The Impact of Increased Number of Acute Care Beds to Reduce Emergency Room Wait Times

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Abstract

Reducing ED wait times is a top health care priority for the Ontario government and hospitals in Ontario are incentivised to meet provincial ED wait time targets.

In this study, we considered the costs and benefits associated with increasing the number of acute-care beds to reduce the time an admitted patient spends boarding in the ED. A shorter hospital LOS has often been cited as a potential benefit associated with shorter ED wait times. We derived a multivariable Cox regression model to examine this association.

We found no significant association between ED boarding times and the time to discharge. Using a Markov model, we estimated an increased annual operating cost of $2.1m to meet the prescribed wait time targets.

We concluded that increasing acute-care beds to reduce ED wait times would require significant funding from hospitals and would have no effect on total length of stay of hospitalized patients.

Acknowledgments

I would like to thank Dr. Alan Forster for not only the support throughout this project but also for the opportunities afforded me in my venture into a new discipline. My thanks also go to Dr. Carl van Walraven for the many model result discussions and for ensuring the right question was always being asked and answered. Dr. Kednapa Thavorn gave valuable input with regards the economic modelling.

Finally, I would like to dedicate this thesis to my Dad who was so excited about this opportunity and would have been so proud.

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Introduction

The effective functioning of the emergency department (ED) is considered by some to be a litmus test for the effectiveness of the health care system as a whole[1]. ED wait times reflect an equilibrium between the demand for and the supply of emergency care; long ED wait times are indicative of a system that is no longer in alignment. To aid in understanding the causes of these long wait times, we categorise and analyse the ED in terms of its input quantities (the patient seeking care and their characteristics), throughput quantities (the resources consumed by the patient from the time of registration to leaving the ED) and output constraints (inhibitors to a patient leaving the ED once emergency care is complete).

Increased inputs into the acute care system have been attributed to the lack of access to primary care physicians and the inappropriate use of the ED for chronic disease management. An aging population has not only resulted in increased ED visits but has also led, due to the complexity of this patient population,[2,3] to increased time spent in the ED and the number of hospital admissions. This trend has been forecasted to persist: a US study projected that ED capacity will need to increase by 10% to account for the increased length of time spent in the ED (as opposed to the increase in the number of ED visits) and that hospital admissions via the ED will increase 23% faster than the population growth over the next 35 years (estimates are based solely on the visits attributed to aging)[3]. This study used current utilisation statistics and superimposed the current age structure of the US population with forecasted demographics from the Census Bureau.

Output quantities have been constrained over recent years by the continuing decline in the number of hospital beds. Canada has seen a sharp decline in the number of hospital beds from 3.8 hospital beds per 1,000 population in 2000 to 2.75 beds per 1,000 population in 2011[4]. Although this decreasing trend in hospital beds has been observed across most OECD countries and is largely attributed to shorter hospital stays and increased day surgeries, Canada is ranked 10th lowest among the 34 OECD countries reporting this statistic and one of only two developed countries in the bottom 10 rankings. Canada is ranked second lowest among the OECD countries for acute-care bed supply with 1.7 beds per 1,000 population (Mexico ranks the lowest at 1.6 acute-care beds per 1,000 population). Over the same time periods, Canada consistently reported acute care bed utilisation in excess of 90%. Detailed OECD hospital bed statistics are included in Appendix A.

In a constrained system such as the acute-care system, increased inputs and altered throughput measures (due to a changing population or a lack of resources that constrain output) results in ED overcrowding and long patient wait times. Emergency department overcrowding is now considered by some to be a serious national and international public health issue[1,5]. The inability of admitted patients to access an inpatient bed is regarded as being the most significant factor in causing emergency department overcrowding in Canadian hospitals[6].

Definition and health impacts of ED overcrowding

The Canadian Association of Emergency Physicians (CAEP) defines ED overcrowding as the inability of the emergency department to meet the demand for quality emergency services on a timely basis[7]. ED overcrowding is evidenced by ambulance diversions, patients leaving without being seen, long ED wait times for patients to see providers or, and long wait times for admitted patients to be transferred to a ward bed. The latter is commonly referred to as "**ED boarding time**". ED overcrowding has been associated with many poor patient outcomes, ranging from patient dissatisfaction and increased hospital length of stay all the way to an increased risk of mortality[8–11]. With 60% of inpatients in Canadian hospitals being admitted via the ED[12], these findings – if they are valid – paint a dire picture for those that access the acute-care system. This has left governments and hospital administrators with the difficult task of identifying solutions to this major health care problem.

Ontario Wait Times strategy

Addressing emergency department wait times was named as one of the Ontario government's top two healthcare priorities in April 2008. The government's emergency department strategy aims to address the various facets of the problem: it seeks to expand alternatives to ED services (input), to increase capacity and to improve processes (throughput and output), as well as to promote the faster discharge of those patients no longer requiring acute care and to increase community and home-based care support (output).

In Ontario, two provincial targets for ED wait times have been set. Hospitals are required and "incentivised" through a Pay for Results program to meet these targets for 90% of patients. For high-acuity patients (those patients who present with conditions that are considered more complex and require longer diagnosis and treatment times and may require hospitalisation), the total time spent in the ED should not exceed **8 hours**; for low acuity patients (those patients with minor uncomplicated conditions), the total time spent in the ED should not exceed **4 hours**. There has been a significant downward trend in ED wait times since the launch of the Ontario Wait Times strategy which shows a strong commitment by all affected parties to resolve the issue. The time spent in the ED for all Ontario visits for 9 out of 10 patients was 9.4 hours in April 2008 and has reduced by 1.3 hours to 8.2 hours by December 2014. The biggest benefactors have been those patients that are admitted to hospital; the 90th percentile for the time this group spent in the ED has fallen from 36.4 hours to 30.1 hours. However, the wait times for this group remain stubbornly above the target of 8 hours. The factors preventing this group of patients receiving an inpatient bed in a timely fashion will need to be the focus of interventions if these wait time targets are to be met.

Increasing acute care beds – a viable intervention?

One proposed solution to this issue of the timely transfer of admitted ED patients into an acute care bed has been to increase the overall supply of beds available within a hospital and to reduce occupancy levels. Bagust et al. modelled the relationship between demand and available bed capacity and showed an elevated risk of bed shortages when occupancy rates exceed 85%[13,14]. The need to create spare-bed capacity is a result of an increasing proportion of hospitalisations originating in the emergency department; this inpatient source is unpredictable in terms of timing, severity and volume on a daily basis. Where there is no spare capacity in the hospital, a new admission must coincide with a discharge else the patient must wait until there is a discharge for an available bed. ED boarding (i.e. an admitted patient waiting for a hospital bed in the ED) results from this mismatch between supply and demand at specific points in time.

The effectiveness of increasing bed availability to decrease ED wait times was addressed in a Health Technology Assessment (HTA) that was conducted by the Alberta Heritage Foundation for Medical Research in February, 2006 to address the lack of knowledge about the effectiveness of the multiple strategies implemented to reduce ED overcrowding[15]. Four primary studies were classified by the authors of the HTA as inpatient bed interventions. Three of the interventions lead to a change in hospital occupancy rates (increased or decreased bed capacity)[16–18]. These interventions were natural experiments and involved a before and after study design. Although only one of these papers was rated of acceptable quality, the results were consistent across the studies, namely, that increasing (decreasing) hospital capacity resulted in shorter (longer) ED wait times. The Capital

Health Region in Edmonton, Alberta chose to open additional acute care beds to reduce ED overcrowding.

A concern in increasing bed supply is that it will address the short term demand but could lead to increased utilisation and negate the intended benefits. This increased utilisation could result from changes in admission or discharge patterns due to the availability of extra beds or simply an increase in elective admissions to the hospital. Studies show that there is no significant relationship between the level of ED overcrowding and the rate of admission[19] or between hospital occupancy rates and the decision to admit a patient via the ED[13]. In addition, admission and discharge criteria can be monitored and acted upon if changes in hospital lengths of stay are noticed. Policies will also need to be put in place to curtail the usage of these beds for elective admissions.

In this thesis, I considered the benefits of a shorter ED length of stay together with the costs associated with increasing the number of acute-care beds. I critically reviewed the literature that researched the association of ED wait times with hospital length of stay and focused on both the statistical models used and the ability of the studies to adjust for potential confounders. I then derived a statistical model that addressed the modelling and data concerns that were raised in the literature review. This model was used to estimate the effect size associated with an increased number of acute-care beds on the time to discharge from the hospital. This was a key input in the Markov model that was subsequently used to determine the investment required by the hospital to comply with the provincial targets.

1. The efficient use of hospital beds

Efficiency is one of the six domains that the Institute of Medicine (IOM) has identified as a measure of quality of care. It is described as avoiding waste, encapsulating both hospital and patient resources and time. Understanding the association between ED boarding time (an admitted patient in the wrong bed) and hospital LOS is an important component of determining where resources are being wasted and where they could be better utilised to create a more efficient acute-care system and improve patient quality of care.

In a literature review conducted in 2008, Bernstein et al.[9] identified three published articles (and an abstract) that measured hospital length of stay as an outcome of ED crowding[20–22]. Two of the three published articles found that extended time spent in the ED was associated with longer hospital LOS. All three studies categorised the exposure measure (ED LOS) and each used a different cut-point. Krochmal[22] dichotomised ED LOS at 24 hours and Bayley[20] at 3 hours. Liew[21] used 4 categories for ED LOS: <=4 hours, 4-8 hours, 8-12 hours, >12 hours. The authors acknowledged that they did not perform a risk of bias assessment for the studies and the review did not supply the information to determine this for ourselves.

We examined the three studies as a preliminary examination of the strength of the evidence. The choice of the 24 hour cut-point was driven by a data limitation and patients were allocated to the 24+ hour group if they were counted in the ED census at midnight. This is an obvious bias since people arriving to the ED at 11:59 pm would be classified as staying in the ED for 24 hours. Bayley et al. considered only those patients who arrived at the ED with chest pains and (based on clinical judgement) they used a 3 hour cut point as being a reasonable time for evaluation and admission of this type of patient. All three studies were observational studies and were conducted at a single site. Concern was raised by one of the authors about the definition of the outcome measure which included the exposure measure and the potential impact on systematic correlation. All three studies had the admission as the unit of analysis with no adjustment for repeated measures in the analysis.

The statistical techniques used to test the association varied between the three studies. Bayley, used the correlation coefficient between EDLOS (defined as the time between triage and physical discharge from the ED) and hospital LOS (defined as the number of days between triage and hospital discharge)as a measure of the association between the two exposure groups and reported no association (r=0.01). Krochmal used a t-test to determine if the mean hospital LOS (which included the time spent in the ED and was measured as the count of midnight census observations) was different between the two exposure groups. The skewed nature of hospital LOS data and the repeated encounters by individual patients violate the assumptions of normal and independently distributed error terms for this test. Liew et al. used multivariate logistic analysis to test the association between ED LOS and a derived dichotomous outcome variable that tested if the hospital LOS was greater than the state average LOS for the diagnosis. Both the state average LOS and the hospital LOS for the individual hospitals included the total time the patient spent in the ED.

There is a concern that these published results are biased. The skewed nature of hospital LOS data was not considered in these studies or was circumvented by arbitrarily dichotomising the outcome. Inappropriate statistical techniques were used to measure the statistical significance of the association and there was little or no adjustment for potential confounders in the analyses. The exposure measure (ED LOS) formed a component of the outcome measure (hospital LOS) for all three articles biasing in favour of an association between the two measures.

We supplemented this review with an updated search of the medical literature and by specifically addressing the statistical methods used to measure the association of ED waiting time with hospital

LOS. Our analysis considered: the methods used to address the skewed nature of hospital LOS; the treatment of continuous variables in the models; the adjustment for repeated measures; and the adjustment for known confounders in the models.

1.1. Literature review

1.1.1. Research question

What is the association between the time spent in the emergency department for admitted patients and the time to discharge from the hospital?

1.1.2. Search strategy

Although the question of interest pertained to ED overcrowding as evidenced by excess time spent in the ED, we purposefully kept the search strategy broad when defining ED crowding measures since this is not a concept that is easily captured in a Medical Subject Heading (MeSH) term or a set of standard keywords. We originally considered a search strategy without any reference to the outcome measure of interest but this resulted in too many unrelated studies. We subsequently chose a broad definition for patient quality of care measures to ensure that we captured all the relevant studies. We searched Medline and Embase to identify all possible studies that investigated patient outcomes associated with ED overcrowding for those patients admitted to the hospital via the ED. We included studies from 1 January 2000 to 8 October 2014, the date the search was conducted, and only included English language studies in the search. We did not restrict our search to any particular study types or patient group. Rather, we chose to exclude studies based on specific eligibility criteria at a later stage.

We used a combination of MeSH terms and keywords to define the concepts of “emergency department”, “admitted patient”, “crowding” and “quality of care”. We used the Boolean operator “OR” within concepts to ensure broad coverage of the use of alternate names for the concepts. We then used the Boolean operator “AND” to reduce the search to studies that contained references to all four concepts. The full search strategy for both Medline and Embase are included in Appendix B and Appendix C respectively.

Eligibility and exclusion criteria

The study population was defined as all adult patients (18 years of age and older) that presented to the ED and who were subsequently admitted as an inpatient. We excluded studies that were exclusively conducted in paediatric emergency departments; studies that represented a mixed population of paediatric and adult populations were included. We further excluded studies that only included a specific subgroup of the general patient population and studies that investigated an overcrowding measure that could not be related back to time spent in the ED (an example is studies that only used ambulance diversions as a measure of ED crowding).

Study selection process

The results of the search strategies were imported into Mendeley, a reference management software tool. Duplicate articles were identified and deleted using the Check for Duplicates function in the software. The remaining titles and abstracts were screened for overall relevance and reviewed against the eligibility criteria. Those articles identified as meeting the eligibility criteria were extracted in full. Articles that investigated the association between the time spent in the ED and hospital LOS were retained. Abstracts, editorials and conference publications were omitted.

Data extraction

The following data items were extracted from the articles:

Author & year of study, Country, Type of healthcare provider and setting, Type of study and cohort definition (including sample size), Exposure measure & definition, Outcome measure & definition, List of confounders, Effect size, Statistical tests and models used (including details on repeated measures, continuous variables and transformation of skewed data).

Assessing the quality of the studies

The studies were evaluated against the following domains: study question and population (was the study question clear and appropriate and the study population adequately described); comparability of subjects; exposure measure (was the exposure measure clearly defined, reliable and valid); outcome measurement (were outcome measures clearly defined, reliable and valid), statistical analysis (were appropriate tests/models used), results and discussion[10,23,24].

The studies included in our review considered the association between the time an admitted patient spends in the emergency department and hospital length of stay. The exposure measure, ED LOS, is one of the most commonly used measures for assessing ED crowding at the throughput level. Both ED LOS and ED boarding are reported as clinical quality measures of timely and effective care and align with the definition of ED crowding which is the inability to provide quality care in a timely fashion. Further, it was also found to correlate with clinical opinion in a 2011 systematic review on ED crowding measures[25]. The patient outcome, length of stay, is used to assess both the quality of patient care and for capacity planning in terms of resource utilisation (including beds, staff, etc.). The validity and usefulness of both the exposure and the outcome measure are well understood and we have focused our attention on the potential measurement biases that could be introduced by using different time points to denote the start and end of both the exposure and outcome measures and by using different cut-points to denote an overcrowded versus a non-crowded ED.

1.1.3. Search results

A total of 897 articles were identified through the Medline and Embase search. 188 of these articles were duplicates. The resultant 709 articles that remained were screened for overall relevance. 614 articles were excluded because they were irrelevant to the study. The remaining 95 full-text articles were assessed against the eligibility criteria. 5 articles met the eligibility criteria and an additional article was identified through scanning the references of the full-text articles[21,26–30]. Length of stay was often found to be the secondary outcome measured in the selected studies with in-hospital mortality being the primary outcome. Reasons for excluding the 90 articles are contained in the PRISMA flow diagram (Figure 1-1).

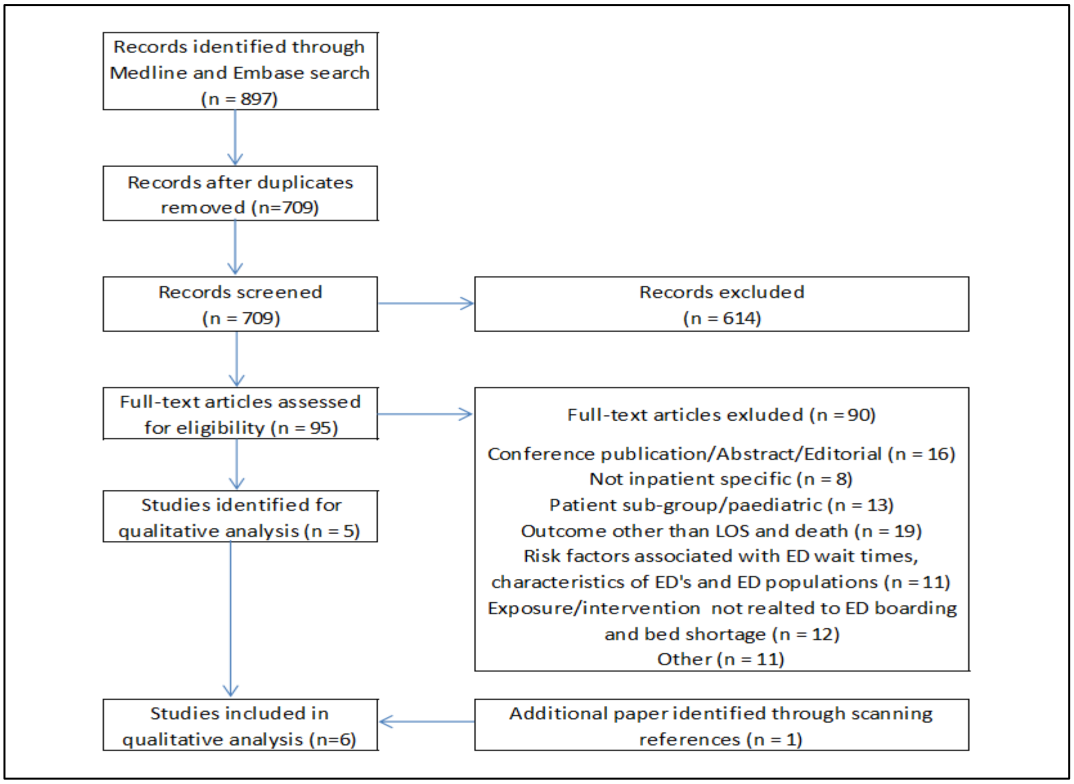
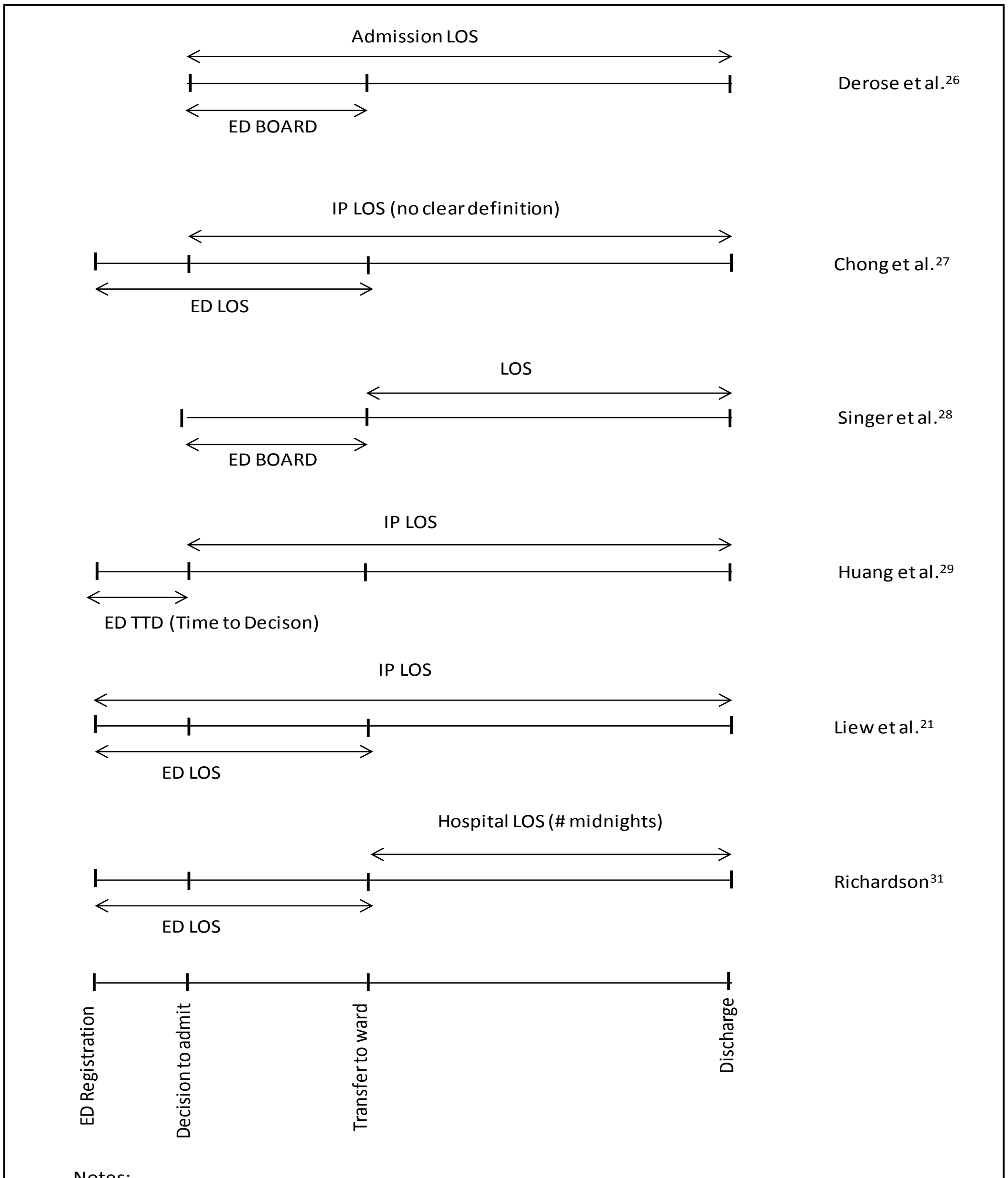


Figure 1-1 PRISMA Flow diagram

All six articles reported a statistically significant association between ED crowding and increased hospital LOS. Various derivatives of time spent in the ED by admitted patients were used to depict the individual patient's exposure to crowding (Figure 1-2).



Notes:
LOS = Length of stay
IP LOS = Inpatient length of stay
ED TTD = Time to decision to admit

Figure 1-2 Graphic representation of the ED length of stay exposure measures and hospital LOS

Three of the articles defined the exposure measure as the total time spent in the ED; this was measured from the time of registration in the ED to the time the patient left the ED. Two studies used ED boarding time as the exposure measure; this was defined as the time from the order to admit until the patient left the ED. Huang et al.[29] used a "delay to admission" exposure which measured the time spent in the ED until the decision to admit (this is not the time the patient left the ED). Figure 1-2 highlights that, in half of the studies, the exposure (time in ED) also contributed to the outcome (hospital LOS).

The articles also used various cut-points to differentiate an overcrowded vs. a non-overcrowded ED. The most common cut-points were chosen to measure current and proposed ED targets set by regulators (4 hours and 8 hours), or to coincide with commonly used terminology in this field of study (such as access block, defined as total ED LOS > 8 hours). Three of the studies[27,29,31] defined the exposure measure as a dichotomous variable, two of the studies[21,28] used 4 or more strata to describe the exposure and only one study[26] retained the continuous nature of ED LOS in the analysis. All the studies were retrospective observational studies.

The oldest of the studies is a stratified cohort study. Richardson[31] found that the mean hospital LOS for those patients that spent longer than 8 hours in the ED was 4.9 days vs 4.1 days for those that spent 8 hours or less in the ED ($p<0.0001$). Richardson also depicted the trend between time spent in the ED and mean hospital LOS as a 'U'-shape with a gradually increasing tail that was also replicated in the other studies. This result implies that the sickest patients receive a bed sooner and highlights the importance of correctly adjusting for patient severity in the analysis and the potential for measurement bias when using a dichotomous variable for the exposure measure.

Two of the studies[27,28] used linear regression to test the strength of the association between the ED exposure measure and hospital LOS without any adjustment for the skewed nature of the data.

Singer et al.[28] found that patients who boarded between 6-12 hours had a ward stay that was on average 0.5 days longer than those that boarded less than 2 hours. A dose-response relationship was observed across the exposure categories. Chong et al. reported that an ED LOS that exceeded 4 hours and an ED LOS that exceeded 8 hours were both significantly associated with a longer IP LOS (adjusting for age and comorbidities).

The Liew et al. article[21] that formed part of the 2008 literature review was also included in this review; the authors used multivariate logistic regression with a dichotomous hospital LOS excess variable as the outcome. The authors found that those with an ED LOS of 8-12 hours were 20% (OR = 1.20, 95% CI (1.10-1.30)) more likely to exceed the state average LOS for the diagnosis, this increased to 50% for those with an ED LOS of greater than 8 hours (OR = 1.49, 95% CI (1.36-1.63)) adjusted for age, sex and time of presentation to the ED.

The remaining two studies[26,29] used a log transformation of the outcome variable (hospital LOS) and then used multivariate linear regression, to model the association. Huang et al.[29] estimated that those admitted patients for whom the decision to admit exceeded 12 hours spent an additional 1.2 days in hospital. While Derose et al.[26] found that the first 14 hours of boarding added an additional 6 hours to the hospitalisation. The studies differed in their ability to adjust for patient complexity and illness severity.

Only two of the studies[26,28] adjusted for clustering at the patient level and there was no mention of a sensitivity analysis for those that did not adjust for these correlated subjects (all the analyses were conducted at the encounter level). Derose et al. tested for non-linearity in the relationships with continuous variables and Huang et al. added a squared term for age although the term was not statistically significant. The extracted data pertaining to the studies is summarised in Table 1-1 and Table 1-2.

