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MSc in Epidemiology and Community Health Thesis Project:

**Is there an association between hospital occupancy and quality of
care?**

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Submitted: September 21, 2000



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Abstract

Statement of the problem: Hospital occupancy is the number of inpatients divided by the number of beds. It has risen over the last two decades in many countries. This thesis will determine if there is an association between hospital occupancy and quality of care.

Setting: The Ottawa Hospital - Civic Campus, a tertiary care teaching hospital in Ottawa, Canada between January 1, 1993 and July 31, 1999

Methods: Daily rates of hospital occupancy and several quality of care indicators were derived using administrative databases. Indicators included: efficiency outcomes (emergency room (ER) delay, hospital length of stay (LOS), off service transfers, bed to bed transfers, and operating room (OR) cancellations); inpatient outcomes (deaths, cardiac arrests, c.difficile infections, medication errors, and falls); and outpatient outcomes (7- and 30- day visits to any ER, urgent readmissions to any hospital, and deaths). Autoregressive Integrated Moving Average (ARIMA) time-series modeling was used to test the association between hospital occupancy and each of the outcomes.

Results: Significant, positive associations were identified between daily occupancy rates and the following outcomes: ER delay, off service transfer, bed to bed transfers, and the proportion of patients dying within 30 days of discharge. Significant negative associations were identified between occupancy and length of stay and hospital deaths.

Conclusion: This study demonstrates that quality of care is associated with hospital occupancy. Further research is required to validate the clinical importance of the efficiency indicators used and to adjust occupancy for case-mix.

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1 Introduction

1.1 Hospital Occupancy

Hospital occupancy is the proportion of hospital beds that have patients in them. It, and its components, are important measures of hospital productivity. The numerator, the number of patients, reflects hospital throughput. The denominator, the number of beds, reflects hospital capacity. Because the capacity of a single hospital can vary over time and different hospitals have different capacities, the number of patients is insufficient as a measure of productivity. Occupancy provides a measure of throughput and capacity that is comparable across time and between hospitals.

In the past two decades, acute care hospitals in many countries have been experiencing a rise in hospital occupancy rates.¹ This is largely due to a reduction of bed numbers, which governments and hospitals have imposed to curb health expenditures.^{1,2} Physicians have adjusted to the limited supply of beds by elevating their threshold for admitting patients to hospital and decreasing hospital lengths of stay. However, despite this change in practice pattern, aging populations have minimized the ability to keep patients out of hospital.¹

Bed reductions have been effective in controlling hospital costs. However, it is not known what effect bed reductions have had on patient care. Because bed reductions appear to be secondary to fiscal pressures and not the health needs of a population, it is possible that bed cuts could create a situation where demand for beds is greater than the supply. Bed shortages could exist if not throughout the entire year, then certainly during certain periods where use of hospital services are known to increase. Indeed, in the last five years there have been well-publicized bed crises affecting emergency services during winter months in the United Kingdom, the United States and Canada.³⁻⁵ This thesis

explores the relationship between hospital occupancy and quality of care.

1.2 Errors in Medicine

As there is no published model relating hospital occupancy and quality, it is necessary to create one. The literature pertaining to errors and “systems” analysis may help to explicate how high hospital occupancy may relate to poor quality. The following section reviews this literature and uses it to derive a model that explains how high occupancy could cause systems problems, which in turn leads to poor care.

Human Errors

If we know why people make errors it will be easier to predict and prevent them. Cognitive psychologists have studied industrial accidents in engineering, aviation, and the military.⁶ This research has proposed that human errors are responsible for most accidents.

The basis of this theory is a conceptualization of how humans perform tasks. Simply, humans use several “tools” to complete any job. These “tools” include problem solving “processors”, memories, effector mechanisms (such as movement and speech), and sensory organs.⁷ The “problem solving processors” can function at low- or high-level. *Low-level processing* is used when we process very large amounts of information very easily, usually in a parallel manner.⁷ An example is our morning routine – washing, dressing, and eating before work. This happens almost automatically. *High-level processing* is the subject of conscious attention and in which we process information sequentially and comparatively slowly. An example is the preparation of a final manuscript for your thesis project. *Short and long term memory* complement the problem solving processors. Memories allow the processing to compare the present situation to past ones. *Effector mechanisms* carry out the tasks as programmed by the problem

solving processors. *Sensory stimuli* then create a feed back loop to allow for continual refinement in the performance of the required task.⁷

Errors most often occur as a result of faulty processing. A *slip* occurs as a result of faulty low-level processing whereas *mistakes* occur due to incorrect “higher-level” processing.⁸ Thus, a *slip* would be to perform the preparations to go to work automatically before realizing it was Saturday morning. A *mistake* would be misinterpreting the data and making an incorrect conclusion on the thesis. *Slips* occur for many reasons. They are most likely to occur during “the performance of highly automated tasks in familiar surroundings when attention is elsewhere because of boredom, pre-occupation or distraction.”⁷ Thus *slips* are errors in which the intention is correct but the action is wrong. *Mistakes* on the other hand occur because of incorrect intentions. *Mistakes* generally occur because humans tend to function well as ‘pattern recognizers’ not as ‘calculators’.⁸ If we come across a new situation, we will try to behave as if we had been in a similar situation and apply rules previously learned to solve it. *Mistakes* occur because of distortion of our memories and application of a rule in an inappropriate setting.

Slips and mistakes can be classified by the factors that led to the faulty processing. One factor that often leads to errors is miscommunication. Communication errors occur because of a misunderstanding on the part of either the transmitter or the receiver of the message, or because the parties assume there is no need to communicate. Fatigue is a common antecedent to communication errors. A second cause of errors is poorly designed equipment. Third, external stress is a common cause of errors. Stress can be divided into environmental (e.g. heat and noise), physiological (e.g. sleep deprivation), and psychological (e.g. anxiety or frustration).⁷ Stress and errors have been

the subject of much academic interest and it has been hypothesized they are related in a U-shaped manner, with performance being best at moderate levels of arousal but deteriorating sharply at low and high levels of stress.⁷

People make errors frequently, yet most do not result in a significant accident. Errors are common because everyone is susceptible to making them and, in most instances, there are more incorrect than correct ways of doing something. Luckily, errors are often inconsequential because they are immediately identified and corrected, or their impact is negligible. However, because of bad luck or “tight coupling” some errors result in significant injury. Bad luck is implicated in accidents when several errors occur sequentially or a critical error occurs at a critical time. “Tight coupling” refers to the risk of injury as a consequence of performing a task incorrectly. Tightly coupled tasks are inherently more susceptible to the effects of errors, for example, neurosurgery demands error free performance. Therefore, in order to understand the relationship of errors and accidents one must consider more than the human factors: the context in which the tasks are performed is also important.

Systems analysis

A system is ‘a collection of equipment, people and processes, each with their own task, but all working towards achieving a common goal.’⁹ For example, a hospital is a collection of health workers, administrative and support staff, using different pieces of equipment to perform various procedures and tasks. Each component has a separate task but the unifying goal is to provide health care to individuals within a community. If the system is not functioning properly, it will not achieve its goal. Systems analysis examines components of the system to identify why errors occur.

Systems breakdown because of active and latent failures.¹⁰ Active failures are

errors with an immediate adverse effect and are generally associated with activities of 'front-line' operators. An example of an active error would be a physician ordering an anti-hypertensive medication for a hypotensive patient. These are the errors that were discussed in the previous section. Latent failures are "decisions or actions, the damaging consequences of which may lie dormant for a long time, only becoming evident when they combine with local triggering factors to breach the system's defenses. Their defining feature is that they were present within the system well before the onset of a recognizable accident."¹⁰ Essentially, latent failures render active failures inevitable. To illustrate this point, we can examine a regional outbreak of hemorrhagic diarrhea secondary to an infected water supply¹¹. The outbreak could be attributable to an error made by the person responsible for monitoring the town's water quality – he may have misinterpreted the results of a test. However, it could also be possible that because of insufficient funding of water monitoring services the testing equipment was inaccurate. If the latter scenario were correct, the latent failure would be the failure to fund water safety programs adequately. Such a setting would make errors made by the front line operators unavoidable.

James Reason, a renowned authority on the study of error occurrence, suggests that latent failures are important for several reasons. First, they often set the necessary conditions for active failures.¹⁰ He states that "major accidents do not arise from a single error but they occur through the unforeseen concatenation of several distinct factors, each one necessary but singly insufficient to cause system breakdown".¹⁰ Combination of latent failures with environmental factors is often important. Let us consider again the contaminated water example. Suppose the identification of the source of the diarrhea occurred on a long weekend. Emergency responses would not occur as quickly on a

weekend as if it occurred on a weekday. Therefore, potential for harm would be much more significant. In addition, bacteria causing the hemorrhage diarrhea were particularly virulent. If a less virulent bacterium was responsible, the outbreak may have had less severe outcomes. Reason states that latent failures often amplify the risk of errors.¹⁰ Returning to the water quality example, the policy decision to decrease funding for water testing would be made for many municipalities, not just one. Therefore, several municipalities are potentially at risk from a single policy decision. Thirdly, latent failures often create poor working conditions. As presented previously, poor environmental conditions can promote error occurrence. Lastly, Reason states that latent failures are frequently the result of the inherent conflict between saving money and safety.¹⁰ For example, under funding can create stressful work environment in which employees are overworked or unmotivated – another common source of errors.¹⁰

To summarize, people frequently make errors. Depending on the system in which these people function, most of these errors are absorbed and are of little consequence. However, latent failures can contribute to error rate and to the probability of errors resulting in harm.

1.3 Hospital Occupancy and Errors

High hospital occupancy levels could decrease quality of care by creating a system where active failures are inevitable. Critical occupancy rates may be a latent failure. If the hospital is at a theoretical threshold of occupancy, patients may not get the attention they require. The practical processes of administering care may become inefficient. Consequently, workers may be more likely to make errors, and the incidence of bad outcomes may increase.

It is important to identify the relationship between external or environmental

factors and quality of care because a better understanding of the factors pertaining to poor care may lead to strategies to improve it. In addition, identifying external factors that cause adverse outcomes may remove some of the blame for mistakes that is currently shouldered by clinicians. This section reviews the literature pertaining to the relationships between quality of care and hospital characteristics. In particular, the relationship between hospital care and service volume and occupancy is discussed. It begins with a general description of how quality of care in a hospital is measured.

Quality of care

There are several approaches to describing high quality care. “Efficient”, “accessible”, “appropriate”, “sensitive” and “excellent” are valid descriptors of high quality care.¹² Health services researchers use indicators of these descriptors to study how well health providers are doing.¹³ An alternative approach is to study bad outcomes¹³ because patients who suffer bad outcomes arguably are more likely to have received poor quality of care than patients with good outcomes.¹⁴ Based on this logic it is a common practice for hospitals to monitor the incidence of specific ‘indicator’ outcomes in order to monitor their quality of care.¹⁴⁻¹⁶

Hospital characteristics and quality of care

Comparing hospital quality using indicators is not new. In 1855, Florence Nightingale published the first report comparing mortality rates in different hospitals.¹⁷ Hospital comparisons continue today and they often generate widespread attention. Also, as in Florence Nightingale’s study, problems in controlling for case mix frequently renders such reports controversial.^{18:19}

Studies comparing variations in quality have led researchers to explore the factors leading to differences.^{16:20-23} Certain hospital characteristics have been demonstrated

consistently to be associated with better care. These characteristics include increased numbers of beds^{16:21;23}, increased volume of service²⁴⁻³¹, teaching hospital status^{16:21-23}, non-profit versus for-profit status^{16:23}, urban location²¹, higher number of board certified specialists^{16:23}, greater percentage of nurses who are registered^{16:23}, greater percentage of admissions that are classified as emergencies²⁰, higher number of primary care physicians per capita in the hospital's catchment area²⁰, greater number of physicians per hospital population²⁰ and higher occupancy rate^{16:23}.

The studies demonstrating that increasing hospital occupancy is associated increasing quality deserves further appraisal. However, it is helpful to first explore why such a relationship might exist.

Hospital volume and assessments of quality

Several publications have associated increased volume with improved outcome. For example, patients with acute myocardial infarction treated at high-volume hospitals had a 10% lower one-month mortality than those treated at low-volume hospitals.²⁴ Similar relationships have been identified for patients undergoing coronary artery bypass graft surgery (CABG)²⁵⁻²⁷, abdominal aortic aneurysm repair²⁸, total hip replacement²⁹, and major cancer surgeries.^{30:31} "Practice making perfect" is the explanation proposed for these observations. Higher volume arguably optimizes the system, and practitioners' skills improve with the repeated performance of a single procedure.²⁸

For a given hospital capacity, higher occupancy means greater volume. Might this, given the association between high volume with better outcomes in the previous citations, explain the positive association between hospital occupancy and quality of care? There are two limitations to this research in extrapolating volume-outcome associations for single interventions to an entire hospital. First, hospitals usually care for

patients with a wide spectrum of health problems. Poor care of even a few of these problems would decrease overall hospital quality of care. Since hospitals cannot have high volumes for all problems they treat, increased overall hospital volume will not necessarily translate into overall improved hospital quality. Second, absolute hospital volume does not consider hospital capacity. For example, think about two hospitals of different capacity. Both could have similar service volumes but that with the smaller capacity would have a higher occupancy. If high occupancy rates induced latent failures, then the smaller hospital would have a lower quality of care despite having a volume that is similar to the larger one.

The two studies positively associating hospital occupancy with quality of care^{16:23} used administrative databases to compare several thousand American hospitals during the 1980's. They controlled for a variety of hospital characteristics and determined the association of *average* annual occupancy with surrogate markers for quality of care. These outcomes included in-hospital mortality and problem rates using measures suggested by the Peer Review Organizations (Appendix 1). The studies^{16 23} found that increased annual average occupancy was associated with improved outcomes. The multivariate analysis determined that hospitals in the lowest occupancy quartile experienced 1- percent higher absolute mortality rate and problem rate than hospitals in the highest occupancy quartile. Both studies concluded that a direct relationship exists between hospital occupancy and quality of care

Four factors may limit the validity of this conclusion. First, the exposure variable used in both studies – the annual average occupancy – could introduce an ecological fallacy bias. This can occur whenever population-based rates for different groups are associated with ecological measures.³² In these studies, an inverse relationship was found

between adjusted hospital mortality rates (a population-based rate) and annual hospital occupancy (an ecological measure).¹⁶ However, within individual hospitals it is possible that mortality increased during periods of high occupancy (exhibit 1). Second, it is difficult to compare individual hospitals because of differences in patient case-mix. If patients at lower-occupancy hospitals were more complicated, associations between occupancy and outcomes could be due to confounding. Although the studies used valid statistical methods to account for patient case-mix, uncontrolled confounding can make such methods unreliable.^{33:34} Furthermore, the studies used data from administrative databases, which may not be of high quality to adjust for patient mix. Thus, all of the confounding secondary to patient mix may not have been removed. For example, socio-economic status is an important predictor of patient outcomes³⁵ and was not included in the analysis.³⁶ Third, it is possible that the American 'market-based' health care system invalidates these studies' conclusions in countries with universal health care. If high-quality American hospitals are more likely to have referred patients, their occupancy rates will be higher than those of poorer quality. Therefore, high occupancy rates would be a *result* – rather than a cause – of high quality care. Indeed, univariate analyses in these studies found that hospital occupancy was significantly associated with factors that one would expect to indicate a better hospital.^{16:23} Hospitals with a higher annual occupancy were more likely to be teaching hospitals, were larger, and had a greater number of board-certified specialists. Although multivariate analyses controlled for these factors, it is possible that other unmeasured factors confounded the association. Finally, and most importantly, the generalizability of these studies is limited by the date in which they occurred – the 1980's. The occupancy rates of the studied hospitals ranged between 40-80% - significantly lower than rates in many hospitals today.² Thus, these studies

cannot determine what occurs to care when hospitals approach full capacity, an important factor since many hospital in today's Ontario health system where hospital occupancy rates often exceed 90%.

In contrast, other studies have suggested that high hospital occupancy rates decrease quality of care. Bagust and colleagues used a discrete-event stochastic simulation model to explore the effect of near-full capacity on hospital efficiency.³⁷ This model assessed hospital system dynamics at various occupancy rates. A "bed crisis", defined as the inability to provide a hospital bed for an acute medical admission, was used to measure hospital efficiency. The study found that bed crises occurred regularly when occupancy rates exceeded 90%. In addition, bed crises continued to occur for several days after the occupancy rate dropped below 90%. Another recent publication studied hospital outcomes in Great Britain and identified an inverse relationship between hospital mortality and the ratio of doctors to the number of patients in the hospital.²⁰ This finding suggests that physicians with excessive caseloads may not perform as well. By extrapolation, the ratio of doctors to hospital population decreases as occupancy increases. This would indicate a possible association between hospital mortality and occupancy. A third publication used a high-quality clinical database to examine the outcomes of critically ill patients who were transferred from intensive care units (ICU).³⁸ This study demonstrated that patients discharged from the ICU at night had a significantly higher hospital mortality than patients discharged during the day (OR=1.46 95% CI=1.18-1.80). Nighttime transfers occurred when the ICU is full. If a critically ill patient requires admission, the doctor in charge of the ICU is forced to discharge a patient who would not normally have gone to the floor at that time. This illustrates how high occupancy can influence physician behavior to decrease quality of care. A fourth

publication, again looking at the ICU population, found that patients of overworked nurses are at higher risk of dying than if nurses are not overworked.³⁹ Each of these papers suggest an association between bad patient outcomes and high workloads.

1.4 Quality of care and outcomes selected for this thesis

As indicated above, there are many methods to study quality of care. This thesis will focus on two types of indicators – bad patient care outcomes and hospital efficiency.

Although patient care outcomes are common indicators of quality of care, their use has limitations. Bad patient care outcomes, such as hospital mortality, are important because they are clinically relevant and readily available. However, investigators must recognize that bad outcomes may occur despite excellent care and good outcomes may occur despite poor care. For example, some patients with pneumonia will die despite receiving appropriate antibiotics and other patients will survive despite receiving incorrect antibiotics. Because of this limitation, alternative outcomes should be used with bad patient outcomes to reflect how care is delivered. For example hospital efficiency may be complementary to bad patient outcomes. If care is not being delivered efficiently then it could be argued that there would be sub-optimal outcomes and increased costs. By studying both processes and outcomes of care there will be a comprehensive understanding of the quality of care at an institution^f.¹⁴

^f An alternative to using bad patient care outcomes is to study adverse events, where an adverse event is an injury caused by a medical intervention.⁸³ Adverse events are more specifically related to quality, but they have their own limitations. First, they are not readily available – some form of surveillance is required to identify injuries. Second, once possible injuries are identified it can be difficult to determine whether medical interventions were responsible. For these reasons adverse events are not used in this thesis.

1.4.1 *Indicators of inefficiency selected for this thesis*

To reflect processes of care this thesis has chosen several indicators of inefficiency. These include emergency room waiting time, length of stay, bed to bed transfer rate, off-service transfer rate, operating room cancellations due to lack of postoperative bed, overtime rates and sick leave rates.

Excessive *emergency room* waiting times are a source of discomfort to patients. They may also result in delays in the institution of therapy, and poor monitoring.

Length of stay is used to compare hospital efficiency. Generally, shorter lengths of stay are desirable from the payer point of view. However, if patients are discharged too early, or in haste, they may be susceptible to having poor outcomes.

Hospital wards are assigned to different medical and surgical services. Health-care providers on each ward develop expertise and knowledge specific to the particular health issues of that service. It is best for patients to be admitted to a particular service to go to the corresponding ward. If they are transferred to a different ward, they are '*off-service*'. Inefficiencies may ensue since doctors must travel to other wards to see their patient. It also negates the use of standard protocols or routines. Finally, quality of care may suffer due to staff that is inexperienced with the special health issues of patients who are usually on a different ward.

Transfers of patients from one area of the hospital to another consume resources, as they require employee time and materials. Some transfers are unavoidable, such as transfers from the emergency room to the ward. However, transfers often occur for purely administrative reasons. For example, some patients are transferred to a private room at admission because no ward bed is available. Subsequently, when a ward bed is free, the patient transfers out of the private room. These administrative transfers are

inefficient and potentially harm quality of care by disrupting the patient and the caregivers.

Operation cancellations are inefficient because they result in an unused, staffed operating rooms (OR). This also increases surgical waiting times, which diminish access to care and potentially increase morbidity and mortality.

Work productivity and quality diminish with fatigue and stress. If employees are working excessive amounts of *overtime*, there could therefore be a reduction in efficiency.

The nursing profession is recognized as one in which *absenteeism* is more prevalent than others.⁴⁰ Employees absent from work create inefficiencies because inexperienced workers must perform the absent employees work duties and regular staff must work harder to cover off the responsibilities of their absent colleagues.

1.4.2 Bad patient care outcomes selected for this thesis

Several bad patient care outcomes were chosen for the thesis. These include mortality, cardiac arrests, nosocomial c.difficile infections, medication errors, falls, return visits to the emergency room and readmissions.

Death is a useful measure of hospital quality because of its clinical importance. Despite the fact that the relationship between death rate and quality is not definitive^{34:41-44}, it remains a principal measure of quality in many peer review publications^{18-20;22;23;25;26;28;45-47} and in the lay press.¹⁹

In-hospital cardiac arrest is a critical event that occurs when a patient has no blood pressure. Its use as an indicator of quality is not as widespread as deaths yet Peer Review Organizations in the United States use it as a screen for quality problems (appendix 1). In one series of cardiac arrests, poor care was implicated in 14% of cases.⁴⁸

In that cohort, medication errors and toxic medication effects were involved in 44% of cases, and insufficient monitoring before the event was found to be responsible in 28%.⁴⁸

Nosocomial infections in general, and *Clostridium difficile* infections in particular, are important bad outcomes for hospital patients.⁴⁹ *C. difficile* is a major cause of antibiotic-associated diarrhea, which results in serious morbidity and sometimes mortality. *C. difficile* infections are related to poor care, as they are associated with excessive, arguably inappropriate, antibiotic use⁵⁰ and poor hand-washing practices.⁵¹

Medication errors are problems in the ordering or delivering of medication, regardless of whether an injury occurred or the potential for injury was present.⁵² Although its true incidence is difficult to determine, medication errors have been found to occur in up to 5% of orders⁵². Most medication errors do not result in injuries. However, due to their incidence, their potential impact upon patient care is huge.⁵² Furthermore, since they are potentially avoidable⁵², medication errors are often monitored for quality improvement purposes.⁵³ Staffing and work assignments are considered to be one significant cause of medication errors.⁵⁴

Falls are an important quality indicator. Similar to medication errors, falls do not necessarily result in bad outcomes or adverse events. However, falls are dramatic events that, in the eyes of family members and health care workers, may reflect poor care of the patient. Studies in the acute care population have focused on patient factors that relate to risk as opposed to hospital or care factors. It is quite evident that elderly frail patients are at risk of falling. However, there is no excuse for inadequate supervision, so prevention of falls has been a focus of quality improvement strategies.

Return visits to the emergency room (ER) following discharge are bad outcomes. The relationship of this outcome to quality of hospital care is unknown. However, in a

study of patients who return to the same ER following previous discharge, care quality was poor for a majority of cases.⁵⁵⁻⁶¹ Similar associations between poor hospital care and return to the ER might therefore be expected.

Emergent re-admissions to hospital following discharge are also bad outcomes. Readmissions to hospital could be due to poor hospital care, unreadiness for discharge, inadequate post hospital care, poor compliance with therapies, or severe underlying illness.⁶² The association between quality of care and hospital readmission has been argued in the literature.⁶² However, three observations suggest that the shorter the time interval between discharge and readmission, the higher the likelihood that the readmission is a result of poor care. First, although readmissions occur in 5-70% of patients (depending upon the time interval and patients studied), the majority are clustered within the first month⁶². Second, of the 1/3 of patients readmitted within a month, 50% have been estimated to be preventable.⁶² Third, interventions to reduce readmissions are successful in certain patient populations.⁶³⁻⁶⁸

1.5 Relationship of hospital occupancy and hospital efficiency and patient outcomes

This thesis hypothesizes that excessively high occupancy rates predispose to system breakdown by introducing a latent failure. This latent failure creates the substrate for increased errors by front line health workers, which could result in higher rates of bad outcomes. Exhibit 2 is a schematic diagram illustrating this proposed relationship.

Specifically, high occupancy rates may directly influence decisions to keep patients out of hospital, stress, workload, and communication. Pressure to reduce the number of inpatients could increase thresholds for patient admission and decrease thresholds for patient discharge. Second, workloads likely increase as hospital occupancy increases (assuming the number of hospital employees remains constant). Excessive workload is

associated with employee fatigue, and stress. These in turn may result in job dissatisfaction and in absenteeism. Absenteeism usually results in less experienced staff performing tasks that are essential to the system. This, in turn, will decrease hospital efficiency. Third, if the hospital occupancy increases and the number of staff remains constant then the workload *per worker* will increase. Fourth, communication will be impeded, as there will be more information to pass on and stressed overworked employees are less likely to effectively communicate. J. Reason argues that increased pressure; stress and workload will result in increased error rates. This thesis proposes that increased error rates will be reflected in increased incidence of bad outcomes and markers for inefficiency.

1.6 Summary

The following points need to be highlighted:

1. The hospital occupancy rate is a function of the number of patients in the hospital *and* the number of beds available.
2. Hospital occupancy rates are increasing in most health care systems. The effect of this increase is unknown.
3. Theoretically, increased occupancy rates may be a latent failure, which in turn increases error occurrence and poor outcomes.
4. The published literature evaluating the relationship of occupancy with outcomes is inconclusive.

2 Objectives of study

The objectives of the study are:

1. To determine if daily occupancy rates are associated with the following markers of hospital efficiency: daily ER waiting times, length of stay, off-service rate, OR cancellation rate, bed-to-bed transfer rate, employee absentee, and overtime rates.
2. To determine if daily occupancy rates are associated with the following in-patient outcomes: daily in-hospital mortality, cardiac arrests, c.difficile infections, medication errors, and falls.
3. To determine if daily occupancy rates are associated with the following post-discharge outcomes: 7- and 30-day ER visit rates, daily 7-and 30- day re-admission, and 7-and 30-day mortality.

3 Methods

3.1 Study design overview

The thesis used a retrospective, observational design to evaluate a single hospital during the period January 1, 1993 to July 31, 1999. Several administrative and clinical databases were used to calculate the daily occupancy rate (the independent variable) and several outcome rates (the dependent variables). Daily rates for the dependent and independent outcomes were calculated and the association between them was determined using Autoregressive Integrated Moving Average (ARIMA) modeling. The Institutional Review Board of the Ottawa Hospital approved the study.

3.2 Hospital Description

The study took place in the Ottawa Hospital, Civic Campus (formerly the Ottawa Civic Hospital^f). This is a publicly funded, tertiary care, teaching hospital in Ottawa, Ontario, Canada. It provides both in-patient and outpatient health services to residents in the Ottawa-Carleton and Outaouais regions. The level of services provided ranges from primary to quaternary care. Annually it averages approximately 180,000 in-patient days, 17,000 operations, and 55,000 emergency department visits.

The hospital's catchment population is approximately one million people, however the region has one other tertiary care hospital and several secondary-care hospitals. In addition, the Ottawa Heart Institute provides tertiary and quaternary cardiac care.

3.3 Patient population

Patients were included in the analysis if they were inpatients at the OCH. Patients

^f As the hospital was known as the Ottawa Civic Hospital (OCH) during the study period, it will be referred to as such in the remainder of the thesis.

were excluded if their in-patient care included the Nursery, Neonatal Intensive Care Unit or were exclusive to the Emergency Room or Surgical Day Care Unit.

3.4 Description of the hospital databases

The OCH has a number of electronic databases that are used for a variety of administrative, clinical, and quality assurance purposes (see exhibit 3). This section describes each database by the following terms: the reason the data is maintained by the hospital, the variables it contains, the method of data entry, and the range of dates for which there is available information.

Admitting Data Management System Database

The Admitting Data Management System (ADMS) database is a relational database^f that stores patient and bed information for the hospital. The Admitting Department uses it for administrative purposes.

The ADMS database contains 129 separate tables with extensive information regarding bed availability and patient information. Two specific tables are relevant for this thesis: the allocation table and bed census table. The allocation table has the total bed availability and total inpatients for each day. It also breaks down the patients and beds by each service and each geographic location. Each row in the bed census table identifies the precise location of a patient along with the precise day, hour, and minute that the patient arrived at that position. Each row also lists the patient's, health insurance plan number, medical service, attending physician, admitting diagnosis, and date of both admission and discharge.

^f A relational database is an information system that is able to store large amounts of data efficiently. It consists of multiple 'tables' that are groupings of 'like'-variables. Each observation within a table has one variable that relates a single observation from that table to an observation in another table.

Data is entered into the tables continuously and automatically. At the time of each admission, discharge, or transfer, hospital clerks update the ADMS. Patient movement within the hospital cannot occur without the correct information entered into the database. The bed census is derived directly from the information as entered by the hospital clerks. Generation of the allocation table occurs automatically using the information as entered in the bed census table. The ADMS database has information on OCH bed allocation and hospital patients discharged after December 31, 1992 and admitted before August 1, 1999.

Emergency Patients Information System Database

The Emergency Patients Information System (EPIS) Database is a relational database that records all emergency health services at the Emergency Department, OCH.

The EPIS database has 48 tables with extensive information pertaining to each patient's visit to the emergency department. The Registration Table is the only one that is relevant for this thesis. This table includes the following variables: patient and visit specific identifiers to track repeat visits for a single patient; disposition from the Emergency Department; and, the date and time of patient arrival, registration, triage, physician assessment, nursing assessment and disposition.

Data entry clerks enter the information into the database. Data is available for the period January 1, 1993 to August 1, 1999.

Canadian Institute for Hospital Information-Discharge Abstract Database at the OCH

The Canadian Institute for Hospital Information-Discharge Abstract Database (CIHI-DAD) at the OCH is a relational database used to store information pertaining to the use of hospital services. It is primarily an administrative database and secondarily a health services research database.

The CIHI-DAD contains a visit and patient unique identifier. For each patient visit there are variables pertaining to the diagnoses and procedures, coded according to the International Classification of Disease-Version 9, clinical modification (ICD-9CM).

Data entry into the CIHI-DAD occurs after patients are discharged from the hospital. Health records analysts abstract information from the patient's paper record, and then enter coded information into the CIHI-DAD. Data is available for the period January 1, 1993 to August 1, 1999.

MediSolutions Databases

MediSolutions Incorporated is a private company contracted by the OCH to perform its payroll services before April 1999. During that period, the OCH forwarded all of its payroll submissions to the company, which processed payroll demands and then forwarded paychecks to the employees via the hospital. The company has all of the payroll demands stored on a database. Their database has information on the following two full time union groups: the Ontario Nursing Association (ONA) and the Canadian Union of Public Employees, Local 576 (CUPE 576). The ONA is a union that represents all the registered nurses employed at the OCH. The CUPE 576 is the union representing all the orderlies and nursing assistants, as well as the clerical, housekeeping and kitchen staff employed at the OCH.

Variables included in the database are: date, union group, hours of employment, hours of overtime, and hours of sick leave

The information in the database derives from the processing of claims from the hospital. Data is available for the period January 1, 1993 to August 1, 1999.

Incident Report Database

The Incident Report Database is a relational database used by the Quality Assurance

committee at the OCH for risk management. It records the occurrence of 'incidents' at the OCH. An 'incident' is an event that may cause an injury to anyone in the hospital (patients, employees, other) and may therefore result in legal liability to the hospital.

The database has the following variables: date, location of incident, status of the person harmed (inpatient, outpatient, employee, other), incident classification (medication errors, falls, blood transfusion errors, security problems or miscellaneous), and incident consequence (insignificant, minor injury, or major injury extending length of stay).

Staff completes incident report forms when they commit or witness an incident (for example, a fall). A nurse and a physician must complete and sign the form before sending it to the medical records department. Employees are encouraged to report incidents. However, despite a managerial philosophy of impunity, incidents may occur and not get recorded. A trained health records analyst then abstracts information from the forms and enters it into the Incident Report Database. Data is available for the period January 1, 1992 until August 1, 1999.

Infection Control Database

The Department of Laboratory Medicine at the OCH uses the Cerner Information System to store and communicate laboratory results. One of the components the Cerner Information System is the Infection Control Database. The sole purpose of the Infection Control Database is the monitoring of specific types of infections that may spread throughout the hospital.

The most reliable and accurate information in the Infection Control Database pertains to clostridium difficile (c.difficile) diarrhea infections. These infections have characteristic symptoms, and there is an inexpensive, simple, gold standard test that

ensures that the diagnosis is a valid one. Hence, the data in this database is sensitive and specific.

The database records each infected patient and the date of the infection. It also records all stool samples in which *c. difficile* testing was ordered. Cases that tested positive within 72 hours of admission are classified as community-acquired. All others are classified as nosocomial. Repeat positives are distinguished from the index test.

Laboratory information pertaining to stool assays is entered into the database directly, as it becomes available. Infection control practitioners collect clinical information and then update the infection control information system. Data is available for the period March 1, 1995 to September 1, 1999.

