospitalist programs have grown substantially over the past decade and are expected to continue to grow at a rate of 10 to 20% per year (Wachter , 2008). In contrast, the Canadian hospitalist program has been around since the early 1990s although the exact date and place it began is up for debate and it was never actually termed the "hospitalist program" (Redemmeier, 1999). In Canada most hospitalists are family physicians who have given up their outpatient practice to focus on inpatient care (Maskey, 2008). The hospitalist model was created in Canada to fill the shortage of internist specialists in hospitals and care for the patients of family physicians who no longer visit hospitals to provide inpatient care to their regular patients. Essentially instead of family physicians traveling from their regular office to the hospital to see one of their patients, a hospitalist would be housed permanently in the hospital to provide care and take responsibility for these patients (Wachter, 2007b)

In the SHR, the hospitalist program was established to take responsibility for those patients that would otherwise not have a defined in-hospital primary care physician. It was formally established at Saskatoon's St. Paul's Hospital on October 1, 2008, and consolidated the Intensive Care Unit (ICU), the Primary Care Unit (PCU), and the Medicine Unit at Saskatoon's City Hospital into one facility at St. Paul's Hospital. It was originally proposed that each hospitalist would be required to spend nine consecutive hours per day in assigned hospital units providing care for 20 to 25 inpatients and performing other duties that benefit and further the operation of the health care facility. Other benefits include offering a reliable continuum of care to hospitalised patients; strengthening recruitment and retention of staff, increasing access to medical beds for inpatients; improving patient throughput; promoting system integration and open dialogue; and efficiently deploying system resources. Hospitalists were hired to fill the shortages of general internal medicine and family physicians; care for the increasing numbers of hospitalized patients that do not have an assigned family physician; and to establish a model to formalise the compensation levels by establishing a base level of compensation for providing care to inpatients (Department of Medicine 2008). The program has recently come up for review to decide upon its future.

Rosenthal et al (2009) found acute care practitioner hospitalists provide additional benefits to the hospital such as outstanding research programs, quality improvement initiatives, teaching and guidance, and patient centred care and/or team centred care movements. Scalise (2006) went so far as to recommend that hospitalists' compensation be linked to quality improvements to encourage them to participate in hospital committees, information technology projects or quality programs instead of basing pay solely on patient care volumes or productivity. These benefits arise from the fact that hospitalists are constantly on call and are able to build their expertise and experiences solely on inpatient care at their hospital. This will also allow other physicians to focus on areas in which they prefer to practice, thus increasing satisfaction and reducing burnout and turnover. Wachter (2001) stated that a hospitalist program can reduce costs and length of stay (LOS), improve outcomes, and increase the efficiency of the hospital. Further it will attract other primary care physicians (family doctors) to the health region who prefer to focus on office practice; this could help alleviate the physician shortage faced in many Canadian communities. Mitchell (2008) reports that hospital medicine needs to focus on such areas as quality improvement, information technology, administration, and research and that by aligning hospitalist incentives with hospital goals these improvements can be realized.

The scope of the literature on the hospitalist model is divided into the primary areas of best practices and recommendations from health care practitioners and researchers examining the financial and economic effects hospitalist models have on the units and hospitals in which they operate. The vast majority of the empirical papers originate out of the United States and either report the effects a hospitalist model has on inpatient length of stay (LOS) and direct costs, or compare a hospitalist unit to a non-hospitalist unit for the sake of economic efficiency, again examining LOS and costs. Only one study has been found that examines the effects a hospitalist program has had on a Canadian hospital, but it offers more of a hypothetical cost-benefit analysis instead of an analysis of the program's economic effects. This thesis will contribute to the literature on Canadian hospital evaluations as well as jointly provide research to aid in the decision analysis for the SHR by analysing the impact the hospitalist program has had on the economic efficiency of St. Paul's Hospital.

2.2 Economic Decision Analysis

Cost-Benefit Analysis (CBA) is a tool commonly used to assess the economic impact competing programs will have on an organization. The research question examined in this thesis is whether the hospitalist model is economically efficient in the Saskatoon Health Region. The alternative to the hospitalist model will be to not run the hospitalist program (Brent 2003). The main approaches to CBA in healthcare were derived from welfare economics and attempted to calculate the willingness-to-pay of the individual for the benefits derived from the product. This was approximated through surveys to the public asking the amount of money they would pay for changes in the risk of death from various causes, avoidance of injury, and maintenance of good health over a period of time (Huhtton 1992).

When applied to the health care industry CBA, and the similar Cost-Effectiveness Analysis (CEA), and Cost Utility Analysis (CUA) (Phelps & Mushlin, 1991), attempt to quantify all costs and benefits of the competing programs and recommend the program with the highest ratio of net benefits to net costs or the greatest expected percentage change (increase) in benefits compared to the percentage change (decrease) in costs. The following costs need to be included:

1. Direct (Salaries and stipend paid to the hospitalist physicians)
2. Indirect (opportunity costs of the resources used, such as the physicians' time, the unit occupied, and the funds allocated directly to the project.)
3. Intangible (patient/ physician satisfaction etc.).

Benefits are also grouped into Direct (increased hospital efficiency through reduced LOS, and improved quality of care for patients), and Intangible (satisfaction, turnover, etc.) (Muennig, 2008). Adapted forms of CBA and CEA are used when markets produce the prices for goods and services that do not reflect the true social opportunity costs. CBA attempts to provide a quantitative analysis that is comparable to private sector appraisal techniques. CEA and CUA attempt to measure the program's effects on the utility of the consumer by utilizing quality of life indicators instead of monetary values (Huhtton, 1992).

The most important step when applying public investments cost-benefit analysis is the selection of projects that are in agreement with the stated welfare function of society. So the planner, group or analyst must determine the outcomes to be achieved through the execution of the project (Terre et al 1973). In the context of this hospitalist program it must be clearly understood that the program was initiated to fill a physician shortage and care for unassigned patients rather than to increase hospital efficiency and reduce costs. This starting point will guide the analysis towards a qualitative or quantitative focus.

Often the goal of CBA is to determine the economic efficiency of the project when compared to alternatives. Economic efficiency is comprised of two aspects, namely, the maximization of the identifiable economic benefit per dollar invested and the minimization of the total dollar costs of the project. Essentially the project must have the highest marginal benefit with the lowest (or most feasible) cost. Thus the project with the greatest economic efficiency will often be the most desirable by society and should be implemented (Terre et al 1973). In the United States, this is the most common motive for a hospitalist program.

In the Canadian context, the hospitalist program was primarily established to deal with a shortage of family physicians caring for inpatients. Specifically SHR implemented this program to "stabilize and improve in hospital patient care, to support the Clinical Teaching Units required by the College of Medicine, to enhance the recruitment and retention of general internal medicine specialists, and to alleviate the current unmanageable workload for the Division of General Internal Medicine, and has developed for reasons that include: shortages of physicians in general internal medicine and family medicine; increasing numbers of hospitalized patients who do not have a regular family physician; and compensation levels for physicians to provide inpatient care." (Dept. of Medicine 2008). In the Canadian medical sector, capital and revenue expenditure decisions are made on the basis of social criteria, not simply on the basis of financial returns to the provider and the ability-to-pay of the consumer (Huhtton, 1992).

The next step in the analysis would be to select a unit of measurement to estimate the costs and benefits of each project. There are several problems when choosing a unit of measurement which can be addressed from either the factor supply side or the output side. As it is common for budgets to be fixed in the present (project expenditures cannot exceed the level of funds available), capital rationing is often measured by today's prices and dollar costs. If the projects were to exceed this fixed budget constraint, the project would be inefficient and completely infeasible. Costs and benefits are commonly recorded in today's prices and would require discounting at an appropriate rate (Terre et al 1973). Due to the nature of this study and the objectives of the program, the primary unit of measurement will be the inpatient length of stay in days.

Practitioners generally recognize four methods of deriving a discount rate. The first is to use the rate of long-term government bonds. Its advantages include that it is simple to determine and is not subject to dramatic fluctuations. The second method uses the opportunity cost rate which is derived from the value society puts on the funds used for the project. This forgone investment opportunity could be recognized by reviewing the rates of return attained and expected through private business/security investment. The third method refers to the social time preference which is used to derive the interest rate. This is the rate the public would use to equate consumption today with consumption in the future. Obviously this rate is subjective and difficult to calculate. The final method is a combination of the last two. This method would establish some minimum discounted cost/benefit ratio for which to grade all projects (Terre et al 1973).

When addressing this problem in terms of output of goods and services, there are debated lines of thought on how to proceed. One group would equate the prices of outputs of public projects to the social marginal costs, which would result in charging the recipient of the output (the public) a price equal to the cost of the benefit received. This would require price discrimination, and would not be directly applicable to this model as public health care eliminates the requirement for consumers to directly pay for care.

The second group believes in establishing a set of shadow prices to assess the public goods and services that do not have a quantifiable market price. When dealing with a finite budget for which to fund and operate a system all alternative decisions are under scrutiny when one project is chosen over another, as the difference in remaining funds can affect the choice of projects into the future. Opportunity costs (or shadow prices) should be incorporated into the full analysis to account for both the direct forgone costs of the alternative but also the indirect forgone alternative uses that could have been undertaken with the funds spent on the original project (Birch et al 1987).However due to the constraints in both time and data availability, this all-encompassing analysis goes far beyond the scope of this thesis. Generally the incorporation of shadow prices becomes difficult when subsequent projects are not readily available to grade.

The third school of thought involves setting output prices equal to the marginal cost, which follows common economic optimization equilibrium. This will involve charging all of society the same price per unit of good/ service despite any differences in benefits (or utility) they receive. This would be the most appropriate form of pricing when dealing with a health care system that is funded and operated publicly (Terre et al 1973).

The final step in CBA is to rank the project for comparison and accept the projects that achieve the stated social welfare function. This can be simply the project with the highest benefit/cost ratio, and/or the one with the highest marginal benefit to marginal cost. This can become exceedingly difficult when intangible costs or benefits dominate the analysis (Terre et al 1973).

When scarce resources are used to fund non-competing or complementary projects the decision of which project to undertake must be based on the equivalence of their marginal benefits. Thus the benefits acquired from additional inputs must be equal for each. But when projects overlap and are not perfectly divisible management must assess the projects for increases in benefits relative to increases in costs. This is not always straight forward when projects do not produce the same net benefits and their costs differ. It is much simpler to judge alternative projects that lead to the same outcomes but require different inputs and costs. Yet these inputs and costs will need to be addressed individually (Birch et al 1987).

There are several pitfalls planners must avoid when ranking their projects. The first is when analysts become so preoccupied with the quantifiable return rates that the social welfare function, which was the basis for undertaking the project, gets neglected. The second is the failure to recognise constraints such as political, legal, physical, and administrative, and would cause the project to be infeasible. The third deficiency occurs when projects are not easily comparable or are not direct alternatives to each other. This complexity of shadow prices can dramatically alter the rate of return of the project and series of subsequent projects. The final problem arises from the simple, and very crucial, choice of the discount rate. An appropriate discount rate must have sound logic and history to justify its use. The discount rate becomes more important as benefits and costs extend into the future (Terre et al 1973).

CBA is very sensitive to identification of the project specifications, the positive (or negative) benefits and negative (or positive) costs. In the hospital perspective, cost incurrence is often considered a project cost while cost reduction or aversion is considered a benefit. If the total cost of the new project is lower than the current project, the difference in costs between the two alternatives could be taken as a benefit to project 2. The cost of project 2 can also then be taken as is, without adjustment, to account for the denominator when running the CBA. Thus care must be taken to ensure that variables (such as project costs) are not double counted as affecting costs (and benefits). These opportunity costs must be accounted for as either a benefit or a cost, again the categorizing of the opportunity cost (as benefits or costs) must be qualified by sound judgement and reasoning as they will affect the outcome of the analysis (Birch et al 1987).

A number of past health CBA papers have assumed the decrease or reduction in costs to be the *only* benefit they measure and make no attempt to measure the economic benefits of each project (such as social welfare). This limits the effectiveness of the analysis to cases where the alternative clearly dominates the other through lower costs. Despite the obvious difficulty in quantifying the value society will place on a health state (sick or healthy), steps must be taken to at the very least to address the intangible costs and benefits if only qualitatively (Birch et al 1987). Although this thesis will deal primarily on the direct and indirect quantitative costs of the hospitalist program run by the SHR, it is an acknowledged part of a larger study that incorporates the qualitative intangible aspects of this program. The findings of the interviews and qualitative analysis incorporating patient and physician satisfaction and opinions conducted by the Hospitalist Advisory Committee cannot be included in this thesis due to confidentiality.

2.3 Agency Theory

In publicly funded health care, physicians are hired by and use the resources of the health region on behalf of the tax payer. The physician then acts as an agent on behalf of the health region to deliver care and medical services to the public, who indirectly owns the medical resources. Fama (1980) examined the efficiency of dividing ownership and control for corporations where the firm is defined as a set of contracts or collection of individual factors of production, governed by personal motivations, contracted together to compete against other teams of contracts. These teams are thus dependent upon each other for survival of the team and their personal wealth. In the firm the separation of ownership (risk bearers) and control (decision managers) is an efficient form of firm structure. Management will be monitored by the managerial labour market.

The ownership of the firm is irrelevant to its operations; however there are advantages to separating the firms' ownership and control. Management is a labour type that directs the activities of inputs and carries out the stipulations of the agreed upon contracts, in general they are the decision makers. Risk bearers are the ones that take on the uncertainty of payoffs (revenues minus costs) resulting from the completion of the contracts. Usually the risk bearers initially provide the funds to purchase the capital and technology needed to carry out the contracts. Thus risk bearing and ownership of the assets is one and the same function (Fama 1980).

But ownership of capital does not equal ownership of the firm. The firm is simply a set of contracts that describes how inputs will be joined to build an output, and how the income from sales will be divided. All the factors of a firm are owned by an agent. The concept that the firm is not owned by its security holders leads into the idea that firm control decisions are not the responsibility of the owners. The manager's role is overseeing and coordinating every contract of the firm, and holds the rights to renegotiate individual input contracts. The risk bearer holds the residual claims and the right to sell the contractual rights. Labour and management are not the only agents of the firm that are presented with a market for their abilities (working for another firm). The owners are also presented with a market for their investments. Modern portfolio theory dictates a portfolio of diverse and numerous securities. So any one owner may hold dozens or even hundreds of firm's residual rights (shares or bonds). The owner would then not hold particular interest in any one firm or the need to act as the control agent. This risk diversification implies a separation of ownership and control (Fama 1980).

The managers do substantially depend on the activities of the firm as it is their primary income source. Also the manager's value on the labour market (their reputation and ability to be hired at other firms) can be viewed as the value of the firm on the securities market. This valuation will act as a control agent for managers (Fama 1980).

