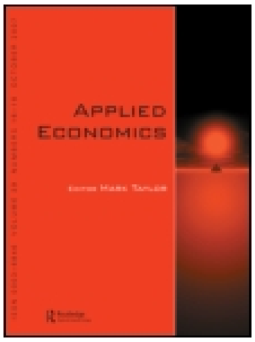

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Demand in New Zealand hospitals: expect the unexpected?

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The health care sector in New Zealand has undergone substantial structural reform since 1983 and stands out relative to other OECD countries, with relatively low per capita health expenditure and a high share of public funding. Efficient allocation of resources in this public dominant health system is therefore paramount. This article uses a national database of hospital admissions to predict hospital demand. We find lagged information on patient demand imperative in formulating an easy to implement approach for predictive purposes. Contrasting predicted with actual demand, we construct an indicator of volatility in unexpected patient demand (at both the hospital and the disease chapter level) and assess its role with regard to patient outcomes. There is consistent evidence that when actual patient numbers exceed predicted, patients stay in hospital significantly longer and are more likely to have an acute readmission.

Keywords: hospital demand; emergency readmission; length of hospital stay

JEL Classification: I12; I18; H51; C50

I. Introduction

Decisions on hospital staffing levels are often made while trying to carefully balance the need to ensure sufficient personnel for quality care, while keeping an eye on minimizing excess costs and operating as efficiently as possible. If too much weight is placed on the cost side of this balancing act, or if the decision-making process is flawed in general, then insufficient personnel could result in poorer patient outcomes that include increased length of stay, a greater risk of readmission and even mortality.

In New Zealand (NZ), the health sector has undergone substantial reform since the early 1980s, with the most recent changes in 2000 reflecting a movement from a market-oriented model (where separate health entities competed against one another for funding) to a more community-focussed approach. It is in the latter that region-specific district health boards (DHBs) have been provided greater mandate to deal with local health needs and preferences.

In this article, we make use of a national database of hospital discharges for the period 2008 to 2012 to estimate the impact of unexpected excess demand on patient outcomes. To begin with, we ask the question – Do hospitals have access to enough information to accurately predict patient demand levels? Reliable prediction models are necessary if we assume that excess demand may result in sub-standard care, which in turn has been shown to increase the likelihood of readmissions (see Ashton *et al.*, 1997; Encinosa and Hellinger, 2008). For instance, Ashton *et al.* (1997) argue that early readmission of a patient (within 30 days) is a valid indicator of quality of care, as they found (via meta-analysis) that the risk of readmission increased by 55% when patients experienced relatively poor levels of care.

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Another recent example is Morris *et al.* (2011) who found evidence of a positive relationship between hospital-acquired conditions and readmissions.

Research on gauging hospital demand/utilization rates is scant (see Dove and Ritchie, 1972; Oliveira, 2002, 2004; Schwierz *et al.*, 2012), and none of the extant literature explicitly make use of lagged information regarding patient levels. This is surprising, given that some of the earliest work on this front, from Feldstein and German (1965) contend that one possible way to predict future demand (or as the authors termed it 'patient-day/population ratio') is to make use of past evidence of demand. In this study, we construct a model to predict patient demand, at the hospital facility level, and find the addition of lagged patient counts from the corresponding week in the prior year clearly improves model fit criteria.

The second research question this study poses is – What is the extent of unexpected patient demand across NZ hospitals? We construct two indicators of volatility to represent shocks to the demand system at both the hospital facility and disease chapter level. Unexpected hospital demand contrasts actual patient counts with predicted patient levels. Summary statistics for this index illustrate that on 20% of days, patient demand deviates around 11%–12% away from the yearly mean, while on 10% of days, demand deviates approximately 17% above and below the yearly mean. Interestingly, we also find substantial variation across regional DHBs in terms of volatility in unexpected demand, which are not correlated with the size of the health entity.

At the disease chapter level, we assess times in which a particular disease chapter may have additional strain on hospital resources and capacity, above and beyond general volatility in demand across the entire hospital. This incremental analysis is the closest proxy to better understand the impact of excess patient demand at the disaggregated department level. In particular, we construct a ratio which contrasts the level of volatility at the disease chapter to that at the aggregate hospital facility level.

The final research question is – Does unexpected demand (whether at the hospital or disease chapter level, or both) influence patient outcomes? We employ the two unexpected demand indicators (described earlier) in a panel regression framework to estimate the role they play in three patient outcomes: length of stay, risk of acute readmission within 30 days and probability of in-hospital death.

The data set used in this study has several advantages for the purposes of our analysis. We make use of an aggregate data set for the nation and split analysis (of variations in unexpected demand) by region and time. This allows our results to be both generalized across NZ, as well as tailored to fit particular regions (when deemed necessary by policy makers), and also allows us to replicate analysis for different years to ensure our results are not year specific, or if there are particular trends over time impacting patient outcomes. There is also detailed information on individual patients in terms of demographics, their socio-deprivation decile and other patient record data that are indicative of severity of the patient's illness.

Overall, our analysis points to adverse outcomes for both elective and acute patients when the hospital facility experiences a greater strain on resources than expected/predicted. In particular, a patient's hospital stay is significantly elongated when NZ hospitals experience excess demand. When drilling down our analysis to the disaggregate level, unexpected excess demand within disease chapters also significantly increase a patient's stay, regardless of whether the patient has an elective or acute admission.

The probability of acute readmission within 30 days is also an outcome of interest in this study and common measure of hospital performance. We draw on recent evidence from Laudicella *et al.* (2013) that highlights potential issues when interpreting readmission rates as a signal of hospital performance. In particular, likelihood of readmission may be inextricably linked with the probability of survival/mortality. It is therefore important to take into account the potential overlap in unobserved characteristics that determine both the outcomes. The following empirical analysis consequently undertakes a Heckman selection model to control for this possibility. Interestingly, we find no evidence of such unmeasured confounders influencing both the probabilities of survival and the readmission.

The article proceeds as follows: Section II surveys the relevant literature on empirically estimating hospital demand and provides background on the NZ health system. Section III details the data employed, as well as descriptive trends over the sample time frame. Section IV presents a framework for predicting hospital demand, which is flexible enough for the Ministry of Health to employ at the aggregate country level, as well as adapt for specific regional DHBs. This section also outlines the construction of two indicators of demand shocks, representing volatility in patient demand at the hospital and disease chapter level. Section V interprets results and Section VI presents final conclusions.