Operating Room Scheduling Office System

The Operating Room Scheduling Office System (ORSOS) is a relational database used at the OCH to manage the surgical operating rooms.

Patient and visit unique identifier information distinguishes cases. ORSOS also records the diagnosis, procedure, the time required for the surgery, and the resources used during the procedure. Finally, it records whether the case was successful or if it had to be cancelled. If cancelled, the reason is recorded.

Clerks working in the operating room enter data at the time of booking and completion of each case. Data is available for the period November 1994 until November 1999.

OHIP database

The Ontario Health Insurance Plan (OHIP) database records all claims for physician services claimed to the provincial health insurance plan from July 1, 1991 to April 1, 2000. All claims record a patient unique identifier, a code for the service

provided, and the date of the service. Emergency room visits are identified using specific codes, unless the ER is on an alternate payment plan (APP). For the present study, emergency room visits between November 1, 1994 and November 15, 1997 were identified. During this study period, none of the ERs in Ottawa or the surrounding area was on an APP.

CIHI-DAD

This is a collection of records, described in the DAD section above, from each hospital in Ontario. Each row has a patient unique identifier, the date of the hospital admission, and the urgency of the admission. The database extends from April 1988 to March 1999. With few exceptions, the database captures all admission to acute hospitals in Ontario.

Ontario Registered Persons Database

This database identifies all people ever registered with the Ontario Health Insurance Program. The date of each person's death, from death certificates completed by physicians, is recorded in the database. The database also captures out-of-province deaths of Ontarians through inter-provincial data sharing programs.

3.5 Description of study variables

This section defines the independent variable, the daily hospital occupancy rate, and the twenty outcome variables of interest. There are three groupings of outcome variables: nine that represent markers of hospital efficiency, five that represent inpatient outcomes, and six that represent post-discharge outpatient events. The following sections define the variables and their units of analyses. They also describe how the variable was derived, its source, and the time interval for which there is valid data.

3.5.1 Daily hospital occupancy

The daily hospital occupancy rate is the proportion of beds occupied by patients on a given day. The numerator is the number of patients occupying beds at midnight plus the patients the number of patients discharged during the previous 24 hours. Ontario hospitals use this definition in claims made to the Ministry of Health. Midnight is the most appropriate time of day for the hospital to identify the status of the beds for the following day because it allows health providers to plan admissions and discharges when they arrive in the hospital in the morning. However, most patients leave in the late afternoon and early evening, thereby leaving beds empty at midnight. Therefore calculating occupancy at that time will underestimate the occupancy. To avoid this, the number of inpatients discharged in the preceding 24 hours is included in the numerator. The denominator is the total number of beds available to patients per day.

The ADMS bed allocation table contains the information for the numerator and denominator. The time series' range is January 1, 1993 to July 31, 2000.

3.5.2 Units of analysis for outcome variables

The unit of analysis varies depending upon the method of analysis (cf. section 3.8.)

The types of variables included and a brief description are:

- i) Number of events per day.
- ii) Daily mean.
- iii) Daily median.
- iv) Incidence, rate, or proportions are the number of people having an event per day divided by the number of people at risk for the event per day.
- v) Excess events per day are the difference between the observed number of events and the expected number of events on any given day (cf. Equation

3.5.1). The expected number of events per day is the number of events that would occur in hospital with p inpatients if the hospital had a standard daily incidence (cf. equation 3.5.2.). The standard daily incidence is calculated based on the average daily incidence for the first year of available data (cf. equation 3.5.3.).

The excess number of events, $\Delta EVENTS_i$ is given by:

$$\Delta EVENTS_i = e_i - E_i \quad (\text{Equation 3.5.1})$$

where e_i is the observed number of events on day i , and E_i is the number of expected events on day i . That is,

$$E_i = p_i \times \left(\frac{e}{p} \right) \quad (\text{Equation 3.5.2})$$

where p_i is the number of inpatients on day i ; and $\left(\frac{e}{p} \right)$ is the average rate over the year for the year selected as the 'standard'. That is,

$$\left(\frac{e}{p} \right) = \left(\sum_{i=1}^{365} \frac{e_i}{p_i} \right) \div 365 \quad (\text{Equation 3.5.3})$$

$\Delta EVENTS_i$ were calculated for all days excluding those in the 'standard' year.

3.5.3 Efficiency outcomes

Daily ER waiting times

The ER waiting time is the number of hours between registration in the Emergency Room (ER) and arrival on the ward for a single patient. The daily ER waiting time is the median wait for all patients admitted on a single day. The median was used because the distribution of the times was not normal.

The EPIS registration table and the ADMS bed census table contain information to

calculate the time interval. The EPIS registration table contains the registration time for all patients seen in the ER and the ADMS bed census table records the time patients arrived on the ward from the ER. To calculate the time interval for each patient admitted it was necessary to link the two databases. All patients admitted through the ER were identified in both the EPIS registration table and the ADMS bed census table. The hospital unique number of the patient and the date of admission were used to link the two tables. The median waiting time for each day was calculated. The time series' range is January 1, 1993 to July 31, 1999.

Daily length of stay

The length of stay (LOS) is the number of days between admission and discharge for each patient. Daily LOS is the mean LOS for all patients discharged on a single day. Mean LOS was used for convention.

The ADMS bed census table contains all of the information necessary to calculate this variable. Each patient's admission is associated with an admission date and discharge date. The length of stay for each patient is the number of days between admission and discharge. Once the calculation of the value of LOS for each patient is made, it is possible to calculate the mean LOS for all patients discharged on a given day. The time series' range is January 1, 1993 to July 31, 1999.

Daily rate transfers to an off-service ward bed

This series indicates the proportion of patients transferred to an off-service ward bed per day. An off-service transfer is defined as a transfer from the ER, the intensive care unit (ICU), the operating room (OR), the recovery room (RR) or the delivery suite to a hospital ward not assigned to the service to which the patient was admitted. The numerator is the number of off-service transfers per day. The denominator is the total

number of transfers from the ICU, the OR, the RR and the delivery suite each day.

The numerator and denominator were calculated from the ADMS bed census table. The database contains information on each transfer that occurs for a given patient from admission to discharge. Several steps were required to identify 'off-service' transfers, including:

i) Creating a time and space map of the service locations;

The step identified the geographic location of every service at the hospital over the study period using the ADMS bed allocation table. This was necessary because many hospital services have changed locations several times over the last several years (see exhibit 5).

ii) Identifying the admitting service for a particular patient;

The second step identified the admitting service for each patient. If there was only one service during a hospitalization, as was the case for 93% of patients, then it was clearly the admitting one. However, if a patient was cared for by more than one service during their hospitalization, the ADMS database does not indicate which service was the admitting one or when the change in services occurred. For example, consider a patient admitted to Family Medicine with abdominal pain who required transfer to General Surgery for appendectomy and post-operative care. In this situation the ADMS database indicates that patient received care from two services but it does not indicate which service was first or when the transfer between services occurred. In the situation where a patient was cared for by two services (6.3% of patients), the admitting service was identified by assuming that the last location occupied by a patient would not be an off-service one. This assumption is safe because each day off-service patients are transferred to their appropriate wards. In the example above, it would be highly unlikely for the

post-operative patient to be anywhere but the surgical ward at the time of discharge.

Using the time map constructed above and, knowing where the patient was at the time of discharge, it was possible to code the admitting service and discharge service for each patient. Considering the example above, because the patient was on the surgical ward at the time of discharge it follows that the admitting service had to be Family Medicine. For the situation where there were more than two services (0.7% of patients), it was impossible to identify the admitting service. Therefore, these patients were excluded from both the numerator and the denominator in analyses dealing with off service transfers.

iii) Identifying the transfers that could potentially lead to off-service transfers;

The third step involved identifying the types of transfers for which it was possible to be transferred to an off-service location. These include transfers from ER, ICU, the delivery suite, the OR and the RR. These locations represent hospital entry points and therefore, from them, patients may be transferred to off-service ward beds. We excluded transfers from one inpatient bed to another, and transfers to the ICU, the delivery room, the nursery, the OR, the RR and the Acute Monitoring Area (AMA). Bed-to-bed transfer will not result in an on-service patient becoming an off-service patient since patients are, with very few exceptions, never transferred from an on-service bed to an off-service one. Transfers to the locations listed above are for specific purposes and by definition they cannot be off service.

iv) Coding each transfer as off-service or on-service

The fourth step involved coding the transfer as “off-service” by applying the time/space map, as described in step *i*, to each transfer. If the transfer location did not correspond to the admitting service’s ward locations then the transfer was off service.

v) *Creating the time series.*

The final step involved creating the time series. Using the transfer date, the number of off service transfers and total number of transfers per day were counted. The daily rate is the number of off-service transfers divided by the number of transfers. The time series' range is from January 1, 1993 to July 31, 1999.

Daily rate of operating room cancellations due to lack of post-operative beds

This series indicates the proportion of operations cancelled due to the lack of a post-operative bed per day. The numerator is the daily number of operations cancelled due to lack of post-operative bed. The denominator is the total number of operations scheduled for that day. Both variables are directly taken from the ORSOS database. The time series' range is from November 1, 1994 to March 31, 1999.

Daily bed-to-bed transfers

A bed-to-bed transfer is a transfer from one hospital bed to another. Two series are used: the daily rate of bed-to-bed transfers for univariate analysis and the daily excess number of bed-to-bed transfers for multivariate analysis. (Please see section 3.8 for an explanation of why it is necessary to use daily excess number of bed-to-bed transfers in the multivariate analysis.)

In order to calculate these variables it is necessary to know the number of bed-to-bed transfers and inpatients per day. The number of bed-to-bed transfers was derived from the ADMS bed census table. The number of inpatients was derived from the ADMS bed allocation table as defined in section 6.3.1. A bed-to-bed transfer includes all transfers from one inpatient bed to another. We excluded transfers to and from expansion beds; "back-to-back" transfers, and transfers to and from certain locations in the hospital.

More specifically:

i) Exclusion of “expansion beds”;

Expansion beds are “virtual beds” that exist within the database but do not exist in reality. They allow transfers to occur in the setting where the “transfer to” bed is temporarily occupied. If these expansion beds did not exist, the transferred patient would need to be discharged and then re-admitted, which would create computational problems for the database administrators. The expansion bed is temporarily “occupied” until the real bed is ready. Because the patients did not physically move, it would be inappropriate to include them in the numerator.

ii) Exclusion of “back-to-back” transfers;

“Back-to-back” transfers are two transfers that occur from one location to another and then back to the same location within twenty minutes. This situation is likely due to an error in data entry, which was corrected in the database by re-transferring the patient back to the original bed. Thus, the patient was never actually physically transferred and therefore, it would be inappropriate to count them in the numerator.

iii) Exclusion of transfers to and from certain locations;

It would be inappropriate to include certain types of transfers, as they do not reflect a transfer from one inpatient bed to another. Examples include transfers from the ER, and to and from the OR, RR, and the delivery room.

The time series’ range is January 1, 1993 to July 31, 1999.

Absentee rate for full time CUPE 576 and ONA employees

The absentee rate is the sick time in hours claimed divided by the regular hours of employment claimed to the payroll service by either full-time CUPE 576 or full-time ONA employees. It is not possible to calculate accurate daily rates because claims may not be submitted in a timely manner. For this reason, quarterly and yearly rates are

presented. The information for these variables is derived from the Medisolutions database. The time series' range is from April 1, 1994 to March 31, 1999.

Daily overtime rate for CUPE 576 and ONA employees

The overtime rate is the hours of overtime claimed divided by the total hours of employment claimed by full-time CUPE 576 or ONA employees. It is not possible to calculate accurate daily rates because claims may not be submitted in a timely manner. For this reason, quarterly and yearly rates are presented. The information for these variables is derived from the Medisolutions database. The time series' range is from April 1, 1994 to March 31, 1999.

3.5.4 In-hospital outcomes

The in-hospital outcomes include deaths, cardiac arrests, *C.difficile* infections, medication errors, and falls. For each of the outcomes, three measures of occurrence were calculated: number of people experiencing at least one event per day, daily incidence, and excess events per day. For each outcome, it is necessary to identify the number of events per day and the number of patients at risk in order to calculate the necessary statistics used in the analysis. The number of patients at risk for all of these outcomes is the number of inpatients, as defined in section 3.6.1. The events were defined and identified as follows.

Daily in-hospital deaths

An in-hospital death occurs when an admitted patient dies. The number of deaths occurring per day is derived from the ADMS bed census table because patient disposition is coded. A specific code identifies patients who die and the death date is the discharge date. Thus, it was possible to identify the number of patients who died on each date.

The period for which there is available data is January 1, 1993 to July 31, 1999. The

standard incidence is based on mortality rates January 1 to December 31, 1993. Excess events are calculated for January 1, 1994 to July 31, 1999.

Daily cardiac arrests

A cardiac arrest occurs when an in-patient is found to have no blood pressure and the cardiac arrest team is activated to perform advanced cardiac life support. To identify the number of cardiac arrests, several steps were required:

- i) *identify all patients who may have suffered a cardiac arrest using the CIHI-DAD.*

The first step was to identify all patients who may have had a cardiac arrest. This is possible because health records analysts (HRA's) will indicate on the discharge abstract if a patient had a cardiac arrest during their admission. The coding for cardiac arrests is complicated because there is a code for the diagnosis "cardiac arrest" and a set of codes for the procedures associated with it. In addition, different HRA's could code cardiac arrests with different combinations of codes for the diagnosis or the procedures. For example, one HRA might identify that a cardiac arrest occurred and code it as diagnosis with no procedure, whereas another might code it as both a procedure and a diagnosis. Therefore, in order to identify every patient that could have had a cardiac arrest, patients with the following coding patterns on their discharge abstract were identified: "cardiac arrest diagnosis and any cardiac arrest procedure", "any cardiac arrest procedure but no cardiac arrest diagnosis", "cardiac arrest diagnosis but no cardiac arrest procedure", and "patients who died and had no cardiac arrest diagnosis or any cardiac arrest procedure".

- ii) *validation of sampling selection criteria.*

Validation of the sampling technique was required because previous studies assessing chart abstraction by HRA's demonstrates that certain conditions are inaccurately coded in

discharge abstracts.⁶⁹⁻⁷¹ The specificity and sensitivity of each coding pattern for identifying cardiac arrest was determined using chart review as the gold standard.

Random samples of one hundred patients from each coding group (four hundred charts in total) were reviewed. It was determined that the following coding patterns reliably identified cardiac arrest: “cardiac arrest diagnosis and any cardiac arrest procedure” (positive predictive value (PPV) = 94%) and “cardiac arrest procedure but no cardiac arrest diagnosis” (PPV=94%). Furthermore, it was determined that the coding pattern, “patients who died and had no cardiac arrest diagnosis or any cardiac arrest procedure” reliably excluded cardiac arrest (NPV=99%). Finally, it was determined that the coding pattern, “cardiac arrest diagnosis but no cardiac arrest procedure”, did not reliably identify or exclude a cardiac arrest (PPV=44%). Based on these results, this entire group of patients had to have their charts reviewed and re-classified as to whether or not they had a cardiac arrest during their admission.

iii) re-coding poorly coded samples

Every patient with the coding pattern “any cardiac procedure but no cardiac arrest diagnosis” was reviewed and objective criteria applied to determine whether a cardiac arrest truly occurred. In order to be classified as a cardiac arrest an event had to occur while the patient was an inpatient, the record must indicate an absence of a palpable blood pressure, and the cardiac arrest team had to have been activated.

iv) merging re-coded sample with other samples

The databases including all reliably coded groups and the re-coded database were merged. This merged file contained all the cardiac arrests by day at the OCH during the study period.

The time series' range is from January 1, 1993 to March 31, 1999. The standard

incidence is based on mortality rates January 1 to December 31, 1993. Excess events are calculated for January 1, 1994 to March 31, 1999.

Daily nosocomial C. difficile infections

Nosocomial C.difficile infections require diarrhoeal symptoms to start more than 72 hours after admission to hospital and the presence of C.difficile toxin in a stool sample. The number of incident cases of nosocomial C. difficile toxin-associated diarrhea per day was derived from the Infection Control Database. Patients were excluded if they were tested and diagnosed after being discharged, or, if after an initial positive test, they had subsequent positive tests during the same hospitalization. The number of confirmed diagnoses by date of onset was calculated. The time series' range is from April 1, 1995 to September 1, 1999. The standard incidence is based on C. difficile infection rates April 1, 1995 to March 31, 1996. Excess events are calculated for April 1, 1996 to July 31, 1999.

Daily medication errors

A medication error occurs when a healthcare provider recognizes an incorrect administration of a medication and the incorrect administration is reported using an incident report form. The number of errors per day is derived from the Incident Report Database. Cases must be inpatients, regardless of the severity of the injury resulting from the medication error. The period for which there is available data is January 1, 1993 to July 15, 1999. The standard incidence is based on medication error rates from January 1 to December 31, 1993. Excess events are calculated for January 1, 1994 to July 15, 1999.

Daily fall rate

A fall occurs when i) a healthcare provider determines that a patient fell and ii) the fall is reported using an incident form. The number of falls per day is derived from the

Incident Report Database. Cases were inpatients and the severity of the injury resulting from the fall was not considered. The period for which there is available data is January 1, 1993 to July 15, 1999. The standard incidence is based on fall rates January 1 to December 31, 1993. Excess events are calculated for January 1, 1994 to July 15, 1999.

3.5.5 Outpatient outcomes

There are six outpatient outcomes: the 7 and 30-day ER re-visit rates, the 7 and 30-day urgent or emergent readmission rates, and the 7 and 30-day death rates. Each outcome is a proportion where the denominator is the number of Ontario patients discharged from the Ottawa Civic Hospital on a given day.

Daily 7-day and 30-day ER re-visit rate

An ER re-visit occurs when an ER physician sees a patient within 7 or 30 days of the patient's discharge from the Ottawa Civic Hospital. The daily ER re-visit rate is the proportion of patients who are seen by an ER physician within 7 or 30 days of their discharge date. To determine the number of patients seen by an ER physician within 7 or 30 days of discharge, the patients discharged home were identified using the ADMS bed census table. A file consisting of the OHIP numbers of these patients was created. This file was linked to the OHIP database at the Institute for Clinical Evaluative Sciences (ICES) to determine if an ER visit to any emergency department in Ontario occurred within the specific time interval. The time series' range is November 1, 1994 to November 15, 1997.

Daily 7-day and 30-day urgent re-admission rate

An urgent re-admission occurs when a patient is re-admitted to any Ontario hospital within 7 or 30 days of discharge from the Ottawa Civic Hospital. The daily urgent or emergent readmission rate is the proportion of patients discharged from the OCH who are

urgently or emergently re-admitted to any Ontario hospital within 7 or 30 days of their discharge date. To identify the number of patients urgently re-admitted within 7 or 30 days of discharge, the patients discharged home each day were identified using the ADMS bed census table. A file consisting of the OHIP numbers of these patients was created. This file was linked to the CIHI-DAD at ICES to determine if patients were urgently re-admitted to any Ontario hospital within the specific time interval. Only admissions that were coded in the CIHI-DAD as urgent or emergent were considered. The time series' range is January 1, 1993 to February 28, 1999.

Daily 7-day and 30-day mortality rate

The daily mortality rate is the proportion of patients that die within 7 or 30 days of discharge from the Ottawa Civic Hospital. To identify the number of patients that die within 7 or 30 days of discharge, the patients discharged home each day of the study were identified using the ADMS bed census table. A file consisting of the OHIP numbers of these patients was created. This file was linked to the vital statistics database at ICES to determine if patients died within the specific time interval after discharge. This database identifies the death date of all Ontarians, regardless of the location of death. The time series' range is January 1, 1993 to February 28, 1999.

3.6 *Software used for data management and statistical analysis*

SAS version 6.12 and Excel 97 are the software programs used to manage and analyze data.

3.7 *Analysis*

3.7.1 *Univariate analysis*

Each variable included in the study (occupancy and the 20 outcomes) was described in terms of its mean, standard deviation, maximum and minimum values, 95th,

75th, 50th, 25th, and 5th percentiles. These are presented for each variable for the entire study period and for each year. For rare events, the Poisson distribution was used to calculate the 95% confidence limits.

Time series plots of individual 'smoothed' time series demonstrate the change in outcome over time. The smoothing procedure used in this analysis is a 29-day moving average centered on the mid-observation. Thus, the 'smoothed' value on a given day is the average value of the 14 days preceding it, the 14 days following it and the value on that day. Unsmoothed plots of hospital occupancy and hospital bed numbers are also presented.

3.7.2 Multivariate analysis

The goal of this analysis is to determine if the independent variable, daily occupancy rate, was associated with each of the dependent outcome variables representing measures of quality of care. The main statistical obstacle in performing such an analysis is the potential for autocorrelation of the measurements for each outcome. Thus, before modeling, it was necessary to test each outcome for evidence of serial dependence. If autocorrelation was present, then the model used must account for it.

Multivariate time series analysis-general description

The difficulty in relating daily rates of the outcome and independent variables arises from the sampling technique. Repetitive sampling on a daily basis can result in the measurements being autocorrelated. That is, the result on day d_i depends on the result on day d_{i-x} . This observation violates one of the principle assumptions in simple regression analysis, that each observation is independent.⁷² Therefore, alternative modeling techniques are necessary. Time series analysis is such a technique.⁷³ A time series is a set of observations for a given measure over time. A plot of these observations versus time

can be used to pictorially demonstrate trends over time, seasonal changes, or cyclical changes. Formal statistical methods, introduced by Box and Jenkins, are available to analyze time series.⁷³ These methods are powerful because they delineate the processes describing a particular time series, that is, how past values effects current or future values.^{73:74} They can be extended to forecast future values, to identify if changes in values are temporally related to events of interest and to relate one or more time series to each other.^{73:74}

The Box-Jenkins technique, or autoregressive, integrated, moving average (ARIMA) modeling, involves modeling the value at time t , as a function of values and errors at previous times, $t-t$. The technique uses three types of processes – differencing (I), autoregressive (AR) and moving average (MA) processes – to model the time series and explain the data. Differencing involves subtracting previous values from the current value. An AR process involves regressing the current value with previous values as given by the equation:

$$Y_t = \sum_{l=1}^p \alpha_l Y_{t-l} + Z_t \quad (\text{Equation 3.7.1})$$

where Y_t is the value of Y at time t , α is the regression parameter, l is the number of lags, p is the order of the AR process, and Z is the error term. An MA process involves regressing the current value with previous random errors as given by the equation:

$$Y_t = Z_t + \sum_{j=1}^q \beta Z_{t-j} \quad (\text{Equation 3.7.2})$$

where Y_t is the value of Y at time t , Z_t is the random error at time t , β is the regression parameter, j is the number of lags, and q is the order of the MA process. An ARIMA model is one in which all three processes are required to explain the time series. A model

is deemed to fit the data if the errors between the measurements calculated by the fitted model and the actual measurements are randomly distributed with mean of zero and a finite variance.

The ARIMA technique can be extended to a regression model to determine the relationship between two time series. This type of model will relate current values of the dependent variable to concurrent values of the independent variable *and* previous values of the dependent variable.⁷⁴

The steps involved in identifying the relationship between the dependent and independent time series are:

1. Testing for autocorrelation in each outcome series.
2. a) If no serial autocorrelation exists then linear regression models can be used to establish a relationship between occupancy and the outcome.
2. b) If serial autocorrelation exists in the outcome series, then an ARIMA regression model is used to establish a relationship between occupancy and the outcome. To fit an ARIMA model the following steps are necessary:
 - i. Ensure that both the dependent and independent time series are stationary.
 - ii. Identify potential AR and MA processes in the dependent time series.
 - iii. Estimate the parameters of the model.
 - iv. Evaluate the adequacy of the model by assessing the residuals.
 - v. Re-fit the model until the residuals are white noise.
 - vi. If more than one model is identified, choose the model that is most parsimonious and minimizes the error variance.
 - vii. Determine if a significant association exists between the dependent and independent time series

Each of the steps in outlined by 2 b) will be described in detail.

Step 1-Testing for autocorrelation in each outcome series

The first step determines if there is autocorrelation in the outcome series. If there is no autocorrelation, then one can conclude that a time series is a white noise process, that is its value at time t_i does not depend on the value of i . However, if it is not white noise then the serial dependence must be accounted for in any analysis.

The Durbin-Watson test determines if a time series is autocorrelated at specific lags.⁷⁴ The null hypothesis is that the time series is not autocorrelated. If one rejects the null hypothesis then one must assume that there is evidence of serial dependence, for at least one lag, which must be accounted for in the analysis. This study measured the Durbin-Watson test at lags one through five and used an alpha of 0.05 to exclude the null hypothesis. Thus, for each variable, if there was a significant test statistic at lag k , there is a less than 5% chance that the time series is not autocorrelated at that particular lag.

Step 2a – Linear Regression.

If the null hypothesis was not rejected at all five lags the time series was classified as white noise. A linear regression model was then used to relate the outcome series to occupancy.

Step 2b – ARIMA modeling

If the null hypothesis was rejected at any of the first five lags, the time series was classified as serial dependent and therefore ARIMA modeling was used.

Step2b) i) Ensuring stationarity in both the dependent and independent time series.

In order to model dependent and independent time series, both must be stationary. Stationarity, strictly defined, implies that the value of the outcome does not depend on the time of the sampling.⁷³ However, for the purpose of multivariate modeling, it is more

loosely defined as not requiring any differencing.⁷⁵ If a time series is non-stationary, it must be transformed before it can be entered into a regression model.

The process of evaluation for stationarity involves judgement and a statistical test. Judgement is used to examine 'rough' and 'smoothed' plots of time series for any evidence of trends over time. In addition, the autocorrelation function (ACF) can be examined for evidence of non-stationarity.^{f, 74} If a time series plot shows obvious trends or cycles then it will likely require some form of differencing. Two patterns in the ACF suggest non-stationarity. An ACF that remains high for many lags suggests that first differencing is necessary. An ACF that demonstrates peaks at a consistent lag suggests that differencing by a span of the same order as the number of lags between peaks. The statistical test for stationarity is the Dickey-Fuller test.⁷⁵ The null hypothesis is that the time series is not stationary. Thus, rejection of the null suggests that the time series is stationary.⁷⁴⁻⁷⁶

If a time series is not stationary, various types of transformations are available to make it so. The most commonly used transformation is differencing. Differencing involves subtracting previous values from the current one. It can be performed one or more times successively to remove trends. Also, differencing over a span will remove cyclical patterns.⁷⁴

Following the differencing procedure, the differenced series needs to be evaluated for stationarity using the same methods outlined above. Note that the process is an

^f The autocorrelation function is a plot of the correlation coefficients at increasing lags. For example, the lag-1 autocorrelation coefficient is the correlation coefficient between Y_t and Y_{t-1} for all t . Likewise the lag- x autocorrelation coefficient is the correlation coefficient between Y_t and Y_{t-x} . The ACF plots these autocorrelation coefficients against the corresponding lag number.

iterative one, first assessing for stationarity then differencing and again testing for stationarity in the differenced series. If the differenced series remains non-stationary, further differencing is required until the time series becomes stationary. After both the dependent and independent time series are deemed stationary, they can be entered into a model.

Step 2b) ii) Identifying the AR and MA processes in the dependent time series

Evaluation of the ACF and partial autocorrelation function (PACF)^f of the dependent time series helps to identify AR, MA or ARMA processes. For an AR process, the ACF exponentially drops to zero and the PACF has a spike at lag p , where p is the order of the AR process. For an MA process, the PACF exponentially drops to zero and the ACF has a spike at lag q where q is the order of the MA process. For an ARMA process the ACF and PACF both drop exponentially to zero and have spikes at lag p in the PACF and lag q in the ACF where p is the order of the AR process and q is the order of the MA process. Note that judgement is used to select the AR and MA terms since there are no statistical rules for selection. Also, identifying the best model is an iterative process of selecting a potential model and determining how it fits the series.

Step 2b) iii) Estimate the parameters of the model

After selecting the order for each process, one estimates the parameters for the model. The model contains the AR, MA terms and the stationary time independent time series (i.e. the occupancy time series).

Step 2b) iv) Evaluate the adequacy of the model by assessing the residuals

^f The partial autocorrelation function is a plot of the partial correlation coefficients at increasing lags. The partial autocorrelation coefficient is the correlation between Y_t and Y_{t+k} after removing their mutual linear dependence on all intervening variables, $Y_{t+1}, Y_{t+2}, \dots, Y_{t+k-2}, Y_{t+k-1}$.

The result of the **ARIMA** modeling is an equation relating current values of the dependent time series to current values of the independent time series, past values of the dependent time series, and an error term. If the model fits the data, then the error terms are random, with a mean of zero and a finite variance. Thus, after estimating the parameters, tests are required to determine if the residuals meet these criteria.

There are several methods to determine if residuals of a model are white noise (i.e. they are random, with a mean of zero and a finite variance). Ljung and Box have described a statistic (the Q statistic), which is used to test the null hypothesis that the error terms are not temporally related. Essentially, it examines the autocorrelation of the residuals at increasing lags. If the autocorrelations are large at any lag, then the Q statistic will exceed a critical value. Rejection of the null hypothesis indicates that the residuals are temporally related, and therefore, the model does not adequately explain the data.⁷⁷ One problem with the Q statistic is that its size depends to a certain extent on the number of observations included in the analysis. If the number of observations is large, then the Q statistic will likely exceed the critical value regardless of the error structure. This problem is especially pertinent to this thesis since the time series used contains up to 2400 observations.

Spectral analysis is a second method of testing the hypothesis that the residuals are white noise. Spectral analysis studies the frequencies of a time series. Identification of the frequencies within a time series will identify any periodicity within it. If the frequencies occur randomly then the time series is white noise. The Kolmogorov-Smirnov test is a formal statistical test for the white noise hypothesis. The null hypothesis is that the frequencies are white noise.⁷⁴

The approach followed here used the Q statistic for initial exploration for white

noise. If there were any significant values, then the autocorrelation coefficients were inspected. If all of the autocorrelation coefficients seemed small (for example, an absolute level of less than 0.05 on a scale that extends from 0 to 1) then it was determined that the Q statistic may have been 'artificially' inflated by the large sample size. In this case, spectral analysis and the Kolmogorov-Smirnov test were used to determine if the residuals were white noise.

Step 2b) v) Re-fit the model until the residuals are white noise

If the residuals are not white noise then additional parameters, not included in the initial model, are necessary to explain the relationship. These are selected by re-inspecting the ACF and PACF plots. Once chosen, estimation of the parameters and testing the residuals tested under the white noise hypothesis occurs as in the previous iteration. There is repetition of this process until the error terms are white noise.

Step 2b) vi) If more than one model is identified, choose the model that is most parsimonious and minimizes the error variance.

It is possible that several models meet the criteria of white noise residuals. In this situation, sequential application of two further criteria will choose the 'best' model. First, each parameter in the model will be included if its association with the current value is at a significance of less than 0.20. If there is more than one model that meets these criteria then the 'best' model is the one that minimizes the error variance.

Step 2b) vii) Determining if there is a significant association between the dependent and independent time series

Once fitted, the most appropriate model contains an estimate and a standard error for the parameter determining the association between the dependent time series and the occupancy time series. The parameter estimate is the amount of change expected in the

outcome variable for a 1% change in the hospital occupancy. Note that any transformation necessary to make either time series stationary must be considered in evaluating the results. The standard error was used to calculate 95% confidence interval of the parameter. Time series were considered to be associated if 95% confidence interval excluded zero.

Multivariate time series analysis-Occupancy as continuous and categorical

Two types of models were fit for each outcome. One model fit the independent variable (hospital occupancy rate) as a continuous measure against the dependent outcome model. The other model categorized occupancy into groupings and assessed the outcome across occupancy groups.

In the case where occupancy was analyzed as a continuous variable, a linear regression model was fit if the time series was not autocorrelated. Otherwise, an ARIMA model was fit. In both cases, the parameter estimated by the model represents the change in the outcome series expected with a 1% change in occupancy.

The other type of analysis modeled occupancy rate as a categorical value. The levels of occupancy for categorization were arbitrarily set at the deciles. If the outcome series was not autocorrelated, ANOVA was used to determine if there were differences in outcome rates between the decile groupings. A significant association was identified if the F test, assessing variance between decile groups, was significant at an alpha of 0.05. For pictorial purposes, the means and 95% confidence intervals for each decile group were plotted. If the outcome series was autocorrelated, then an ARIMA model was fit with the decile groups identified by nine dummy variables using the lowest decile group as the reference. In the ARIMA model, the parameter estimate for each dummy variable represents the change in outcome rate for that particular occupancy rate category as

compared to the lowest occupancy rate category. To graphically represent the effect of occupancy, the outcome rate in the lowest occupancy rate decile group was identified. Estimates of the outcome rate in other occupancy rate decile groups were estimated using the parameter estimates from the ARIMA model. 95% confidence intervals were also plotted. Significance was inferred if the 95% confidence intervals excluded the mean value in the lowest decile group. No correction was made for multiple comparisons.

The two models complement each other. The first model contains more information, as occupancy rate changes within a category are not lost. However, non-linear relationships may not be captured. The second model demonstrates non-linear effects, for example, threshold effects or U-shaped relationships.

