Spatial patterns in excess winter morbidity among the elderly in New Zealand

by

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Abstract

It has been established in New Zealand and internationally that morbidity and mortality tends to rise during colder winter months, with a typical 10-20% excess compared to the rest of the year. This study sought to investigate the spatial, temporal, climatic and demographic patterns and interactions of excess winter morbidity (EWMb) among the elderly in New Zealand. This was achieved through analysis of acute hospital admissions in New Zealand between 1996 and 2013 for all patients over the age of 60 with an element of circulatory or respiratory disease (N=1,704,317) including a primary diagnosis of circulatory (N=166,938) or respiratory (N=62,495) disease. A quantitative approach included ordinary least squares and negative binomial regression, graphical analysis and age standardisation processes. Admission rates and durations were regressed against a set of 16 cold spell indicators at a national and regional scale, finding significant spatial variation in the magnitude of EWMb. EWMb was ubiquitous across New Zealand despite climatic variation between regions, with an average winter excess of 15%, and an excess of 51% for chronic obstructive pulmonary disease (COPD). Statistically significant relationships were found between hospital admission durations and cold spells up to 28 days prior; however the magnitude would not be expected to have a significant impact on hospital resources. Nonetheless, there is potential for preventative public health strategies to mitigate less severe morbidity associated with cold spells. Patients over the age of 80 were particularly vulnerable to EWMb; however socioeconomic deprivation and ethnicity did not affect vulnerability. Patients residing in areas of high socioeconomic deprivation or identifying with Maori or Pacific Island ethnicity experienced significantly shorter admissions than other groups, and this warrants further investigation. Further investigation into winter COPD exacerbations and non-climatic factors associated with the EWMb are recommended. A comprehensive understanding of EWMb will enable preventative measures that can improve quality of life, particularly for the elderly population.

Abbreviations

ASR – Age Standardised Rate

CAU - Census Area Unit

COPD – Chronic Obstructive Pulmonary Disease

CSVH – Coefficient of Seasonal Variation in Hospitalisations

ERP – Estimated Resident Population

EWH – Excess Winter Hospitalisations

EWM – Excess Winter Mortality

EWMb – Excess Winter Morbidity

ICD – International Statistical Classification of Diseases and Health Related Problems

MOH – Ministry of Health

NMDS – National Minimum Dataset

NZDep – New Zealand Deprivation Index

SNZ – Statistics New Zealand

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1 Introduction

1.1 General overview

An annual winter surge of hospital admissions stretches healthcare resources, both in New Zealand and in temperate climates internationally (Davie, Baker, Hales, & Carlin, 2007; Healy, 2003). Excess winter morbidity (EWMb) and mortality (EWM) is a well-documented phenomenon under which illness or death occurs at a greater rate during winter months, associated with lower outdoor temperatures. Winter mortality rates have been found to be 18% higher than non-winter rates in New Zealand, with evidence that the elderly are particularly vulnerable (Davie et al., 2007). The causal process for EWM and EWMb has not been established, although has been posited as a complex interaction of temporal, climatic and demographic factors.

There is a wealth of literature investigating EWM and EWMb, with the majority taking a disease-driven approach, reflecting an origin in medicine; however fewer studies focus on the cross-disease phenomena (Telfar-Barnard, 2010). This thesis takes a broad approach to EWMb, looking at not only the temporal and climatic conditions driving the phenomenon in New Zealand, but also demographic and spatial covariates and confounders. Respiratory and cardiovascular illnesses are particularly sensitive to temperature and make up a significant proportion of winter excess mortality and morbidity (Wilkinson, 2001). EWM has been well studied across Europe, finding that populations residing in temperate climates such as the United Kingdom are more vulnerable to this phenomenon than those in more extreme winter environments such as Scandinavian countries (Healy, 2003; Keatinge et al., 1984; Laake & Sverre, 1996). It has been postulated that this is due to a physiological adaption by individuals residing in cold climates (Analitis et al., 2008; Keatinge, Donaldson, Bucher, Jendritsky, & al, 1997). New Zealand has a temperate climate with distinct regional differences, which lend well to a study of the spatial variation of EWM and morbidity. One prior study has analysed the spatiality of EWM in New Zealand, but looked at all causes of mortality and age groups together, and only divided the country into four regions (Davie et al., 2007).

The elderly are expected to comprise an increasing proportion of the total population in the near future, and this is expected to have adverse impact on the provision of social services, particularly health care (Cornwall & Davey, 2004; Stephenson & Scobie, 2002). It is worthwhile to understand where this population will interact with the healthcare system and how environmental conditions such as weather may impact their demand for health services (Ministry of Health, 2002; Nissen, New Zealand, & Statistics New Zealand, 2009).

1.2 Aims and Objectives

The primary aim was to categorise elderly populations that are vulnerable to excess winter morbidity and make policy recommendations to reduce burden on the healthcare system, by means of:

1. Understanding variation of excess winter morbidity amongst the elderly across New Zealand
2. Understanding how climate and socioeconomic deprivation are related to the variation in excess winter morbidity amongst the elderly across New Zealand
3. Identifying factors affecting the length of stay for circulatory and respiratory disease related hospitalisations of the elderly in New Zealand

These objectives were achieved through the application of geospatial and statistical analysis to records of hospital admissions of the elderly in New Zealand for circulatory and respiratory disease. This thesis investigates the magnitude of EWMb and its relationship with demographic, temporal and climatic factors. Spatial variation in EWMb is explored by comparing hospital admissions across eight main centres throughout New Zealand.

1.3 Thesis outline

This thesis is arranged into six chapters – introduction, background, methodology, results, discussion and conclusion.

The introduction provides the broader context to the study, motivations behind the research, and outlines aims and objectives.

The background chapter will outline firstly the global context of EWM and EWMb by summarising individual and population level studies that measure and explain the phenomenon. There is a detailed summary and critique of methodologies previously employed in this field, along with a discussion of confounding factors that modify the relationship between winter, cold spells and mortality or morbidity. Finally, the New Zealand context is detailed with a description of the demographic changes anticipated with an ageing population, the subsequent impacts on demand for healthcare, and fiscal impact on the government.

The methodology chapter outlines the datasets and methods of analysis employed to investigate the objectives of the thesis. For each of the four major sources of data, there is a detailed description including an overview of how they have been collected, which variables they measure, and the steps taken to clean and process the data into a suitable form for analysis. A series of cold spell indicators was developed from a national climate database, and the rationale and process of developing of this process is explained. Eight main urban centres are the focus of analysis for spatial variation of hospitalisations, with a map and summary of these areas. Regression models were developed to relate hospital admission rates and durations to the characteristics of patients, patient's neighbourhoods, and climate. The process of developing these models is discussed with reference to the characteristics of the datasets and statistical literature.

The results chapter outlines findings of the analysis, arranged in three sections based upon the variables being analysed. The first section proffers summary statistics that describe the characteristics of patients in the hospital admissions dataset and the cold spell indicators. The second section analyses hospital admission rates, initially through summary statistics and graphical analysis, and then with the results of regression models for hospital admissions applied at a national and regional scale. The third section analyses hospital admission duration, with summary statistics initially, and then through regression analysis at a national and regional scale.

The discussion chapter takes results from the results chapter and places them in context with relevant literature and background statistics about the population. Findings are discussed in four main sections –

demography, long term changes, seasonality and temperature, and spatial patterns. The demography section looks at the covariance of age, ethnicity and socioeconomic deprivation, and how they affect patterns of hospitalisation. Changes in the characteristics of hospital admissions over the 18 years of data studies are discussed in the long term changes section. The seasonality and temperature section discusses how variation in hospital admissions and duration is associated with the winter season and cold spell indicators. Spatial patterns in hospital admissions are discussed with reference to spatial variation of demographic composition, and how spatial variation modifies the seasonality and temperature relationships. The discussion is concluded with several suggestions for future research and a summary of the research implications.

The conclusion summarises the context of this research, the methodologies employed, and reiterates the results and implications.

2 Background

This chapter assesses background literature relevant to this thesis and provides context to the subsequent methodology chapter. The phenomenon of EWM and EWMb is first described with reference to predominantly international literature. The issue of the ageing population is then described with particular reference to New Zealand statistics and literature.

2.1 Excess winter mortality and morbidity

EWM or EWMb is a well-documented phenomenon under which deaths or illnesses respectively occur at a greater rate during the winter season. This is associated with, but not necessarily caused by, lower ambient temperatures. This results in higher demand for health services, however the causality beneath the relationship and options for mitigation have not been widely researched (Mercer, 2003). Extended stays in hospital by the elderly are commonly associated with this phenomenon and have a significant adverse effect on overall health service delivery (Dewar, 1999; Donaldson & Wedzicha, 2014).

EWM and EWMb have been extensively studied at a population level, particularly in Europe, and have been demonstrated to vary significantly between countries. Table 1 summarises the magnitude of EWM across New Zealand and Europe, showing that with 18% higher mortality during the winter season, New Zealand is above the average level of EWM internationally. During cold spells, mortality was found to increase up to 12.8% in The Netherlands (Huynen, Martens, Schram, Weijenberg, & Kunst, 2001). Even small decreases in temperature are associated with increases in mortality, with a 1^{0}C fall in temperature below the annual mean associated with a 1.35% increase in natural deaths across Europe, and 1.5% increase in the United Kingdom alone (Analitis et al., 2008; Aylin et al., 2001). Extremely high temperatures during summer in some climates also have an adverse impact on health, resulting in a parabolic relationship whereby both extremely high and low temperature increase mortality and morbidity, with elderly more vulnerable to both than other age groups (Gouveia, 2003).

Table 1:- International comparison of excess winter mortality rates, comparing winter mortality rates to non-winter. Emphasis added to New Zealand to highlight the context of this research.

Country	*Excess winter mortality*	*95% confidence interval*
Finland[1]	10%	7 – 13%
Netherlands[1]	11%	9 – 13%
Germany[1]	11%	9 – 13%
Luxembourg[1]	12%	8 – 16%
Denmark[1]	12%	10 – 14%
Belgium[1]	13%	9 – 17%
France[1]	13%	11 – 15%
Austria[1]	14%	12 – 16%
Italy[1]	16%	14 – 18%
New Zealand[2]	**18%**	**6 – 32%**
Greece[1]	18%	15 – 21%
UK[1]	18%	16 – 20%
Ireland[1]	21%	18 – 24%
Spain[1]	21%	19 – 23%
Portugal[1]	28%	25 – 31%
[1] 1988-97 (Healy, 2003); [2] 1980-2000 (Davie et al., 2007)		

2.1.1 Theoretical foundation

Winter seasons are associated with lower temperatures and altered behaviours, which lead to a number of adverse health impacts. Respiratory and cardiovascular illnesses are particularly sensitive to falls in temperature, as well as viral and bacterial infections (Bull & Morton, 1978; Davie et al., 2007; World Health Organization, 1985). Part of the winter excess is hypothesised to result from physiological changes associated with temperature, including the higher level of energy expended to maintain body temperature (West & Lowe, 1976).

Circulatory and respiratory diseases exhibit strong seasonality, so even countries with low levels of these diseases can exhibit high levels of EWM and EWMb (Curwen, 1991; Fares, 2013). Cardiovascular disease, a subset of circulatory disease, is responsible for approximately 50% of deaths due to natural causes in developed countries, and are most prevalent in the elderly (Mercer, 2003). Chronic obstructive pulmonary disease (COPD), which encompasses a group of respiratory diseases such as bronchitis and emphysema, is the fourth leading cause of death in New Zealand with acute exacerbations increasing during winter (Broad & Jackson, 2003; Donaldson & Wedzicha, 2014). Lower temperatures cause increases in the pressure and viscosity of blood, and increased concentration of fibrinogen, a blood clotting agent. This induces an inflammatory reaction within the cardiovascular system which increases risk of acute cardiovascular diseases such as stroke and heart failure (Fares, 2013; Keatinge et al., 1984; Mercer, 2003; Vallance, Collier, & Bhagat, 1997).

Thermoregulatory behaviours of populations will vary significantly between locations, largely in response to climate, with residents of extremely cold climates taking a more rigorous approach to wearing appropriate clothing, and insulating and heating buildings (Donaldson, Ermakov, Komarov, McDonald, & Keatinge, 1998; Eng & Mercer, 1998). The winter season is also associated with changes in lifestyle behaviours which will also impact health. The winter season is associated with changes in physical activity and diet (Donaldson & Keatinge, 2002); decreased time spent outdoors, reducing absorption of Vitamin D and potentially weakening the immune system (Cannell et al., 2006); and an increased time spent in close proximity with others, increasing opportunities for the transmission of airborne viral and bacterial infections (Fares, 2013).

It has been suggested that elderly are more vulnerable to EWM not just because of generally poorer health, but specifically due to a reduced capability to regulate body temperature (Hong et al., 2003; Mercer, 2003; Wagner & Horvath, 1985). Elderly are more vulnerable to mortality from acute illness, with a study of influenza-like illness in Denmark finding that the elderly made up 88% of deaths (Nielsen, Mazick, Glismann, & Mølbak, 2011). Looking specifically at British elderly over the age of 65, Wilkinson et al. (2004) noted 31% higher mortality during the winter season.