II. Literature Review

Predicting patient demand

Early research along the lines of modelling hospital patient levels began with Feldstein and German (1965) who argued that there are three possible ways to predict future demand. This included (i) using past evidence on demand, (ii) using past evidence on supply/availability of beds and/or (iii) understanding other factors that may affect use. While this line of enquiry began in the 1960s, since then, there has been minimal attention paid to gauging hospital demand and assessing the impact of unpredictable fluctuations in demand on patient care. Nevertheless, the importance of this issue has long been recognized in the literature. For instance, Rasmussen (1991–1992) argues that insufficient hospital personnel (a common consequence of inadequate predictions regarding patient demand) can affect the ability of nursing services (which provide the bulk of patient care within the hospital) to practice according to legal requirements. This results in potential threats to patient safety, as well as nurse and hospital liability. The importance of specific staff to patient ratios motivated legislation in California in July 2003, creating mandated minimum patient-to-nurse ratios for the region's hospitals. Analysis of data prior to this legislation by Aiken *et al.* (2002) found that on average each additional patient per nurse was associated with a 7% increased probability of dying within 30 days of admission. The likely contributing factors were higher emotional exhaustion and greater job dissatisfaction for nurses; both of which were found to be strongly associated with patient-to-nurse ratios. However, while legislated minimum ratios for nurses-to-patients may seem like an appealing and simple policy directive, it is likely that it will be most effective in situations where there is minimal variation in size and type of population served (and hence hospital facility). In NZ, there are 20 DHBs, and within these, 29 major hospital facilities vary substantially in size, characteristics of patients, demand for services, etc. For example in 2012, the number of discharged hospital episodes per facility varied from 5495 at Greymonth Base hospital (West Coast DHB) to 126 466 at Auckland city hospital (Auckland DHB). Besides differences in volume, facilities also differ greatly with respect to proportion of acute hospital episodes, and along with that average hours in intensive care units (ICUs). For instance, acute events accounted for 66% of discharged episodes at Middlemore hospital (Counties Manukau DHB) and 11% at Burwood hospital (Canterbury DHB). Given these variations, at the facility level, it is unlikely that mandated and uniform levels of nurse-to-patient ratios across NZ are going to be effective. It is also worth noting that recent research by Cook *et al.* (2012) that presents analysis of California's AB394 (mandated minimum nurse staff levels) actually finds that failure to rescue rates did not disproportionately decrease for hospitals affected by this legislation.[1]

As indicated earlier, the literature on understanding hospital utilization rates is meagre. In addition to this, the frameworks employed thus far are not consistent. For instance, Oliveira (2002) uses a flow demand model that represents a system that considers both population and hospital points, and demand is taken as a concept that relates each population point to a supply location. The author finds that several key individual factors increase the probability of a hospital admission, such as smoking and weight level. Neighbourhood level effects in terms of socio-economic pockets of poverty were also found to have a positive impact on hospital utilization.

Recent research by Schwierz *et al.* (2012) on this front measures foreseeable demand as dependent on department and hospital fixed effects, monthly dummies, day of the week dummies and a dummy for public holidays. We contend in the following analysis that practitioners, in addition to the above information, are more flexible in their predictions and can base staffing decisions partly on lagged information regarding demand at the same time in the preceding year. Additionally, our aim in this article is to create a model that is easy for hospitals to implement should they wish to predict forthcoming utilization rates. We therefore don't include variables that may be difficult for hospitals to measure explicitly or average out for a large region – such as the weather. This factor includes a range of sub-categories such as hours of sunshine, temperature, millimetres of rainfall, etc. Some components of this factor may be relevant in certain circumstances (e.g. Mastrangelo *et al.* (2007) finds the duration of a heatwave to be a significant influence on hospital admissions), but this variable or set of variables may be too difficult or not readily available for hospitals to average out for the large geographical areas that they serve.

Impact of unexpected patient demand

How hospitals and particular departments (which we proxy with disease chapters in the following analysis) cope with deviations from foreseeable demand is the focus of this article, within the context of NZ. There are two ways to view this issue. Hospital staff may be overloaded because of excess volatility in patient demand and/or due to supply side constraints. The latter of these contributing factors could encompass a shortage of required medical personnel and/or hospital beds and other necessary infrastructure capacity.

Many prior studies examine the impact of a high staff–to-patient ratio on patient and staff outcomes, without understanding the cause of the elevated staff workload. Additionally, the evidence from prior literature on this front is mixed. Clarke *et al.* (2002) reported the likelihood of needlestick injuries was threefold greater when hospitals were stretched and staff levels were low. Aiken *et al.* (2002) reported negative outcomes of lean staffing ratios with respect to the Maslach Burnout Inventory, with

[1] Cook *et al.* (2012) do find evidence of a significant negative link between nurse-to-patient ratios and failure to rescue when viewing it in a cross-sectional fashion, but the authors caution that there are difficulties associated with drawing causal inferences from these results.

nurses being more likely to burnout. In another relevant study, Tarnow-Mordi *et al.* (2000) use UK data over the period 1992 to 1995 and link increased probability of death with greater than average patients in the ICU. On the other hand, Needleman *et al.* (2002) find that greater staffing of nurses doesn't always reduce adverse outcomes for patients. For example, while they did find a negative relationship between staff levels and poor patient outcomes for registered nurses, there was an insignificant relationship between these two variables with respect to licensed practical nurses. Furthermore, there was an insignificant impact for an increase in either type of nurse in terms of in-patient mortality. Similarly, Robertson and Hassan (1999) also found that in the majority of their analyses that higher staffing levels were not associated with adverse outcomes for Medicare patients being treated for chronic pulmonary disease (except when staffing intensities increased for respiratory-specific practitioners). Dobkin (2003) also found, for a Californian hospital, no evidence of mortality rates increasing when patients were admitted during the weekend, when staff levels are low.

To the best of our knowledge there are only two recent examples of research that go beyond assessing the impact of staff workload issues and investigate more explicitly the cause of these issues, by examining the impact of patient demand shocks. Evans and Kim (2006) use hospital discharge data over the period 1996–2000 to estimate the impact of a substantial influx in patients on the 2 days that follow admission. Focussing on patients admitted on Thursday, they find some evidence of demand shocks on Friday and Saturday reducing the length of stay for Thursday admissions and increasing their probability of readmission. While their results are statistically significant, the authors caution the reader to the fact that the impacts are quantitatively small. Recent research by Schwierz *et al.* (2012) focusses on acute care hospitals in Germany in 2004. They find that hospitals are relatively well prepared to deal with unexpected volatility in demand and that there is minimal impact on patient outcomes. We begin our empirical analysis by employing a similar approach to Schwierz and colleagues with respect to estimating foreseeable demand, but then branch out further when it comes to estimating the impact of excess demand on patient outcomes. In particular, in addition to assessing the influence of excess demand at the hospital level, we construct an indicator of volatility at the disease chapter level to investigate the impact of fluctuations in patient demand at the disaggregated department level. We also control for unobservables that may be jointly impacting the probability of survival and readmission, via a Heckman selection model. Furthermore, relative to prior literature our unique data set allows us to examine outcomes over time, and at both the national and the regional level.