The firm is pressured by the outside managerial labour market to grade and reward managers based on performance. Internally managers will tend to monitor each other; both top down and bottom up. Each manager is affected by the success of the firm and thus each manager is concerned about the performance of the other managers, and will monitor their action accordingly. Each manager will be disciplined by his superior; the top manager can only be reined in by the board of directors. But since the board cannot be made up of owners, due to the numerous and diverse owners who take less relative interest in the single firm, the top managers will step in to compete for the board. These manager-board members are the most responsible for the firm success and will be judged the most severely on the securities and labour markets (Fama 1980).

To resolve the agency problem of managers not acting in the best interests of the owners, Fama (1980) first takes the scenario where the manager is also the sole owner. Here the manager will take from the firm until his yield is equal to the marginal expected utility of a dollar used to consume or invest outside the firm. As he is also the owner he is consuming from his own wealth. When the manager is not also the owner he would have an incentive to take more from the firm than his contract entails. If the manager is not required to settle up for what he has taken ex post then this will be accounted for in the ex-ante contract, this will result in the manager consuming more on the job than he has already paid for it.

Assuming the manager's future wages are a marketable asset and the revision of his wage contract ex post depends on his current performance and his fulfillment of the contracts, he will not take extra from the firm as this will negatively affect the value of his human capital. The costs to his future wage and reputation will be affected by his current actions on the contract with the firm (Fama 1980).

The manager's wage is negotiated based on the expected value of his marginal product. To ensure a manager does not consume more and give less effort after the contract is signed a mechanism for ex post enforcement is built into the model. Future expected marginal products are derived from the past differences in the actual marginal product and what was forecasted. Thus there is an averaging effect and results in a full ex post settling up. This is not affected by managers switching firms.

The manager's wage is dependent on the full past performance of the manager and the wages thus result in a full ex post settling up that cannot be avoided. His wage is the expected value of his future marginal product, which is based on past marginal product. Thus the manager's performance directly affects his wage. His shirking in one period will be accounted for in the next. This ex post settling up makes the manager accountable for his action in this period and resolves the incentive problem. Thus owners of the firm need not be concerned about the agency problems as the managers will be compensated accordingly to their performance as measured by the labour market (Fama 1980).

2.4 Empirical Studies

As mentioned previously the majority of empirical papers examine American hospitalist models in their designated institutions. Wachter et al 2002 compiled the empirical papers for the five years (1996 through September 2001) following the program's introduction of the program in the United States. Their goal was to gage the hospitalist model's impact on American hospitals with respect to use of resources, quality of care, patient satisfaction, and the quality of teaching. They found 19 published studies reporting the clinical and financial outcomes of hospitalist models. The majority of the studies found a significant decrease in hospital resource use, most often measured by hospital costs which had an average 13.4% decrease, and an average drop in length of stay of 16.6%. There were reports of improved quality as measured by decreased readmission and mortality rates, this would infer that quality of care is at least not dropping. Patient satisfaction was unaffected by the hospitalist programs since the surveys showed no changes to patient demeanour. The authors conjectured that those studies in which researchers failed to find significant results lacked proper control groups. Overall the authors concluded that the evidence supports hospitalist model improvements in hospital efficiency without reducing quality of care or patient satisfaction (Wachter et al 2002). The following details a few empirical studies of the hospitalist model, mostly analysing its effect on the economics of operating a hospital.

The only Canadian empirical paper, (Hong et al 2010) examining the hospitalist program focussed solely on one common problem, infections associated with hospital stay, resulting from the quality of care, and ran a sensitivity analysis of the potential benefits of a new hospitalist program. The paper used hypothesized benefits and did not evaluate the effects an established hospitalist program has on the quality of care. Hong et al (2010) undertook a cost-benefit analysis of bloodstream infections among haemodialysis patients (BSI's) in Canada, a common infection resulting from complications during a hospital stay, which dramatically increases the costs to the health care provider. The data was retrieved from the Canadian Institute of Health Information database over a 6 month period and involved cases of BSI from a pool of procedures. Using the survey of American health institutions they hypothesized a possible 20% to 30% reduction in BSIs through the employment of a hospitalist program. By using the cost of acute care hospital stays by medical condition in Canada in 2004 to 2005 to estimate the costs of BSI per stay and adjusting for inflation, they were able to estimate the current BSI treatment cost. To perform the CBA the authors took the additional costs to run the hospitalist program and compared them to the potential cost savings resulting from a 10% to 30% reduction in BSI. The authors found a breakeven point at a 16.6% reduction in BSI occurrences (Hong, et al. 2010).

Metlzer et al (2002) examined 6511 patients who were admitted to the general medicine service at the University of Chicago between 1997 and 1999. Patients were cared for by either one of two hospitalists or one of 52 non-hospitalist teams. Within the total sample, 24.8% of the patients were assigned to hospitalist teams while the remainder were treated by non-hospitalist teams. Between the two groups, age, sex, diagnosis mix, and Charlson index score (a measure of morbidity) did not significantly differ, thus the groups were analytically comparable.

The results of the generalized linear models showed average adjusted length of stay was 0.29 days shorter for the patients under the care of a hospitalist in the first year During the second year, the reduction was 0.49 days , a significant drop considering the number of patients seen per year.. Average adjusted costs were however not significantly lower for the hospitalists in year 1 but 782 USD lower in year 2. Combining years 1 and 2 showed no difference in the 30 day mortality rates between the two groups, but when examining year 2 alone, the hospitalist 30 day mortality was 1.8% lower. Using multivariate analysis the researchers showed relative resource usage and in-hospital mortality decrease with physician experience in inpatient care. (Meltzer, et al. 2002).

Rifkin et al (2004) examined all inpatient admissions during 2001 in the department of medicine at a community based teaching hospital. Data was collected for attending records (hospitalist or non-hospitalist care provider), length of stay, and principle diagnosis related group (DRG), which places the patients into similar samples of illness or other afflictions. The authors ran a bivariate analysis on each physician group and a two-level hierarchical multivariate random intercept regression model with the patients as the first level and the physician as the second. The researchers coded the output a “1” if the patient LOS was greater than the DRG adjusted standard LOS or “0” otherwise. They wanted to examine the impact of physician level characteristics on patient LOS while controlling for patient severity. The difference between a hospitalist and a non-hospitalist is expressed as the probability that a hospitalist was involved when LOS exceeded the average.

Their main findings were that for a given principal DRG, hospitalists’ patients were not as likely to exceed average LOS as non-hospitalists’ patients. When controlling for years since physician graduation (experience), patient age, and admission volume to the units, the hospitalists’ patients were still less likely to have an above average LOS (Rifkin, et al. 2004).

Dynan et al (2009) used qualitative methods to develop a quantitative approach for hypothesis testing to examine the hospitalist knowledge of patients and practices. They follow past literature that suggests hospitalists have lower costs or charges for caring for patients when compared to traditional practices. This resulted in a shorter LOS and reduction in diagnostic services all the while not lowering the quality or intensity of care. By examining all the patients admitted to the University Hospital in Cincinnati for hospitalists and non-hospitalists from June 2006 to July 2007, they found evidence of cost savings through reduced LOS and more efficient diagnostics. Further, while some hospitalists vary in their diagnostic procedure (some are more efficient than others), all result in lower diagnostic and ancillary charges when compared to physician lead teaching teams. (Dynan, et al. 2009)

Through interviews with the director of general internal medicine and surveys of physicians the authors gathered details about the program to facilitate the development of the research. These interviews showed that hospitalists see themselves as aiming to provide efficient low-cost care without diminishing quality (Dynan, et al. 2009). This is an important piece in discovering the motivation or social welfare function of this hospitalist program.

Dynan et al (2009) analyzed the patient level data over a one year period. This data reported hospital administrative data, as well as the patient LOS, 15-day, and 30-day readmission, and hospital mortality. The authors controlled for the severity of the patient though the use of the 30 comorbidities index identified by Elixhauser et al (1998) which grades the patients severity based on a list of known conditions, afflictions, and alignments.

They obtained the following results. First when controlling for patient severity the hospitalist program had $1713 less total charges per patient which was a statistically significant reduction compared to the costs incurred by non-hospitalists. Second LOS is significantly shorter by 1.5 days when the patient was admitted for intensive care, but not when admitted to general care. Third, there was no significant difference between groups in the 15/30 day readmission rate or in-hospital mortality rate. Finally, the authors found that certain hospitalists were more efficient in terms of shorter length of stay and fewer diagnostic tests, while others demonstrated a trade-off between the numbers of tests run on a patient and the amount of time they were kept in hospital. The authors conjectured that these results show hospitalists at different stages of expertise, where the most efficient are more experienced with delivering hospital care.

Overall Dynan et al (2009) found that hospitalists have significantly shorter LOS (0.395 days shorter) which turns into 9.5 hours quicker bed turnover. Hospitalists incur lower charges, both in total and when broken down (radiology, labs, blood banks, prescriptions, etcetera.). There was no significant difference in the 15/30 day readmissions or in-hospital mortality between the hospitalist and non-hospitalist physicians. Thus hospitalists are on average more efficient diagnosticians than teaching-team members as they incur fewer charges for tests. They also enhance hospital throughput by reducing LOS without diminishing quality of care.

Gregory et al (2003) examined the effects of the hospitalist model from the point of view of the hospital's economics. This impact on economics was taken in terms of length of stay, changes in the costs per day, patient throughput, reimbursement outcomes, the total costs of the hospitalist program, and the incremental profitability. This analysis was conducted at the Tufts-New England Medical Centre. They took three study periods of six consecutive weeks each. The hospitalist group was taken during August and September 1998, with two control groups of non-hospitalist data from the six weeks before and after the study period. The data obtained included the patient demographics, utilization, and discharge disposition which identified such variables as where the patient is to be discharged to, and the level of care to be received. The authors used the Medicare case-mix index to approximate patient severity. Additionally the patient length of stay, direct costs of care (which covered costs related to delivering care such as nursing, medication, supplies and tests), and net revenues were also recorded. To account for the incremental hospitalist costs the authors examined the physician salary level relative to their productivity, or the number of patients cared for per day. The net revenues were recorded as charges to third party payers minus contractual adjustment. Incremental net revenues were expressed as average net revenues per day (Gregory et al 2003)

The overall hospitalist economic effect in Gregory et al (2003) was measured as the incremental revenues minus costs, or the incremental contribution margin. The authors made several assumptions:

(1) the arrival of patients to the unit is random,

(2) their lengths of stay are distributed randomly,

(3) length of stay does not decrease with the increase of patient arrivals,

(4) when the unit is at capacity new patients looking for care are not admitted to this unit and are admitted to another hospital.

The authors found statistically significant differences in length of stay, cost per case, and cost per day. Hospitalist patient length of stay was 1.29 days shorter with the inclusion of observation days, and 1.5 days shorter without the observation days. Direct hospital costs were $540 lower per case for the hospitalist group. The incremental contribution margin of the hospitalist was around $1.44 per patient or $1,285 per year not counting the throughput effect of lower length of stay. (Gregory et al 2003)

The costs savings arise due to the reduction in LOS, even though the total laboratory, consulting, radiology, and medication costs did not decline. Thus there will be a breakeven mix of reduced LOS and increased per diem charges. This can be a major benefit given many hospitals are at capacity and increased throughput results in the increased contribution margin of this hospitalist model. Thus not only is the model benefiting society with the increase of patients cared for but also will increase the revenues to the hospital. (Gregory et al 2003)

Lindenauser et al 2007 conducted a retrospective study of patients over 18 years of age who were admitted and cared for from September 2002 to June 2005 to 45 hospitals throughout the US. The severity of the patients was controlled by limiting the sample to patients that suffered from a defined list of conditions. Multivariate analysis was used to compare the quality and outcomes of care provided by the sampled physicians. In total there were 284 hospitalists, 993 general internists, and 971 family physicians. The results showed that patients cared for by hospitalists had a shorter length of stay (0.4 days shorter; P value<0.001) and lower costs (268 USD lower; P value=0.02) and similar inpatient mortality rates and 14-day readmission rates when compared to the general internists. When compared to the family physicians the hospitalists again had shorter LOS (0.4 days shorter; P value<0.001), insignificant difference in costs (125 USD lower; P value=0.33), and similar mortality and readmission rates. Thus the hospitalists were slightly more efficient and less costly without reducing the quality of care, as measured by the 14-day readmission and inpatient mortality rates, when compared to general internists, yet when compared to family physicians the hospitalists had only minor differences.

Not all papers were able to find statistical improvements associated with a hospitalist program. Tingle et al (2001) measured the direct costs, laboratory charges, radiology charges, total charges, LOS, and mortality of two inpatient teams (residence faculty and the hospitalist unit) that work in parallel. They do not share patients or consult each other. The residence team consisted of 1st, 2nd, and 3rd year residents and attending family physician faculty members. The hospitalist group was comprised of 5 general internists that have no teaching responsibilities. Both teams provided care within an intensive care unit, coronary care unit, general adult ward, and observation unit (Tingle et al 2001).

The authors examined the patients admitted to both units from April 1998 to June 1999. They used ANOVA to analyze and compare the variances, while adjusting for differences in the severity of patients. Chi-squared tests were used to assess the differences in gender distribution and to compare mortality rates. Student t tests were employed to detect demographic and severity differences. Outliers of charges, costs, and LOS were truncated at 3 standard deviations above the mean, and a retrospective power test analysis was performed to determine the number of cases needed to detect a $1000 difference in total charges and 0.5 days reduction in LOS. The results of the paper showed mean total lab and radiology charges were slightly lower for the hospitalist group but were not significantly different, and mean LOS and direct costs were however higher for the hospitalist group yet not significant after adjusting for severity. Thus overall the authors were unable to detect any statistically significant difference between the two groups (Tingle and Lambert 2001).

Brownell et al 1995, proved in their study of eight Manitoba hospitals during the fiscal years 1989-90, 1990-91, and 1991-92 that Canadian hospitals do have statistically significant variation in patient length of stay. Even when adjusting for severity and social characteristics they showed that approximately 189 beds between the eight hospitals (ranging from 0 to 40 in each) could have been saved if all the hospitals were run as efficiently as the top hospital. The authors controlled for patient severity and affliction by grouping them into homogenous diagnostic and surgical groups through the use of the Refined Diagnosis Related Group (RDRG) software. This software categorizes and subdivides patients into diagnostic or surgical groups (Brownell and Roos, 1995).

Along with age and sex the analysis controlled for socioeconomic characteristics. Since hospitals serve patients from several areas and because poorer patients require longer hospital stays, the authors added three variables. Patients were grouped into quintiles of neighbourhoods ranging from poorest to wealthiest income levels as derived from the 1986 Canadian census. Patients were classified as being residents of the core area (inner city) of Winnipeg, since this area was known for low-income housing, high rates of poverty, single parent families, and high unemployment. The authors also considered finally whether the patient had treaty status, since "native people are the most disadvantaged in Canadian society and are disproportionately likely to be treated in the three hospitals serving the core area of Winnipeg"(Brownell et al, 1995, pg. 676).