In many cases, variation in EWM and EWMb between locations is not explained by variation in temperature; this may be due to physiological adaption, whereby residents acclimatise to the extreme climates after sustained exposure. This hypothesis is supported by population level studies comparing EWM rates between different climates across Europe (Analitis et al., 2008; Bull & Morton, 1978; Gordon, 2003; Keatinge et al., 1997; Kendrovski, 2006; Mercer, 2003; Monteiro, Carvalho, Góis, & Sousa, 2013). As an extreme example, one study of Yakutsk, Eastern Sibera, found no evidence of EWM despite extremely cold temperatures (Donaldson et al., 1998).

2.1.2 Methodologies

2.1.2.1 Mortality, morbidity or hospitalisation

Studies of excess winter mortality and morbidity investigate largely the same phenomenon, albeit at different stages, with mortality representing a more severe, uncommon outcome than morbidity. Mortality studies tend to be more common, potentially due to mortality data being universally reported. Morbidity as a concept is well defined, however it cannot be measured directly (Thacker et al., 2006); instead excess winter hospitalisation (EWH), a subset of EWMb, is commonly used as proxy based on hospital admission records (Telfar-Barnard, 2010). Some studies have gained access to data on the rate of GP visits to gain an understanding of less severe instances of morbidity than hospitalisations, although such data contains the noise of routine, minor GP visits in addition to acute weather related complaints (Hajat & Haines, 2002; Rudge & Gilchrist, 2005). EWM studies with a seasonal approach have used mortality or hospitalisation records to compare age standardised rates (ASR) of mortality or morbidity between winter months and the remainder of the year (Bull & Morton, 1978; Crighton, Moineddin, Upshur, & Mamdani, 2003; Mann et al., 2009).

2.1.2.2 Length of admission

The length of hospital admission is a significant determinant of hospital costs and can vary significantly between diagnoses and societal groups. The level of socioeconomic deprivation in a patient's residence can be a significant determinant; however the effect differs between diagnoses. Overall in New Zealand, patients from the least deprived areas spend longer in hospital on average than those from more deprived areas; however there is evidence that for patients admitted for treatment of severe mental illness or COPD, those from more deprived areas tend to spend longer in hospital (Abas, Vanderpyl, Robinson, Prou, & Crampton, 2006; Agboado, Peters, & Donkin, 2012; Ministry of Health, 2011). Maori patients tend to experience shorter hospital admissions than non-Maori; and men tend to experience longer admissions than woman in New Zealand (Ministry of Health, 2011). While the effect of seasonality and cold spells on admission rates has been well studied internationally, few studies have analysed the effect of environmental conditions on the average length of stay, despite the significant potential for impact on hospital operation. One UK study of hospital admissions for stroke in a predominantly elderly sample found no difference in length of admission between seasons despite finding higher admission rates in winter periods (Myint, Vowler, Woodhouse, Redmayne, & Fulcher, 2007).

2.1.2.3 Defining winter

Winter can be considered as purely a weather phenomenon associated with lower temperatures, or a broader set of behaviours associated with weather patterns. The most common approach in prior studies has been to define a winter period, typically of four months, and derive a ratio of mortality or morbidity rates during the winter period to the summer period or the remainder of the year. While this simple approach avoids the need for meteorological data, it simplifies adverse weather into a discrete time period, and does not take into account of the health impact of low temperatures at other times of the year. Furthermore, this method will understate the excess of winter morbidity in regions with heat-related morbidity during summer. Looking specifically at the impact of low temperatures rather than seasonality on EWM/Mb, some studies have taken a time series approach, developing cold spell indices that take into account the duration and severity of cold weather, and use temperatures as an explanatory variable for daily or weekly mortality or morbidity rates to derive the relationship.

With the majority of studies conducted in the Northern Hemisphere, winter was commonly defined as December, January, February and March. This approach is used in deriving the Excess Winter Mortality Ratio (EWMR) or Index (EWMI) from Curwen (1991), which has been adopted by a number of subsequent studies. Similar indices are referred to as Coefficient of Seasonal Variation in Mortality (CSVM) (Healy, 2003) and Excess Winter Death Index (EWDI) (Davie et al., 2007). Other studies refined this further in response to specific local climates, such as restricting the winter period as December and January (Maheswaran, Chan, Fryers, McManus, & McCabe, 2004). Alternatively, Rau (2006) in a Northern Hemisphere study compared deaths from January to March with those from July to

September. A New Zealand study compared a winter period of June to September to the remainder of the year, October to May (Davie et al., 2007).

2.1.2.4 Temperature

Studies following a time series approach of relating outside temperature to hospital admissions or mortality face the additional problem of accommodating for the time lag between falls in temperature and health events. Modelling this lag will account for the time taken for an individual to fall ill following a fall in temperature, as well as the time spent ill before they manifest in official statistics as a hospital admission or death. The lag effects of cold spells varies between conditions, with an increase in respiratory illnesses typically presenting after cold spells (Keatinge et al., 1997). An increase in stroke and heart attacks is typically observed 1-4 days following a fall in temperature (Bull & Morton, 1978; Hong et al., 2003), and pneumonia after a week (Bull & Morton, 1978). An increase in general cardiovascular and respiratory complaints has been observed 6-15 days following a cold spell (Hajat & Haines, 2002). Analitis et al. (2008) noted increased mortality up to 23 days following a fall in temperature. Studies of the impact of temperature on mortality have used regressions to standardise mortality to an average temperature and quantify the relative risk of death associated when temperature deviates from the average (Gouveia, 2003; Keatinge et al., 1997). One study of Scotland found a 1^{0}C fall in temperature was associated with a 1% increase in mortality after a week (Gemmell, 2000). The relationship between health and temperature is not necessarily linear, so some studies have defined temperature thresholds in order to isolate insignificant falls in temperature. Hajat & Haines (2002) found that temperatures below 5 degrees Celsius were associated with strong increase in GP consultations. Threshold effects are more commonly accounted for in the more sophisticated approach of defining cold spells. The way in which temperature varies between locations (climate) is discussed subsequently in relation to the spatiality of EWM.

2.1.2.5 Cold spell

Falls in temperature of a mild nature or brief duration do not have the same adverse impact on health as sustained or severe cold spells, so a number of cold spell indices have been developed to consistently define and quantify cold spells. These indices vary in their thresholds for severity and duration; for instance the Australian index defines cold spells as at least four consecutive nights with a minimum temperature within the lowest 10^{th} percentile (Monteiro et al., 2013). Bull & Morton (1978) found that falls in temperature sustained for 1-3 weeks were associated with increased rates for heart attacks, strokes and pneumonia in the United Kingdom. Monteiro et al., (2013) found that a number of cold spell indices were correlated with excess hospital admissions for COPD during winter in Porto, Portugal. Excess hospital admissions were discernible up to 15 days following the end of the cold spell, but not during the cold spell. Laake & Sverre (1996) found that variation in EWM between years in the UK was correlated with variation in average temperature. Monteiro et al., (2013) noted that the persistence of cold spells was a more important determinant of morbidity in the general population than the severity of the cold spell; however low absolute temperatures were a risk factor for vulnerable populations, such as the elderly.

2.1.2.6 Confounders

Given the broad range of social, environmental and housing factors related to EWM, the presence of confounders has been widely researched. Air pollution has been hypothesised as contributing towards EWM, however the complex relationship between air pollution and illness in general makes accurate quantification of confounders complicated, especially with wide variation in pollution and exposure found between seasons and even within small areas (Fares, 2013; Fukuda, Hider, Epton, Jennings, & Kingham, 2011). A study of 15 European cities found no evidence of air pollution impacting EWM (Analitis et al., 2008). The relationship between EWM and socioeconomic deprivation has been studied extensively in the UK, often testing the hypothesis that less wealthy households cannot afford sufficient home heating and are therefore more vulnerable to low temperatures. A number of both regional and small area studies in the UK have found no correlation between socioeconomic deprivation and EWM (Aylin et al., 2001; Lawlor, Maxwell, & Wheeler, 2002; Maheswaran et al., 2004; Shah & Peacock, 1999; Wilkinson, 2001). This is despite a strong correlation between socioeconomic deprivation and cardiovascular disease and respiratory illness which make up a significant portion of EWM (Crombie, Kenicer, Smith, & Tunstall-Pedoe, 1989; Feinstein, 1993). More generally, all-cause mortality exhibits a strong socioeconomic gradient in New Zealand, associated with differences between ethnic groups (Tobias & Yeh, 2006).

The circulation of influenza has a significant influence on winter morbidity (Nicholson, 2003), and studies have utilised data on influenza circulation as a control variable for morbidity (Donaldson & Keatinge, 2002; Gemmell, 2000; Wilkinson et al., 2004), however influenza supervision data in New Zealand is more suited to clinical rather than research purposes (Fukuda et al., 2011). Despite strong seasonality in mortality due to circulatory and respiratory illness, there was no evidence of seasonality in drug prescriptions for these illnesses in Ireland, possibly due to acute onset of these conditions leading to mortality (Moran, Johnson, & Johnson, 2000).

The relationship between outdoor temperatures and health can be mediated by indoor temperatures, which have been associated with higher EWM in New Zealand (Moller, 2011), although similar studies in the United Kingdom have found strongly mixed results (Aylin et al., 2001; Keatinge et al., 1997; Wilkinson, 2001). The relationship between outdoor and indoor temperatures can be confounded by the thermal properties of homes and behaviours in heating, and thus the lower thermal quality of housing in temperate climates is often provided as an explanation of higher EWM in temperate climates. Few studies have attempted to control for housing quality, as few datasets exist with sufficient depth, breadth and accuracy (Rau, 2006; Telfar-Barnard, 2010; Wilkinson et al., 2004). One such study conducted in New Zealand found that although EWH in New Zealand was significantly associated with housing types, it was not associated with the age of construction, which itself is associated with the level of thermal insulation. New Zealand houses are typically large and poorly insulated and heated, although with increasing adoption of heating technology such as insulation and heatpumps, households have tended towards warming their houses to warmer temperatures than previously (Howden-Chapman et al., 2009). The national census of dwellings indicates a distinct North-South gradient in heating, with dwellings in the colder Southern regions the least likely to not have a source of heating (Statistics New Zealand, 2013c).

2.1.2.7 Spatiality

Spatial variation in EWM has been well-studied in Europe, finding mixed results within the United Kingdom (Curwen, 1991; Laake & Sverre, 1996; Wilkinson et al., 2004), strong variation across Europe (Analitis et al., 2008), and a strong regional association within Sweden (Gyllerup, Lanke, Lindholm, & Scherstén, 1991). The only study of spatiality in New Zealand found no evidence, however this analysis divided the country into only four regions, with substantial heterogeneity within each; for instance one region encompassed the entire South Island (Davie et al., 2007). Distinct regional differences in mortality in New Zealand have been documented, with higher life expectancy in predominantly urban regions compared to rural regions, possibly exacerbated by economic reform in 1980s which had a particularly adverse impact on rural areas (Pearce, Dorling, Wheeler, Barnett, & Rigby, 2006). Spatial differences will be confounded by compositional factors such as population health and housing quality, and contextual factors, particularly climate. Climate was associated with the most significant differences in winter excess; however absolute temperature did not explain variation between countries as often hypothesised. Instead, populations in more temperate climates appear to be more vulnerable to EWM or EWMb than those in particularly cold locations (Healy, 2003; Laake & Sverre, 1996). Differences in mortality and morbidity reporting exist between countries due to different legal regimes and diagnostic protocols (Crombie et al., 1989). Notwithstanding, valid comparisons can be made between diverse jurisdictions in terms of the relative magnitude differences between seasons (Healy, 2003).

2.2 Ageing population

The demographic profile of a nation is fundamental to the governmental planning, both in terms of demand for services and the supply of labour. The median age of the usually resident population in New

Zealand has increased from 32 in 1996 to 38 in 2013, and is projected to continue increasing (Statistics New Zealand, 2013c). This rapidly ageing population is expected to significantly increase demand for healthcare and social services whilst simultaneously decreasing the relative size of the labour market, and by association, reducing the proportion of taxpayers. With far higher utilisation of healthcare and social services by the elderly, patterns in the spatial distribution of elderly, driven by internal migration, may bear a significant impact on the provision of these services. As the elderly population increases in size, it is increasingly unsuitable to characterise and service the group homogenously; instead a more in depth understanding of elderly with higher needs is necessary. Ageing of the population is expected to continue until 2100, so permanent, long-term solutions are required to manage this change (Kowal, Towers, & Byles, 2014).