NZ background

Since the 1980s, NZ's health system has undergone a series of radical reforms. In all, there have been three major restructures to the health system in the last three decades, along with a myriad of smaller structural shifts that have altered the way in which health services are funded, organized and delivered. In 1983 legislation was passed to create Area Health Boards (AHBs), and there was a move to population-based funding for hospital care (previously funding was based on historical allocations and further negotiated additions) (Pool *et al.*, 2009). In 1993, a 'purchaser/provider' market-oriented model was introduced (Ministry of Health, 2012), and four regional health authorities were formed to 'purchase' health care from a range of providers, to produce health gains for the populations of their respective regions. This competitive internal market system was theoretically expected to result in greater efficiency and in practice resulted in geographically separate health entities heavily competing on the health market, developing independent process and structures, and substantially reducing the level of coordination and collaboration across regions. In 2000, NZ moved from this market-oriented model to a more community-oriented approach. Via implementation of the NZ Public Health and Disability Act in 2000, 21 DHBs were created, with a mandate to cover primary and other health sectors (Gauld, 2009). The creation of the DHB structure resulted in decentralization of planning and funding functions to the local level, such that DHBs are given direct responsibility for their respective communities. The motivation for this being that decision making at the local level enhances close ties with the community, and quicker reaction to community needs and preferences. There are now 20 DHBs (Southland and Otago DHBs merged in May 2009) that are responsible for the provision of health and disability services in their geographic area.

Since 2007 there has also been visible emphasis on greater levels of hospital efficiency and performance. Annual health targets have been introduced, and these include reducing hospital expenditure, increasing elective discharges and immunization rates for children under 2 years, etc. Consequently, our sample timeframe (2008–2012) covers a time over which hospitals are under the spotlight for improving their levels of efficiency.

III. Data

The National Minimum Dataset (NMDS) is a unit record national collection of public and private hospital discharge information, for inpatients and day patients who are formally admitted to an institution for treatment in NZ.

Across our sample period of 1 January 2008 to 31 December 2012, the NMDS contains 5 175 279 discharged hospital events. The majority of events are acute admissions (51.16%), followed by arranged (28.03%) and waiting list admissions (20.81%). An acute admission is defined as an unplanned admission on the day of presentation, whereas an arranged admission is a planned admission within 7 days of specialist's referral. The final category of waitlist admissions are also planned, but the admission date is 7 or more days after the referral decision is made. In the following analysis, we group together waitlist and arranged into a category denoted as 'elective'.

Given that around three quarters of health funding and the majority of day-to-day business in the health system are administered by the 20 regional DHBs, our attention is confined to hospital events at the DHB level (95%). As a consequence to this decision, events delivered by private health groups (4.49%), trust or incorporated society (0.5%) and other publicly funded agencies (0.02%) were excluded from our final sample. We also drop rare events, such as elective admission of a privately funded patient or psychiatric patient returned from leave of more than 10 days (209 events). The final sample size is therefore reduced from 5 175 279 to 4 625 474 DHB level hospital discharge events across 5 years (see Appendix for a distribution of events by DHBs and a description of context relevant facts regarding each DHB area – such as population size, ratio of urban to rural and proportion above median income). This sample corresponds to 1 803 783 unique patients.

This data set is well suited to the purpose of this study and has a number of advantages relative to data used in prior empirical studies. For instance, this sample allows regional analysis (based on DHB level), as well as investigation of trends in unexpected hospital demand over time, given the availability of data from 2008 to 2012. Variations across region and time are valuable extensions to the literature in this field. For instance, Schwierz *et al.* (2012) focussed on one region in Germany and for the year 2004, Evans and Kim (2006) also examined outcomes only within one region in the United States (California). Most importantly, having an aggregate source of hospital admissions for the whole country makes it easy to make inferences as to what is the most appropriate model hospitals could use to predict demand – i.e. generating a 'one size fits all' model that would be easy for hospitals to implement.

The NMDS contains relevant information regarding patient characteristics (such as age, gender and ethnicity), individual risk factors (such as clinical complexity level, hours on medical ventilation, etc.) and patient outcomes (death within hospital, excess length of stay relative to the average length by diagnoses and emergency readmission). The descriptive statistics of the sample and definitions of all relevant variables are provided in Table 1. Following Evans and Kim (2006) we divide the sample along the lines of low versus high risk. This is done at the aggregate level, as well as for the sub-categories of acute and elective admissions. We expect a priori that patients in the acute high risk category will be more susceptible to adverse health outcomes. A patient is regarded as high risk if their primary diagnosis belongs to one of 50 primary diagnoses with the highest mortality rate among the top 100 primary diagnoses with the highest mortality count in the data.

In general, low-risk patients appear to be more likely to be younger and female, relative to individuals in the high-risk category. As expected risk factors such as the clinical complexity level are lower for low-risk individuals. Additionally, with respect to patient outcomes, low-risk patients are clearly less likely to exceed the average length of stay based on their diagnoses, die in hospital or require an acute readmission within 30 days of discharge.

While Table 1 presents means and SDs of the aggregate sample for NZ over the period 2008–2012, we have also conducted descriptive analysis for each year separately and then used *t*-tests to ascertain whether the means have increased/decreased or remained static over the sample period. The results of these tests are denoted with 'Up', 'Down' or '–' to signify a significant increase, decrease or no significant change between 2008 and 2012. For instance, the average age increased for most categories in Table 1.

As expected, Table 1 shows that the likelihood of in-hospital death has decreased over the sample period (for all categories but elective high risk). This is expected given the regular advances in medical science. The most interesting and noteworthy trends in Table 1 are in terms of the other two patient outcomes – excess length of stay and risk of readmission. We find that a patient's hospital stay has significantly decreased across all categories in Table 1. This is an indication that hospitals are increasingly likely to promote patient discharge as soon as feasible. Additionally, the likelihood of acute readmission in the 30 days following discharge significantly increased over the sample period. For instance, not reported in the table for the sake of brevity, the readmission rate effectively doubled for elective low-risk patients over the sample period (from 3.3% to 5.7%). Analogous figures for the high-risk category were a jump from 8.7% to 12%. Coupled with the trends in excess length of stay, is this a sign that NZ hospitals are pushing patients out the door too early? Are these outcomes influenced by unexpected demand and consequently insufficient quality care? For instance, Heggestad (2002) finds for Norway a positive association between average length of stay and the patient/nurse ratio, with respect to elderly patients' (at least 67 years of age) risk of readmission. In the next section we therefore focus on predicting demand at both the aggregate and the regional level in NZ to ascertain whether hospitals have access to enough information to be able to accurately predict patient demand.