Table 1-1 Summary of study characteristics

Author	Publication year	Country	Type of HC & setting	Study design	Study objective	Inclusion/Exclusion criteria	Cohort	Confounders
Derose et al.	2014	US	Multi-hospital 13 EDs forming part of an integrated health system in Southern California. 3.5m members None of the EDs classified as American College of Surgeons level 1 or 2 trauma centres	Retrospective cohort	Inpatient outcome Examine relationship between the individuals experience of ED crowding and admission LOS	Adult patients (> 17 yrs) Patients placed in observation status, hospice patients Transfers from other hospitals	1 Jan 2008 - 31 Dec 2010 136,740 patients with 208,706 visits Adult inpatients (> 17 yrs)	age strata, sex, race, comorbidities (Elixhauser), primary hospital discharge diagnosis, ambulance arrival, triage heart rate & BP, triage score
Chong et al.	2013	Australia	Single site Mixed adult & paediatric tertiary hospital Annual ED census 65,633 Serves population 700,00	Retrospective cohort	Clinical outcomes that are affected by ED wait time targets (4 and 8 hours) Is EDLOS associated with IPLOS		Admissions via the ED during 2007 65,633 ED presentations with 15,886 admissions to hospital	age, comorbidities
Singer et al.	2011		Suburban, academic ED Annual ED census 90,000	Retrospective cohort	Patient orientated outcome To explore the association between ED boarding and clinically important patient outcomes (hospital mortality & LOS)		All patients admitted to the hospital from the ED and discharged between October 2005 - September 2008 41,256 admissions from ED	age, sex, race, weekend, shift, comorbidities (Elixhauser) All continuous variables were converted to indicator variables (no testing for functional form)
Huang et al.	2010	Canada	Large multisite acute-care teaching hospital Two adult Ends	Retrospective cohort	Health and economic impact The impact of emergency department admission delays on inpatient LOS and total IP cost	Adult patients (>= 18 yrs)	ED presentations between 1 April 2006 - 30 March 2007 and subsequently admitted 13,460 admissions (10,847 unique patients)	age, age^{2}, gender, arrival by ambulance, admission to ICU or surgery (vs. general ward), case mix group, ED triage category, site
Liew et al.	2003	Australia	Three metropolitan hospitals in Melbourne 3 campuses 740 acute-care beds Annual ED census 100,000+	Retrospective cohort	Considered a patient outcome To examine the relationship between ED LOS and inpatient LOS (IPLOS)	Included those discharged directly from the ED Excluded those who died in the ED Excluded those transferred to short stay observation units, specialised programmes, transferred to other facilities	Inpatient admissions 1 July 2000 - 30 June 2001 18,619 admissions via ED (53%) 665 excluded due to missing data 17,954 admissions in final analysis	age, sex, campus, time of ED presentation
Richardson	2002	Australia	Single site Canberra 500 bed mixed adult and paediatric tertiary hospital Serves population of 500,000	Retrospective cohort	Relationship between access block and patient outcomes in hospital. Inpatient LOS is one of the simplest measures of hospital outcome and resource use	Those discharged or transferred directly from the ED Those that were inpatients at time of ED presentation	All patients admitted through the ED to an inpatient bed during 1999 48,430 presentations to the ED 11,906 eligible admissions	Age, triage category, hour of arrival in ED, month of arrival in ED, diagnosis, time of arrival on inpatient ward

Table 1-1 Summary of study characteristics (cont.)

Author	Publication year	Exposure measure	Outcome measure	Multivariate results
Derose et al.	2014	ED LOS Defined as registration time until the patient left the ED or arrived at the inpatient ward Boarding time The time period (hours) after the order to admit until the index patient left the ED or arrived at the inpatient ward ED LOS > 48 hours removed from analysis (0.1%)	Admission LOS Time of admission order to time of hospital discharge or patient death Includes boarding time All inpatients had an assignable outcome (discharge alive or in-hospital death)	The first 14 hours of ED boarding adds an additional 6 hours to the overall hospital LOS
Chong et al.	2013	ED LOS Dichotomised at 4 hours and 8 hours	IPLOS Defined as total hospital stay (EDLOS included in the IPLOS measure)	ED LOS IPLOS (mean ± SD) <= 4 hrs 2.3 days ± 4.5 days 4 - 8 hrs 3.6 days ± 7.2 days 8 - 12 hrs 5.2 days ± 7.1 days 12 - 24 hrs 6.3 days ± 7.7 days > 24 hrs 7.2 days ± 11.3 days
Singer et al.	2011	ED boarding ED boarding: defined as ED LOS >=2 hrs after decision to admit. The time interval between calling in the admission and physically leaving the ED. Categorised 2-5, 6-11, 12-24, 24+	Hospital LOS Hospital LOS: defined as the time interval between admission to the inpatient floor and hospital discharge (Does not include ED boarding)	ED Boarding Δ Hospital LOS days < 2 hrs reference 2 - 6 hrs 0.23 (0.00 - 0.46) 6 - 12 hrs 0.49 (0.08 - 0.90) 12 - 24 hrs 0.74 (0.25 - 1.23) 24 + hrs 1.93 (0.79 - 3.06)
Huang et al.	2010	ED admission delay Defined as ED time to decision to admit > 12 hours Binary variable	IP LOS Defined as the time from decision to admit to discharge from hospital (incl ED boarding time)	Admission delay associated with 12.4% (6.6 - 18.5) change in hospital LOS
Liew et al.	2003	ED LOS Defined as the time from ED presentation to transfer to a ward Categorised at 4,8 and 12 hours	IPLOS -SALOS > 0 Where IPLOS is defined as the time from ED presentation to discharge from hospital and SALOS is the state average IPLOS for the diagnosis group Dichotomised (positive vs. <=0)	ED LOS OR <= 4 hrs 0.68 (0.63 - 0.74) 4 - 8 hrs 1.00 8 -12 hrs 1.20 (1.10 - 1.30) > 12 hrs 1.49 (1.36 - 1.63)
Richardson	2002	Access block Defined as total ED time of more than 8 hours. ED time is the difference to the nearest minute between the recorded time of arrival in the ED and the recorded time of transfer to the ward	IP LOS Defined as the number of midnights between transfer from the ED and discharge from hospital. Floor of 1 day and a cap of 10 days Does not include EDLOS	No adjusted analysis Mean LOS for the access block group was 4.9 (95% CI 4.7 - 5.1) days compared with 4.1 (95% CI 4.0 - 4.2) days in the no-block group

Table 1-2 Summary of statistical modelling techniques

Author	Publication year	Final sample size	Statistical model	Competing risks considered	Adjustment for clustering at patient level	Adjustment for clustering at hospital/site level	Adjustment for skewed data	Modelling continuous variables
Derose et al.	2014	208,706 admissions	Wilcoxon rank-sum test used for univariate analysis GEE with linear link function Admission LOS log transformed for skewed data	No	Yes	Yes	Yes (log transformation of LOS)	Included square and cubic terms where non-linearity was observed 6 age strata
Chong et al.	2013	15,886 admissions	Linear regression	No	No	N/A	No	4 age strata ED LOS dichotomised at 4 hours and 8 hours
Singer et al.	2011	41,256 admissions	Linear regression GEE methods used to adjust for multiple visits	No	Yes	N/A	Not specified	All continuous variables categorised ED boarding categories 2-5, 6-11, 12-24, 24+
Huang et al.	2010	13,460 admissions	Kaplan-Meier survival curves for univariate analysis Linear regression with log transformation of LOS	No	No	Yes	Yes (log transformation of LOS)	Time to decision to admit dichotomised at 12 hours Quadratic term added for age (not supported)
Liew et al.	2003	17,954 admissions	ANOVA for difference in mean IPLOS and excess LOS for the 4 EDLOS groups Logistic regression	No	No	No	N/A (LOS dichotomised)	Age dichotomised at 65 years EDLOS categories <=4, 4-8, 8-12, >12
Richardson	2002	11,906 admissions	T-test for difference in means between the access block and no block groups Sub-group analyses	No	N/A	No	Yes (capped LOS at 10 days)	N/A

Bias assessment and quality rating

The studies in general posed a clear question and gave enough information to determine comparability of the exposure groups, except for the two earlier studies.

The exposure measure used in the majority of the studies was ED LOS, which incorporated a measure of emergency care and a portion of inpatient care for those patients that boarded in the ED until a ward bed became available. The EDLOS exposure measure and the outcome measure overlapped in 2 of the studies[21,27]. In other words, an increase of the exposure variable (ED LOS) automatically resulted in an increased outcome (hospital LOS) thus making the interpretation of the regression coefficients difficult and potentially biasing any positive association.

Two studies[26,28] considered the association between ED boarding and inpatient LOS. ED boarding time excluded the time spent in the ED prior to the decision to admit and the exposure measure therefore ignored the care received by the patient during this time and therefore any improvement in health status. This too can lead to a biased result if the model does not adjust for changes in patient acuity during this time. The outcome measure used by Derose et al. included the time spent boarding in the ED while Singer et al. excluded this ED boarding time to circumvent the potential bias in overlapping exposure and outcome measures. However, this is an incomplete measure of inpatient care and could also bias results. For example, two patients with a similar total hospital length of stay could have very different ward times (reflecting only the time spent on the ward and excluding any boarding time) and ED boarding times based purely on the availability of beds. This would lead to a long ED board time being associated with a short ward time and a short ED board time with a long ward time.

Dichotomising ED LOS to distinguish an overcrowded versus a non-overcrowded ED is also complicated by this overlap between emergency care and inpatient care. Does this cut-point determine the time at which quality emergency care can no longer be delivered in a timely fashion or when the care received in the emergency department becomes less effective compared to care received elsewhere in the hospital (ED boarder)? We have also highlighted the potential for biased results when using a single cut-point due to the possible ‘U’- shaped trend between ED LOS and inpatient LOS.

The skewed nature of hospital length of stay data was dealt with differently in the various studies. Univariate testing for associations was most commonly conducted by testing for a statistical difference in the mean hospital LOS among the various ED exposure groups. Although this is not an appropriate statistical test for skewed data since the mean is sensitive to outliers, the test is considered to be conservative when the assumption of normality is violated for large samples. Derose et al. used the Wilcoxon rank-sum test, a nonparametric technique, to test for a difference in location for the different ED LOS categories. Huang et al. used Kaplan-Meier survival curves to graphically represent the difference in times to discharge between the exposure groups but did not test for statistical significance (these curves are also are also likely biased as the authors did not account for competing events).

The adjustment for the skewed nature of the data in the multivariate analysis – when considered - was achieved by either converting the outcome variable into a dichotomous variable or by using a log transformation of the outcome variable. Log transforming the outcome measure, requires a back transformation of the parameter estimates to reflect the association between the covariates and the outcome on the original (non-transformed) scale. However, these back transformed estimates no longer reflect the mean hospital length of stay but rather the geometric mean which is asymptotically equivalent to the median. Caution is required if extrapolating these results to a measure of total resource utilisation as denoted by hospital LOS (the authors do not mention any smearing techniques to adjust for this).

The logistic regression model was appropriately applied to the dichotomous outcome variable but the usefulness of the results is questionable since the association does not indicate the extent of the excess. Of the remaining three studies, two of the studies did not adjust for the skewed nature of the data and the Richardson study did not perform multivariate analysis.

The purpose of modelling hospital LOS plays an important role in the way the analysis is conducted. An admitted patient’s current association with the hospital can terminate in a number of ways. The patient can be discharged alive (discharged home or transferred to another facility), the patient can leave against medical advice or the patient can die in the hospital. The discharge disposition is irrelevant if the purpose of modelling LOS is for capacity planning since the mean hospital LOS simply needs to reflect average resource utilisation for the patient population. However, if hospital LOS is to be used as a patient quality indicator then the impact of the discharge disposition on length of stay should be considered. Discharge due to death is often associated with a shorter length of stay[32] which can bias the results if deaths are treated in a similar fashion in the model. The effect of the covariates on the different discharge dispositions might also differ. A hospital LOS model that allows for the modelling of the effects of covariates in the presence of competing events is advocated[33,34]. A competing event is defined as an event that precludes or dramatically alters the chance of the event of interest occurring[35]. This adjustment can be achieved by restricting the analysis to only those admitted patients that are discharged alive or by assigning the longest LOS to those patients that die. None of the studies adjusted for competing risks although the stated objective for most of the studies was to assess patient quality of care.

Severity of illness was poorly captured in the papers. Singer et al. purposefully excluded any adjustment for risk of mortality and severity of illness, while Liew et al. used age as the only measure of patient complexity. Four of the papers used a comorbidity score or the individual comorbidities to capture patient complexity. Huang et al. used 350 dummy variables in their multivariable regression model to capture homogenous patient complexity groupings. Most of the studies highlighted the possibility of residual confounding due to this inability to account for the severity and complexity of the patient (mainly due to the use of administrative data for the study purpose).

Two of the studies discussed potential cost savings if ED wait times could be reduced due to the associated decrease in hospital LOS, however this saving was considered gross of any intervention costs which could be very misleading. Single site concerns were raised as well as the representativeness of the studied hospital and emergency department.

We did not rate any of the studies to be of an acceptable quality. Table 1-3 summarises our assessment of the quality of the studies. We scored Model Integrity as unacceptable if any of the following modelling errors were present: overlap between the outcome measure and exposure measure; ED wait time modelled as a dichotomous variable; no adjustment for patient severity (other than initial ED triage score); and no adjustment for the skewed nature of hospital LOS.

Table 1-3 Quality of studies

Author	**Publication year**	**Study question & study population**	**Comparability of subjects**	**Exposure measure**	**Outcome measure: Definition**	**Outcome measure: Competing Risks**	**Outcome measure: No overlap with exposure**	**Statistical analysis: Adjustement for patient severity**	**Statistical analysis: Model integrity**	**Results & discussion**
Derose et al.	2014	✓	✓	✓	✓	×	×	✓	×	×
Chong et al.	2013	×	×	×	×	×	×	×	×	×
Singer et al.	2011	✓	✓	✓	✓	×	✓	×	×	✓
Huang et al.	2010	✓	✓	✓	✓	×	✓	×	×	✓
Liew et al.	2003	✓	×	✓	✓	×	×	×	×	×
Richardson	2002	✓	×	✓	✓	×	✓	×	×	✓

Rating criteria:

Study question & population: Was the study question clear and appropriate? Was the study population adequately described?

Comparability of subjects: Were baseline characteristics adequately described to allow for adjustment of confounders in analysis and to determine generalizability

Exposure measure: Was the exposure measure clearly defined - was there a clear start and end point to the exposure

Outcome measure: Was the outcome measure clearly defined? Were competing risks identified? Was there a clear delineation between the exposure and outcome measure?

Statistical model: Was patient severity & complexity adequately captured? Model integrity: Were appropriate statistical tests/models used? Was the skewed nature of the data identified and controlled for? Did the model account for overlapping exposure and outcome measures? Was clustering at the patient and hospital level adjusted for? Did the authors test for linearity of continuous variables or categorise?

Results & discussion: Were point estimates and confidence intervals for the association supplied? Were potential biases or unmeasured confounding highlighted? Were the results consistent with other studies? Were the results generalizable to other studies?

Table based on *Quality of Studies* table contained in Systematic Review[10]

The complexities of assessing an exposure in a retrospective observational study and in a very heterogeneous patient population that is further compounded by a time-related exposure and outcome measure, an outcome measure that is a composite outcome (discharge alive, death, left against advice), and a highly skewed outcome measure is evidenced by the multiple techniques that have been used to test whether ED length of stay is associated with inpatient length of stay.

None of the statistical models used, allowed for the effective modelling of competing events or addressed our concerns regards potential measurement biases in both the exposure and outcome measures. We consequently chose to investigate the statistical models commonly used to model hospital LOS and to assess the ability of these models to reduce the potential biases that have been explored in this section.

1.2. An assortment of statistical models

We return to our view of hospitalisation as a trajectory from a state of poor health that requires hospitalization to an improved health state that no longer requires acute hospital care. The time taken to progress from a worse health state to an improved health state is reflected as the hospital length of stay. This definition implies that length of stay is a non-negative metric: it can either be measured as a count of discrete time intervals between the admission and discharge date or as a continuous variable (measuring the time between the time of admission and discharge). Furthermore, length of stay data is usually highly skewed to the right. The distribution of the error terms also tend to be positively skewed and heteroscedastic. A LOS model must consider both the non-normality of the data and the requirement of a positive mean. Failing to do so will lead to questionable inferences from the model.

Additive and linear models are not considered appropriate to measure length of stay since these models can produce negative predicted values. The assumptions of the linear model pertaining to normally distributed error terms and constant variance of the error terms are also usually violated when modelling length of stay data. The advantage of the linear model is that it models the mean LOS which is a prerequisite if the purpose for modelling is to determine the effect of the covariates on total LOS.

A log transformation of the dependent variable can be used to adjust for the skewed nature of the data and then a linear regression model can be used to model the association between the log of the dependent variable and the independent variables. To determine the association between the covariates and the dependent variable on the original scale, one must back transform the model $(\log(y) = \beta x \rightarrow Y = e^{\beta x})$. Doing so produces a multiplicative model and addresses the concerns of negative predictive values as 1 unit change in β is associated with $\left(e^{\beta} - 1\right) * 100\%$ in Y (a percentage change in Y). However, this model no longer models the mean length of stay but rather the median length of stay ($e^{\frac{1}{n}\sum \ln(LOS_i)} = (\prod LOS_i)^{\frac{1}{n}} = geometric\ mean\ of\ LOS \sim median\ LOS$) and one cannot extrapolate the median to the total population as one would the mean of the population.

Generalised linear models that use a log link function are a class of multiplicative models that allow us to model the mean hospital LOS and can account for the skewed nature of the data. These models can be applied to both discrete and continuous variables by using different distribution functions. Discrete variables are modelled using the Poisson or negative binomial distribution. Continuous variables with a skewed distribution can be modelled using the gamma distribution.

Survival analysis is commonly used to measure time to event data. It does not assume normality of the data (or any underlying distribution if choosing to model as semi-parametric) and allows for censoring. The ability to censor patients allows us to model competing risks which we have identified as key to modelling hospital LOS as a quality of care indicator. Survival analysis also allows us to adjust for factors that influence the time to discharge and where the values that these factors acquire can vary over time as well as where the effect of a factor on the time to discharge can vary over time.

Austin et al.[36] compared a group of statistical models commonly used to model length of stay data on a cohort of patients that underwent CABG surgery. The models included: a linear model, a linear model with log transformation of hospital LOS, a Cox model and generalised linear models with a log link function and one of the following conditional distributions: Poisson, negative binomial, normal or gamma. They did not censor on any type of discharge disposition and all variables were patient characteristics known at baseline and fixed for the duration of the hospitalisation. They compared the consistency among the models to classify the same set of covariates as being significantly associated with an increased hospital LOS and the predictive capabilities of the models.

The Cox model and the generalised linear model using the Poisson, negative binomial or gamma distributions demonstrated reasonably good consistency in classifying the variables. They found that the linear regression model with no adjustment for the skewed nature of hospital LOS and the generalised linear model using the normal distribution were the most divergent of all the models. It is evident that model choice can therefore impact the measured association between a variable and hospital LOS.

The Cox model did not perform well in predicting LOS in Austin's study. It is unclear from the article how the risk-adjusted survivor function was estimated from the proportional hazards model. The most commonly used method that is readily available in software packages is to estimate these functions using the mean of the covariates but this method does not adequately describe the survival function for a heterogeneous patient population.

The class of generalised linear models seem to be a good model fit for hospital length of stay when the purpose of the study is to model resource utilisation for capacity planning. These models cater to: the skewed nature of the data; the requirement that the mean is positive; and were shown to predict patient length of stay well. However, these models cannot effectively model censored observations. Further, these models can only measure ED length of stay at a single point in time or as an average over a time interval and the effect of ED length of stay is assumed to be constant over time[37].

As the results from these models are often used to inform policy and strategy, it is vital that we choose a model that will allow definitions of the variables that will minimise bias and that best emulates the study question.

1.3. Proposed model

The purpose of this study was to assess the impact of increasing acute-care beds to reduce emergency room wait times for admitted patients. A commonly reported patient outcome that is associated with long ED wait times is increased hospital length of stay. We assessed the statistical models that have been used in the published studies to measure this association (see Section 1.1) and have highlighted concerns about the statistical models used, the potential measurement biases in the exposure and outcome measures, and (most importantly) the lack of differentiation when considering the discharge disposition. We also summarised the characteristics of the statistical models commonly used to model length of stay data to determine if any of these models could address our concerns.

The time-related nature of both ED LOS and hospital LOS lends itself to considering the use of survival analysis to model the association between ED boarding time and hospital LOS. Considering this together with the ability to model censored observations, address competing risks, and account for time-dependent covariates, we proposed that a survival model be used to model the time until discharge from the hospital.

We described the event of interest as discharge from the hospital. We modelled both death and left against advice as competing risks. The time origin for this model (i.e. t=0) was the **initial registration in the ED** which is considered to be the time at which the patient is first exposed to the risk of discharge from the hospital. The exposure of interest was defined as the time spent boarding in the ED (i.e. **time in ED from decision to admit to ward transfer**). We modelled this exposure as a time-varying covariate since this value is not known at baseline. We also included potential confounders in the model, most importantly an accurate measure of severity of illness, as well as variables that are known to affect hospital length of stay.

Length of stay as a stand-alone metric has been criticised as a performance indicator due to the strong influence that discharge disposition has upon the measure. We have already addressed the impact of death on hospital length of stay by modelling this as a competing risk. Patients no longer requiring acute-care may be prevented from leaving the hospital due to the lack of long term care beds in the community. Instead of creating another competing risk we included an alternate level of care indicator as a time-dependent covariate in the model.

The articles all referred to the inability to fully adjust for patient severity of illness and complexity when using administrative data. We supplemented the administrative data with laboratory test results. We further attempted to capture the idiosyncratic nature of individual patients by identifying the type of bed the patient occupied at various stages during their hospitalisation (which is indicative of the level of nursing care received). Both the laboratory test results and the type of bed occupied by the patient were captured as time-varying covariates and thus enabled us to better model the trajectory to improved health and discharge.

2. Study objectives

This purpose of this study was two-fold; the first objective was to build a statistical model to determine if ED boarding time was associated with hospital length of stay. The second objective was to determine the investment that would be required by the hospital to increase the number of acute-care beds such that 9 out of 10 admitted patients would be transferred to a ward bed within 6 hours of the decision to admit. A cost benefit analysis was conducted to determine the costs and benefits associated with the intervention.

3. Methods

This section describes the methods that were followed to measure both the association between the time spent boarding in the ED and hospital length of stay and the economic impact of increasing the number of acute-care beds on ED wait times.

3.1. Study design and setting

This study was a retrospective cohort study of all adult patients of The Ottawa Hospital (TOH) who were admitted to a medicine service via the emergency department during the period 1 January 2011 to 31 December 2013. The medicine service includes those patients admitted to general internal medicine and medicine's sub-specialities (including cardiology, respirology, neurology, hematology and nephrology) as well as to a family medicine service provider. This grouping explicitly excludes paediatrics, obstetrics, oncology as well as surgical patients and mental health patients. Those patients transferred to a nursing unit within the general medicine service that require a higher level of care are also excluded. The patients are followed until their association with the hospital is terminated. This termination can take the form of being discharged home, a transfer to another facility, in-hospital mortality or leaving against medical advice. Those patients not discharged as at 31 October 2014 were considered censored.

The Ottawa Hospital is a tertiary-care, academic hospital that comprises two acute-care campuses with a total of 910 beds. The Ottawa Hospital is the largest acute-care hospital in Canada and is the largest adult referral centre servicing a population of 1.2 million people in Ottawa and Eastern Ontario. The hospital had an average annual ED census of 156,253 over the study period and patient admissions exceeded 48,000 per year for the period[38]. The emergency rooms at both campuses comprise 20 monitored and 20 non-monitored beds with an additional 9 emergent psychiatric beds. The hospital also has an urgent care area where patients who are less acute are seen.

3.2. Study population

All patients aged 18 years and older who visited an ED at The Ottawa Hospital and who were subsequently admitted to a medicine service during the study period were included in the study. Patients that were initially admitted to a medicine service and then subsequently transferred to another hospital service while boarding in the ED were excluded from the study. Patients who were transferred to an ICU bed while boarding in the emergency room remained in the analysis. Patients that were transferred from or to another acute-care hospital were excluded from this study because the current hospital stay would not reflect a complete acute-care visit and the emergency care that the patient received might also have started elsewhere.

3.3. Data sources

The demographic and clinical patient data used for this analysis was extracted from The Ottawa Hospital Data Warehouse (TOHDW). The Data Warehouse is an electronic store of administrative and automated clinical data that is collected at the hospital. TOHDW is fed by the various transactional information systems of the hospital including the patient registration system, a clinical data repository (containing laboratory, pharmacy, radiology and clinical notes), the case costing system and patient discharge abstracts, which contains coded information pertaining to the patient diagnosis and procedures performed during the hospitalisation. This information is coded from the patient's medical chart after discharge and is based on the International Statistical Classification of Diseases and Related Problems, 10th revision – Canada (ICD-10-CA). TOHDW enables the assimilation of data across disparate source systems and allows one to obtain a more complete picture of a patient visit.

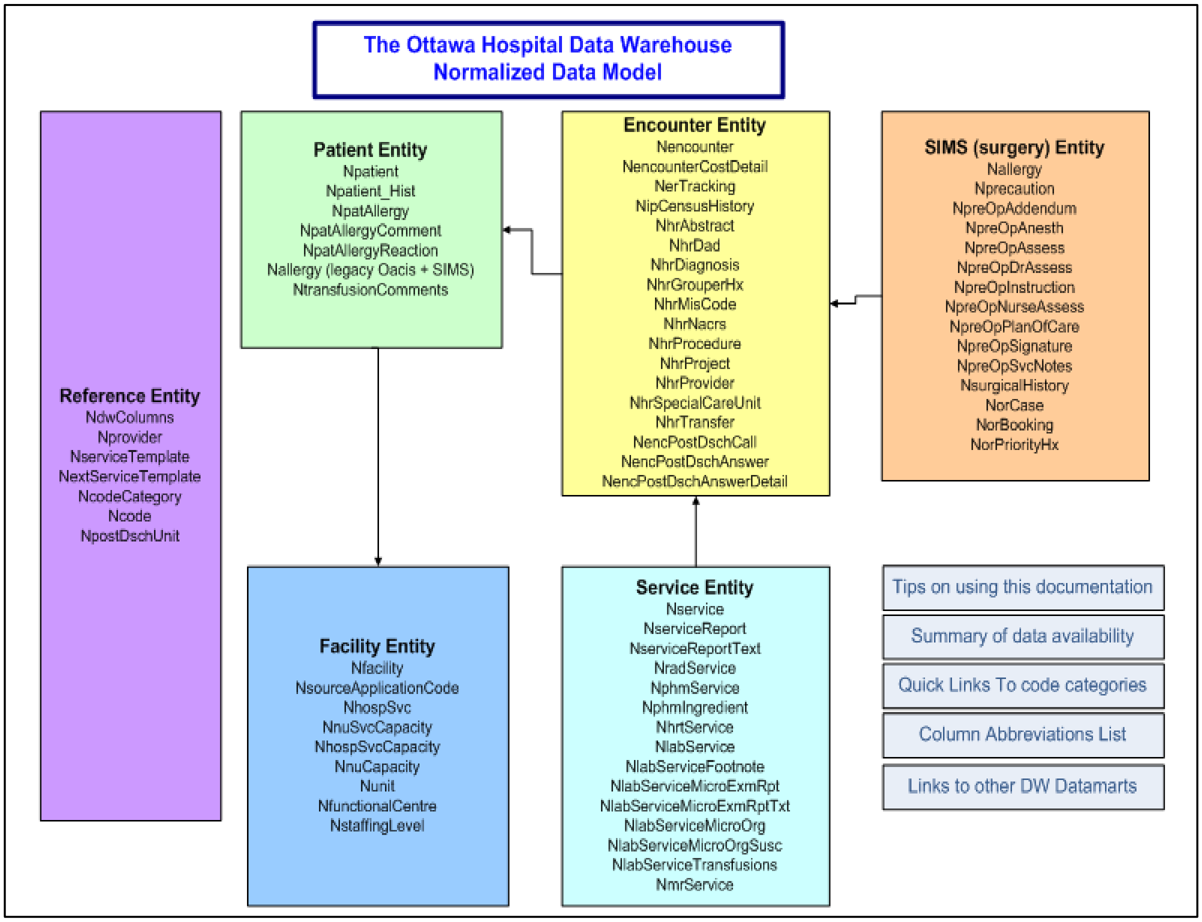


Figure 3-1 The Ottawa Hospital Data Warehouse schematic

TOHDW is comprised of six main entities (Figure 3-1), five of these relate to the patient, their diagnoses and the type of care received and services consumed, as well as detailing the physical location and composition of the team providing the service. Within each of these entities is a series of connected tables. Each table in TOHDW contains a unique identifier that allows linkage among the tables and ultimately enables the linkage of all the records pertaining to an individual patient. These tables are updated via a batch process. Most of the data are updated on a nightly basis except for the health records abstracts data which is usually lagged by about 6 weeks. These data are only captured after the patient is discharged from the hospital and also requires various data quality checks before it is submitted to the Canadian Institute for Health Information (CIHI).