2.2.1 Demographic changes

Alongside other developed nations, New Zealand is experiencing strong population ageing, driven by decreasing fertility and rising life expectancy, and a significant cohort approaching older age en masse. A significant increase in births followed World War II, with the cohort born between 1946 and 1965 termed 'baby-boomers', who are beginning to enter older age (Commission for Financial Literacy and Retirement Income, 2013). With the absolute number of elderly people increasing whilst births and mortality is low, elderly are increasingly significantly as a proportion of the population. The population over the age of 60 is expected to increase from 19.2% to 28.8% by 2050, and those over the age of 80 are projected to increase 220% over this period (Kowal et al., 2014). Fertility rates have fallen since the baby-boomers were born, from 4.3 children per woman in 1961 to 2.1 in 2011; this is the minimum required to replace the population in the long term, discounting the impact of migration (Statistics New Zealand, 2013b). This has been driven by trends of woman having fewer children, having children at older ages, and in many cases forgoing childbirth altogether. Life expectancy has continued to increase in New Zealand, with the median life expectancy for a female born in 1940 of 78.3 years, rising to 86.4 for a female born in 1970 (Statistics New Zealand, 2014b). Migration drives population growth in New Zealand to a much higher degree than many other countries, and will become increasingly important to growing the population in future. This are however a multitude of economic and social factors driving migration, both domestically and internationally, so it can be difficult to forecast and it can induce uncertainty in overall population forecasts (Department of Labour, 2007).

The baby boomer cohort in general is far healthier than previous cohorts, as demonstrated by sustained increases in life expectancy. However, as the elderly increase in size relative to the population, the absolute number of elderly with multiple significant health issues will increase and induce complexity and demand for health services (Bryant, Teasdale, Tobias, Chenung, & McHugh, 2004; Kowal et al., 2014).

2.2.2 Health demand

Individuals with poor health tend to demand more health services, and as poor health rises with age, so does health service demand (Bryant et al., 2004). Although the elderly population is expected to grow significantly, rates of morbidity among the elderly be mitigated as life expectancy and medicine advances. A number of distinct health trends are changing the types of health services demanded; for instance a growing awareness of healthy lifestyles has increased regular exercise and decreased smoking in some groups. However, this may be outweighed by an increase in diseases associated with obesity in other groups (Organisation for Economic Co-operation and Development, 2011).

As many comparable countries are undergoing this change simultaneously, it remains unclear exactly how increase in life expectancy will affect morbidity in New Zealand. The period of morbidity preceding death is of most interest in forecasting the impact of an ageing population on demand for health services.

The majority of health expenditure incurred on an individual across their lifetime is determined by the length and severity of morbidity preceding death, with health expenditure increasing exponentially after the age of 50, and a quarter of lifetime health expenditure incurred in the final year (Bryant et al., 2004; Wanless, 2002). Several theories with mixed empirical support have been put forward to predict how the onset of serious disability and illness will change as medical advances extend life expectancy, each hinging on assumptions around the age of morbidity onset, relative to the age of death (Cornwall &

Davey, 2004; Fries, 1980; Graham, Blakely, Davis, Sporle, & Pearce, 2004; New Zealand Treasury, 2012).

The three broad scenarios are:

- The crisis, or expansion of morbidity scenario considers that the age of onset will remain constant even as life expectancy increases, resulting in an extended period of morbidity
- The receding horizon, or dynamic equilibrium scenario considers that the age of onset will be postponed by the same extent as life expectancy increases, such that the period of morbidity remains constant
- The compressed morbidity scenario considers that the onset of morbidity will be postponed substantially more than life expectancy increases, thus the period of morbidity preceding death will become shorter.

2.2.3 Fiscal impact

The makeup of society is changing as a result of population ageing; as elderly increase as a proportion of the population, the working population will decrease as a proportion of the population. This will affect government finances significantly, as the taxpaying population decreases at the same time as demand for health and social services increases. This is exemplified well by the median age, with which 50% of the population are older and younger; this is expected to increase from 37.4 in 2013 to 42.3 in 2050 (Kowal et al., 2014).

The dependency ratio of a society provides a simplified measure of the number of elderly relative to the working-age population, referred to in terms of the ratio of people aged 65+ to those aged 15-64. This measure belies many factors such as the age at which people choose to retire and rates of participation in the labour force, but provides some utility in understanding how society might provide for its elderly, both directly in terms of social and health service workers, and indirectly in terms of taxpayers. The dependency ratio is expected to fall from 5.0 in 2011 to 2.6 in 2036 (Commission for Financial Literacy and Retirement Income, 2013). Social norms and behaviours around retirement age will evolve over time; many individuals over the age of 65 will continue in paid employment; however it can be generally expected a significant proportion of the elderly age group will retire. The healthcare sector is particularly concerned about the impact of this change on the ability to recruit staff in light of increased demand (Cornwall & Davey, 2004).

Healthcare costs are forecast to increase as the elderly comprise an increasing proportion of the population, and as advances in medicine extend the lives of those in poor health (Cornwall & Davey, 2004). Concurrently, developments in technology and treatment, spurring on ever-increasing patient expectations, will further stretch health funding as patients expect higher levels of service (Blank & Burau, 2010). In New Zealand, the government bear the majority of this burden, with 80% of total health expenditure incurred by the government (Bryant et al., 2004). The share of GDP consumed by publicly-funded health spending is projected to increase from 6.9% to 11.1% by 2060 (New Zealand Treasury, 2012). In future, a proportionately larger health budget will be supported by a proportionately smaller taxpaying population.

Hospitals represent a significant cost centre for public healthcare in New Zealand (New Zealand Treasury, 2014), with acute admissions through the emergency department being particularly expensive (Adam, Evans, & Murray, 2003). The cost of a day spent in one of New Zealand's five highest-tiered hospitals was estimated to cost $440 in 2005, excluding specific medical expenses such as diagnostics and medication (World Health Organization, n.d.). Accordingly, a considerable focus has been placed by successive governments on achieving cost efficiencies in this area, with a concerted focus to reduce the average length of hospital stay in the 1990s and 2000s (Malcolm, 2007). Following this has been a focus on avoiding unnecessary use of hospital emergency departments, largely in response to overcrowding and delays in treatment in emergency departments (Ardagh & Richardson, 2004).

3 Methodology

This chapter introduces the methods used throughout this research to meet the objectives identified in the introduction.

1. Understanding variation of excess winter morbidity amongst the elderly across New Zealand
2. Understanding how climate and socioeconomic deprivation contribute towards the variation in excess winter morbidity amongst the elderly across New Zealand
3. Identifying factors affecting the length of stay for circulatory and respiratory disease related hospitalisations of the elderly in New Zealand

EWMb is analysed using an administrative datasets of hospital admissions across New Zealand in relation to historical climate data. Administrative records of deaths were of insufficient quality and detail for statistical analysis of EWM.

3.1 Data sources

Data was obtained from four major sources, outlined in Table 2 below.

Table 2:- Description of key datasets

Dataset	***Publisher***	***Source***
National Climate Database ('CliFlo')	National Institute of Water and Atmospheric Research (NIWA)	http://cliflo.niwa.co.nz/
Hospitalisations - National Minimum Dataset (NMDS)	Ministry of Health (MoH)	Compact Disc
Census of Population and Dwellings	Statistics New Zealand (SNZ)	http://www.stats.govt.nz/Census.aspx
Index of Socioeconomic Deprivation (NZDep)	Department of Public Health, University of Otago	http://www.otago.ac.nz/wellington/departments/publichealth/research/hirp/otago020194.html

3.1.1 Climate

The National Climate Database is administered by the National Institute of Water and Atmospheric Research (NIWA) and collates observations form 6500 climate stations across New Zealand since 1850, including 600 current stations (National Institute of Water and Atmospheric Research, 2014). For the purposes of this study, analysis was restricted to the 78 stations with complete daily measurements of daily maximum and minimum temperatures for the period of 1996-2013, concordant with the period of hospitalisation incidents obtained from the Ministry of Health.

3.1.2 Hospitalisations

Data for hospitalisation incidents was obtained from the Ministry of Health (MOH) National Minimum Dataset (NMDS) which electronically records all public hospital admissions in New Zealand since 1993 (Ministry of Health, 2013). This study obtained anonymised records for all 1,733,343 hospital admissions meeting the following criteria:

- Admitted between 1996 and 2013 inclusive
- Acute admission
- Patient over the age of 60 at the time of admission
- Primary and/or secondary diagnosis coded as either
    - Diseases of the circulatory system
    - Diseases of the respiratory system

The primary diagnosis associated with each admission is coded under the International Statistical Classification of Diseases and Related Health Problems (ICD) ninth revision (Ministry of Health, 2013). Given the prominence of respiratory and circulatory disease in EWMb, analysis was restricted to hospital events attributable to these diseases. Under the ICD ninth revision classification, these are classified as "Diseases of the circulatory system" and "Diseases of the respiratory system", with a list of diseases comprised in each category described in Table 3 (World Health Organization, 1979). These two chapters contain both acute and chronic diseases, and it was anticipated that both will exhibit a relationship with temperature when analysis reflects the time for onset of chronic disease. This has been reflected in prior studies, where chronic diseases such as pneumonia have been associated with falls in temperature (Bull & Morton, 1978). The variables obtained for each hospitalisation event are described in Table 4.

Table 3:- List of sub categories within ICD circulatory and respiratory disease categories (World Health Organization, 1979)

Category	***Sub-category***
Diseases of the circulatory system (ICD-9-CM-1 390-459)	Acute Rheumatic Fever Chronic rheumatic heart disease Hypertensive disease Ischemic heart disease Diseases of pulmonary circulation Other forms of heart disease Cerebrovascular disease Diseases of arteries, arterioles, and capillaries Diseases of veins and lymphatics, and other diseases of circulatory system
Diseases of the respiratory system (ICD-9-CM-1 460-519)	Acute respiratory infections Other diseases of the upper respiratory tract Pneumonia and influenza Chronic obstructive pulmonary disease and allied conditions Pneumoconioses and other lung diseases due to external agents Other diseases of respiratory system

Table 4: -Variables obtained on hospital admission records from the National Minimum Dataset (Ministry of Health, 2013)

Variable	***Description***
Event end type code	Describes the hospitalisation event, for instance discharge or death
Event start date	Date of admission
Event end date	Date of discharge or event end
Event end code	Type of end to the admission, such as discharge or death
Gender	Patient gender when admitted
Age at admission	Patient age when admitted
Domicile code (patient)	Domicile of patient’s residence
Area unit code	Census area unit of the patient’s residence
Census year	Census year associated with area unit
Priority Ethnic code	Ethnicity of patient, prioritised in the case of multiple ethnicities (SNZ prioritisation algorithm ranks minorities ahead of European ethnicities)
Domicile code (facility)	Domicile of health facility
Principal diagnosis code	ICD code of principal diagnosis
Secondary diagnosis	ICD code of secondary diagnosis

3.1.3 Population

Population estimates were obtained from Statistics New Zealand (SNZ), which publishes the estimated resident population (ERP) at a sub-national level from the five-yearly Census of Population and Dwellings. The interval between the 2006 and 2013 censes was extended due to the 2011 Christchurch earthquake in 2011 (Statistics New Zealand, 2013a). SNZ also produces yearly ERP counts to account for population change in the years between censes through a modelling process that adjusts census ERP counts with more frequent administrative data on births, deaths and migration (Statistics New Zealand, 2014c).

3.1.4 Deprivation

Socioeconomic deprivation at a small-area level is indicated by the series of NZDep indices developed following each national census. The NZDep index is derived at meshblock level, which is the smallest geographic areas defined by SNZ for the purpose of census collection, containing a median of 110 individuals in urban areas and 60 in rural areas (Statistics New Zealand, 2014a)). An aggregated form of NZDep was used to match the resolution of the NMDS data, using census area units (CAU), which contain a median of 2000 individuals (Statistics New Zealand, 2012). The NZDep index comprises an ordinal scale with a uniform distribution ranging from 1 to 10, where higher scores represent higher levels of deprivation relative to society as a whole, as measured by an accumulation of deficits (Atkinson, Salmond, & Crampton, 2014). The index is derived through a weighting process which combines nine census variables, as shown in Table 5. These variables have been changed over time to reflect changes in society, for instance communication was measured in terms of access to a telephone prior to 2013, but in 2013 was measured in terms of access to the internet (Atkinson et al., 2014).

Table 5:- Dimensions of deprivation from Census used in NZDep Index 2013 (Atkinson et al., 2014, p.8). *Equivalised households are adjusted to control for household composition

Dimension of Deprivation	***Description***
Communication	People aged <65 with no access to the Internet at home
Income	People aged 18-64 receiving a means tested benefit
Income	People living in equivalised* households with income below an income threshold
Employment	People aged 18-64 unemployed
Qualifications	People aged 18-64 without any qualifications
Owned home	People not living in own home
Support	People aged <65 living in a single parent family
Living space	People living in equivalised* households below a bedroom occupancy threshold
Transport	People with no access to a car

3.2 Analysis

3.2.1 Tools

RStudio 0.98.994 formed the core of analysis, with Microsoft Excel 2010 and ESRI ArcMap 10.2 processing some inputs and generating outputs. Cleaning, processing and analysis of the NMDS dataset was undertaken in RStudio, with summary datasets transferred into Excel for graphing. All other datasets were cleaned and processed in Excel prior to joining with the NMDS dataset in RStudio. Spatial analysis was undertaken in ArcMap before transfer into RStudio, and ArcMap was also used in mapping.