Excess events versus incidence

In creating the models for bed-to-bed transfers and for all of the inpatient outcomes, excess events are used as opposed to incidence. For these particular outcomes, mathematical coupling occurs when incidence is compared to occupancy rate. This occurs because the number of inpatients is in the denominator of the dependent variable as well as the numerator of the independent variable. Therefore, as occupancy (i.e. the numerator in the occupancy time series) increases, the rate of the outcome series decreases (because its denominator increases). Coupling is a problem in this thesis because the occurrence of dependent outcomes are rare. To avoid this problem, the analysis used a standard rate to identify the expected events that would occur in a hospital of p inpatients. The analyses used the average daily rate for the first year of the study to calculate the standard rates. The parameter estimate in these models relates the change in the excess events expected for a unit change in occupancy rates.

Efficiency outcomes

The contemporaneous occupancy rate is the independent variable in the models testing the relationship between hospital occupancy and each of the dependent variables: mean ER delay, off service rate and OR cancellation rate. The occupancy rate on the day before is the independent variable in the models testing the relationship between occupancy with both bed-to-bed transfer rate and median length of stay.

Inpatient outcomes

The contemporaneous occupancy rate is the independent variable in the models testing the relationship between hospital occupancy and each of the following dependent variables: excess hospital deaths, cardiac arrests, falls and errors. The model testing the relationship between hospital occupancy and excess C.difficile infections uses the occupancy rate three days before the diagnosis as the independent variable. The reason occupancy three days before the diagnosis is used to reflect the delay between infection with the bacteria and development of the disease.

Outpatient outcomes

The occupancy rate on the day before discharge is the independent variable in the models testing the relationship between hospital occupancy and each of the following outcomes: ER visit rates, urgent readmission rates, and death rates.

4 Results

4.1 Univariate

Occupancy rates, bed numbers, and patient numbers are displayed in exhibits 6 and 7 and appendices 2 and 3.

The hospital reduced the number of beds and inpatients during the study period. The average daily number of beds available for patients in 1993 was 610 whereas in 1999 it was only 416. The mean occupancy rate did not change significantly. The daily occupancy rate over the seven-year study period is 89.6%, with an average of 88.2% in 1993 compared with an average of 90.3% in 1999.

Despite no significant increase in average yearly occupancy, there are two features of the plot that deserve further mention. First, there was a large increase in the number of days where occupancy rates exceeded 95% (exhibits 8 and 9). Early in the decade the proportion of days where occupancy exceeded 95% was 0.06 whereas in 1997 and onwards this proportion nearly tripled with a peak of 0.22 in 1999. The increase in the number of days with occupancy greater than 95% coincides with the large reduction in the number of beds occurring in the spring of 1996. Second, there are large day-to-day and week-to-week fluctuations. Between successive days, there are absolute differences in occupancy as large as 22%. Also, absolute differences in mean weekly occupancy between successive weeks were as large as 13%.

4.1.1 Efficiency

Exhibits 10 to 23 display the univariate statistics for the efficiency outcomes: daily ER delay, daily length of stay, bed to bed transfer rate, off service rate, OR cancellation rate, the absentee rate and the overtime rate.

Exhibits 10 and 11 display the univariate statistics for *daily ER delay*. In 1999, it

took over an hour longer to move from the ER to the hospital ward than it did in 1993. In 1993, patients waited an average of five hours and 24 minutes between arriving at the ER to being transferred to the floor. In 1999, this wait increased to six hours and 36 minutes. Also there was excessive ER delays for a greater proportion of days. In 1993, there was a median delay of seven hours less than five percent of the days. In 1999, a seven-hour delay was quite common, occurring more than one quarter of the time. Inspection of the smoothed time series suggests that this increase in average waiting time was gradual over time.

The univariate statistics for *daily length of stay* are provided in exhibits 12 and 13. The mean length of stay decreased slightly during the study period. In 1993, the average length of stay was six and three quarter days and in 1999 it was six and a half days. The decrease occurred gradually over the study period.

Exhibits 14 and 15 illustrate the univariate statistics for the *bed to bed transfer rate*. The proportion of patients transferred from one bed to another was approximately 6% per day. The transfer rates increased over time and the inflection point of the smoothed time series appearing to be 1996. The yearly averages of the daily rates also increase in 1996. Between 1993 and 1999 there is a one percent absolute increase in the proportion of patients transferred.

Exhibits 16 and 17 display the *off service transfer rate*. Off service transfers, which are patient transfers from the ER, ICU, OR, RR, or delivery suite to a hospital ward not corresponding to the service to which the patient belongs, occurred frequently. Up to one in nine patients in these hospital areas were transferred to off-service locations with an average off-service rate for the entire study period of 11.7%. There is no discernible long-term trend seen over the study period. There are, however, large day-to-

day fluctuations.

Exhibits 18 and 19 present the univariate statistics for *the daily operating room cancellation rate*. The cancellation of an operation due to the lack of a post-operative bed was a rare event. This occurred only 51 times between 1994 and 1999. The daily OR cancellation rate was zero on more than 75% of the days during this period. However, there were several days when the proportion of cases cancelled exceeded 5%. There were also clusters of days when there was a higher frequency of cancellations. These tended to occur during the winter months.

Exhibits 20 to 23 present the univariate statistics for the overtime rate and the absentee rate for ONA and CUPE 576 employees. Overtime rates doubled in both union groups during the study period although the nursing union started at a higher level. A dramatic feature of exhibit 21 is the overtime rate in the ONA union, which increased to a rate of 45% by the end of the study period. Absentee rate demonstrated no trend throughout the study but there were seasonal variations with peaks in the winter and valleys in the summer. The absentee rate was considerably higher in the nursing union than in CUPE 576. Please note that the statistics are aggregated by year and by quarter. Because accurate daily data was not available, these outcomes were not used in multivariate analyses.

4.1.2 Inpatient Outcomes

Exhibits 24 to 38 illustrate the univariate statistics for the following inpatient outcomes: death, cardiac arrests, c.difficile infections, medication errors, and falls.

The univariate statistics for *daily death rate* and *daily number of deaths* are in exhibits 24 to 26. The average in-hospital mortality is 4.2 deaths per 1000 patient days. This means that, on average, two to three patients died each day at the OCH.

The rate of death appears to increase over time. However, the number of deaths did not increase. Thus, the increased rate reflects a smaller number of patients at risk with the same numbers of patients dying.

The univariate statistics for *daily cardiac arrest rate* and *the daily number of deaths* are in exhibits 27 to 29. Cardiac arrests are infrequent events with no arrest occurring on greater than 75% of the days during the study period. Consequently, the average incidence is low: 0.6 cases per 1000 patient days. There were fluctuations during the year but they did not follow any specific pattern. In addition, although the rate appears to increase during the study period, this is neither statistically nor clinically meaningful. Interestingly, the number of cardiac arrests did not vary over time. Thus, the increased rate of cardiac arrests reflects fewer patients being at risk for the event. As previously mentioned the number of inpatients dramatically decreased during the study period.

The univariate statistics for the *daily rate of c.difficile infections* and *the daily number of c.difficile infections* are presented in exhibits 30 to 32. The incidence of these infections increased nearly fourfold during the study period (0.4 cases per 1000 patient days in 1995 to 1.5 cases per 1000 patient days in 1999). The largest jump in rates occurred in 1998. The rate increased periodically, indicating outbreaks. Also, the baseline rates were much higher in the latter period of the study, suggesting the risk of transmission between outbreaks increased during the observation period.

The univariate statistics for the incidence of *medication errors* and *the daily number of medication errors* are presented in exhibits 33 to 35. The average incidence was 2.0 errors per 1000 patient days. The error rates varied quite dramatically in an apparently seasonal pattern. There was no change in error rates during the study.

The univariate statistics for the *incidence of falls* and the *daily number of falls* are in exhibits 36 to 38. At least one fall on 75% of the study days. There were days in which the incidence exceeds 20 cases per 1000 patient days, meaning that 10 falls were identified and recorded on those days. The average incidence of falls was 4.6 falls per 1000 patient days. There was no persistent increase in falls throughout the study period. However, there were large fluctuations of rates.

4.1.3 *Outpatient outcomes*

Exhibits 39 to 50 display the following outpatient events: 7 and 30 day ER re-visits, 7 and 30 day readmissions, and 7 and 30 day death rates.

The *rates of ER re-visits at 7 and 30 days post discharge* are presented in exhibits 39 to 42. Such visits occurred within a week following discharge from the Ottawa Civic Hospital in approximately 1 of every 20 patients (proportion = 4.9%). This rate doubles at thirty days by which time close to 10% of discharged patients will visit an ER. The rate of ER re-visits increased during the study period. The relative increase in the rates between 1994 and 1997 was greater for the 30-day outcome (a 43% relative increase for the 30-day revisit rate versus a 19% relative increase for the 7-day revisit rate).

Urgent re-admissions to any Ontario hospital at 7 and 30 days post discharge are in exhibits 43-46. Similar to the ER revisit rate, the re-admission rate increases throughout the study period. The relative increase in rates between the first full year and the last full year of the study was greater for the 7-day rates (a 75% relative increase for the 7-day re-admission rate versus a 37% relative increase for the 30-day re-admission rate). At 7 days, the readmission rates in 1993 were 2.0%, which increased to 3.5% by 1999. At 30 days, readmission rates in 1993 were 3.5%, which increased to 4.8% in 1999.

The 7 and 30 community death rates are in exhibits 47-50. Deaths occurred infrequently during the first week following discharge (average of 0.23%, or 1 in 400 patients discharged). Predictably, this rate was higher at 30 days post discharge (average = 1.00% or 1 in 100 patients discharged). The mortality rates following discharge did not increase during the study period in either the 7 day or 30 day observation.

4.2 *Multivariate analysis*

Please see appendix 4 for the ARIMA models relating occupancy to each of the outcome variables. The fitted model, used to regress daily hospital occupancy with each outcome time series, is presented. The table provides the Differencing, AR and MA processes in the model, as well as the estimate of the occupancy rate parameter. For example, the model for ER delay required no differencing but had an AR term of order 2 and an MA term of order (2)^f. The parameter estimate is also indicated. Appendix 5 provides a detailed description of the model building process used for these analyses.

Efficiency outcomes are presented in exhibits 51-57. Inpatient outcomes are presented in exhibits 58-63. Outpatient outcomes are presented in exhibits 64-71.

4.2.1 *Efficiency Outcomes*

Daily ER delay increased with occupancy rate (exhibit 51 and 53). The increase in waiting time is linear. The median delay increased 20 minutes (95% CI = 12,24 minutes) with a 10% increase in occupancy (exhibit 51). Comparing days when the hospital has an occupancy in the highest versus lowest decile, patients spent on average 24 minutes longer waiting to be transferred to the ward (95% CI = 12,33 minutes)

^f The notation to describe an ARIMA model is set by convention. The bracketed term indicates that the order of the process includes only a lag 2 term. Conversely, if there is no bracketing, as is the case for the

(exhibit 53).

The relationship of *length of stay* and previous day's occupancy is complex. There is a statistically non-significant decrease in length of stay for people discharged on day i as the occupancy rate for day $i-1$ increases. The LOS decreased 0.2 days with a 10% increase in occupancy (95% CI = -0.4, 0.0 days) (exhibit 51). However, most of this apparent decrease occurred at the highest extreme of occupancy (exhibit 54). There was no appreciable decrease in length of stay as previous day's occupancy rate increases until occupancy rate exceeds 94% at which a significant decrease in length of stay was seen. When the hospital occupancy was in the highest decile, the length of stay was 0.5 days less than when hospital occupancy was in the lowest decile (95% CI = 0.2-0.8 days) (exhibit 54).

Off-service rate increased with occupancy rate (exhibits 51 and 55). The proportion of patients transferred to off-service locations from the ER, ICU, OR, RR or delivery suite to the ward increased by 3.6% with each 10% increase in occupancy rate (95% CI = 3.6, 3.6%) (exhibit 51). The change in off service rate appeared when occupancy exceeded 86% (exhibit 55). Below this level, the rate was stable around 7%. However, as occupancy rates increased above 86% the off service rate increased linearly, such that the off service rate in the highest decile group was 12.2% (95% CI = 11.2, 13.5%).

There is a non-significant increase in the *percentage of operations cancelled due to lack of a post-operative bed* as occupancy rate increases (exhibits 51 and 56). The change in cancellations increased by 0.2% (95% CI = -0.2, 0.4%) with a 10% increase in occupancy.

AR term in this model, then the model consists of a lag 1 term and a lag 2 term.

The number of patients *transferred* per day increased with the occupancy rate.

There was an increase of 2.8 (95% CI = 2.0, 3.7) excess transfers with each 10% increase in occupancy rate (exhibit 52). The standardized number of transfers increased linearly with occupancy rate (exhibit 57).

4.2.2 *Inpatient Outcomes*

Deaths decreased as occupancy increased (exhibits 58-59). The number of excess deaths decrease significantly by 0.15 (95% CI = 0.02, 0.29) with every 10% increase in the occupancy rate. A similar relationship is evident on examination of the plot comparing the standardized number of deaths versus occupancy rate group.

No relationship exists between *cardiac arrests* and occupancy rates. The analysis using occupancy rate as a continuous variable demonstrates a decrease of 0.06 excess events per day (95% CI = -0.11, 0.00) with an increase in occupancy of 10% (exhibit 58). Although this effect approaches statistical significance, it is not clinically relevant. Additionally, the plot of standardized number of cardiac arrests versus occupancy-rate groups suggests that no clear relationship exists (exhibit 60).

Medication errors, falls, and c. difficile infections are not associated with hospital occupancy (exhibits 58, 61-63).

4.2.3 *Outpatient Outcomes*

The percentage of patients *returning to an ER following discharge* is not associated with occupancy rate on the day before discharge (exhibits 64-65). The percentage of patients visiting an ER within a week of discharge increased by 0.07% (95% CI = -0.15%, 0.66%) with a 10% increase in the occupancy rate. Within a month of discharge, visits decrease by -0.52% (95% CI = -1.42, 0.38) with a 10% increase in the occupancy rate. Neither of these changes in rates is statistically significant. Analysis

using decile groupings of occupancy also do not suggest that ER visits are positively associated with occupancy (exhibit 66 and 67). In fact, there may be a trend towards decreasing 30 day ER visit rate (exhibit 67).

Re-admissions rates to acute care hospitals are not associated with the occupancy rate on the day before discharge (exhibits 64-65). The percentage of patients re-admitted within a week appears to decrease by 0.25% (95% CI = 0.01, 0.49) with a 10% increase in occupancy according to the analysis of occupancy as a continuous variable. However, upon inspection of the plot of readmission and occupancy rate group, there is no discernible relationship. As well, occupancy rate on the day before discharge does not appear to influence the 30-day readmission rate (exhibits 68-69).

Death rate at one month following discharge appears to increase as the occupancy rate on the day before discharge increases (exhibit 64-65). The proportion of patients dying within one month increases by 0.22 percent as the hospital's occupancy rate increases by 10% (95% CI = 0.21, 0.22) (exhibit 65). The same significant relationship exists when using occupancy rate deciles to assess for an association ($p < 0.05$) (see exhibit 71). No such association exists using seven day mortality rates (see exhibits 64 and 70).

5 Discussion

5.1 Is there a relationship between quality of care and hospital occupancy?

This thesis conclusively demonstrates that hospital occupancy affects the care of hospitalized patients. As the hospital's occupancy rate increases: patients wait longer in the ER; they undergo more bed-to-bed transfers; they are transferred to off-service locations more often; and they spend less time in hospital. Despite the influence upon these processes of care, the thesis did not convincingly show a change in patient outcomes either in hospital or after discharge. These findings and the limitations of the supporting research will be discussed in an order analogous to patient care in the hospital - with pre-admission events, intra-hospital events and post hospital events presented sequentially.

Pre-admission events - It is reasonable that hospital occupancy directly causes increased waiting time in the ER, increased off-service transfer rates, and increased bed-to-bed transfers. First, the analysis demonstrates a significant statistical relationship between them. Second, their association appears to be linear, suggesting a "dose - response" effect. Third, the explanation for such a relationship is easy to postulate. Increased occupancy means there are fewer beds for new patients. Therefore, it takes longer to find a bed for an ER admission and the probability of finding a bed on the correct ward decreases. Fourth, the results are consistent with previous, published theoretical models. As discussed in the introduction, Bagust et al recently published a model based on hypothetical data demonstrating a similar effect.³⁷

These inefficiencies are important indicators of quality inasmuch as they relate to access, process, outcomes, and satisfaction. Although not well described in the published literature, waiting times in ER, off-service rates, and bed-to-bed transfers likely relate to

each of these dimensions of quality. An increased ER waiting time could have several effects. First, it contributes to dissatisfaction with care.⁷⁸ Second, if the ER is full of patients who are not supposed to be there, the staff will find it difficult to concentrate on new patients arriving. Lastly, providers and equipment in the ER may not be specialized for the care of a particular health problem. Patients transferred off-service may also be affected in several ways. These patients may have a delay in specific therapies or investigations and may not be monitored appropriately. Both of these effects may negatively influence processes, outcomes and satisfaction. Bed to bed transfers may impact care in two ways. First, unnecessary patient transfers may create anxiety or distress for patients. Second there will be a discontinuity in nursing care. Although all of these potential quality problems are speculative, they are all plausible.

Further research in this area could address the specific questions arising above. To improve the work completed in this thesis, primary data collection is necessary since existing administrative databases are insufficient in scope and quality. For example, using the existing data, we could determine the effect of increased ER waiting time on in-hospital mortality. However, it would be impossible to ascertain its effects on other dimensions of quality, such as patient satisfaction or the ordering of medications. The research could also be more directed. Sub-populations of the overall hospital population should be sampled, as the strength of any purported association between processes of care and outcomes of care will be dependent on the patient population. For example, it is probably more important for an elderly male with severe congestive heart failure to be cared for by appropriate specialists in the appropriate location than it is for a young woman with an ankle fracture.

The observed statistical relationship between occupancy and ER delay, bed to bed

transfers and off-service transfers is likely valid. Data accuracy and completeness, a potential problem with administrative databases, probably do not affect these particular outcomes (see section 5.2).

Hospital events – In-patient outcomes change very little as the hospital fills with patients. There is a statistically significant decrease in death rates with increases in occupancy and a trend towards decreasing cardiac arrests with increases in occupancy. Cardiac arrests, c.difficile infections, falls and medication errors are not associated with hospital occupancy according to this analysis.

The negative association of death rate and occupancy rate is opposite to that hypothesized. I postulated that increases in occupancy would increase error occurrence and subsequently bad outcomes, such as death. However, the observed results are consistent with the study by Hartz et al²³ (see section 1.2.2) in which annual occupancy rate was determined to be negatively associated with annual hospital mortality. A possible explanation for the observation includes an improvement in service delivery with patient volume, that is ‘practice making perfect’. Alternatively, the relationship may be due to a confounding factor.

It is unlikely that service delivery improves with occupancy rates. First, most of the time occupancy rates are between 84 and 94% (it was within this narrow range approximately 8/10^{ths} of the study period). Therefore, most daily changes in occupancy are less than 5%. It is hard to believe that skill level would change with such small changes in occupancy. Secondly, one would expect that any improvement in the hospital staff’s skill would occur gradually. Exhibit 7 demonstrates that there is no persistent trend in occupancy - rather it fluctuates daily about a constant level. Thus, if one were to implicate improving skill levels as a cause for the association, skill levels would improve

and deteriorate daily, a highly unlikely pattern of performance.

The observed association is more likely due to a confounding factor, specifically, severity of patient illness. In order for confounding to explain the relationship between occupancy and mortality, severity of patient illness must be associated with both mortality and occupancy, but, in opposite directions. Severity of illness will, of course, be *positively* associated with hospital mortality rates because the greater the proportion of severely ill patients, the higher the expected mortality rate. In contrast, severity of patient illness may be *negatively* associated with occupancy rates. This could occur because of how hospital beds are utilized. In an ideal world, only acutely ill patients would be admitted to acute care hospitals. However, due to a lack of community resources, patients who are not acutely ill are often admitted to acute-care beds. This would increase hospital occupancy rates while, at the same time, reduce the overall patient severity of illness. To determine if this confounding indeed explains the negative association between occupancy and death rates, future research in which a daily mortality rate adjusted for severity of patient illness is required.

The number of self-reported medication errors or falls does not change with hospital occupancy. This finding suggests these events are independent of occupancy of the hospital, which is contrary to the hypothesis described in the introduction. Alternatively, the lack of an observed association could be a function of poor data. There might be a recording bias inherent in the self-reporting process of incidents. As workload increases, the reporting of events may decrease. Thus, as occupancy increases proportionally fewer incidents will be reported and one is less likely to identify an association with occupancy.

Based on the data, one must conclude that hospital c. difficile infection rate is

unlikely to be strongly influenced by the occupancy of the hospital. I initially hypothesized that, as occupancy increased, hospital workers became busier and infection control practices became progressively more neglected. The lack of a statistical relationship could refute this hypothesis. There are alternative explanations to explain the lack of an association. First, it is quite clear that, in addition to the increased baseline incidence, there are several outbreaks. One interpretation for this pattern is that once there are a critical number of cases, an epidemic is inevitable.⁷⁹ Occupancy rates may be an important factor in the initiation of the epidemic. However, once started the infection may spread between patients regardless of the occupancy. Conversely, if there were no cases in the hospital, then there is no risk of the diseases spreading, irrespective of infection control practices. In both settings, the daily incidence would be independent of occupancy. Second, there could be discordance between occupancy at the hospital and ward levels resulting in bias. Suppose that the hospital as a whole is relatively unoccupied, but a particular ward is maximally occupied. If there were a *c.difficile* outbreak associated with the high ward occupancy, it would appear as if there was a negative association between overall hospital occupancy and *c.difficile* infections. This potential bias is probably more important for *c.difficile* infections than it is for the other outcomes in this study, as health workers spread *c.difficile* toxin from patient to patient. Therefore, outbreaks are more likely to occur locally on a ward as opposed to throughout the hospital and one would expect ward occupancy to be more important than hospital occupancy. Further studies, exploring ward occupancy and ward infection rates will identify if this hypothesis is correct.

The positive association between hospital occupancy rates and the rate of OR cancellations due to a lack of post-operative beds is not statistically significant. If these

cancellations are indeed caused by increases in occupancy rate, the relationship may be statistically insignificant. This is because in order for operations to proceed, a post-operative bed is required in either the intensive care unit (ICU) or the surgical recovery room (RR). The number of beds in the RR is more flexible than in the hospital as a whole because patients need to remain in the RR for only short periods of time after their case. If a bed is needed, patients can usually be transferred to other parts of the hospital without much notice. In general, because operative cases are priorities, patients from beds in RR are preferentially transferred. Therefore, OR cancellations for lack of postoperative beds are very rare. Only when the hospital is extremely occupied, with a high proportion of surgical or critically ill patients needing ICU or RR beds, will there be an increased rate of OR cancellations due to lack of a post-operative bed. Another reason the observed association may be insignificant is the method of data collection used by the OR. Patients are entered into the ORSOS database only if their surgeon notifies the OR clerks of a booking. Therefore, if a surgeon is particularly busy she may not bother booking new cases. In this situation, occupancy rate would affect access to care; however, the ORSOS database would be insufficient to identify it.

This thesis suggests that physician behavior changes as the hospital occupancy reaches full capacity. Exhibits 51 and 54 demonstrate a non-significant negative association between previous day's occupancy rate and the length of stay of patients discharged on that day. This finding suggests physicians discharge patients at an earlier time, potentially before they are ready to go, when there is a lack of bed resources. Presumably, the physician arrives at the hospital to learn that the hospital is at full capacity, and therefore, must discharge patients. It is possible that these patients might not be ready for discharge, as they normally stay longer. Against this hypothesis,

however, is the lack of association between occupancy and ER visits, urgent re-admissions and community death rates (see Outpatient events, below).

Outpatient events – If patients were being discharged too early at excessive occupancy, then one would expect that more bad patient outcomes would occur in the early post-discharge period. Indeed there is a statistically and clinically significant increase in the crude 30-day mortality following discharge as the occupancy rate the day before discharge increases. However, the case for *premature* discharge is weakened by the fact that ER visits or urgent re-admissions did not increase in a similar manner than death. One might expect these to be more sensitive markers for poor hospital or post-discharge care than early deaths for two reasons. First, more patients return to ER or need readmission than die. Therefore, presuming that the care factors leading to ER revisits and readmission are the same as those leading to death, one should expect a more significant relationship. Second, it is easier to comprehend a causative link between return visits to the ER and readmission with poor care during the hospitalization. For example, a patient that develops a c.difficile infection following discharge often leads to a return to the hospital because that was where the surgery took place. A death on the other hand, is likely more related to the underlying illness than the care received. For these two reasons, it is possible that the observed association between occupancy and 30 day community death rate may be a spurious one.

Could patients be discharged prematurely and not have an increased ER visit rate or urgent readmission rate? The answer to this question depends on whether community health services could compensate for the deficiencies in care. If, for example, a patient had a conscientious family doctor who was able to respond to the patient's problems quickly, then errors related to the premature discharge may be negated. In the example

above, if the physician could see the patient within the first few days of discharge, she would probably make a presumptive diagnosis of c.difficile infection and treat accordingly.

Thus, the conclusion that hospital occupancy does not impact on post discharge care may be biased by the inadequacy of ER visits, re-admissions, and post discharge mortality to reflect quality of patient care. In order to identify how well these outcomes reflect quality of care, a prospective cohort study is needed. The proposed study should measure: clinical readiness for discharge; the appropriateness of care at the time of discharge; the effectiveness of the communication with the community caregivers; patient's satisfaction with care; compliance with follow up interventions; and identification of adverse events (where an adverse event is defined as an injury due to medical intervention).⁶²

Summary – In summary, this study found that occupancy has an effect on how patients are cared for in the hospital. If one considers the markers for inefficiencies as latent failures then it is possible that they could result in increased active errors. Despite this, no consistent positive relationship was observed between patient outcomes and hospital occupancy. The absence of an association could be real as each of the outcomes is related to several factors that are likely much more important than active errors related to hospital occupancy. However, there are study design factors that affect the validity of this conclusion. First, the study used crude rates as opposed to rates adjusted for hospital case mix. Second, the study looked at hospital rates as opposed to rates on specific wards.

Does this thesis demonstrate a relationship between hospital occupancy and quality of care? The answer to this question is “a qualified yes”. “Yes”, because the

analysis demonstrates that hospital occupancy rates are associated with efficiency of service delivery. “Qualified” because the study does not identify a conclusive relationship with the outcomes used by health services researchers as indicators of quality. I believe strongly that this “qualification” does not negate the affirmative conclusion. As discussed, these indicators are not ideal for measuring quality. Further research is required to identify precisely what effect occupancy has on access, processes, satisfaction and outcomes of care.

5.2 General limitations in study design threatening validity, generalizability, and inclusiveness

There are several limitations in study design that deserve mention. These will be presented in terms of validity, generalizability, and inclusiveness. Validity refers to the truthfulness of the results. Generalizability refers to whether the results can be extended beyond the study hospital. Inclusiveness refers to the scope of the research.

Validity – the main threat to this study’s validity is data quality. Under most circumstances, the quality of administrative data is less than that of primary data. However, in many cases administrative data can be of sufficient quality to use in health services research.⁸⁰

Accuracy of information is difficult to determine in any retrospective study. However, I believe that the data used in this thesis are accurate enough to make confident conclusions. First, most of the outcomes were derived from information that is required for the day-to-day operations of the hospital and patient care. If the information were inaccurate, there would be serious problems in admitting, transferring or discharging patients. Second, most of the outcomes were objective counts of occurrences. For example, the number of inpatients, the length of stay, the number of patients dying and

the number of patients readmitted are easily defined.

Despite a reasonable comfort level with most of the data, there are certain outcomes whose quality of data is questionable, specifically, the cardiac arrest, incident reports and payroll data. The cardiac arrest data was derived from the CIHI-DAD. Health record analysts update the CIHI-DAD by reviewing medical records to identify diagnoses and procedures and record them using ICD-9-CM codes. A *priori* knowledge that this process can be inaccurate⁸¹ mandated an extensive chart review to assess the validity of coding. This review identified inaccurate coding and, therefore, the group of patients miscoded was reclassified using a chart review and objective criteria. Thus, the cardiac arrest rate used in the study is valid. The Incident Report database contains information on medication errors and falls. These incidents are self-reported, meaning that health workers must identify and report them. Studies evaluating incidence reporting indicate that it may be inaccurate since workers may not realize when errors or falls occur. In addition, there are several incentives to not report them.⁸² Unfortunately, it is impossible to retrospectively evaluate this method's sensitivity and specificity. Although these outcomes were included in the analysis, their accuracy is unknown. Therefore, any conclusions based on this data should be made cautiously. The payroll database is inaccurate for daily data but probably accurate if data is aggregated over longer time periods. Most claims are submitted on time. However, claims are occasionally withheld. For example, if the ward manager does not have accurate hours for a particular employee, she may wait to submit the claim until the next pay period. Because accounting for payments must add up for each pay period, there may be days in which there are zero or even negative payroll hours. This effect will be diminished if the data is aggregated over several pay periods.

Other threats to validity in any study are its analytic technique. Three potential limitations in this thesis are the statistical modeling, the inability to adjust for case mix, and the unit of analysis used.

The ARIMA model is the most appropriate way to deal with the lack of independence in the outcomes. Other parametric methods, such as Poisson regression for rare events, linear regression for continuous outcomes and logistic regression for binomial outcomes necessitate independence in the error term.⁷² Since this assumption is unmet for most of the outcomes in this study, they are invalid techniques in this setting. Therefore, ARIMA modeling is the most appropriate statistical method for this analysis.

The validity of the association (or lack of it) between occupancy and patient outcomes is limited by inability to control for case mix. It is impossible to control for this type of confounding because data on co-morbidity is currently abstracted based on an entire admission. Using diagnoses identified during the hospitalization, the expected death rate for a case is calculated. That type of risk adjustment would be correct if the *admission* is the unit of analysis. However, the adjustment is inappropriate for this thesis because *daily* mortality rates were used. If one were to use discharge data to adjust for case mix, one would be forced to consider the expected death rate to be equivalent for every day a patient was in hospital. This assumption is incorrect, as patients' risks of dying change over time. For example, consider a patient who is very ill at the time of admission but then stabilizes and remains in hospital for a prolonged time. His expected *daily* mortality rate would approximate the *admission's* expected rate only at the beginning of his hospital stay. For the majority of his stay however, his expected *daily* death rate would be much lower than that predicted by his discharge diagnoses. New methods to use administrative data to adjust for a patient's daily acuity of illness and

therefore, daily risk of death need to be identified if one is to perform appropriate adjustments for case mix.

Using hospital rates instead of ward or service rates also limits the conclusions of the study. As discussed previously, there can be discordance between occupancy rates at the ward and hospital levels. If occupancy is associated with outcomes at the ward level but not at the hospital level, then one will not identify the relationship by studying an entire hospital. Future studies must stratify by ward or service.

Generalizability – This study of a moderately sized, Canadian teaching hospital in an urban center is generalizable to other settings with the following provisos. First, the results may not extend to hospitals whose average occupancy is well below full capacity. The average occupancy rates in this study approximated 90% and daily rates were often above 95%. The effect of occupancy on efficiency is probably much less at lower levels of occupancy, as suggested by exhibits 53-55. The graphs of emergency room delay (exhibit 53) and off service rate (exhibit 55) show that most of the change in the outcome occurred after occupancy exceeds 90%, and the plot of length of stay demonstrates that most of the change occurs above occupancy rates greater than 95%. Thus, if hospital occupancy never exceeds 90% these changes may not occur.

Second, the findings will not be generalizable to hospitals in which the majority of admissions are not emergencies. Some hospitals provide primarily “elective” services and therefore, can plan cases accordingly. It would be easier to run at close to capacity in such an institution because one knows how many patients will arrive each day. Third, smaller, non-teaching hospitals or those in rural settings may not have the same demand on beds or logistical problems as the one in the study. For example, the Ottawa Civic Hospital has many services and wards. If a rural hospital has only 60 beds total with two

wards and is staffed by a general surgeon and a handful of generalist physicians the chances and implications of being off service are quite different.

Inclusiveness – The study included a broad range of outcomes over reasonable periods, but its scope is limited in several regards. First, it does not examine pre-hospital events. The proportion of patients turned away from the hospital per day, which is important for a referral center, is not captured. Currently, there is no method of capturing all of the patients referred to the Ottawa Civic Hospital. Second, the study looks at occupancy and event rates at a hospital level. It may be that studying rates for specific wards would be more helpful in identifying a relationship. Third, it is impossible to examine processes of care in more detail than the crude manner used in this thesis. It would be very helpful to have detailed information on diagnoses, investigations and therapies. At this time, such descriptive databases do not exist at this hospital, making it impossible to study these outcomes in a retrospective way.

5.3 *Implications of this research*

Based on this research, it would be difficult to argue that there needs to be more beds at the Ottawa Civic Hospital and by extension, the acute care sector. Occupancy rates are essentially the same in 1999 as they were in 1993, even though there are almost 1/3 fewer beds. This implies that patients will usually utilize available beds. Second, this study did not find any increases in the incidence of bad patient outcomes with increases in hospital occupancy rates. Without any convincing positive association between outcomes and occupancy, there is little impetus to increase beds either across the board or at peak occupancy periods.