Table 1. Definitions and descriptive statistics for sample: 2008–2012

	Definition	Low risk	High risk	Acute low risk	Acute high risk	Elective low risk	Elective high risk
Age	Age in years	46.50 (26.44) Up***	68.52 (18.64) Up***	46.00 (27.30) Up***	68.78 (18.73) Up***	47.11 (25.31) Up***	66.73 (17.91) Up***
Share of men	Dummy variable: 1 if male; 0 otherwise	0.44 (0.50) Up**	0.53 (0.50) Down*	0.47 (0.50) Down***	0.53 (0.50) Down*	0.39 (0.49) Up***	0.52 (0.50) –
Share of Maori/Pacific peoples	Dummy variable: 1 if Maori or Pacific peoples; 0 otherwise	0.24 (0.43) –	0.18 (0.38) Up***	0.26 (0.44) –	0.18 (0.38) Up***	0.23 (0.42) Down*	0.16 (0.36) –
Share of Asian	Dummy variable: 1 if Asian; 0 otherwise	0.06 (0.23) Up***	0.04 (0.19) Up***	0.06 (0.23) Up***	0.04 (0.20) Up***	0.06 (0.23) Up***	0.03 (0.16) –
Share of NZ European	Dummy variable: 1 if NZ European; 0 otherwise	0.67 (0.47) Up***	0.76 (0.43) –	0.66 (0.47) Up***	0.75 (0.43) –	0.69 (0.46) Up**	0.79 (0.41) –
Share of other ethnicity	Dummy variable: 1 if other ethnicity; 0 otherwise	0.03 (0.17) Down***	0.03 (0.16) Down***	0.03 (0.16) Down***	0.03 (0.16) Down***	0.03 (0.17) Down***	0.03 (0.17) Down**
Clinical complexity level	Clinical severity, ordinal scale from 0 to 4 where 0 = the least severe, 4 = most severe	0.74 (1.29) Up***	2.38 (1.45) Up***	0.86 (1.35) Down***	2.42 (1.44) Up**	0.59 (1.20) Up***	2.08 (1.50) Up***
Cost weight	A nonnegative continuous variable designed to weight a base rate payment	0.98 (2.50) Down***	2.22 (4.49) Down***	0.93 (2.34) Down***	1.93 (2.63) Down***	1.04 (2.69) Down*	4.21 (10.35) Down***
Hours mechanical ventilation[a]	Hours on mechanical ventilation while the patient was in the intensive care unit (ICU)	1.51 (27.87) –	11.46 (55.76) –	2.19 (34.03) –	11.94 (54.99) –	0.75 (18.87) Up*	7.43 (61.73) –
Share of operative cases	Dummy variable: 1 if event has any operative procedure codes recorded; 0 otherwise	0.60 (0.49) Up***	0.73 (0.44) Up***	0.39 (0.49) Up***	0.74 (0.44) Up**	0.85 (0.36) Up***	0.66 (0.47) Up***
Death	Dummy variable: 1 if the event ended with the death of the patient; 0 otherwise	0.008 (0.086) Down***	0.15 (0.35) Down***	0.011 (0.103) Down***	0.15 (0.36) Down***	0.004 (0.059) Down***	0.12 (0.32) –
Excess length of stay	Adjusted length of stay as deviation of the individual from the average length of stay by diagnosis and DHB	0.000 (20.05) Down***	0.000 (68.47) Down***	−0.057 (17.366) Down***	−2.447 (22.659) Down***	0.07 (22.95) Down***	16.88 (182.13) Down***
Emergency readmission	Dummy variable: 1 if acute readmission up to 30 days after discharge; 0 otherwise	0.07 (0.26) Up***	0.10 (0.30) Up***	0.09 (0.29) Up***	0.10 (0.30) Up***	0.05 (0.22) Up***	0.11 (0.31) Up***
Number of events		4 531 034	94 440	2 505 852	82 485	2 025 182	11 955

Notes: SDs are in parentheses.
A significant increase, decrease and no significant change between 2008 and 2012 are denoted with ‘Up’, ‘Down’ and ‘–’, respectively.
[a]Hours on mechanical ventilation is based on a smaller sample of patients admitted to the ICU.
***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

IV. Empirical Analysis

Demand

Given the high share of public funding in NZ in the health care sector (approximately 83.2% of total health spending in 2010), efficient allocation of public resources are paramount. This involves having sufficient personnel and infrastructural capacity at local hospitals and therefore being able to make predictions regarding hospital demand. It is important at this juncture to point out a caveat with the following analysis. This empirical investigation focusses on the demand side of utilization rates at NZ hospitals. We are therefore assuming that if reasonable predictions about patient demand are made in advance, staffing numbers can be adjusted, and capacity is flexible enough to adapt to those predictions.

As outlined earlier, empirical studies that investigate hospital demand are sparse (see Schwierz *et al.* (2012), Oliveira (2002) and (2004) and Dove and Ritchie (1972)) and often do not specifically account for previous demand levels. We expect that staffing levels in hospitals are planned based on the following factors: (i) demand during the same time in the previous year, (ii) seasonal patterns and (iii) public holidays and weekends. These factors are expected to result in variations in hospital demand that are foreseeable to hospital management, and therefore should not affect the quality of healthcare if fully captured in planning decisions.

To model predictable hospital demand we employ a regression of patient counts for hospital h within DHB d on day t (Equation 1). The covariates used in our regression analysis (fixed effects) include monthly dummies, day of the week dummies, a dummy for public holidays, yearly dummies and patient counts in the last 360–365 days. $\boldsymbol{\alpha}$, β, $\boldsymbol{\gamma}$ and $\boldsymbol{\theta}$ are the corresponding parameters to be estimated in the regression analyses.

$$P_{ht} = \beta_{0h} + \boldsymbol{\alpha_h M}_t + \boldsymbol{\gamma_h D}_t + \boldsymbol{\theta_h Y}_t + \beta_{1h}H_t + \beta_{2h}P_{ht-360} + \cdots + \beta_{7h}P_{ht-365} + u_{ht} \qquad (1)$$

where

P_{ht} = patient counts at hospital h on day t
$\boldsymbol{M}_t$ = dummies for each month from February to December, with January being the reference
$\boldsymbol{D}_t$ = dummies for Tuesday, Wednesday, … and Sunday, with Monday being the reference
$\boldsymbol{Y}_t$ = dummies for year 2009, 2010, … and 2012, with 2008 being the reference
H_t = a dummy variable for public holiday
P_{ht-360} = patient counts at hospital h 360 days before
P_{ht-365}= patient counts at hospital h 365 days before
u_{ht} = random error

It is the last set of variables that prove to be crucial in predicting hospital demand and oddly absent from relevant past models (e.g. Schwierz *et al.*, 2012 for Germany; and Oliveira, 2002). To illustrate the importance of these lagged variables, we compared model fit criteria (R^2) with and without the lags. For a fixed effects model using the aggregate sample, the explained variance increases from 30% to 55%, both the values significant at the 1% level. Interestingly, for Equation 1 at the hospital facility level, there is a wide range in the rate at which the R^2 values increase. On average, across the 29 hospitals, R^2 increases by just over 4%. However, it is notable that for two of the biggest hospitals (Auckland and Canterbury), R^2 increases by 14% and 22% respectively. These results signal that larger scale hospitals have more to gain when predicting demand, if they make use of information from the prior year.