3.4. Creating the study cohort

All admissions to a medicine service at the General and Civic campuses of The Ottawa Hospital that originated in the ED and that fell within the study period were identified in the inpatient *Census History* table. The admission date and time reflected in this table corresponds to the decision to admit time and marks the start of inpatient care for the admitted patient. The patient however might still reside in the ED if no ward bed is available. This status is denoted by the nursing unit in the inpatient *Census History* table and will retain the value of 'ERCH' or 'ERGH' until the patient is transferred to a ward bed or is discharged directly from the emergency department. This table captures all transfers between hospital services and nursing units and reflects both the level of care and the provider of care during the patient's hospitalisation. A patient that requires isolation is also flagged in this table as well as when isolation is discontinued. This table therefore tracks the pathway that an individual patient follows during their hospitalisation and tracks the health state of the patient as captured by the hospital service, level of care and any other bed specifics. Some studies have considered using this pathway as a means of capturing the idiosyncratic nature of a patient when patient specific characteristics are unavailable or to supplement this data[39–41]. We identified admissions that entailed a transfer to a non-medicine service while the patient was still boarding in the ED and deleted these admissions from the analytic data set as these patients would not occupy a medicine bed on leaving the ED.

Patient and encounter characteristics were then extracted from the *Encounter* table so that specific exclusion criteria could be applied to the admission cohort. Age at admission was calculated as the number of years between the patient's birth date and the admission date. Patients younger than 18 years of age were excluded from the analysis. This table also contains the type of institution the patient was transferred from or to after discharge from The Ottawa Hospital. We used this information to exclude all patients that were transferred from or to another acute-care setting. After establishing the eligibility of individual admissions that occurred in the study period, we linked the inpatient encounter to the emergency room visit that resulted in the admission.

The emergency room visit is recorded as a separate encounter to the inpatient encounter in the *Encounter* table. An admitted patient that met the inclusion criteria was mapped to the appropriate emergency room visit by matching on a unique patient identifier and by using a date matching algorithm to determine which ED visit was associated with the specific hospital encounter. The ED visit was flagged as the ED visit that resulted in the admission if: the ED registration time occurred before the admission time and the time denoting the end of emergency care fell within the inpatient encounter or was within 5 hours of the start of the inpatient encounter; or the inpatient encounter was contained within the emergency care visit. An inpatient encounter for which an ED visit could not be matched using the above algorithm was excluded from the study. Date and time stamps related to the ED visit were extracted from the *ER Tracking* table.

A random encounter was then selected for each patient that formed a part of this study cohort; this allowed analysis at the patient level without violating the assumption of independent observations.

3.5. Study outcome

The study outcome was hospital length of stay. This was defined as both the occurrence of a specific termination event and the time until the event. We defined the event of interest as discharge from the hospital. This included both those patients that were discharged home as well as those patients that were transferred to a non-acute facility (we purposefully excluded those who were transferred to another acute-care facility). In-hospital mortality and leaving against medical advice were considered competing events as both these events precluded the patient from experiencing a planned medical discharge. The time to the event was calculated from the time of registration in the ED until the time of discharge from the hospital and was measured to the closest minute. This outcome measure is also referred to as hospital LOS in the analysis. The discharge disposition was extracted from the *Encounter* table. A discharge disposition of *NOT DISCHARGED* was assigned to those patients that were still hospitalised at the end of the study. These patients were also considered censored in the analysis.

3.6. Exposure measure

Since the results of this model were used to inform the economic evaluation for increasing the number of acute-care beds, we chose the time an admitted patient spent boarding in the ED as the exposure measure of interest.

ED boarding time was defined as a time-varying covariate since its value is not known at baseline. The time-varying covariate was defined as the cumulative time spent boarding in the ED on a 6-hourly basis from the decision to admit until the patient was transferred to a ward bed. Since the actual time spent boarding in the ED would not be exactly divisible by 6 hours, the last period that a patient spent boarding was lengthened so as to correspond to the actual time spent boarding in the ED.

In the first chapter we raised concerns about using only the time spent boarding in the ED as the exposure measure. To address this concern, we also modelled the time spent receiving emergency care in the emergency room. We calculated this measure as the difference in hours between the time of registration in the ED (t=0) and the decision to admit time, which denotes the time at which the patient transitions from emergency care to inpatient care. This variable was also modelled as a time-varying covariate using 6-hourly time intervals and depicted the cumulative time spent receiving emergency room care on a 6-hourly basis until the decision to admit was made. ED LOS was therefore modelled as two distinct time-varying variables: the time spent in the ED receiving emergency care (ED Time to Decision (ED TTD)) and the time spent in the ED receiving inpatient care (ED boarding).

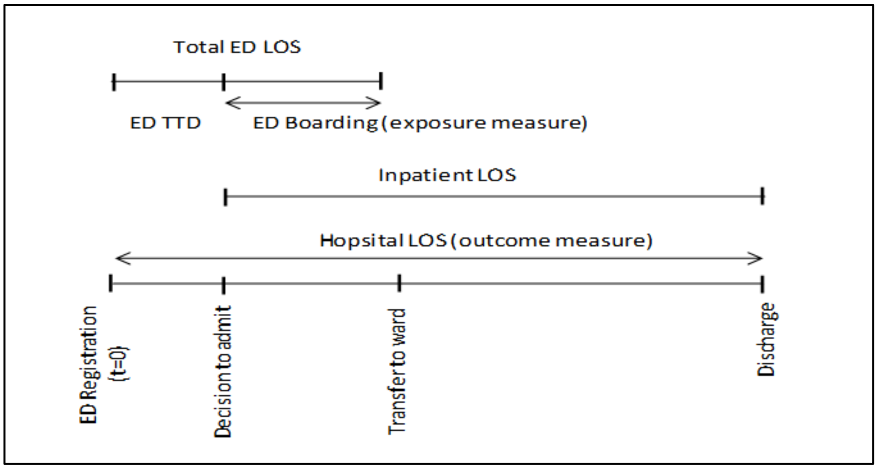


Figure 3-2 Graphic depiction of the exposure and outcome measures

3.7. Other covariates

3.7.1. Adjusting for case-mix and complexity

Although we restricted our analysis to only those patients that were admitted to a medicine service, the patient mix that was admitted through the ED to this service still represented a very heterogeneous population. To adjust for patient case-mix and other patient demographics, we followed a similar approach to that utilised by the Canadian Institute for Healthcare Information (CIHI)[42]. CIHI uses a combination of admission diagnosis, type of patient (medical vs surgical), and a complexity measure which encompasses age and pre-existing comorbidities to derive homogeneous patient groupings with the purpose of describing expected LOS and resource utilisation for hospital patients.

We categorised the admission diagnosis (defined as the diagnosis that was responsible for the majority of resource utilisation during the hospitalisation and that was present at the time of admission and not a result of the hospitalisation), using the grouping methodology employed by Escobar et al. in the derivation of the Kaiser Permanente Inpatient Risk Adjustment Model (KP-IRAM)[43]. This entailed the grouping of all possible ICD-9 admission codes into 44 broad diagnostic categories based on relative similarity from a disease standpoint. Where categorisation or scoring algorithms used ICD-9 codes, we mapped the ICD-10-CA codes to ICD-9 codes.

Pre-existing comorbidities were extracted from ICD codes for chronic diagnoses in the discharge abstracts table and the Elixhauser Score was calculated to reflect the chronic disease burden for each patient. This index summarises the 30 Elixhauser comorbidity groups into a single number that was found to be significantly associated with in-hospital mortality and health resource utilisation[44]. The score can assume a value between -19 to +89. Preadmission and post-admission comorbidities were identified from previous hospitalisations at TOH using a 5-year period look back. Only preadmission comorbidities were considered for the current hospitalisation.

We used multiple other measures to adjust for patient severity. The first indicator of patient frailty and severity was the arrival of the patient at the ED by ambulance. Patients arriving at a Canadian ED are triaged and assigned a score defined by the 5-level Canadian Triage and Acuity Scale (CTAS). The five groupings are: CTAS I (Resuscitation), CTAS II (Emergent), CTAS III (Urgent), CTAS IV (Semi-urgent) and CTAS V(Less urgent) and reflect the decreasing need for immediate physician attention and constant nursing care. The assigned score is a first assessment of patient severity and precedes any laboratory tests and results. Most of the studies in the literature review considered this initial acuity score as a predictor of hospital LOS although some noted that this was a point in time measure and not necessarily reflective of severity[21]. We included this as a potential predictor in our model as initial bed assignments could be based on this assigned score. We created a three level emergency room triage category by grouping CTAS levels I and II to represent a higher acuity level and CTAS level IV and V to represent a lower level of acuity.

A Laboratory-based Acute Physiology Score[43] (LAPS) was also used to measure and adjust for patient severity. This score is based on the results of 14 laboratory tests (serum albumin; serum chloride; arterial pH, PaCO2, and PaO2; bicarbonate; total serum bilirubin; blood urea nitrogen; serum creatinine; serum glucose; serum sodium; serum troponin I; hematocrit; and total white blood cell count). The initial score is based on the test results obtained 24 hours preceding hospitalisation. A higher LAPS is associated with a higher physiologic derangement. The LAPS can assume a value between 0 and 256. We defined the LAPS score as a time-varying variable and ascertained the score at 6 hourly intervals from the time of registration in the ED. The results from the laboratory tests were held constant until a new result was reported for the patient. The time-varying nature of this acuity score allowed us to adjust for patient severity at different stages of boarding in the ED and to adjust for improvement during ED boarding time which could lead to a shorter hospital length of stay (or vice versa).

Finally, we considered the type of nursing care that a patient received as indicative of the acuity of the patient. The type of nursing care comprised: the care received in the emergency room while boarding, the care received on a general ward, the care received when requiring a higher level of care in an ICU or the level of care that is appropriate when a patient no longer requires acute-care and is designated as an alternate level of care patient. We derived a time-varying covariate that captured the nursing care that a patient received using a 6 hourly time interval. This level of care variable was defined with the following categories: *ED, ED BOARD (admitted patient receiving emergency room nursing care), WARD (nursing care associated with acute-level of care), ICU (nursing care in an Intensive Care Unit), AMA (nursing care in an Acute Monitoring Area) and ALC (this often reflects the same level of care as a patient requiring acute-care although the patient no longer requires this level of care)*.

We also adjusted for patient age and sex. Both were identified as being associated with hospital length of stay in the literature review. Older patients are considered to be more complex and require a longer evaluation time in the ED and on discharge might require a long-term care bed which could impede discharge from the hospital and result in a longer LOS.

3.7.2. Adjusting for hospital- and encounter-specific risk factors

We hypothesised that patients at a specific hospital site would tend to exhibit hospital lengths of stay that were more similar. This could be driven by potentially different care processes, discharge patterns and specialists available at the various sites. The hospital site might also service a specific patient population depending upon location and services offered. We adjusted for this potential clustering at the hospital site level using stratification in the statistical analysis.

Hospitals are also known to block discharge patients with discharges increasing on a Friday. The majority of discharges also happen during the day shift. Arrival at the ED outside of 'office-hours' and on weekends has been associated with delays in evaluation and treatment time in the ED due to a longer turn-around time on diagnostics[21]. The day of the week and the time a patient presents to the ED could therefore affect both the time spent in the ED and the time to discharge due to these block discharge patterns. We hypothesised that those who presented to the ED "after hours" (between 6pm and 6am) or over a weekend (defined as an admission between 6pm on Friday and

6am on Monday) could potentially have a shorter hospital LOS due to these discharge patterns and that hospital LOS could be an artefact of these decisions. We expected the weekend effect to attenuate over time but that the time difference would persist.

We also considered the seasonal influences on hospital LOS. Winter months are associated with influenza season and with an increased number of ED visits, higher hospital occupancy rates and longer hospital lengths of stay due to a sicker population[30]. Hospital occupancy was also considered a potential confounder for the association between ED length of stay and hospital length of stay. Previous studies have suggested that once a hospital reaches capacity and is unable to take on new patients the case mix of patients could change and only represent the sickest of patients[30,31].

Isolation practices at a hospital may also affect the time spent waiting for a bed as well as the hospital length of stay. Not only does the patient have to wait in the ED until a ward bed becomes available but the bed also needs to meet specific isolation requirements. Isolation protocols govern how long a patient should be isolated and who is allowed to discontinue isolation having a potential impact on hospital length of stay.

These patient and hospital specific risk factors are summarised in Table 3-1. We also note the type of variable as well as whether the variable will be modelled as a fixed variable or a time-varying variable.

Table 3-1: Description of model covariates

Variable	**Fixed/Time-varying**	**Type**
Age at admission	Fixed	Continuous
Patient gender	Fixed	Binary
Admission diagnosis Classified into 44 possible disease related categories	Fixed	Categorical
Elixhauser score An index that combines the 30 Elixhauser comorbidities	Fixed	Continuous

Variable	Fixed/Time-varying	Type
into a single comorbidity burden score 5-year look-back period for hospital admissions at TOH		
Arrival at ED by ambulance	Fixed	Binary
Hospital admission at TOH over the past 6 months	Fixed	Binary
Nursing care (health status of patient) ED, EDBOARD, WARD, AMA, ICU, ALC	Time-varying	Categorical
Laboratory-based Acute Physiology Score (LAPS)	Time-varying	Continuous
Isolation status	Time-varying	Binary
Campus code (General or Civic)	Fixed	Binary
ER triage category CTAS I & CTAS II CTAS III CTAS IV & CTAS V	Fixed	Ordinal
ED registration between 6pm and 6am	Fixed	Binary
ED registration over weekend (Friday 6pm – Monday 6am)	Fixed	Binary
Hospital occupancy at time of ED registration (site specific)	Fixed	Continuous
ED boarding time	Time-varying	Continuous
ED time to decision (ED TTD)	Time-varying	Continuous

3.8. Statistical analysis

3.8.1. Statistical software

All data manipulation and statistical analyses in this study was performed using SAS, Version 9.3 (Cary, NC) and Microsoft Excel, Version 14.0.7106.5003.

3.8.2. Exploratory analysis

We explored the distributions of each covariate listed above. We identified potential outliers and investigated the validity of these observations. We also sought to describe the patient characteristics of those patients that comprised the tail end of the ED length of stay distributions. The tails of the distributions were defined as: the upper 1st percentile of time spent receiving emergency care in the ED, time spent boarding in the ED and the total time an admitted patient spent in the ED. We ensured that the analytic dataset contained no instances of negative duration for the total ED length of stay as well as the two derivatives thereof.

Baseline patient characteristics and hospital risk factors were described using medians and inter-quartile ranges for continuous data and proportions for categorical data. We summarised the ED length of stay variables using means (± standard deviation) and medians (inter-quartile range). The categorical time-varying variables were described as the proportion experiencing the event at any time during the hospitalisation. The baseline characteristics and the summarised time-varying variables were calculated for both the random sample, which represented a randomly selected encounter for each patient in the study cohort, as well as for all eligible encounters during the study period.

We also categorised the time to planned medical discharge into quartiles and used these four categories together with in-hospital mortality and left against medical advice to represent six termination categories and used descriptive statistics to evaluate the association between the patient characteristics and interim patient outcomes (ED LOS and other time-varying covariates) with these six termination categories.

3.8.3. Modelling the time to planned medical discharge

Survival analysis was used to model the time to discharge. The period of observation started at the time of patient registration in the ED and the observation period ended when the patient's association with the hospital terminated or the patient was censored at the study end (31 October 2014). We defined the event of interest as discharge, incorporating the events of discharged home or transferred to a non-acute facility. A patient's association with the hospital could also terminate as a result of a patient dying in hospital or discharging themselves against medical advice. Both these events would preclude the possibility of a planned medical discharge and were therefore considered as competing risks for the event of interest.

We used two different methodological approaches to model competing risks. The first approach treated those patients that experienced a competing event as censored. This approach assumes that the time to the different events are independent or at a minimum that the events are non-informative (i.e. the information gleaned from the occurrence of an event does not add to the information known only from the measured covariates in predicting the occurrence of the other event). Under this approach we constructed a proportional hazards model for the cause-specific hazard. This is the most commonly used method for dealing with competing events.

The cause-specific hazard function for a planned medical discharge at time t is defined as the instantaneous risk of a planned medical discharge given that the patient has not experienced any termination event by time t (**Equation 3-1**).

$$h_j(t) = \lim_{\delta t \to 0} \frac{P(t \leq T < t + \delta t, J = j | T > t)}{\delta t}$$

Equation 3-1 Cause specific hazard function for event type j

Non-independence between the different event times can lead to biased coefficient estimators. This problem can be minimised by ensuring that covariates that are common to more than one type of event are included in the model. Another approach is to use the Fine-Gray[45] model and to model the sub-distribution hazard which is the primary modelling technique employed in this study.

The sub-distribution hazard for a planned medical discharge at time t is the instantaneous risk of a planned medical discharge (given that the patient is still hospitalised at time t) or the patient died or left against medical advice prior to time t (**Equation 3-2**).

$$\boldsymbol{\lambda_j(t) = \lim_{\Delta t \to 0} \left\{ \frac{P[t \leq T < t + \Delta t, J = j | T > t \cup (T < t \cap J \neq j)}{\Delta t} \right\}}$$

Equation 3-2 Sub-distribution hazard function for event type j

We examined the impact of these modelling choices on estimating the probability of the occurrence of a planned medical discharge using cumulative incidence functions (CIF), and on the effect of the association between the covariates and the hazard functions using Cox-regression models and adjusted risk sets. We then constructed a multivariable Cox regression model for both the cause-specific and sub-distribution hazard functions and modelled the effect of ED boarding time on the daily hazard of planned medical discharge, adjusted for the identified patient and encounter specific covariates.

3.8.3.1. Model assumptions

Both the Kaplan-Meier estimate and the Cox regression model assume independence of survival times and non-informative censoring. We ensured the independence of survival times by conducting the analysis at the patient level by randomly selecting a unique hospitalisation per patient in the study cohort. We also considered the possibility of clustering at the hospital level that could arise due to different care processes and sub-specialities at the two campuses. We adjusted for this level of clustering using stratified analysis.

The nature of the study implies that no study participant is lost to the study and the only censoring would be administrative censoring at the end of the study period which meets the definition of non-informative censoring. The study period was chosen such that each patient had at least 8 months of follow-up time which would limit most administrative censoring. We have however introduced censoring into this study by classifying – in the non-competing risk model – those that experienced a competing event as censored. We minimised the impact of informative censoring by modelling covariates that related to multiple events and used sub-distribution hazard functions as the primary statistical model in the analysis.

The Cox regression model has an additional requirement of proportional hazards which implies that the effect of the covariate on the hazard not change over time. This assumption was tested at both the univariable as well as the multivariable level.

3.8.3.2. Modelling decisions

We constructed multiple datasets to incorporate the time-varying variables and to adjust for competing risks in the analysis.

3.8.3.2.1. Time-varying variables (counting process approach)

The analytic dataset for our sample cohort is characterised by a single record reflecting the randomly chosen hospital encounter for each patient and which contains all the patient and encounter specific information related to that specific hospitalisation. We have termed this dataset the *non-count* dataset. The ED length of stay variables and other categorical variables classified as time varying were captured as fixed variables in this dataset. The ED length of stay variables reflect the complete time spent boarding in the ED and the complete time spent receiving emergency care in the ED. The categorical variables were captured as indicator variables indicating if the event occurred at any time during the hospitalisation.

A second dataset was then created to capture the time-varying nature of these variables. The patient's total encounter, measured as the time from initial registration in the ED until the patient experienced the event of interest or a competing event, was divided into 6-hourly time-intervals. Each 6-hourly time-interval was reflected as a separate observation for the patient, the start time for each interval was defined as the ending time of the previous time-interval. Time-invariant variables were held constant over all the intervals. We measured the value for each of the time-varying covariates at the 6-hourly intervals. A time-varying covariate that did not change in value during a 6 hour time interval was held constant using the most recent value until a change in value was recorded. The last interval was adjusted such that the exact time of the terminating event was reflected in the analytic dataset (data pertaining to the termination event was not rounded to the nearest 6 hours). The first interval and all sub-intervals were coded as censored events until the last interval which reflected the actual terminating event. We coded 5 terminating event types: 0 (censored); 1 (discharged home); 2 (transferred to a non-acute care setting); 3 (in-hospital mortality) and 4 (left against doctor's advice). We termed this analytic dataset the *count* dataset.

3.8.3.2.2. Creating the sub-distribution analytic dataset

The inherent difference between the cause-specific hazard function and the sub-distribution hazard function is encapsulated in the definition of the risk sets, the number of people considered to be at risk of experiencing the event, which in turn influences the estimation of the hazard.

The risk set for the cause-specific hazard excludes, from future risk sets, those that experience the competing event. The risk set for the sub-distribution hazard function on the other hand retains in the risk set patients who experience a competing event and uses these observations as a proxy for those that will not experience the event of interest in the population[46]. The manner in which this *proxy* patient is retained in the dataset after experiencing a competing event and contributes to the denominator until the end of follow-up depends on whether the study population had censored events. A censoring distribution is applied to these patients where the weights assigned at each time point for each patient are defined by the conditional probability of not being censored after the competing event. A participant that experiences a competing event in a study that is characterised by complete data[45] (i.e. all the participants experience the event of interest or the competing event) is retained in the risk set with a weighting of 1 until the very end of follow-up (assumes the longest follow-up time).

We constructed additional datasets to account for competing risks for both the *non-count* and the *count* datasets. For the *non-count* analytic dataset, the time to the event for those that experienced a competing event was modified to represent the longest time to a planned medical discharge in the sample cohort. For the *count* analytic data set, an additional line was added to each patient that experienced a competing event with a start time that corresponded to the time of the competing event and an end time that was the same as the longest time to a planned medical discharge in the sample cohort. The values for all the other covariates were kept the same for this additional line that was added to the dataset.

3.8.3.2.3. Stratification

To adjust for clustering at the site level, we included the campus code as a strata variable. Stratification allows a different baseline hazard ratio to be modelled for each level of the stratification. Stratification also allows us to adjust for a nominal categorical variable with a large number of levels and which is not a predictor of interest[47]. We therefore included the admission diagnosis as a strata variable as well. This prevented the introduction of 44 indicator variables into the model and allowed the modelling of a unique baseline hazard ratio for the different admission diagnoses which too could exhibit a level of clustering. As we have chosen to stratify by two categorical variables, we have modelled a unique baseline hazard ratio for each admission diagnosis by campus.

3.8.3.3. Univariable analysis

We modelled the cumulative incidence function (CIF) for a planned and unplanned discharge and described the effect of covariates on the hazard functions. We initially tested the proportional hazards assumptions for the time-invariant variables by plotting $\log(-log\hat{S}(t))$ versus $\log(t)$. These plots display parallel lines for the different levels of the covariates if the proportional hazard assumption is valid. We categorised continuous variables into strata to conduct this test. We used the *non-count* dataset adjusted for competing risks to conduct these tests. The graphical test for the proportional hazards assumption was supplemented by defining an interaction term of the covariate with $\log(time)$and we tested if the interaction term was significant using a bi-variable Cox regression model stratified by campus and admission diagnosis.

For those covariates that showed a significant association with time, we investigated the change in the effect of the covariate on the hazard over a sub-group of the range of times observed in the study. If the changes in the effect of the covariates on the hazard over time were not considered to be important, we chose to model the time averaged effect of these covariates on the hazard.

3.8.3.4. Multivariable modelling

We constructed a multivariable Cox regression model for the cause-specific hazard functions for planned medical discharge and for the most common competing event, in-hospital mortality. These models contained all potential predictors of hospital length of stay previously identified. We also constructed a multivariable Cox regression model for the sub-distribution hazard function for planned medical discharge using the same covariates (treating all other events as competing events). We initially assumed a linear form for the association between the log of the hazard and each of the continuous variables. All three models were stratified by campus and admission diagnosis.

We investigated the predictors that had a strong influence on the cause-specific hazard for the primary competing event (in-hospital mortality) to understand the impact of a reduced or over-representation of patients with these covariates in the risk set that could potentially influence the cause-specific hazard for a planned medical discharge. We also investigated covariates that had a strong influence on the cause-specific hazard function but no effect on the sub-distribution hazard function for a planned medical discharge.

We then used fractional polynomials to determine the functional form of the continuous variables for the sub-distribution hazard function. We restricted the definition of the continuous variable to a first-degree fractional polynomial of the form $\beta_i X^p$ and restricted the range of powers that p could assume from the following list: $\{-2, -1, -0.5, 0, 0.5, 1, 2, 3\}$ where X^0 denotes $\log(X)$. We used the MFP algorithm[48] adapted for time-varying covariates to identify the best fit fractional polynomial for each continuous variable and to simultaneously reduce the model to only include significant predictors. We used a p-value of 0.05 to adjudicate statistical significance. The two ED length of stay covariates were forced to be included in the model.

3.8.3.5. Identification of influential data points

Due to the known highly skewed nature of ED length of stay data and its susceptibility to outliers, we tested the ED length of stay covariates for influential data points. We used the DFBETA output measure available in PROC PHREG to conduct the test. We used the non-count analytic dataset to initially identify potential influential observations. Once identified, the impact of the inclusion/exclusion of these observations using the *count* dataset could then be determined. The DFBETA measures the change in the estimated coefficient of a predictor when an observation is deleted from the analytic dataset. We considered any observation that changed the value of the parameter by more than 1 standard deviation for the covariate as an influential observation.

Neither of the ED length of stay measures was found to have influential data points (the largest change for ED boarding was 15% of the standard deviation). A sensitivity analysis was conducted to supplement this analysis.

3.8.3.6. Model assessment

We used the concordance index as a measure of model discrimination and employed a definition for concordance that was developed by Kremer et al. to measure model discrimination for survival models that accounted for censoring, tied events and time-varying covariates[49]. For survival analysis, concordance is defined as the fraction of all evaluable pairs for which the predictor score is greater in the individual who experiences the event earlier. An evaluable pair is any pair of observations for which the censored event is not the earlier of the two events. A completely random prediction has a score of 0.5. We compared the discriminatory ability of the fully adjusted model with time-varying covariates to a model that was restricted to only baseline data.

3.8.3.7. Sensitivity analysis

A sensitivity analysis was conducted to test the susceptibility of the results to potential outliers as well as to time-varying covariates that could lead to reverse causation.

By introducing time-varying covariates into the model (ie covariates for which the value of the covariate can change over time) we introduced the risk of reverse-causation. We considered if there were any time-varying variables that could be affected by the likelihood that the duration would end. An example would be the time-varying covariate LOC. A patient boarding in the ED and who is expected to be discharged soon (either dead or alive) might remain in the ED and not be transferred to a ward bed due to the termination event being imminent. A sensitivity analysis was conducted which removed all patients discharged directly from the ED and the impact of the removal of these patients on the association between ED boarding time and the time to planned medical discharge was analysed. We also tested the sensitivity of the results to patients deemed ALC at some stage during their hospitalisation since this too could lead to reverse-causation. The risk set is ever decreasing as patients are discharged from hospital and this could lead to an over representation of ALC patients among those with a longer length of stay in the hospital.