However, before dismissing the effect of hospital occupancy, it must be recognized that this research is a starting point. The research suggests that further work is needed

before the effect of hospital occupancy on quality of care is more fully understood and firm recommendations regarding bed supply can be made. Areas of research that would help understand the relationship better include a more thorough assessment using different processes or outcomes of care. Also, using a different measure of a hospital's capacity to provide service other than occupancy might improve our understanding of the relationship.

This thesis did demonstrate an effect on crude processes of care, such as ER delay and therefore, more research looking at specific processes of care in high-risk populations may demonstrate clinically relevant effects. For example, one needs to assess if hospital occupancy is associated with the incidence of medication errors. Also, one needs to address the question using a different unit of analysis. For example, if ward occupancy as opposed to hospital occupancy were studied, then the purported association may be more demonstrable.

Second, one could argue that bad patient outcomes, such as death rates, are only one aspect of quality. Therefore, they should not be used to conclude that no association exists between occupancy and quality. Alternatively, adverse events may be a better outcome. Adverse events, defined by the Institute of Medicine as "injuries due to medical intervention"⁸³, are theoretically more closely related to occupancy rates than outcomes such as mortality. Recall the conceptual model linking occupancy and quality of care (exhibit 2). In that model, active errors are induced by latent "system" failures. Since many active errors are absorbed without causing accidents the incidence of bad outcomes may not change despite their occurrence. For example, consider a patient with congestive heart failure (CHF) presenting to hospital when it is at full capacity. The overworked physician may misinterpret the chest x-ray and subsequently diagnose

pneumonia as well as CHF. This patient could suffer an allergic reaction to the inappropriately prescribed antibiotic but his overall condition should improve. This active error would not be identified in the bad patient outcomes used in this study, but if the outcome were adverse events, then it would be. Because adverse events are theoretically more closely associated with the effects of occupancy, future analyses should consider them as an outcome.

Third, it is arguable that occupancy is not the best predictor variable to reflect hospital “busy”-ness. Hospital occupancy was chosen because it reflected a measure of the capacity to provide service as well as how busy the hospital is. It was predicted that hospitals at occupancy rates of 80% were less busy and more capable to provide service than hospitals at 100% occupancy. However, occupancy alone ignores the effect of case mix and turnover. The case mix of the patients is definitely going to affect how busy hospital workers are, as well as the risk of bad patient outcomes, irrespective of occupancy. If a hospital is 100% occupied with stable patients, workers are unlikely to be overburdened with tasks. Furthermore, if the hospital is full, then large numbers of patients cannot be admitted. If, however, the hospital is 80% occupied then, because it is relatively empty, a large number of admissions can be accommodated. This will greatly increase workload. To improve the utility of occupancy as a measure of “busy”-ness, research is needed to produce valid adjustments for the case mix and patient turnover on a particular day.

In summary, it is too early to conclusively state that occupancy does or does not have a large impact on quality of care. We can state that certain processes of care are associated with quality. This information will probably not sway policy makers to increase the number of beds. However, the results of the thesis should prove valuable for

further evaluation of the effects of occupancy on care.

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7 Exhibits

7. Exhibits

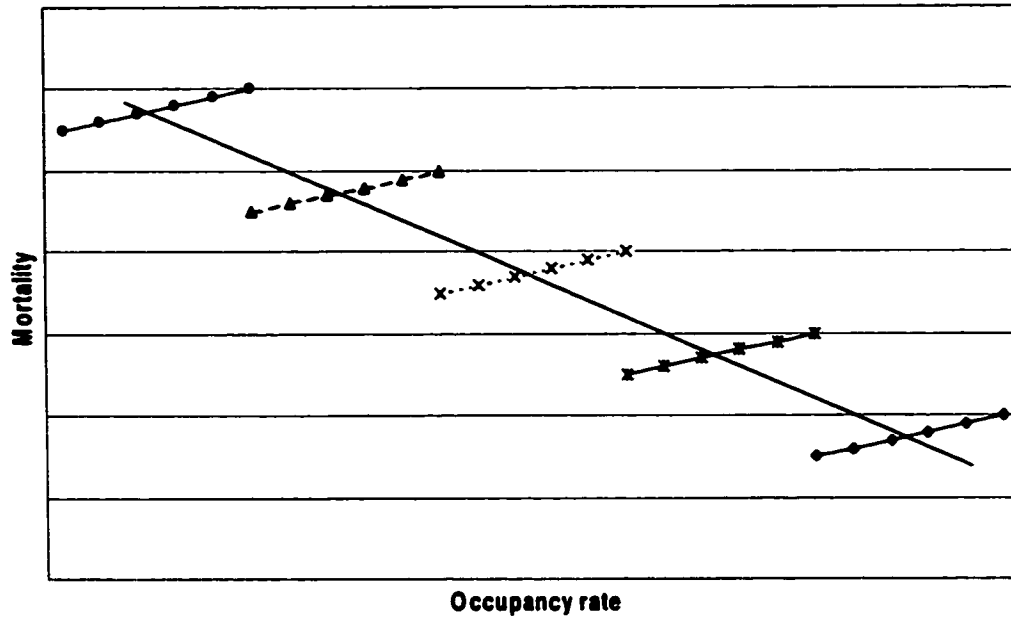


Exhibit 1 How the 'Ecological Fallacy' could bias the association between hospital occupancy and mortality.

This plot of hypothetical data compares hospital occupancy (horizontal axis) with hospital mortality (vertical axis). Five hypothetical hospitals are plotted. Within each hospital, mortality increases as occupancy increases. However, a line regressing the mean mortality rate and mean occupancy for each hospital (represented by the dark line) suggests the opposite, that mortality decreases as occupancy increases.

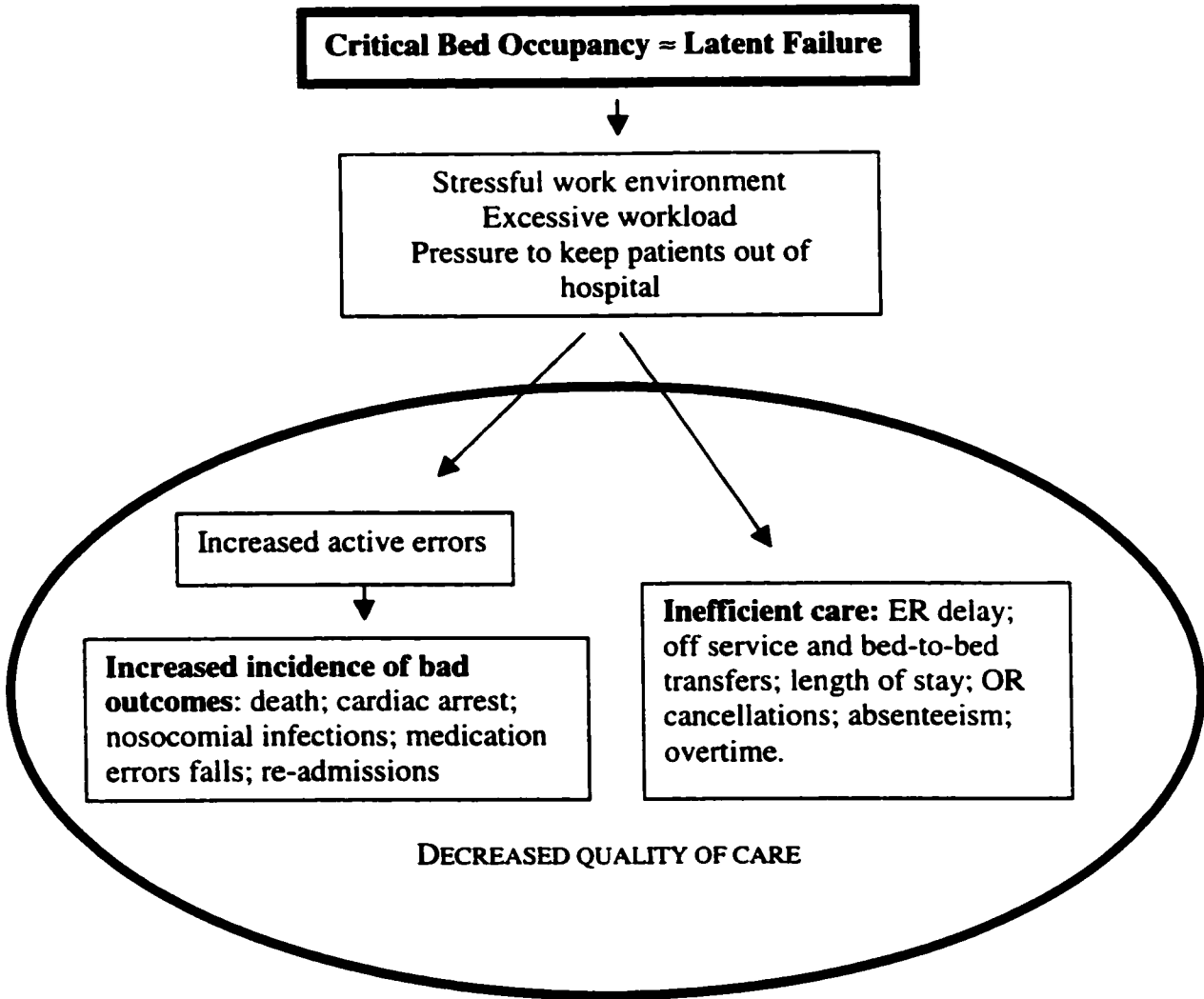


Exhibit 2 Proposed relationship between bed occupancy and quality of care.

Increased occupancy is a latent failure in the hospital system. Latent failures make active errors inevitable. Consequently there might be increased numbers of bad outcomes and markers for inefficiency.

The hypothesized relationship between high bed occupancy and quality of care and efficiency is by means of increased workload, increased pressure to discharge patients early, decreased ability to admit patients to desired areas of the hospital and increased employee stress. **Decreased ability to move patients to desired areas of the hospital** may decrease efficiency as demonstrated by OR cancellations, ER discharge times, ER waiting times, bed to bed transfers and off service transfers. **Workload**, by preventing adequate monitoring of patients could also relate to quality of care as demonstrated by increased fall rate, medication error rate and cardiac arrest rate. **Workload** may also prevent adequate infection control measures as demonstrated by increased nosocomial infection rate. **Pressure to discharge patients** could force physicians to send patients home too early. This could relate to quality of care as demonstrated by increased re-admission rate, ER re-visit rate, 30-day mortality rate and decreased length of stay. **Employee stress, workload, pressure to discharge patients and inability to move patients** may impact significantly on patient satisfaction.

Database	Source	Time Interval
ADMS	Admitting department, OCH	January 1, 1993-September 1, 1999
EPIS	Emergency Department, OCH	January 1, 1993-July 30, 1999
ORSOS	Operating room, OCH	November 1, 1994-March 29, 1999
Med2020	Medical records department, OCH	January 1, 1993-March 31, 1999
Cerner-Infection Control	Department of Laboratory Medicine, OCH	April 1, 1995-September 1, 1999
Incident Report	Medical records department, OCH	January 1, 1993-July 30, 1999
Payroll	Medisolutions, Inc	March 1, 1994-March 20-1999
ICES-Vital Statistics	ICES	January 1, 1993-February 28, 1999
ICES-CIHI	ICES	January 1, 1993-February 28, 1999
ICES-OHIP	ICES	November 1, 1994-November 15, 1997

Exhibit 3 Databases at the OCH

Exhibit 4 Definition of study variables and data source

Variable	Numerator	Data Source	Denominator	Data Source
Daily bed occupancy	The number of inpatients each day. This is defined as patients that are in beds at midnight each day plus patients that occupied beds during some period of that day.	ADMS	The total beds available per day.	ADMS
Length of stay	Median length of stay for patients discharged to home on a given day.	ADMS	Per day.	----
Daily medication error rate	The number of medication errors on a given day.	Incident Report DB	The number of inpatients per day.	ADMS
Daily early re-admission rate	The number of patients readmitted within 14 days of discharge date.	ICES-CIHI-DAD	The total number of patients discharged on that date.	ADMS
Daily early emergency room (ER) re-visit rate	The number of patients seen in the ER within 30 days of discharge date.	ICES-OHIP	The total number of patients discharged on that date.	ADMS
Daily 30 day mortality rate	The number of patients that die within 30 days of discharge date.	ICES-Vital Statistics	The total number of patients discharged on that date.	ADMS
Daily mortality rate	The number of in-patients who die per day.	ADMS	The number of inpatients per day.	ADMS
Daily cardiac arrest rate	The number of cardiac arrests per day.	CIHI-DAD	The number of inpatients per day.	ADMS
Daily fall rate	The number of inpatients that fall per day.	Incident Report DB	The number of inpatients per day.	ADMS
Daily c. difficile infection rate	The number of incident cases of hospital acquired c. difficile infections diagnosed per day.	Infection Control DB	The number of inpatients per day.	ADMS
Daily ward transfer time	The median duration in minutes between the time of registration in ER and admission to the hospital for patients admitted.	EPIS (registration time), ADMS (admit time)	per day	

Variable	Numerator	Data Source	Denominator	Data Source
Absentee rate for full-time nurses	The number of hours claimed for sick leave by full time nurses each day.	Medisolutions DB	The total number of hours of employment claimed by nurses each day.	Medisolutions DB
Overtime rate for full-time nurses	The number of hours claimed for overtime by full time nurses each day.	Medisolutions DB	The total number of hours of employment claimed by nurses each day.	Medisolutions DB
Absentee rate for full-time CUPE 576 employees	The number of hours claimed for sick leave by full time CUPE 576 employees each day.	Medisolutions DB	The total number of hours of employment claimed by CUPE 576 employees each day.	Medisolutions DB
Overtime rate for full-time CUPE 576 employees	The number of hours claimed for overtime by full time CUPE 576 employees each day.	Medisolutions DB	The total number of hours of employment claimed by CUPE 576 employees each day.	Medisolutions DB
Daily bed to bed transfers rate	The number of bed to bed transfers per day	ADMS	The number of inpatients per day.	ADMS
Daily off-service transfer rate	The number of transfers to off service locations per day.	ADMS	The number of transfers per day.	ADMS
Daily operating room cancellation rate	The number of operations cancelled per day.	ORSOS	The number of operations per day.	ORSOS

Exhibit 4 (continued). Variable definition and data source.

Year	Occupancy								
	Mean	Std ^{††}	Max	P95	P75	P50	P25	P5	Min
1993	88.2	4.5	97.5	95.1	91.4	88.3	85.3	80.3	75.6
1994	90.0	3.8	98.1	95.5	93.1	90.3	87.6	83.5	77.6
1995	88.3	4.2	99.8	95.5	91.2	88.3	85.4	81.0	76.7
1996	88.6	4.4	105.9	95.2	91.7	88.8	85.7	81.5	72.3
1997	90.4	4.4	102.8	97.4	93.6	90.4	87.6	83.5	78.2
1998	91.1	4.4	101.4	98.2	94.0	91.2	88.0	83.8	78.2
1999 [†]	90.9	4.9	102.7	97.8	94.7	90.6	88.3	82.8	75.8
Total	89.6	4.5	105.9	96.6	92.8	89.7	86.6	82.5	72.3

[†]Until July 30, 1999.

Exhibit 6 Occupancy rates at the Ottawa Civic Hospital, 1993-1999

^{††}Std = Standard deviation, Max = maximum value, P95= 95th percentile, Min = minimum value

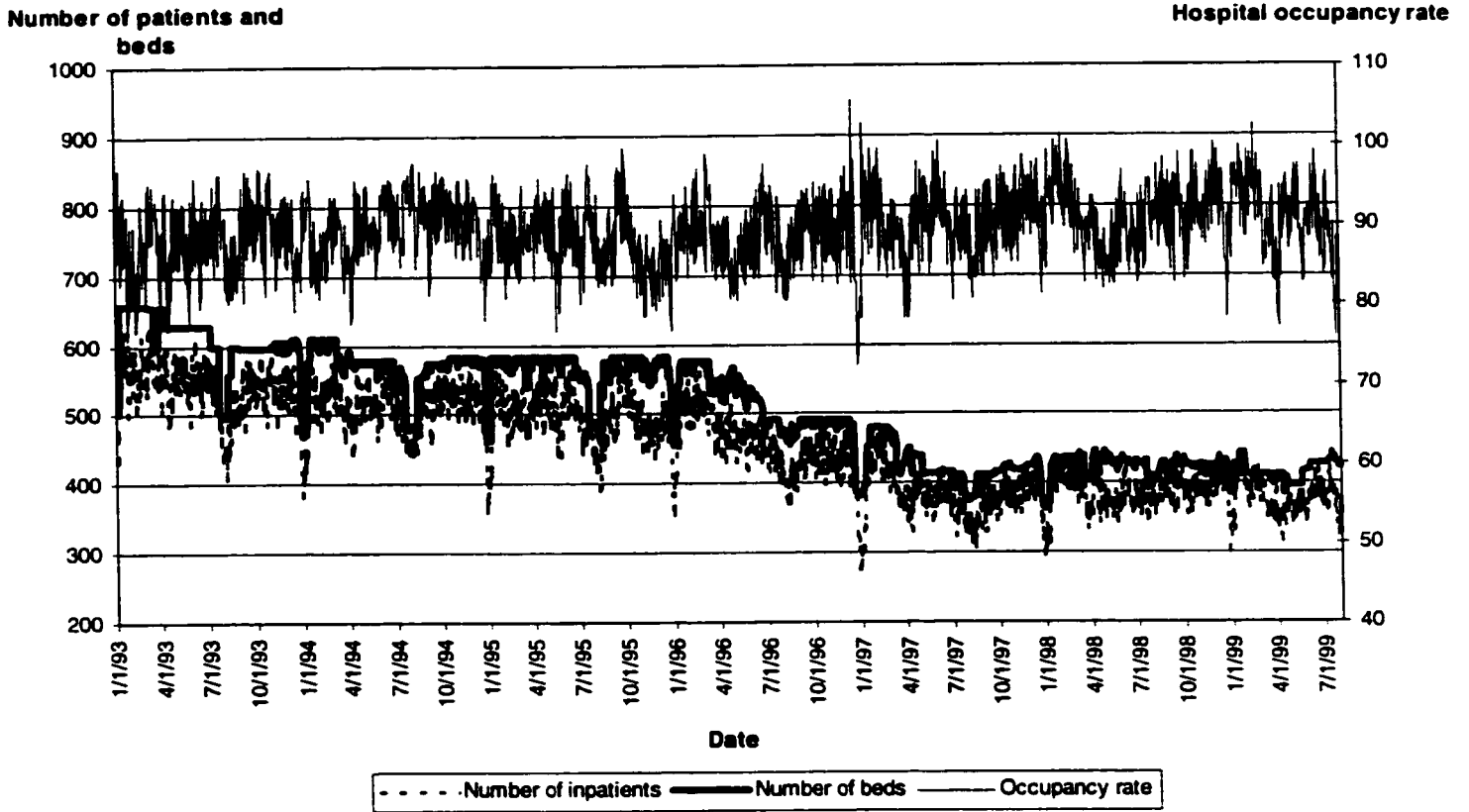


Exhibit 7 Time series plots of daily occupancy, number of inpatients and number of available beds at the Ottawa Civic Hospital, 1993-1999.

Year	Number of days occupancy		Proportion of days	
	rate exceeds 95 %	Number of days	occupancy rate exceeds 95 %	
1993	23	365	0.06	
1994	32	365	0.09	
1995	25	365	0.07	
1996	23	366	0.06	
1997	59	365	0.16	
1998	73	365	0.20	
1999 ¹	46	210	0.22	
Total	281	2401	0.12	

¹Until July 30, 1999.

Exhibit 8 Proportion of days in which occupancy rate exceeds 95% at the Ottawa Civic Hospital, 1993-1999.

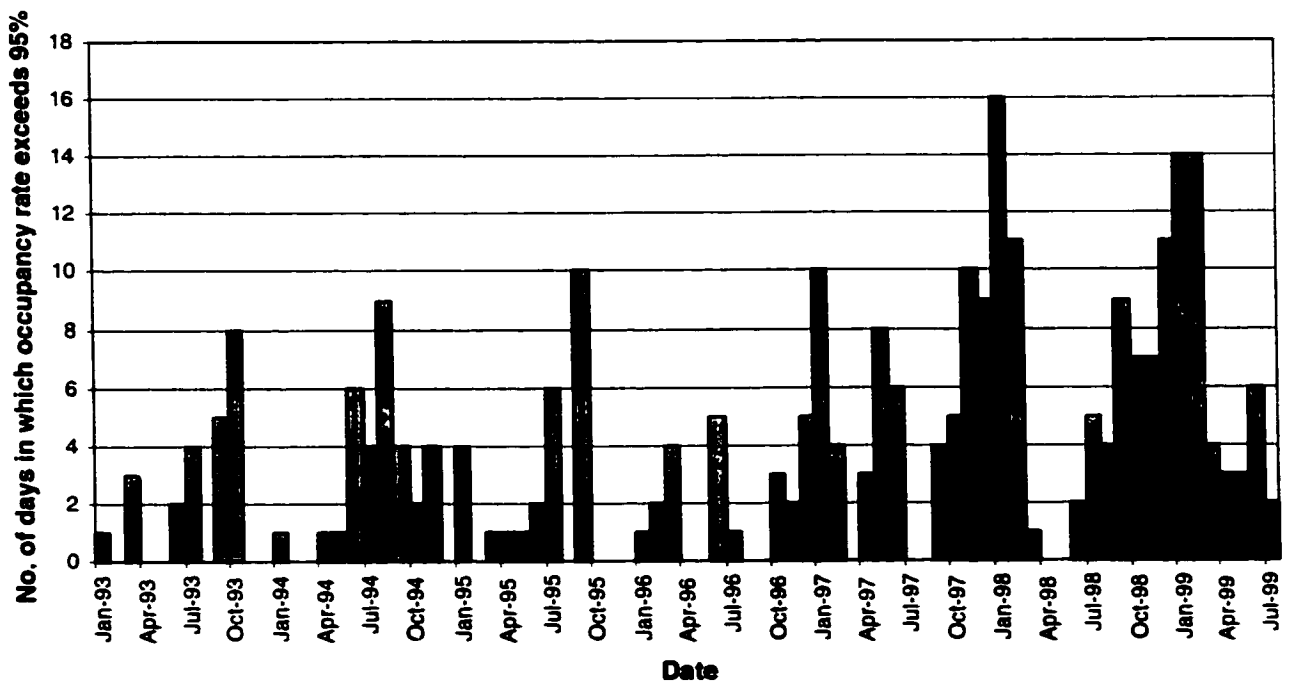


Exhibit 9 Histogram plotting the number of days per month in which occupancy exceeds 95% and date at the Ottawa Civic Hospital, 1993-1999

Year	Delay (hours)								
	Mean	Std	Max	P95	P75	P50	P25	P5	Min
1993	5.5	0.9	8.6	7.1	6.0	5.4	4.8	4.2	3.5
1994	5.6	1.0	9.3	7.4	6.2	5.6	4.9	4.0	3.4
1995	5.8	1.0	8.6	7.4	6.5	5.7	5.2	4.3	2.8
1996	6.0	1.0	9.4	7.6	6.5	5.9	5.3	4.5	3.6
1997	6.3	1.2	11.2	8.3	7.1	6.2	5.5	4.5	3.1
1998	6.4	1.1	9.9	8.3	7.1	6.3	5.8	4.7	3.1
1999 ¹	6.6	1.6	15.4	9.1	7.3	6.5	5.5	4.5	3.5
1993-99	6.0	1.2	15.4	8.0	6.7	5.9	5.2	4.3	2.8

¹Before July 30, 1999.

Exhibit 10 Median delay between arrival in the ER and transfer to the ward (in hours) at the Ottawa Civic Hospital, 1993-1999.

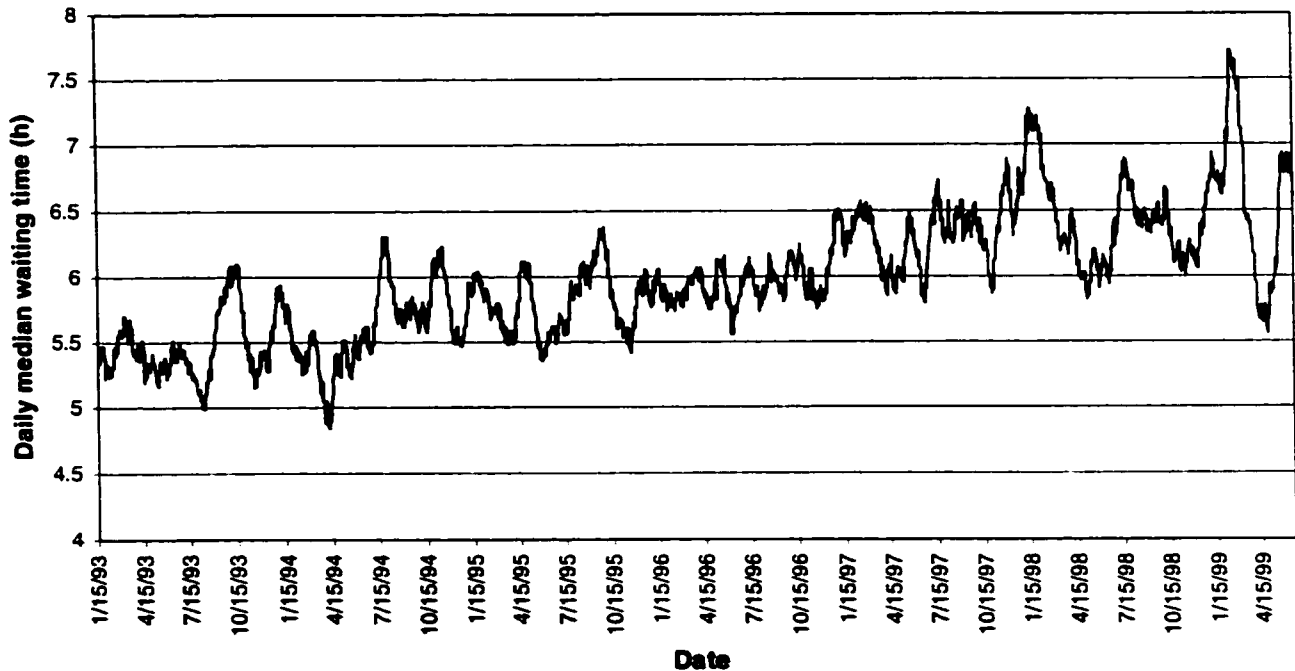


Exhibit 11 Time series plot of the daily median delay in hours between arrival in the ER and transfer to the ward at the Ottawa Civic Hospital, 1993-1999 (smoothing achieved using a 29 day moving average)

Year	Daily mean length of stay								
	Mean	Std.	Max	P95	P75	P50	P25	P5	Min
1993	6.7	1.9	16.0	10.0	7.9	6.6	5.5	4.0	1.0
1994	7.1	2.2	16.8	10.8	8.4	6.7	5.5	4.0	3.2
1995	6.8	2.1	16.1	10.6	7.8	6.4	5.3	4.1	2.7
1996	6.6	2.0	13.8	10.3	7.8	6.3	5.1	3.6	2.8
1997	6.3	2.3	21.7	9.9	7.3	6.0	4.8	3.4	2.4
1998	6.4	2.5	27.6	10.7	7.5	6.0	4.9	3.5	2.3
1999 ¹	6.5	2.3	24.1	10.1	7.6	6.4	4.9	3.4	2.8
1993-99	6.6	2.2	27.6	10.4	7.8	6.3	5.2	3.7	1.0

¹Before July 30, 1999.

Exhibit 12 Mean length of stay for patients at the Ottawa Civic Hospital, 1993-1999

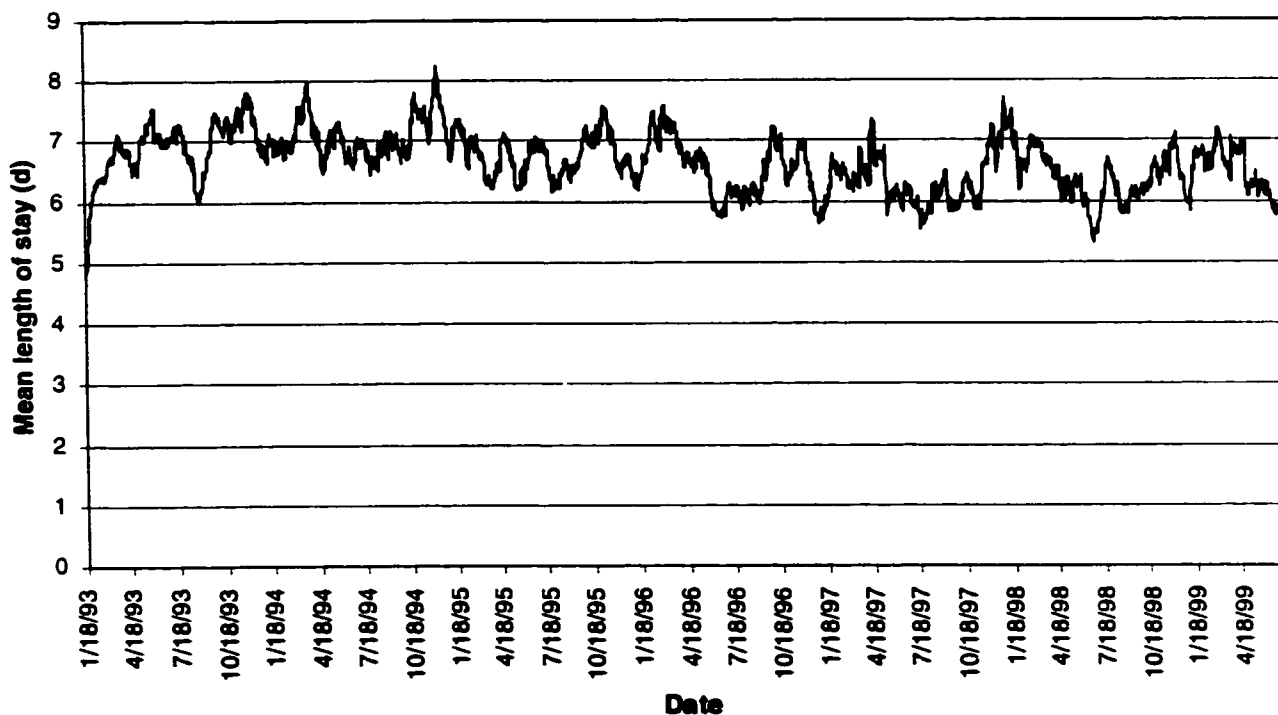


Exhibit 13 Time series plot of the daily mean length of stay at the Ottawa Civic Hospital, 1993-1999 (smoothing achieved using a 29 day moving average)

Year	Percentage of patients transferred (%)								
	Mean	Std.	Max	P95	P75	P50	P25	P5	Min
1993	5.6	2.0	15.8	8.8	6.9	5.7	4.2	2.8	1.7
1994	5.4	1.7	13.9	8.3	6.4	5.2	4.2	2.9	1.6
1995	5.3	1.7	11.6	8.0	6.4	5.2	4.1	2.6	1.1
1996	5.9	1.7	11.5	8.7	7.0	5.7	4.7	3.3	1.3
1997	6.4	1.9	12.6	9.7	7.5	6.2	5.2	3.6	1.5
1998	6.7	2.0	12.7	9.8	8.1	6.7	5.3	3.5	2.6
1999 ¹	6.6	1.9	12.0	9.7	7.9	6.6	5.3	3.7	2.3
Total	5.9	1.9	15.8	9.2	7.2	5.8	4.6	3.0	1.1

¹Before July 30, 1999.