Regression results are not reported for brevity sake but can be obtained from the authors upon request. Given that it is the unforeseeable (unexpected) variation in demand that may impact quality of care and lead to adverse patient outcomes, we next make use of daily predicted patient counts and contrast these with actual counts. Unexpected demand is measured as the ratio of actual/predicted, and centred on 1, such that the values for this index reflect the percentage difference between yearly mean demand and daily demand.

Results for the whole sample (Panel A) indicates that on 20% of days (the 10th and 90th percentile) admissions are approximately 12% higher or lower than expected. Further variation is illustrated if viewing the 5th and 95th percentiles, which indicates that on 10% of days, admissions are approximately 17% higher or lower than expected. Comparable figures for the North-Rhine Westphalia region in Germany, by Schwierz *et al.* (2012), point to potentially less variation in unexpected demand for NZ hospitals. They find that patient demand on 10% of days (5th and 95th percentile) is nearly 30% away from expectations. Interestingly, further analysis proves this difference is not necessarily a result of differences in volatility of demand between NZ and Germany. The main difference between Schwierz *et al.* (2012)'s analysis and this study in terms of measuring unexpected demand is that we explicitly include lagged information on patient counts. If we don't include lags in Equation 1, then we attain similar index values to the German study – specifically values for the 5th and 95th percentile of 0.72 and 1.29, respectively.

Nevertheless our analysis clearly points to volatility in unforeseen patient demand, which is not skewed in either a positive or a negative direction. Panel B breaks the results down by DHB, and we find that demand shocks

Table 2. Distribution of actual and unexpected demand in NZ hospitals

			Percentile						
Demand	Mean	SD	5th	10th	25th	50th	75th	90th	95th
Panel A: Full sample 2008–2012									
Actual	1	0.168	0.744	0.817	0.914	1.011	1.093	1.168	1.233
Unexpected	1	0.135	0.829	0.884	0.948	1.001	1.055	1.119	1.171
Panel B: Regional/DHB sub-samples									
Unexpected: Auckland	1	0.058	0.930	0.951	0.975	1.001	1.027	1.053	1.072
Bay of Plenty	1	0.098	0.849	0.889	0.947	1.000	1.055	1.113	1.159
Canterbury	1	0.118	0.817	0.875	0.947	1.002	1.059	1.128	1.177
Capital and Coast	1	0.069	0.906	0.926	0.966	1.002	1.038	1.073	1.098
Counties Manukau	1	0.320	0.626	0.795	0.947	1.002	1.061	1.195	1.297
Hawke's Bay	1	0.075	0.893	0.920	0.958	1.000	1.044	1.083	1.110
Hutt Valley	1	0.072	0.897	0.922	0.961	1.003	1.044	1.079	1.099
Lakes/Rotorua	1	0.088	0.870	0.901	0.948	1.000	1.057	1.105	1.130
Mid Central	1	0.075	0.905	0.931	0.965	1.002	1.037	1.075	1.104
Nelson Marlborough	1	0.121	0.807	0.860	0.927	1.002	1.075	1.141	1.192
Northland	1	0.180	0.703	0.785	0.910	0.999	1.086	1.203	1.295
Otago and Southland	1	0.087	0.875	0.905	0.956	1.003	1.051	1.097	1.125
South Canterbury	1	0.101	0.853	0.888	0.942	1.000	1.060	1.122	1.160
Tarawhiti	1	0.116	0.830	0.867	0.925	0.997	1.075	1.140	1.182
Taranaki	1	0.094	0.869	0.902	0.948	1.003	1.056	1.107	1.134
Waikato	1	0.100	0.842	0.890	0.952	1.003	1.050	1.111	1.158
Wairarapa	1	0.123	0.811	0.856	0.921	0.998	1.074	1.153	1.200
Waitemata	1	0.078	0.887	0.917	0.962	1.002	1.041	1.083	1.112
West Coast	1	0.127	0.808	0.854	0.924	1.001	1.072	1.154	1.207
Whanganui	1	0.101	0.843	0.882	0.940	1.003	1.064	1.120	1.157
Panel C: Yearly sub-samples									
Unexpected 2008	1	0.153	0.829	0.881	0.945	0.999	1.053	1.116	1.167
Unexpected 2009	1	0.112	0.841	0.888	0.946	0.998	1.053	1.115	1.165
Unexpected 2010	1	0.123	0.831	0.883	0.947	0.998	1.052	1.118	1.176
Unexpected 2011	1	0.145	0.832	0.885	0.947	1.000	1.052	1.118	1.168
Unexpected 2012	1	0.140	0.806	0.879	0.955	1.012	1.064	1.128	1.178

in the health system are unrelated to the scale of the hospital facility. For instance, the three regions with the smallest deviations from the yearly mean are Auckland, Capital and Coast and Mid Central. These regions are very different from one another. As Appendix shows, Auckland is highly urbanized, has less poverty and is three times the size of Mid Central (in terms of patient counts), which is more rural and contains more poverty. At the other end of the spectrum, Counties Manukau and Northland experience the most volatile patient demand, deviating around 30% away from the yearly mean. Again, Counties Manukau is more than double the size in terms of hospital events, compared to Northland, so we cannot use size of regional sub-sample to justify differences in unexpected patient demand. The importance of this regional analysis is that policymakers need to be aware of the potential differences in ability to predict patient count across regions, when they demand increased cost efficiency, which requires reliable predictability in expected patient counts.

Unexpected demand within disease chapter

We next construct an index to capture unexpected demand at the disease chapter level. This is an important construct to control for in the following regressions, as it captures volatility at a more disaggregate level. It is easy to motivate if we imagine that when the hospital on average is under pressure in terms of capacity, there may not necessarily be an impact on all areas of the hospital. To capture this possible incremental impact arising from increased pressure at the department level, we use as a proxy within-disease chapter volatility in demand.[2] Disease chapters are classified under the International Classification of Diseases-10 codes of primary diagnosis. For example, hospital admissions with primary diagnosis codes of

[2] Unfortunately our data set does not include information on department categories.