We further tested the sensitivity of the model results to potential outliers. These included those patients that boarded for longer than 24 hours in the ED as well as patients that formed part of the top 1% of hospital length of stay. We also sought to understand the impact of those patients that were isolated at admission on the model results. Finally, we compared the model results that were obtained for the randomly selected hospitalisation for each patient during the study period to all hospitalisations that occurred during the study period. We did not adjust for clustering at the patient level.

3.9. Economic analysis

The results from the Cox regression model were then used to inform the effectiveness measure of increasing the number of acute-care beds to reduce ED wait times and in turn to reduce the time spent in hospital as an inpatient in an economic model.

3.9.1. Study objective

The primary objective of the economic analysis was to determine the costs and benefits associated with an increase in the number of acute-care beds at The Ottawa Hospital.

3.9.2. Type of economic analysis

We conducted a cost benefit analysis and assigned a monetary value to the benefits of increasing the number of acute-care beds. The benefits of a shorter ED wait time and hospitalisation are monetised by the reduction in nursing costs associated with the reduced time and the level of staffing. The analysis was conducted from the perspective of The Ottawa Hospital and only costs and benefits that **directly impacted the hospital** were considered. We only considered the costs that related to the single hospitalisation that was selected for the sample study. Costs that were incurred outside of this hospitalisation were not considered. The costs and benefits were also only limited to patients that were admitted to hospital from the ED. We did not consider the potential benefits of a less crowded ED for those that visited the ED and were not admitted.

3.9.3. Target population & outcomes

We used the same study cohort that was defined in deriving the statistical association between ED boarding time and the time to planned medical charge. The Cochrane Effective Practice and Organisation of Care (EPOC)[50] group recommends that outcomes that affect both the patient and the decision maker be considered when evaluating health system interventions. The patient outcomes modelled in the analysis pertain to the time spent boarding in the ED and the total hospital length of stay for the admitted patient. The same definitions as used in the statistical model apply to the economic analysis. Both these outcomes are also associated with utilisation and resource usage from the hospital perspective. These same outcomes together with the associated costs for both ED boarding time and hospital length of study were modelled. A quality of care outcome which was measured as the ability of the hospital to meet the recommended ED wait time benchmarks was also considered.

3.9.4. Intervention

The intervention that was modelled in the cost benefit analysis was the increase in acute-care beds within the medicine service at The Ottawa Hospital such that 90% of admitted patients were transferred to a ward bed within 6 hours. This equates to an effective increase of 50 staffed beds across the two campuses. Alternative interventions such as the increase of non-acute care beds fell outside of the domain of this analysis. However, the timely transitioning of alternate level of care patients to the right bed was modelled as part of the sensitivity analysis.

3.9.5. Model Structure

A Markov model was developed to conduct the analysis. The cohort was followed from the decision to admit time until the patient's association with the hospital was terminated. The termination event was modelled as an absorbing state. The absorbing states that were modelled were: *HOME* (patients discharged home), *TRANSFER* (patients transferred to a non-acute setting), *DEATH* (in-hospital mortality) and *LEFT* (patients that left against medical advice). A patient cannot exit an absorbing state. It also signifies a termination point for the accrual of time and costs. The cohort Markov model simulates the proportion of the cohort in each of the health states at each point in time and describes the incidence of events associated with the population at each time point[51].

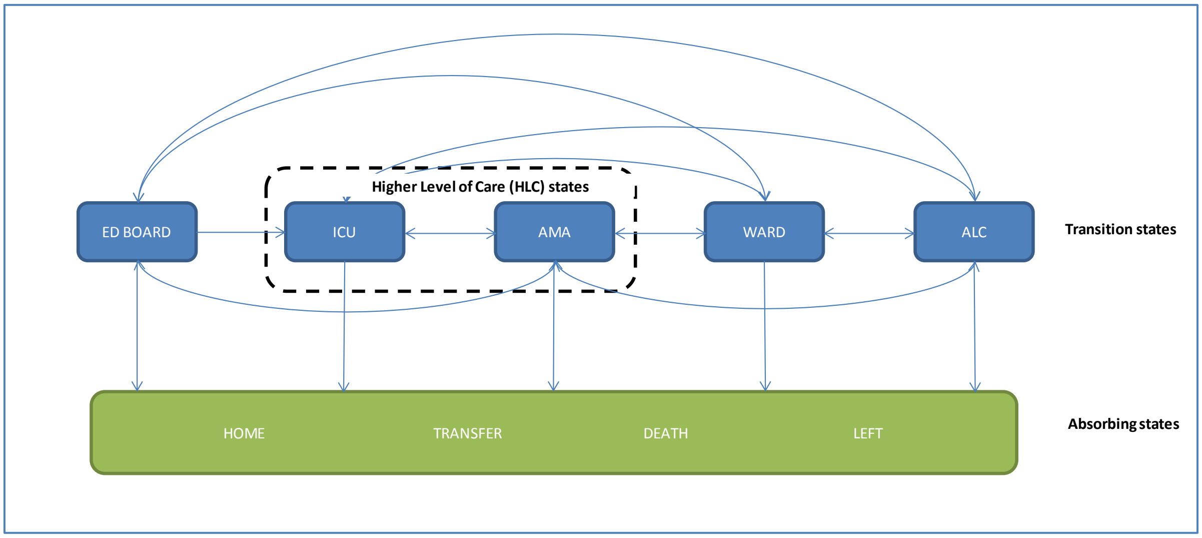


Figure 3-3 Markov model

We used the nursing unit to which the patient was assigned at each time point to capture the different health states that a patient could experience from the time of admission to discharge from the hospital. The specific health states modelled were: ED BOARD (all admitted patients start with a decision to admit via the ED – all patients in the cohort must start in this state), WARD, AMA, ICU, and ALC.

The probability of transitioning between the states and eventually to an absorbing state was derived from the study cohort. For each 6-hourly interval we considered all possible combinations of start and end health states. A count of all patients for each unique combination was then used to empirically derive the 6-hour transition probabilities. These transition probabilities represent the transition probabilities averaged over all patient and encounter characteristics. We also assumed that these transition probabilities were time-invariant (Table 3-2).

Table 3-2 6-hourly transition probability matrix

	ED	EDBOARD	WARD	ALC	AMA	ICU	HOME	TRANSFER	DEATH	LEFT
ED	0.29	0.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EDBOARD	0.00	0.54	0.39	0.00	0.04	0.00	0.02	0.00	0.00	0.00
WARD	0.00	0.00	0.96	0.01	0.00	0.00	0.03	0.00	0.00	0.00
ALC	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00
AMA	0.00	0.00	0.05	0.00	0.93	0.00	0.01	0.00	0.00	0.00
ICU	0.00	0.00	0.01	0.00	0.00	0.97	0.00	0.00	0.01	0.00
HOME	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
TRANSFER	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
DEATH	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
LEFT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

A Markov process has the concept of no memory. This implies that the current state fully describes the patient and all patients within that health state are homogenous. The time already spent in that health state and the path followed to get to that health state are not relevant. We have perpetuated this characteristic of a Markov process in our model and have not tried to model around this.

The effect size of the increased number of acute-care beds on the probability of transitioning from an ED bed to a WARD bed was determined using a simulation that was conducted by the Institute of Healthcare Optimization (IHO). IHO used all admissions at TOH arising in the ED and with a subsequent admission to a medicine bed over the period 1 Jan 2011 – 31 December 2012 to derive the optimal number of beds to meet various wait time thresholds. The medicine service at TOH currently has 201 staffed beds with an inpatient census of 225. The results from the IHO simulation model indicated that 251 staffed beds would be required to ensure that 90% of patients admitted via the ED received a ward bed within 6 hours. We only modelled the impact of increased bed supply on transition times from an ED bed to a WARD bed. We did not model the impact of this increased bed supply on transition probabilities from other types of beds (for example, increasing the number of ward beds might decrease exit block from ICU beds).

The effect size of the shorter ED boarding times on hospital length of stay was derived from the sub-distribution hazard function for planned medical discharge as modelled using the Cox regression model and adjusting for known patient and hospital risk factors.

We used a cycle length of 6 hours and a time horizon equal to the longest observed time to discharge. Capturing the longest observed hospital length of stay was essential since the results of the Markov model were used to determine the increased annual operating costs associated with the increased bed intervention and outlier observations would impact the modelled average length of stay and associated costs.

3.9.6. Costs

The costs for the analysis were derived from the case costing data at The Ottawa Hospital. For each type of bed occupied, the nursing cost per patient per hour was estimated. Only direct nursing costs were included in the economic model. The other costs that comprise a hospital stay such as linen, food, drugs, laboratory services, etc. are assumed to be the same irrespective of the type of bed the patient occupies. The only costs assigned to the intervention were the costs related to staffing the additional beds whilst retaining the current nurse to patient ratio. The capital costs required to facilitate this initiative, such as purchasing equipment and upgrading facilities for the additional beds, were not included in the model. The resultant analysis therefore depicts the increased operating costs for the additional beds.

A further model assumption in determining the costs was that the number of patients did not increase with the increase in beds. This assumption was needed to ensure that the increased costs associated with the increased number of beds was not simply distributed to additional patients resulting in no incremental cost to an admission but nullifying any benefits associated with increased hospital capacity.

We averaged the direct nursing costs across all nursing units that belonged to the same primary activity (ED, ICU, AMA, and WARD). Hospital occupancy levels were used to derive the increased costs. The average occupancy rate over all seasons was used. This takes account of the increased cost for seasons where the number of patients is lower (summer months) and for lower costs where the number of patients increases over the winter months (Table 3-3).

A patient designated ALC will typically occupy a *WARD* bed and thus the costs associated with a health state of ALC is the same as for a general ward bed. The medicine service at The Ottawa Hospital is currently running at more than 100% occupancy, implying that medicine patients are admitted to a bed outside of this service in addition to excess boarding times waiting for a bed to become available. We assumed that these beds, currently being used by admitted patients from the medicine service, will be fully utilised by elective admissions and emergency visits where applicable under the increased beds scenario. We will test this assumption as a deterministic sensitivity test since the hospital occupancy rate is an important factor in driving the increased cost.

All costs are in Canadian dollars as at October 2013.

Table 3-3 Direct nursing costs

		Increased hourly nursing cost per admission			
Type of nursing care	**Current Cost (Hourly)**	**Medium season**	**High season (Winter)**	**Low Season (Summer)**	**Average**
ED	24.83	24.83	24.83	24.83	24.83
WARD	19.93	21.95	21.10	24.56	22.19
AMA	45.38	45.38	45.38	45.38	45.38
ICU	84.69	84.69	84.69	84.69	84.69
# Patients		228	237	204	225
# Current beds		201	201	201	201
# increased beds scenario		251			251
Current occupancy (within medicine service)		113.4%	118.0%	101.3%	112.2%
Expected occupancy (within medicine service)		90.8%	94.5%	81.2%	89.8%

3.9.7. Deterministic sensitivity analysis

A wide range of sensitivity analyses were conducted to determine the impact of changes to the cost benefit analysis of the proposed intervention. These included modelling the sensitivity of the cost of the intervention to: changes in occupancy within the medicine service, changes to the effect size of the increased beds intervention, changes to the average hospital LOS and changes to direct nursing costs. We also modelled various scenarios that describe the impact of ALC patients occupying acute-care beds on hospital nursing costs.

3.9.8. Probabilistic sensitivity analysis

We further supplemented the deterministic sensitivity analysis by quantifying the impact of the uncertainty around the model inputs. We conducted a probabilistic sensitivity analysis using a

Monte-Carlo simulation. We derived probability distributions for the transition probabilities and the effect size of a shorter ED boarding time (HR). 1000 random draws from a cumulative beta distribution were used to describe the uncertainty around the transition probabilities for each of the starting health states thus creating 1000 transition probability matrices that were used in the analysis. The uncertainty around the hazard of a shorter ED boarding time was described using a log normal distribution. The economic model was recalculated 1000 times and the estimated reduction in hospital length of stay, increased cost per encounter and increased annual operating costs were calculated.

Details pertaining to all model inputs and parameters for the probability distributions are contained in Appendix E.

4. Results

4.1. Creation of the study cohort

The initial dataset contained 30,059 ED visits that resulted in an admission to a medicine service at The Ottawa Hospital for the period 1 January 2011 to 31 December 2013. After applying the eligibility criteria and data quality checks, the resultant dataset contained 28,559 admissions (Figure 4-1). 0.2% of the admissions were excluded due to a change to the medicine service after admission and while the patient was boarding in the ED; these could be data capture errors that were subsequently corrected. 1.5% of the admissions were transferred to a higher level of care while boarding in the ED; these are retained in the analysis as this is only a temporary change to the admitting service as these patients are expected to return to a ward bed. 0.1 % of the excluded admissions related to patients that were younger than 18 years of age at the time of admission and 4.6% of the patients originated in other acute-care setting or were discharged from TOH to another acute-care setting. We were unable to match the inpatient encounter to the ED visit that gave arise to the admission using the date matching algorithm for 0.1% of the admissions. The resultant 28,559 admissions are associated with 19,313 individual patients. A unique admission per patient was randomly chosen for further analysis. The resultant analytic dataset therefore consists of 19,313 unique patients and a randomly chosen admission for each of these patients if the patient had more than one admission during the study period.

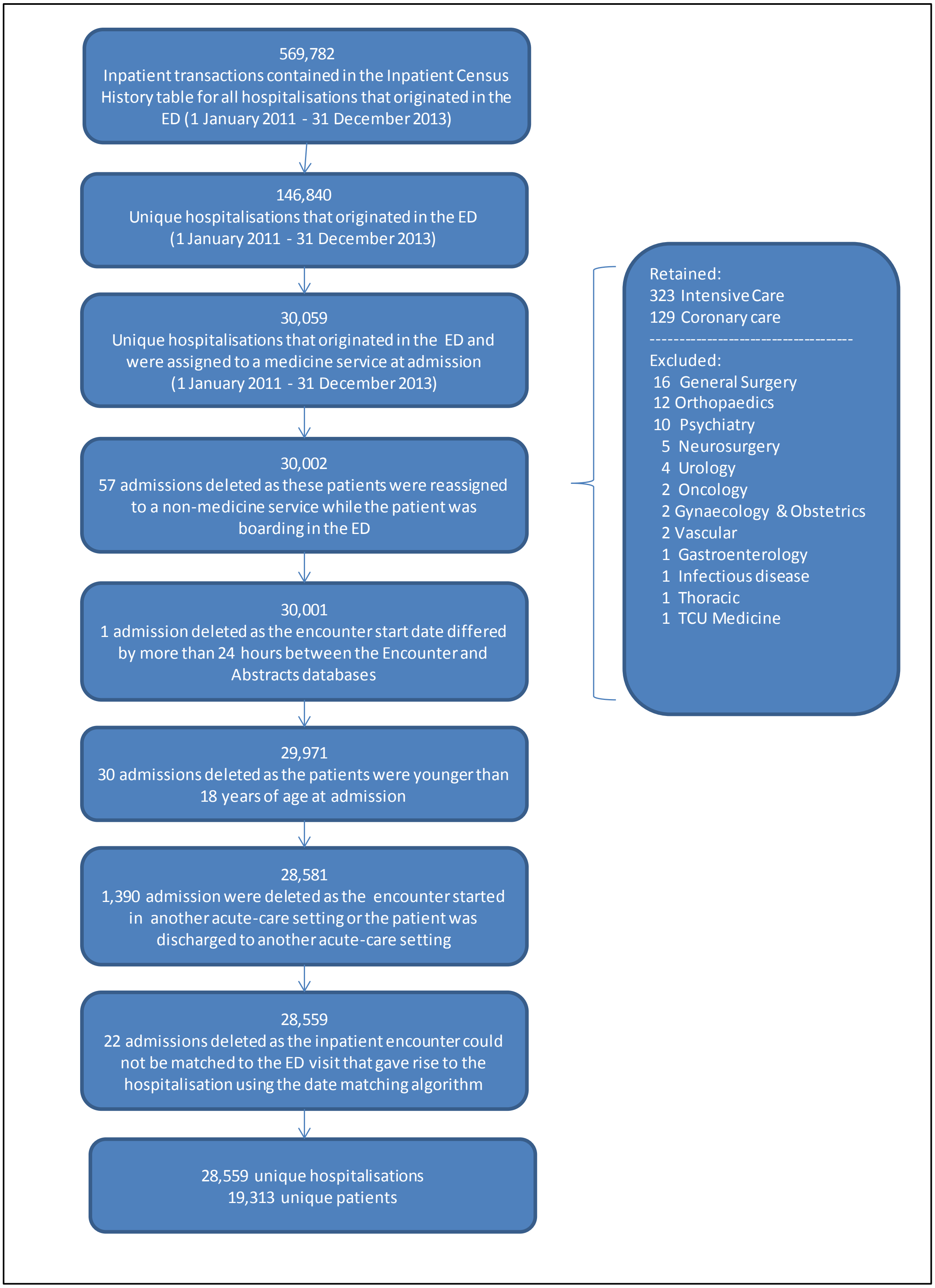


Figure 4-1 Deriving the study cohort

4.2. Cohort characteristics

The median age for the sample was 72 years (IQR 56-83 years) and males and females were approximately equally represented. 34.8 % of ED registrations occurred after 6pm and before 6am the following morning and 30.8% of ED registrations occurred over a weekend (Friday 6pm – Monday 6am). Just over half of all admitted patients arrived at the ED by ambulance. The most common admission diagnoses for the study sample were infections (excluding urinary infections, hepatitis, sepsis, meningitis) (7.5%), pneumonia (7.0%) and COPD (6.8%).

The median Elixhauser comorbidity score for the sample cohort was 5 with an interquartile range of 0-11, depicting a diverse patient population group when considering the interaction of pre-existing conditions on the length of hospital stay. Hypertension (uncomplicated), diabetes (with or without complications), fluid and electrolyte disorders and cardiac arrhythmias were the most prevalent comorbidities in the study sample. The contribution of the various comorbidities to the Elixhauser score are reflected in brackets in Table 4-1. The Elixhauser score for the study cohort ranged from -11 to +49 out of a possible range of -19 to +89.

The Laboratory-based Acute Physiology Score (LAPS) at admission also reflected a sick population with a range of severity. The median LAPS score was 39 (IQR 25-54). The LAPS ranged from 0 to 159 for the study cohort compared to a possible range of 0 to 256.

Patients required different levels of care during the hospitalisation; 3.2% of admitted patients required admission to an ICU and 10.7% required a stay in an Acute Monitoring Area (AMA). 12.6% of patients were classified as an alternate level of care patient during their hospitalisation, this status denotes a patient that no longer requires acute-care services but continues to use hospital resources while they wait to be discharged to a more appropriate setting. Almost 1 in 5 patients required a certain level of isolation at the time of admission and 1 in 3 patients was isolated at some point during their hospitalisation.

All patients in the sample experienced a terminating event at the end of the study period. 85.4% of patients were discharged home or transferred to a non-acute facility, 8.8% of patients died in-hospital and less than 1% left against medical advice. The mean boarding time for patients admitted to a medicine service for the study period was 10.8 hours with a mean total ED LOS of 19.6 hours. The mean hospital length of stay for the sample cohort was 10.8 days with a median length of stay of 5.3 days. The mean inpatient length of stay was 10.5 hours with a median of 5 days.

Table 4-1 Characteristics of the sample cohort

Characteristics and outcomes	**Random sample (n = 19,313)**	**All encounters (n = 28,559)**
Age at admission, yrs Median (IQR)	72 (56-83)	71 (56-83)
% Male	48.7	48.6
% Arrival by ambulance	53.6 0.05% missing	54.8 0.05% missing
LAPS, Median (IQR)	39 (25-54)	40 (25-55)
ER Triage Code %		
CTAS level I – Resuscitation	3.2	2.9
CTAS level II – Emergent	50.7	51.2
CTAS level III – Urgent	44.2	44.1
CTAS level IV – Semi-urgent	1.8	1.6
CTAS level V – Non-urgent	0.1	0.1
% General Campus	53.2	55.0
% Night shift (6pm – 6am)	34.8	35.2
% Weekend (Friday 6pm – Monday 6am)	30.8	31.1
% Previous admission within the last 6 months	20.8	33.5
Hospital occupancy, median (IQR)	0.97 (0.94-1.00)	0.97 (0.94-1.00)
Elixhauser Comorbidity Score, median (IQR)	5 (0-11)	6 (0-12)
Most common Elixhauser Comorbidities (index weight),%		
Hypertension, Uncomplicated (0)	37.5	41.3
Diabetes, Complicated (0)	22.3	25.7
Fluid and Electrolyte Disorders (5)	19.8	24.6
Cardiac Arrhythmia (5)	19.2	22.7
Diabetes, Uncomplicated (0)	19.1	21.6
Chronic Pulmonary Disease (3)	16	20.5
Congestive Heart Failure (7)	15.3	19.3
Solid Tumor without Metastasis (4)	10.3	12
Other Neurological Disorders (6)	9.7	10.7
Renal Failure (5)	9.2	10

Characteristics and outcomes	Random sample (n = 19,313)	All encounters (n = 28,559)
Alcohol Abuse (0)	5.4	6.6
Metastatic Cancer (12)	5.4	6.6
Deficiency Anemia (-2)	5	6.5
Depression (-3)	4.9	6.2
Pulmonary Circulation Disorders (4)	4.8	5.8
Liver Disease (11)	4.7	5.4
Coagulopathy (3)	4.1	4.8
Most common admission diagnoses, %		
Infections (excluding urinary infections, hepatitis, sepsis, meningitis)	7.5	7.5
Pneumonia	7.0	6.7
Chronic obstructive pulmonary disorder	6.8	8.1
Neurologic problems, mental disorders, and senility (excluding seizures and drug overdoses)	6.3	5.8
Stroke	6.1	4.7
Urinary tracts infections	4.9	5.2
Gastrointestinal bleeding	4.7	5.0
Congestive heart failure	4.4	5.3
Miscellaneous conditions (ICD-9: certain V codes, and all E codes)	4.4	4.1
Catastrophic conditions	3.4	3.5
Ingestions and benign tumors	3.1	3.0
Other cardiac conditions	2.8	2.5
Sepsis	2.7	2.7
Non-malignant hematologic	2.5	3.2
Fluid and electrolyte	2.4	2.5
Acute renal failure	2.3	2.3
Acute myocardial infarction	2.3	1.9
Atherosclerosis and pulmonary vascular disease	2.1	1.9
Seizure	2.0	1.9
	0.1% missing	0.1% missing
Season, %		
Fall	25.1	25.2
Spring	25.2	25.0
Summer	24.0	24.5
Winter	25.6	25.3
Outcomes		
Termination event, %		
Home	76.6	77.8
Transferred	13.7	13.5
Death	8.8	7.6
Left	0.9	1.1
Not discharged	0.0	0.0
% Isolation required at admission	18.8	21.1
% ICU admissions	3.2	3.2
% AMA admissions	10.7	10.1
% Surgery required during hospitalisation	1.0	0.9
% Isolation required during hospitalisation	28.4	30.7
% ALC status during hospitalisation	12.6	12.1
Total ED length of stay, hours		
Mean±SD	19.6±13.4	19.5±13.3
Median (IQR)	17.3 (9.8-25.4)	17.0 (9.8-25.2)
90th percentile vs 8 hour target	*34.0*	*33.8*
ED boarding time, hours		

Characteristics and outcomes	**Random sample (n = 19,313)**	**All encounters (n = 28,559)**
Mean±SD	10.8±12.5	10.6±12.4
Median (IQR)	6.7 (1.7-15.8)	6.5 (1.6-15.6)
ED time to decision, hours		
Mean±SD	8.8±5.1	8.84±5.0
Median (IQR)	8.0 (5.5-11.0)	8.0 (5.6-11.0)
Hospital length of stay, days		
Mean±SD	10.8±19.6	10.9±20.2
Median (IQR)	5.3 (2.9-11.1)	5.5 (3.0-11.1)
Inpatient length of stay, days		
Mean±SD	10.5±19.5	10.6±20.2
Median (IQR)	5.0 (2.5-10.7)	5.1 (2.6-10.7)

Abbreviations: SD=Standard Deviation; IQR=Interquartile Range; ALC=Alternate Level of Care; ICU=Intensive Care Unit; AMA= Acute Monitoring Area, LAPS = Laboratory-based Acute Physiology Score

4.3. Exploratory analysis

4.3.1. Descriptive analysis

A plot of total ED length of stay versus mean inpatient length of stay (where inpatient LOS is defined as the time from the decision to admit until the patient is discharged from the hospital) shows an increasing trend as the total time spent in the ED increases. The plot also shows a widely divergent relationship prior to 8 hours.

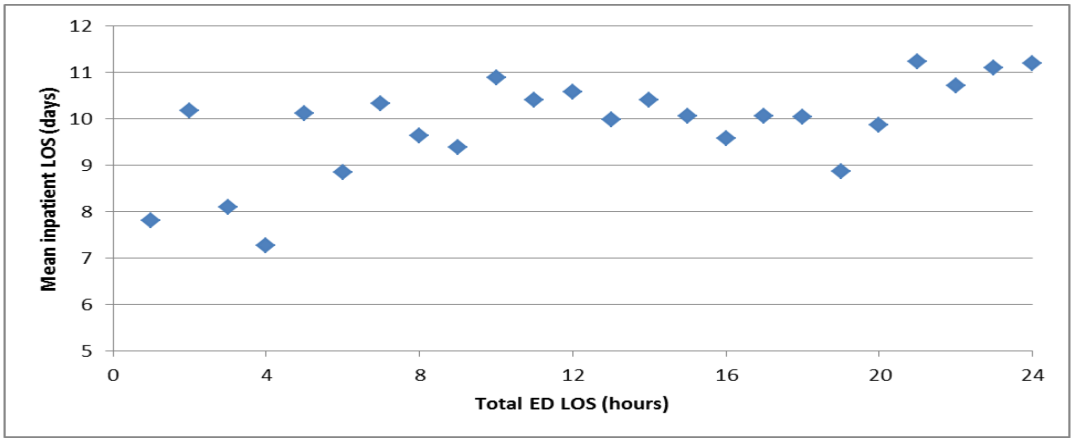


Figure 4-2 Relationship between mean inpatient length of stay and total time in the emergency department

Figure 4-3 seems to depict a U-shaped slope with a longer inpatient LOS associated with both those that board in the ED for less than 8 hours and for those that board in the ED for longer than 16 hours.