By employing multi linear regression analysis the authors produced several models, first by separating the RDRGs then combining them to establish the LOS for all eight individual hospitals. Assuming the hospital with the lowest LOS to be the most efficient the authors examined the expected LOS of the other seven hospitals with their actual LOS. The results showed that even when controlling for severity and socioeconomic characteristics of patients certain hospitals still had significantly higher LOS when compared to the most efficient hospital and to the group average. Moreover, the authors compared these results to American average LOS and concluded that these eight Manitoba hospitals could further increase efficiency if US standards were adopted (Brownell et al, 1995). This paper supports the theory that Canadian hospitalist models can be measured by their effects on hospital efficiency (as in American papers) despite differences in health systems and motivations behind the initiation of the hospitalist program.

CHAPTER 3:

Hypotheses

The existing literature indicates the hospitalist model's effects on other North American hospitals (Dynan et al 2009, Gregory et al 2007, Lindenauser et al 2007, Gregory et al 2003, and Wachter et al 2002). Interpreting these results leads to the following hypothesis about the hospitalist program operating in the SHR. First it has been documented in the United States that the operation and employment of hospitalist physicians has most often lead to the reduction in average patient LOS when compared to non-hospitalist general practitioners. Brownell et al (1995) have shown that reductions in patient LOS are possible through process improvements in the Canadian context. This leads to our first hypothesis.

Hypothesis 1: The Hospitalist program has reduced patient Length of Stay.

Business process re-engineering does not always bear the intended outcomes immediately. Often there is a time lag between initiation of the new program/ system and its true results. This can be caused by several factors including the development of new skills, application of existing skills in new areas, political and operational resistance, or a failure to accept the new paradigm by employees and/or managers (Asif et al 2009, Attaran 2000, Stoddard et al 1996). Kuo et al (2010) identified that the average patient LOS decreases over time. The authors attributed this to the new hospitalists adjusting to their new environment and roles while honing their skills with caring of inpatients. This same adjustment and improvement over time can be expected in the SHR and is captured by our second hypothesis.

Hypothesis 2: The LOS relating to Hospitalist patients will decrease with time.

Before July 2010 the hospitalists were paid a fixed stipend and the Health Region billed and collected funds from the government for the fee of service delivered by the hospitalist. This directly reduced the cost of funding the program. After July 2010 the hospitalist fixed stipend was reduced substantially but the physician now bills and collects the fee-for-service. This variable pay is directly linked to the services provided and the length of stay of the patient. The per-day fee decreases as length of stay increases. This creates an incentive for hospitalists to reduce length of stay to increase patient throughput and increase income. This hypothesis stems from Ellis et al (1986) where they examined physician actions under various types of provider reimbursements. Under the retrospective system, known in Canada as the fee-for-service system, physicians provide too many services as the additional services generate extra revenues. This profit maximising behaviour would also explain a reduction in length of stay if it corresponded to the possibility of higher revenue.

The actions of the physician can be explained by Fama (1980). The hospitalist (agent) is entrusted with a level of control over the delivery of care to patients (fulfillment of contracts), on behalf of the Health Region (principal). There is a degree of separation between ownership and control since the hospitalist does not operate his/her own private practice. The hospitalist would then be motivated to maximise profits by increasing services provided and patient throughput. But this behaviour is also governed and limited by internal and external controls. Physicians are monitored and reviewed by both peers and supervisors, and the need to maintain a professional reputation is important. Thus any excess profits taken in this period, such as increasing patient throughput by prematurely discharging them, will negatively affect future earnings. This is caused by the poor practices negatively affecting the readmission rate and/or other quality measures such as patient satisfaction, and the physicians' professional reputation would be harmed. This blow to the physicians' reputation can have future implications on their pay and advancement, and will dissuade them from completely maximising revenues to the point of reducing the quality of care.

McGuire (2000) and McGuire et al (1991) identify that there exists a high level of information asymmetry within the health care service industry. The high degree of complexity inherent in medical services and the relative inexperience of patients with most medical procedures create this high level of information asymmetry. The patient is unsure of the expected outcome of the procedure and must rely on the advice of the physician. Physician induced demand is created when the physician is able to influence the level and quantity of health services provided above what is necessary.

Hypothesis 3: Length of Stay has been reduced due to the change in Hospitalist payment structure.

Reduction in length of stay and/or resource usage is only one aspect of the hospitalist outcomes. Quality must also be measured to ensure patient health is not adversely affected by a change in efficiency. Although the quality of health care can be measured with many different factors, previous literature uses the readmission and mortality rates since the data is readily available. If the program can be shown to decrease or maintain the readmission and mortality rates, it can be concluded that the program improves or maintains the quality of care provided. Results from the literature have shown that although the hospitalist programs have not consistently reduced the readmission and mortality rates, they have not increased them. Thus the program has not adversely affected the quality of care provided. Our fourth and fifth hypotheses examine the program's effect on the quality of care.

Hypothesis 4: Hospitalist inpatient readmission rates will decrease.

Hypothesis 5: Hospitalist inpatient mortality rates will decrease.

These hypotheses will be tested using multivariate regression analysis of the dependent variables Length of Stay, readmissions, and raw mortality rate.

CHAPTER 4:

4.1 Methodology

In order to conduct an analysis of the hospitalist programs in the Saskatoon Health Region, Strategic Health Information and Planning Services (SHIPS) has extracted the data and provided retrospective de-identified patient level data from St. Paul’s (and Saskatoon City Hospital as the Intensive Care Unit (ICU), Primary Care Units (PCU), and the Medicine Units were consolidated to St. Paul's from October 2008 to January 2009), reporting the data such as length of stay, Resource Intensity Weight (resource usage), readmissions, raw in hospital mortality, Case Mix Groups (patient diagnosis), patient characteristics (age and sex), and patient demographics, including income, socio-economic status, as derived from the Stats Canada 2006 survey and the patient postal code of residence. Table 1 lists and describes all variables used. The time period covers January 1 2007 to November 30 2010 for the fiscal years April through March. The health region analysts extracted data from are St. Paul’s Hospital, Saskatoon City Hospital, and Royal University Hospital (readmission data only). The Biomedical Research Ethics Board (Bio-REB) at the University of Saskatchewan granted ethics approval (Bio #10-216).

The dependent variables include inpatient length of stay of the initial admission and subsequent readmissions following discharge where the reason for readmission is related to the previous admission. These readmissions are chosen by identifying the diagnosis code and ensuring they are related to the original ailment. Any readmissions not directly related to the initial admission would be assumed to be a missed diagnosis that otherwise would have been addressed and subsequent care would be referred to other specialized care facilities. In addition to the readmission rate, the in-hospital raw mortality rate is recorded, and other discharge codes are provided such as transfer to other care facilities or special care units and discharges home.

The independent or test variables are the funding spent on the hospitalist program through the Saskatoon Health Region. The funding was provided on an annual aggregate level. These figures were adapted for our research by dividing the annual funding by the annual total length of stay of all the patients in our sample. This provided a cost per LOS day of the hospitalist program for each fiscal year. In addition, we include dummy variables that identify admissions before and after the Health Region began funding the hospitalist program (April 1 2008) as well as, the actual date of admission. We also include another dummy variable to identify the admissions before and after the change in hospitalist pay from fixed to fixed plus variable (July 1 2010).

Several control variables will be employed in the models which include patient characteristics such as age in years of each patient and gender. Severity is controlled for by the inclusion of the Resource Intensity Weight (RIW). The RIW variable is a measure of the relative amount of hospital resources used to treat a diagnosis given patient characteristics and length of stay. Higher RIW scores indicate cases that require higher levels of hospital care and thus higher patient severity. RIW scores are calibrated annually so that the average inpatient acute care case in Canada has a value of one. Actual patient RIW will not be used in models involving our measure of LOS since LOS is already used to calculate this measure of RIW. In its place we use estimated Resource Intensity Weight (ERIW) calculated using the Canadian Institute for Health Information (CIHI) patient cost estimator index and actual patient age, gender, and diagnosis. This new measure of estimated resource usage will serve as our proxy for patient severity without our dependent variable directly affecting its calculation. Patient socioeconomic demographics will be identified through linking their postal code residency to the Stats Canada 2006 census tracks. To develop measures of income, education, and lineage for each patient, we consider each neighbourhood's average income for residents over 16 years of age, the percentage of residents with a post-secondary education, and the percentage of residents with aboriginal heritage.

Patient Case Mix Group (CMG) is a variable designed and used by the Health region to aggregate acute care for patients with similar clinical and resource-utilization characteristics. This diagnostic tool is also used by CIHI to develop the average length of stay of a given patient's age and gender throughout Canada (CIHI 2010). This national expected LOS is deducted from each patients actual LOS given their age, gender, and CMG in our sample. This new measure is used as an additional independent variable to test the hospitalist program's effects on patient LOS above or below what would be expected nationally.

The most responsible physician is provided, that identifies which hospitalist was ultimately responsible for delivering care to the particular patient. With this information we are able to identify any differences in length of stay through physician techniques.

Regression analysis is conducted using two primary models and four relating sub-sample models. These ordinary least squares and binary logistic regression models will take the form:

$$\boldsymbol{Ln(LOS_i) = \alpha + \sum \beta_i TEST_i + \sum \beta_i CONTROLS_i + \varepsilon_i}$$

$$\boldsymbol{LOGIT(P_i) = \alpha + \sum \beta_i TEST_i + \sum \beta_i CONTROLS_i}$$

The Y variables of the models correspond to the three dependent variables LOS (patient length of stay of initial admission), MORT (the raw in hospital mortality rate), and READ_LOS (the 30 day readmission rate). The $\boldsymbol{TEST_i}$ along with its coefficient $\boldsymbol{\beta_i}$**,** represents four test statistics: HEXP (level of funding spent of the hospitalist program), HOSP (hospitalist dummy variable), ADMIT_DATE (date of admission), and POSTCHG (post change in hospitalist payment structure), for each patient *i* at time *t*.

CONTROLS$_i$ represents the multiple control variables in the model along with their related coefficients $\boldsymbol{\beta_i}$. Models examining patient LOS will be specified using ordinary least squares regression and models exploring the readmission and mortality rates will utilize binary logistic regression. Due to the nature of health care data, our measure of patient LOS is not normally distributed so it has been transformed using natural logarithms. Variables relating to in-hospital mortality and the readmission rates are coded as 0 and 1 given the outcome of the event. Therefore binary models such as logistic or probit must be employed to analyze the hospitalist programs' effect on the probability of the event occurring.

4.2 Descriptive Statistics

Table 2.1 shows the descriptive statistics of the dependent, independent, and control variables. Taking the sample from January 1 2007 to November 30 2010 produces a total of 12,667 observations. The total LOS of the initial admission of each patient ranges from 1 to 147 days with a mean of 10.16 and skewness of 3.9824. This positive skewness and non-negative range indicates this is count data, and needs to be transformed for our OLS model to apply. The readmission data indicates a large number of observations with a value of zero which may be better modeled using a binomial logistic regression. The patient characteristics data shows the average patient age is 68, and the data is distributed evenly between males and females.

CIHI provides analysis on the health care industry at the provincial and national levels, creating their measures and indexes by excluding atypical cases where actual LOS exceeds predetermined trim points. This explains why the average expected LOS (ELOS) is notably smaller than the actual average length of stay by nearly 5 days, 5.52 compared to 10.16 respectively. To account for this we have split our data base into subsamples. The subsamples include the observations where patient LOS is less than or equal to the Expected Length of Stay (ELOS) measure provided by CIHI given the patient characteristics and diagnosis. The other sub sample contains the observations whose patients LOS exceeds the ELOS. The robustness of these results will be tested by repeating the analysis with subsamples above and below ELOS plus one and two standard deviations. The creation of the typical and atypical groups addresses the issue of identifying and classifying high-LOS observations as outliers. The high-LOS observations do not fall under the true definition of outliers since they are not errors in the sample, but do differ from those observations with smaller LOS. Table 2.2 and 2.3 present the descriptive statistics for the two subsamples.

Table 3 presents the Pearson Correlation Matrix for our sample. The data is interrelated as expected. Average income is positively related to education (0.77) and age (0.20). Age is negatively related to being discharged home (-0.32) and positively related to being discharged to another care facility/ unit (0.24). Age confirmed to be a large determinant of LOS, with a positive correlation of 0.33. RIW has the highest correlation with actual LOS (0.79).This is due to LOS being an input in the calculation of RIW. Due to this fact, RIW will not be used in any regression involving LOS as the dependent variable.

CHAPTER 5

Results of Regressions

5.1 Hypothesis 1: The Hospitalist Program has reduced patient Length of Stay.

To test whether the hospitalist program has improved hospital efficiency through a reduction in patient length of stay we develop the following model specification for both the below and above ELOS sub samples. Since actual LOS is made of non-negative integer values, we will be taking the natural logarithm of the dependent variable (LOS) to determine the appropriate relationship.

$$Ln(LOS_i) = \alpha + \sum \beta_i TEST_i + \sum \beta_i CONTROLS_i + \varepsilon_i$$

Tables 4.1 through 4.6 present the regression results for the atypical (LOS above ELOS + 0, 1, and 2 Standard Deviation) and typical (LOS below ELOS + 0, 1, and 2 Standard Deviation) subgroups respectively. The test statistic HEXP, the annual dollar of funding per LOS day, has a statistically insignificant coefficient in all of the sub groups containing observations with LOS below ELOS, indicating that additional funding spent on the hospitalist program does not improve delivery of care efficiency for patients with lower LOS. This result is further supported by the regression using the dummy variable HOSP to indicate admissions during the hospitalist program. The coefficient of the variable HOSP is not statistically significant and has no effect on patients' LOS being shorter or longer than non-hospitalist admissions in any of our three subgroups below ELOS.

Examining Tables 4.1 through 4.3 Columns 2 and 3, for the regressions with the atypical subgroup, the test variables HEXP and HOSP both have statistically significant positive coefficients at 1% level of confidence, 0.00156 and 0.0628 respectively in our sub-sample of LOS above ELOS plus zero standard deviations. The coefficients are again significant, 0.00103 (HEXP), and 0.03906 (HOSP), at the 5% level of significance in our sub-sample of LOS above ELOS plus 1 standard deviation, and neither variable is significant in our final subsample, LOS above ELOS plus 2 standard deviations. Interpreting these results implies that as we increase the funding spent per LOS day by one dollar, the expected LOS will increase between 0.156% to 0.103% in the groups with ELOS plus 0 and +1 standard deviations, and the inpatient admissions during the hospitalist program had expected LOS that were 6.28% to 3.906% higher than our non-hospitalist group. These results are contrary to our hypothesis 1 and other empirical papers where funding spent by the Saskatoon Health Region on the hospitalist program has not improved hospital efficiency by reducing inpatient LOS. The hospitalist program had no statistically significant effect on LOS for patients with low LOS, and effectively increased expected LOS for atypical cases.