Table 3. Distribution of unexpected demand within disease chapter

	Mean	SD	Percentile 5th	10th	25th	50th	75th	90th	95th
Full sample 2008–2012									
	0.034	0.044	−0.014	0.000	0.012	0.023	0.044	0.076	0.119
Selected regional/DHB sub-samples									
Auckland	0.018	0.012	0.001	0.006	0.010	0.016	0.023	0.036	0.042
Capital Coast	0.019	0.012	−0.001	0.007	0.012	0.017	0.022	0.034	0.043
Canterbury	0.058	0.073	−0.017	0.009	0.017	0.034	0.074	0.157	0.211
West Coast	0.052	0.057	−0.038	−0.005	0.019	0.043	0.077	0.115	0.165

A00-B99 fall into Chapter I: certain infectious and parasitic diseases; C00-D48 = Chapter II: neoplasms and so on.[3] We focus on disease chapters, rather than individual-level diagnosis information as the latter results in small sample sizes. For instance, Chapter XI encompasses diseases of the digestive system, including disorders of tooth development, inflammatory conditions of jaws, disturbances of salivary glands, etc. More specifically, Chapter XI includes 427 different specific diagnosis codes in this data set, some of which only occur once or twice in the entire sample period (e.g. fistula of the appendix). If we control for difference in variation of excess demand relating to a specific diagnosis relative to variation in excess demand at the hospital level, this could place a lot of weight on a small number of cases, biasing our estimates of the impact of unexpected demand at the diagnosis level. Schwierz *et al.* (2012) go down this route, of assessing variation in demand at the diagnosis level, and their rationale is that such variation in this dimension captures unobservable risk. They expect that demand at the patient diagnosis level will match variation in excess demand at the hospital level and that if it doesn't, then this is an indicator of unobservable severity of case. In contrast to their study, we contend that risk can be captured by making use of patient record information that is indicative of severity of illness. We control for two measures of severity – clinical complexity level (ordinal scale from 0 = least severe to 4 = most severe) and cost weight (in a nonlinear fashion). For the latter of these measures, we assume a higher cost weight is a signal of a more severe illness.

We therefore construct an 'unexpected disease-chapter demand' index in the following fashion: for each disease chapter j within hospital h, we calculate a ratio of the number of admissions on days with excess demand (i.e. a day where predicted patient count is less than the actual), relative to the total admissions for that particular disease chapter. This is denoted by r_{jh}. Then for each hospital h, we measure the ratio of the number of days with excess demand, relative to total days. This is denoted by r_h. The difference between volatility in demand at the disease chapter level relative to that at the hospital level is denoted by $UD_{jh}\left(= r_{jh} - r_h\right)$. When this difference is positive, there are excess admissions in disease chapter j on days with excess demand in hospital h. Table 3 presents the descriptive statistics for the whole sample in terms of UD_{jh}, as well as selected DHBs.[4]

It is apparent that admissions on the basis of disease chapter are not evenly distributed across the days in which the hospital experiences excess demand. In particular, for the whole sample, for 5% of events, there are 1.4% less admissions per disease chapter on days of excess demand at hospital level; and for another 5% of cases, there are 11.9% more admissions per disease chapter on days of excess demand at the hospital level. The top end of this distribution spectrum indicates substantial unevenness when comparing volatility in demand between the hospital and disease chapter. Furthermore, the importance of regional analysis is emphasized here, as sub-group analysis by DHB reveals far ranging regional variation in UD_{jh} across NZ. For instance, in Auckland, we can infer from the 95th percentile of this index that for 5% of events, there are just over 4% more admissions per disease chapter on days of excess hospital demand. The comparable figure for Canterbury is 21.1%, and for the West Coast is 16.5%. It is important to note again that unexpected demand (this time at the disease chapter) is unrelated to size of facility. Canterbury and West Coast are the two DHBs that experience the greatest volatility in this type of unexpected demand, and the former is the 3rd largest DHB, while the latter is the smallest in NZ.

Patient outcomes

To assess the impact of unexpected demand at both the hospital and disease chapter level on patient outcomes, we

[3] See World Health Organisation (2013) for a full list of the 22 disease chapters. (found at http://apps.who.int/classifications/icd10/browse/2010/en)

[4] In the interest of space saving, we have not presented the results for all 20 DHBs, but these can be obtained from the author upon request.

focus on three negative outcomes: excess length of stay, acute readmission within 30 days of discharge and in-hospital death. Starting with our sample of 4 625 474 events (shown in Table 1), we eliminate observations that have the potential to distort average effects of demand on patient outcomes, that is, individuals below the age of 18 at discharge (20.73%) and above the age of 75 (16.74%). The first group has a very low probability of adverse health outcomes (total in-hospital mortality rate of 0.15%) and the second has a higher than average mortality rate (3.48%), that is likely not to be linked to the quality of care. Psychiatric inpatient events (1.2%) and events with a discharge reason other than regularly ended or death (i.e. transfer discharge, self-discharge, etc., 8.72%) were also excluded from the following analysis. This results in a sample of 2 610 460 events, to which we employ a panel regression model for patient i with illness/diagnosis j in hospital h at day t:

$$E_{ijht} = \delta_0 + \delta_1 UH_{ht} + \delta_2 UD_{jh} + \boldsymbol{\varepsilon X}_{ijht} + \boldsymbol{\theta T}_t + \boldsymbol{\tau F}_h + w_{ijht} \tag{2}$$

$$R^*_{ijht} = \delta_0 + \delta_1 UH_{ht} + \delta_2 UD_{jh} + \boldsymbol{\varepsilon X}_{ijht} + \boldsymbol{\theta T}_t + \boldsymbol{\tau F}_h + v_{ijht} \tag{3}$$

$$Z_{ijht} = \delta_0 + \delta_1 UH_{ht} + \delta_2 UD_{jh} + \boldsymbol{\varepsilon X}_{ijht} + \boldsymbol{\theta T}_t + \boldsymbol{\tau F}_h + q_{ijht} \tag{4}$$

where

E_{ijht} = excess length of stay for patient i with illness j in hospital h at day t

R_{ijht} = dummy indicating whether patient i with illness j in hospital h on day t has an acute readmission, conditional on survival of current admission

Z_{ijht} = is a dummy indicating in-hospital mortality

UH_{ht} = unexpected demand at hospital level = excess demand at day t in hospital h

UD_{jh} = unexpected demand within disease chapter = excess demand at disease chapter level, above the level of hospital demand volatility, for illness j in hospital h

$\boldsymbol{X}_{ijht}$ = vector of patient's characteristics: male; dummies for patients aged 30–39, 40–49, 50–59, 60–69 and 70–75 and interactions between male and age groups[5]; dummies for patient clinical complexity level; whether the admission was operative, the number of secondary diagnoses; and the hours on mechanical ventilation. We also include a set of deprivation index dummies capturing the socio-economic status of the area the patient resides. This vector also includes controls for severity of patient illness, for which we assume a nonlinear relationship with patient outcome – specifically, cost weight and cost weight squared

$\boldsymbol{T}_t$ = vector of dummies denoting the years (2009–2012), days of the week (Tuesday–Sunday), months of the year (February–December) and whether the day is public holiday

$\boldsymbol{F}_t$ = vector of dummies for each hospital, with Middlemore hospital being the reference group.