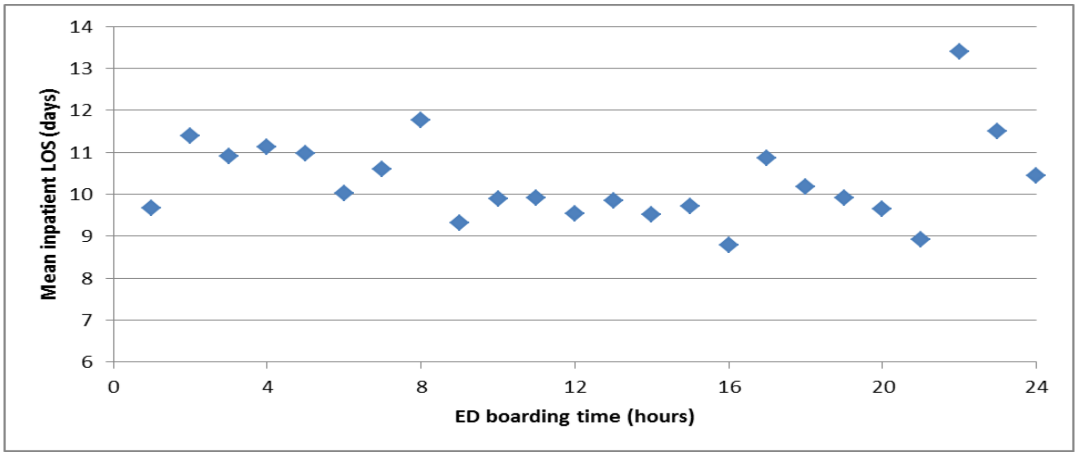


Figure 4-3 Relationship between mean inpatient length of stay and time spent boarding in the emergency department

Association between covariates and termination events

After categorising the time to planned medical discharge into quartiles and treating these four categories together with in-hospital mortality and left against medical advice as different terminating events, we found that those patients that died in hospital or formed part of the top quartile for the time to planned medical discharge had higher comorbidity burdens. The LAPS at admission was also found to increase as the time to planned medical discharge increased and was highest for those who died in hospital (Table 4-3). The median (IQR) hospital LOS for those that experienced a planned medical discharge was 5.2 days (2.9-10.7 days) versus 8.5 days (4.0-18.1 days) for those who died in hospital (Table 4-2). Those patients that left against medical advice had a hospital length of stay similar to those patients that comprised the bottom two quartiles of those patients that experienced a planned medical discharge.

Table 4-2 Hospital LOS distribution statistics by termination event

	Planned medical discharge	In-hospital mortality	Left against doctor's advice
Hospital LOS, days			
Mean±SD	10.5±19.2	15.2±22.7	4.6±7.3
Median (IQR)	5.2 (2.9-10.7)	8.5 (4.0-18.1)	2.2(1.1-4.3)

Almost half of the patients that comprised the highest quartile of hospital LOS for those patients that experienced a planned medical discharge were classified as ALC patients. ICU and AMA admissions showed an increasing association with LOS as depicted in Table 4-3 as did those patients that were isolated at some stage during their hospitalisation.

Males were more likely to have a shorter hospital LOS but were also more likely to die in hospital. Arriving at the hospital by ambulance was more prevalent in those that spent longer in the hospital and those that died in hospital. Older patients also tended to stay in hospital longer and were also more likely to die in hospital. Those that were assigned the most severe CTAS score at the time of triage in the ED also spent longer in hospital and were more likely to die in hospital.

Table 4-3 Patient characteristics and outcomes categorised by termination event

		Discharged home or transferred				Competing events		
Median hospital LOS	**Overall** **n = 19,313** **5.3 days**	**LOS Q1** **n = 4,423** **1.9 days**	**LOS Q2** **n = 4,388** **3.9 days**	**LOS Q3** **n = 4,126** **7.3 days**	**LOS Q4** **n = 4,126** **20.2 days**	**Death** **n = 1,690** **8.5 days**	**Left** **n = 169** **2.2 days**	**p-value†**
Age at admission, yrs median (IQR)	72 (56-83)	63 (46-78)	68 (53-81)	72 (58-83)	78 (64-86)	83 (72-89)	51 (36-64)	<0.001
% Male	48.7	51.3	49.4	47.6	45.1	51.1	56.8	<0.001
% Arrival by ambulance	53.6	40.4	47.4	54.4	66.7	71.0	52.7	<0.001
LAPS at admission, median (IQR)	39 (25-54)	33 (20-48)	36 (23-52)	40 (25-55)	41 (27-55)	53 (38-69)	34 (25-46)	<0.001
ER Triage Code, %								<0.001
CTAS level I – Resuscitation	3.2	2.7	2.1	3.0	3.3	7.7	4.7	
CTAS level II – Emergent	50.7	53.6	51.9	51.7	44.4	52.3	55.0	
CTAS level III – Urgent	44.2	41.8	43.7	43.6	50.0	39.2	39.1	
CTAS level IV – Semi-urgent	1.8	1.8	2.1	1.7	2.1	0.8	1.2	
CTAS level V – Non-urgent	0.1	0.1	0.2	0.1	0.1	0.1	0	
% General campus	53.2	52.9	54.3	55.5	49.9	54.9	42.0	<0.001
% Night shift	34.8	42.0	29.7	36.5	31.3	33.6	39.6	<0.001
% Weekend	30.8	31.2	35.6	27.2	29.0	29.9	34.3	<0.001
% Previous admission*	20.8	16.5	19.9	22.1	21.6	28.3	24.3	<0.001
Hospital occupancy, median (IQR)	0.97 (0.94-1.00)	0.97 (0.93-1.00)	0.97 (0.93-1.00)	0.97 (0.94-1.00)	0.97 (0.94-1.00)	0.97 (0.94-1.00)	0.97 (0.94-1.00)	<0.001
Elixhauser Comorbidity Score, median (IQR)	5 (0-11)	3 (0-7)	5 (0-10)	5 (0-11)	6 (0-13)	11 (5-17)	3 (0-7)	<0.001
% Isolation at admission	18.8	16.2	20.3	20.3	17.5	20.5	24.3	<0.001
% ICU admission	3.2	0.2	0.4	1.8	5.8	16.5	2.4	<0.001
% AMA admission	10.7	5.2	8.4	11.6	16.2	15.9	5.9	<0.001
% Surgery during hospitalisation	1.0	0.1	0.2	0.8	3.2	1.2	0.0	<0.001
% Isolation during hospitalisation	28.4	18.5	26.3	29.6	36.3	37.1	28.4	<0.001
% ALC status during hospitalisation	12.6	0.1	0.8	6.2	45.7	13.0	6.5	<0.001
Total ED length of stay, hours								
mean±SD	19.6±13.4	18.0±10.7	19.6±13.3	19.9±13.9	20.9±14.9	19.7±14.9	20.3±10.6	<0.001
median (IQR)	17.3 (9.8-25.4)	16.4 (9.6-23.7)	17.2 (9.6-25.7)	17.4 (9.9-25.7)	18.5 (10.4-26.7)	16.8 (9.6-25.2)	19.6 (11.6-26.2)	<0.001
ED waiting & evaluation time, hours								
mean±SD	8.8±5.1	8.2±4.5	8.9±4.9	8.9±5.1	9.5±5.7	8.3±5.0	9.3±4.6	<0.001
median (IQR)	8.0 (5.5-11.0)	7.6 (5.2-10.4)	8.0 (5.6-11.1)	7.9 (5.5-11.0)	8.5 (5.9-11.8)	7.5 (5.2-10.4)	8.6 (6.0-11.9)	<0.001
ED boarding time, hours								
mean±SD	10.8±12.5	9.8±9.9	10.7±12.4	11.1±13.1	11.4±13.9	11.4±14.1	10.9±9.4	<0.001
median (IQR)	6.7 (1.7-15.8)	7.1 (1.5-14.9)	6.1 (1.6-15.8)	6.7 (1.7-16.0)	6.6 (1.7-16.6)	7.1 (1.8-16.1)	9.0 (3.5-15.5)	0.002

SD = standard deviation; IQR = Interquartile range; ICU = Intensive Care Unit; AMA = Acute Monitoring Area, ALC = Alternate Level of Care

**Previous admission at TOH within the past 6 months*

† 1-way ANOVA analysis for means, Kruskal-Wallis test for medians and χ^2 statistic for proportions

Patient pathways and termination events

Table 4-4 summarises the association between the type of bed a patient occupies on leaving the ED (ED exit path) and the time spent boarding in the ED as well as the time to the termination event for the patient. Those patients that were discharged directly from the ED showed the longest ED boarding times and the shortest hospital lengths of stay. The entire hospital length of stay for this group of patients occurred in the ED. These patients comprised 5.3% of the study cohort and could potentially skew ED performance statistics. Those awaiting transfer to a non-acute facility had a longer hospital stay for both the group discharged directly from the ED and for those discharged from a hospital bed.

Table 4-4 Patient pathways and association with ED length of stay measures and time to termination event

			%	Mean time to termination event, days	Mean ED LOS, hours	Mean ED boarding time, hours	% Home	% Transfer	% Death	% Left
Termination event		HOME	76.6%	8.6	19.3	10.5	100.0%			
		TRANSFER	13.7%	20.9	21.2	11.9		100.0%		
		DEATH	8.8%	15.2	19.7	11.4			100.0%	
		LEFT	0.9%	4.6	20.3	10.9				100.0%
ED exit path		HOME	4.4%	1.2	28.7	20.2	100.0%			
		TRANSFER	0.2%	1.4	33.3	24.4		100.0%		
		DEATH	0.5%	1.0	24.4	17.6			100.0%	
		LEFT	0.2%	0.9	22.1	12.7				100.0%
	HLC	ICU	1.5%	12.9	16.5	9.8	65.7%	10.6%	22.6%	1.1%
		STEPDOWN	12.9%	11.9	20.0	12.8	68.3%	17.8%	13.1%	0.8%
		PACU	0.2%	12.4	10.8	6.8	66.7%	26.2%	7.1%	0.0%
		WARD	76.8%	11.4	18.8	9.6	77.5%	13.9%	7.9%	0.7%
		ALC	3.4%	8.1	25.6	15.6	83.1%	11.2%	4.7%	1.1%
Patient pathway		ED-WARD	68.4%	8.2	18.6	9.6	80.7%	12.3%	6.3%	0.8%
		ED-HLC-WARD	8.8%	12.2	19.8	12.5	67.5%	20.6%	11.6%	0.4%
		ED	5.3%	1.2	28.3	19.9	84.3%	3.5%	8.9%	3.3%
		ED-HLC	4.5%	4.6	17.9	11.0	73.4%	6.9%	17.9%	1.8%
		ED-WARD-LLC	3.8%	52.1	21.8	10.5	54.7%	38.3%	6.8%	0.3%
		ED-LLC	2.8%	5.3	25.3	15.3	87.0%	8.7%	3.2%	1.1%
		ED-WARD-HLC-WARD	2.4%	22.2	18.4	9.6	59.7%	22.6%	17.8%	0.0%
		ED-WARD-HLC	1.2%	12.3	16.0	8.2	26.1%	2.1%	71.8%	0.0%
		ED-LLC-WARD	0.5%	18.6	26.1	16.4	69.9%	19.4%	10.8%	0.0%
		ED-HLC-WARD-LLC	0.3%	56.6	23.6	14.9	47.0%	48.5%	4.5%	0.0%

Abbreviations: HLC=Higher Level of Care, ICU=Intensive Care Unit, PACU = Post-anaesthesia Care Unit, ALC=Alternate Level of Care

Patients transferred to a bed associated with a lower level of care during their hospitalisation had a longer hospital LOS and also tended to wait longer for a ward bed while in the ED (Table 4-4, Figure 4.4).

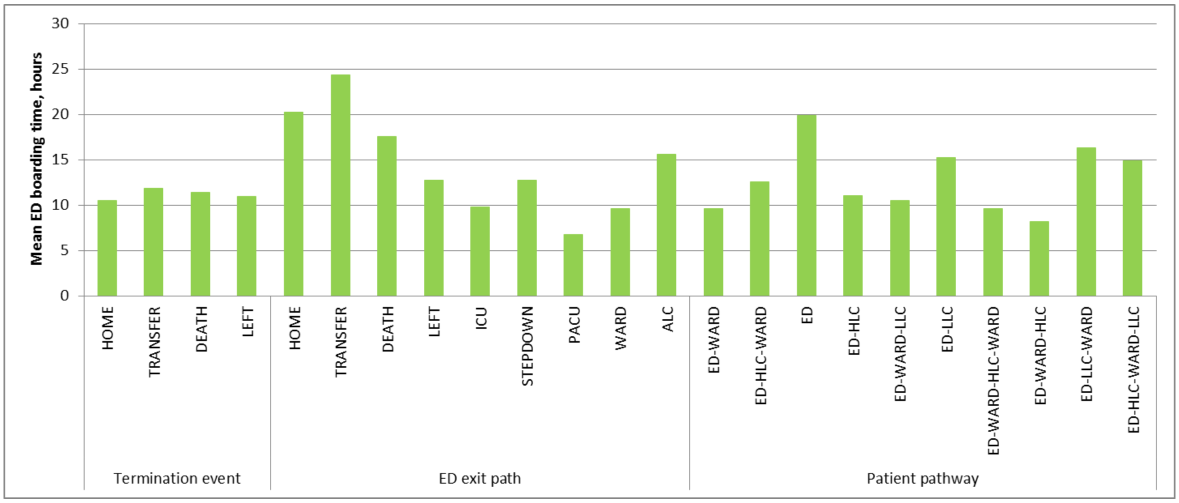


Figure 4-4 ED boarding time by patient pathway

These patient pathways were then supplemented with specific patient characteristics that captured complexity and severity (Figure 4-5). These included patient age, the Elixhauser score and a measure that captured the baseline risk of death[43] and that incorporated, age, sex, admission urgency, a comorbidity measure and the LAPS at admission.

Those patients designated as requiring a lower level of care before discharge appear to have a longer hospital stay irrespective of the type of termination event. Within a hospital pathway (i.e. those patients that follow the same pathway prior to discharge), length of stay appears to be associated with a higher comorbidity burden and a higher severity score as measured by the baseline risk of death. Patients that left against medical advice tended to be younger, had a lower comorbidity burden and were less ill. Table 4-5 details the proportion of patients that comprised these pathways over the 3-year study period.

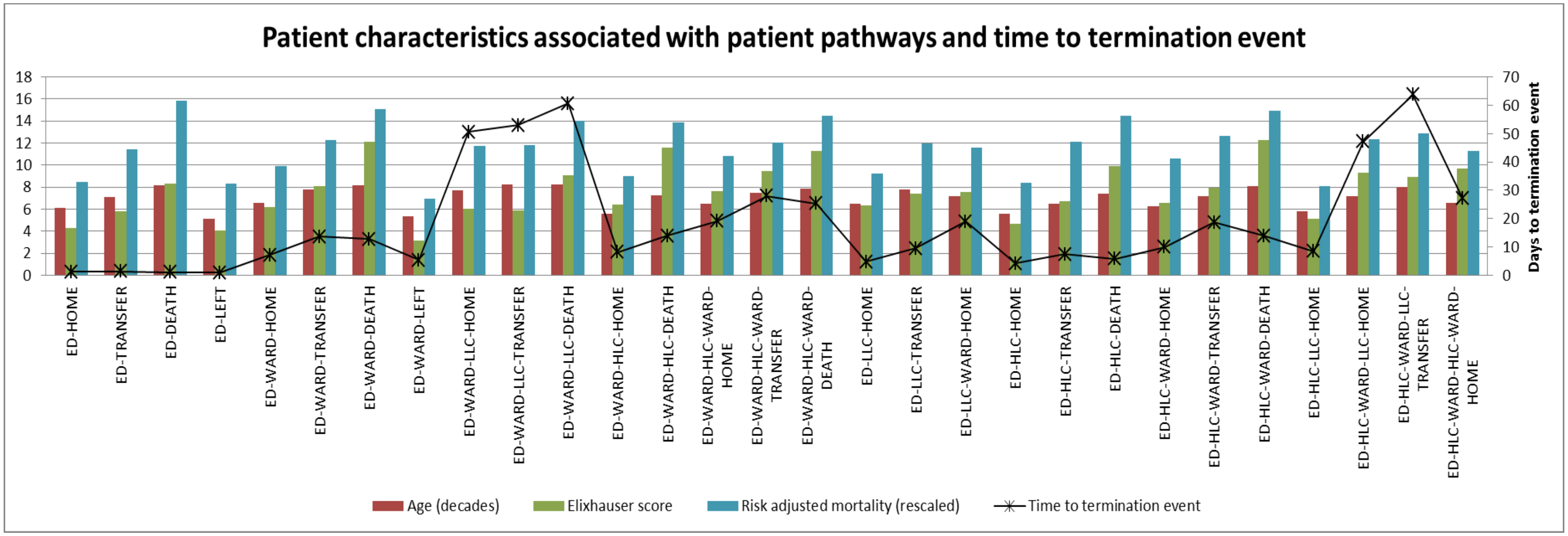


Figure 4-5 Time to termination event from time of ED registration as categorised by patient pathway and patient characteristics

Table 4-5 Proportion of patients that comprise the different hospital bed flow and discharge categories (1 January 2011 – 31 December 2013)

	Discharge, n (%)			
Hospital pathway†	**Home**	**Transfer**	**Death**	**Left**
ED	866 (4.5)	36 (0.2)	91 (0.5)	34 (0.2)
ED-WARD	10,654 (55.2)	1,620 (8.4)	828 (4.3)	103 (0.5)
ED-WARD-LLC	404 (2.1)	283 (1.5)	50 (0.3)	2 (0.0)
ED-WARD-HLC	62 (0.3)	5 (0.0)	171 (0.9)	0 (0.0)
ED-WARD-HLC-WARD	275 (1.4)	104 (0.5)	82 (0.4)	0 (0.0)
ED-LLC	469 (2.4)	47 (0.2)	17 (0.1)	0 (0.0)
ED-LLC-WARD	65 (0.3)	18 (0.1)	10 (0.1)	0 (0.0)
ED-HLC	640 (3.3)	60 (0.3)	156 (0.8)	16 (0.1)
ED-HLC-WARD	1,144 (5.9)	349 (1.8)	196 (1.0)	7 (0.0)
ED-HLC-LLC	39 (0.2)	12 (0.1)	4 (0.0)	0 (0.0)
ED-HLC-WARD-LLC	31 (0.2)	32 (0.2)	3 (0.0)	0 (0.0)
ED-HLC-WARD-HLC-WARD	35 (0.2)	20 (0.1)	9 (0.0)	0 (0.0)

†Only depicted hospital pathways that had 30 or more patients over the 3-year study period

4.3.2. *Distributions and tail events*

Both ED boarding time and hospital LOS are highly skewed to the right and are characterised by fat tails. ED boarding times ranged from almost immediate transfer to a hospital bed to a wait time of 180.6 hours for a hospital bed.

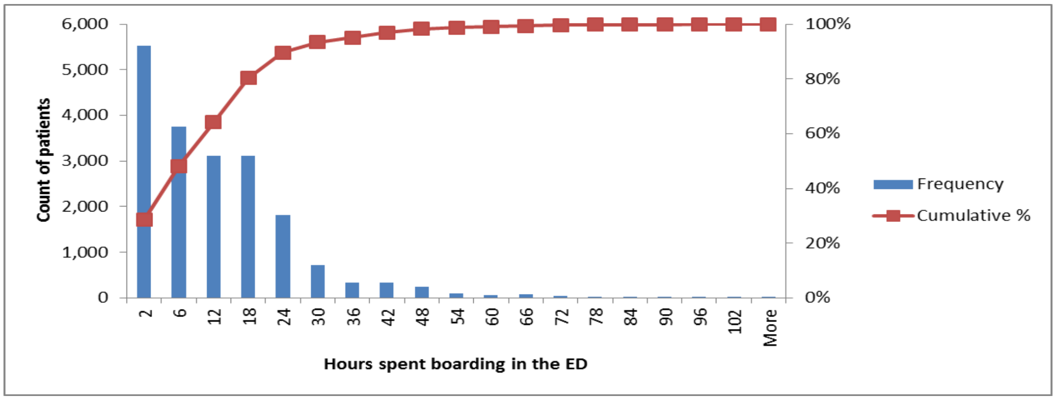


Figure 4-6 Frequency distribution of the time spent boarding in the ED

<u>Total ED length of stay tail events</u>

150 patients had a total ED length of stay that exceeded 72 hours (the upper 1st percentile of admissions had a total ED length of stay that exceeded 68.9 hours). Fitting a univariable logistic model, we found that the odds of total ED LOS exceeding 72 hours is 3.4 times higher for those that required isolation at time of admission versus those that did not require isolation (OR=3.43 95% CI 2.48-4.75).

Table 4-6 Comparing the mean and median total ED LOS by isolation status at time of admission

	N	**Mean±SD**	**Median (IQR)**
No isolation at admission	15,677	19.0±12.5	16.7 (9.6-24.9)
Isolation required at admission	3,636	22.3±16.4	19.5 (11.3-27.3)

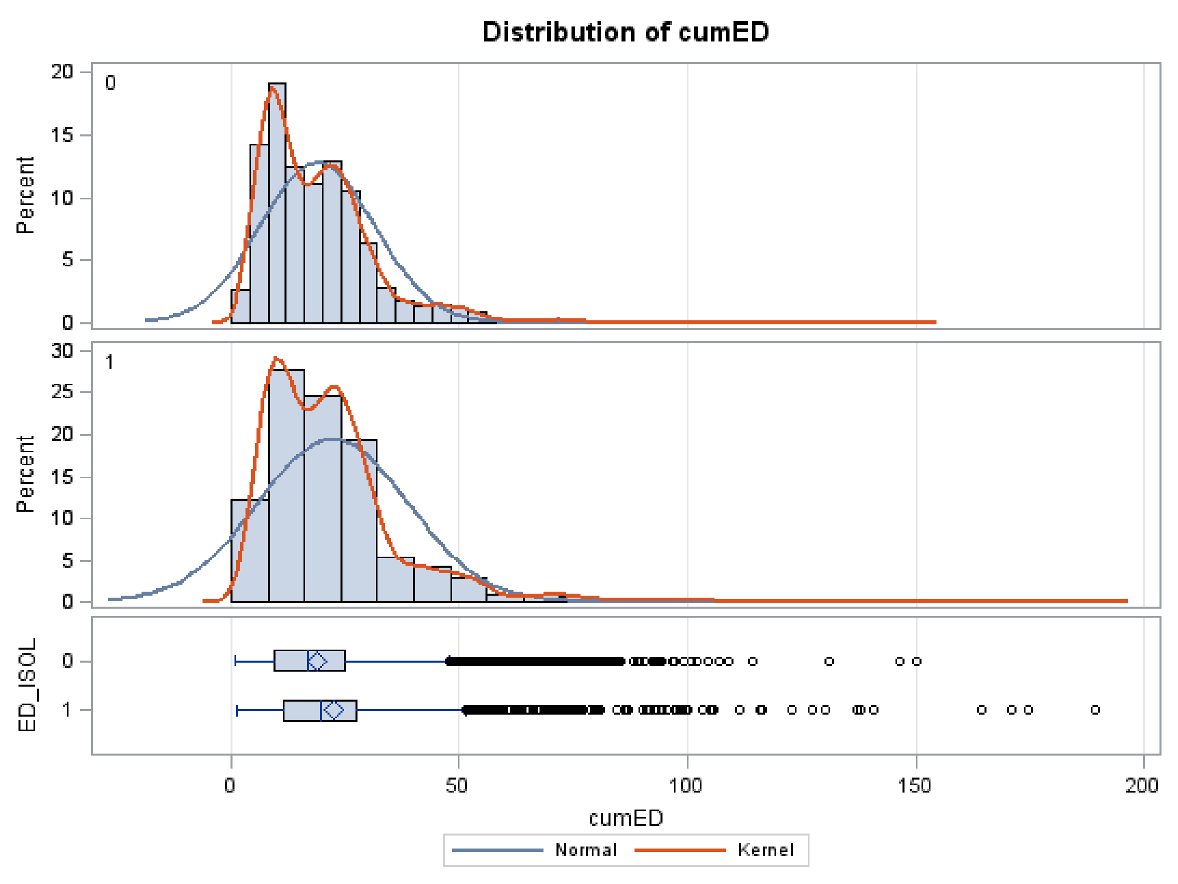


Figure 4-7 Comparing the distributions of total ED LOS by isolation status at time of admission

On average 3.3 hours were added to the ED length of stay for patients who required isolation (Table 4-6). We further analysed the patients that constituted the tail of the total ED length of stay distribution and found that the excess ED LOS in this group was driven by longer ED boarding times and not by the evaluation and treatment time in the ED (Table 4-7). Among those patients that had a total ED LOS that exceeded 72 hours, those that required isolation at admission waited on average an additional 13 hours in the ED (Table 4-7). These patients were required to wait not only for a ward bed but for a bed that provided the required level of isolation as well.

Table 4-7 Comparing the mean and median ED LOS measures for those patients that have a total ED LOS that exceeds 72 hours by isolation status at time of admission

	N	Total ED LOS (hours) Mean	ED Boarding (hours) Mean	ED Other (hours) Mean
No isolation at admission	84	83.5	72.0	11.5
Isolation required at admission	66	96.5	85.7	10.9

Emergency room evaluation and treatment time tail events

We also examined the characteristics of those patients who spent longer than 24 hours in the ED receiving emergency room care (before the decision to admit). This represented the upper 1% of time spent in the emergency room before the decision to admit. The maximum length of stay was just under 51 hours. There were 325 patients over the three year study period that exceeded the 24 hours.

Table 4-8 highlights the admission diagnoses that occur more frequently among those that made up the tail of the emergency care distribution versus the general study sample. More time might be required to evaluate or treat these conditions prior to admission to the hospital.

Table 4-8 Admission diagnoses associated with the upper 1st percentile of emergency room care

Admission diagnosis	Tail %	Sample %
Arthropathies	6.80%	1.80%
Neurological and mental disorders (excluding drug overdoses)	11.10%	6.30%
Fractures and dislocations	4.90%	0.90%
Gastrointestinal bleeding	7.70%	4.70%
Miscellaneous conditions (ICD-9: certain V codes, and all E codes)	7.40%	4.40%
All other trauma	3.40%	0.80%
Hip fracture	2.50%	0.60%

Patients that arrived during an evening shift were less likely to be a part of this tail group. The odds of being in this group were reduced by 39.4% for patients who arrived between 6pm and 6am versus those that arrived between 6am and 6pm (OR = 0.61 95% CI 0.47-0.78).

Emergency room boarding time tail events

1% of patients boarded in the ED for longer than 59.2 hours with a maximum boarding time of 180.6 days. Patients that comprised the tail of this distribution were sicker, older and more complex (Table 4-9). Tail events were all associated with higher hospital occupancy rates.

Table 4-9 Characteristics of patients that boarded in the ED for longer than 60 hours

	ED boarding exceeded 60 hours		**p-value**
	No N=19,128	Yes N=185	
Risk Adjusted Mortality			
Mean±SD	0.12±0.14	0.18±0.17	<0.0001
Median (IQR)	0.07 (0.02-0.18)	0.12 (0.04-0.25)	
Age at admission			
Mean±SD	68±19	72±18	0.0093
Median (IQR)	72 (56-83)	75 (61-86)	
Elixhauser Comorbidity Score			
Mean±SD	6.8±7.5	9.1±8.1	<0.0001
Median (IQR)	5 (0-11)	7 (3-14)	
Hospital occupancy			
Mean±SD	0.97±0.05	1.00±0.04	<0.0001
Median (IQR)	0.97 (0.94-1.00)	1.00 (0.98-1.02)	
% Weekend registration in ED	0.31	0.41	0.0023

Patients that arrived at the ED over a weekend were at a higher risk of being a part of this tail group. The odds of boarding for longer than 60 hours is 1.57 times higher for those that arrived on a weekend versus those that arrived during the week (OR=1.57 95% CI 1.17-2.11). Hospitals employ a bed management strategy to create capacity for new admissions over the weekend due to the low frequency of discharges over this period by block discharging patients on a Friday. Even with this protocol in place, new admits on a weekend are at risk of long ED boarding times as soon as these emptied beds are filled.