Exhibit 14 Percentage of patients undergoing bed to bed transfers each day at the Ottawa Civic Hospital, 1993-1999

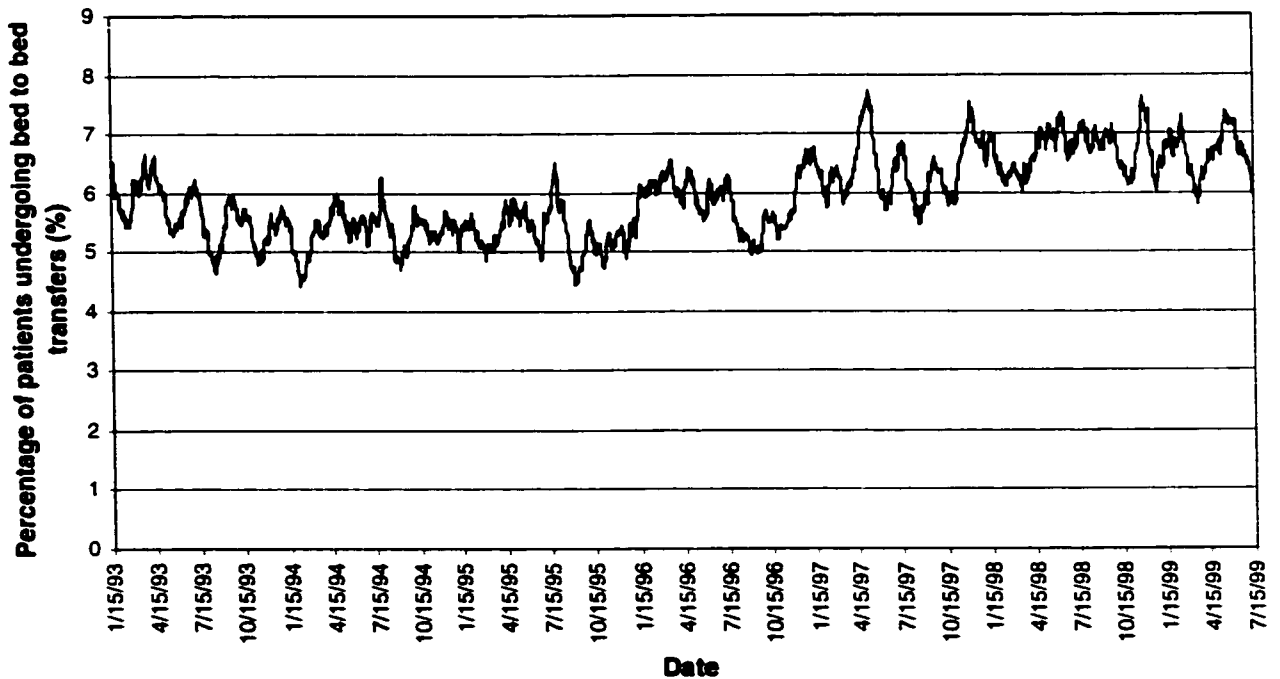


Exhibit 15 Time series plot of the daily percentage of patients undergoing bed to bed transfers at the Ottawa Civic Hospital, 1993-1999 (smoothing achieved using a 29 day moving average)

Year	Percentage of patients transferred to an 'off-service' bed (%)								
	Mean	Std.	Max	P95	P75	P50	P25	P5	Min
1993	11.3	7.0	37.5	23.7	14.8	10.4	6.4	2.0	0.0
1994	12.7	7.6	50.0	26.2	16.7	11.9	6.9	2.9	0.0
1995	10.2	6.9	34.6	21.8	15.0	8.6	5.0	0.0	0.0
1996	11.6	7.9	51.2	26.8	15.2	10.7	6.1	0.0	0.0
1997	10.7	6.6	30.2	22.2	14.9	10.5	5.4	0.0	0.0
1998	12.4	7.2	45.0	25.8	16.7	11.6	6.9	2.3	0.0
1999 ¹	13.5	8.1	40.0	26.8	19.5	13.3	7.0	0.0	0.0
1993-99	11.7	7.4	51.2	25.0	16.0	10.8	6.3	1.9	0.0

¹Before July 30, 1999.

Exhibit 16 Percentage of patients transferred to off service location from any of the following locations-ER, ICU, OR at the Ottawa Civic Hospital, 1993-1999

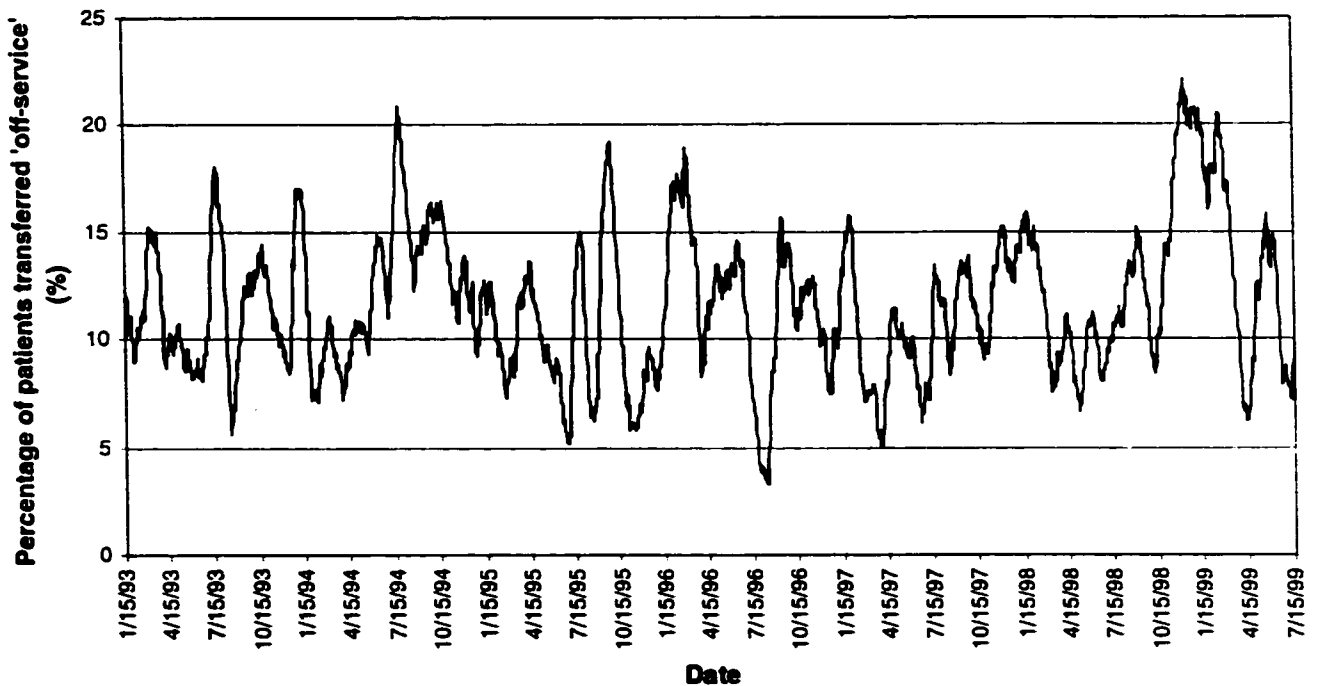


Exhibit 17 Time series plot of the daily percentage of patients transferred to an off service location at the Ottawa Civic Hospital, 1993-1999 (smoothing achieved using a 29 day moving average)

Year	Percentage of cases cancelled due to lack of post-operative bed (%)								
	Mean	Std.	Max	P95	P75	P50	P25	P5	Min
1994 ^I	0.7	4.8	37.5	1.4	0.0	0.0	0.0	0.0	0.0
1995	0.4	2.7	33.3	1.4	0.0	0.0	0.0	0.0	0.0
1996	0.1	0.6	5.9	0.0	0.0	0.0	0.0	0.0	0.0
1997	0.1	0.9	14.3	0.0	0.0	0.0	0.0	0.0	0.0
1998	0.2	0.7	6.8	1.5	0.0	0.0	0.0	0.0	0.0
1999 ^{II}	0.8	3.2	25.0	3.1	0.0	0.0	0.0	0.0	0.0
1994-99	0.3	1.9	37.5	1.3	0.0	0.0	0.0	0.0	0.0

^IAfter November 1, 1994

^{II}Before March 29, 1999

Exhibit 18 Percentage of operations cancelled due to the lack of a post operative bed at the Ottawa Civic Hospital, 1994-1999

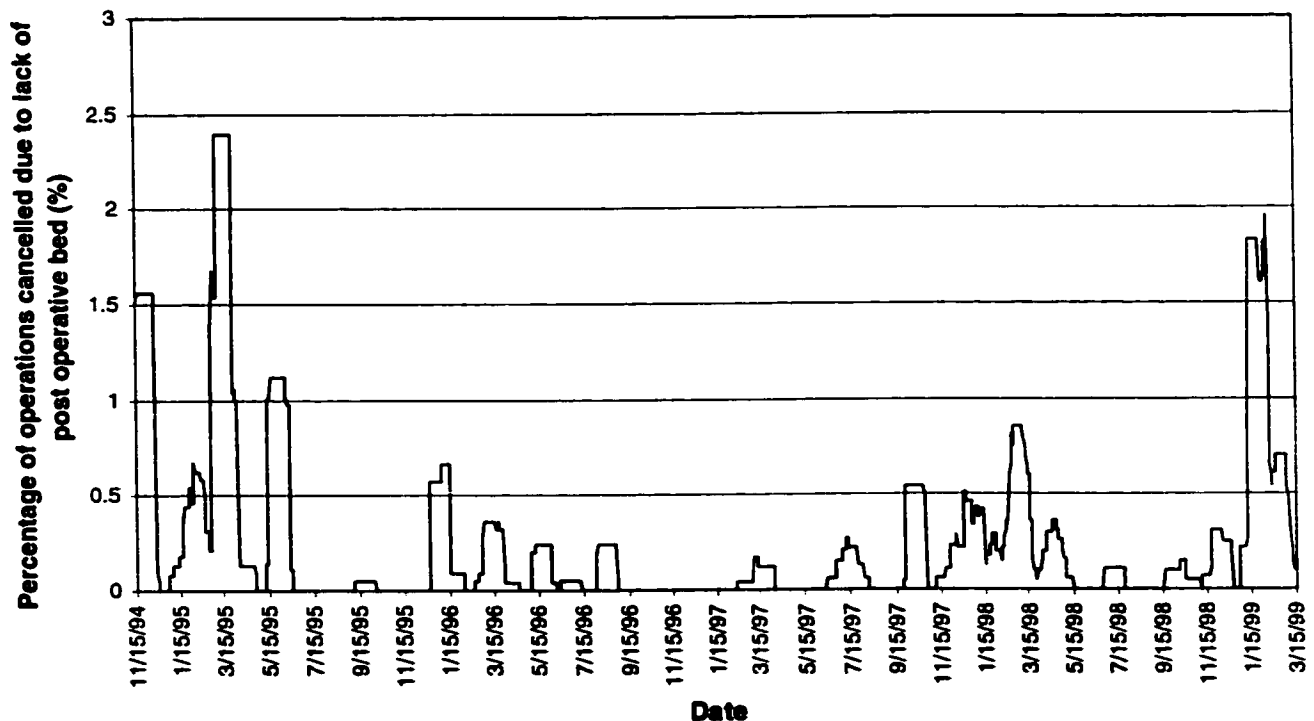


Exhibit 19 Smoothed time series plot of the daily percentage of operations cancelled due to a lack of a post operative bed at the Ottawa Civic Hospital, 1994-1999

Year	No. of days	ONA			CUPE		
		Overtime hours	Total hours	Overtime rate	Overtime hours	Total hours	Overtime rate
1994 ⁱ	286	235037	1076449	21.8	70285	1084832	6.5
1995	365	322614	1359773	23.7	113618	1371405	8.3
1996	366	210743	1210632	17.4	79109	1267905	6.2
1997	365	277249	1165472	23.8	95914	1145827	8.4
1998	365	439958	1274438	34.5	139718	1191947	11.7
1999 ⁱⁱ	79	164412	352180	46.7	44042	286598	15.4
1994-99	1826	1650013	6438944	25.6	542686	6348514	8.6

ⁱAfter March 19, 1994

ⁱⁱBefore March 20, 1999

Exhibit 20 Overtime rate for full time ONA and CUPE 576 employees at the Ottawa Civic Hospital, 1994-1999

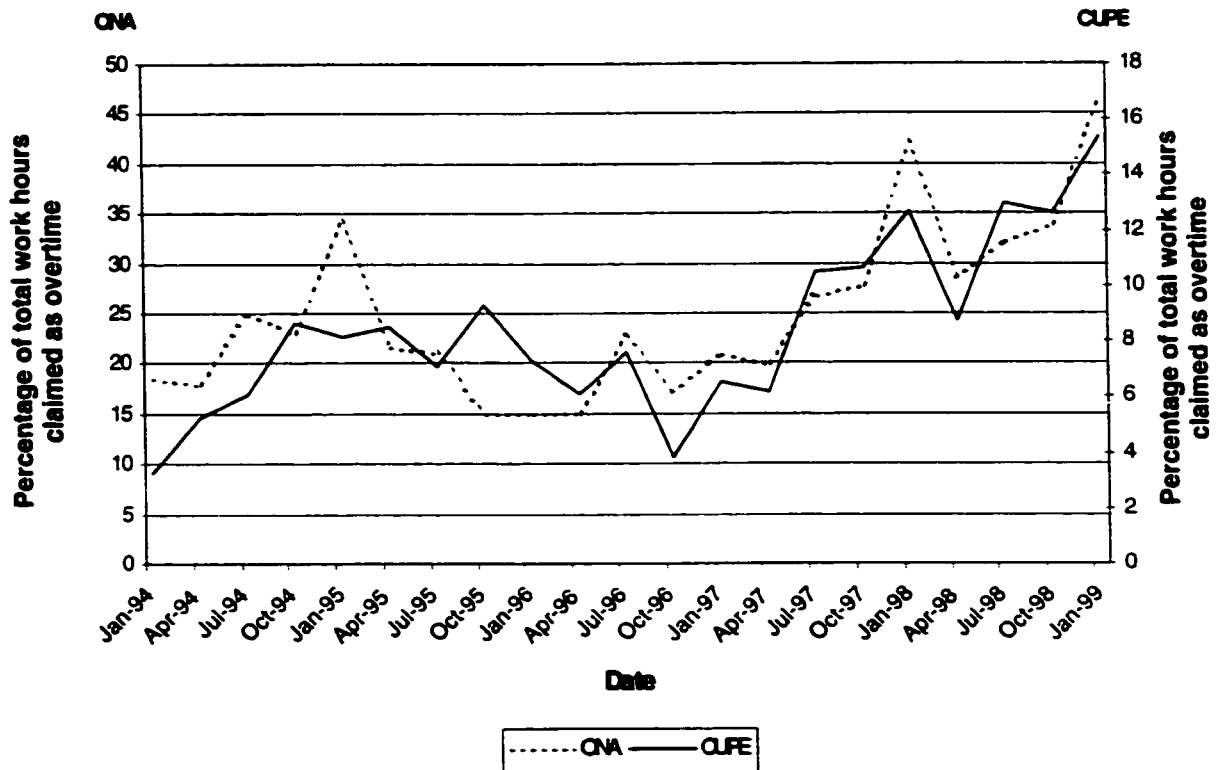


Exhibit 21 Smoothed time series plot of the daily overtime rate for full time ONA and CUPE 576 employees at the Ottawa Civic Hospital, 1994-1999

Year	No. of days	ONA			CUPE		
		Sick hours	Regular hours	Sick rate	Sick hours	Regular hours	Sick rate
1994 ^I	286	77229	841442	9.2	62299	1014550	6.1
1995	365	99566	1037203	9.6	80538	1257779	6.4
1996	366	100195	999921	10.0	72232	1188793	6.1
1997	365	90281	888258	10.2	62357	1049909	5.9
1998	365	83918	834522	10.1	67397	1052245	6.4
1999 ^{II}	79	17909	187778	9.5	16215	242558	6.7
1994-99	1826	469098	4789124	9.8	361038	5805834	6.2

^IAfter March 19, 1994

^{II}Before March 20, 1999

Exhibit 22 Sick leave rate for full time ONA and CUPE 576 employees at the Ottawa Civic Hospital, 1994-1999

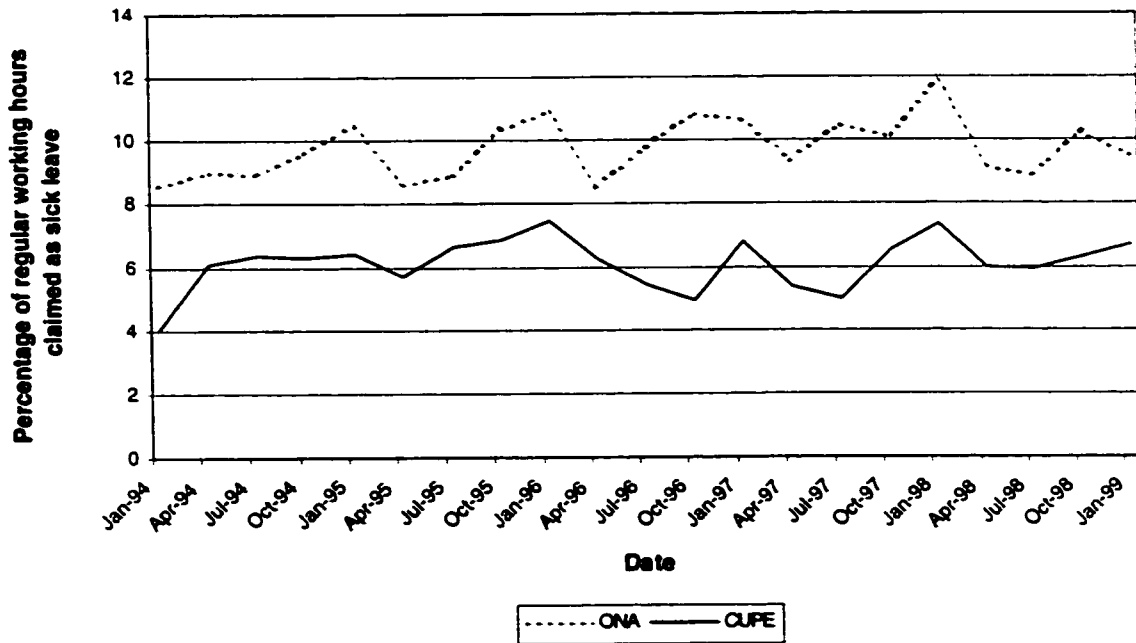


Exhibit 23 Smoothed time series plot of the daily sick leave rate for full time ONA and CUPE 576 employees at the Ottawa Civic Hospital, 1994-1999

Year	Mortality (deaths per 1000 patient days)							
	Mean (95% CI)	Max	P95	P75	P50	P25	P5	Min
1993	3.2 (3.1, 3.4)	11.4	7.4	5.1	3.5	1.7	0.0	0.0
1994	3.5 (3.3, 3.7)	11.2	8.6	5.4	3.7	1.9	0.0	0.0
1995	4.1 (3.9, 4.3)	15.3	8.8	5.8	4.0	2.0	0.0	0.0
1996	4.2 (4.0, 4.4)	18.1	10.1	6.3	4.0	2.1	0.0	0.0
1997	4.8 (4.5, 5.0)	19.8	10.4	7.2	4.9	2.5	0.0	0.0
1998	5.1 (4.9, 5.4)	17.7	12.3	7.5	5.0	2.6	0.0	0.0
1999 ¹	4.7 (4.4, 5.0)	24.5	11.5	7.2	3.9	2.5	0.0	0.0
1993-99	4.2 (4.1, 4.3)	24.5	10.0	5.8	3.9	2.0	0.0	0.0

¹Before July 30, 1999.

Exhibit 24 Incidence rate of death at the Ottawa Civic Hospital, 1993-1999

Year	Number of events per day							
	Mean (95% CI)	Max	P95	P75	P50	P25	P5	Min
1993	1.7 (1.6, 1.9)	6	4	3	2	1	0	0
1994	1.8 (1.7, 1.9)	6	4	3	2	1	0	0
1995	2.0 (1.9, 2.2)	7	4	3	2	1	0	0
1996	1.9 (1.7, 2.0)	6	5	3	2	1	0	0
1997	1.8 (1.7, 2.0)	8	4	3	2	1	0	0
1998	2.0 (1.8, 2.1)	7	5	3	2	1	0	0
1999 ¹	1.8 (1.6, 2.0)	8	4	3	2	1	0	0
1993-99	1.9 (1.8, 1.9)	8	4	3	2	1	0	0

¹Before July 30, 1999.

Exhibit 25 Number of deaths per day at the Ottawa Civic Hospital, 1993-1999

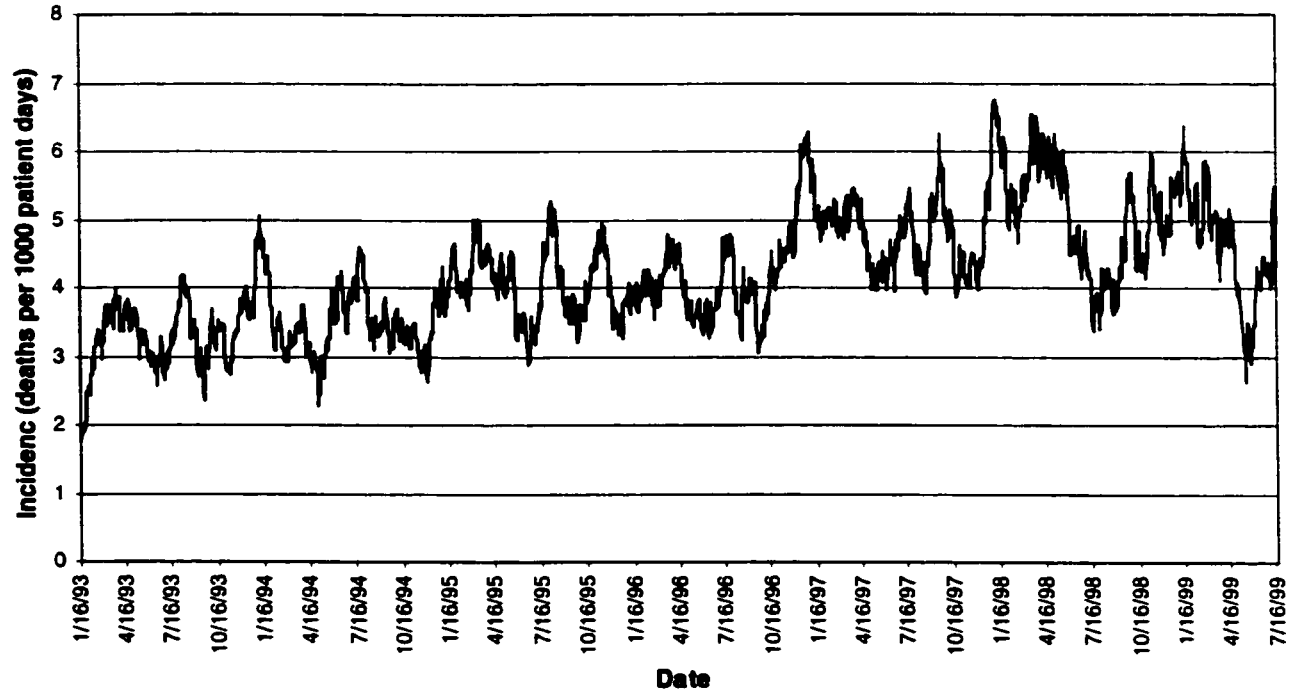


Exhibit 26 Smoothed time series plot of the daily incidence rate of death at the Ottawa Civic Hospital, 1993-1999

Year	Incidence (cases per 1000 patient days)							
	Mean (95% CI)	Max	P95	P75	P50	P25	P5	Min
1993	0.5 (0.4, 0.6)	5.6	2.2	0.0	0.0	0.0	0.0	0.0
1994	0.4 (0.3, 0.5)	4.1	2.1	0.0	0.0	0.0	0.0	0.0
1995	0.6 (0.5, 0.6)	4.9	2.2	0.0	0.0	0.0	0.0	0.0
1996	0.6 (0.6, 0.7)	10.0	3.2	0.0	0.0	0.0	0.0	0.0
1997	0.7 (0.6, 0.8)	7.4	3.0	0.0	0.0	0.0	0.0	0.0
1998	0.8 (0.7, 0.9)	12.7	3.0	2.4	0.0	0.0	0.0	0.0
1999 ¹	0.3 (0.2, 0.5)	2.8	2.6	0.0	0.0	0.0	0.0	0.0
Total	0.59 (0.56, 0.62)	12.7	2.8	0.0	0.0	0.0	0.0	0.0

¹Prior to March 31, 1999.

Exhibit 27 Incidence of cardiac arrest at the Ottawa Civic Hospital, 1993-1999

Year	Number of events per day							
	Mean (95% CI)	Max	P95	P75	P50	P25	P5	Min
1993	0.3 (0.2, 0.3)	3	1	0	0	0	0	0
1994	0.2 (0.2, 0.2)	2	1	0	0	0	0	0
1995	0.3 (0.2, 0.3)	2	1	0	0	0	0	0
1996	0.3 (0.2, 0.3)	3	1	0	0	0	0	0
1997	0.3 (0.2, 0.3)	3	1	0	0	0	0	0
1998	0.3 (0.3, 0.4)	5	1	1	0	0	0	0
1999 ¹	0.1 (0.1, 0.2)	1	1	0	0	0	0	0
1993-99	0.3 (0.3, 0.3)	5	1	0	0	0	0	0

¹Prior to March 31, 1999.

Exhibit 28 Number of cardiac arrests per day at the Ottawa Civic Hospital, 1993-1999

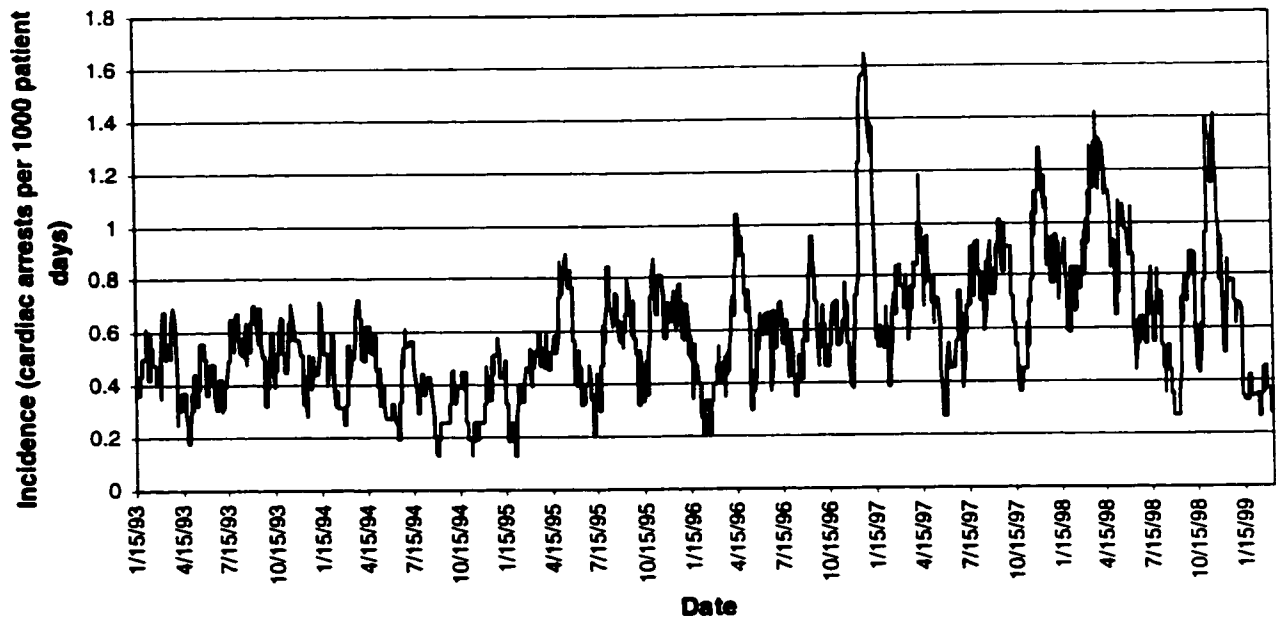


Exhibit 29 Smoothed time series plot of the daily incidence of cardiac arrests at the Ottawa Civic Hospital, 1993-1999

Year	Incidence (cases per 1000 patient days)							
	Mean (95% CI)	Max	P95	P75	P50	P25	P5	Min
1995 [†]	0.4 (0.3, 0.5)	4.2	2.2	0.0	0.0	0.0	0.0	0.0
1996	0.5 (0.5, 0.6)	9.9	2.4	0.0	0.0	0.0	0.0	0.0
1997	0.4 (0.4, 0.5)	7.0	2.7	0.0	0.0	0.0	0.0	0.0
1998	1.1 (1.0, 1.2)	10.0	4.9	2.5	0.0	0.0	0.0	0.0
1999 [‡]	1.5 (1.3, 1.6)	10.1	5.3	2.7	0.0	0.0	0.0	0.0
Total	0.8 (0.7, 0.80)	10.1	3.0	1.9	0.0	0.0	0.0	0.0

[†]After April 1, 1995.

[‡]Before September 1, 1999

Exhibit 30 Incidence of c.difficile infections at the Ottawa Civic Hospital, 1995-1999

Year	Number of events per day							
	Mean (95% CI)	Max	P95	P75	P50	P25	P5	Min
1995 [†]	0.2 (0.2, 0.3)	2	1	0	0	0	0	0
1996	0.2 (0.2, 0.3)	4	1	0	0	0	0	0
1997	0.2 (0.1, 0.2)	3	1	0	0	0	0	0
1998	0.4 (0.4, 0.5)	3	2	1	0	0	0	0
1999 [‡]	0.6 (0.5, 0.7)	4	2	1	0	0	0	0
1995-99	0.3 (0.3, 0.3)	4	1	1	0	0	0	0

[†]After April 1, 1995.

[‡]Before September 1, 1999

Exhibit 31 Number of c.difficile infections diagnosed per day at the Ottawa Civic Hospital, 1995-1999

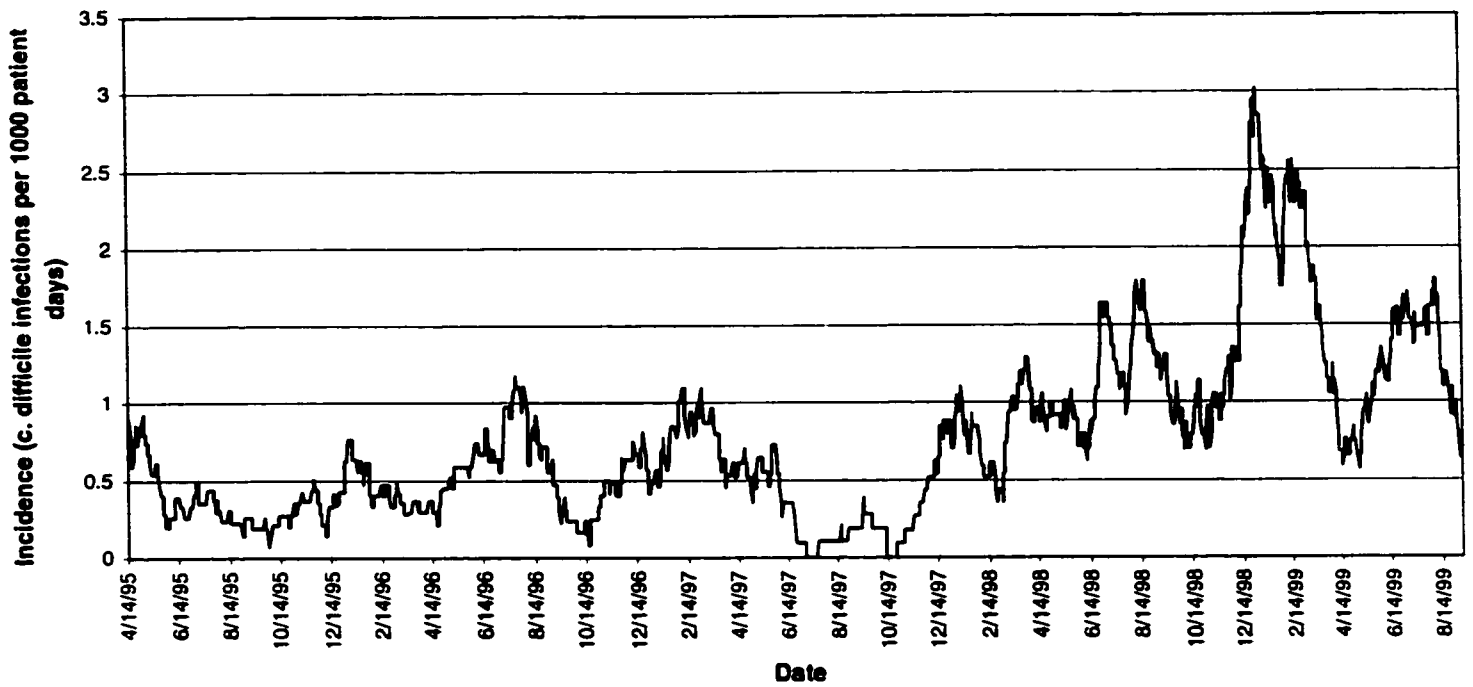


Exhibit 32 Smoothed time series plot of the daily incidence of c.difficile infections at the Ottawa Civic Hospital, 1995-1999

Year	Incidence (cases per 1000 patient days)							
	Mean (95% CI)	Max	P95	P75	P50	P25	P5	Min
1993	1.9 (1.8, 2.0)	7.6	5.5	3.4	1.8	0.0	0.0	0.0
1994	2.0 (1.9, 2.1)	11.3	5.8	3.6	1.9	0.0	0.0	0.0
1995	2.1 (2.0, 2.3)	12.5	6.4	3.7	2.0	0.0	0.0	0.0
1996	1.9 (1.8, 2.0)	9.9	6.3	2.4	2.0	0.0	0.0	0.0
1997	1.8 (1.7, 2.0)	10.4	5.9	2.7	0.0	0.0	0.0	0.0
1998	2.0 (1.9, 2.0)	13.7	7.2	2.7	2.4	0.0	0.0	0.0
1999 ¹	1.8 (1.6, 2.0)	13.0	5.5	2.7	0.0	0.0	0.0	0.0
Total	2.0 (1.9, 2.0)	13.7	5.9	2.8	1.9	0.0	0.0	0.0

¹Before July 15, 1999.