Examining the other control variables of patient characteristics and socio economic residency, we see results that confirm our initial intuitions about factors that affect LOS. Patient age is positively associated with the actual LOS for both the typical and atypical admissions; education (as measured by the percentage of population with post-secondary education in the neighbourhood of patient residency) is both positively associated with the actual LOS for the admissions above and below ELOS plus 0 standard deviations. However, gender and being from a neighbourhood with a higher percentage of residents from aboriginal decent does not affect patient LOS.

Variables were included for the nine hospitalists (labelled A though I to maintain their anonymity) whose average patient LOS was statistically different from the other 30 physicians. These nine were identified by executing the student-t test and comparing the average LOS of the patients care for by each hospitalist respectively, to the average patient LOS of the entire sample. Using dummy variables we see that patients cared for by 3 of the hospitalist A and B had significantly higher LOS for patients with typical LOS, and only hospitalist C had significantly lower patient LOS for admissions with typical LOS. Patients with atypical LOS cared for by these hospitalists were not shown to have statistically different LOS amongst the various physicians. This implies there was no distinct difference in physician practice when caring for inpatients with atypically long hospital stay. There is however evidence that shows significant differences in patient LOS amongst physicians in the typical subgroups. These differences may be the result of physicians being more experienced in delivering care, and/or different physician preferences and practices relating to patient discharge. More research will be needed to determine the cause of these findings.

5.2 Hypothesis 2: Patient LOS decreases with time.

To test the change in LOS over time we replace the test variable in the above OLS model with the date of admission. Tables 4.1 to 4.6 Column 4, show quadratic relationships between the dates of admission and actual patient LOS for our atypical subsamples and typical subsample below ELOS +2 standard deviations. Patient LOS is shown to slightly rise then fall as the hospitalist program progresses through these subsamples. To aid in the analysis we create a subsample of the final year of the observations in order to estimate the increase or decrease in LOS over the following year. Table 5.1 presents the OLS model for the most recent dates of admission. Due to insignificance the quadratic term is removed. This model shows a negative linear relationship between the date of admission and the average patient LOS. As admission date increases by one additional day, the actual inpatient LOS decreases by 0.046% per day or 15.59% per year. Extending this decrease from the most recent average LOS of 9.63 days, average patient LOS will decrease by 1.5 days. We can expect the relationship to change from linear to quadratic as the physicians become their most efficient and the marginal reduction in LOS decreases. Thus, we anticipate that the average LOS would level off at some point in the future.

Table 2.4, provides the average LOS for each fiscal year in our sample. Average LOS is shown to increase from 8.84 days in the 2006-07 fiscal year, to 10.33 and 11.67 days in the fiscal years 2007-08 and 2008-09 respectively. Subsequently the average LOS declines to 10.06 days in the fiscal period 2009-10 and 9.48 days in the final period 2010-11. To test if this change in LOS over time can be attributed to the hospitalist program, we add a new variable HOPS_Admit_date, which is the product of the date of admission and the hospitalist dummy variable, and run the regression model on each sample. Additionally we applied the hospitalist dummy variable to the control variables to test if the patient characteristics differ between hospitalist and non-hospitalist observations.

Tables 5.2 presents the results of the regression identifying the effects the hospitalist program has on the reduction in patient LOS over time. The quadratic variable Admit_Date^2 is removed due to it insignificance. The results show a negative linear relationship between the date of admission and patient LOS with a statistically significant coefficient at the 1% level for the entire sample. However the hospitalist date variable has a statistically positive coefficient at the 1% level. The sample has an admission date coefficient of -0.00016, interpreting that for each day, LOS is expected to decrease by 0.016%. The coefficient for the admission date variable for the hospitalist observations is 0.000007, interpreting that patient LOS decrease by 0.0153% per day during the hospitalist program. These results show that the hospitalist program cannot be attributed to the decreasing patient LOS over time. Conversely our results show that during the hospitalist program, patient LOS decreases less over time than our non-hospitalist sample. The decrease in patient LOS in both samples would be the result from some other time- dependent factor such as physician experience and professional development.

5.3 Hypothesis 3: The change in payment structure will reduce LOS.

We further subdivided the data into two samples corresponding to the five months before and after the change in hospitalist payment structure. Before July 2010 the hospitalists were paid a fixed stipend and the Health Region billed and collected funds from the Government for the fee-for-service delivered by the hospitalist. This directly reduced the cost of funding the program as the fixed cost of the hospitalists' pay was being offset by the collections of the variable fee-for-service payments. After July 2010 the hospitalist fixed stipend was reduced substantially and the hospitalist in turn billed and collected for the fee-for-service directly. This variable pay is directly linked to the services provided and the length of stay of the patient. The per-day fee decreases as length of stay increases. This creates an incentive for hospitalists to reduce length of stay to increase patient throughput and increase income.

This sub division produced 1365 observations after the change in payment structure (July 1 2010 to November 30 2010) with an average LOS of 9.2 days and 1379 observations before the change with a mean LOS of 10.06 days. These means are statistically different from each other at the 1% significance level. Examining the data, there does not appear to be a significant amount of discharges around LOS days 30 to 32. The rate of discharge continues to decline by the same rate over this period. Following the approach of dividing our sample between typical and atypical cases provides similar results. The change in payment structure is shown to reduce patient LOS by 6.77% (statistically significant at the 10% level) in the below ELOS plus 0 standard deviations sample, 5.49% (statistically significant at the 10% level) below ELOS plus 1 standard deviation, and 6.07% (statistically significant at the 10% level) below ELOS plus 2 standard deviations, as per Tables 4.4 to 4.6 Columns 5. The variable representing the change in payment structure does not have a statistically significant coefficient in any of the three atypical LOS samples above ELOS.

The OLS regressions testing the effect of the payment structure change on the difference between actual and expected LOS are presented in Table 4.1 to 4.6 Columns 5. By multiplying the before payment change average LOS in each typical subgroup by the respective coefficients of the regression models, we are able to quantify the change in LOS days. The results show for the typical admissions subgroup below 0 standard deviations, that by changing the hospitalist compensation from fixed to variable the average LOS decreased by 0.30 days, or 7 hours and 14 minutes, to just over 4.6 days. Below ELOS plus 1 standard deviation subgroup, the average LOS decreased by 0.23 days. Over 2 standard deviations subgroup, the average LOS decreased by 0.23 days. For the atypical admission subgroup there is no statistical evidence to suggest that the change in payment structure affects the efficiency. Although this is not a large figure, this has the effect of increasing hospital throughput by an estimated 36 to 129 admissions per year for typical observations, given the average annual admissions in our samples. This decrease in the average LOS supports our hypothesis that the change from fixed to variable compensation has indeed provided an incentive to increase efficiency by reducing patient LOS.

5.4 Hypothesis 4: Hospitalist inpatient readmission rates will decrease.

To test the quality of care, the readmissions of patients for procedures relating to the initial admission is examined to determine if reduced LOS of the initial admission has reduced the effectiveness of the services, thereby resulting in the patient having to be readmitted subsequently for the same affliction, or other ailments that should have been diagnosed during the original examination. A reduction in the readmission rate may indicate an improvement in the quality of care provided. To test the effect of the hospitalist program on the readmission rate we code each readmission as 1 if the patient was readmitted for reasons relating to the previous admission and 0 otherwise. We then employ binary logistic regression on our four test variables, hospitalist funding per day LOS, hospitalist dummy variable, date of admission, and post change in hospitalist compensation dummy variable. We include all previous control variables and physician dummy variables in the binary logistic models.

Table 6 presents the results of the binary logistic regressions and the impact of hospitalist funding on readmission. As the variable HEXP has a negative coefficient (-0.0022) that is not statistically significant, no conclusions can be made on the effects of hospitalist funding on readmissions. This does not support the hypothesis that quality of care provided is being improved due to the funding of the hospitalist program, but it does not disprove it completely due to the statistical insignificance. Examination of the control variables shows that none have statistically significant coefficients. The physician dummy variables indicated two out of the six hospitalists we included with statistically different patient LOS also had significant positive effects on patient readmission. The percentage of patients being readmitted for relating treatments following discharge is expected to be 30.26% and 12.28% higher for patients cared for by hospitalists C and F respectively at a 1% and 5% level of significance. This indicated patient readmissions are related to qualitative physician specific factors. Due to personal experience and professional judgement, different physicians do have different readmission rates.

The binary logistic regression model tests the hospitalist program dummy variable, HOSP, on the readmission rate. As before the test variable has a negative coefficient (-0.0875) which is not statistically significant. As this is not significantly different from zero, this does not support our hypothesis that the program has improved quality and/or effectiveness of care provided. We also note that the control and dummy variables all have similar signs, magnitude, and statistically significance, including the statistical significance of hospitalists C and F.

We further test the effects of the date of admission and the change in hospitalist compensation on the readmission rate. These regressions add greater depths to our results given these factors were shown to affect patient LOS. Both the coefficients for variables ADMIT_DATE and POSTCHG are not statistically significant and thus have no effect on the rate of readmission of patients following discharge. Although the expected LOS has decreased as the program continued and subsequently due to the change in payment structure, the quality and effectiveness of care has not decreased as measured by patient readmissions.

5.5 Hypothesis 5: Hospitalist inpatient mortality rate will decrease.

In addition to the readmission rate we also include the raw mortality rate of inpatients cared for by the hospitalist program to measure effectiveness and quality of care provided. The raw mortality rate is measured by creating the dummy variable MORT, were 1 indicated the patient died while in care of a hospitalist or 0 otherwise. We used a binary logistic regression to test the effect of the hospitalist program, hospitalist funding, admission date, and change in payment structure on the raw mortality rate. Additionally we included the control variables for illness severity, characteristics, and socio economic residency and the physician dummy variables for our six hospitalists with statistically different patient length of stay. The results are presented in Table 7.

The four test variables HEXP, HOSP, ADMIT_DATE, and POSTCHG do not have statistically significant coefficients. This does not support our hypothesis that the quality and effectiveness of care as measured by the raw mortality rate has been improved by the introduction, and funding of the hospitalist program. Although the time factors (in other words, admission date) and post change in hospitalist payment both have reduced patient length of stay, neither factors have any effect on in-patient raw mortality. This shows that quality of care is not affected by increased efficiency. The only control variables that were shown to have any effect on the raw mortality rate are patient age, gender, and the Resource Intensity Weight rating as determined by the patient diagnosis. In agreement with Evans and Stoddart (1990) and Acton (1975), age and gender, where males have a shorter life expectancy, are shown to positively affect the probability of mortality as both have statistically significant coefficients at the 1% level. Resource Intensity Weight, our measure of illness severity is shown to be positively related to the raw mortality rate of patients cared for by hospitalists with a coefficient that has a 1% level of statistical significance.

5.6 Economic Effects of the Hospitalist Model

Using the coefficients from our regression models, we produce a modified cost benefit analysis. A traditional approach to CBA would be inappropriate given the nature of the hospitalist project in the SHR. This hospitalist program did not have a large upfront cost, alternatively all the costs and benefits are incurred in the same period thus suggesting that, there is no need to discount future periods to calculate the net benefit. Further, the hospitalist program was not established to directly decrease costs. So a CBA examining only the monetary costs and benefits would not address other quantitative benefits such as patient throughput. The costs and benefits are quantified using information received through direct interviews with SHR employees and reports produced by SHR.

Tables 8.1 through 8.12 present our economic analysis of the hospitalist program based on changes in patient LOS. The analysis represents one hospitalist physician providing services for 1 year comprised of 48 weeks. The hospitalist is expected to care for 20 to 25 patients at a time, and is responsible of all services and care provided to them. The direct cost of the hospitalist program is represented by the fixed stipend paid to each hospitalist equalling \$6,500.00 per week of service or \$312,000.00 per year. The direct benefits are represented by the reduction in LOS and resulting increase in patient throughput. The SHR fee-for-service payment schedule is used to quantify one day LOS and patient discharge. Currently all hospitalist and non-hospitalist General Practitioners receiving fee-for-service compensation receive a fee for each inpatient they are responsible for based on the scale \$30.20 per day for the first 30 days and \$23.80 per day thereafter for patients cared for under General Practice, plus an additional $12.10 per discharge.

Since there is a high demand for open beds in the Province of Saskatchewan, it is assumed the hospitalist will always operate with the maximum amount of patients under the set limits (20 to 25). The benefits are calculated as per the following formula:

$$(\,Number\ of\ Patients\ Admitted\ per\ year) \times (Original\ Average\ LOS) \times \sum (Applicable\ FFS\ Payments)$$

Table 8.1 shows the current average LOS (9.63 days) over the last year of the data, November 2009 to November 2010. The analysis assumes the hospitalist will care for 20 to 25 patients at a time, and has a fixed 336 days to bill FFS (48 weeks * 7 days). Given the average LOS the total number of patients that can be cared for in the year ranges from 697 to 872 per hospitalist, and the total FFS earned ranges from $211,171.31 to $264,191.37.

The coefficient for the date of admission from the regression model of the natural log of patient LOS shows there is a significant negative relationship between the date of admission and the average LOS. Average LOS is expected to decrease by 0.04643% or 15.59% over the following year. Give the Regina Qu'Appelle Health region established their program with the expectation of decreasing LOS by 17%, this forecast is reasonable.

Table 8.2 presents the effects on patient throughput and change in benefits due to the expected decrease in average LOS by 15.59%. The additional patients that can be seen during the year range from 129 to 161. This increase in patient throughput translates into direct benefits of $39,083.36 to $48,778.45 per year if the average LOS does not reduce further. Unfortunately these benefits cannot be attributed solely to the hospitalist program since our analysis shows the decrease in patient LOS occurred in both the hospitalist and non-hospitalist samples.

We conduct a similar analysis quantifying the effects the change in payment structure on the SHR. Following the process outlined above, Tables 8.3 to 8.8 presents the analysis of the hospitalist program before and after the change in payment structure for our typical subgroups 0, +1, and +2 standard deviations below the average day LOS. Table 8.4 shows that the change in payment structure, from the fixed stipend to the smaller stipend plus the fee-for-service subsidies, has reduced average LOS by 6.07% in the subgroup below 0 standard deviations, as reported in Table 4.4 Column 5. This lower LOS has resulted in an increased patient throughput of 36 to 44 in our model year, or a direct benefit of $5,840.06 to $7,137.85. The typical subgroup below +1 standard deviation had a 5.49% decrease in average LOS, resulting in an increase of 55 to 69 more patients being cared for and a direct benefit of $7,670.15 to $9,622.55. The typical subgroup below +2 standard deviations showed a 6.77% decrease in average LOS, resulting in an increase in hospital throughput of 103 to 129 additional patients, and a direct benefit of $11,754.40 to $14,721.43. Due to the insignificant regression results in the atypical subsamples, this analysis cannot be applied to patients with LOS above our established trim points.