The patients that comprised the tail were also more likely to be discharged directly from the ED versus those patients transferred to a general ward bed. Those that were transferred to a bed that required a lower level of care on discharge from the ED were also at a higher risk of being a part of this tail group versus a patient that was transferred to a general ward bed (Figure 4-8 where TCU = Transitional Care Unit).

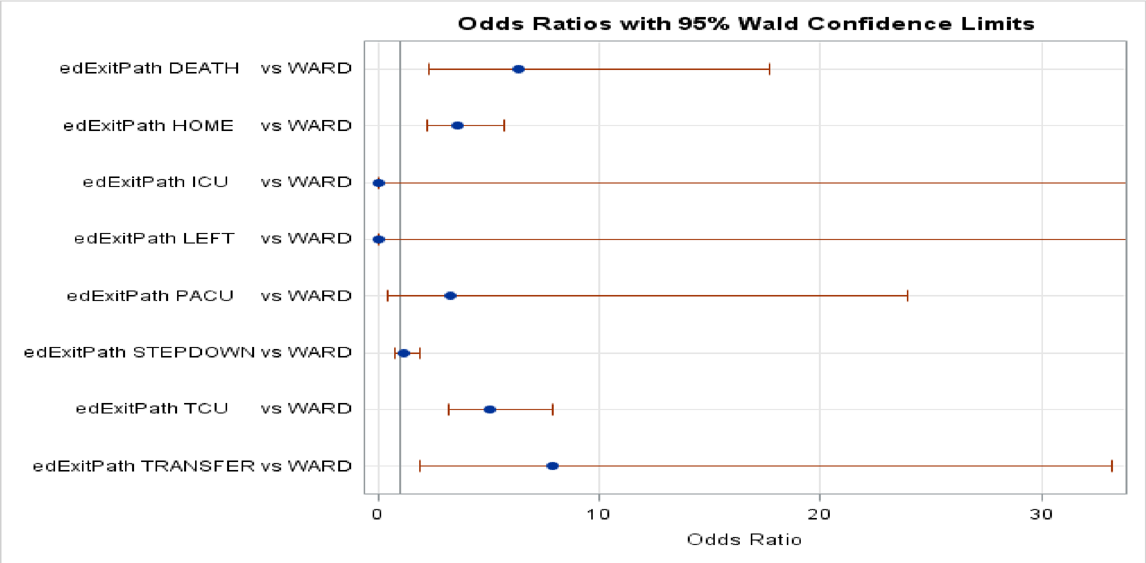


Figure 4-8 Unadjusted OR for the association between ED exit path and ED boarding time that exceeded 60 hours

4.4. Statistical modelling of associations

4.4.1. Univariable analysis

<u>Summarising time to event data in the presence of competing risks</u>

The probability of a planned medical discharge by 30-days is depicted in Figure 4-9 using the Cumulative Incidence Function (CIF) as well as the Kaplan-Meier estimate, where the probability of the event is calculated as 1-KM.

The Kaplan-Meier estimate at 30-days obtained by treating in-hospital deaths and left against medical advice as censored is 0.09. The probability of a planned medical discharge from the hospital by 30-days using this estimate is 0.91 (1-0.09) which is higher than the estimate using the

CIF (0.85). The estimate of the probability of discharge from hospital using the Kaplan-Meier estimate ignores the possibility that some patients might die prior to discharge or leave against medical advice and thus overstates the risk of the event when competing risks are present. The premise for the Kaplan-Meier estimate is that everyone will eventually experience the event which is not plausible when a patient experiences a competing event.

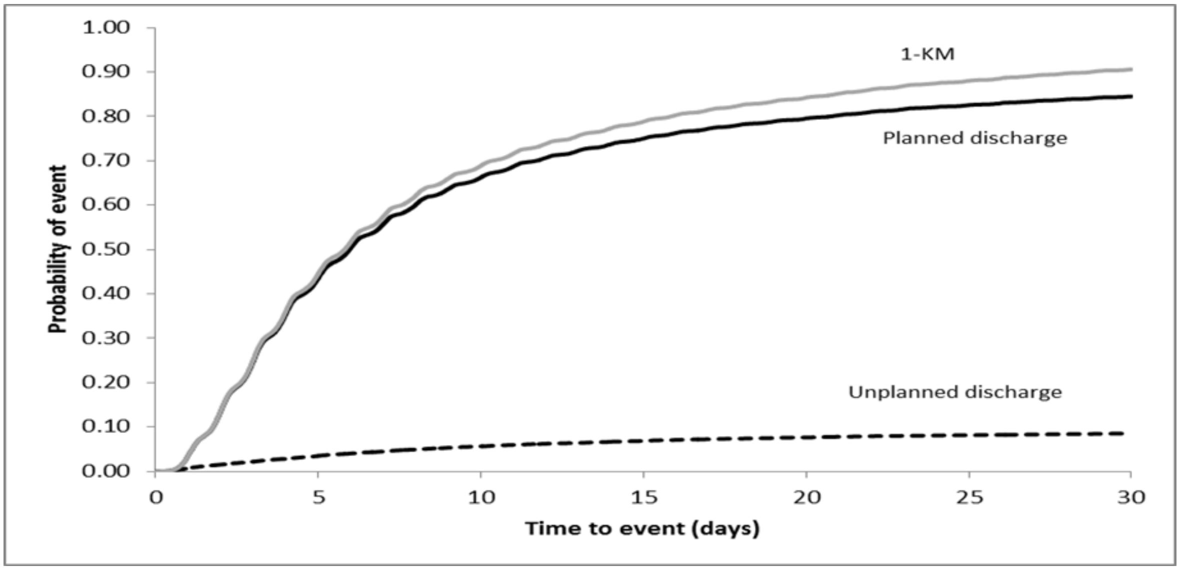


Figure 4-9 Cumulative incidence curves for the event of interest and the competing events that lead to an unplanned discharge (death and left against advice)

The impact of the different risk sets on the effect of a covariate on the hazard function for a particular failure type is also evident in this analysis. Using the log-rank test and the traditional Kaplan-Meier survival curve and associated hazard function, we found that ER triage category was significantly associated with the time to planned medical discharge ($p<0.0001$ Figure 4-10). However, when applying the Fine-Gray test, we found that this covariate was no longer significantly associated with the time to planned medical discharge (Figure 4-10, Figure 4-11).

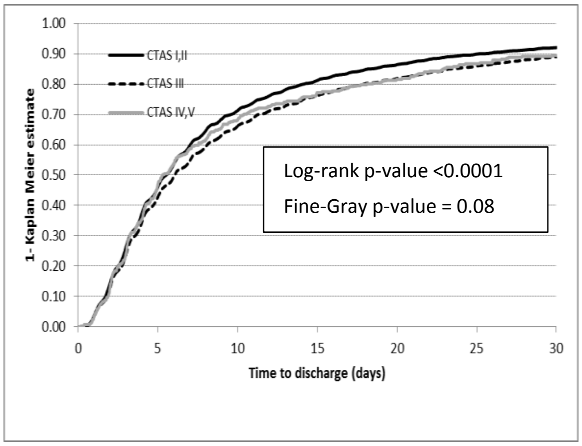


Figure 4-10 'Probability' of planned medical discharge by ER Triage category (1-Kaplan-Meier)

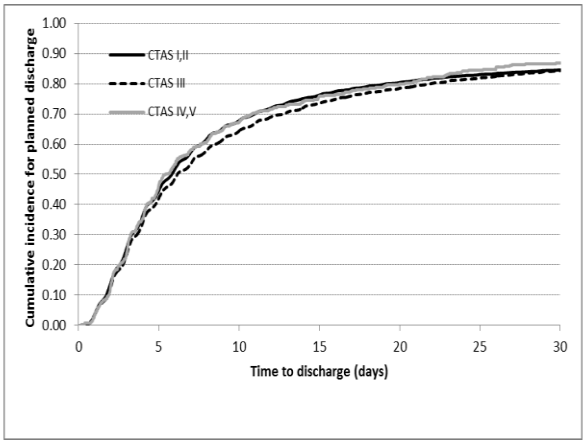


Figure 4-11 Probability of planned medical discharge by ER Triage category (CIF)

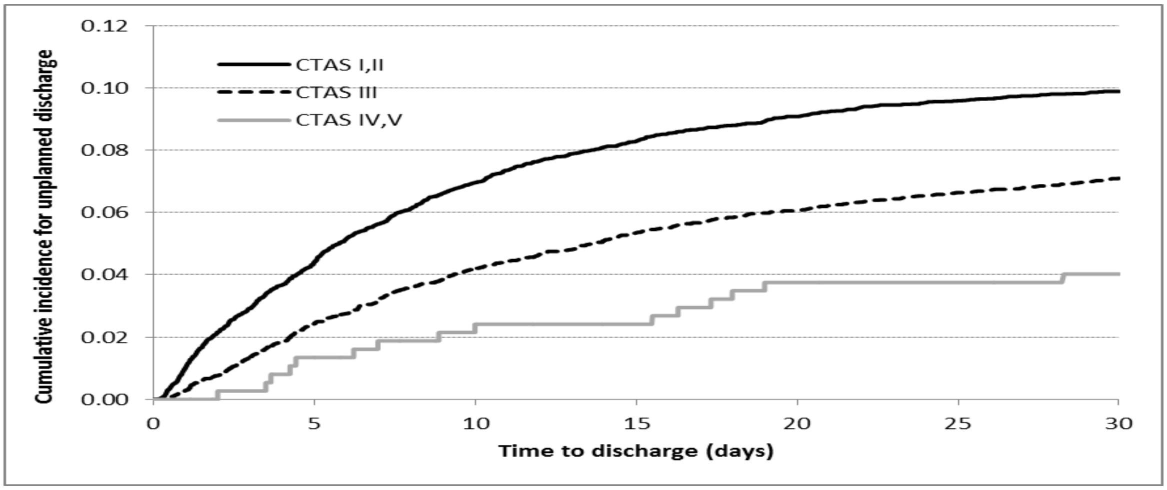


Figure 4-12 Cumulative incidence for unplanned medical discharge by ER Triage category

The log-rank statistic indicates that assuming a hypothetical scenario that in-hospital deaths did not occur and no patient left against medical advice, the probability of a planned medical discharge would be different between ER triage categories. However, the plot of the cumulative incidence curves for an unplanned discharge (in-hospital mortality or left against medical advice) highlighted that those that were categorised as CTAS I or CTAS II had a higher incidence of death compared to those in the lower severity triage categories. Although the log-rank test implies that those triaged with a higher acuity at ED registration tend to have a shorter hospital length of stay (higher probability of discharge), this grouping also has a higher incidence of in-hospital mortality, such that once adjusting for this competing event, the difference in hospital lengths of stay between the ER triage categories is no longer significant[52].

We further investigated the effect of the ER Triage category on time to discharge by adding an interaction term with $\log(time)$ to a univariable Cox regression model. The model was stratified by campus and admission diagnosis. The acuity of the patient at the time of arrival at the ED was found to significantly increase the sub-distribution hazard of discharge for the first 3 days of hospitalisation; thereafter the covariate was not significant (Table 4-10). The cause-specific HR remained significant over the observed time-periods and the observed effect remained relatively constant which is consistent with the prior analysis.

Table 4-10 Time-dependent effect of ER Triage category on the sub-distribution and cause-specific hazard ratios for discharge from hospital (CTAS I & CTAS II vs CTAS III)

Time to discharge	Sub-distribution HR	Cause-specific HR
t = 0.5 days	1.12 (1.05, 1.19)	1.06 (0.99, 1.14)
t = 1 day	1.14 (1.06, 1.22)	1.06 (1.00, 1.13)
t = 3 days	1.08 (1.03, 1.13)	1.06 (1.01, 1.11)
t = 10 days	1.04 (1.00, 1.08)	1.06 (1.02, 1.10)
t = 30 days	1.01 (0.98, 1.04)	1.06 (1.02, 1.09)
t = 100 days	0.98 (0.94, 1.01)	1.05 (1.02, 1.09)
t = 300 days	0.94 (0.91, 0.98)	1.05 (1.01, 1.09)

CTAS I and CTAS II represent a higher level of severity

The weekend effect and block discharge

The survival curves depicted in Figure 4-13 reflect the estimated probability of surviving a discharge. The probability of surviving a discharge after 6 days (or being hospitalised for longer than 6 days) for those patients who registered at an ED over the weekend was 0.4491 compared to 0.5167 for those patients who registered at the ED during the week. The median survival time (or hospital LOS) for weekend registration was 5.24 days vs 6.17 days for non-weekend registrations.

The plot of the estimated survival function for weekend registrations lies below the curve for non-weekend registrations for hospital lengths of stay between 4 to 7 days. This time interval corresponds with a Friday discharge for those admitted over the previous weekend. This pattern is repeated on a weekly basis (Figure 4-13 with hospital LOS depicted to 30-days). It appears as though the block discharge of patients on a Friday is associated with hospital LOS. We hypothesised that this effect would attenuate over time, but that does not seem to be the case as the higher probability of a planned medical discharge seems to persist to at least 30 days for those registering at an ED over the weekend.

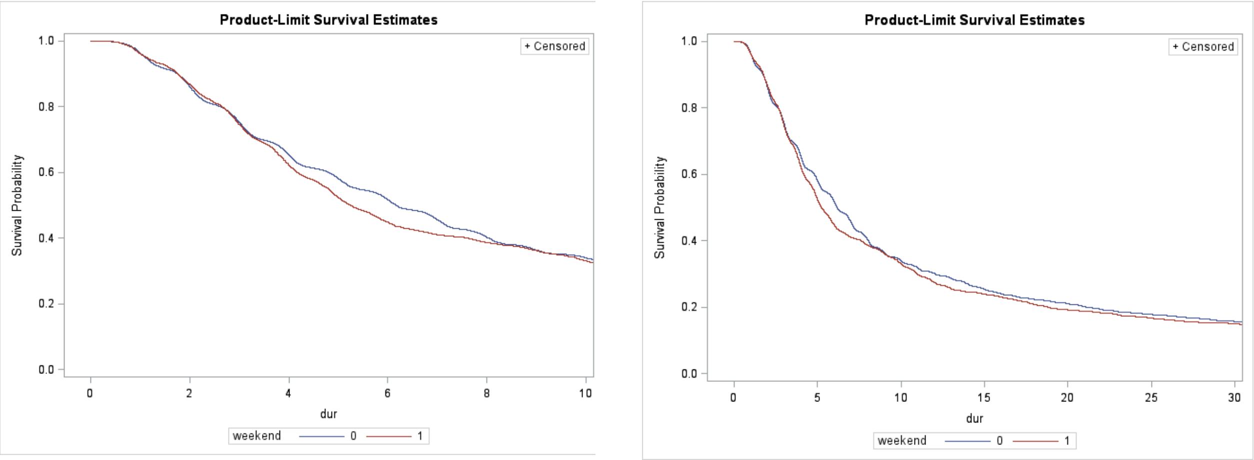


Figure 4-13 Plot of the survivor curves stratified by ED registration on a weekend

Investigating the time dependent effect of this covariate on the daily hazard of discharge, we found that the effect attenuated slightly as the time to discharge increased (Table D-1). We chose to model the effect of this covariate as time averaged for the range of times observed in the data.

Tests for non-proportionality

The plots of $\log(-log\hat{S}(t))$ versus $\log(t)$ for the time-invariant variables (arrival by ambulance, Elixhauser Score, hospitalisation in previous 6 months, LAPS at admission and patient age) depicted parallel lines and satisfied the test for PH (Appendix D). The plot stratified by shift (depicting an ED registration after hours) violated the assumption of proportional hazards as the two lines crossed at several points. The interaction term between shift and $\log(time)$ was found to be significant (p<0.0001). We investigated the HR for an after-hours shift versus a non-shift for a subset of times observed in the data. We found that the hazard ratio attenuated over time but since shift was not a predictor of interest we chose to model the effect of shift on discharge as the time averaged effect (Table D-2).

4.4.2. Multivariable analysis

We modelled the cause-specific hazards for both a planned medical discharge and in-hospital mortality (since those patients that left against medical advice comprised less than 1% of the sample cohort, we did not model this as a separate failure type) as well as the sub-distribution hazard for a planned medical discharge. For the preliminary regression models, we retained all covariates in the model as some covariates were not significant when accounting for competing risks. We also initially assumed that the relationship between the continuous variables and the log hazard of the daily risk of a planned medical discharge were linear.

The increase in the risk of the daily probability of planned medical discharge for every hour spent boarding in the ED, after adjusting for all the other variables in the model, differed by 0.2% between the sub-distribution model (accounting for competing events) and the cause-specific model (under the assumption that the patient can only experience the event of interest) and is close to the null for both models (Table 4-11). Since the event of interest is time to discharge, a HR less than 1 indicates that the factor prolongs the hospital LOS (i.e. decreases the risk of discharge).

Table 4-11 Comparison of the cause-specific HR and the sub-distribution HR for planned medical discharge

Variable	Cause-specific HR (Planned medical discharge)		Cause-specific HR (In-hospital mortality)		Sub-distribution HR (Planned medical discharge)		sdHR - csHR†
	HR (95% CI)	p-value	HR (95% CI)	p-value	HR (95% CI)	p-value	
Cumulative ED Board, hour	1.00 (1.00, 1.00)*	<.0001	1.00 (1.00, 1.01)**	0.4525	1.00 (1.00, 1.00)***	0.1761	0.20%
Cumulative ED TTD, hour	0.98 (0.98, 0.99)	<.0001	0.97 (0.96, 0.98)	<.0001	0.99 (0.99, 0.99)	<.0001	0.70%
Age (Decades)	0.94 (0.93, 0.95)	<.0001	1.42 (1.35, 1.49)	<.0001	0.94 (0.93, 0.95)	<.0001	0.30%
Sex, Female	0.97 (0.94, 1.00)	0.0401	0.96 (0.87, 1.06)	0.4249	0.98 (0.95, 1.01)	0.207	1.30%
CTAS I & II vs CTAS III	1.04 (1.01, 1.08)	0.0106	1.25 (1.12, 1.40)	<.0001	1.01 (0.98, 1.04)	0.5161	-3.20%
CTAS IV & V vs CTAS III	1.04 (0.93, 1.16)	0.4686	0.75 (0.44, 1.30)	0.3055	1.03 (0.92, 1.15)	0.5941	-1.10%
Arrival by ambulance, Yes	0.76 (0.73, 0.78)	<.0001	1.14 (1.01, 1.28)	0.0302	0.76 (0.74, 0.79)	<.0001	0.50%
Shift, (6pm-6am) vs (6am-6pm)	1.08 (1.04, 1.11)	<.0001	0.98 (0.88, 1.09)	0.7287	1.05 (1.02, 1.09)	0.0018	-2.40%
Weekend vs weekday	1.05 (1.01, 1.08)	0.0124	0.98 (0.87, 1.11)	0.7709	1.04 (1.01, 1.08)	0.0244	-0.50%
Fall vs Summer	1.02 (0.98, 1.07)	0.3113	0.93 (0.80, 1.08)	0.3265	1.02 (0.98, 1.07)	0.2928	0.10%
Spring vs Summer	1.03 (0.98, 1.07)	0.2558	1.03 (0.89, 1.19)	0.6634	1.03 (0.99, 1.07)	0.192	0.40%
Winter vs Summer	1.02 (0.98, 1.07)	0.4034	1.03 (0.89, 1.20)	0.6525	1.02 (0.97, 1.06)	0.4777	-0.30%
Hospital occupancy (deciles)	0.95 (0.92, 0.99)	0.0085	1.03 (0.91, 1.16)	0.6335	0.95 (0.91, 0.98)	0.0021	-0.80%
Previous admission, Yes	0.92 (0.88, 0.95)	<.0001	1.24 (1.11, 1.40)	0.0003	0.89 (0.86, 0.93)	<.0001	-2.30%
Elixhauser score	0.99 (0.98, 0.99)	<.0001	1.01 (1.00, 1.02)	0.0022	0.99 (0.99, 0.99)	<.0001	0.30%
LAPS	0.99 (0.99, 0.99)	<.0001	1.04 (1.04, 1.04)	<.0001	0.99 (0.99, 0.99)	<.0001	-0.20%
Isolation, Yes	0.80 (0.76, 0.84)	<.0001	1.10 (0.96, 1.25)	0.1667	0.80 (0.77, 0.84)	<.0001	0.20%
LOC ALC vs WARD	0.70 (0.66, 0.75)	<.0001	0.34 (0.27, 0.42)	<.0001	1.31 (1.24, 1.38)	<.0001	60.50%
LOC AMA vs WARD	0.49 (0.44, 0.54)	<.0001	0.98 (0.77, 1.26)	0.8844	0.47 (0.43, 0.52)	<.0001	-1.70%
LOC ED vs WARD	0 (0, 7.986E+25)	0.7842	0 (0, 1.42E+143)	0.9465	0 (0, 6.293E+24)	0.7696	0.00%
LOC EDBOARD vs WARD	2.07 (1.88, 2.27)	<.0001	1.54 (1.11, 2.13)	0.0094	1.11 (1.02, 1.21)	0.0121	-95.60%

Abbreviations: sdHR = sub distribution hazard ratio, csHR = cause specific hazard ratio, ED TTD = Time to decision to admit

Hazard ratios for Cumulative ED board increased to 3 decimals: * csHR = 0.997 (0.995, 0.998); ** csHR = 1.002 (0.997, 1.006); ***sdHR = 0.999 (0.998, 1.000)

† sdHR – csHR = the impact of risk sets on covariate effect size (difference between the sub-distribution HR and the cause-specific HR)

We found that the patient risk factors: arrival by ambulance, isolation status and level of nursing care were strongly associated with the cause-specific hazard function for planned medical discharge. ER triage category, a hospitalisation in the previous 6 months, patient age and the levels of care denoted ALC, ICU and ED boarders were strongly associated with the cause-specific hazard of in-hospital mortality. These strong associations with a competing risk could lead to an under or over representation of patients with these characteristics in the risk set when modelling the cause-specific hazard function for the event of interest.

The effect of this under-representation is seen in the slightly attenuated effect sizes when comparing the hazards for the cause-specific model and the sub-distribution model (ICU: csHR = 0.15 vs sdHR = 0.12, previous hospitalisation: csHR = 0.92 vs sdHR = 0.89). Overall the only significant differences in the effects of the covariates between the cause-specific and sub-distribution models were those patients designated ALC and those patients boarding in the ED.

The cause-specific HR for planned medical discharge for a patient designated ALC is 0.7 (95% CI 0.66-0.75). This implies that the risk of the daily probability of a planned medical discharge is reduced by 30% for a patient that is designated ALC vs an acute-patient occupying a general ward bed, adjusted for all other variables in the models and assuming that the patient cannot experience an unplanned medical discharge (which is considered to be much lower for this group). The sub-distribution HR is 1.31 (95% CI 1.24-1.38) which implies that the risk of the daily probability of a planned medical discharge increases by 31% when accounting for competing events. This result seems counter intuitive since ALC status usually leads to a delay in discharge and to a longer hospital length of stay.

We added a time interaction term to the LOC variable to better understand this association and to help to explain the effect. We found the effect of ALC status vs an acute-care patient on the daily hazard of discharge changes significantly over time (Table 4-12).

Table 4-12 Testing the proportional hazard assumption for the LOC covariate

Time (days)	LOC vs WARD	HR 95% CI
0.5	EDBOARD vs WARD	2.27 (2.03, 2.53)
1	EDBOARD vs WARD	1.63 (1.48, 1.79)
2	EDBOARD vs WARD	3.16 (2.76, 3.61)
3	EDBOARD vs WARD	1.33 (1.21, 1.47)
4	EDBOARD vs WARD	1.17 (1.05, 1.30)
5	EDBOARD vs WARD	1.05 (0.94, 1.17)
0.5	ALC vs WARD	0.02 (0.02, 0.03)
1	ALC vs WARD	0.03 (0.03, 0.05)
2	ALC vs WARD	0.05 (0.04, 0.06)
3	ALC vs WARD	0.06 (0.05, 0.08)
4	ALC vs WARD	0.07 (0.06, 0.09)
5	ALC vs WARD	0.08 (0.07, 0.10)
10	ALC vs WARD	0.12 (0.10, 0.15)
30	ALC vs WARD	0.23 (0.20, 0.27)
100	ALC vs WARD	0.44 (0.39, 0.49)
200	ALC vs WARD	0.64 (0.59, 0.70)
300	ALC vs WARD	0.83 (0.77, 0.89)
400	ALC vs WARD	0.94 (0.88, 1.01)

Time (days)	LOC vs WARD	HR 95% CI
0.5	AMA vs WARD	0.63 (0.53, 0.75)
1	AMA vs WARD	0.59 (0.51, 0.69)
2	AMA vs WARD	0.67 (0.54, 0.83)
3	AMA vs WARD	0.57 (0.50, 0.65)
4	AMA vs WARD	0.55 (0.49, 0.63)
5	AMA vs WARD	0.54 (0.48, 0.61)
10	AMA vs WARD	0.51 (0.46, 0.56)
30	AMA vs WARD	0.46 (0.41, 0.50)
0.5	ICU vs WARD	0.12 (0.06, 0.22)
1	ICU vs WARD	0.12 (0.07, 0.21)
2	ICU vs WARD	0.11 (0.06, 0.23)
3	ICU vs WARD	0.12 (0.07, 0.20)
4	ICU vs WARD	0.12 (0.08, 0.20)
5	ICU vs WARD	0.12 (0.08, 0.19)
10	ICU vs WARD	0.13 (0.09, 0.19)
30	ICU vs WARD	0.13 (0.10, 0.18)

The proportional hazard assumption is clearly violated for this time-varying variable. We removed ALC from the time-varying LOC variable and modelled ALC designation as a separate time-varying variable that identified if a patient was designated as ALC at each 6 hour interval. We also included an interaction term with $\log(time)$ to correctly account for the time-dependent nature of ALC.

We determined the functional form of the continuous variables and statistically significant covariates using the MFP algorithm. We forced the retention of both the time-varying ED length of stay variables in the model and set $\alpha=0.05$ to determine statistical significance for inclusion of the other covariates in the model. Sex and ER Triage category were dropped from the model. The best fist degree functional polynomial for all the continuous variables except age and LAPS were found to be linear. The best fit functional polynomial for age and LAPS was a cubed function. The final model is depicted in Table 4-12.

Final Cox regression model

After adjusting for patient characteristics and hospital risk factors, we found that ED boarding time was not significantly associated with risk of discharge and hospital LOS ($_{sd}$HR= 0.992, 95% CI 0.984-1.001, Table 4-13). The daily hazard of discharge is decreased by 0.8% for every 6 hours spent boarding in the ED; this equates to an estimated increase in the overall hospitalisation of 1.2 hours for each extra 6 hours spent in the ED awaiting for a bed (for an average length of stay of 6.2 days).