Exhibit 33 Incidence of medication errors at the Ottawa Civic Hospital, 1993-1999

Year	Number of events per day							
	Mean (95% CI)	Max	P95	P75	P50	P25	P5	Min
1993	1.0 (0.9, 1.1)	4	3	2	1	0	0	0
1994	1.0 (0.9, 1.1)	5	3	2	1	0	0	0
1995	1.0 (1.0, 1.2)	6	3	2	1	0	0	0
1996	0.9 (0.8, 1.0)	5	3	1	1	0	0	0
1997	0.7 (0.6, 0.8)	4	2	1	0	0	0	0
1998	0.8 (0.7, 0.9)	5	3	1	1	0	0	0
1999 ¹	0.7 (0.6, 0.8)	5	2	1	0	0	0	0
1993-99	0.9 (0.9, 0.9)	6	1	1	0	0	3	0

¹Before July 15, 1999.

Exhibit 34 Number of medication errors per day at the Ottawa Civic Hospital, 1993-1999

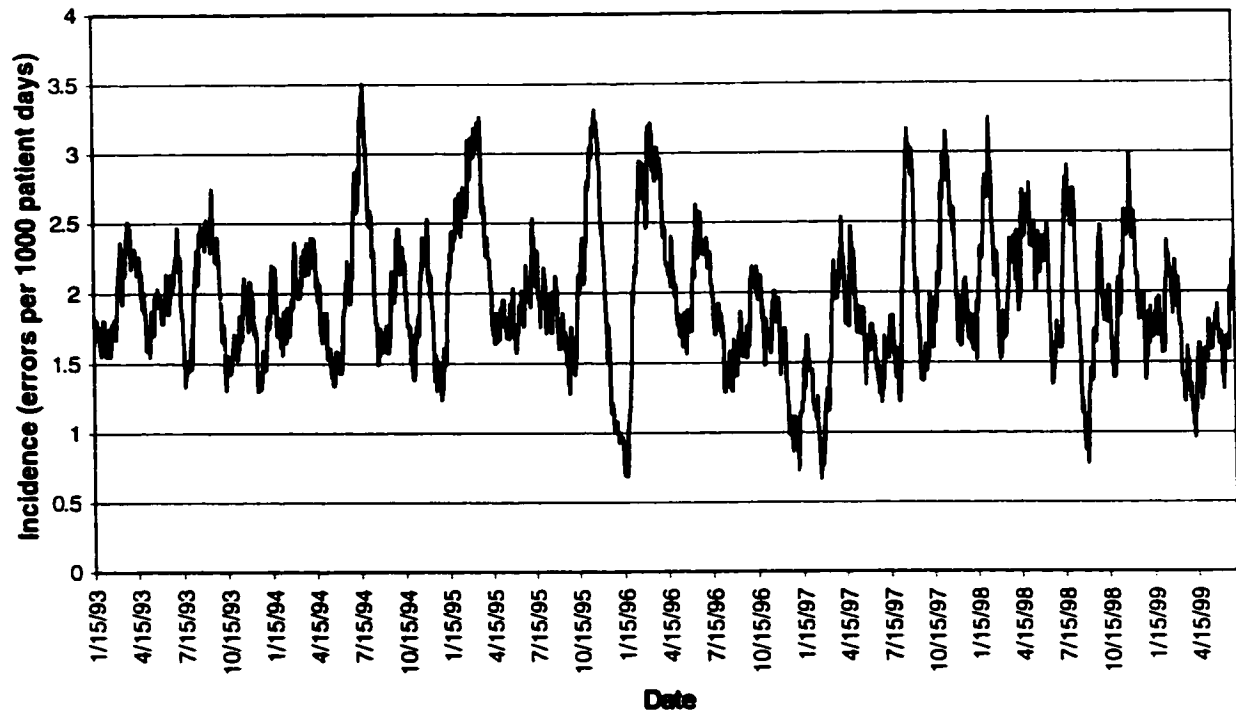


Exhibit 35 Smoothed time series plot of the daily incidence of medication errors at the Ottawa Civic Hospital, 1993-1999

Year	Incidence (cases per 1000 patient days)							
	Mean (95% CI)	Max	P95	P75	P50	P25	P5	Min
1993	4.5 (4.2, 4.7)	20.3	9.8	6.3	3.8	1.9	0.0	0.0
1994	4.6 (4.2, 4.9)	14.6	10.1	6.2	4.0	2.0	0.0	0.0
1995	4.8 (4.6, 5.0)	18.7	10.7	6.5	4.1	2.1	0.0	0.0
1996	5.4 (5.2, 5.7)	17.7	12.4	7.5	4.9	2.3	0.0	0.0
1997	4.5 (4.3, 4.7)	15.2	10.9	6.0	4.3	2.5	0.0	0.0
1998	4.4 (4.2, 4.7)	17.7	11.6	6.2	3.0	2.4	0.0	0.0
1999 ¹	3.6 (3.3, 3.8)	13.3	8.7	5.5	2.7	0.0	0.0	0.0
Total	4.6 (4.5, 4.7)	20.3	10.7	6.6	4.1	2.2	0.0	0.0

¹Before July 15, 1999.

Exhibit 36 Incidence of falls at the Ottawa Civic Hospital, 1993-1999

Year	Number of events per day							
	Mean (95% CI)	Max	P95	P75	P50	P25	P5	Min
1993	2.4 (2.2, 2.5)	10	5	3	2	1	0	0
1994	2.4 (2.2, 2.5)	8	5	3	2	1	0	0
1995	2.4 (2.2, 2.5)	9	5	3	2	1	0	0
1996	2.5 (2.3, 2.6)	9	5	3	2	1	0	0
1997	1.7 (1.6, 1.9)	6	4	2	2	1	0	0
1998	1.7 (1.6, 1.9)	7	4	2	1	1	0	0
1999 ¹	1.4 (1.2, 1.5)	5	3	2	1	0	0	0
1993-99	2.1 (2.4, 2.2)	10	5	3	2	1	0	0

¹Before July 15, 1999.

Exhibit 37 Number of falls per day at the Ottawa Civic Hospital, 1993-1999

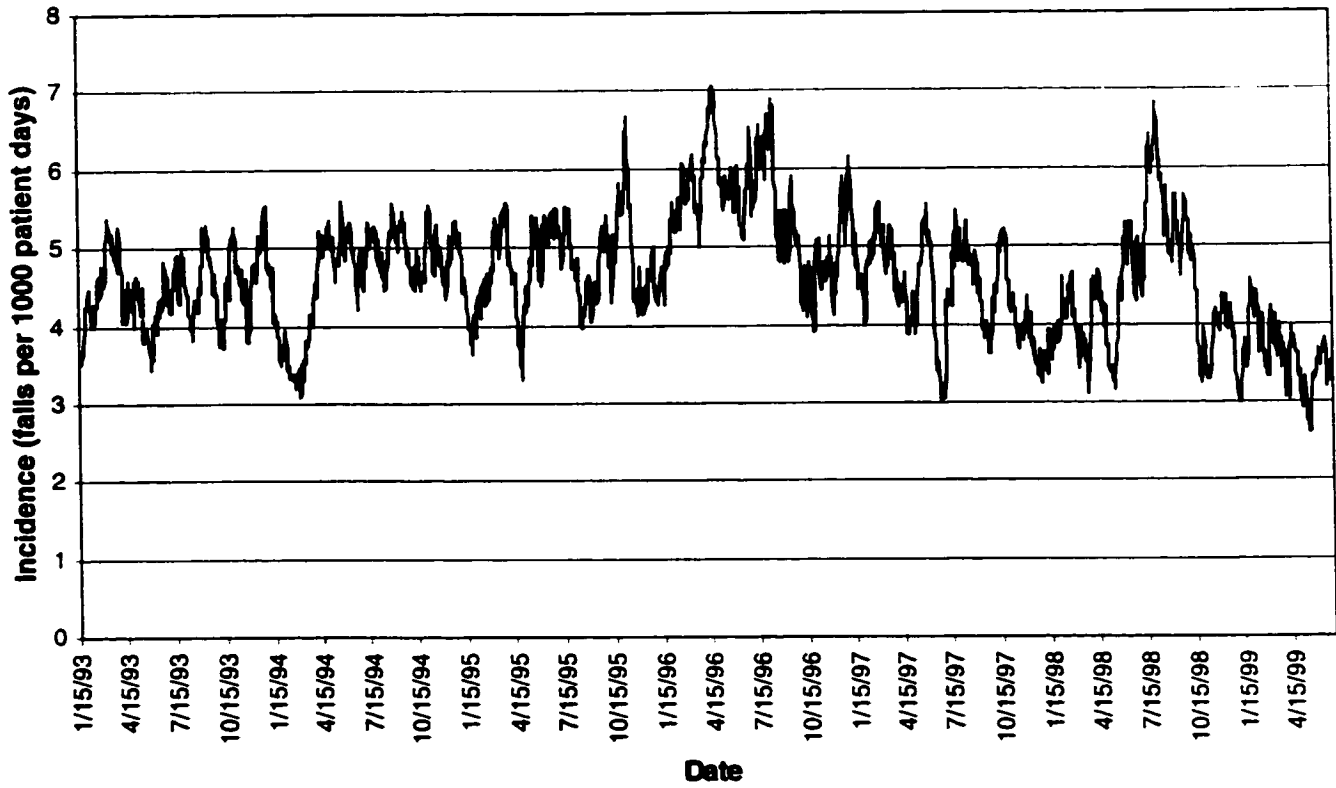


Exhibit 38 Smoothed time series plot of the daily incidence of falls at the Ottawa Civic Hospital, 1993-1999

Year	Percentage of patients with outcome (%)								
	Mean	Std.	Max	P95	P75	P50	P25	P5	Min
1994 ^I	4.8	4.7	20.0	15.2	5.7	3.7	1.9	0.0	0.0
1995	4.2	3.7	28.6	10.5	5.8	3.5	1.9	0.0	0.0
1996	4.9	4.2	27.6	11.9	7.3	4.2	1.8	0.0	0.0
1997 ^{II}	5.7	4.5	25.7	14.0	7.9	5.0	2.3	0.0	0.0
1994-97	4.9	4.2	28.6	12.2	7.0	4.0	2.0	0.0	0.0

^IAfter November 1, 1994

^{II}Before November 15, 1997

Exhibit 39 Percentage of patients returning to any Ontario ER within 7 days of discharge from the Ottawa Civic Hospital, 1994-1997^{III}

Year	Percentage of patients with outcome (%)								
	Mean	Std.	Max	P95	P75	P50	P25	P5	Min
1994 ^I	7.8	6.6	41.9	17.8	9.6	6.8	3.2	0.0	0.0
1995	7.9	6.4	57.1	19.2	10.4	6.5	4.0	0.0	0.0
1996	9.6	6.3	41.4	21.2	13.4	8.5	4.7	1.9	0.0
1997 ^{II}	11.2	7.3	44.4	23.3	15.2	10.2	5.9	1.9	0.0
1994-97	9.4	6.8	57.1	21.4	12.8	8.0	4.7	0.0	0.0

^IAfter November 1, 1994

^{II}Before November 15, 1997

Exhibit 40 Percentage of patients returning to any Ontario ER within 30 days of discharge from the Ottawa Civic Hospital, 1994-1997^{III}

^{III}Time interval is limited by the availability of data. ER's in the region have used alternative payment plans in the Ottawa region at various times.

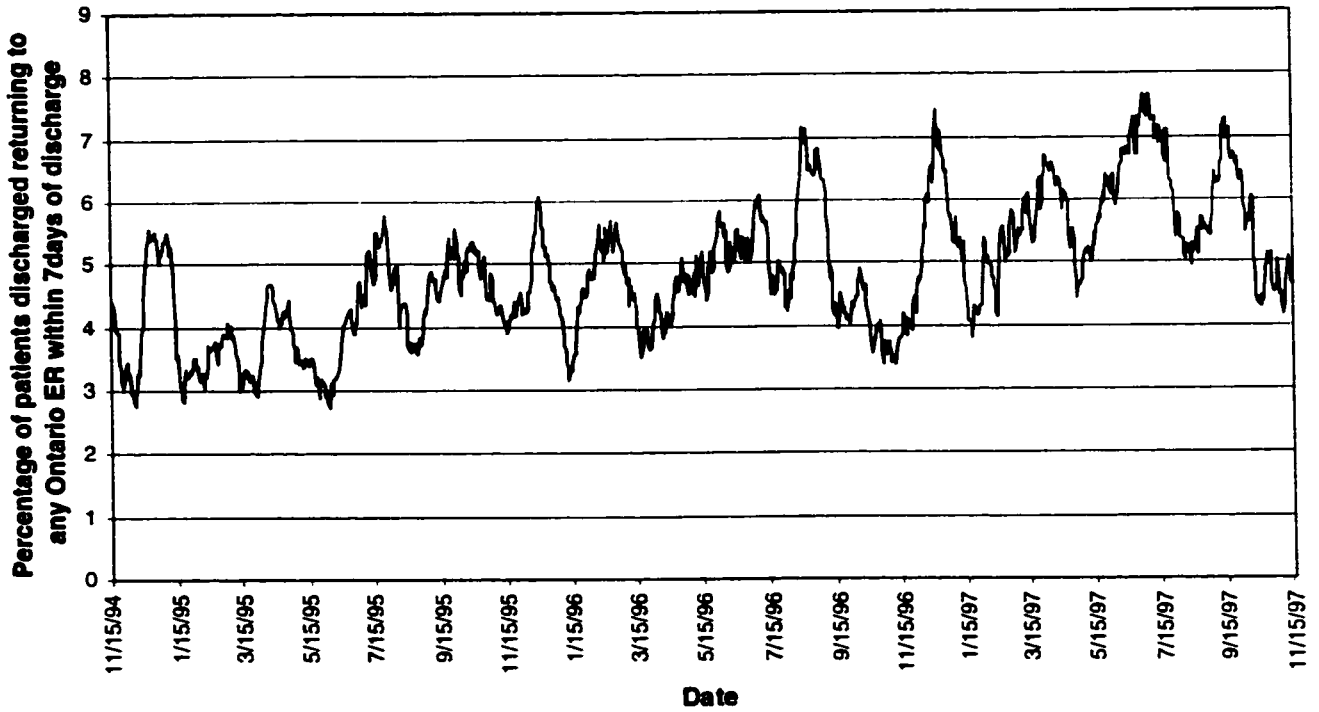


Exhibit 41 Smoothed time series plot of the daily percentage of patients returning to any Ontario ER within 7 days of discharge date from the Ottawa Civic Hospital, 1994-1997

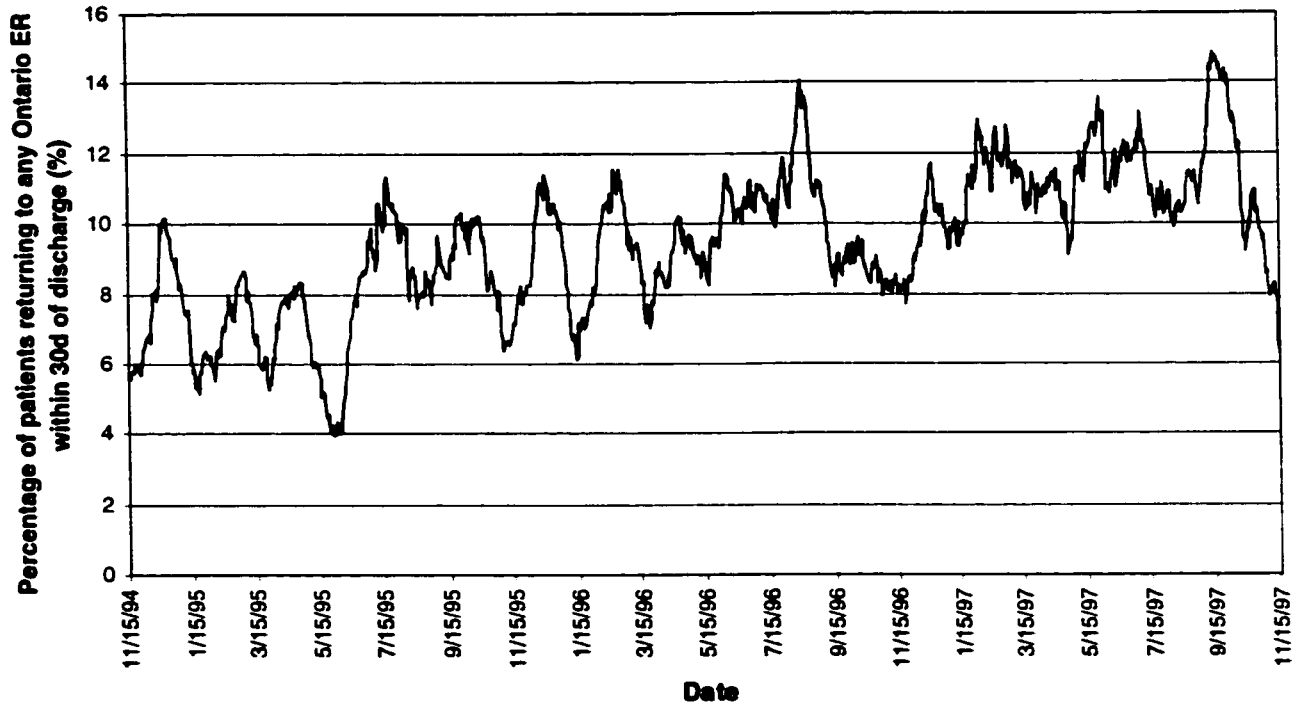


Exhibit 42 Smoothed time series plot of the daily percentage of patients returning to any Ontario ER within 30 days of discharge from the Ottawa Civic Hospital, 1994-1997

Year	Percentage of patients with outcome (%)								
	Mean	Std.	Max	P95	P75	P50	P25	P5	Min
1993	2.0	2.4	16.7	6.7	3.0	1.8	0.0	0.0	0.0
1994	2.0	2.1	11.1	5.8	3.1	1.9	0.0	0.0	0.0
1995	2.3	2.5	15.6	7.0	3.7	1.9	0.0	0.0	0.0
1996	2.9	2.6	14.0	7.7	4.6	2.3	0.0	0.0	0.0
1997	3.7	3.1	18.8	9.4	5.4	3.1	1.8	0.0	0.0
1998	3.5	2.8	14.9	8.7	5.1	3.2	1.7	0.0	0.0
1999 ¹	2.9	2.9	12.9	9.1	4.9	2.2	0.0	0.0	0.0
1993-99	2.7	2.7	18.8	7.9	4.1	2.2	0.0	0.0	0.0

¹Before February 28, 1999

Exhibit 43 Percentage of patients urgently readmitted to any Ontario hospital within 7 days of discharge from the Ottawa Civic Hospital, 1993-1999

Year	Percentage of patients with outcome (%)								
	Mean	Std.	Max	P95	P75	P50	P25	P5	Min
1993	3.5	3.1	22.2	9.3	5.1	3.0	1.5	0.0	0.0
1994	3.7	3.1	14.9	9.4	5.4	3.2	1.6	0.0	0.0
1995	4.2	3.3	15.6	10.2	6.1	3.8	2.0	0.0	0.0
1996	4.6	3.1	15.0	10.7	6.5	4.2	2.2	0.0	0.0
1997	5.2	3.6	18.2	11.5	7.3	4.9	2.6	0.0	0.0
1998	4.8	3.5	22.2	10.9	6.5	4.4	2.4	0.0	0.0
1999 ¹	5.0	3.5	15.2	12.1	6.5	4.2	2.4	0.0	0.0
1993-99	4.4	3.4	22.2	10.4	6.3	3.9	2.0	0.0	0.0

¹Before February 28, 1999

Exhibit 44 Percentage of patients urgently readmitted to any Ontario hospital within 30 days of discharge from the Ottawa Civic Hospital, 1993-1999

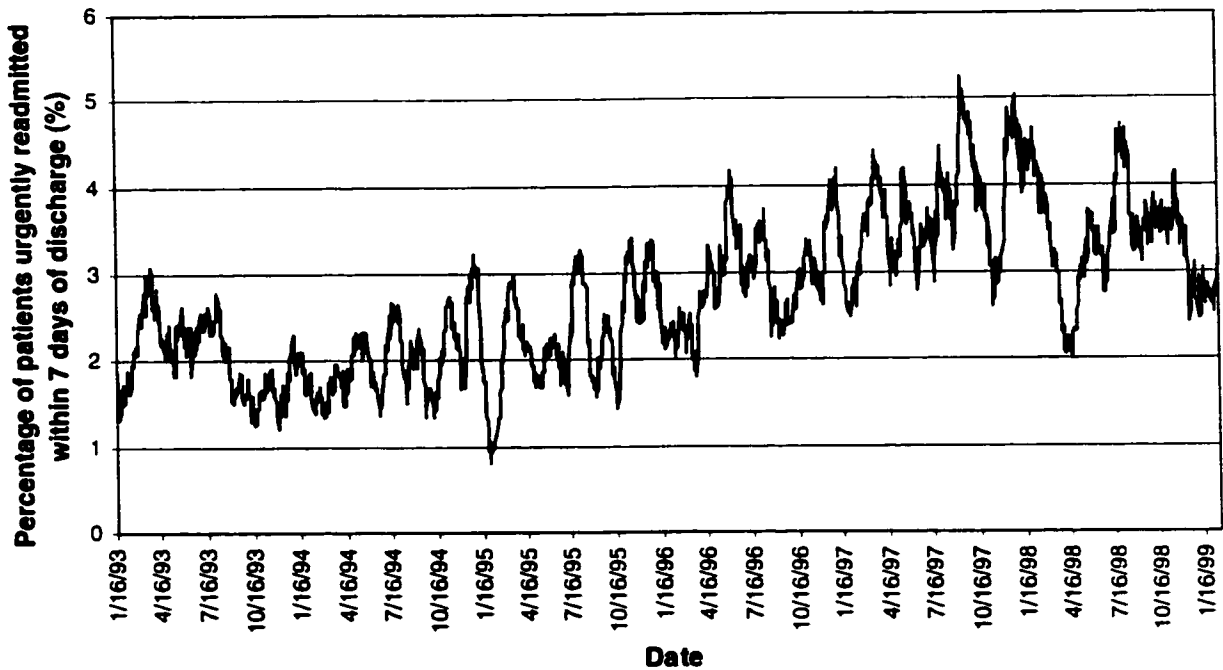


Exhibit 45 Smoothed time series plot of the daily percentage of patients readmitted to the any Ontario hospital within 7 days of discharge from the Ottawa Civic Hospital, 1993-1999

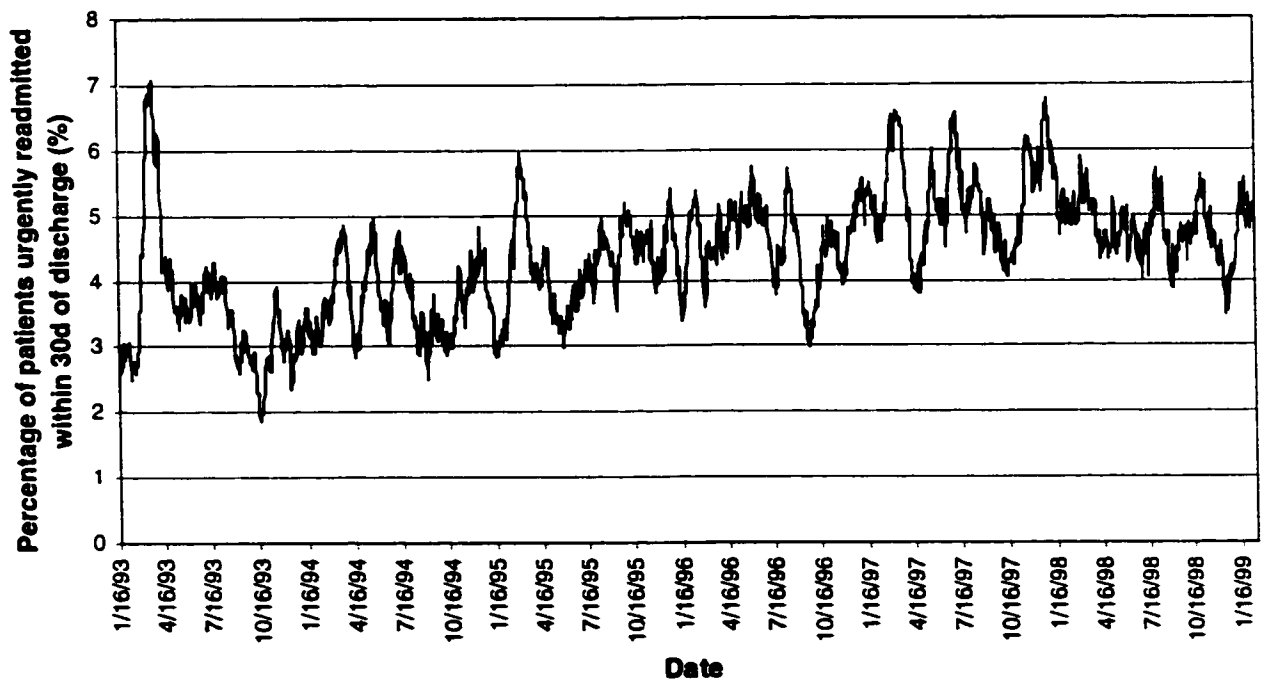


Exhibit 46 Smoothed time series plot of the daily percentage of patients readmitted to the any Ontario hospital within 30 days of discharge from the Ottawa Civic Hospital, 1993-1999

Year	Percentage of patients with outcome (%)								
	Mean	Std.	Max	P95	P75	P50	P25	P5	Min
1993	0.2	0.6	4.0	1.9	0.0	0.0	0.0	0.0	0.0
1994	0.2	0.7	5.3	2.0	0.0	0.0	0.0	0.0	0.0
1995	0.2	0.6	3.7	1.8	0.0	0.0	0.0	0.0	0.0
1996	0.3	0.7	4.4	2.0	0.0	0.0	0.0	0.0	0.0
1997	0.2	0.7	5.6	2.0	0.0	0.0	0.0	0.0	0.0
1998	0.3	0.8	3.9	2.2	0.0	0.0	0.0	0.0	0.0
1999 ¹	0.2	1.0	6.5	2.6	0.0	0.0	0.0	0.0	0.0
1993-99	0.2	0.7	6.5	2.0	0.0	0.0	0.0	0.0	0.0

¹Until February 28, 1999

Exhibit 47 Percentage of patients dying within 7 days of discharge from the Ottawa Civic Hospital, 1993-1999

Year	Percentage of patients with outcome (%)								
	Mean	Std.	Max	P95	P75	P50	P25	P5	Min
1993	0.9	1.5	9.1	3.5	1.8	0.0	0.0	0.0	0.0
1994	0.9	1.3	8.2	3.5	1.9	0.0	0.0	0.0	0.0
1995	1.1	1.6	13.5	3.9	1.9	0.0	0.0	0.0	0.0
1996	1.1	1.4	8.7	3.6	2.1	0.0	0.0	0.0	0.0
1997	1.0	1.5	6.3	3.9	2.1	0.0	0.0	0.0	0.0
1998	1.0	1.5	7.9	3.9	2.0	0.0	0.0	0.0	0.0
1999 ¹	0.8	1.4	6.5	3.6	1.6	0.0	0.0	0.0	0.0
1993-99	1.0	1.5	13.5	3.8	2.0	0.0	0.0	0.0	0.0

¹Until February 28, 1999

Exhibit 48 Percentage of patients dying within 30 days of discharge from the Ottawa Civic Hospital, 1993-1999

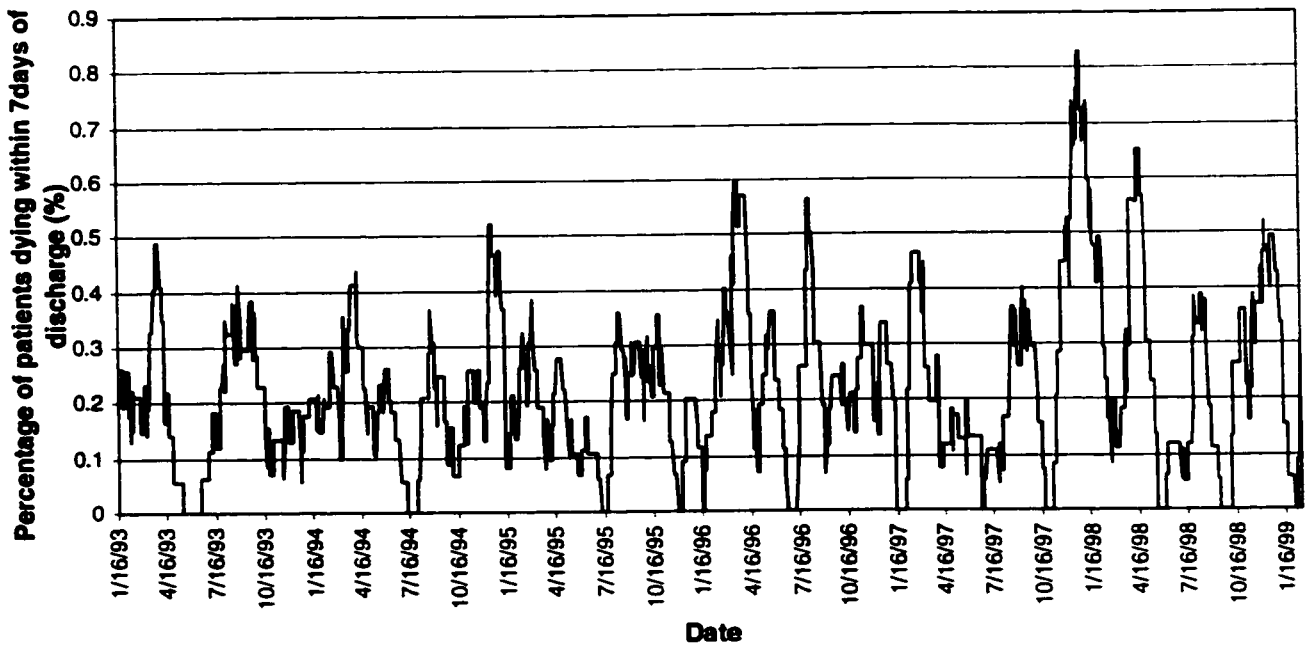


Exhibit 49 Smoothed time series plot of the daily percentage of patients dying within seven days of discharge from the Ottawa Civic Hospital, 1993-1999

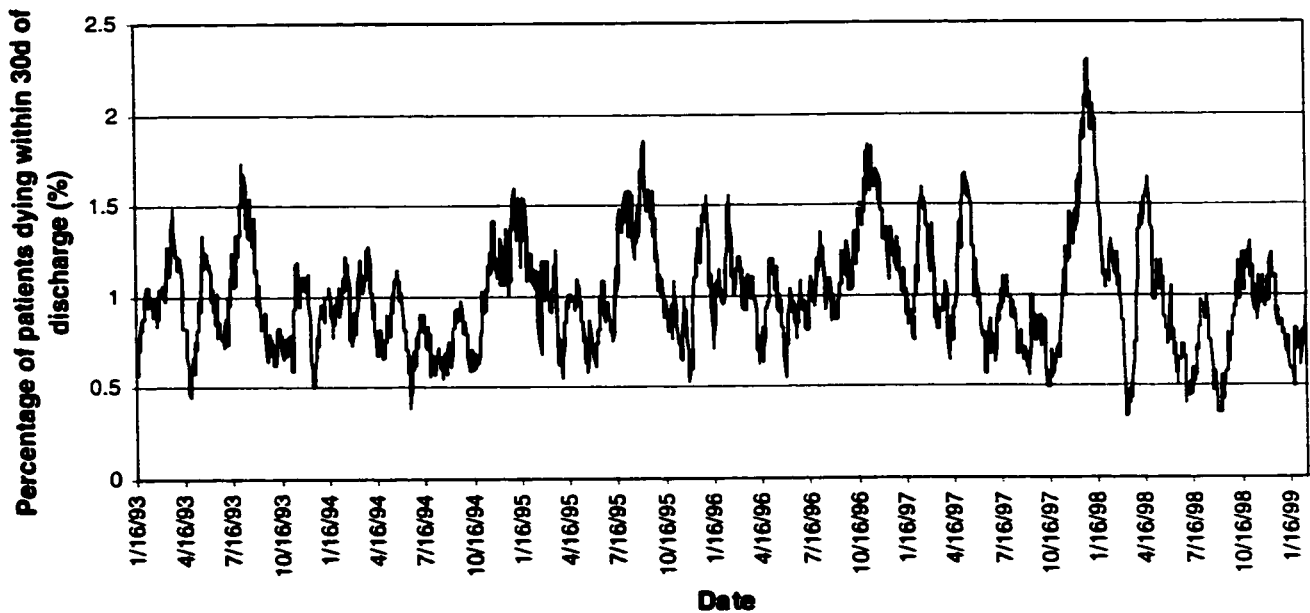


Exhibit 50 Smoothed time series plot of the daily percentage of patients dying within 30 days of discharge from the Ottawa Civic Hospital, 1993-1999

Outcome	Mean (95% CI)	Absolute change in outcome measure with a 10% increase in occupancy (95% CI)
ER delay (hours)	5.98 (5.93, 6.03)	0.29 (0.19, 0.39)
Length of stay (days) [†]	6.63 (6.53, 6.73)	-0.19 (-0.41, 0.03)
Percentage of patients transferred off-service (%)	11.65 (11.3, 12.0)	3.6 (3.59, 3.60)
Percentage of operations cancelled due to lack of postoperative bed (%)	0.25 (0.17, 0.33)	0.15 (-0.07, 0.36)

[†]Outcomes compared with occupancy rate one day before date of discharge.