$w_{ijht}, v_{ijht}, q_{ijht}$ = random errors

In estimating Equation 2, we use linear regression and report coefficient estimates. Equation 3 is estimated in two ways. The first approach is to undertake a standard univariate probit model for assessing the determinants of readmission probability, conditional on survival of the current admission. In the second approach, we assume that the latent variable R^*_{ijht} drives the observed outcome of being readmitted (R_{ijht}), through the following equations:

$$R_{ijht} = \begin{cases} 1 & \text{if } R^*_{ijht} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Assuming that the determinants of survival (S_{ijht}) can be estimated via a univariate probit:

$$S^*_{ijht} = \delta_0 + \delta_1 D_{ht} + \delta_2 U_{jh} + \boldsymbol{\varepsilon X}_{ijht} + \boldsymbol{\theta T}_t + \boldsymbol{\tau F}_h + e_{ijht} \tag{6}$$

The error terms from Equations 3 and 6 are jointly distributed as bivariate normal, with a correlation parameter of ρ. By employing Equations 3 and 6 together in a Heckman sample selection framework, we allow for the potential of unobservable confounders influencing both the probability of survival and the probability of readmission. This is an important alternative model to trial, as Laudicella *et al.* (2013) show using UK data that there is a significant negative residual correlation (ρ) between the probit on survival and the probit on readmission. This suggests that the risk of readmissions for the patients who didn't make it would have been significantly higher, had they survived. This was further illustrated in Laudicella *et al.*'s research by the conditional probability of a readmission for some of the age groups (relative to the reference group of 65–70) almost doubling once the authors had controlled for sample selection. In both the univariate probit model, as well as the sample selection bivariate probit model, we report marginal effects in the discussion that follows.

[5] Age 18–29 is the excluded reference group.

In our final model (Equation 4), we estimate another probit and provide marginal effects for the probability of an in-hospital death.

V. Results

Aggregate sample

The key results for the aggregate sample, based on utilizing the models outlined in 'Patient outcomes', are presented in Table 4. In particular, we provide estimates for the variables related to unexpected excess demand. All other covariates listed in $\boldsymbol{X}_{ijht}$, $\boldsymbol{T}_t$ and $\boldsymbol{F}_t$ are included but not reported for the sake of brevity. In general, we find older males patients who live in a more deprived region, have increasing number of secondary diagnoses and have a higher cost weight are more likely to experience a longer hospital stay and a greater probability of readmission.

Focussing on the results for Panel A, as unexpected demand increases (whether at the hospital or within disease chapter), a patient's hospital stay is lengthened, and this result is usually significant at the 1% level. To literally interpret the coefficient estimates for unexpected demand at the hospital level, lets pose a simple hypothetical example. Let's say the predicted daily patient count at a hospital facility is 1000 patients,[6] and from the sample size figures in Table 4, we can deduce that these 1000 are on average spread across the categories of elective low/high risk and acute low/high risk in the following proportions: 46.2%, 0.2%, 52.6% and 1%. We can infer from Table 4 that if there was a demand shock and actual daily patients increased by 100% (i.e. doubled), length of stay would increase by 0.129 days per elective low-risk patient and by 1.69 days per acute high-risk patient. To put this in more realistic terms, when actual patients increase by 10% above the predicted level (i.e. 46 more patients above the predicted 462 for elective low risk and by one more patient above the predicted 10 for acute high risk), length of stay will increase by between 0.0129 and 0.169 days per patient, respectively. While these results are strongly significant, they may not seem like a sizeable effect. However, if we consider that this is the impact on each patient, then on the day of this 10% demand shock, the total increase in stay across the patient population would be 22.77 days.[7] These findings are larger in magnitude than those found by Schwierz *et al.* (2012), where the authors go on to conclude that hospitals in North-Rhine Westphalia (Germany) are relatively well prepared to deal with demand shocks. Interestingly, they also find that demand shocks lead to an apparent steering of elective patients discharged earlier, and discharges of acute patients postponed. In contrast, except for elective high-risk cases (which account for just 0.2% of the sample), all categories of patient (whether elective or acute) experience a longer stay when the hospital is hit with a demand shock.

The estimated effects for unexpected demand within disease chapter are for a 100% increase in the proportion of admissions on days of excess hospital demand, for a particular disease chapter. Therefore, for elective low-risk patients, when the proportion of admissions for a disease chapter increases by 10% on days of excess hospital demand, a patient's hospital stay increases by just over 1 day. The impacts are larger for high-risk patients (whether elective or acute), where the length of stay increases by 3.7 days and 3.05 days respectively (all significant at the 1% level).

In terms of results within Panel B, where the outcome is probability of readmission within 30 days, we conduct two different models. Marginal effects in the shaded cells represent results from a probit on readmissions, which is of course conditional on these patients having survived their first admission. Marginal effects in the nonshaded cells represent findings from a Heckman sample selection model, where we allow for the possibility that unobservables are influencing both the probability of readmission and the likelihood of survival in the first admission. Interestingly, while three out of four subgroups in Panel B (Table 4) exhibit a negative ρ (residual correlation between Equations 3 and 6), none of them are statistically significant, and all are small in magnitude. Therefore, our results signal that for those who have died, the risk of readmission would have been marginally higher (had they survived), relative to those that did survive, but this difference is small and statistically insignificant. This implies that the sample of survivors can be used to make inferences regarding the probability of readmission with respect to our demand shock variables. Nevertheless, we will interpret the marginal effects from both the standard probit model and the sample selection model and show that there is very little difference between the two sets of results in the majority of cases. This finding is in contrast to that by Laudicella *et al.* (2013), who report a significant negative $\rho = -0.56$, based on a UK sample. We speculate that the additional controls employed in our regression framework, relative to that by Laudicella *et al.* (2013), may be the reason why they find significant evidence of unobservables at play, and we do not. Specifically, including measures of severity of illness (clinical complexity level, cost weight and cost weight

[6] This is close to the 2012 average daily patient count in Auckland DHB of 1037.
[7] This figure is derived from adding the impact in each patient category in Table 4 and assuming a 10% demand shock = (462*1.1*0.0129) + (2*1.1*0) + (526*1.1*0.0248) + (10*1.1*0.169).