Extending our analysis further we quantify the effects of the introduction of the hospitalist program on patient throughput in Tables 8.9 through 8.12. The atypical subgroups over 0 and 1 standard deviation are the only significant coefficients from our OLS models examining the relationship between patient LOS and the dummy variable identifying the hospitalist program. Thus these will be the only groups that can be tested using our analysis. This average atypical patient LOS for the hospitalist program over 0 standard deviations is 6.28% higher than the non-hospitalists observations, from Table 4.1 Column 2. This increase in LOS has resulted in a decrease of 15 to 19 patients cared for in our given physician year or a cost of $319,003.36.36 to $320,870.93 including the paid stipend. The atypical subgroup above +1 standard deviation showed the average patient LOS increased by 3.91% following the introduction of the hospitalist program, as per Table 4.2 Column 2. This would cause 5 to 6 fewer patients to be admitted in our year for a cost of 315,037.83 to $315,645.39 per hospitalist per year as per our above analysis.

CHAPTER 6

Conclusion

The implementation of the hospitalist program, whereby physicians do not maintain an outpatient practice, and primarily treat in-patients, has been documented to increase efficiency without reducing quality of care in several hospitals across the United States. This thesis studies the hospitalist program and its effects on efficiency and effectiveness as initiated by the Saskatoon Health Region. We have expanded the body of research by extending economic health care research and agency theory in the Canadian health care context. Results of multivariate regression models show that the hospitalist program initially had negative effects on the efficiency of the delivery of care in regards to increased patient length of stay for admissions with atypically long hospital stays and no significant effect on short stay admissions. The hospitalist program has demonstrated no effect on the quality and effectiveness of care as measured by patient readmissions and in hospital raw mortality rates. This was documented through the statistical insignificance of the results.

The models do however show evidence of increased physician efficiency over time as the physicians become more skilled and adept at diagnosing and treating patients, familiarize themselves with the hospital and its staff, and develop their level of professional expertise. Our analyses show that as time progresses, patient length of stay reduces. But there is no definitive evidence to determine whether this is a direct result of the hospitalist program or the experience of the individual physicians. If the reduction in LOS persists into the near future, average patient length of stay would decrease by 1.5 days in one year as per our forecasted change in hospital stay over time. Given the average LOS of 9.6 days per patient in the final year of our sample, and the modelled admissions of 697 to 872 per year per hospitalist, this translates into an additional 129 to 161 patients being admitted and cared for by a physician per year.

After the change in hospitalist pay from a fixed amount to a smaller stipend plus the variable fee-for-service charge, our models show that common patient length of stay below the national average significantly decreases in our final sample period. Our analysis further shows that this increase in efficiency has not had a negative impact on quality of care as displayed in the readmission or raw mortality rates. Although the change from fixed to variable pay has produced a profit maximising incentive for hospitalists to reduce length of stay to effectively increase pay, the outcome has not been negative.

The adapted cost benefit analysis presented in this thesis shows that although the direct annual dollar cost exceeds direct dollar benefits and the hospitalist program is not shown to directly improve hospital efficiency, there are significant gains in terms of patient throughput at the physician level over time. These are the main findings for the Saskatoon Health Region regarding the effectiveness of the hospitalist program. Further this thesis does not take into account any qualitative effects of the hospitalist program such as patient satisfaction, continuity of care post discharge, or physician satisfaction that have been investigated by the Health Region. Saskatchewan is known to have a shortage of physicians and thus the ability of the Saskatoon Health Region to hire and keep physicians is an important goal. Physician satisfaction and preferences are important to attract new hires and prevent burnout. This study does not take into account physicians that would prefer the employment of the hospitalist program as opposed to a practice of caring for in/out patients, such as a family physician. Unfortunately due to confidentiality issues the qualitative findings of the Hospitalist Advisory Committee could not be included in this thesis.

This thesis is a tool to aid the Saskatoon Health Region in evaluating the hospitalist program by determining the quantitative effects it has had on the efficiency and quality of inpatient care delivery. Additional qualitative research will be conducted by the care group that was established to review the hospitalist program. Future research would be beneficial as data becomes available to determine if this efficiency in care delivery persists over time, and to extend the study on the affects financial incentives and individual physician practices have on the delivery of care.

References

Acton, JP. (1975) Non-Monetary Factors in Demand for Medical services: Some Empirical Evidence. Journal of Political Economy. 83(3): 595-614.

Asif Muhammadm, Bruijinm Erik, Douglas Alex, Fisscher Olaf. (2009) Why Quality Management Programs Fail: A Strategic and Operations Management Perspective. *International Journal of Quality and ReliabilityManagement*. Vol. 26 No. 8 pp. 778-794.

Attaran Mohsen. (2000) Why does Reengineering Fail? A Practical Guide for Successful Implementation. *The Journal of Management Development*. Vol 19 pp. 794

Birch, Stephen, and Donaldson, Ca. (1987) Application of Cost-Benefit Analysis to Health Care. *Journal of Health Economics 6.*: 211-225

Brent, Robert J. (2003)*Cost-Benefit Analysis and Health Care Evaluations.* Northampton: Edward Elgar Publishing Limited,.

Cammarata, J.F. "The hospitalist: Creating a Patient-Focused Paradigm for Change(2005)." *Journal of the American Medical Directors Association, 9(3),*,: 162-164.

Canadian Institute for Health Information (2010), Patient Cost Estimator- Methodogical Notes and Glossary, http://secure.cihi.ca/cihiweb/en/downloads/PCE_methnotes_e.pdf

Dynan, Linda, Rebecca Stein, Guy David, Laura C Kenny, Mark Eckman, and Amy D Short(2009). "Determinants of hospitalist Efficiency: A Qualitative and Quantitative Study." *Medical Care Research and Review*,: 682-702.

Elixhauser, A. Steiner, C., Harris, D. R., and Coffey, R. M. (1998). “Comorbidity measures for use with administrative data”. *Medical Care, 36, 8-27*

Evans, RG., Stoddart GL. (1990). “Producing Health Capital and the Demand for Health”. *Journal of Political Economy 80 (2),* 223-225

Fama, Eugene (1980). “Agency Problems and the Theory of the Firm” *Journal of Political Economy*, 1980, 88(2), pp. 288-307

Gregory, Douglas, Walter Baigelman, and Ira B Wilson(2003). "Hospital Economics of the hospitalist ." *Health Serv Res*,: 905-918.

Hong, Zhoyong, Jun Wu, Clem Tisdell, Crystal O'leary, and James Gomes(2004). "Cost-benefit Analysis of Preventing Nosocomial Bloobstream Infections among Hemodialysis Patients in Canada in." *Value in Health*, 2010 : 42-45.

Huhtton, J. (1992). Cost-benefit analysis in health care expenditure decision-making. *Health Economics* , 231-216.

Jones AM. 2000. Health econometrics. *In The Handbook of Health Economics*, vol. 1A, Culyer AJ, Newhouse JP
(eds). Elsevier: Amsterdam; 265–346.

Kup, Yong-Fang, and James S Goodwin(2010). "Effect of hospitalists on Length of Stay in the Medical Population: Variation According to Hospital and Patient Characteristics." *The American Geriatrics Society,*: 1649-1657.

Lindenauer, Peter K, Michael B Rothberg, Penelope S Pekow, Christopher Kenwood, Evan Benjamin, and Andrew Auerbach(2007). "Outcomes of Care by hospitalists, General Internist, and Family Physicians." *New England Journal of Medicine,*.

Maskey, J.M. (2008)"change of place and pace: Family physicians as hospitalists in Canada." *Canadian Family Physician,*: 669-670.

McGuire, TG. (2000) "Physician Agency". Handbook of Health Economics, edited by JP Newhouse & AJ Culyer. Amsterdam: North Holland

McGuir, TG, Pauly, M. (1991). "Phisycian Response to Fees with Multiple Payers". Journal of Health Economics. 10: 385-410

Meltzer, David, Willard G. Manning, Jeanette Morrison, Manish Shah, and Lei Jin. "Effects of Physican Experience on Cost ans Outcomes on an Academic General Medicine Service: Results of a trial of hospitalists." *Annals of Internal Medicine* , 2002: 866-874.

Mitchell, D.M. (2008)"The Expanding or Shrinking Universe of the hospitalist." *Journal of hospitalist Medicine,*: 288-291.

Muennig, Peter. (2008) *Cost-Effectiveness Analyses in Health A Practical Approach2nd ed.* San Francisco: Jossey-Bass,.

Norbert, Marcel. (2008)*hospitalist Program Proposal*. Proposal, Saskatoon: College of Medicine, Uniniversity of Saskatchewan, and Saskatoon Regional Health Authority (Saskatoon Health Region - "SHR) Department of Medicine,.

Phelps, Charles E, and Alvin I Mushlin. (1991)"On the (Near) Equivalent of Cost-Effectiveness and Cost-Benafit Analysis." *International Journal of Technology Assessment in Health Care,*: 12-21.

Redemmeier, Donald. (1999) "A Canadian Perspective on the American hospitalist Movement." *Arch Intern Med,*: 1665-1668.

Rifkin, William D, Eric Holmboe, Hannah Scherer, and Hernan Sierra. (2004) "Comparison of hospitalist and Nonhospitalist in Inpatient Length of stay adjusted for patient and physician characteristics." *General Internal Medicine,*: 1127 to 1132.

Rosenthal, L.D., and J. Guerrasio. (2009) "Acute Care Nurse Practitioner as hospitalist: Role Description. AACN." *Advanced Critical Care,,*: 20(2), 133-136.

Scalise, Dagmara. (2006) hospitalist: in house docs can ease some vexing problems." *Hospitals & Health Networks,*: 56.

Stoddard, D. B., Jarvenpaa, S. L., & Littlejohn, M. (1996). The reality of business reengineering: Pacific bell's centrex provisioning process. *California Management Review*, Vol. 38(3) pp. 57-57.

Tale, Norbert C, and Dale W: Ameiss, Albert P Warnke (1973). "Cost/ Benefit Analysis of Public Projects." *Management Accounting (pre 1986),*: 54, 7, pg 34.

Tingle, L.E., Lambert, C.T. (2001)"Comparison of a family practice teaching service and a hospitalist model: Costs, charges, length of stay, and mortality ." *Family Medicine*,: 33 (7), pp. 511-515.

Tingle, Leslie E, and Tim Lambert(2001). "Comparison of a Family Practice Teaching Service and a hospitalist Model: Costs, Charges, Legnth of Stay, and Mortality." *Family Medicine*,: 511-515.

Wachter, B. (2007b) "Canadian hospitalists: A North-of-the-Border Lesson in Negotiation." *Wachter's World Blog: The hospitalist*,,.

Wachter, Robert(2008). "The State of hospital medicine in 2008." *Medical clinics of North America*,: 265-273.

Wachter, Robert(2001). "The Benefit of Using hospitalists". *Health Forum Journal,:* 34-37

Wachter, Robert M, and Lee Goldman(2002). "The hospitalist Movement 5 years latter." *JAMA*,: 487-494.

APPENDIX: TABLES

Table 1: Definition of Variables

Variable	Definition
Dependent	
LOS	The length of stay in days of each patient admission.
ReAd_LOS	The length of stay in days of each patient re-admission, where the diagnosis is related to the initial admission.
Mort	In hospital raw mortality; 1 if the patient died while hospitalized, 0 otherwise.
Control and Independent	
Hexp	The annual dollar amount spent per day length of stay on the hospitalist program. Calculated as the total funding expenditure on the hospitalist program in the given fiscal year divided by the total patient day's length of stay cared for by hospitalists.
Hosp	Dummy variable indicating 1 for admissions under the hospitalist program and 0 otherwise.
Postchg	Dummy variable indicating 1 for admissions after the change in physician payment structure and 0 otherwise.
Abor	The percentage of population of aboriginal descent in the patient's neighborhood of residence.
Educ	The percentage of population of with post-secondary education in the patient's neighborhood of residence.
Age	The age in years of the patient.
Fem	Dummy variable indicating patient gender; 1 for females and 0 for males.
RIW	Resource Intensity Weight, measures the relative amount of hospital resources expected to be consumed during the delivery of care given he patients characteristics and diagnosis.
ERIW	Expected Resource Intensity Weight, the measure of severity, calculated using the CIHI patient cost estimator index and actual patient age, gender, and diagnosis.
HA	Dummy variable indicating the hospitalist; 1 for hospitalist 3 and 0 otherwise.
HB	Dummy variable indicating the hospitalist; 1 for hospitalist 8 and 0 otherwise.
HC	Dummy variable indicating the hospitalist; 1 for hospitalist 11 and 0 otherwise.
HD	Dummy variable indicating the hospitalist; 1 for hospitalist 19 and 0 otherwise.
HE	Dummy variable indicating the hospitalist; 1 for hospitalist 21 and 0 otherwise.

HF	Dummy variable indicating the hospitalist; 1 for hospitalist 22 and 0 otherwise.
ETLOS	Expected length of stay calculated from the Canadian Institute of Health Information index, for the admitted patient given characteristics and diagnosis.

Table 2.1: Summary Statistics

This table contains summary statistics for the data in the entire sample.