Exhibit 51 Relationship between efficiency outcomes and occupancy rate

Outcome	Mean (95% CI)^{††}	Absolute change in the number of events with a 10% increase in occupancy (95% CI)^{††}
Bed-to-bed transfers [†]	1.19 (0.84, 1.53)	2.82 (1.97, 3.68)

[†]Outcomes compared with occupancy rate one day before date of discharge.

^{††}1993 is the base year.

Exhibit 52 Relationship between excess bed to bed transfers and occupancy rate

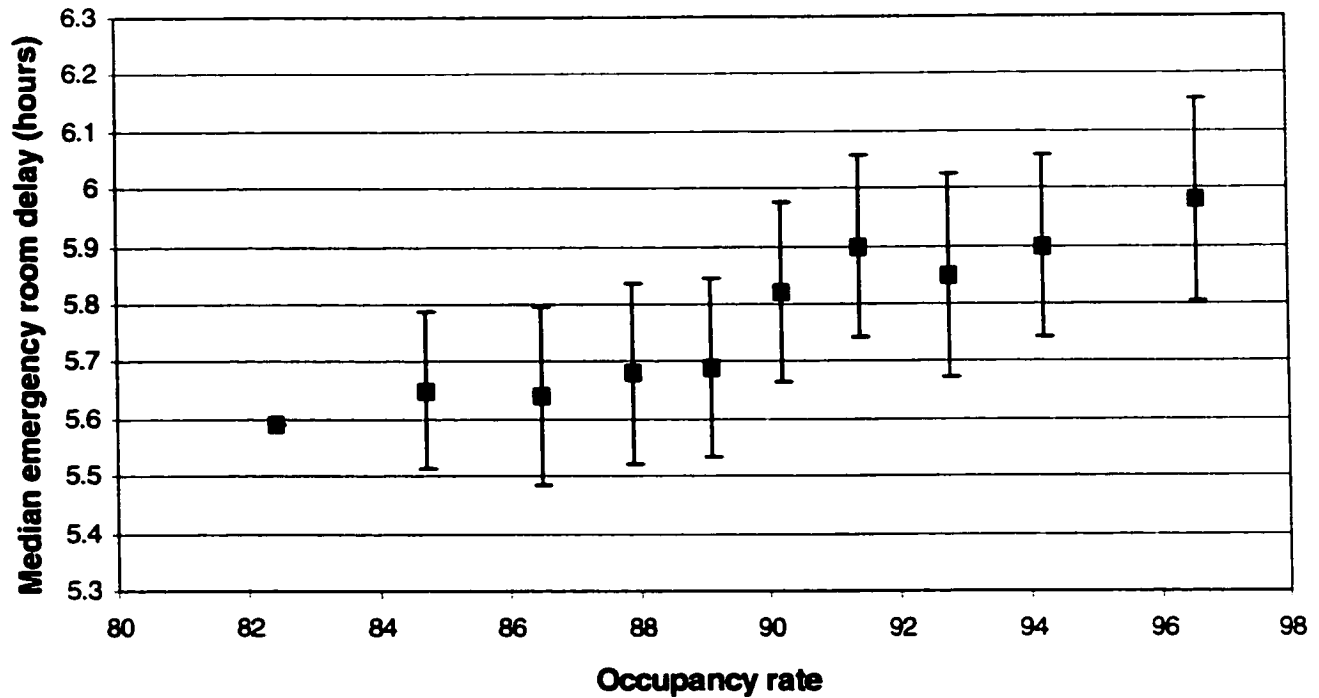


Exhibit 53 Median emergency room delay versus occupancy rate decile

The median ER delay within each occupancy rate category is plotted against the mid-point of each category. The ER delay in the lowest decile category is the actual delay in the study sample, whereas the ER delay in the higher nine categories are predicted by the ARIMA model. The 95% confidence limits of the estimates are presented. Similar plots are presented for exhibits 54-57, 59, 61-63, and 66-70.

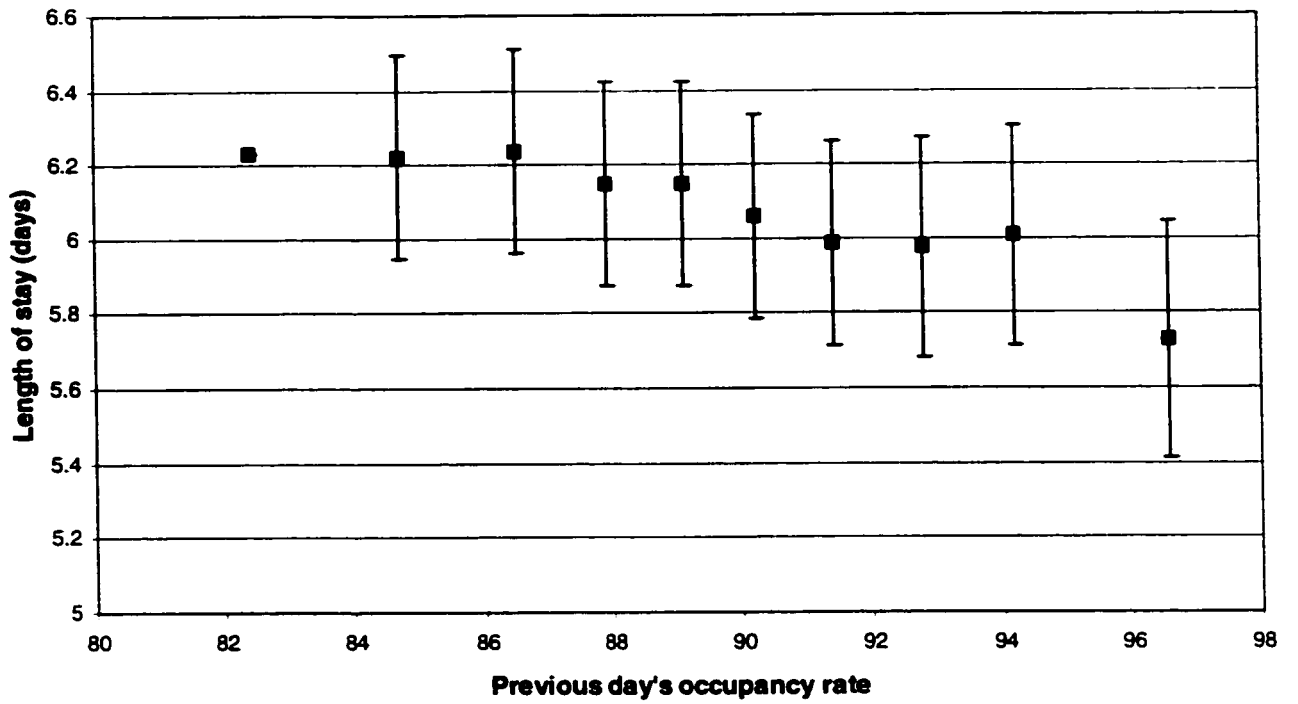


Exhibit 54 Mean length of stay versus previous day's occupancy rate decile

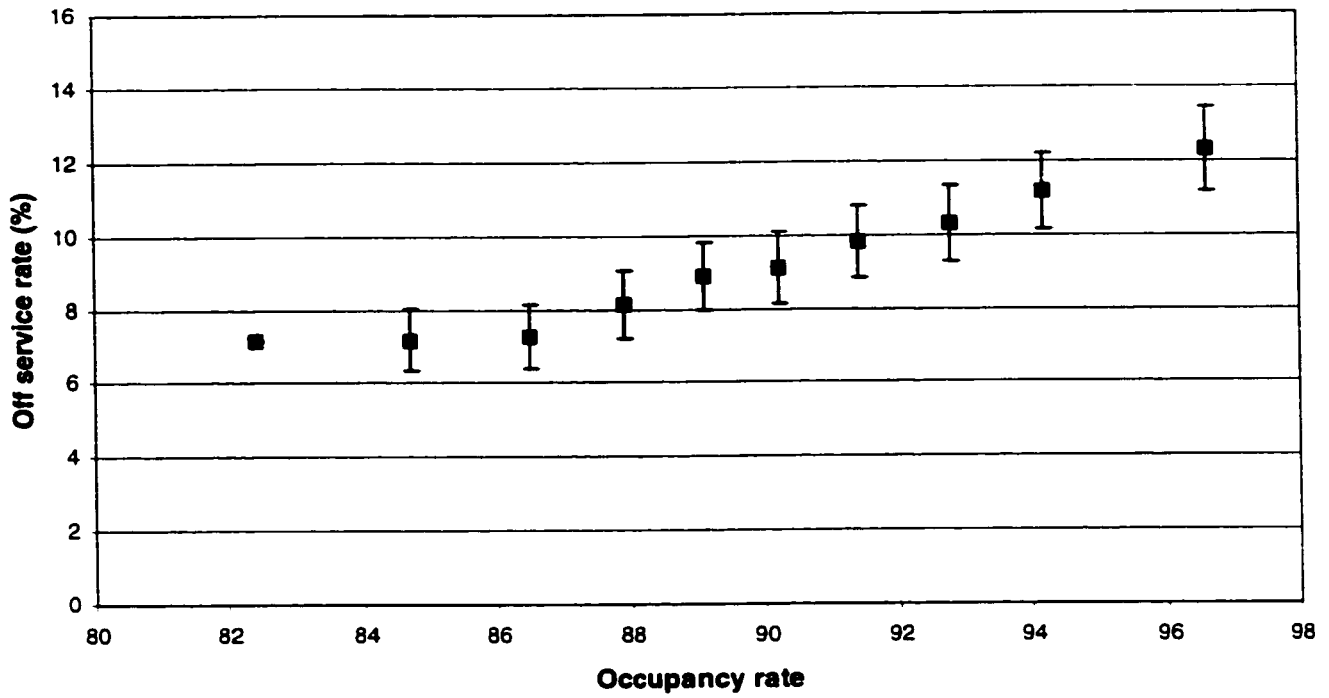


Exhibit 55 Off service rate versus occupancy rate decile

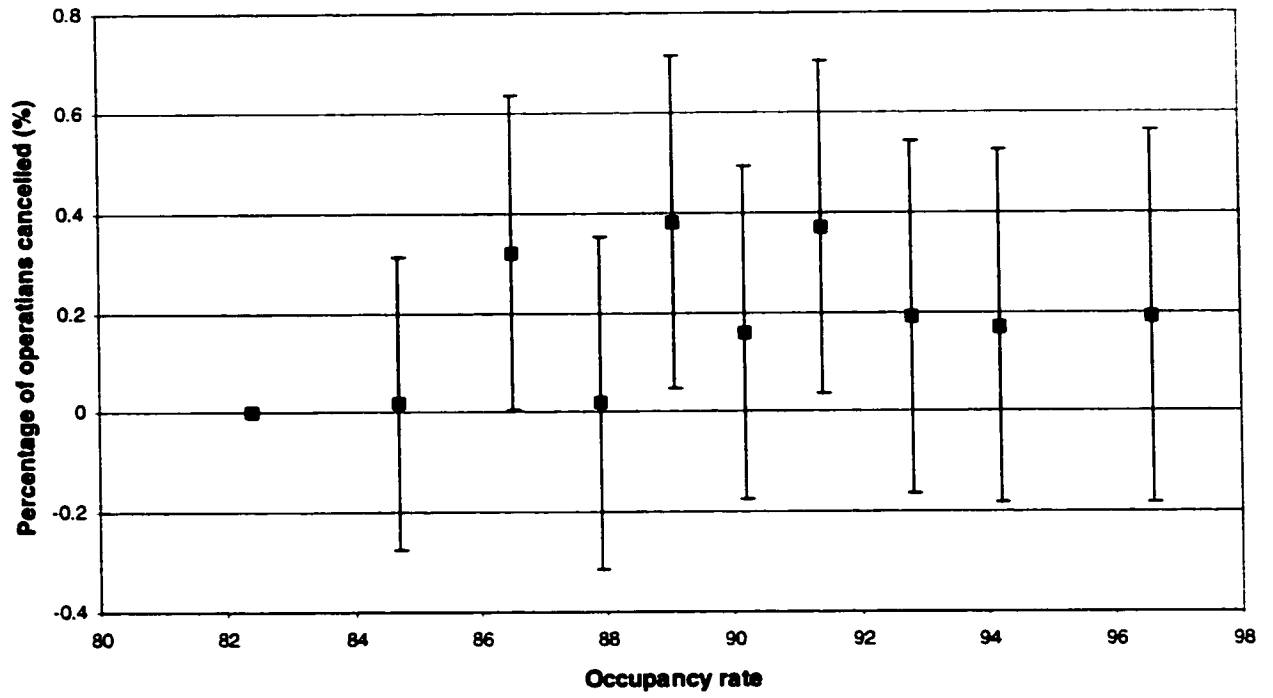


Exhibit 56 Percentage of operations cancelled versus occupancy rate decile

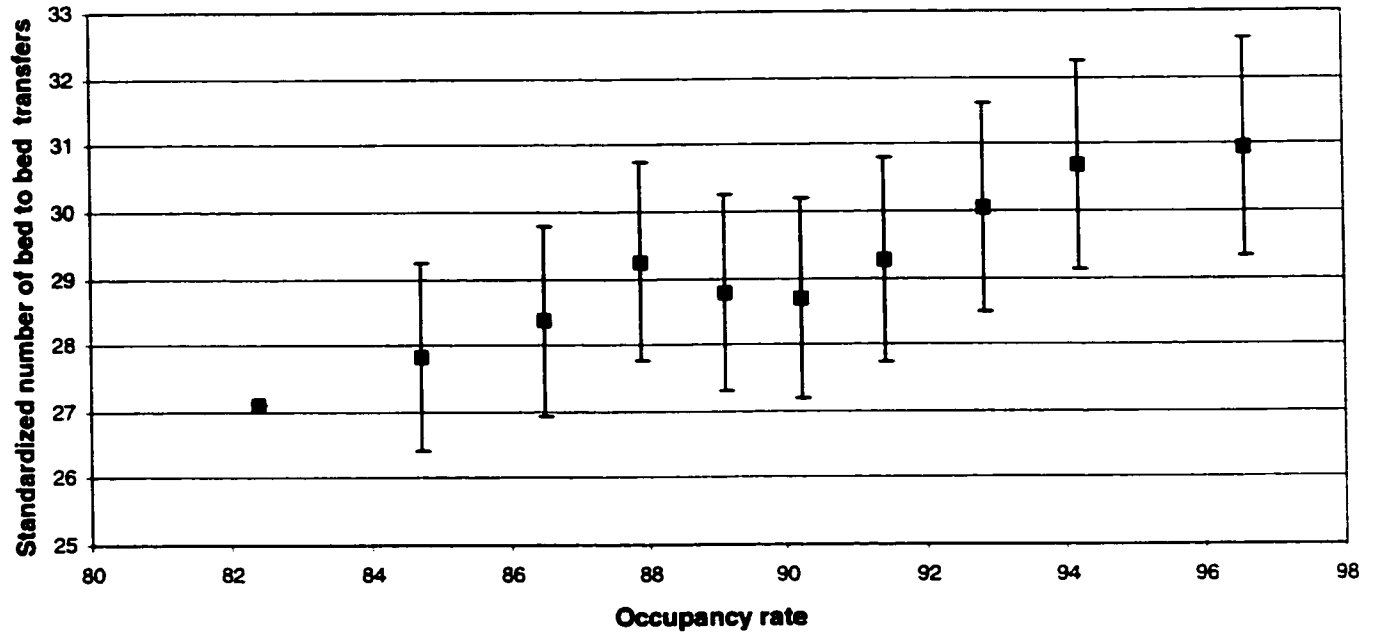


Exhibit 57 Standardized number of bed to bed transfers versus occupancy rate decile

Outcome	Mean (95% CI) ⁱⁱ	Absolute change in excess events with a 10% increase in occupancy (95% CI) ⁱⁱ
Deaths	0.39 (0.33, 0.44)	-0.15 (-0.29, -0.02)
Cardiac arrests ⁱⁱⁱ	0.04 (0.02, 0.06)	-0.06 (-0.11, 0.00)
C.difficile infections ⁱ	0.14 (0.11, 0.17)	-0.06 (-0.15, 0.02)
Medication errors	0.03 (0.00, 0.07)	0.04 (-0.06, 0.14)
Falls	0.08 (0.02, 0.14)	-0.07 (-0.22, 0.08)

ⁱOutcomes compared with occupancy rate three days before the diagnosis of c.difficile infection.

ⁱⁱ1993 is the base year.

ⁱⁱⁱOutcome rate is not autocorrelated. Therefore, linear regression used.

Exhibit 58 Relationship between excess inpatient events and occupancy rates

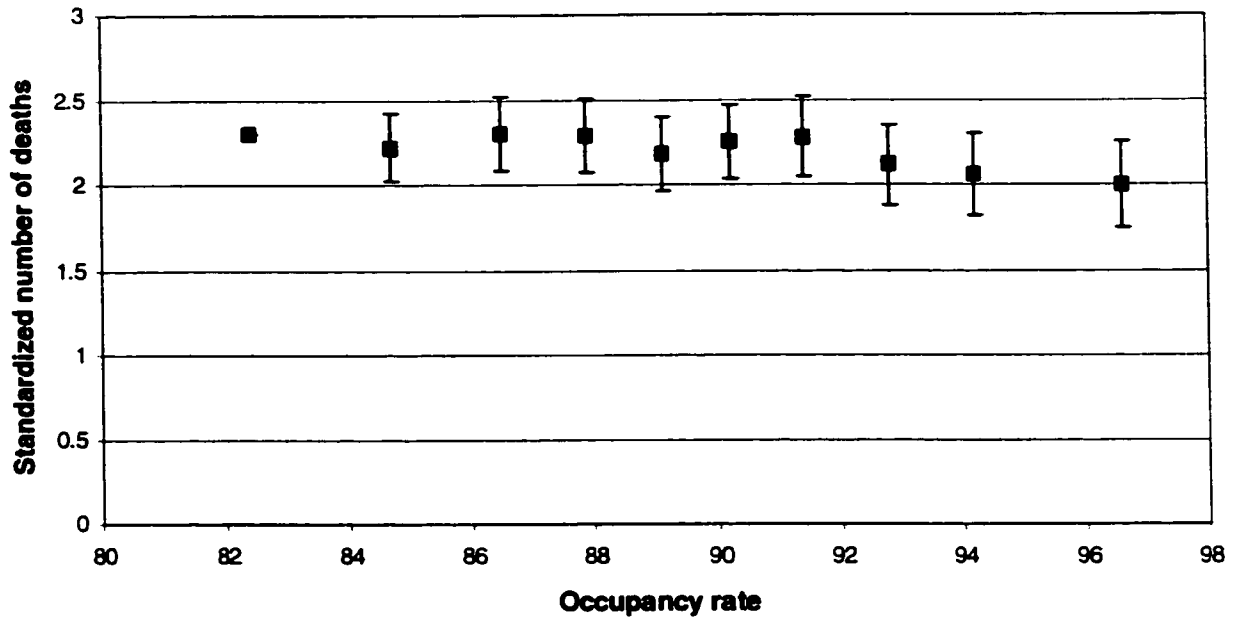


Exhibit 59 Standardized number of deaths versus occupancy rate decile

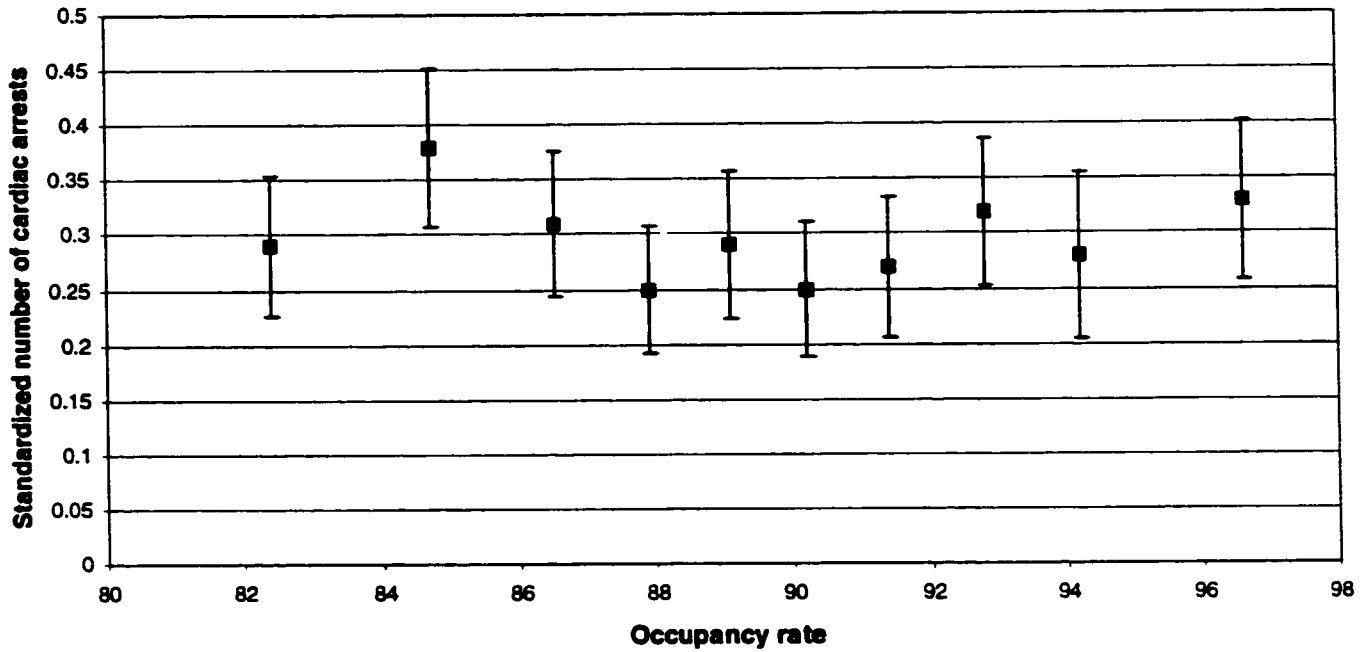


Exhibit 60 Standardized number of cardiac arrests versus occupancy rate decile

The mean daily number of excess cardiac arrests is plotted against the midpoint of each occupancy rate category. Because this time series was not autocorrelated then ARIMA modeling was not necessary and the estimates are the actual numbers realized from the study. The error bars represent 95% CI's of the means. The rates between decile groups are not statistically different according to ANOVA. A similar plot is presented in exhibit 71.

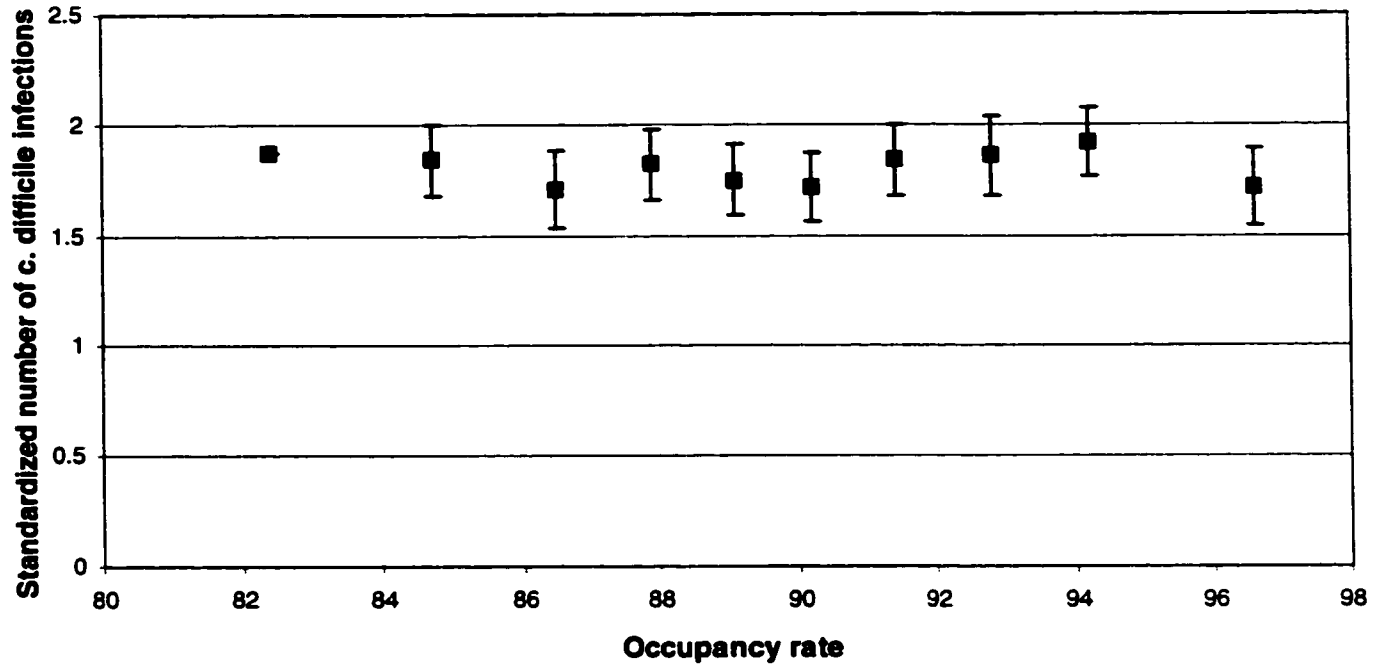


Exhibit 61 Standardized number of c.difficile infections versus occupancy rate decile

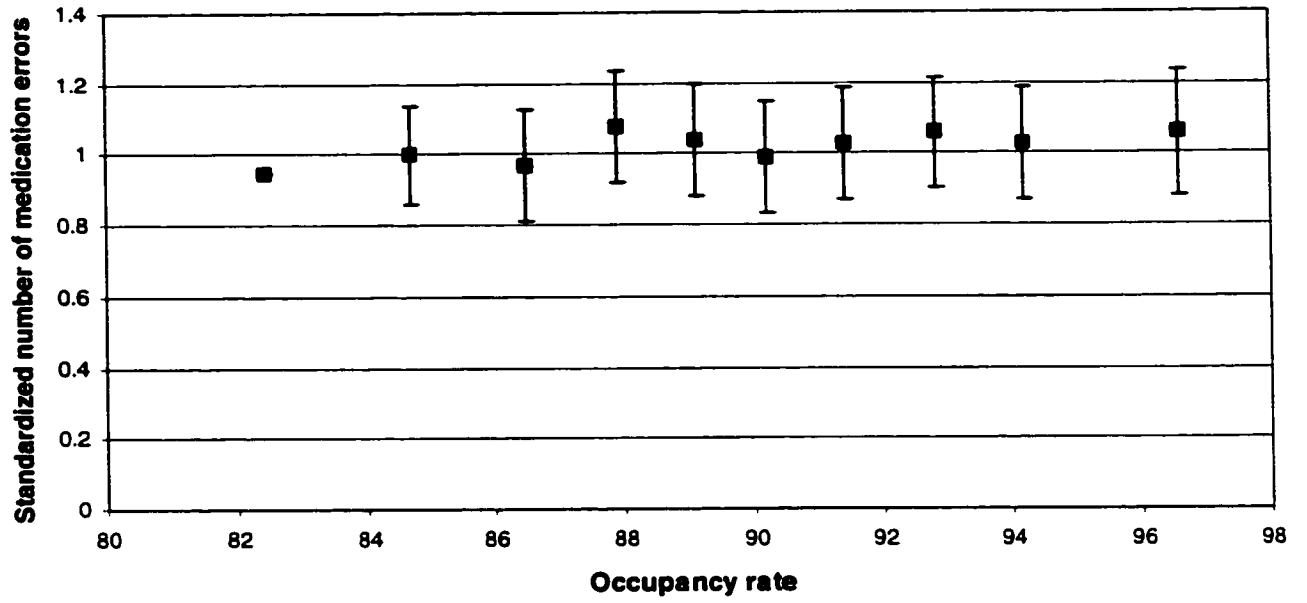


Exhibit 62 Standardized number of medication errors versus occupancy rate decile

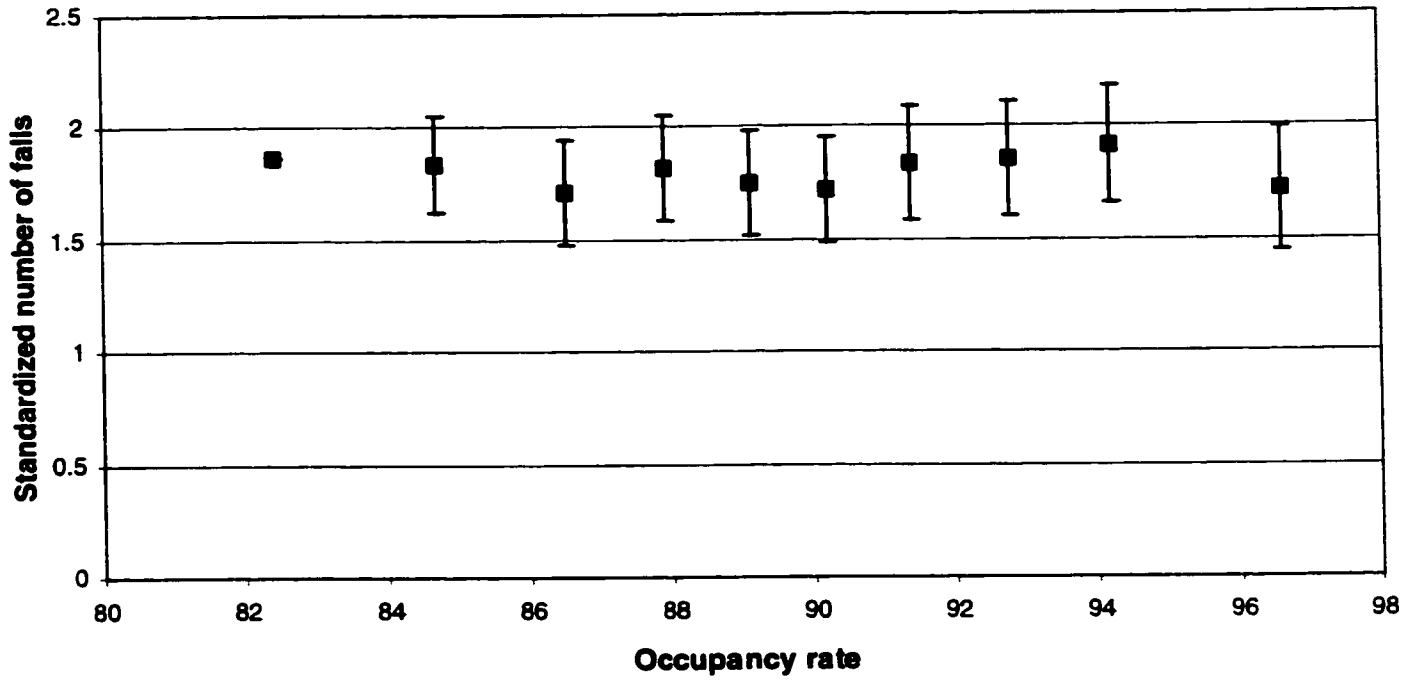


Exhibit 63 Standardized number of falls versus occupancy rate decile

Outcome	Mean (95% CI)	Absolute change in event rate with a 10% increase in occupancy (95% CI)
ER –visits ¹	4.80 (4.62, 4.98)	0.07 (-0.15, 0.66)
Urgent re-admissions ¹	2.73 (2.61, 2.84)	-0.25 (-0.01, -0.49)
Deaths ¹	0.23 (0.20, 0.26)	0.00 (-0.06, 0.07)

¹ Outcomes compared with occupancy rate one day before date of discharge.

Exhibit 64 Relationship between seven-day outpatient outcomes and occupancy rate

Outcome	Mean (95% CI)¹	Absolute change in event rate (cases per 100 patients discharged) with a 10% increase in occupancy (95% confidence interval)
ER –visits ¹	9.20 (8.90, 9.50)	-0.52 (-1.42, 0.38)
Urgent re-admissions ¹	4.35 (4.20, 4.50)	-0.25 (-0.57, 0.07)
Deaths ^{1,ii}	1.00 (0.98, 1.06)	0.22 (0.21, 0.22)

¹ Outcomes compared with occupancy rate one day before date of discharge.

ⁱⁱ 30 day community death rate is not autocorrelated. Therefore, linear regression is used.