Table 4-13 Effect of ED boarding time on the time to planned medical discharge for those patients admitted to a medicine service at TOH via the ED, January 2011 – 31 December 2013

	Adjusted sub-distribution HR (95% CI)	p-value
Exposure to time spent in the ER		
ED boarding time, 6 hours	0.99 (0.98, 1.00)	0.0703
ED Time to Decision, 6 hours	0.93 (0.92, 0.95)	<.0001
Patient & encounter characteristics		
Age at admission (in decades, cubed)	1.00 (1.00, 1.00)	<.0001
Elixhauser comorbidity score, 10 points	0.87 (0.85, 0.89)	<.0001
Hospital admission in previous 6 months	0.90 (0.87, 0.94)	<.0001
Arrival by ambulance	0.77 (0.74, 0.79)	<.0001
Arrival at ER after 6pm and before 6am	1.06 (1.03, 1.10)	0.0003
Arrival at ER over weekend*	1.04 (1.01, 1.08)	0.0162
Hospital occupancy (deciles)	0.94 (0.91, 0.98)	0.0008
Time-varying covariates		
LAPS (units of 10, cubed)	1.00 (1.00, 1.00)	<.0001
Type of bed (level of care)		
WARD	REF	
AMA – Acute Monitoring Area	0.47 (0.43, 0.51)	<.0001
ICU – Intensive Care Unit	0.14 (0.11, 0.18)	<.0001
Isolation	0.80 (0.76, 0.83)	<.0001
ALC status at 1 day	0.03 (0.02, 0.04)	
ALC status at 5 days	0.08 (0.06, 0.10)	
ALC status at 11 days	0.12 (0.10, 0.14)	
ALC status at 35 days	0.23 (0.20, 0.27)	
ALC status at 100 days	0.45 (0.40, 0.50)	
ALC status at 200 days	0.67 (0.61, 0.73)	

The model is stratified by campus and primary condition

We found that those variables which captured the complexity and severity of the patient had the strongest effect on the daily hazard of discharge; these included a patient's comorbidity score, arrival by ambulance, isolation status and patients requiring a higher level of nursing care (AMA and ICU). Patients designated ALC also had a pro-longed length of stay alluding to the need for long term care beds in the community.

4.4.3. *Model assessment*

The hospital length of stay model was discriminative with a concordance probability of 0.660 (95% CI 0.655—0.664). The inclusion of time-varying variables in the model increased the discriminatory ability of the model. The concordance probability using only baseline covariates was 0.536 (95% CI 0.533-0.540) which is only slightly better than a random prediction.

4.4.4. *Sensitivity analysis*

We found no difference in the model results for the predictor of interest (ED boarding time) when including all hospitalisations that occurred during the study period and that met the eligibility requirements. We also satisfied ourselves that by modelling the predictor of interest as a time-varying variable that the results are not a result of reverse causation (tested the effect of excluding those patients that were discharged directly from the ED and who were not transferred to a ward bed). The same holds for the time-varying nature of ALC. Potential outliers had no effect on the measured association between ED boarding time and hospital length of stay.

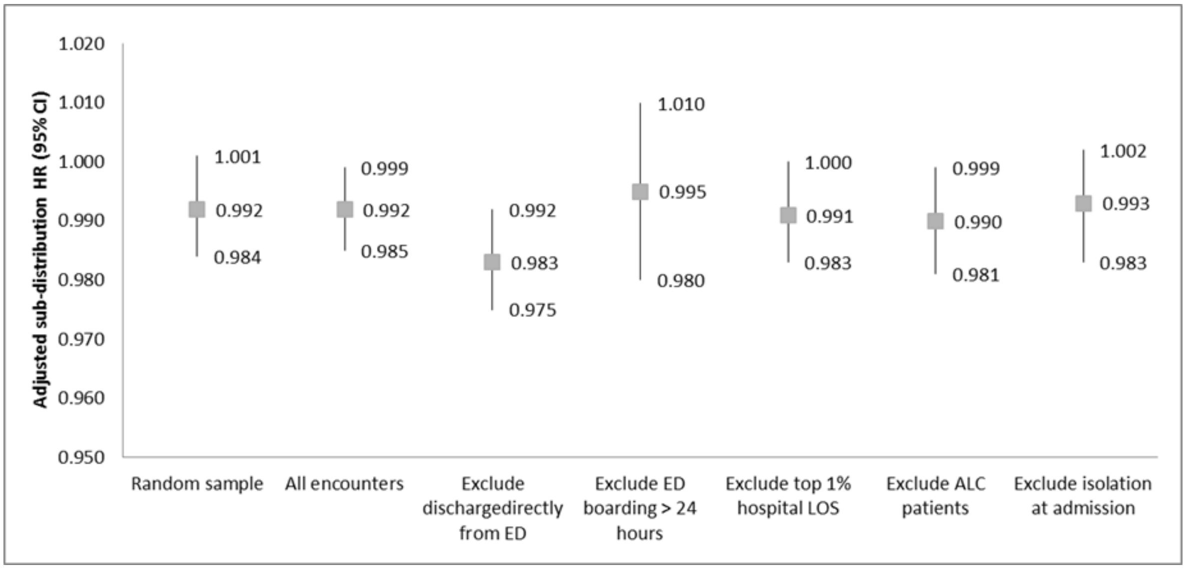


Figure 4-14 Model sensitivity analysis for the association between ED boarding time (in units of 6 hours) and hospital LOS accounting for in-hospital mortality and left against medical advice.

4.5. Economic evaluation

4.5.1. Base-case analysis

The cost associated with increasing the number of acute-care beds to reduce ED boarding times such that 90% of patients are transferred to a ward bed within 6 hours resulted in an increased cost per admission of $263.79. Assuming an average daily inpatient census for medicine patients of 225 and an inpatient length of stay of 10.15 days (after increasing the number of acute-care beds), the estimated annual increase in operating costs for TOH is $2,139,163 (Table 4-16). It is important to note that these results assume that the increased bed capacity is only utilised for emergency medicine patients and that these additional beds are not utilised by other elective admissions and thus negate the spare capacity created. It also assumes that current discharge practices do not change due to the availability of the extra beds and in so doing impact hospital LOS.

The results of this model are based on the monetised benefits of: substituting more expensive ED nursing care for less expensive ward nursing care; the modelled benefits of receiving a ward bed sooner and being able to transition to other states within the model (based on the modelled transition probabilities); and a small decrease in inpatient length of stay due to the intervention. These benefits are offset against the costs associated with creating bed capacity in the hospital and ensuring the availability of a bed on the ward at the time the decision is made to admit the patient in the ED (Table 4-15).

Table 4-14 Impact of the increased acute-care beds intervention on ED boarding, hospital LOS and nursing cost per admission (Base case analysis)

	Current bed capacity	Increased bed capacity	Incremental cost & benefit
Average ED boarding (hours)	10.85	1.85	-9.00
Average LOS (days)	10.26	10.15	-0.12
Average nursing cost per admission ($)	$5,624.69	$5,888.48	$263.79

Table 4-15 Cost benefit analysis of the increased acute-care beds intervention

Cost drivers	**Increased cost per admission**
Benefits	**$423.75**
Reduced ED nursing costs	$223.45
Other modelled benefits of receiving a ward bed sooner	$200.30
Costs	**$687.27**
Ward nursing costs	$687.27
Substitution of ED nurses with ward nurses	*$179.37*
Cost of creating capacity	*$507.90*
Net estimated increased cost per admission	**$263.79**

Table 4-16 Cost of meeting the Ontario Wait Time Strategy

				ED boarding times # Patients* that receive a ward bed within the specified time intervals (%)			
# Beds	**# Inpatients**	**Increased cost per encounter**	**Expected annual cost**	**6 hours**	**12 hours**	**18 hours**	**24 hours**
201	225			11 (46)	16 (71)	19 (84)	21 (91)
251	225	$264	$2,139,163	21 (90)	23 (99)	23 (100)	23 (100)
Additional number of patients that receive a bed				10	7	4	2

**Based on 23 admissions per day to a medicine service via the ED*

The benefit of the increased beds and creating the additional capacity has the biggest benefit at the short end of the ED boarding curve. Patients that are admitted while the newly created beds are not occupied receive a bed almost immediately. However once these beds are fully occupied, the wait time for a newly admitted patient after the intervention is similar in length to prior to the bed expansion (Table 4-15). This is a pattern that was evidenced when analysing the association between patients that comprised the tail end of ED boarding times and admission over a weekend. Even with a bed management strategy in place to free up beds before a weekend, once these beds were occupied, newly admitted patients were forced to wait until a patient was discharged from hospital.

4.5.2. Deterministic sensitivity analysis

Although we found no significant association between ED boarding time and hospital length of stay, a sensitivity analysis that assumed no benefits (i.e. a patient boarded for the same length of time before and after the intervention and the time to planned medical discharge did not change) resulted in an increased cost of $1.8m (Table 4-20). The model therefore assigns a benefit attributable to these patients now being modelled as WARD patients, rather than ED boarders, and their ability to transition to the other health states in the model as defined by the transition probabilities.

The results are particularly sensitive to hospital occupancy levels. This is because the costs related to this fixed intervention (assumed no ability to flex staff at low occupancy levels) are spread over fewer patients leading to an increased cost.

A scenario that assumed that ALC patients could be discharged in the same fashion as a ward patient not designated ALC showed that the cost of increasing acute-care beds could be reduced by $1.3m. This is due to a reduction in the average hospital length of stay for the study cohort. The hospital would also benefit from an estimated once-off saving of $7.6m in the first year of the implementation of a solution for ALC patients in the acute-care setting. ALC patients were responsible for increasing the average length of stay of the cohort by 2 days. The modelled average inpatient length of stay reduced to 8.17 days from 10.26 days when ALC patients were modelled similarly to non-ALC acute-care patients. The cost of the intervention for the hospital would also be greatly reduced if the patient-to-nurse-ratio could be changed within the hospital for those patients designated ALC. Table 4-17 summarises the results of the deterministic sensitivity analysis.

Table 4-17 Results of the deterministic sensitivity analysis

	Model results		**Model sensitivity**	
Scenario	**Increased cost per admission**	**Expected annual cost**	**Δ cost per admission**	**Δ cost per annum**
Base-case	$264	$2,139,163		
Assumed the intervention delivered no benefits	$499	$4,000,096	$235	$1,860,933
Occupancy reduced by 10%	$828	$6,717,197	$565	$4,578,034
Decreased nursing costs by 10%	$223	$2,045,261	($41)	($93,902)
Increased nursing costs by 10%	$290	$2,353,080	$26	$213,916
Change in effect size upper 95% CI HR=1.008 (95% CI 0.999-1.016) Daily hazard of discharge for a 6 hour decrease in time spent boarding	$252	$2,049,624	($12)	($89,540)
Change in effect size lower 95% CI HR=1.008 (95% CI 0.999-1.016) Daily hazard of discharge for a 6 hour decrease in time spent boarding	$277	$2,240,759	$13	$101,595
Assumed an effect size of 6 hours HR=1.04	$232	$1,894,626	($32)	($244,537)
Assumed an effect size of 24 hours HR=1.20	$77	$646,084	($187)	($1,493,079)
Reduced average LOS for cohort by 2 days Replaced current ALC patients with the same discharge probabilities as a WARD patient together with the increased bed intervention This resulted in a decrease in hospital LOS of 2 days This represented a potenital once-off saving to the hospital as this LOS would become the new base-case scenario	($753)	($7,584,284)	($1,017)	($9,723,447)
ALC patients replaced with WARD patients The annual operating costs of the intervention would decrease by $831,946 if ALC patients were discharged efficiently	$130	$1,307,217	($134)	($831,946)
Reduced the nursing costs for ALC patients (12% of beds were assigned a higher patient to nurse ratio)	($41)	($332,791)	($305)	($1,806,372)

Note: The deterministic sensitivity analysis only changed one model input at a time.

We assumed no change in ED boarding times or changes to the transition probabilities except those specifically modelled in the scenario.

4.5.3. Probabilistic sensitivity analysis

The distribution of possible increased annual operating costs as derived by the Monte Carlo simulation are depicted in Figure 4-15. There is a 5% probablity that the costs could exceed $3,052,230. This higher cost is associated with a longer hospital LOS and/or a smaller benefit in the reduction in hospital LOS due to the intervention (Table 4-18).

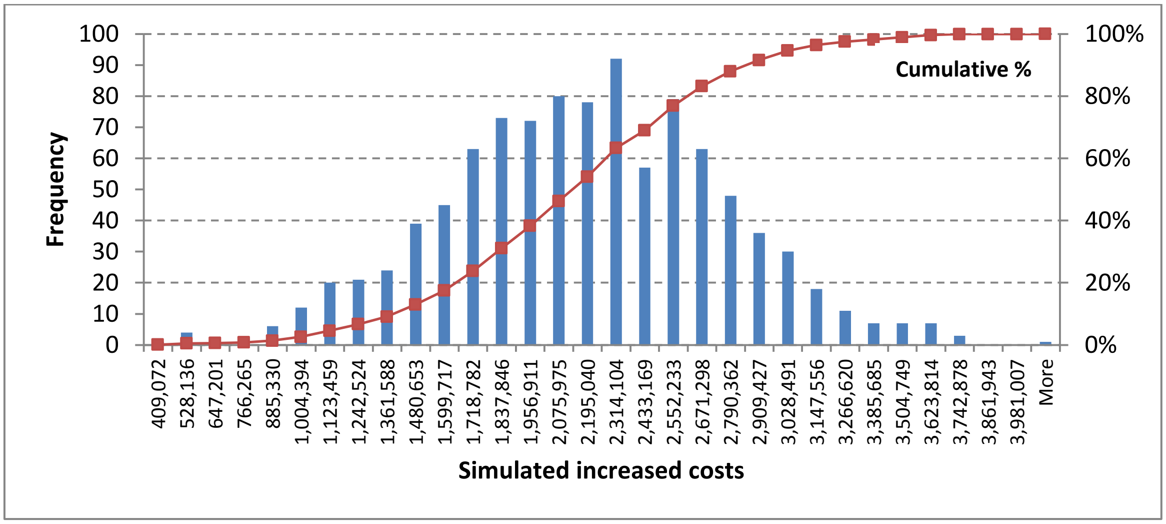


Figure 4-15 Monte Carlo simulation results

Table 4-18 Probabilistic sensitivity analysis for the increased acute-care beds intervention

	Model outputs				
Distribution statistics	**LOS (Days) Current bed capacity**	**LOS (Days) Increased bed capacity**	**Reduced hospital LOS (Hours)**	**Increased cost per admission**	**Increased annual cost**
95th percentile	10.50	10.31	2.18	$377	$3,052,230
Average	10.27	10.14	-2.76	$263	$2,128,425
Median	10.26	10.15	-2.69	$265	$2,141,362
5th percentile	10.03	9.98	-8.04	$144	$1,172,070

5. Discussion

We found no significant association between the time spent boarding in the ED and hospital length of stay after adjusting for competing risks (in-hospital mortality and left against advice) and patient and hospital risk factors independently associated with hospital length of stay.

Two of the studies in the literature review examined the association between ED barding time (the time interval from the decision to admit to discharge from hospital) and hospital length of stay. Both these studies found a significant association between ED boarding time and hospital length of stay. Singer et al.[28] showed that those that boarded between 2-6 hours spent 0.23 days longer on the ward than those that boarded for less than 2 hours. This increased to 0.49 days for those boarding between 6-12 hours; 0.74 days for those boarding between 12-24 hours and 1.93 days for those boarding for more than 24 hours. The authors did not correct for the skewed nature of length of stay data and no adjustment was made for patient severity or risk of mortality. There was also no adjustment in the model or data for competing risks.

Derose et al.[26] found that the first 14 hours of ED boarding added 6 hours to the admission length of stay and reported that boarding in the ED was not simply a substitute for time spent on the ward. Our model estimates that 14 hours of ED boarding would decrease the daily hazard of discharge by 1.9% (although not statistically significant) and translates to an average increase in inpatient length of stay of 2.7 hours, 95% CI (-0.25 hours; 5.12 hours). Our results therefore refute the finding that the care received as an inpatient boarding in the ED is not equivalent to the care that would be received on the ward as is evidenced by a longer time to discharge from the hospital. Derose did not consider the impact of competing events in their analysis.

Huang et al.[29] used a 12 hour cut-point applied to the time interval from arrival in the ED to the decision to admit to define a delayed ED encounter and a measure that was indicative of a system that was not functioning as it should. They found that patients that were delayed in this fashion had an inpatient length of stay that was on average 1.2 days longer than those for whom the time to decision to admit was 12 hours or less. Although this time interval was not the predictor of interest in our study, we adjusted for this time spent receiving emergency care in our model. We found that for every 6 hours spent receiving emergency care, the daily hazard of discharge decreased by 6.7% (95% CI: 5.0%-8.5%, Table 4-12). We found that those in our sample cohort that spent longer than 12 hours in the ED before the decision to admit was taken had on average an inpatient length of stay that was 0.5 days longer.

It would seem that a delayed decision to admit has a larger impact on hospital length of stay than the time an inpatient spends boarding in the ED waiting for a bed. We did not divide this time interval into waiting time and evaluation and treatment time. It is therefore difficult to ascertain if this increased length of stay is due to delays in treatment or residual confounding where we haven't been able to adequately adjust for the peculiarities of this group of patients that require additional evaluation and treatment time in the ED. Analysing the group of patients that form part of the upper 1% of time spent in the emergency room prior to the decision to admit, we found that the odds of being part of this group was increased 64% if the patient registered in the ED between 6am and 6pm (the busiest time in the ED) and this could allude to delays in receiving care. We also found that certain admission diagnoses were prevalent among this group possibly requiring a longer evaluation and treatment time.

None of the studies that comprised the literature review used survival analysis or a modelling technique that was able to account for competing risks or time-varying variables. Length of stay data is epitomised by outliers and a non-normal statistical distribution lending itself to a model that does not assume any distribution. A hospital stay is also terminated in different ways, each of which has an impact on the length of stay statistic. The mean LOS for patients that died in hospital was 15.2 days, for those that left against medical advice the mean LOS was 4.6 days and for those that had a planned medical discharge the mean LOS was 10.5 days. Averaging over these discharge dispositions could lead to erroneous conclusions especially when considering length of stay as a patient quality metric and a performance measurement. We used a Cox regression model that allowed the modelling of a specific termination event accounting for the other events and that did not make any assumptions about the underlying distribution of the data.

Authors that comprised the literature review raised concerns about using the time spent boarding in the ED as part of both the exposure measure and the outcome measure. 5.3% of patients in our study cohort were discharged directly from the ED (prior to being transferred to a ward bed). For this group of patients the exposure measure and outcome measure would be identical. We were able to model the exposure time in the ED as a time-varying covariate and adjust for any improvement in the health state of the patient during this time using a laboratory based physiology score. The laboratory score also provided data of a high quality that could be used to adjust for severity that was not open to coding errors as most of the other variables used to adjust for severity are.

We found that isolation status had a significant effect on the daily probability of discharge. The daily probability of discharge was reduced by 20% for a patient that was classified as requiring some level of isolation. Hospital isolation protocols govern isolation periods and who may discontinue isolation potentially impacting hospital length of stay for these patients. The impact of isolation status also adds a new dimension to understanding access block as patients remain in the ED until a ward bed that meets the specific isolation requirements becomes available. We found that isolation at admission added on average an additional 13 hours to the total ED LOS time for those that comprised the tail for ED length of stay. Further research regards the impact of isolation protocols on bed capacity planning and management in hospitals is required.

The estimated annual investment required by TOH to ensure that 90% of patients admitted to a medicine service are transferred to a ward bed within 6 hours is $2,139,163. A sensitivity analysis showed that this annual increase in nursing costs could be reduced by $831,946 if those patients designated ALC could be efficiently discharged to a facility that provided a lower level of nursing care when needed. This saving is driven by a drop in the average inpatient LOS from 10.3 days to 8.2 days.

Our analysis has shown that hospital length of stay will not be impacted by moving patients to a ward bed sooner. However, the fact that these patients still reside in a bed that is meant for emergency care remains a concern. Current ED wait time targets require that 9 out of 10 admitted patients have a total ED LOS of 8 hours. The 90th percentile for ED length of stay for TOH over the 3 year study period was 34 hours. TOH will need to increase bed capacity (or reduce occupancy levels) to achieve the wait time target. This can be achieved by TOH increasing the number of acute-care beds at its two campuses. A more efficient solution would be a health-system solution that led to an increase in alternate level of care beds outside of the acute-care system such that a patient designated as ALC could be discharged to these beds without delay and supplemented with a smaller increase in the number of acute-care beds.

Study limitations

The analysis is based on admissions at a single Canadian, tertiary-care academic hospital and results might not be generalizable to other settings. The hospital is characterised by high occupancy rates and long ED wait times for admitted patients and hospital staff might have adapted to working under these conditions. Since we modelled the association between ED boarding time and hospital length of stay using the sub-distribution model, the results of this study can only be generalised to hospitals with similar competing event rates. This study was a retrospective cohort study using administrative data and limited clinical data and as such we are restricted in our ability to fully adjust for case-mix and the complexity and severity of illness. We have however supplemented the usage of ICD codes with both a laboratory physiology score and by dynamically capturing the nursing care the patient received to alleviate both the paucity of information associated with administrative data and the accuracy thereof.

We were unable to quantify all the potential benefits associated with increasing acute-care beds. We did not quantify the benefits of the increased beds intervention for admitted patients prior to the decision to admit or for visitors to the ED who were not admitted. We estimated that the increased beds would lead to a reduction of 8 hours in ED boarding time on average per admission. With an average 23 patients admitted via the ED across the two campuses on a daily basis this equates to approximately 8 additional beds available across the two campuses on a daily basis. The benefits associated with this 10% increase in ED bed capacity have not been quantified.

Case costing data was used to derive the average nursing costs per hour for the different levels of nursing care. We used the actual costs accrued for the 2013/2014 financial year up until the 31 October 2013. As this does not represent a full financial year, the period did not include the winter months which are known to be associated with higher occupancy levels and thus the average nursing costs could be understated as the full impact of overtime nursing costs would not be captured. The model results are also sensitive to the average hospital LOS both prior to and post the increased bed intervention. For hospitals with a shorter hospital LOS, the cost of the intervention would be reduced.

6. Conclusion

The reduction in ED boarding times by increasing acute care beds addresses the factor most often associated with ED crowding, viz. the inability to move an admitted patient to a ward bed. This reduction in ED overcrowding should improve ED efficiencies and patient outcomes related to timely and effective care[9]. The fact that we found no association between the times a patient spent boarding in the ED and hospital LOS has significant implications for hospitals that are required to meet the provincial ED wait time targets.

The economic model has shown the potential investment that a hospital would need to make to meet the provincial ED wait time targets if the hospital were to act in isolation. The analysis also showed that increasing acute-care beds is not the most efficient solution if alternate level of care beds could be increased in the community.

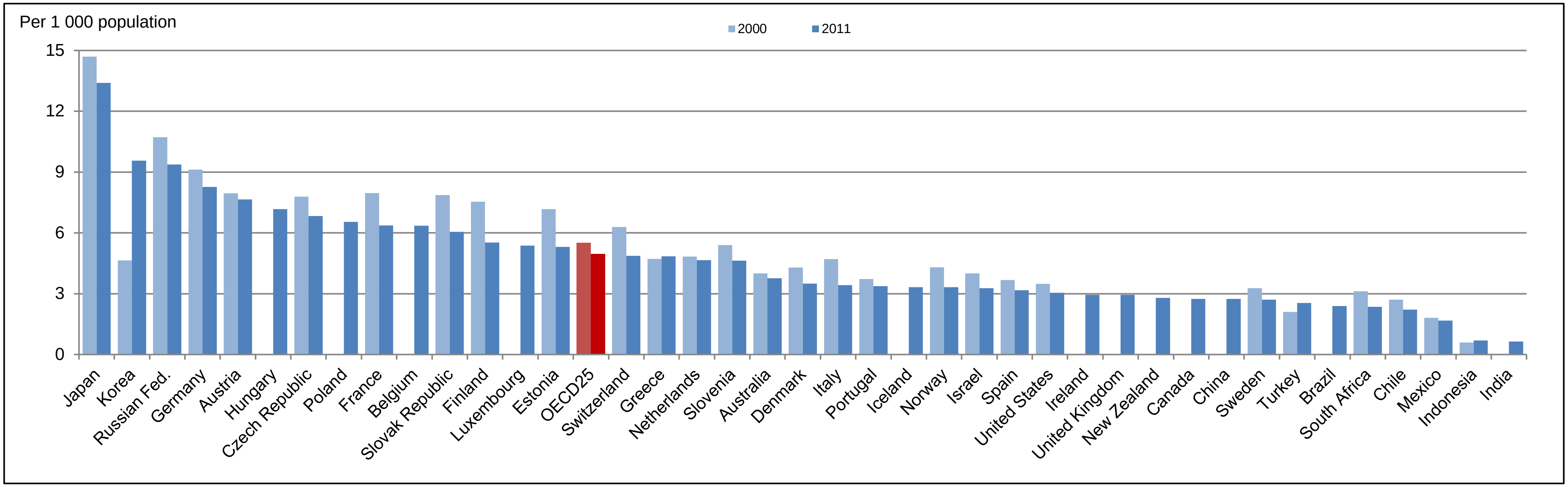
It is therefore suggested that an alternate approach to the current Pay for Results program be considered to meet the ED wait time targets for admitted patients. The wait times for this patient group remain stubbornly above the targets set under the Wait Times Strategy. This excess wait time is largely due to the time spent waiting for an acute-care bed and our study results suggest that the inpatient care received while boarding is equivalent to the care that would be received on the ward as measured by hospital LOS.