Variable	N	Minimum	Maximum	Mean	Median	Std Dev	Skewness	Kurtosis	Variance
Dependent									
LOS	12667	1.0000	147.0000	10.1581***	6.0000	13.4245	3.9824	21.5850	180.2171
ReAd_LOS	12667	0.0000	148.0000	0.6767***	0.0000	4.7118	12.5019	216.8661	22.20064
Died	12667	0.0000	1.0000	0.0790***	0.0000	0.2698	3.1213	7.7437	0.072785
Control and Independent									
Hexp	12666	0.0000	44.0871	22.7777***	38.3145	19.8229	-0.6699	-1.5123	392.9491
Hosp	12667	0.0000	1.0000	0.6646***	1.0000	0.4722	-0.6972	-1.5142	0.2229
Postchg	12667	0.0000	1.0000	0.1070***	0.0000	0.3091	2.5436	4.4704	0.0955
abor	12667	0.0032	0.5824	0.1102***	0.0978	0.0967	2.9845	11.2692	0.00936
educ	12667	0.2453	0.6633	0.4586***	0.4133	0.0863	-0.0518	-0.7871	0.007454
Age	12667	16.0000	103.0000	68.6014***	74.0000	18.9744	-0.7782	-0.1910	360.028
fem	12667	0.0000	1.0000	0.5191***	1.0000	0.4997	-0.0766	-1.9944	0.249653
RIW	12667	0.1380	58.5834	1.6135***	0.9513	2.4116	7.9489	104.3837	5.815819
HA	12667	0.0000	1.0000	0.0587***	0.0000	0.2350	3.7569	12.1160	0.05522
HB	12667	0.0000	1.0000	0.0521***	0.0000	0.2222	4.0313	14.2535	0.049393
HC	12667	0.0000	1.0000	0.1176***	0.0000	0.3222	2.3740	3.6366	0.1038
HD	12667	0.0000	1.0000	0.0691***	0.0000	0.2536	3.3990	9.5550	0.064311
HE	12667	0.0000	1.0000	0.0669***	0.0000	0.2498	3.4684	10.0312	0.0624
HF	12667	0.0000	1.0000	0.0026***	0.0000	0.0510	19.5177	379.0012	0.0026
ETLOS	12667	1.0000	31.4191	5.5213***	5.0000	2.6453	1.2805	3.5332	6.9978

Asterisks *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 2.2: Summary Statistics

This table contains summary statistics for the data for our Typical Sub Sample (Below Expected LOS + 0 Standard Deviations)

Variable	N	Minimum	Maximum	Mean	Median	Std Dev	Skewness	Kurtosis	Variace
Dependent									
LOS	5298	1.0000	17.0000	3.3411***	3.0000	2.0802	1.3770	2.8614	4.327106
ReAd_LOS	5298	0.0000	85.0000	0.5610***	0.0000	3.9303	11.5000	168.8498	15.44739
Died	5298	0.0000	1.0000	0.0791***	0.0000	0.2699	3.1202	7.7387	0.072846
Control and Independent									
Hexp	5298	0.0000	44.0872	27.8383***	38.3150	19.8148	-0.6758	-1.5080	392.6277
Hosp	5298	0.0000	1.0000	0.6657***	1.0000	0.4718	-0.7028	-1.5066	0.222578
Postchg	5298	0.0000	1.0000	0.1068***	0.0000	0.3089	2.5463	4.4854	0.095438
abor	5298	0.0032	0.5824	0.1082***	0.0978	0.0927	2.9975	11.9135	0.008599
educ	5298	0.2453	0.6633	0.4569***	0.4133	0.0861	0.0008	-0.7791	0.007406
Age	5298	16.0000	103.0000	67.7554***	73.0000	19.8498	-0.7286	-0.3904	394.0153
fem	5298	0.0000	1.0000	0.4977***	0.0000	0.5000	0.0091	-2.0007	0.250042
RIW	5298	0.1380	19.3647	0.8587***	0.7902	0.5369	9.5631	274.5883	0.288304
HA	5298	0.0000	1.0000	0.0447***	0.0000	0.2067	4.4059	17.4188	0.042741
HB	5298	0.0000	1.0000	0.0393***	0.0000	0.1942	4.7460	20.5325	0.037726
HC	5298	0.0000	1.0000	0.1444***	0.0000	0.3515	2.0240	2.0974	0.123568
HD	5298	0.0000	1.0000	0.0664***	0.0000	0.2491	3.4827	10.1330	0.062038
HE	5298	0.0000	1.0000	0.0683***	0.0000	0.2523	3.4228	9.7190	0.063671
HF	5298	0.0000	1.0000	0.0028***	0.0000	0.0531	18.7190	348.5328	0.002824
ETLOS	5298	1.0000	31.4191	6.0280***	5.6322	2.8041	1.1725	3.6805	7.863178

Asterisks *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 2.3: Summary Statistics

This table contains summary statistics for the data for our atypical Sub Sample (Above Expected LOS + 0 Standard Deviations)

Variable	N	Minimum	Maximum	Mean	Median	Std Dev	Skewness	Kurtosis	Variance
Dependent									
LOS	7369	2.0000	147.0000	15.0593***	10.0000	15.7877	3.3198	14.3520	249.2515
ReAd_LOS	7368	0.0000	148.0000	0.7599***	0.0000	5.2003	12.3986	211.0443	27.0428
Died	7369	0.0000	1.0000	0.0790***	0.0000	0.2697	3.1227	7.7533	0.072752
Control and Independent									
Hexp	7369	0.0000	44.0872	27.7341***	38.3150	19.8300	-0.6659	-1.5206	393.229
Hosp	7369	0.0000	1.0000	0.6637***	1.0000	0.4725	-0.6933	-1.5198	0.223224
Postchg	7369	0.0000	1.0000	0.1071***	0.0000	0.3092	2.5421	4.4634	0.095619
Abor	7369	0.0032	0.5824	0.1117***	0.0978	0.0995	2.9655	10.8030	0.0099
Educ	7369	0.2453	0.6633	0.4598***	0.4133	0.0865	-0.0895	-0.7882	0.007486
Age	7369	16.0000	103.0000	69.2097***	74.0000	18.2964	-0.8058	-0.0464	334.758
Fem	7369	0.0000	1.0000	0.5345***	1.0000	0.4988	-0.1385	-1.9814	0.248841
RIW	7369	0.2276	58.5834	2.1562***	1.2639	3.0143	6.4418	67.6435	9.086161
HA	7369	0.0000	1.0000	0.0687***	0.0000	0.2529	3.4120	9.6443	0.06396
HB	7369	0.0000	1.0000	0.0613***	0.0000	0.2400	3.6570	11.3770	0.057583
HC	7369	0.0000	1.0000	0.0984***	0.0000	0.2979	2.6974	5.2777	0.088718
HD	7369	0.0000	1.0000	0.0710***	0.0000	0.2568	3.3423	9.1733	0.065945
HE	7369	0.0000	1.0000	0.0658***	0.0000	0.2480	3.5028	10.2721	0.061493
HF	7369	0.0000	1.0000	0.0024***	0.0000	0.0494	20.1633	404.6667	0.002437
ETLOS	7369	1.0000	25.9706	5.1570***	4.9000	2.4616	1.3510	3.3006	6.0593

Asterisks *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 2.4: Summary Statistics

This table contains summary statistics for the fiscal years contained in the sample.

Variable	N	Minimum	Maximum	Mean	Median	Std Dev	Skewness	Kurtosis	Variance
Fiscal Year									
2006-07	889	1	104	8.8459***	6	9.7055	3.3571	17.2300	94.1958
2007-08	3363	1	271	10.3321	6	15.4977	5.3535	46.4561	240.181
2008-09	3050	1	206	11.6587***	6	18.3163	4.3544	25.6891	335.4882
2009-10	3135	1	257	10.0618	6	156.9904	12.5295	64.5848	156.9904
2010-11	2240	1	199	9.4794**	6	11.2503	5.0138	50.4716	126.5695

The fiscal year LOS means are tested to be statistically different from the entire sample mean. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 3: Pearson Correlation Matrix

This table contains the pair wise correlation coefficients for variables.

	hexp	*abor*	*educ*	*ave_inc*	*Admit_ date*	*Age*	*fem*	*RIW*	*read_ LOS*	*LOS*	*Died*	*Home*	*Other*	*cxlos*	*ETLOS*
hexp	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.
abor	0.00	1	.	.	.	.	.	.	.	.	.	.	.	.	.
educ	0.01	0.18***	1	.	.	.	.	.	.	.	.	.	.	.	.
ave_inc	0.02*	0.07***	0.77***	1	.	.	.	.	.	.	.	.	.	.	.
Admit_date	0.79***	0.00	-0.01	0.01	1	.	.	.	.	.	.	.	.	.	.
Age	0.00	-0.01	0.22***	0.20***	-0.01	1	.	.	.	.	.	.	.	.	.
fem	-0.01	0.01*	0.08***	0.06***	0.00	0.08***	1	.	.	.	.	.	.	.	.
RIW	0.03***	0.04***	0.00	-0.01	-0.01	0.05***	-0.02***	1	.	.	.	.	.	.	.
read_LOS	-0.01	0.01	0.02**	0.01	-0.01	0.02*	0.00	0.00	1	.	.	.	.	.	.
LOS	0.02**	0.01	0.06***	0.04***	-0.04***	0.12***	0.02***	0.77***	0.00	1	.	.	.	.	.
Died	0.00	-0.01	0.04***	0.03***	-0.01	0.17***	-0.02*	0.10***	-0.04***	0.07***	1	.	.	.	.
Home	-0.01	0.01	-0.09***	-0.08***	-0.01	-0.32***	-0.05***	-0.23***	-0.01	-0.28***	-0.38***	1	.	.	.
Dist_Other	0.01	-0.01	0.07***	0.07***	0.01	0.24***	0.06***	0.18***	0.03***	0.26***	-0.19***	-0.84***	1	.	.
cxlos	0.02**	0.01	0.05**	0.04***	-0.04***	0.12***	0.02**	0.78***	0.01	0.98***	0.07***	-0.27***	0.25***	1	.
ETLOS	0.02*	0.00	0.10***	0.10***	0.01	0.33***	0.02*	0.17***	0.01	0.19***	0.15***	-0.24***	0.17***	0.19***	1

Asterisks *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 4.1: Atypical - Above ELOS + 0 Standard Deviations

	1	2	3	4
VARIABLES		Ln(LOS)		
Hosp	0.06280***			
	(0.0172)			
HExp		0.0016***		
		(0.0004)		
Admit_Date			0.0081***	
			(0.0019)	
Admit_Date^2			-2.280E-7***	
			(5.028E-8)	
PostChg				-0.0433
				(0.0309)
ERIW	0.6189***	0.6189***	0.6178***	0.5792***
	(0.0193)	(0.0193)	(0.0193)	(0.0334)
Educ	0.2486***	0.2480***	0.2332***	0.2349
	(0.0992)	(0.0992)	(0.0908)	(0.1805)
Abor	0.0348	0.0346	0.0392	0.0913
	(0.0775)	(0.0775)	(0.0775)	(0.1534)
Age	0.0061***	0.0061***	0.0061***	0.0042***
	(0.0004)	(0.0004)	(0.0004)	(0.0009)
Female	0.0159	0.0160	0.0163	-0.0071
	(0.0159)	(0.0159)	(0.0159)	(0.0311)
HA	0.0466	0.0467	0.0256	0.2630
	(0.0339)	(0.0339)	(0.0340)	(0.4413)
HB	0.0445	0.0443	0.0398	0.0138
	(0.0310)	(0.0310)	(0.0310)	(0.0636)
HC	0.0066	0.0065	0.0017	-0.0387
	(0.0284)	(0.0284)	(0.0284)	(0.0517)
HD	0.0837***	0.0838***	0.0838***	0.1338**
	(0.0315)	(0.0315)	(0.0315)	(0.0548)
HE	-0.0628**	-0.0634**	-0.0818**	
	(0.0316)	(0.0316)	(0.0321)	
HF	-0.1505	-0.1502	-0.1959	
	(0.1338)	(0.1338)	(0.1328)	
Constant	1.2090***	1.2078***	-71.4286***	1.4416***
	(0.0497)	(0.0497)	(16.0543)	(0.0947)
Observations	7369	7369	7369	1636
R-Squared	0.2105	0.2106	0.2111	0.1953
F-Value	163.43	163.43	151.43	32.83
Prob (F-Stat)	<.0001	<.0001	<.0001	<.0001

This table presents Ordinary Least Squares regression estimation. The dependent variable is the difference between initial admission length of stay per patient and the national average given the patients age, gender, and diagnosis. The test variables are HOSP, HEXP, ADMIT_DATE, and POSTCHG. Refer to appendix for variable descriptions. Regressions are estimated using robust standard errors and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 4.2: Atypical - Above ELOS + 1 Standard Deviation

	1	2	3	4
VARIABLES		Ln(LOS)		
Hosp	0.03906**			
	(0.0188)			
HExp		0.0010**		
		(0.0004)		
Admit_Date			0.0235***	
			(0.0043)	
Admit_Date^2			-2.962E-7***	
			(5.338E-8)	
PostChg				-0.0343
				(0.0315)
ERIW	0.4678***	0.4676***	0.4640***	0.4473***
	(0.0188)	(0.0188)	(0.0187)	(0.0343)
Educ	0.1425	0.1421	0.1252	0.0906
	(0.0965)	(0.0965)	(0.0965)	(0.1874)
Abor	0.0168	0.0161	0.0270	-0.0118
	(0.0810)	(0.0810)	(0.0812)	(0.1599)
Age	0.0033***	0.0033***	0.0033***	0.0004
	(0.0005)	(0.0005)	(0.0005)	(0.0009)
Female	-0.0018	-0.0018	-0.0008	-0.0317
	(0.0170)	(0.0170)	(0.0169)	(0.0318)
HA	0.0062	0.0074	-0.0254	-0.0625
	(0.0380)	(0.0380)	(0.0380)	(0.3713)
HB	-0.0277	-0.0278	-0.0358	-0.0734
	(0.0338)	(0.0338)	(0.0336)	(0.0635)
HC	0.0454	0.0454	0.0365	0.0050
	(0.0302)	(0.0302)	(0.0301)	(0.0546)
HD	0.0377	0.0379	0.0410	-0.0246
	(0.0320)	(0.0320)	(0.0317)	(0.0516)
HE	-0.0228	-0.0229	-0.0557	
	(0.0356)	(0.0356)	(0.0362)	
HF	-0.1504	-0.1497	-0.2127	
	(0.1362)	(0.1366)	(0.1350)	
Constant	1.9458***	1.9433***	-464.535***	2.2046***
	(0.0537)	(0.0537)	(84.514)	(0.0987)
Observations	4901	4901	4901	1109
R-Squared	0.1567	0.1569	0.1620	0.1544
F-Value	75.69	75.79	72.69	16.68
Prob (F-Stat)	<.0001	<.0001	<.0001	<.0001

This table presents Ordinary Least Squares regression estimation. The dependent variable is the difference between initial admission length of stay per patient and the national average given the patients age, gender, and diagnosis. The test variables are HOSP, HEXP, ADMIT_DATE, and POSTCHG. Refer to appendix for variable descriptions. Regressions are estimated using robust standard errors and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 4.3: Atypical - Above ELOS + 2 Standard Deviations