Exhibit 65 Relationship between 30-day outpatient outcomes and occupancy rate

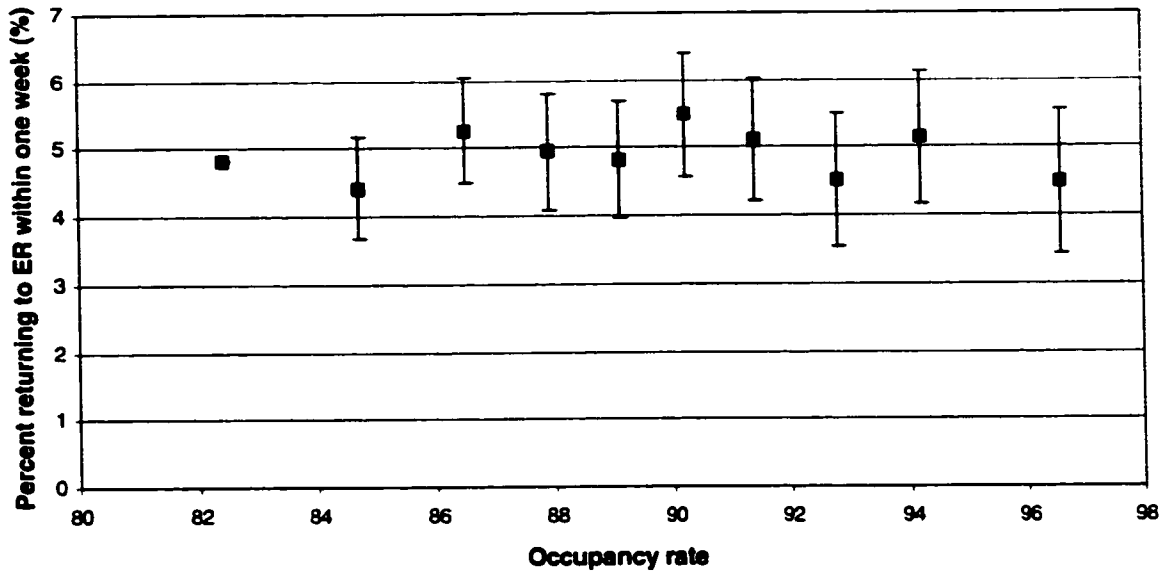


Exhibit 66 Percentage of patients returning to any Ontario ER within seven days of discharge of the Ottawa Civic Hospital versus occupancy rate decile

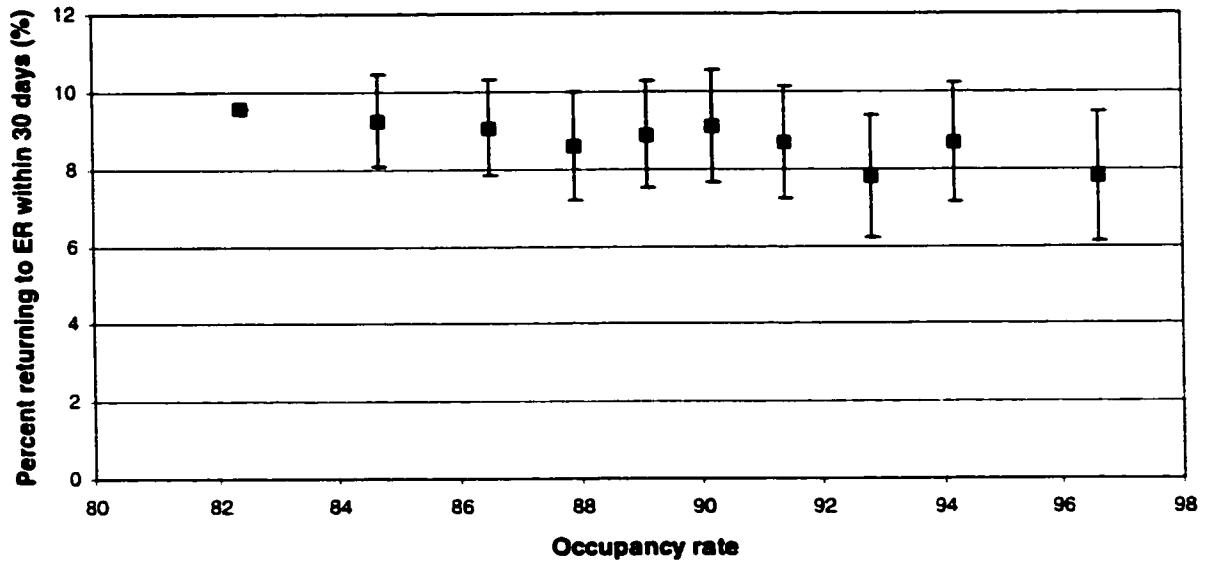


Exhibit 67 Percentage of patients returning to any Ontario ER within 30-days of discharge of the Ottawa Civic Hospital versus occupancy rate decile

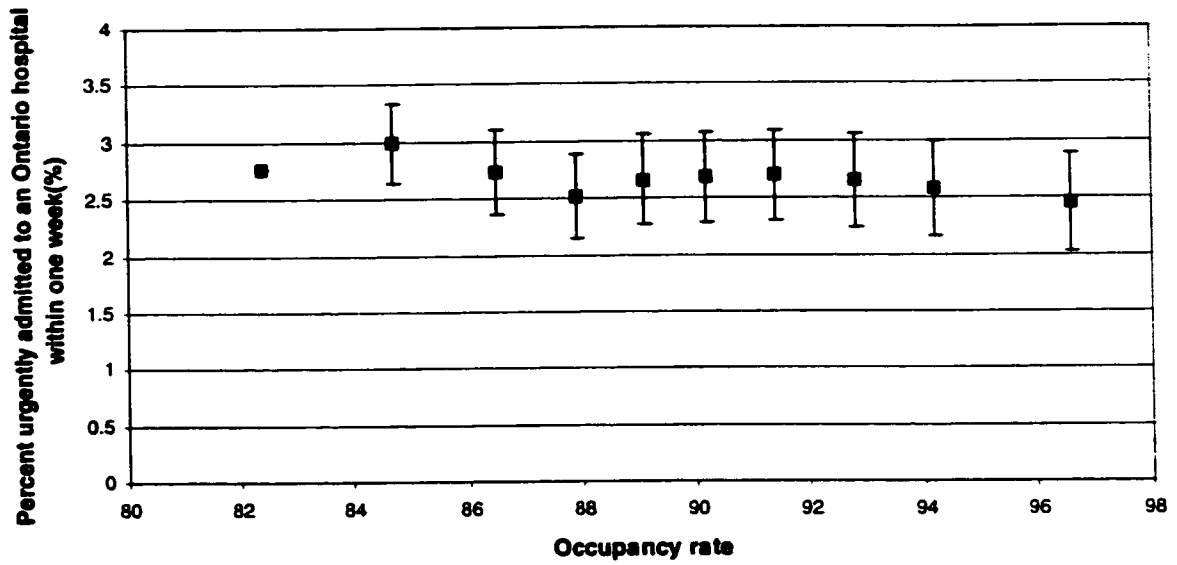


Exhibit 68 Percentage of patients urgently readmitted to any Ontario hospital within seven days of discharge from the Ottawa Civic Hospital versus occupancy rate decile

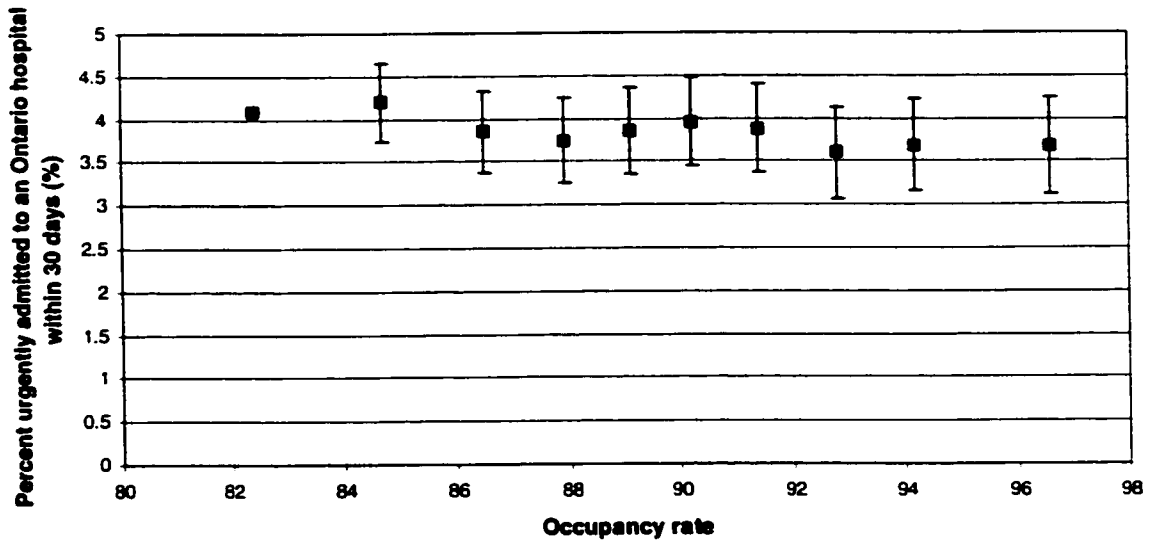


Exhibit 69 Percentage of patients urgently readmitted to any Ontario hospital within 30 days of discharge from the Ottawa Civic Hospital versus occupancy rate decile

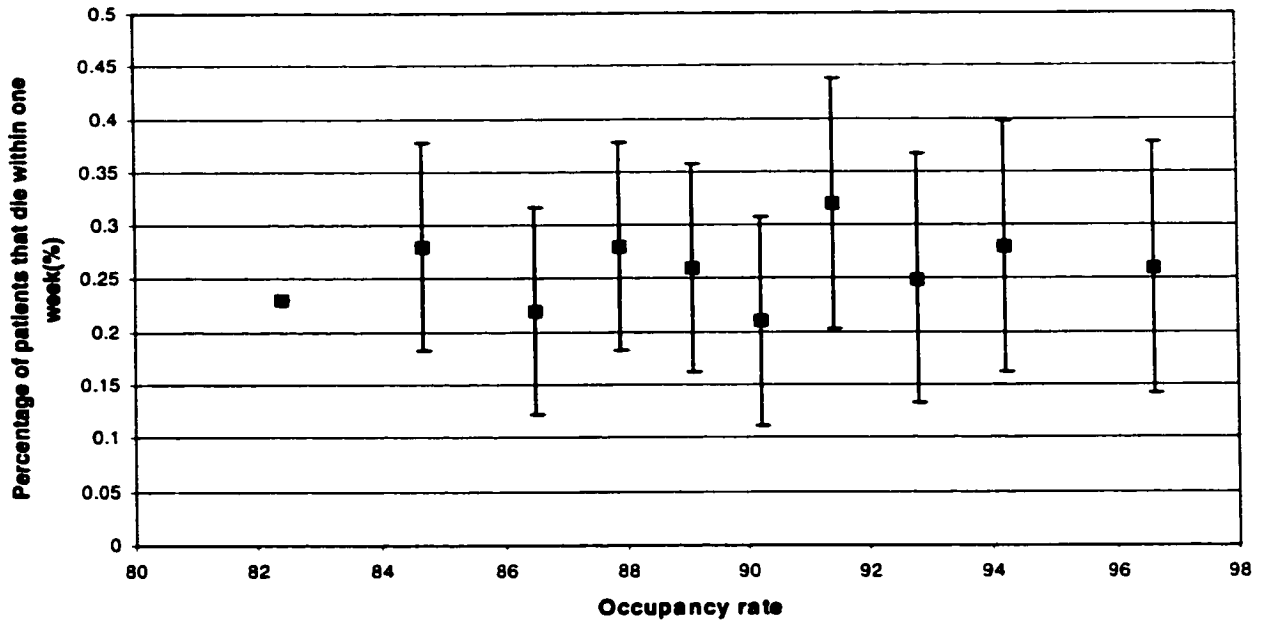


Exhibit 70 Percentage of patients dying within seven days of discharge from the Ottawa Civic Hospital versus occupancy rate decile

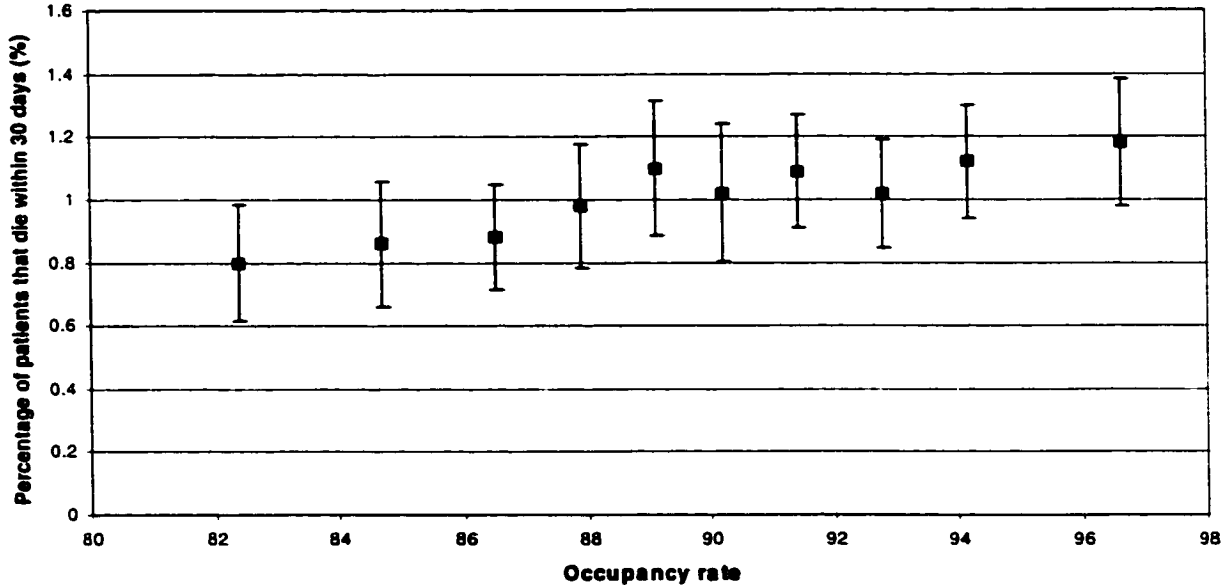


Exhibit 71 Percentage of patients dying within thirty days of discharge from the Ottawa Civic Hospital versus occupancy rate decile*

*Please note that the outcome time series "percentage of patients dying within thirty days of discharge" is not auto-correlated. Therefore, the mean and 95% CI's of each decile group are plotted. The rates between decile groups are different $p < 0.05$.

8. Appendices

Appendix 1 Peer Review Organization's method for problem rate identification

Peer Review Organizations evaluate quality of hospital care by reviewing about a quarter of their hospital records. Charts are selected by a number of criteria, for example, all patients who are re-admitted within 31 days of discharge would be selected. Once a chart is selected for review, nurses apply a set of 20 explicit criteria screens to the record. The list of these screening criteria is below. If the chart fails any of the criteria, a physician advisor determines if there was good quality of care and appropriate utilization of resources. The confirmed problem rate is the number of cases with a quality problem confirmed by the physician divided by the total number of admissions reviewed.

Generic quality screens used by Peer Review Organizations

1. Adequacy of discharge planning.

Medical stability of patient at discharge

2. Blood pressure high or low on day before or day of discharge.
3. High temperature on day before or day of discharge.
4. Low pulse within 24 hours of discharge.
5. Abnormal results of diagnostic services that are not addressed or explained in the medical record.
6. IV fluids or drugs on the day of discharge.
7. Purulent or bloody drainage of postoperative wound within 24 hours prior to discharge.

Deaths

8. During or following elective surgery.
9. Following return to intensive care unit, coronary care or special care unit within 24 hours of being transferred out.
10. Other unexpected death.

Nosocomial infections

11. Temperature increase of more than 2 degrees more than 72 hours from admission.
12. Indication of an infection following an invasive procedure.
13. Unscheduled return to surgery within same admission for same condition as previous surgery or to correct operative problem.

Trauma suffered in the hospital

14. Unplanned removal or repair of a normal organ.
15. Fall with injury or untoward effect.
16. Life-threatening complications of anesthesia.
17. Life threatening transfusion error or reaction.
18. Hospital acquired decubitus ulcer.
19. Care resulting in serious or life threatening complications not related to admitting signs and symptoms.
20. Major adverse drug reaction or medication error with serious potential for harm or resulting in special measures to correct (e.g. intubation, cardiopulmonary resuscitation, gastric lavage) including but not limited to the following: incorrect antibiotic ordered by the physician; no diagnostic studies to confirm which drug is correct; serum drug levels not performed as needed; diagnostic studies or other measures for side effects not performed as need.

Appendix 2 Number of inpatients at the Ottawa Civic Hospital, 1993-1999.

Year	Patients								
	Mean	Std	Max	P95	P75	P50	P25	P5	Min
1993	537	43	625	593	566	545	516	444	383
1994	511	36	587	554	537	518	494	448	360
1995	496	38	583	553	522	499	474	424	355
1996	452	46	561	523	480	454	427	379	276
1997	383	33	479	440	402	383	361	329	295
1998	387	24	438	423	404	390	372	351	301
1999 ¹	378	25	441	423	394	377	362	341	316
Total	454	71	625	560	517	453	391	351	276

¹Until July 30, 1999.

Appendix 3 Number of beds at the Ottawa Civic Hospital, 1993-1999

Year	Beds								
	Mean	Std	Max	P95	P75	P50	P25	P5	Min
1993	610	43	659	659	629	605	596	496	468
1994	568	34	611	611	582	575	564	478	460
1995	562	32	584	584	582	576	558	479	456
1996	510	45	577	577	544	491	486	456	382
1997	423	28	481	481	435	417	411	379	363
1998	425	13	447	439	433	427	424	396	371
1999 ¹	416	15	444	441	427	413	406	395	385
Total	507	81	659	629	579	491	427	395	363

¹Until July 30, 1999.

Appendix 4 ARIMA models using occupancy as a continuous variable

Outcome		Differencing (d)	Autoregressive parameters (p)	Moving average parameters (q)	Occupancy parameter estimate (SE)**
Efficiency	ER delay	0	2	(2)	0.03 (0.01)
	Off service transfer rate	0	2	(1,6)	0.36(0.03)
	Length of stay***	span 7	(2)	(1,5,6,7)	0.02 (0.01)
	OR cancellations	0	(1,7)	(2)	0.01 (0.01)
	Excess transfers	span 7	2	(1,7)	0.28 (0.045)
Inpatient Events	Excess deaths	0	(1,2,3,9)	(1,2,3,9)	-0.02 (0.01)
	Excess cardiac arrests*	-	-	-	-
	Excess c.difficile infections****	0	5	3	-0.01 (0.00)
	Excess medication errors	0	1	1	0.00 (0.01)
	Excess falls	0	0	(3)	-0.01 (0.01)
	7day ER visits***	0	1	1	0.01 (0.02)
	7day urgent readmissions***	0	(1,6,7)	(1,5,6,7)	0.03 (0.01)
Outpatient events	7day deaths***	0	(5)	0	0.00 (0.00)
	30day ER visits***	0	1	(1,9)	-0.05 (0.05)
	30day urgent readmissions***	0	(1,7)	1	-0.02 (0.02)
	30day deaths*,***	-	-	-	-

* These two outcome time series are not auto-correlated. Therefore they were modelled using linear regression and ANOVA.

** Parameter estimate represents the change in the outcome for every 1% change in hospital occupancy rate. Values are rounded to two significant digits.

*** Previous day's occupancy rate used in the model

**** Occupancy rate three days prior to the diagnosis of the infection used

Appendix 5 ARIMA modelling

Step 1. Testing for autocorrelation in the daily post discharge 7-day ER visit rate time series.

a) using the Durbin-Watson statistic:

Durbin-Watson Statistics

Order	DW	PROB<DW
1	1.7943	0.0001
2	1.8343	0.0019
3	1.8251	0.0012
4	1.8202	0.0010
5	1.8802	0.0227

Since the statistic is significant at each of the five lags, one concludes that there is evidence of autocorrelation.

b) using the Ljung-Box Q-statistic (LBQ):

To Lag	LBQ	DF	Prob	Autocorrelations						
6	27.91	6	0.000	0.094	0.055	0.057	0.078	0.028	0.056	
12	36.09	12	0.000	0.057	0.008	0.042	0.035	-0.029	-0.015	
18	40.52	18	0.002	-0.017	-0.013	-0.013	0.000	0.053	0.020	
24	48.05	24	0.002	0.010	-0.005	-0.013	0.079	0.003	-0.009	

Since the LBQ is significant at all lags, one rejects the null hypothesis that the time series is white noise.

Summary: Because there is evidence of autocorrelation, it would be inappropriate to use linear regression analysis. Go to step 2b)

Step 2b Fit ARIMA model

- i) Ensure that the daily post discharge 7-day ER visit rate time series is stationary
- a) Review the time series (see exhibit 41) – Potentially an increasing trend when looking at time series
- b) Assess the ACF plot

			Autocorrelations																						
Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std	
0	0.0017405	1.00000												*****											0
1	0.00016373	0.09407											.	**											0.030029
2	0.00009572	0.05500											.	*											0.030293
3	0.00009842	0.05655											.	*											0.030383
4	0.00013597	0.07813											.	**											0.030478
5	0.00004853	0.02788											.	*											0.030658
6	0.00009697	0.05571											.	*											0.030681
7	0.00009868	0.05670											.	*											0.030772
8	0.0000143	0.00821											.	.											0.030866
9	0.00007234	0.04156											.	*											0.030868
10	0.00006071	0.03488											.	*											0.030918
11	-0.0000506	-0.02906											.	.											0.030954
12	-0.0000268	-0.01540											.	.											0.030978
13	-0.0000301	-0.01732											.	.											0.030985
14	-0.0000227	-0.01307											.	.											0.030994
15	-0.0000234	-0.01342											.	.											0.030999

.* marks two standard errors

The ACF plot is indicative of non-stationarity if it does not taper to zero. On inspection of the ACF plot since the autocorrelation coefficients approximate zero there is no evidence of non-stationarity.

- c) Assess the Dickey Fuller test for stationarity.

Augmented Dickey-Fuller Unit Root Tests

Type	Lags	RHO	Prob<RHO	T	Prob<T	F	Prob<F
Zero Mean	0	-426.039	0.0001	-16.2301	0.0001	--	--
	1	-203.487	0.0001	-10.0895	0.0001	--	--
	2	-114.393	0.0001	-7.3836	0.0001	--	--

Because the T-test is significant the null hypothesis of non-stationarity is rejected.

Because criteria "b" and "c" are satisfied one concludes that there is no need for differencing of the dependent time series: daily post discharge 7-day ER visit rate time series

i) Ensure that the daily occupancy rate time series is stationary

- a) Review the time series (see exhibit 7) – No obvious trend when looking at the occupancy time series
- b) Assess the ACF plot

Lag	Covariance	Correlation	Autocorrelations																	Std				
			-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6		7	8	9	1
0	19.140686	1.00000																						0
1	13.845023	0.72333										.												0.030029
2	7.495225	0.39159										.												0.042957
3	3.665583	0.19151										.												0.046063
4	2.575757	0.13457										.												0.046776
5	3.912936	0.20443										.												0.047123
6	7.226737	0.37756										.												0.047916
7	9.221222	0.48176										.												0.050528
8	6.089208	0.31813										.												0.054513
9	1.603893	0.08379										.												0.056162
10	-0.829955	-0.04336										.	*											0.056274
11	-1.290355	-0.06741										.	*											0.056304
12	0.412354	0.02154										.	.											0.056377
13	4.434596	0.23168										.												0.056385
14	6.569846	0.34324										.												0.057237
15	4.054386	0.21182										.												0.059064
16	-0.137127	-0.00716										.	.											0.059745
17	-2.417788	-0.12632										.												0.059745
18	-2.458468	-0.12844										.												0.059986
19	-0.289826	-0.01514										.	.											0.060233
20	3.697862	0.19319										.												0.060237
21	5.749430	0.30038										.												0.060793
22	3.110854	0.16253										.												0.062117
23	-1.037994	-0.05423										.	*											0.062499
24	-3.448531	-0.18017										.												0.062541

Note that there are obvious peaks at lags 7, 14 and 21. This pattern in the ACF suggests that a span 7 differencing is required to make the series stationary.

d) For the span 7 differenced series, assess the Dickey Fuller test for stationarity.

Augmented Dickey-Fuller Unit Root Tests

Type	Lags	RHO	Prob<RHO	T	Prob<T	F	Prob<F
Zero Mean	0	-301.618	0.0001	-13.2115	0.0001	--	--
	1	-366.473	0.0001	-13.5248	0.0001	--	--
	2	-421.287	0.0001	-13.2753	0.0001	--	--

The differenced time series is stationary, therefore, use it in subsequent analysis.

ii) Identify potential AR and MA processes in the dependent time series

Autocorrelations

Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std
0	0.0017405	1.00000																						0
1	0.00016373	0.09407												. **										0.030029
2	0.00009572	0.05500												. *										0.030293
3	0.00009842	0.05655												. *										0.030383
4	0.00013597	0.07813												. **										0.030478
5	0.00004853	0.02788												. *										0.030658
6	0.00009697	0.05571												. *										0.030681
7	0.00009868	0.05670												. *										0.030772
8	0.0000143	0.00821												. . .										0.030866
9	0.00007234	0.04156												. *										0.030868
10	0.00006071	0.03488												. *										0.030918
11	-0.0000506	-0.02906												* . .										0.030954
12	-0.0000268	-0.01540												. . .										0.030978

Inverse Autocorrelations

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	-0.07089												* . .										
2	-0.03018												* . .										
3	-0.02262												. . .										
4	-0.06435												* . .										
5	0.00416												. . .										
6	-0.04460												* . .										
7	-0.04817												* . .										
8	0.01401												. . .										
9	-0.03855												* . .										
10	-0.02453												. . .										
11	0.03662												. *										
12	0.01822												. . .										

Partial Autocorrelations

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	0.09407												. **										
2	0.04656												. *										
3	0.04776												. *										
4	0.06725												. *										
5	0.01063												. . .										
6	0.04413												. *										
7	0.04058												. *										
8	-0.01095												. . .										
9	0.03164												. *										
10	0.01828												. . .										
11	-0.04521												* . .										
12	-0.01813												. . .										

There are peaks in the ACF and PACF plots at lag 1. Both plots appear to diminish immediately after that particular lag. There is another peak in both plots at lag 4.

Estimate the model with $p=1$ and $q=1$.

Parameter	Estimate	Approx. Std Error	T Ratio	Lag	Variable	Shift
MU	0.04840	0.0018459	26.22	0	ER_VIS_R	0
MA1,1	0.77284	0.08964	8.62	1	ER_VIS_R	0
AR1,1	0.84743	0.07518	11.27	1	ER_VIS_R	0
NUM1	0.00007048	0.0002994	0.24	0	OCCU1_RT	0

Variance Estimate = 0.00170077

The parameter estimate, representing a change in the proportion of patients returning to the ER within 7 days of discharge for a 1% change in occupancy rate on the day before discharge is given by NUM1. To calculate the change expected with a 10% increase this value is multiplied by 10.

iii) Evaluate the adequacy of the estimated model by assessing the residuals.

Autocorrelation Check of Residuals

To Lag	Autocorrelations								
LBO	DF	Prob							
6	2.18	4	0.703	0.008	-0.019	-0.010	0.026	-0.016	0.022
12	7.57	10	0.670	0.025	-0.020	0.024	0.019	-0.048	-0.024
18	13.11	16	0.665	-0.031	-0.024	-0.020	-0.008	0.053	0.014
24	21.04	22	0.518	0.003	-0.012	-0.028	0.074	-0.005	-0.024
30	29.48	28	0.388	-0.013	0.037	0.071	0.012	0.024	0.010
36	35.77	34	0.385	-0.032	0.031	0.007	0.004	0.023	0.054
42	39.99	40	0.471	0.033	-0.021	0.019	-0.024	0.010	-0.034
48	47.87	46	0.397	-0.002	0.023	0.035	-0.029	-0.046	-0.046

The LBQ is not significant at any lag. Thus the null hypothesis that the residuals are white noise cannot be rejected. The model is determined to be potentially acceptable.

For illustrative purposes, assess the residuals using spectral analysis. Recall that the null hypothesis is that the time series is a white noise process. For the Kolmogorov-Smirnov statistic the critical value is dependent on the number of ordinates (which is given by $M-1$). The critical value for the $\alpha = 0.05$ is given by the formula: $1.36(m-1)^{-0.5}$:

----- Test for White Noise for variable RESIDUAL -----

Parameters: M-1 = 550

Bartlett's Kolmogorov-Smirnov Statistic:

Test Statistic = 0.0213

The critical value is 0.0580. Thus, one cannot reject the null hypothesis, again suggesting that the residuals are white noise.

Attempt to identify other models

Try a $p=1$ $q=(1,4)$

Parameter	Estimate	Std Error	T Ratio	Lag	Variable	Shift
MU	0.04841	0.0017983	26.92	0	ER_VIS_R	0
MA1,1	0.68197	0.14019	4.86	1	ER_VIS_R	0
MA1,2	-0.03679	0.03331	-1.10	4	ER_VIS_R	0
AR1,1	0.75525	0.13154	5.74	1	ER_VIS_R	0
NUM1	0.00009026	0.0002982	0.30	0	OCCU1_RT	0

Variance Estimate = 0.0017004

Autocorrelation Check of Residuals

To	Autocorrelations									
Lag	LBQ	DF	Prob							
6	1.56	3	0.668	0.009	-0.012	0.000	0.003	-0.029	0.018	
12	6.94	9	0.643	0.028	-0.016	0.030	0.025	-0.044	-0.020	
18	12.51	15	0.640	-0.029	-0.021	-0.015	-0.004	0.057	0.016	
24	20.04	21	0.519	0.007	-0.008	-0.028	0.072	-0.007	-0.022	
30	28.58	27	0.382	-0.010	0.037	0.072	0.012	0.026	0.010	
36	35.13	33	0.367	-0.035	0.029	0.006	0.005	0.024	0.055	
42	39.17	39	0.462	0.034	-0.019	0.019	-0.025	0.009	-0.031	

The second model is felt to be inferior to the first for the following reasons:

- the LBQ statistics are not significant, indicating the residuals are probably white noise. The model is potentially acceptable.
- the second moving average term at lag 4 is not significant.
- the variance of the residuals is marginally greater than in the first model.

A similar procedure is carried out using dummy variables for each of the deciles of occupancy rate. The estimation of the parameters and the LBQ statistics up to lag 48 are presented below:

Approx.

Parameter	Estimate	Std Error	T Ratio	Lag	Variable	Shift
MU	0.04839	0.0018126	26.70	0	ER_VIS_R	0
MA1,1	0.70418	0.13069	5.39	1	ER_VIS_R	0
MA1,2	-0.03909	0.03251	-1.20	4	ER_VIS_R	0
AR1,1	0.77147	0.12289	6.28	1	ER_VIS_R	0
NUM1	-0.0039448	0.0037962	-1.04	0	DEC1_1	0
NUM2	0.0045660	0.0039733	1.15	0	DEC1_2	0
NUM3	0.0014461	0.0043991	0.33	0	DEC1_3	0
NUM4	0.0002441	0.0043641	0.06	0	DEC1_4	0
NUM5	0.0068400	0.0045692	1.50	0	DEC1_5	0
NUM6	0.0030134	0.0045915	0.66	0	DEC1_6	0
NUM7	-0.0029297	0.0050116	-0.58	0	DEC1_7	0
NUM8	0.0032854	0.0049699	0.66	0	DEC1_8	0
NUM9	-0.0031067	0.0053707	-0.58	0	DEC1_9	0

Variance Estimate = 0.00169105

To Lag	LBQ	DF	Prob	Autocorrelations						
6	2.17	3	0.539	0.008	-0.007	-0.003	0.007	-0.038	0.018	
12	8.14	9	0.520	0.033	-0.018	0.025	0.032	-0.045	-0.018	
18	12.02	15	0.677	-0.027	-0.019	-0.012	0.001	0.045	0.014	
24	18.84	21	0.595	0.002	-0.010	-0.025	0.069	-0.004	-0.022	
30	27.31	27	0.447	-0.011	0.036	0.074	-0.000	0.024	0.005	
36	34.35	33	0.403	-0.037	0.031	0.008	0.007	0.030	0.054	
42	37.97	39	0.517	0.035	-0.016	0.016	-0.017	0.007	-0.033	
48	45.88	45	0.435	0.004	0.026	0.035	-0.027	-0.042	-0.049	

The model is a good one as the LBQ statistics are not significant at all lags. The parameter estimates and their significance are provided. Note that the parameter estimate signifies the change in proportion of patients returning to the ER within 7 days as the occupancy rate on the day before discharge changes from the lowest occupancy rate decile to that particular decile.

In order to create exhibit 66 the lowest decile group is determined. Using this information and the estimates identified by the ARIMA model for each decile, the rate of ER visits within each decile group is calculated.

Level of OCCU1_RT	-----ER_VIS_R-----	
	Mean	SD
dec1	0.04806370	0.04497570

Based on this the daily return to ER visit within 7 days of discharge rate in the lowest occupancy rate decile is 4.8%. The parameter estimates for each decile group are added to this value.