3.2.2 Temperature

The minimum temperature on each day at each of the 78 weather stations was compared with the 10th and 1st percentile for temperatures in the 28 days prior at that location. From this a dichotomous true or false variable indicated if the minimum for each day was within the coldest 10% or 1% for the preceding 28 days. The separate 10th and 1st percentile variables serve as an indicator of the severity of cold spells preceding an individual's admission to hospital, with 1st percentile representing severe cold spells and 10th percentile representing moderate cold spells. This percentile approach was developed based on the indices identified in Monteiro et al. (2013), with the advantage that these indices are relative to each climate and therefore do not require specification of an arbitrary temperature threshold. Such an approach would have been inappropriate in comparing such diverse climates as those present across New Zealand. These Boolean counts of temperature in the 1st and 10th percentile were aggregated up to periods 1-7, 1-14, 1-21 and 1-28 days prior, to produce a count of the number of 1st and 10th percentile days in the preceding days to assess the cumulative impact of cold spells on hospital admissions. To assess the specific lagged impact of cold spells on hospital admissions, the number of 1st and 10th percentile days was aggregated for periods 7-14, 14-21 and 21-28 days prior. By definition, the 1st percentile indicators are effectively a subset of the 10th percentile indicators, so significant correlations were expected between the temperature indicators. In order to maintain the assumptions of regression, multicollinearity was investigated to avoid regression of sets of variables with significant levels of correlation. A correlation matrix with Pearson correlation coefficients was employed as the variables are linearly related. These coefficients were carefully considered in the process of regression model design.

3.2.3 Processing

3.2.3.1 Hospitalisations

Hospitalisation records from the NMDS dataset were cleaned, recoded and derived into new variables more appropriate to the topics of interest and suitable for regression analysis. After incomplete records were removed, admissions were grouped into one of three groups – all (1,704,317 admissions), circulatory (166,938) and respiratory (62,495) diagnoses. The all diagnoses group included cases where the primary or secondary diagnosis was due to diseases of the circulatory or respiratory system. The circulatory and respiratory groups are subsets of the all diagnoses group, where the primary diagnoses was circulatory or respiratory respectively.

Records without a valid CAU code were removed, thus all incidents could be joined to the temperature records of their nearest weather station. The start and end date of each admission record were subtracted to derive the length of admission in integer days, with admissions in excess of 120 days considered outliers and removed from the dataset. Patient ethnicity was aggregated to one of five broad ethnic groups – European, Maori, Pacific Islander, Asian or other. Dummy variables were produced for Maori and Pacific Islander ethnicity groups as these were found to be significant factor in admissions. A dummy variable for winter admissions was derived in the manner described by (Davie et al., 2007), for admissions beginning during the four-month winter period of June-September.

3.2.3.2 Adding geography

Hospitalisations in the NMDS dataset were represented spatially through the CAU code of each patient's residential address. The CAU was used to join hospitalisation records with other variables associated with specific geographic locations – temperature variables, socioeconomic deprivation, and population counts. All populated CAU were spatially joined the nearest weather station measured in terms of shortest Euclidean distance. From this, each admission record was attached to the cold spell indicators derived from the weather station nearest to the patient's residence. Socioeconomic deprivation, as estimated by NZDep, is derived from five-yearly census data with each index an estimate of deprivation at the time of the census. Each hospital admission record was joined to the NZDep score of the patient's CAU, as derived from the census administered closest to their date of admission. The five-yearly NZDep scores were interpolated as specified in Table 6.

Table 6:- Protocol for interpolating NZDep socioeconomic deprivation scores to hospital admissions

Year (Census, NZDep index)	***Attributed to admissions beginning in***
1996	1996 – 1998
2001	1999 – 2003
2006	2004 – 2009
2013	2010 – 2013

Analysis of admission rates requires a defined area with a known population and consistent admission count data. Daily admission counts for towns and small cities were too inconsistent for robust statistical analysis; hence admission rates were only derived for patients residing in one of the largest eight urban centres in New Zealand. Over half of the national population resides in one of these eight urban centres, summarised in Table 7 and illustrated in Figure 1. These eight main centres represented 1,011,351 admissions of patients in the all diagnosis group, 100,761 for the circulatory diagnosis group, and 39,679 for the respiratory diagnosis group. These main centres were defined following SNZ urban area classifications rather than territorial authority boundaries, as urban area classifications are likely to better reflect climatic relationship between CAU than the social boundaries of territorial authorities (Statistics New Zealand, 2003). Admissions were aggregated to one of the eight cities according to the CAU of the patient's residence. Several of these main centres included more than one weather station; in these cases the average reading from each weather station was applied to all admissions originating from the urban area.

Table 7:- List of main urban areas used for analysis, listed in descending order of their populations as recorded by the 2013 national census

Main centre	***Population (2013 Census)***
Auckland	1,418,000
Wellington	397,900
Christchurch	379,100
Hamilton	212,000
Napier-Hastings	125,300
Tauranga	123,500
Dunedin	119,100
Palmerston North	83,800

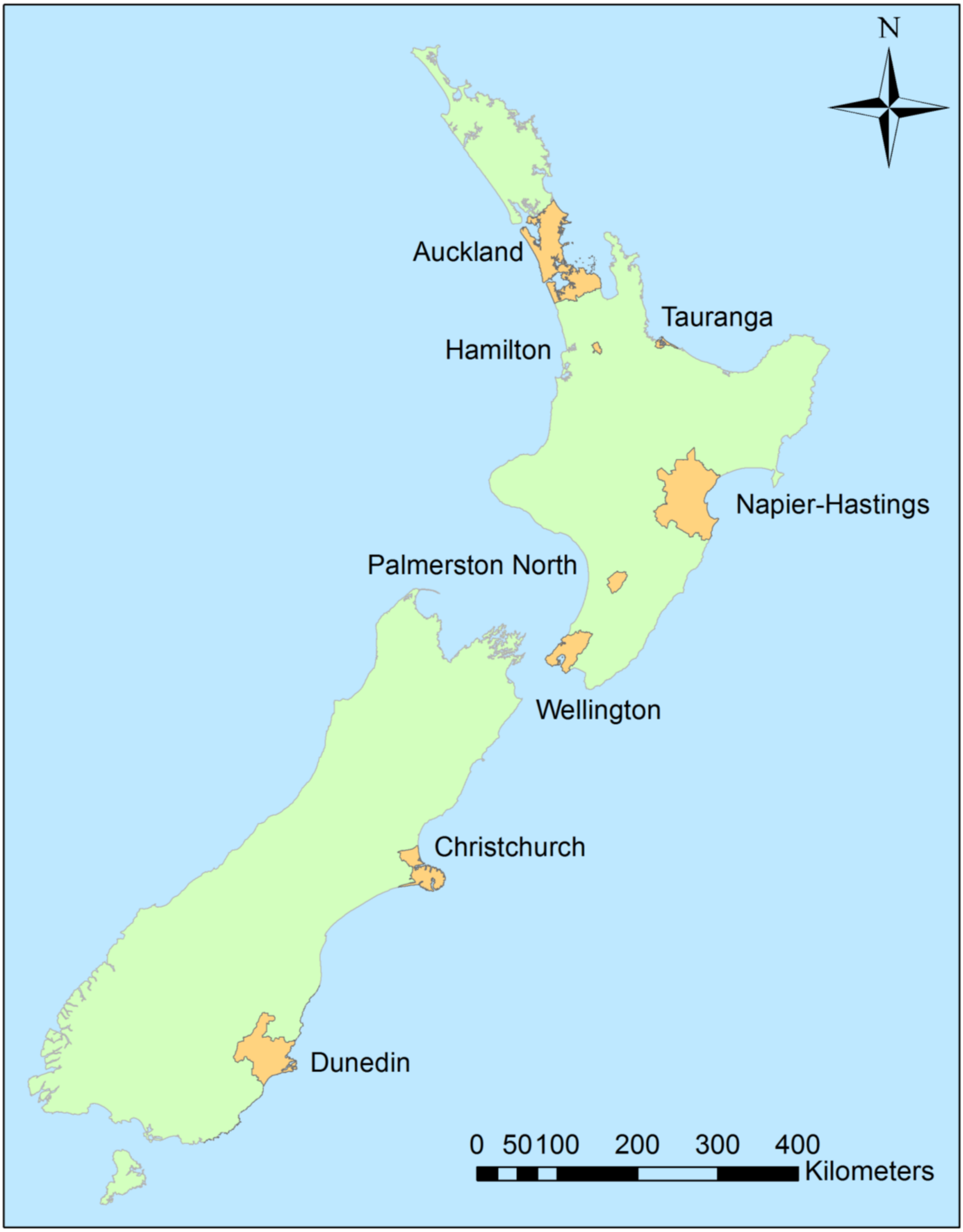

Figure 1:- Map of New Zealand, with the eight main centres illustrated in orange

3.2.4 Admission rates

3.2.4.1 Age standardisation

ASR were derived from incident counts, the relevant area population from SNZ yearly ERP, and the World Health Organisation standard population age distribution (Ahmad et al., 2001). This was derived using 5-year age groups, to concord with SNZ ERP, with hospitalisations grouped according to the patient's age on the date of admission. The SNZ annual ERP was used instead of the five year census ERP as using an out-of-date population can distort age-standardised rates where there are rapid changes in population. This was found in Auckland as the rapidly growing population lead to an overestimation of hospitalisation rates due to the underestimation of population from out-of-date census estimates.

3.2.4.2 Seasonal admission rates

In order to estimate the magnitude of EWH, ASR for hospitalisations were compared between the winter season of June to September and the remainder of the year through a morbidity rate ratio. This followed the Coefficient of Seasonal Variation in Mortality (CVSM) method outlined in Davie et al (2007) which adapts the method of Healy (2003) to a southern hemisphere climate such as that of New Zealand. The adapted formula for the Coefficient of Seasonal Variation in Hospitalisation (CSVH) expresses the percentage that winter hospitalisations are higher than non-winter hospitalisations.

3.2.4.3 Monthly admission rates

Although age standardisation is preferable as it enables valid comparison of incidence between diverse populations, age standardisation is not possible where the age distribution of the underlying population is unknown (Ahmad et al., 2001). In the case of the NZDep index, which groups the population into deciles, the age distribution of the population in each decile is unknown. In these cases, hospital admissions in each dimension were expressed as a proportion of all hospital admissions for the relevant decile. For example, hospital admissions for each month and NZDep decile were expressed as a proportion of total hospital admissions for each decile, in order to demonstrate different seasonal patterns between deciles.

3.2.4.4 Daily admission rates

Daily admission rates were derived for each day of the 18 years covered by the data, for each of the eight main centres, and age standardised to the ERP of each main centre during the relevant year. Regression modelling was conducted on these daily admission rates to understand how temperature variables explained variation in admissions, with reference to the broad winter:non-winter indicator used in prior studies. Daily admission rates exhibited a normal distribution, hence a linear model using ordinary least squares (OLS) regression was appropriate (Kutner, 2005). This model estimated the magnitude and significance of the relationship between daily admission rates and each of the 16 temperature indicators alone, for all, respiratory and circulatory admissions separately. From this, a regression model drawing upon the strongest temperature indicator was developed separately for all, respiratory and circulatory admissions, and for each of the eight main centres.

3.2.5 Admission duration

3.2.5.1 Mean length of admission

The average length of hospital admission offers an indication as to the complication of a hospital admission (McAleese & Odling-Smee, 1994). As the length of admission variable was derived in integers and variation in the average length of hospital admission can be subtle between seasons and groups of the population, a mean function was chosen instead of median, as it provides greater resolution beyond integers. This reason was considered to outweigh the suitability of a median function in providing an unbiased indicator of the positively skewed length of stay variable.

3.2.5.2 Length of admission modelling

For length of admission modelling, the dataset was restricted to admissions with non-zero admission lengths, which reduced all admissions by 8%, circulatory admissions by 7% and respiratory admissions by 5%. It is standard practice to remove day cases from length of stay analysis, as a considerable number of patients are admitted and discharged on the same day, which is recorded as an integer of zero (Ministry of Health, 2011). Diagnostic tests indicated that the admission duration variable was over-dispersed, as the variance of 54.91 days was far greater than the mean of 6.47 days (Long, 1997). As the admission duration variable was not normally distributed and over-dispersed, and designed to exclude zero-day admissions, a zero-truncated negative binomial regression model was chosen. A backward stepwise process was used to select models, in which a model comprising of all variables was built. From this, the variables were progressively removed to increase the quality of the model as measured by the Akaike Information Criterion (AIC), which ranks the quality of models by trading off goodness-of-fit and complexity (Bozdogan, 1987). This was calculated using the log likelihood ratio and number of terms in each model, and favours models that explain the dataset well without a large number of variables.

4 Results

Results are discussed in three sections, beginning with an overview of the dataset and summary statistics of the variables. A section is dedicated to each of hospital admission rates and admission duration, with each beginning with a broad overview of descriptive statistics leading into analysis at a higher resolution. Results are described in terms of three diagnosis groups – all, circulatory and respiratory. The all diagnosis group includes all circulatory and respiratory related diagnosis, which includes hospitalisations in which the primary or secondary diagnosis is for circulatory and/or respiratory disease. The circulatory and respiratory groups are a subset of the all group, and include only hospitalisations where the primary diagnosis is for circulatory or respiratory disease respectively. The statistical significance of results is noted where relevant, with all statistically significant results emboldened and a single asterisk indicating a 5% significance level, double asterisk indicating a 1% significance level, and triple asterisk indicating a 0.1% significance level.