	1	2	3	4
VARIABLES		Ln(LOS)		
Hosp	0.0221			
	(0.0211)			
HExp		0.0006		
		(0.0005)		
Admit_Date			0.0243***	
			(0.0046)	
Admit_Date^2			-3.068E-7***	
			(5.819E-8)	
PostChg				-0.0178
				(0.0338)
ERIW	0.3775***	0.3774***	0.3734***	0.3393***
	(0.0191)	(0.0191)	(0.0191)	(0.0352)
Educ	0.1242	0.1237	0.1080	0.0556
	(0.1065)	(0.1065)	(0.1062)	(0.1971)
Abor	-0.0444	-0.0451	-0.0321	-0.0725
	(0.0883)	(0.0883)	(0.0879)	(0.1703)
Age	0.0015***	0.0015***	0.0015***	0.0016
	(0.0005)	(0.0005)	(0.0005)	(0.0010)
Female	-0.0149	-0.0149	-0.0153	-0.0324
	(0.0186)	(0.0186)	(0.0185)	(0.0342)
HA	0.0693	0.0705	0.0351	0.1709
	(0.0444)	(0.0443)	(0.0443)	(0.4711)
HB	-0.0276	-0.0276	-0.0390	-0.0786
	(0.0382)	(0.0382)	(0.0378)	(0.0701)
HC	0.0447	0.0447	0.0337	0.0147
	(0.0320)	(0.0320)	(0.0318)	(0.0592)
HD	0.0206	0.0207	0.0225	-0.0461
	(0.0344)	(0.0344)	(0.0340)	(0.0551)
HE	0.0331	0.0331	-0.0039	
	(0.0400)	(0.0400)	(0.0407)	
HF	-0.2677	-0.2670	-0.3350**	
	(0.1652)	(0.1655)	(0.1646)	
Constant	2.4265***	2.4246***	-479.71***	2.7014***
	(0.0593)	(0.0593)	(92.135)	(0.1064)
Observations	3463	3463	3463	779
R-Squared	0.1241	0.1242	0.1333	0.1183
F-Value	40.75	40.79	40.82	8.56
Prob (F-Stat)	<.0001	<.0001	<.0001	<.0001

This table presents Ordinary Least Squares regression estimation. The dependent variable is the difference between initial admission length of stay per patient and the national average given the patients age, gender, and diagnosis. The test variables are HOSP, HEXP, ADMIT_DATE, and POSTCHG. Refer to appendix for variable descriptions. Regressions are estimated using robust standard errors and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 4.4: Below ELOS + 0 Standard Deviations

	5	6	7	8
VARIABLES		Ln(LOS)		
Hosp	0.0001			
	(0.0159)			
HExp		0.00003		
		(0.0004)		
Admit_Date			0.0003	
			(0.0018)	
Admit_Date^2			-8.926E-9	
			(4.935E-8)	
PostChg				-0.0677*
				(0.0337)
ERIW	0.5297***	0.5298***	0.5295***	0.5592***
	(0.0200)	(0.0200)	(0.0200)	(0.0342)
Educ	0.2415***	0.2413***	0.2414***	0.3347*
	(0.0904)	(0.0904)	(0.0903)	(0.2011)
Abor	-0.0006	-0.0006	-0.0023	0.1959
	(0.0824)	(0.0824)	(0.0825)	(0.1917)
Age	0.0046***	0.0046***	0.0046***	0.0033***
	(0.0004)	(0.0004)	(0.0004)	(0.0009)
Female	0.0008	0.0008	0.0014	0.0406
	(0.0147)	(0.0147)	(0.0147)	(0.0339)
HA	0.1600***	0.1604***	0.1559***	0.4891
	(0.0347)	(0.0347)	(0.0348)	(0.5621)
HB	0.0377	0.0377	0.0377	0.0918
	(0.0385)	(0.0385)	(0.0385)	(0.0819)
HC	-0.0722***	-0.0721***	-0.0733***	-0.0455
	(0.0213)	(0.0213)	(0.0213)	(0.0509)
HD	0.0240	0.0240	0.0242	-0.0579
	(0.0295)	(0.0295)	(0.0295)	(0.0587)
HE	-0.0054	-0.0053	-0.0096	
	(0.0286)	(0.0286)	(0.0289)	
HF	-0.0669	-0.0669	-0.0712	
	(0.1125)	(0.1125)	(0.1128)	
Constant	0.0403	0.0395	-2.4416	0.0581
	(0.0456)	(0.0456)	(15.744)	(0.1005)
Observations	5298	5298	5298	1108
R-Squared	0.2689	0.2689	0.2690	0.2693
F-Value	162.03	162.03	149.54	33.63
Prob (F-Stat)	<.0001	<.0001	<.0001	<.0001

This table presents Ordinary Least Squares regression estimation. The dependent variable is the difference between initial admission length of stay per patient and the national average given the patients age, gender, and diagnosis. The test variables are HOSP, HEXP, ADMIT_DATE, and POSTCHG. Refer to appendix for variable descriptions. Regressions are estimated using robust standard errors and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 4.5: Below ELOS + 1 Standard Deviation

	5	6	7	8
VARIABLES		Ln(LOS)		
Hosp	-0.0180			
	(0.0144)			
HExp		-0.00004		
		(0.0003)		
Admit_Date			-0.0067*	
			(0.0035)	
Admit_Date^2			8.406E-8	
			(4.447E-8)	
PostChg				-0.0549*
				(0.0301)
ERIW	0.4036***	0.4036***	0.4041***	0.4433***
	(0.0164)	(0.0164)	(0.0164)	(0.0308)
Educ	0.0969	0.0971	0.1014	0.0586
	(0.0816)	(0.0816)	(0.0816)	(0.1768)
Abor	0.0791	0.0790	0.0807	0.3204**
	(0.0722)	(0.0722)	(0.0722)	(0.1607)
Age	0.0047***	0.0047***	0.0047***	0.0041***
	(0.0004)	(0.0004)	(0.0004)	(0.0008)
Female	0.0205	0.0205	0.0200	0.0295
	(0.0134)	(0.0134)	(0.0134)	(0.0302)
HA	0.1717***	0.1720***	0.1740***	-0.7832
	(0.0285)	(0.0285)	(0.0285)	(0.6087)
HB	0.1176***	0.1176***	0.1184***	0.1401**
	(0.0337)	(0.0337)	(0.0337)	(0.0701)
HC	-0.1269***	-0.1269***	-0.1257***	-0.0647
	(0.0204)	(0.0204)	(0.0204)	(0.0460)
HD	-0.0124	-0.0124	-0.0120	-0.1441**
	(0.0269)	(0.0269)	(0.0269)	(0.02563)
HE	0.0154	0.0156	0.0182	
	(0.0260)	(0.0260)	(0.0260)	
HF	-0.0503	-0.0502	-0.0398	
	(0.1143)	(0.1143)	(0.1143)	
Constant	0.4698***	0.4696***	134.002*	0.4907***
	(0.0416)	(0.0416)	(0.0416)	(0.0897)
Observations	7766	7766	7766	1635
R-Squared	0.1644	0.1644	0.1647	0.1793
F-Value	127.14	127.14	117.60	29.55
Prob (F-Stat)	<.0001	<.0001	<.0001	<.0001

This table presents Ordinary Least Squares regression estimation. The dependent variable is the difference between initial admission length of stay per patient and the national average given the patients age, gender, and diagnosis. The test variables are HOSP, HEXP, ADMIT_DATE, and POSTCHG. Refer to appendix for variable descriptions. Regressions are estimated using robust standard errors and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 4.6: Below ELOS + 2 Standard Deviations

	5	6	7	8
VARIABLES		Ln(LOS)		
Hosp	-0.0119			
	(0.0143)			
HExp		-0.0003		
		(0.0003)		
Admit_Date			-0.0090**	
			(0.0035)	
Admit_Date^2			1.133E-7**	
			(4.09E-8)	
PostChg				-0.0607**
				(0.0297)
ERIW	0.3476***	0.3476***	0.3483***	0.3598***
	(0.0157)	(0.0157)	(0.0157)	(0.0312)
Educ	0.0936	0.0938	0.0999	0.0238
	(0.0811)	(0.0811)	(0.0811)	(01765)
Abor	0.0715	0.0714	0.0733	0.3479**
	(0.0708)	(0.0708)	(0.0706)	(0.1583)
Age	0.0051***	0.0051***	0.0051***	0.0052***
	(0.0004)	(0.0004)	(0.0004)	(0.0008)
Female	0.0289**	0.0289**	0.0280**	0.0395
	(0.0134)	(0.0134)	(0.0134)	(0.0299)
HA	0.2053***	0.2050***	0.2097***	0.0102
	(0.0271)	(0.0271)	(0.0271)	(0.4667)
HB	0.1590***	0.1591***	0.1601***	0.1915***
	(0.0318)	(0.0318)	(0.0318)	(0.0667)
HC	-0.1555***	-0.1555***	-0.1535***	-0.0781*
	(0.0210)	(0.0210)	(0.0210)	(0.0462)
HD	0.0038	0.0038	0.0039	-0.0645
	(0.0272)	(0.0272)	(0.0273)	(0.0545)
HE	0.0164	0.0165	0.0228	
	(0.0259)	(0.0259)	(0.0262)	
HF	-0.0826	-0.0826	-0.0657	
	(0.1199)	(0.1199)	(0.1202)	
Constant	0.6321***	0.6329***	179.914***	0.6557***
	(0.0417)	(0.0417)	(69.760)	(0.0894)
Observations	9204	9204	9204	1965
R-Squared	0.1259	0.1260	0.1265	0.1268
F-Value	110.36	110.38	102.40	23.61
Prob (F-Stat)	<.0001	<.0001	<.0001	<.0001

This table presents Ordinary Least Squares regression estimation. The dependent variable is the difference between initial admission length of stay per patient and the national average given the patients age, gender, and diagnosis. The test variables are HOSP, HEXP, ADMIT_DATE, and POSTCHG. Refer to appendix for variable descriptions. Regressions are estimated using robust standard errors and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 5.1: Final Time period of Sample

	9
VARIABLES	Ln(LOS)
Admit_Date	-0.00046***
	(0.00014)
ERIW	0.3806***
	(0.0330)
Educ	0.0753
	(0.1781)
Abor	0.5332***
	(0.1412)
Age	0.0070***
	(0.0009)
Female	-0.0400
	(0.0308)
Constant	9.0281***
	(2.5556)
Observations	3483
R-Squared	0.0848
F-Value	53.65
Prob (F-Stat)	<.0001

This table presents Ordinary Least Squares regression estimation. The dependent variable is the difference between initial admission length of stay per patient and the national average given the patients age, gender, and diagnosis. The test variable is ADMIT_DATE. Refer to appendix for variable descriptions. Regressions are estimated using robust standard errors and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 5.2: Hospitalist time effect on LOS

	9
VARIABLES	Ln(LOS)
Admit_Date	-0.00016***
	(0.00004)
Hosp_admit_date	0.000007***
	(0.00000)
ERIW	0.38510***
	(0.0341)
Hosp_ERIW	0.02260
	(0.0408)
Educ	0.5278***
	(0.1671)
Hosp_Educ	-0.3240
	(0.2064)
Abor	-0.04344
	(0.1446)
Hosp_Abor	0.2801
	(0.1776)
Age	0.00855***
	(0.0008)
Hosp_Age	-0.00087
	(0.0010)
Female	0.03769
	(0.0281)
	0.01921
	(0.0349)
Constant	6.7991***
	(1.3936)
Observations	12667
R-Squared	0.0904
F-Value	104.74
Prob (F-Stat)	<.0001

This table presents Ordinary Least Squares regression estimation. The dependent variable is the difference between initial admission length of stay per patient and the national average given the patients age, gender, and diagnosis. The test variable is ADMIT_DATE. Refer to appendix for variable descriptions. Regressions are estimated using robust standard errors and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 6: Readmission

	13	14	15	16
VARIABLES		ReAd_LOS		
HExp	-0.0022			
	(0.0020)			
Hosp		-0.0875		
		(0.0856)		
Admit_Date			-0.0000	
			(0.0001)	
PostChg				0.2061
				(0.1232)
Abor	-0.3247	-0.3248	-0.3232	-0.3223
	(0.4471)	(0.4471)	(0.4468)	(0.4467)
Educ	0.4162	0.4151	0.4074	0.4233
	(0.4881)	(0.4881)	(0.4878)	(0.4876)
Age	0.0004	0.0004	0.0004	0.0004
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Female	-0.1208	-0.1205	-0.1201	-0.1222
	(0.0809)	(0.0809)	(0.0809)	(0.0809)
RIW	-0.0343	-0.0343	-0.0350	-0.0348
	(0.0217)	(0.0217)	(0.0217)	(0.0217)
HA	-0.2256	-0.2254	-0.1983	-0.1660
	(0.1962)	(0.1963)	(0.1972)	(0.1946)
HB	0.0339	0.0339	0.0318	0.0334
	(0.1863)	(0.1863)	(0.1863)	(0.1863)
HC	0.3026***	0.3026***	0.3067***	0.3148***
	(0.1174)	(0.1174)	(0.1174)	(0.1174)
HD	0.2357	0.2358	0.2341	0.2325
	(0.1512)	(0.1512)	(0.1512)	(0.1512)
HE	0.0875	0.0866	0.0944	0.1254
	(0.1621)	(0.1622)	(0.1635)	(0.1629)
HF	0.1222**	0.1222**	0.1232**	0.1263***
	(0.4889)	(0.4889)	(0.4893)	(0.4890)
Constant	-2.9789***	-2.9799***	-2.8007	-3.0707***
	(0.2503)	(0.2503)	(1.7808)	(0.2452)
Observations	12667	12667	12667	12667
AIC	5146.26	5146.27	5146.27	5146.78
Likelihood Ratio	23.47	21.95	20.94	23.48
Likelihood (DF)	13	13	13	13
Pr > ChiSq	0.0364	0.0380	0.0513	0.0239

This table presents Binary Logistic regression estimation. The dependent variable is the inpatient readmission rate. The test variables are HOSP, HEXP, ADMIT_DATE, and POSTCHG. Refer to appendix for variable descriptions. Regressions are estimated using robust standard errors and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 7: Mortality

	9	10	11	12
VARIABLES		MORT		
HExp	0.0000			
	(0.0017)			
Hosp		0.0011		
		(0.0732)		
Admit_Date			-0.0000	
			(0.0000)	
PostChg				0.0354
				(0.1104)
RIW	0.1039***	0.1039***	0.1038***	0.1039***
	(0.0099)	(0.0099)	(0.0099)	(0.0099)
Abor	-0.5041	-0.5041	-0.5032	-0.5040
	(0.3992)	(0.3992)	(0.3993)	(0.3992)
Educ	0.0938	0.0938	0.0946	0.0967
	(0.4025)	(0.4024)	(0.4025)	(0.4024)
Age	0.0485***	0.0485***	0.0485***	0.0485***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Female	-0.2608***	-0.2608***	-0.2606***	-0.2612***
	(0.0685)	(0.0685)	(0.0685)	(0.0685)
HA	0.1413	0.1414	0.1277	0.1454
	(0.1345)	(0.1347)	(0.1357)	(0.1327)
HB	0.0637	0.0637	0.0627	0.0634
	(0.1465)	(0.1465)	(0.1466)	(0.1465)
HC	-0.0626	-0.0626	-0.0647	-0.0616
	(0.1121)	(0.1121)	(0.1122)	(0.1121)
HD	-0.0029	-0.0029	-0.0031	-0.0027
	(0.1316)	(0.1316)	(0.1316)	(0.1316)
HE	-0.0590	-0.0590	-0.0678	-0.0546
	(0.1427)	(0.1427)	(0.1439)	(0.1431)
HF	0.4216	0.4216	0.4129	0.4261
	(0.6217)	(0.6217)	(0.6220)	(0.6219)
Constant	-6.1305***	-6.1306***	-5.5073***	-6.1355***
	(0.2607)	(0.2608)	(1.5179)	(0.2574)
Observations	12667	12667	12667	12667
AIC	7003.80	7003.80	7003.80	7003.80
Likelihood Ratio	564.57	564.57	564.74	564.67
Likelihood (DF)	12	12	12	12
Pr > ChiSq	<.0001	<.0001	<.0001	<.0001