Table 4. Patient outcomes

	Elective admissions				Acute admissions			
	Low risk		High risk		Low risk		High risk	
Panel A: Excess length of stay								
Unexpected demand at hospital level	0.129***		−0.128		0.248***		1.690***	
Unexpected demand within disease chapter	10.092***		37.007***		9.414***		30.527***	
R^2	0.449		0.435		0.385		0.398	
N	1 205 793		5824		1 373 470		25 373	
Panel B: Probability of readmission within 30 days								
Unexpected demand at hospital level	0.002	0.001	0.072	0.078	0.049***	0.052***	0.059*	0.066**
Unexpected demand within disease chapter	−0.025**	−0.057***	1.923***	2.158***	0.198***	0.206***	3.043***	2.969***
Rho/pseudo R^2	−0.006	0.043	−0.028	0.029	0.002	0.019	−0.008	0.028
N	1 205 793		5824		1 373 470		25 373	
Panel C: Probability of in-hospital death								
Unexpected demand at hospital level	−0.00005*		0.010		–		–	
Unexpected demand within disease chapter	−0.0003		−0.403**		–		–	
Pseudo R^2	0.398		0.246		–		–	
N	1 180 446		5786		–		–	

Notes: Results from Panel A are based on a linear regression, whereas results from B and C are marginal effects estimates from probit models.
Panel B presents results from a Heckman selection model and a standard probit model; the marginal effects for the latter are in the shaded cells.
All regressions include the following controls: $\boldsymbol{X}_{ijht}$ (male, dummies for age groups 30–39, 40–49, 50–59, 60–69 and 70–75, interactions between male and age groups, clinical complexity level, whether admission was operative, number of secondary diagnoses, hours on mechanical ventilation, deprivation index of the area the patient resides in, cost weight and cost weight squared), $\boldsymbol{T}_t$ (vector of dummies for years, months of the year, days of the week and if the day is a public holiday) and $\boldsymbol{F}_t$ (vector of hospital dummies).
***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

squared) are likely to be capturing a broad range of determinants of both probability of survival and readmission.

Unexpected demand at the hospital level appears to only influence the probability of readmission for acute cases. For instance, if unexpected demand increases, let's say actual daily patient numbers rise by 10% above prediction, then the probability of readmission increases by 0.49% and 0.59% for acute low- and high-risk cases, respectively. The comparable figures when we don't control for sample selection bias are 0.52% and 0.66%. Therefore, we notice minimal difference between the two models, as expected given the small and insignificant ρ in each patient category.

Apart from elective low-risk cases, we also find that unexpected demand at the disease chapter increases the probability of readmission. The marginal effects are particularly pronounced for high-risk cases. For instance, when the proportion of admissions for a disease chapter increases by 10% on a day the hospital is experiencing excess demand, a patient's risk of readmission increases by 19.23% and 30.43% for elective high-risk and acute high-risk cases, respectively.

Panel C of Table 4 presents results from a probit model for in-hospital death.[8] Marginal effects for elective admissions indicate that, for the most part, there is minimal impact on probability of death when there are unexpected demand shocks at a hospital. One unexpected finding is the negative marginal effect (−0.403, significant at the 5% level) for unexpected demand within disease chapter in the elective high-risk category. The marginal effects estimate points to risk of death decreasing by 4% when the proportion of admissions for a disease chapter increases by 10% on a day the hospital is experiencing excess demand. To explain why this result appears to be at odds with expectations and with the general trend for adverse outcomes illustrated in panels A and B, we need to first remember that elective high-risk cases constitute a very small proportion of our total patient sample – just 0.2%. Additionally, we could speculate that this unexpected finding is the result of medical staff perhaps going into 'triage' mode when there is an unexpected demand shock and a patient's life is on the line and that high-risk cases may therefore benefit in such circumstances.

A final empirical step replicated the analysis from Table 4 for separate years – the start of the sample (2008) and the end of our time frame (2012). While we don't provide results here, for the sake of brevity,[9] it is important to note that the majority of results were qualitatively similar to those in Table 4, irrespective of whether we focussed on 2008 or 2012. This is good evidence that our overall findings for adverse outcomes when there is a patient demand shock, in terms of length of stay and risk of readmission, are relatively robust and have been consistent across time over the last 5 years in NZ.

VI. Conclusions

In this study, we have made two main contributions. First, we have put forth an empirical model to predict hospital demand across the NZ health sector. The predicted patient count model would be easy to implement and could be adapted to specific regional DHBs if necessary. There was some evidence that the regions of Counties Manukau and Northland experience the most volatile patient demand, making predictions a tougher exercise in these DHBs. In an extension to the literature, we found lag variables important in improving model fit criteria in our prediction regressions. Such a framework is new to the NZ health literature and can offer policy makers greater understanding of which regional DHBs are subject to less foreseeable demand, compared to other regions. Further region-specific research could pursue reasons why this may be the case.

Second, we employed an aggregate data source based on all hospital admissions across NZ to assess the impact of unexpected demand shocks on patient outcomes. In general, we find a patient's length of stay is significantly lengthened when there is demand shock at the hospital level, and this is further amplified if the patient is in a disease chapter experiencing additional strain on resources. Similarly, unexpected demand increases the probability of readmission, with these estimates being much larger for high-risk cases. We make use of both the Heckman sample selection framework and a standard probit approach when investigating determinants of readmission and find very little difference in results. Our study argues that sample selection at patient level may already be captured in the probit model, with the use of broad indicators of illness severity, such as cost weight and clinical complexity level.

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[8] In Panel C, results are only available for elective admissions, due to the small sample size for acute admissions.
[9] Results can be obtained from the author upon request.

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Appendix. Distribution of events by DHBs and regional descriptives

NZ regional DHBs	Hospital events	% of sample	Urban (%)	Population size	Proportion above median income (%)
Counties Manukau	530 196	11.46	93	433 086	50
Auckland	586 021	12.67	99.8	404 619	54
Canterbury	502 803	10.87	84	466 407	48
Waitemata	433 451	9.37	94	481 611	53
Waikato	429 304	9.28	78	339 189	48
Capital and Coast	288 249	6.23	99	266 658	56
Northland	244 338	5.28	51	148 440	43
Otago and Southland	265 857	5.75	77	286 224	45
Bay of Plenty	229 088	4.95	79	194 931	45
Mid Central	170 622	3.69	67	158 841	45
Hawke's Bay	171 519	3.71	87	148 248	46
Hutt Valley	136 563	2.95	98	136 101	53
Nelson Marlborough	129 641	2.8	78	130 062	46
Taranaki	123 555	2.67	77	104 277	47
Lakes	117 020	2.53	81	98 319	48
Whanganui	79 669	1.72	81	62 208	42
South Canterbury	63 954	1.38	50	53 877	43
Tairawhiti	51 839	1.12	71	44 463	42
Wairarapa	40 974	0.89	76	38 613	45
West Coast	30 811	0.67	58	31 329	42
Total	4 625 474	100			

Sources: National Minimum Dataset for hospital events. Urban (%) sourced from individual DHB reports ranging from 2004 to 2012 and Pool *et al.* (2009). Population size and proportion above median income sourced from 2006 census.