4.1 Summary Statistics

Binary variables are summarised in Table 8 below for all respiratory and circulatory related, respiratory only and circulatory only admissions. This table shows for each individual characteristic the number and percentage of the total for each diagnosis group. The sample exhibits similar characteristics across the three diagnosis groups, with the sample evenly split between male and females, and predominantly European ethnicity. The winter variable indicates admissions occurring within the four month period of June to September, with a percentage over 33% indicating disproportionately higher admissions within this period compared to the remainder of the year. The all admission and circulatory admission group exhibits disproportionately higher admissions in this period; this is discussed in greater detail in the hospital admissions – monthly patterns section.

Table 8:- Summary statistics for binary variables

	All respiratory and circulatory related (primary or secondary diagnosis)		***Respiratory (primary diagnosis)***		***Circulatory (primary diagnosis)***	
	n	*%*	*n*	*%*	*n*	*%*
	1704317		62495		166938	
Male gender	846063	50%	29695	48%	84130	50%
Winter admission	628704	37%	20467	33%	62151	37%
Ethnicity: European	1384745	83%	48985	79%	133453	81%
Maori	140382	8%	6212	10%	13958	8%
Pacific	69212	4%	3555	6%	8244	5%
Asian	39726	2%	1536	2%	4735	3%
other	43571	3%	1371	2%	4114	3%

Table 9 provides summary statistics for continuous and interval variables. The three diagnosis groups show a similar mean age at admission, averaging 76 years overall. This has increased over the period of the dataset, from 74.99 years in 1996 to 76.35 years in 2013. The NZDep index is based on a decile system, with a median score of six indicating that the admissions dataset represents patients from slightly more deprived neighbourhoods than the national average. This admissions dataset exhibited an age gradient across NZDep deciles, with 22% of patients in the least deprived areas aged 85 and over, compared to 12% in the most deprived areas. The median admission duration ranged from 4-5 days. As the mean of the temperature indicators for 1st and 10th percentile minimum temperatures are greater than 0.10 and 0.01 respectively, this indicates a greater likelihood of being admitted on such low temperature days. Figure 2 portrays the spatial variation in climate across New Zealand, with all eight main centres exhibiting a similar pattern across the year, with the coldest temperatures in June, July and August. Temperature is associated with a North-South gradient, with the northernmost cities of Auckland and Tauranga generally warmest, and the two South Island cities of Christchurch and Dunedin generally the coldest.

Table 9:- Summary statistics for continuous and interval variables

	All circulatory and respiratory related diagnosis				*Respiratory disease diagnosis*		*Circulatory disease diagnosis*	
	Mean	*Median*	*Min*	*Max*	*Mean*	*Median*	*Mean*	*Median*
Age at admission	75.95	76	60	114	76.81	77	76.19	76
NZDep	5.925	6	1	10	6.044	6	5.955	6
Admission duration (zero-day included)	5.954	4	0	120	6.472	5	6.403	4
Admission duration (zero-day excluded)	6.474	4	1	120	6.792	5	6.889	5
10th percentile on day of admission	0.111	0	0	1	0.1089	0	0.1088	0
1st percentile on day of admission	0.045	0	0	1	0.0438	0	0.0436	0
10th percentile days in 7 days prior	0.782	0	0	7	0.7817	0	0.7755	0
10th percentile days in 14 days prior	1.569	1	0	14	1.567	1	1.556	1
10th percentile days in 21 days prior	2.355	2	0	21	2.338	2	2.33	2
10th percentile days in 28 days prior	3.148	3	0	28	3.115	3	3.119	3
1st percentile days in 7 days prior	0.313	0	0	7	0.3126	0	0.3103	0
1st percentile days in 14 days prior	0.627	0	0	14	0.6292	0	0.6229	0
1st percentile days in 21 days prior	0.941	1	0	21	0.9383	1	0.9324	1
1st percentile days in 28 days prior	1.259	1	0	28	1.252	1	1.248	1
10th percentile days 7-14 days prior	0.787	0	0	7	0.7852	0	0.7805	0
10th percentile days 14-21 days prior	0.786	0	0	7	0.7707	0	0.7746	0
10th percentile days 21-28 days prior	0.793	0	0	7	0.7889	0	0.7889	0
1st percentile days 7-14 days prior	0.315	0	0	7	0.3167	0	0.313	0
1st percentile days 14-21 days prior	0.314	0	0	7	0.3092	0	0.3098	0
1st percentile days 21-28 days prior	0.318	0	0	7	0.3139	0	0.316	0

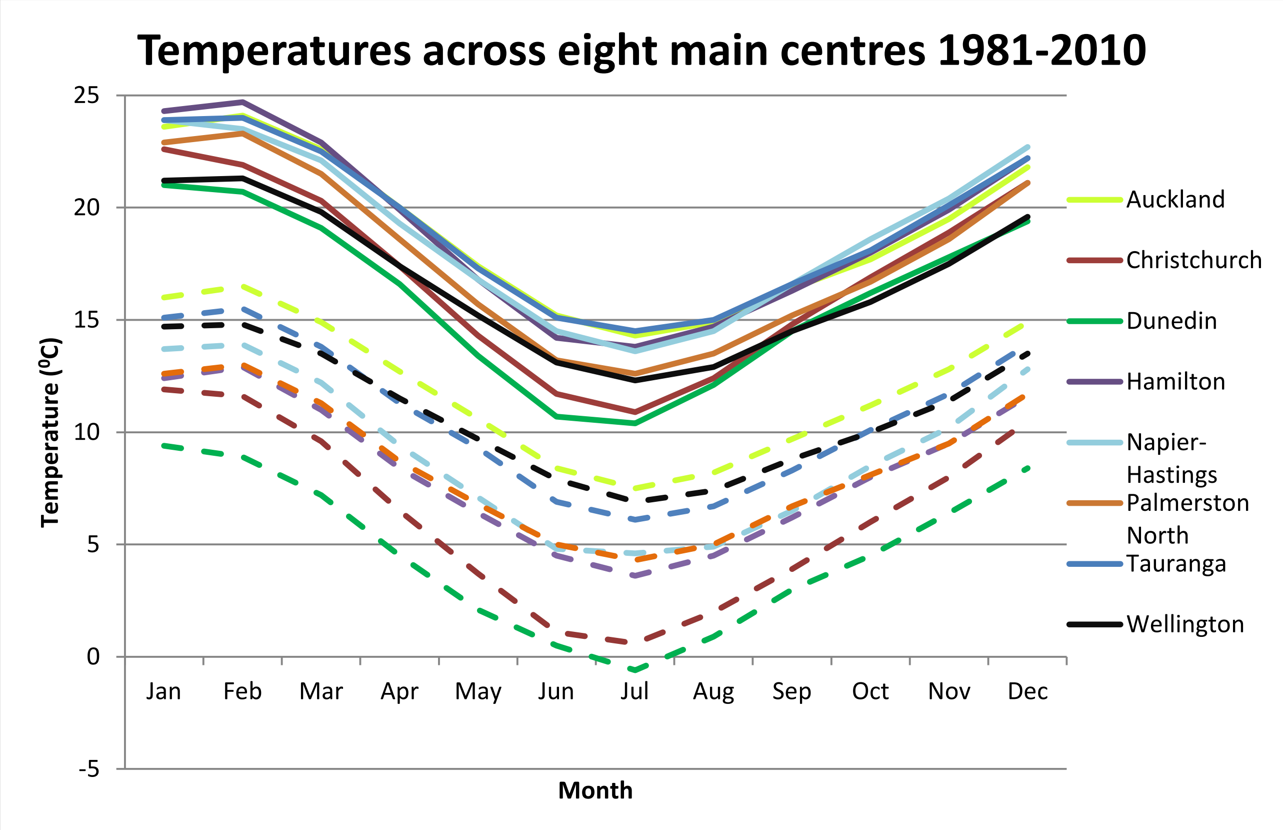

Figure 2:- Graph of minimum and maximum temperatures across New Zealand's eight main centres for the period 1980 to 2010. Solid line indicates mean monthly maximum temperature, and dashed line indicates mean monthly minimum temperature.

As the all admissions diagnosis group draws from admissions with primary or secondary diagnosis for respiratory or circulatory disease, a number of admissions are subject to a primary diagnosis outside these two diagnosis groups. Figure 3 shows the distribution of primary diagnoses in the all admissions groups, with the majority of the dataset comprised of admissions with a primary diagnosis of respiratory or circulatory disease. Two ICD categories relating to pregnancy and the perinatal period were excluded as there were no cases in the dataset diagnosed in either category, as the dataset only include patients aged over 60.

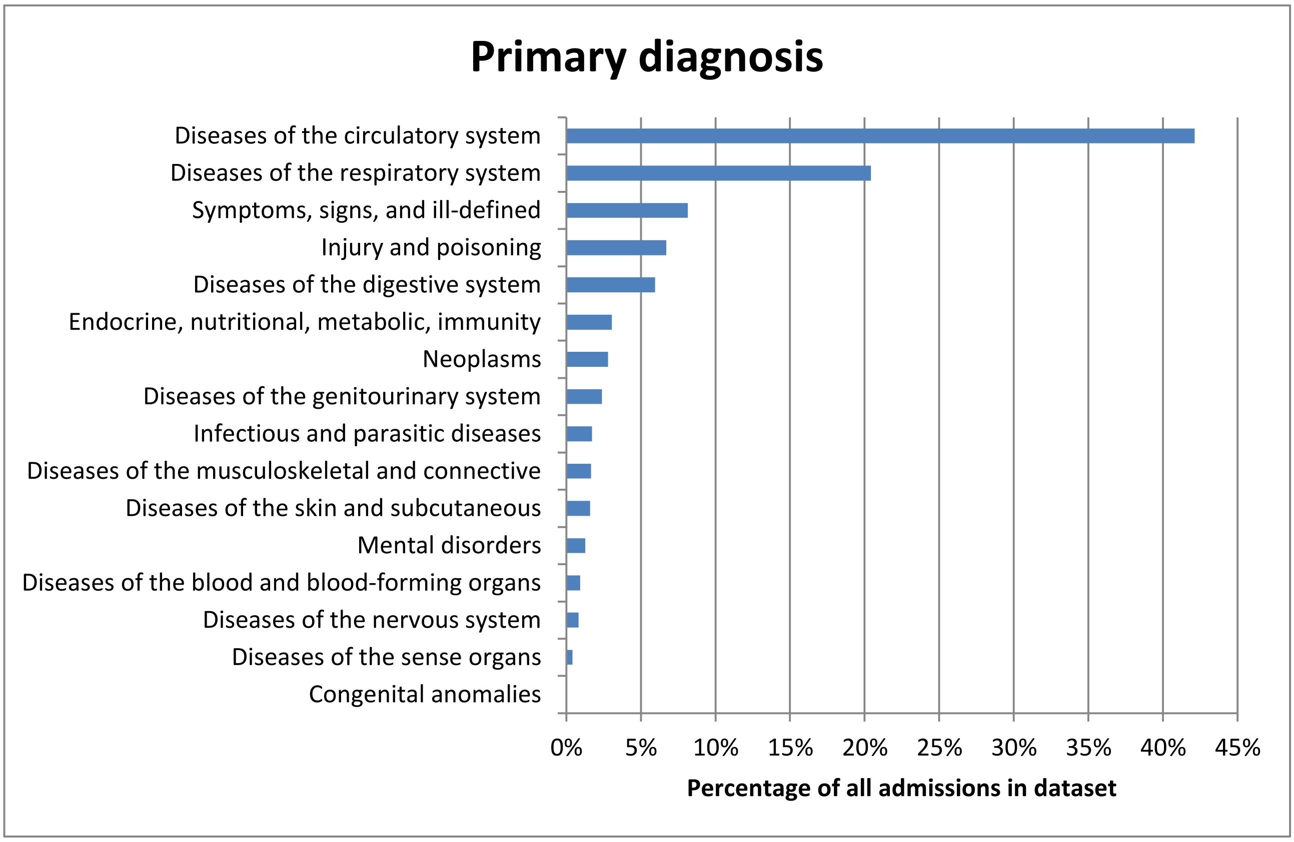

Figure 3:- Distribution of primary diagnosis for the admissions dataset (drawn from admissions with a primary and/or secondary diagnosis of respiratory or circulatory disease

Due to the nested nature of the temperature variables, correlations between were thoroughly analysed in a cross-correlation matrix to avoid multicolinearity when specifying regression models. Table 10 shows correlations between each of the 1st and 10th percentile temperature indicators, covering temperatures on the day of admission up to 28 days prior to admission. The correlation between the 1st and 10th percentile temperatures on the day of admission was 60%. The correlation between temperature on the day of admission and in the 7 days prior to admission was 40% for the 1st percentile and 43% for the 10th percentile. 1st percentile and 10th percentile temperatures up to 7, 14, 21 and 28 days prior to admission were correlated by 70-71%. Correlations between overlapping time periods, such as 1-7 days and 1-14 days were higher, between 74-88% for 10th percentile days, and 73-88% for the 1st percentile days. Indicators for 7-14, 14-21 and 21-28 days prior were subsets of indicators for 1-14, 1-21 and 1-28 days prior to admission respectively. For 1st percentile days these indicators were correlated by 51%-73%, and for 10th percentile days were correlated by 51-74%.