Appendices

A. OECD Statistics

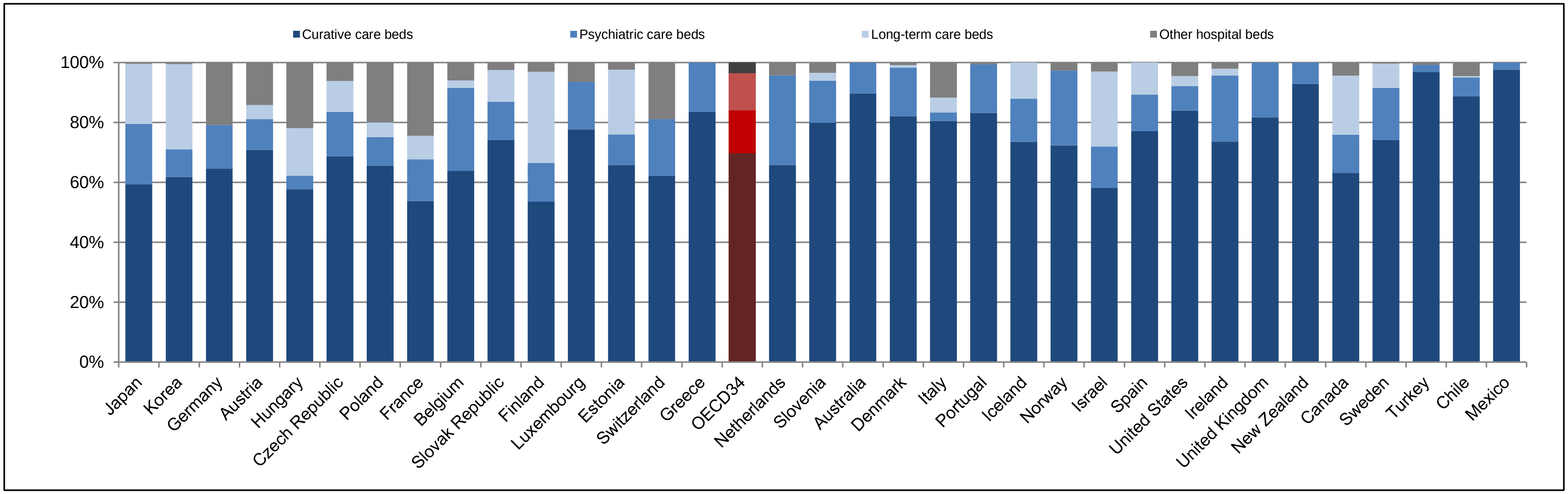
Health at a Glance 2013 - © OECD 2013
Chapter 4
Version 1 - Last updated: 31-Oct-2013

4.3.1. **Hospital beds per 1 000 population, 2000 and 2011 (or nearest year)**



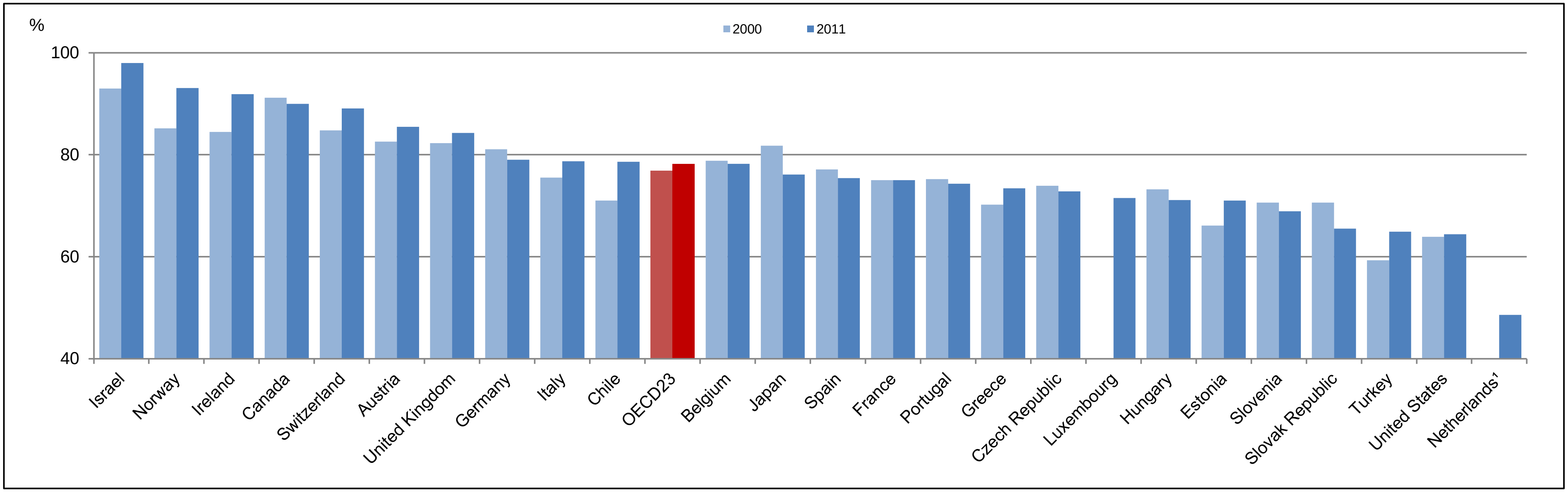
Information on data for Israel: http://dx.doi.org/10.1787/888932315602.
Source: *OECD Health Statistics 2013*, http://dx.doi.org/10.1787/health-data-en.

4.3.2. **Hospital beds by function of health care, 2011 (or nearest year)**



Note: Countries ranked from highest to lowest total number of hospital beds per capita.
Information on data for Israel: http://dx.doi.org/10.1787/888932315602.
Source: *OECD Health Statistics 2013*, http://dx.doi.org/10.1787/health-data-en.

4.3.3. **Occupancy rate of curative (acute) care beds, 2000 and 2011 (or nearest year)**



1. In the Netherlands, hospital beds include all beds administratively approved rather than those immediately available for use.

Information on data for Israel: http://dx.doi.org/10.1787/888932315602.

Source: *OECD Health Statistics 2013*, http://dx.doi.org/10.1787/health-data-en.

B. Medline search strategy

Research question

What is the association between the time spent in the emergency department for admitted patients and the time to discharge from the hospital?

Search strategy

ED wait times final - Medline

8 October 2014

1. exp Emergency Service, Hospital/
2. (emergency adj2 department*).tw.
3. (emergency adj2 room*).tw.
4. (emergency adj2 ward*).tw.
5. (emergency adj2 service*).tw.
6. casualty department.tw.
7. (accident adj2 emergency).tw.
8. (ED adj2 overcrowd*).tw.
9. (ED adj2 crowd*).tw.
10. (ER adj2 overcrowd*).tw.
11. (ER adj2 overcrowd*).tw.
12. 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11
13. exp Hospital Bed Capacity/
14. Bed Occupancy/
15. Crowding/
16. overcrowd*.tw.
17. crowd*.tw.
18. (board* adj2 time*).tw.
19. (ED adj2 board*).tw.
20. (hospital adj2 bed* adj2 capacit*).tw.
21. Access block.tw.
22. Ambulance Diversion/
23. ambulance diversion.tw.
24. (ED adj2 wait adj2 time*).tw.

25. (wait adj2 time* adj2 target*).tw.

26. (bed adj2 occupancy).tw.

27. 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26

28. Inpatients/

29. Hospitalization/

30. Patient Admission/

31. (admit* adj2 patient*).tw.

32. 28 or 29 or 30 or 31

33. Risk Management/

34. "Length of Stay"/

35. (time adj2 treatment).tw.

36. patient outcome*.tw.

37. hospital mortality/ or mortality, premature/

38. critical care/ or intensive care/

39. Patient Readmission/

40. exp "Quality of Health Care"/

41. exp Economics/

42. Total Quality Management/

43. (impact adj2 delay*).tw.

44. (patient adj2 outcome*).tw.

45. (impact adj2 care).tw.

46. mortality.tw.

47. (quality adj2 care).tw.

48. 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47

49. 12 and 27 and 32 and 48

C. Embase search strategy

ED wait times - Embase

8 October 2014

1. exp emergency health service/
2. exp emergency ward/
3. (emergency adj2 department*).tw.
4. (emergency adj2 room*).tw.
5. (emergency adj2 ward*).tw.
6. (emergency adj2 service*).tw.
7. casualty department.tw.
8. (accident adj2 emergency).tw.
9. (ED adj2 overcrowd*).tw.
10. (ED adj2 crowd*).tw.
11. (ER adj2 overcrowd*).tw.
12. (ER adj2 crowd*).tw.
13. 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11 or 12
14. exp hospital bed capacity/
15. exp hospital bed utilization/
16. exp "crowding (area)"/
17. overcrowd*.tw.
18. crowd*.tw.
19. (board* adj2 time*).tw.
20. (bed* adj2 capacit*).tw.
21. (bed* adj2 occupan*).tw.
22. access block.tw.
23. exp ambulance diversion/
24. ambulance diversion.tw.
25. 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24
26. 13 and 25
27. exp hospital patient/
28. exp hospitalization/

29. exp hospital admission/

30. (admit* adj2 patient*).tw.

31. inpatient*.tw.

32. 27 or 28 or 29 or 30 or 31

33. 26 and 32

34. "length of stay"/

35. (time adj2 treat*).tw.

36. (patient adj2 outcome*).tw.

37. exp mortality/ or exp premature mortality/

38. intensive care/

39. ICU.tw.

40. hospital readmission/

41. health care quality/

42. (impact adj2 delay*).tw.

43. (patient adj2 outcome*).tw.

44. (impact adj2 care).tw.

45. mortality.tw.

46. exp "cost benefit analysis"/

47. (quality adj2 care).tw.

48. 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47

49. 33 and 48

50. limit 49 to (english language and yr="2000 - Current")

D. Statistical modeling: Testing the proportional hazard assumption

Table D-1 Time-dependent effect of weekend on the sub-distribution hazard ratio

Time to discharge	Unadjusted HR†
t = 0.5 days	1.10 (1.02, 1.18)
t = 1 day	1.09 (1.02, 1.16)
t = 3 days	1.08 (1.02, 1.13)
t = 10 days	1.06 (1.02, 1.10)
t = 30 days	1.05 (1.02, 1.08)
t = 100 days	1.04 (1.00, 1.07)
t = 300 days	1.02 (0.98, 1.07)

† Cox regression model stratified by campus and admission diagnosis

Table D-2 Time-dependent effect of shift (ED registration after 6pm and prior to 6am) on the sub-distribution hazard ratio

Time to discharge	HR (95% CI)
t = 0.5 days	1.22 (1.14, 1.31)
t = 1 day	1.20 (1.13, 1.27)
t = 3 days	1.16 (1.10, 1.21)
t = 10 days	1.12 (1.07, 1.16)
t = 30 days	1.08 (1.04, 1.11)
t = 100 days	1.04 (1.01, 1.08)
t = 300 days	1.00 (0.97, 1.04)

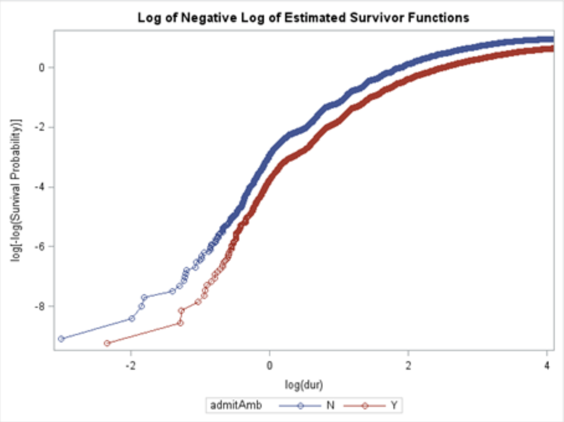


Figure D-1 Arrival by ambulance

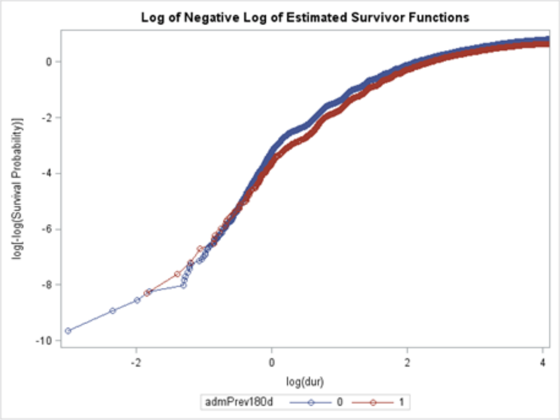


Figure D-2 Hospitalisation in the previous 6 months

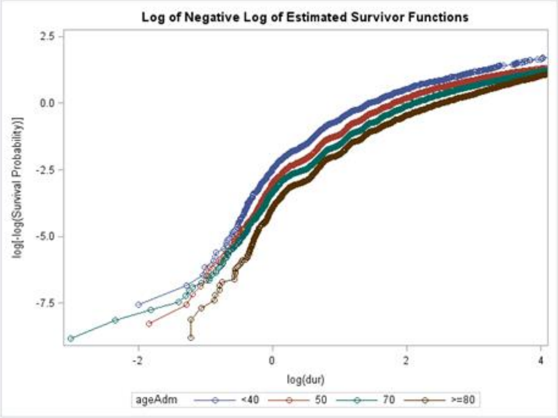


Figure D-3 Age at admission

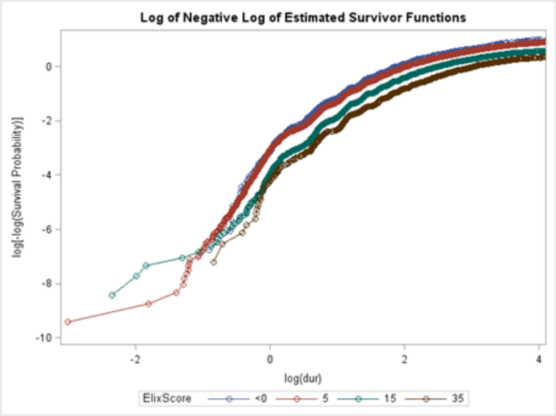


Figure D-4 Elixhauser score

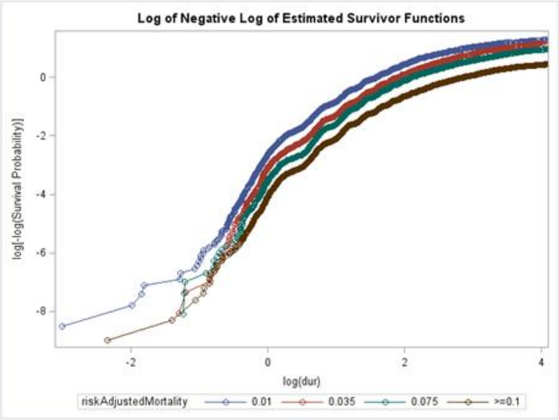


Figure D-5 Escobar score at admission

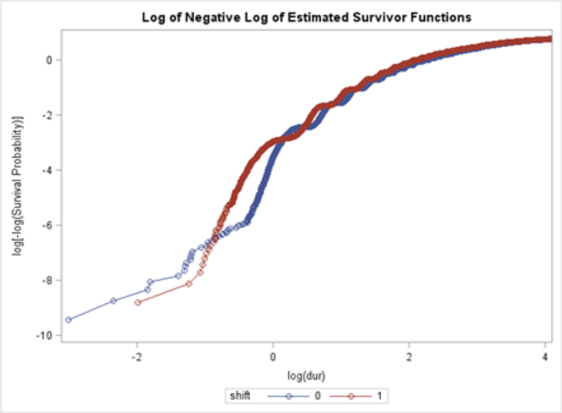


Figure D-6 Shift (registration at ED after hours)

E. Markov model: Model inputs and assumptions

Table E-1 Markov model inputs

Parameters	Base estimate	Probability distribution*	Source
Transition probabilities - current bed capacity			
Probability of remaining in an ED bed in a single cycle	0.54242	Beta(21183, 17870)	All transition probabilities are empirically derived from the underlying cohort for each 6 hourly cycle
Probability of transitioning from an ED bed to a WARD bed in a single cycle	0.39290	Beta(15344, 23790)	
Probability of transitioning from an ED bed to ALC status in a single cycle	0.00079	Beta(31, 39022)	
Probability of transitioning from an ED bed to an AMA bed in a single cycle	0.03654	Beta(1427, 37626)	
Probability of transitioning from an ED bed to an ICU bed in a single cycle	0.00469	Beta(183, 38870)	
Probability of discharge home from an ED bed within a single cycle	0.01910	Beta(746, 38307)	
Probability of discharge to a non-acute setting from an ED bed within a single cycle	0.00077	Beta(30, 39023)	
Probability of death while in an ED bed within a single cycle	0.00200	Beta(78, 38975)	
Probability of left against advice from an ED bed within a single cycle	0.00079	Beta(31, 39022)	
Probability of remaining in a WARD bed in a single cycle	0.96229	Beta(479654, 18796)	
Probability of transitioning from a WARD bed to ALC status in a single cycle	0.00533	Beta(2659, 495791)	
Probability of transitioning from a WARD bed to an AMA bed in a single cycle	0.00091	Beta(452, 497998)	
Probability of transitioning from a WARD bed to an ICU bed in a single cycle	0.00069	Beta(344, 498106)	
Probability of discharge home from a WARD bed within a single cycle	0.02509	Beta(12508, 485942)	
Probability of discharge to a non-acute setting from a WARD bed within a single cycle	0.00314	Beta(1563, 496887)	
Probability of death while in a WARD bed within a single cycle	0.00231	Beta(1152, 497298)	
Probability of left against advice from a WARD bed within a single cycle	0.00024	Beta(118, 498332)	
Probability of remaining in the ALC status in a single cycle	0.98765	Beta(502, 220411)	
Probability of transitioning from ALC status to a WARD bed in a single cycle	0.00227	Beta(218185, 2728)	
Probability of transitioning from ALC status to an AMA bed in a single cycle	0.00008	Beta(18, 220895)	
Probability of transitioning from ALC status to an ICU bed in a single cycle	0.00004	Beta(9, 220904)	

Parameters	Base estimate	Probability distribution*	Source
Probability of discharge home from ALC status within a single cycle	0.00471	Beta(1041, 219872)	
Probability of discharge to a non-acute setting from ALC status within a single cycle	0.00455	Beta(1006, 219907)	
Probability of death while in ALC status within a single cycle	0.00064	Beta(142, 220771)	
Probability of left against advice from ALC status within a single cycle	0.00005	Beta(10, 220903)	
Probability of remaining in an AMA bed in a single cycle	0.93198	Beta(1477, 30732)	
Probability of transitioning from an AMA bed to a WARD bed in a single cycle	0.04586	Beta(38, 32171)	
Probability of transitioning from an AMA bed to ALC status in a single cycle	0.00118	Beta(30018, 2191)	
Probability of transitioning from an AMA bed to an ICU bed in a single cycle	0.00298	Beta(96, 32113)	
Probability of discharge home from an AMA bed within a single cycle	0.01406	Beta(453, 31756)	
Probability of discharge to a non-acute setting from an AMA bed within a single cycle	0.00118	Beta(38, 32171)	
Probability of death while in an AMA bed within a single cycle	0.00255	Beta(82, 32127)	
Probability of left against advice from an AMA bed within a single cycle	0.00022	Beta(7, 32202)	
Probability of remaining in an ICU bed in a single cycle	0.97021	Beta(282, 21840)	
Probability of transitioning from an ICU bed to a WARD bed in a single cycle	0.01275	Beta(0, 22122)	
Probability of transitioning from an ICU bed to ALC status in a single cycle	0.00000	Beta(68, 22054)	
Probability of transitioning from an ICU bed to an AMA bed in a single cycle	0.00307	Beta(21463, 659)	
Probability of discharge home from an ICU bed within a single cycle	0.00253	Beta(56, 22066)	
Probability of discharge to a non-acute setting from an ICU bed within a single cycle	0.00063	Beta(14, 22108)	
Probability of death while in an ICU bed within a single cycle	0.01067	Beta(236, 21886)	
Probability of left against advice from an ICU bed within a single cycle	0.00014	Beta(3, 22119)	
Transition probabilities - increased bed capacity			
Probability of remaining in an ED bed in a single cycle	0.10000		
Probability of transitioning from an ED bed to a WARD bed in a single cycle	0.83532		
Probability of remaining in a WARD bed in a single cycle	0.96222		
Probability of discharge home from a WARD bed within a single cycle	0.02516		

Parameters	**Base estimate**	**Probability distribution***	**Source**
Probability of discharge to a non-acute setting from a WARD bed within a single cycle	0.00314		
Costs ($)			
Cost of 1 cycle in an ED bed	148.97	Fixed	Nursing costs are derived from The Ottawa Hospital Case Costing data These are fixed costs and are not dependent on the number of patients but rather on the number of staffed beds
Cost of 1 cycle in a WARD bed	119.58	Fixed	
Cost of 1 cycle in an ICU bed	508.15	Fixed	
Cost of 1 cycle in an AMA bed	272.30	Fixed	
Cost of 1 cycle in ALC status	119.58	Fixed	
Cost of 1 cycle in a ward bed after increasing the number of staffed acute care beds	133.15	Fixed	The increased cost is based on the cost associated with the increased number of staff needed to retain the current nurse to patient ratio
Other			
Effect of increasing acute-care beds in terms of reducing the time spent boarding in the ED waiting for a WARD bed	0.10000	Beta(2153, 239)	90% of those boarding in the ED have a ward bed within 6 hours (IHO simulation)
Effect of a decrease in ED board time on the hazard of planned medical discharge	1.00266	Log normal(-0.008, 0.004)	Derived from the Cox regression model for an 8 hour reduction in ED boarding This is applied to WARD beds only as the intervention is only specific to WARD beds
Number of admitted medicine patients	225	Fixed	Derived from the daily census of medicine patients across the two campuses
Current number of staffed beds	201	Fixed	Hospital census data
Increased bed scenario	251	Fixed	IHO simulation
Cycle length	6 hours		
Time horizon	481 days		

*Transition probabilities were characterised by beta distributions. The hazard ratio was characterised by a log normal distribution. Nursing costs were assumed fixed as were as the number of patients and beds. The beta distributions are specified by alpha (the number of events) and beta (the number of non-events). The log normal distribution is specified by the mean and standard deviation.

F. Markov model: Simulation results

Cohort simulation for the first 3 days – Current bed capacity

					1 Day				2 Days				3 Days
	0 hours	6 hours	12 hours	18 hours	24 hours	30 hours	36 hours	42 hours	48 hours	54 hours	60 hours	66 hours	72 hours
	0	1	2	3	4	5	6	7	8	9	10	11	12
	0	0.25	0.5	0.75	1	1.25	1.5	1.75	2	2.25	2.5	2.75	3
ED	1.0000	0.5424	0.2942	0.1596	0.0866	0.0470	0.0255	0.0138	0.0075	0.0041	0.0022	0.0012	0.0006
WARD	-	0.3929	0.5929	0.6888	0.7285	0.7381	0.7318	0.7173	0.6986	0.6780	0.6567	0.6353	0.6143
AMA	-	0.0365	0.0542	0.0619	0.0641	0.0636	0.0617	0.0592	0.0563	0.0534	0.0506	0.0479	0.0453
ICU	-	0.0047	0.0075	0.0092	0.0103	0.0111	0.0117	0.0122	0.0125	0.0129	0.0131	0.0133	0.0135
ALC	-	0.0008	0.0034	0.0068	0.0106	0.0145	0.0183	0.0221	0.0257	0.0292	0.0325	0.0357	0.0387
Home	-	0.0191	0.0399	0.0611	0.0824	0.1033	0.1237	0.1436	0.1628	0.1814	0.1994	0.2168	0.2337
Transfer	-	0.0008	0.0025	0.0046	0.0070	0.0095	0.0120	0.0145	0.0169	0.0193	0.0216	0.0239	0.0261
Death	-	0.0020	0.0041	0.0063	0.0085	0.0106	0.0127	0.0147	0.0167	0.0186	0.0205	0.0223	0.0241
Left	-	0.0008	0.0013	0.0017	0.0020	0.0023	0.0025	0.0027	0.0029	0.0031	0.0033	0.0034	0.0036
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
AVG EDBOARD (HRS)	10.85	0.5424	0.2942	0.1596	0.0866	0.0470	0.0255	0.0138	0.0075	0.0041	0.0022	0.0012	0.0006
AVG LOS	10.26	0.9773	0.9522	0.9262	0.9001	0.8743	0.8491	0.8245	0.8007	0.7775	0.7552	0.7335	0.7125
AVG COST	5,624.69	145.54	133.70	128.47	123.99	119.97	116.26	112.77	109.44	106.26	103.20	100.25	97.40

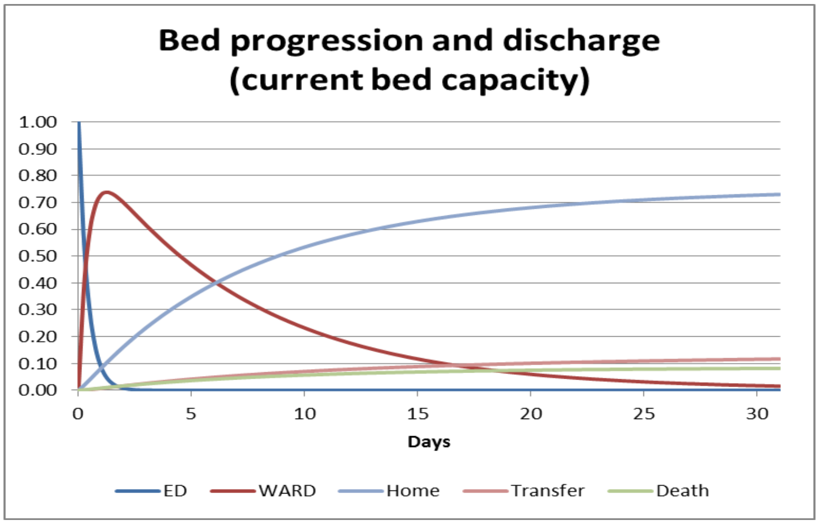
Cohort simulation for the first 3 days – Current bed capacity

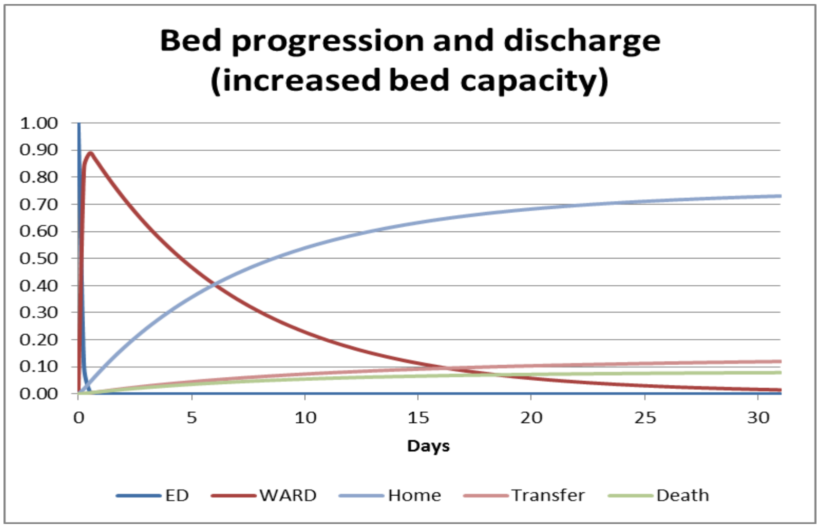
					1 Day				2 Days				3 Days
	0 hours	6 hours	12 hours	18 hours	24 hours	30 hours	36 hours	42 hours	48 hours	54 hours	60 hours	66 hours	72 hours
	0	1	2	3	4	5	6	7	8	9	10	11	12
	0	0.25	0.5	0.75	1	1.25	1.5	1.75	2	2.25	2.5	2.75	3
ED	1.0000	0.1000	0.0100	0.0010	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
WARD	-	0.8353	0.8890	0.8656	0.8356	0.8058	0.7771	0.7493	0.7226	0.6968	0.6720	0.6480	0.6249
AMA	-	0.0365	0.0385	0.0371	0.0354	0.0338	0.0322	0.0307	0.0294	0.0281	0.0268	0.0256	0.0245
ICU	-	0.0047	0.0057	0.0063	0.0068	0.0073	0.0078	0.0082	0.0085	0.0089	0.0092	0.0094	0.0097
ALC	-	0.0008	0.0054	0.0101	0.0146	0.0189	0.0231	0.0270	0.0307	0.0342	0.0375	0.0406	0.0436
Home	-	0.0191	0.0426	0.0657	0.0881	0.1097	0.1305	0.1507	0.1701	0.1889	0.2070	0.2245	0.2413
Transfer	-	0.0008	0.0035	0.0064	0.0092	0.0120	0.0146	0.0172	0.0197	0.0222	0.0246	0.0269	0.0291
Death	-	0.0020	0.0043	0.0065	0.0087	0.0108	0.0128	0.0148	0.0167	0.0186	0.0204	0.0221	0.0238
Left	-	0.0008	0.0011	0.0013	0.0015	0.0017	0.0019	0.0021	0.0023	0.0025	0.0027	0.0028	0.0030
	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
AVG EDBOARD (HRS)	1.85	0.1000	0.0100	0.0010	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AVG LOS	10.15	0.9773	0.9486	0.9201	0.8925	0.8658	0.8401	0.8152	0.7911	0.7679	0.7454	0.7237	0.7027
AVG COST	5,888.48	138.55	133.95	130.04	126.32	122.72	119.24	115.88	112.62	109.47	106.42	103.46	100.60

G. Markov model: Progression charts

Proportion of the cohort in each of the depicted states before and after the increased bed capacity

(not all the transition states are depicted)





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