This table presents Binary Logistic regression estimation. The dependent variable is the inpatient raw mortality rate. The test variables are HOSP, HEXP, ADMIT_DATE, and POSTCHG. Refer to appendix for variable descriptions. Regressions are estimated using robust standard errors and t-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 8.1 Current Annual Average LOS							
Costs: Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS	Total LOS Days Billed	GP Hospital Care Fee ($30.20 perday)	# of patient seen in 48 weeks	Hospital Discharge Fee ($12.10)	Total FFS Earned
$ 312,000.00	20	9.631515	336	$ 202,737.61	697	$ 8,433.70	$ 523,171.31
$ 312,000.00	21	9.631515	336	$ 212,918.12	732	$ 8,857.20	$ 533,775.32
$ 312,000.00	22	9.631515	336	$ 223,098.63	767	$ 9,280.70	$ 544,379.33
$ 312,000.00	23	9.631515	336	$ 233,279.15	802	$ 9,704.20	$ 554,983.35
$ 312,000.00	24	9.631515	336	$ 243,459.66	837	$ 10,127.70	$ 565,587.36
$ 312,000.00	25	9.631515	336	$ 253,640.17	872	$ 10,551.20	$ 576,191.37

Table 8.2 Forecasted Decrease in LOS by 15.59%											
Costs: Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS	Total LOS Days Billed	GP Hospital Care Fee ($30.20 perday)	# of patient seen in 48 weeks	Hospital Discharge Fee ($12.10)	Total FFS Earned	Change in FFS	# of new patients seen	Cost per Patient	"Benefits"
$ 312,000.00	20	8.130	336	$ 202,795.59	826	$ 9,994.60	$ 212,790.19	$ (310,381.12)	129	$ 290.87	$ 39,083.36
$ 312,000.00	21	8.130	336	$ 212,861.72	867	$ 10,490.70	$ 223,352.42	$ (310,422.90)	135	$ 290.87	$ 40,901.19
$ 312,000.00	22	8.130	336	$ 223,173.36	909	$ 10,998.90	$ 234,172.26	$ (310,207.07)	142	$ 290.87	$ 43,021.99
$ 312,000.00	23	8.130	336	$ 233,239.49	950	$ 11,495.00	$ 244,734.49	$ (310,248.86)	148	$ 290.87	$ 44,839.82
$ 312,000.00	24	8.130	336	$ 243,305.61	991	$ 11,991.10	$ 255,296.71	$ (310,290.65)	154	$ 290.87	$ 46,657.65
$ 312,000.00	25	8.130	336	$ 253,617.25	1033	$ 12,499.30	$ 266,116.55	$ (310,074.82)	161	$ 290.87	$ 48,778.45

Table 8.3 Pre Payment Change Average Typical LOS (Below 0 Standard Deviations)							
Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS (A-typical)	Total LOS Days Billed	GP Hospital Care (Average)	# of patient seen in 48 weeks (Ave)	Hospital Discharge ($12.10) (A-Typ)	Total FFS Earned
$ 312,000.00	20	4.970992	136	$ 81,817.56	545	$ 6,594.50	$ 88,412.06
$ 312,000.00	21	4.970992	136	$ 86,021.03	573	$ 6,933.30	$ 92,954.33
$ 312,000.00	22	4.970992	136	$ 90,074.38	600	$ 7,260.00	$ 97,334.38
$ 312,000.00	23	4.970992	136	$ 94,127.73	627	$ 7,586.70	$ 101,714.43
$ 312,000.00	24	4.970992	136	$ 98,331.20	655	$ 7,925.50	$ 106,256.70
$ 312,000.00	25	4.970992	136	$ 102,384.55	682	$ 8,252.20	$ 110,636.75

Table 8.4 Post Payment Change Average LOS 6.07% Decrease (Typical observations Below 0 Standard Deviation)										
Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS (A-typical)	Total LOS Days Billed	GP Hospital Care (Average)	# of patient seen in 48 weeks (Ave)	Hospital Discharge ($12.10) (A-Typ)	Total FFS Earned	# of new patients seen	Cost per Patient	"Benefits"
$ 312,000.00	20	4.669253	136	$ 81,927.65	581	$ 7,030.10	$ 88,957.75	36	150.123969	$ 5,840.06
$ 312,000.00	21	4.669253	136	$ 86,016.98	610	$ 7,381.00	$ 93,397.98	37	150.123969	$ 6,002.29
$ 312,000.00	22	4.669253	136	$ 90,106.31	639	$ 7,731.90	$ 97,838.21	39	150.123969	$ 6,326.73
$ 312,000.00	23	4.669253	136	$ 94,195.64	668	$ 8,082.80	$ 102,278.44	41	150.123969	$ 6,651.18
$ 312,000.00	24	4.669253	136	$ 98,284.98	697	$ 8,433.70	$ 106,718.68	42	150.123969	$ 6,813.41
$ 312,000.00	25	4.669253	136	$ 102,374.31	726	$ 8,784.60	$ 111,158.91	44	150.123969	$ 7,137.85

Table 8.5 Pre Payment Change Average Typical LOS (Below +1 Standard Deviations)							
Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS (A-typical)	Total LOS Days Billed	GP Hospital Care (Average)	# of patient seen in 48 weeks (Ave)	Hospital Discharge ($12.10) (A-Typ)	Total FFS Earned
$ 312,000.00	20	4.217125	200	$ 120,861.97	949	$ 11,482.90	$ 132,344.87
$ 312,000.00	21	4.217125	200	$ 126,847.76	996	$ 12,051.60	$ 138,899.36
$ 312,000.00	22	4.217125	200	$ 132,960.90	1044	$ 12,632.40	$ 145,593.30
$ 312,000.00	23	4.217125	200	$ 138,946.69	1091	$ 13,201.10	$ 152,147.79
$ 312,000.00	24	4.217125	200	$ 145,059.84	1139	$ 13,781.90	$ 158,841.74
$ 312,000.00	25	4.217125	200	$ 151,045.62	1186	$ 14,350.60	$ 165,396.22

Table 8.6 Post Payment Change Average Typical LOS 5.49% Decrease (Typical observations Below + 1 Standard Deviation)										
Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS (A-typical)	Total LOS Days Billed	GP Hospital Care (Average)	# of patient seen in 48 weeks (Ave)	Hospital Discharge ($12.10) (A-Typ)	Total FFS Earned	# of new patients seen	Cost per Patient	"Benefits"
$ 312,000.00	20	3.985605	200	$ 120,846.74	1004	$ 12,148.40	$ 132,995.14	55	127.357187	$ 7,670.15
$ 312,000.00	21	3.985605	200	$ 126,865.00	1054	$ 12,753.40	$ 139,618.40	58	127.357187	$ 8,088.52
$ 312,000.00	22	3.985605	200	$ 133,003.63	1105	$ 13,370.50	$ 146,374.13	61	127.357187	$ 8,506.89
$ 312,000.00	23	3.985605	200	$ 139,021.89	1155	$ 13,975.50	$ 152,997.39	64	127.357187	$ 8,925.26
$ 312,000.00	24	3.985605	200	$ 145,040.16	1205	$ 14,580.50	$ 159,620.66	66	127.357187	$ 9,204.17
$ 312,000.00	25	3.985605	200	$ 151,058.42	1255	$ 15,185.50	$ 166,243.92	69	127.357187	$ 9,622.55

Table 8.7 Pre Payment Change Average Typical LOS (Below + 2 Standard Deviations)

Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS (A-typical)	Total LOS Days Billed	GP Hospital Care (Average)	# of patient seen in 48 weeks (Ave)	Hospital Discharge ($12.10) (A-Typ)	Total FFS Earned
$ 312,000.00	20	3.378159	241	$ 145,277.05	1424	$ 17,230.40	$ 162,507.45
$ 312,000.00	21	3.378159	241	$ 152,520.49	1495	$ 18,089.50	$ 170,609.99
$ 312,000.00	22	3.378159	241	$ 159,763.94	1566	$ 18,948.60	$ 178,712.54
$ 312,000.00	23	3.378159	241	$ 167,109.41	1638	$ 19,819.80	$ 186,929.21
$ 312,000.00	24	3.378159	241	$ 174,352.86	1709	$ 20,678.90	$ 195,031.76
$ 312,000.00	25	3.378159	241	$ 181,596.31	1780	$ 21,538.00	$ 203,134.31

Table 8.8 Post Payment Change Average Typical LOS 6.77% Decrease (Typical observations Below + 2 Standard Deviation)

Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS (A-typical)	Total LOS Days Billed	GP Hospital Care (Average)	# of patient seen in 48 weeks (Ave)	Hospital Discharge ($12.10) (A-Typ)	Total FFS Earned	# of new patients seen	Cost per Patient	"Benefits"
$ 312,000.00	20	3.149457	241	$ 145,238.49	1527	$ 18,476.70	$ 163,715.19	103	102.020397	$ 11,754.40
$ 312,000.00	21	3.149457	241	$ 152,562.24	1604	$ 19,408.40	$ 171,970.64	109	102.020397	$ 12,439.12
$ 312,000.00	22	3.149457	241	$ 159,790.88	1680	$ 20,328.00	$ 180,118.88	114	102.020397	$ 13,009.73
$ 312,000.00	23	3.149457	241	$ 167,114.62	1757	$ 21,259.70	$ 188,374.32	119	102.020397	$ 13,580.33
$ 312,000.00	24	3.149457	241	$ 174,343.26	1833	$ 22,179.30	$ 196,522.56	124	102.020397	$ 14,150.93
$ 312,000.00	25	3.149457	241	$ 181,571.89	1909	$ 23,098.90	$ 204,670.79	129	102.020397	$ 14,721.53

Table 8.9 Pre Hospitalist Average Atypical LOS (Atypical observations over 0 Standard Deviation)

Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS (A-typical)	Total LOS Days Billed	GP Hospital Care (Average)	# of patient seen in 48 weeks (Ave)	Hospital Discharge ($12.10) (A-Typ)	Total FFS Earned
$ -	20	15.0593	195.467277	$ 117,790.83	259	$ 3,133.90	$ 120,924.73
$ -	21	15.0593	195.467277	$ 123,703.11	272	$ 3,291.20	$ 126,994.31
$ -	22	15.0593	195.467277	$ 129,615.40	285	$ 3,448.50	$ 133,063.90
$ -	23	15.0593	195.467277	$ 135,527.68	298	$ 3,605.80	$ 139,133.48
$ -	24	15.0593	195.467277	$ 141,439.96	311	$ 3,763.10	$ 145,203.06
$ -	25	15.0593	195.467277	$ 147,352.24	324	$ 3,920.40	$ 151,272.64

Table 8.10 Hospitalist Average LOS 6.28% Increase (Atypical observations over 0 Standard Deviation)

Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS (A-typical)	Total LOS Days Billed	GP Hospital Care (Average)	# of patient seen in 48 weeks (Ave)	Hospital Discharge ($12.10) (A-Typ)	Total FFS Earned	# of new patients seen	Cost per Patient	"Benefits"
$ 312,000.00	20	16.00502	195.467277	$ 117,937.82	244	$ 2,952.40	$ 120,890.22	-15	454.79086	$ (319,003.36)
$ 312,000.00	21	16.00502	195.467277	$ 123,738.04	256	$ 3,097.60	$ 126,835.64	-16	454.79086	$ (319,470.25)
$ 312,000.00	22	16.00502	195.467277	$ 129,538.26	268	$ 3,242.80	$ 132,781.06	-17	454.79086	$ (319,937.14)
$ 312,000.00	23	16.00502	195.467277	$ 135,338.48	280	$ 3,388.00	$ 138,726.48	-18	454.79086	$ (320,404.04)
$ 312,000.00	24	16.00502	195.467277	$ 141,622.06	293	$ 3,545.30	$ 145,167.36	-18	454.79086	$ (320,404.04)
$ 312,000.00	25	16.00502	195.467277	$ 147,422.28	305	$ 3,690.50	$ 151,112.78	-19	454.79086	$ (320,870.93)

Table 8.11 Pre Hospitalist Average Atypical LOS (Atypical observations over 1 Standard Deviation)							
Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS (A-typical)	Total LOS Days Billed	GP Hospital Care (Average)	# of patient seen in 48 weeks (Ave)	Hospital Discharge ($12.10) (A-Typ)	Total FFS Earned
$ -	20	19.7174	130	$ 78,005.98	131	$ 1,585.10	$ 79,591.08
$ -	21	19.7174	130	$ 82,174.24	138	$ 1,669.80	$ 83,844.04
$ -	22	19.7174	130	$ 86,342.49	145	$ 1,754.50	$ 88,096.99
$ -	23	19.7174	130	$ 89,915.29	151	$ 1,827.10	$ 91,742.39
$ -	24	19.7174	130	$ 94,083.55	158	$ 1,911.80	$ 95,995.35
$ -	25	19.7174	130	$ 97,656.34	164	$ 1,984.40	$ 99,640.74

Table 8.12 Hospitalist Average LOS 3.906% Increase (Atypical observations over 1 Standard Deviation)										
Stipend (48 weeks)	Patients Cared for at a time (20-25)	Average LOS (A-typical)	Total LOS Days Billed	GP Hospital Care (Average)	# of patient seen in 48 weeks (Ave)	Hospital Discharge ($12.10) (A-Typ)	Total FFS Earned	# of new patients seen	Cost per Patient	"Benefits"
$ 312,000.00	20	20.48756	130	$ 77,959.27	126	$ 1,524.60	$ 79,483.87	-5	595.46548	$ (315,037.83)
$ 312,000.00	21	20.48756	130	$ 82,290.34	133	$ 1,609.30	$ 83,899.64	-5	595.46548	$ (315,037.83)
$ 312,000.00	22	20.48756	130	$ 86,002.69	139	$ 1,681.90	$ 87,684.59	-6	595.46548	$ (315,645.39)
$ 312,000.00	23	20.48756	130	$ 89,715.03	145	$ 1,754.50	$ 91,469.53	-6	595.46548	$ (315,645.39)
$ 312,000.00	24	20.48756	130	$ 94,046.10	152	$ 1,839.20	$ 95,885.30	-6	595.46548	$ (315,645.39)
$ 312,000.00	25	20.48756	130	$ 97,758.45	158	$ 1,911.80	$ 99,670.25	-6	595.46548	$ (315,645.39)