Table 10:- Correlation matrix showing correlation coefficients between each of the temperature variables

	10th percentile on day of admission	***1st percentile on day of admission***	***10th percentile days in 7 days prior***	***10th percentile days in 14 days prior***	***10th percentile days in 21 days prior***	***10th percentile days in 28 days prior***	***1st percentile days in 7 days prior***	***1st percentile days in 14 days prior***	***1st percentile days in 21 days prior***	***1st percentile days in 28 days prior***	***10th percentile days 7-14 days prior***	***10th percentile days 14-21 days prior***	***10th percentile days 21-28 days prior***	***1st percentile days 7-14 days prior***	***1st percentile days 14-21 days prior***	***1st percentile days 21-28 days prior***
10th percentile on day of admission	100%	60%	43%	30%	25%	20%	32%	22%	18%	15%	1%	1%	-2%	1%	1%	-1%
1st percentile on day of admission	60%	100%	24%	17%	15%	12%	40%	28%	23%	20%	1%	2%	-1%	1%	1%	-1%
10th percentile days in 7 days prior	43%	24%	100%	74%	60%	51%	70%	52%	43%	36%	9%	3%	-2%	7%	2%	-1%
10th percentile days in 14 days prior	30%	17%	74%	100%	84%	73%	51%	70%	60%	51%	74%	8%	1%	52%	6%	0%
10th percentile days in 21 days prior	25%	15%	60%	84%	100%	88%	43%	60%	71%	63%	64%	60%	5%	44%	42%	4%
10th percentile days in 28 days prior	20%	12%	51%	73%	88%	100%	37%	52%	63%	71%	56%	56%	51%	40%	39%	36%
1st percentile days in 7 days prior	32%	40%	70%	51%	43%	37%	100%	73%	60%	51%	5%	3%	0%	6%	3%	-1%
1st percentile days in 14 days prior	22%	28%	52%	70%	60%	52%	73%	100%	84%	72%	52%	6%	2%	73%	6%	1%
1st percentile days in 21 days prior	18%	23%	43%	60%	71%	63%	60%	84%	100%	88%	45%	43%	4%	62%	60%	4%
1st percentile days in 28 days prior	15%	20%	36%	51%	63%	71%	51%	72%	88%	100%	39%	40%	37%	54%	54%	51%
10th percentile days 7-14 days prior	1%	1%	9%	74%	64%	56%	5%	52%	45%	39%	100%	9%	3%	70%	7%	2%
10th percentile days 14-21 days prior	1%	2%	3%	8%	60%	56%	3%	6%	43%	40%	9%	100%	9%	5%	70%	6%
10th percentile days 21-28 days prior	-2%	-1%	-2%	1%	5%	51%	0%	2%	4%	37%	3%	9%	100%	3%	5%	70%
1st percentile days 7-14 days prior	1%	1%	7%	52%	44%	40%	6%	73%	62%	54%	70%	5%	3%	100%	6%	2%
1st percentile days 14-21 days prior	1%	1%	2%	6%	42%	39%	3%	6%	60%	54%	7%	70%	5%	6%	100%	6%
1st percentile days 21-28 days prior	-1%	-1%	-1%	0%	4%	36%	-1%	1%	4%	51%	2%	6%	70%	2%	6%	100%

4.2 Hospital admissions

4.2.1 Overview

Over the 18 years studied, ASR of hospital admissions have increased in every elderly age group, with admissions of patients over the age of 85 significantly higher than all other age groups, as shown by the orange line in Figure 4. This pattern is evident across all admissions related to respiratory or circulatory disease as well as admissions with a primary diagnosis for circulatory (Figure 5) or respiratory (Figure 6) disease. The composition of the 85+ age group was tested as it comprises a wider age range than the other age groups, including patients between 85 and 114 years of age. Over the period of the data, 67% of admissions in the 85+ age group were in fact patients aged 85-89, with 65% for admissions with a primary diagnosis for respiratory or circulatory diseases. Significantly lower population numbers in the 90+ age group explain this difference, despite an overall higher propensity for admissions in the 85+ group. Age standardisation could not be conducted at any finer resolution than these broad age groups due to the resolution of ERP from SNZ. This demonstrates that the significantly higher rate of admissions among those aged 85 and over is not an artefact of the age group boundaries, but does show a significantly higher rate of admission for this age group. Hospitalisation rates for the elderly varied between main centres and over time, as shown in Figure 7. Despite the volatility of these series, it is clear that some centres have typically higher or lower admission rates– with Christchurch and Tauranga towards the lower end and Dunedin consistently towards the higher end of the range shown. Admissions with a primary diagnosis for circulatory (Figure 8) or respiratory (Figure 9) are more volatile, reflecting the low number of cases involved, although the same broad trends are present.

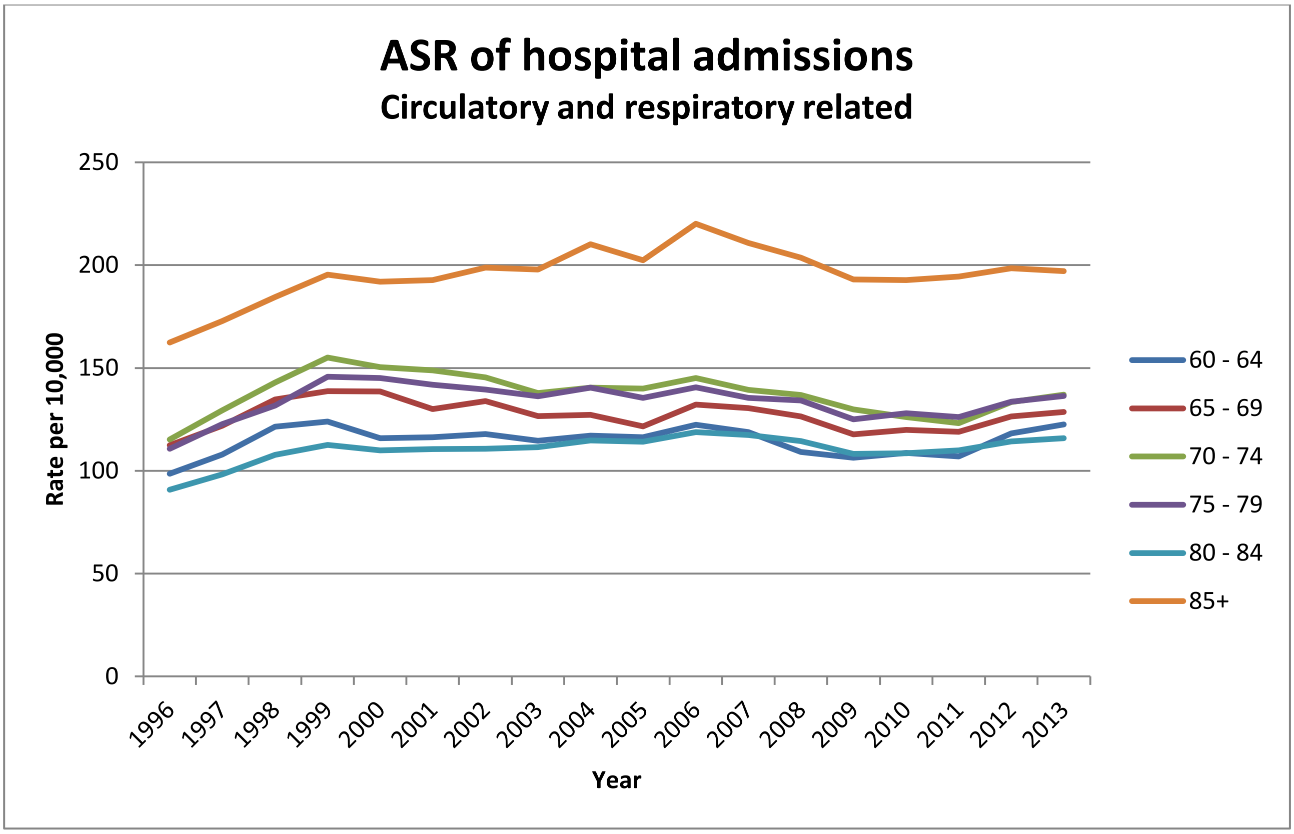

Figure 4:- Age Standardised Rates (ASR) of hospital admissions by year of admission and age group, for all circulatory and respiratory related admissions

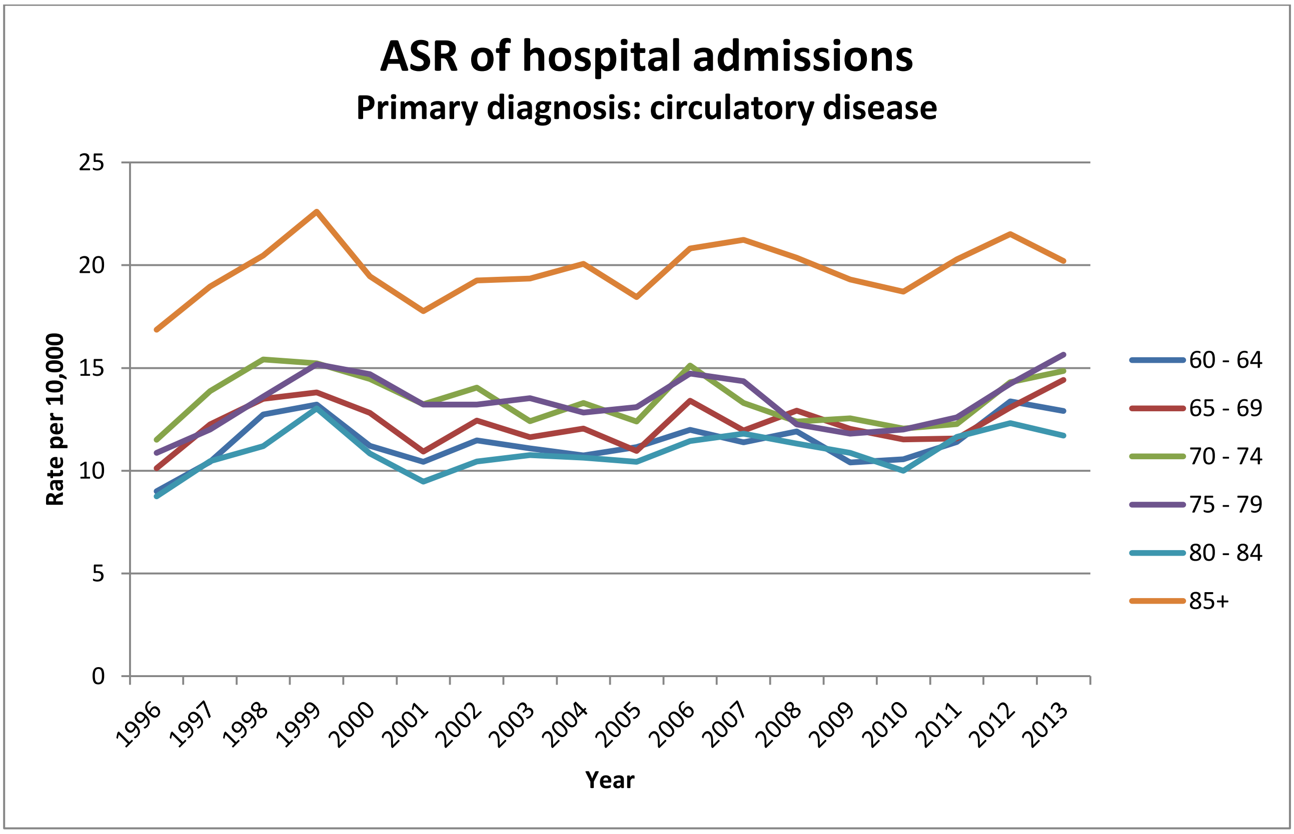

Figure 5:- Age Standardised Rates (ASR) of hospital admissions by year of admission and age group, for admissions with a primary diagnosis of circulatory disease

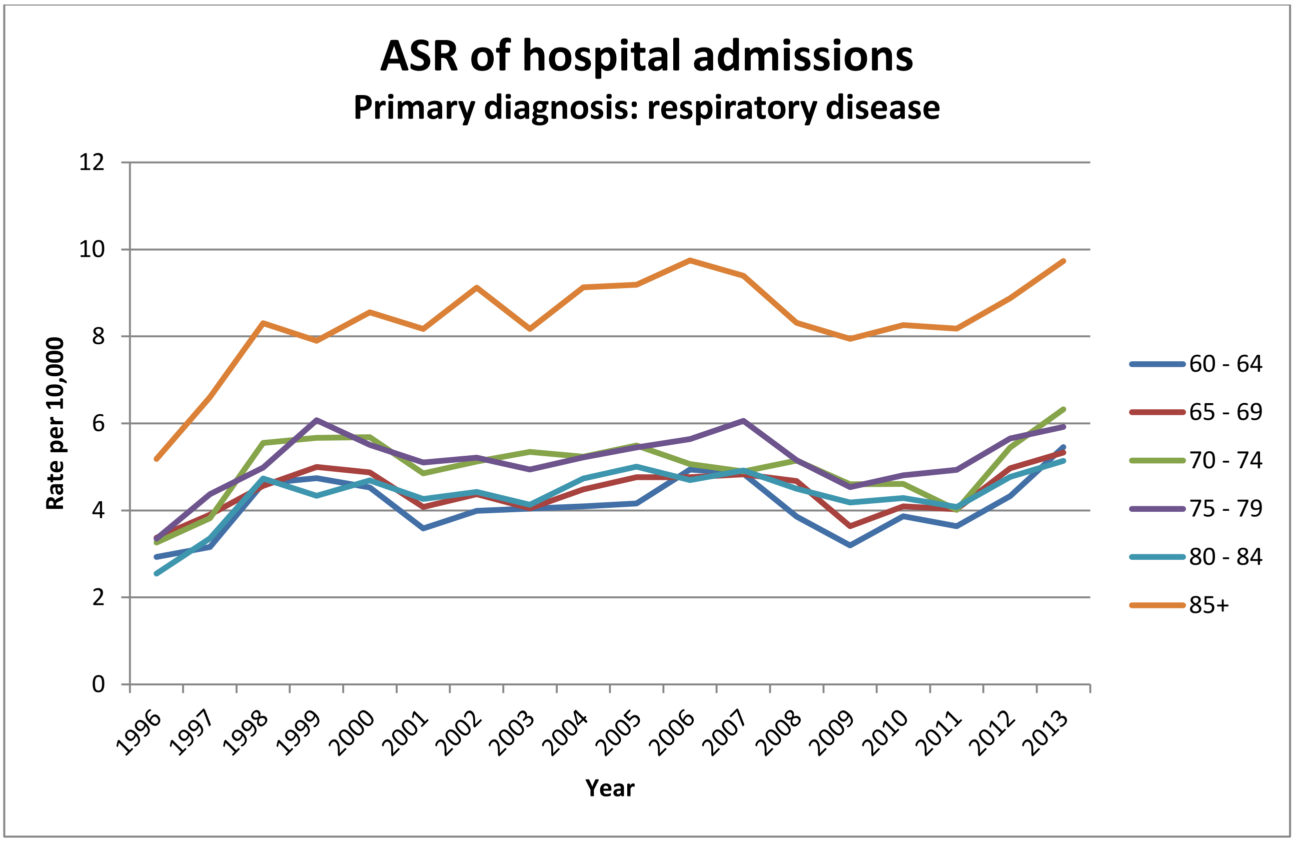

Figure 6:- Age Standardised Rates (ASR) of hospital admissions by year of admission and age group, for admissions with a primary diagnosis of respiratory disease

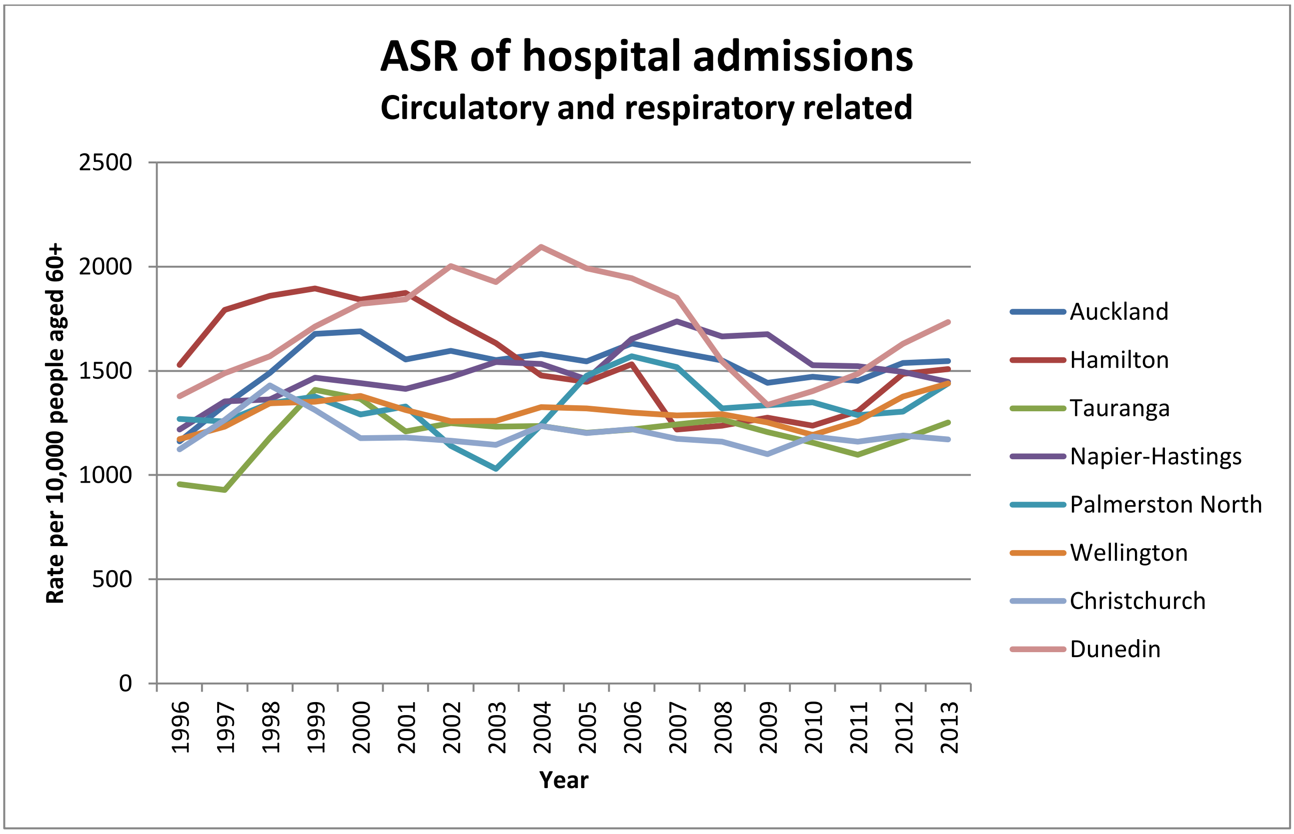

Figure 7:- Age Standardised Rates (ASR) of hospital admissions for each of the eight main centres by year of admission, for circulatory or respiratory disease related admissions

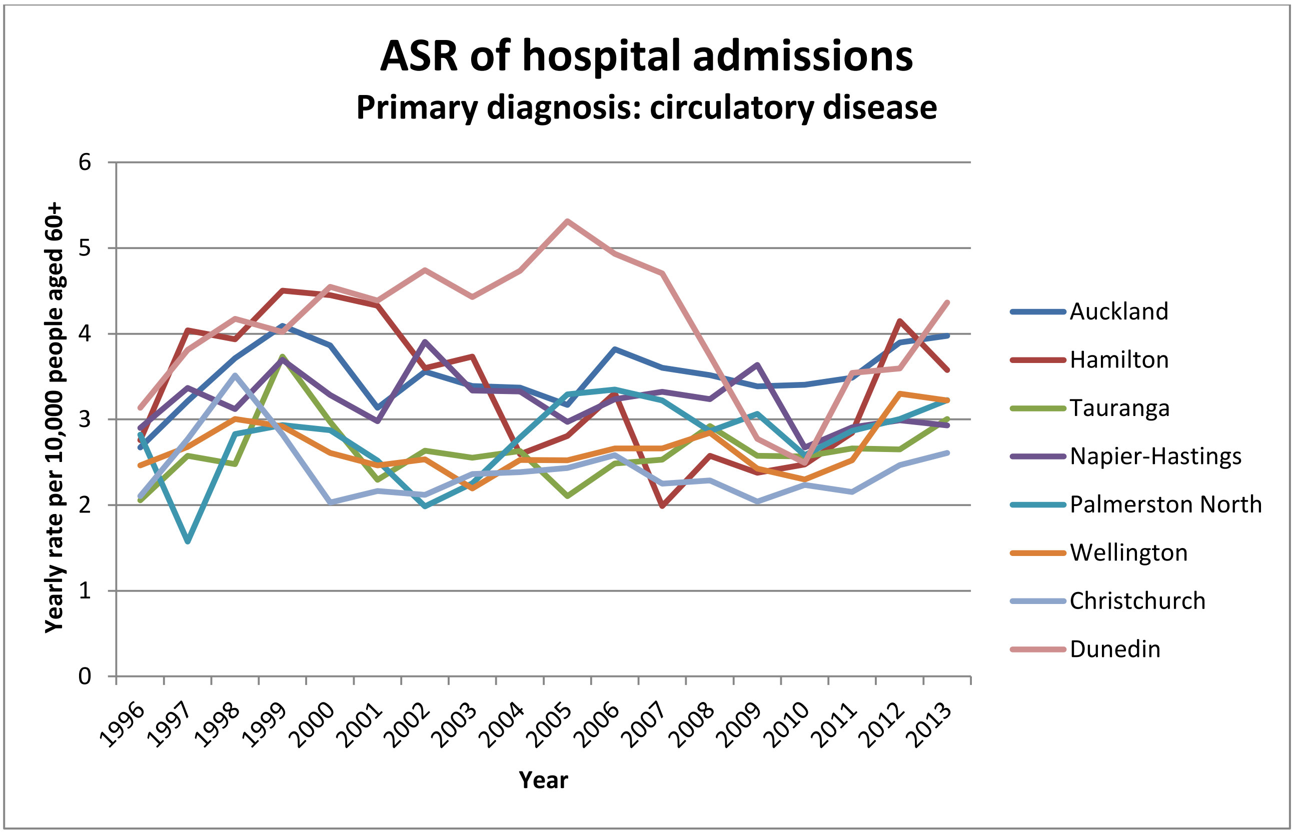

Figure 8:- Age Standardised Rates (ASR) of hospital admissions for each of the eight main centres by year of admission, for admissions with a primary diagnosis of circulatory disease

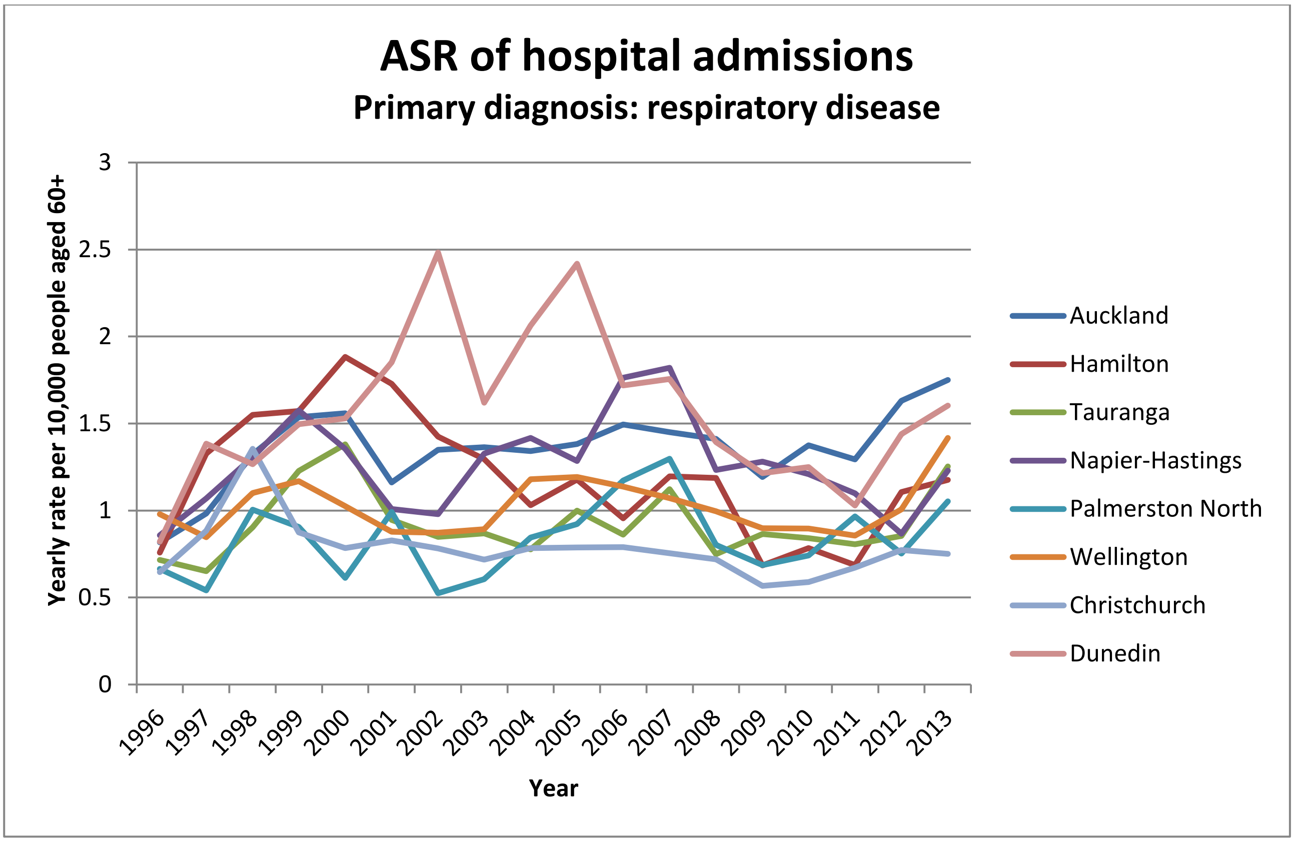

Figure 9:- Age Standardised Rates (ASR) of hospital admissions for each of the eight main centres by year of admission, for admissions with a primary diagnosis of respiratory disease

Figure 10 demonstrates how the admission age profile varies between ethnic groups, with 21% of European ethnicity admissions from patients aged 85+, compared to only 4% and 6% for Maori and Pacific Island ethnicities. This is only partly explained by the younger age distribution of Maori and Pacific Island ethnicities, as shown in Figure 11. Admissions of patients aged 85 and over identifying with Maori or Pacific Island ethnicities are notably low, even lower than that of the most socioeconomically deprived decile (Figure 12). It is not possible to produce age standardised admission rates for ethnic groups or NZDep deciles as the population for each age group in each ethnic group or decile is not known.

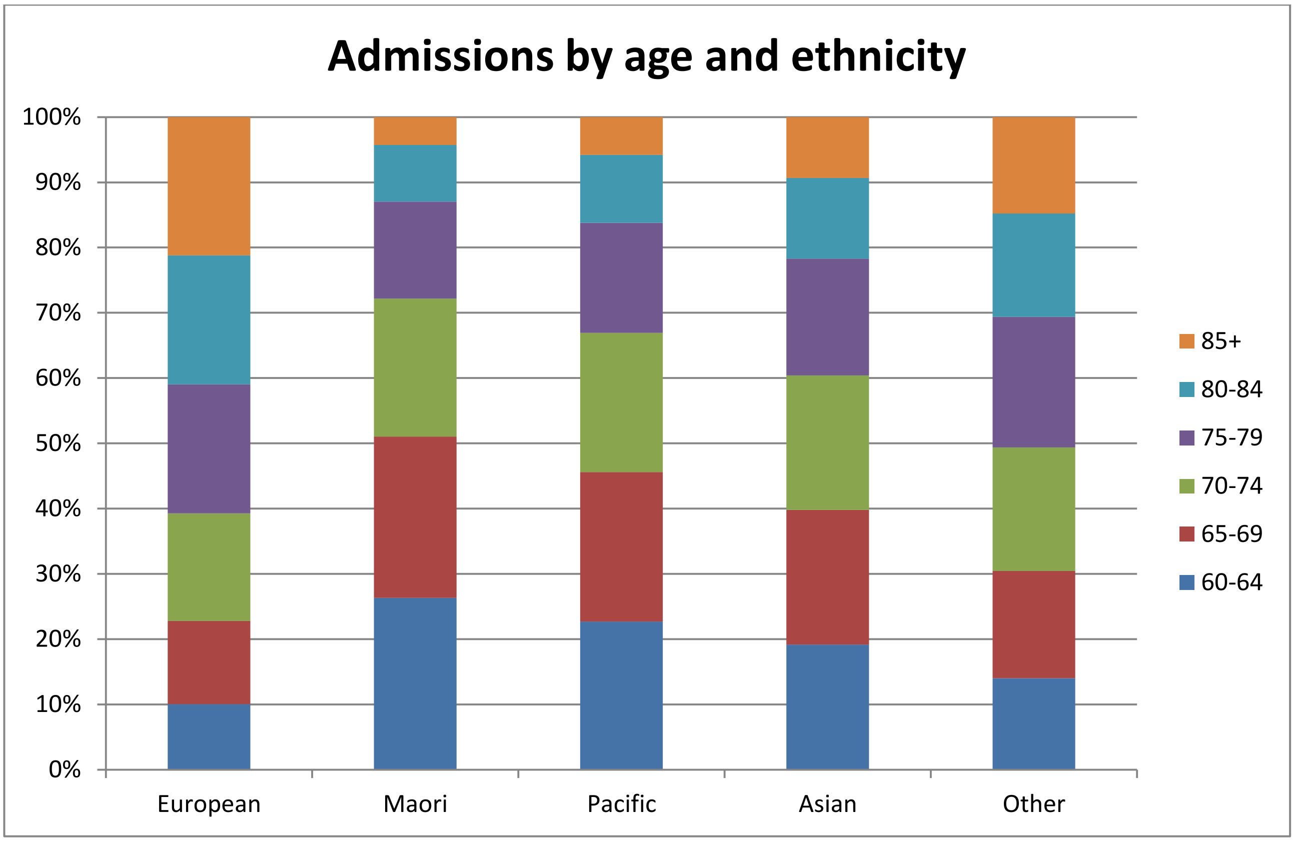

Figure 10:- Graph of the age distribution of patients admitted for each ethnic group, expressed as a percentage of the total hospital admissions for each group in the dataset

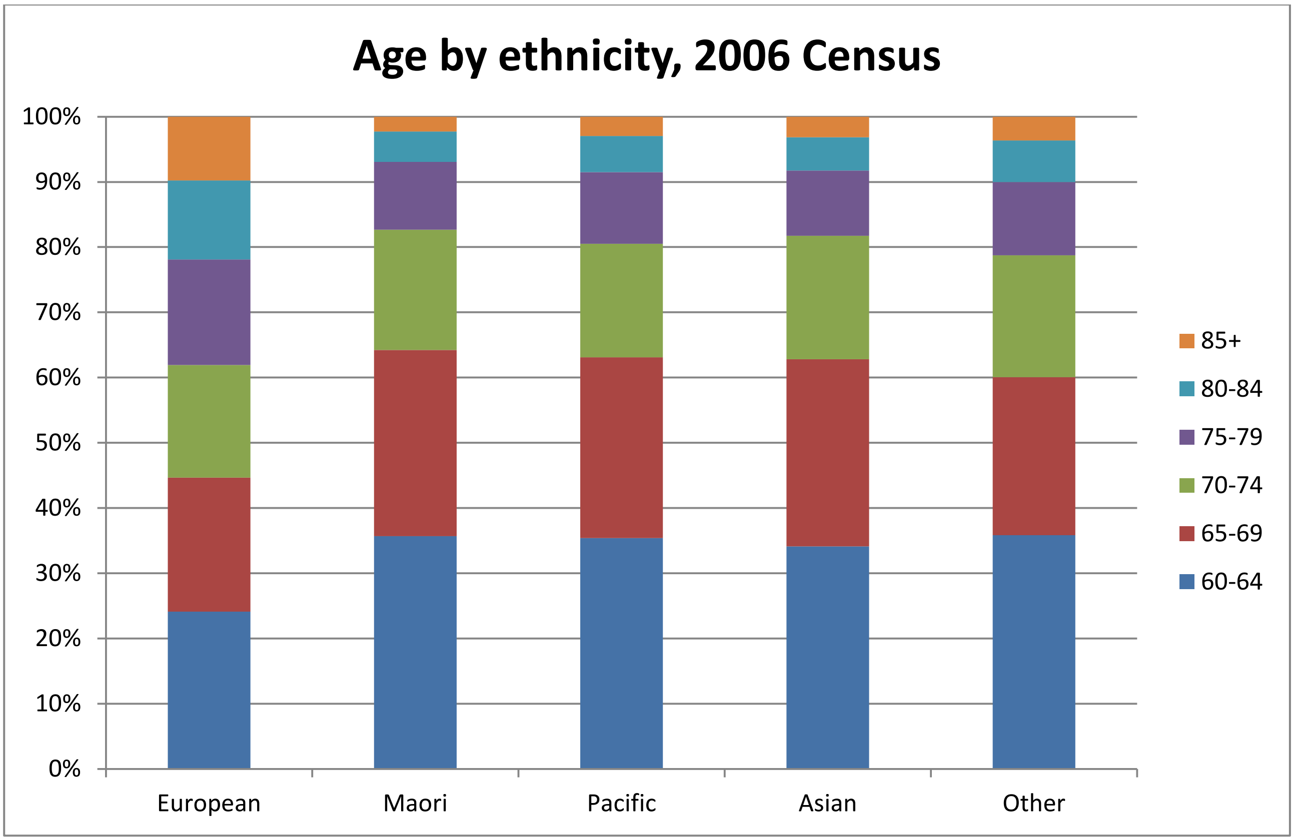

Figure 11:- Graph of the age distribution of the population aged 60 and over for each ethnic group, as measured by the 2006 Census of population and dwellings

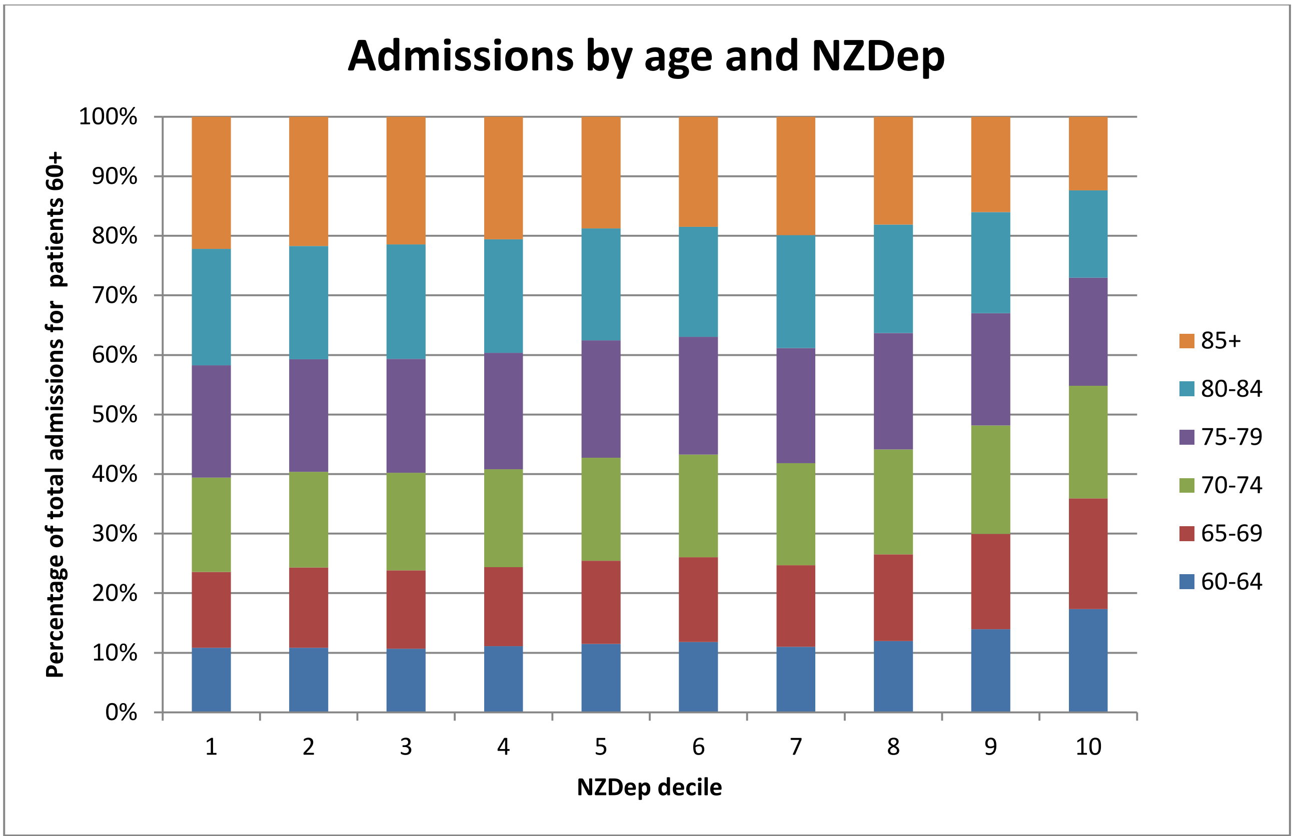

Figure 12:- Graph of the age distribution of patients aged 60 and over for each NZDep socioeconomic deprivation decile, expressed as a percentage of the total hospital admissions in the dataset for each decile.

4.2.2 Monthly patterns

Hospitalisations vary throughout the year, with a clearly defined increase during winter months, culminating in a peak during July. Figure 13 below expresses hospital admissions each month as a percentage of total admissions for each age group. This demonstrates not only a peak of admissions during July, but also shows that older age groups, particularly ages 80 - 84 and 85+, experience a more pronounced peak of admissions in winter than other age groups. This may suggest that older elderly are more vulnerable to the effects of winter. Monthly patterns in hospital admissions for circulatory disease, shown in Figure 14, exhibit a slightly different pattern to all admissions in Figure 13, also showing a peak of admissions during July but with a high level of admissions maintained through August and September additionally. Respiratory disease hospital admissions do not show any clear variation between months, as shown in Figure 15.

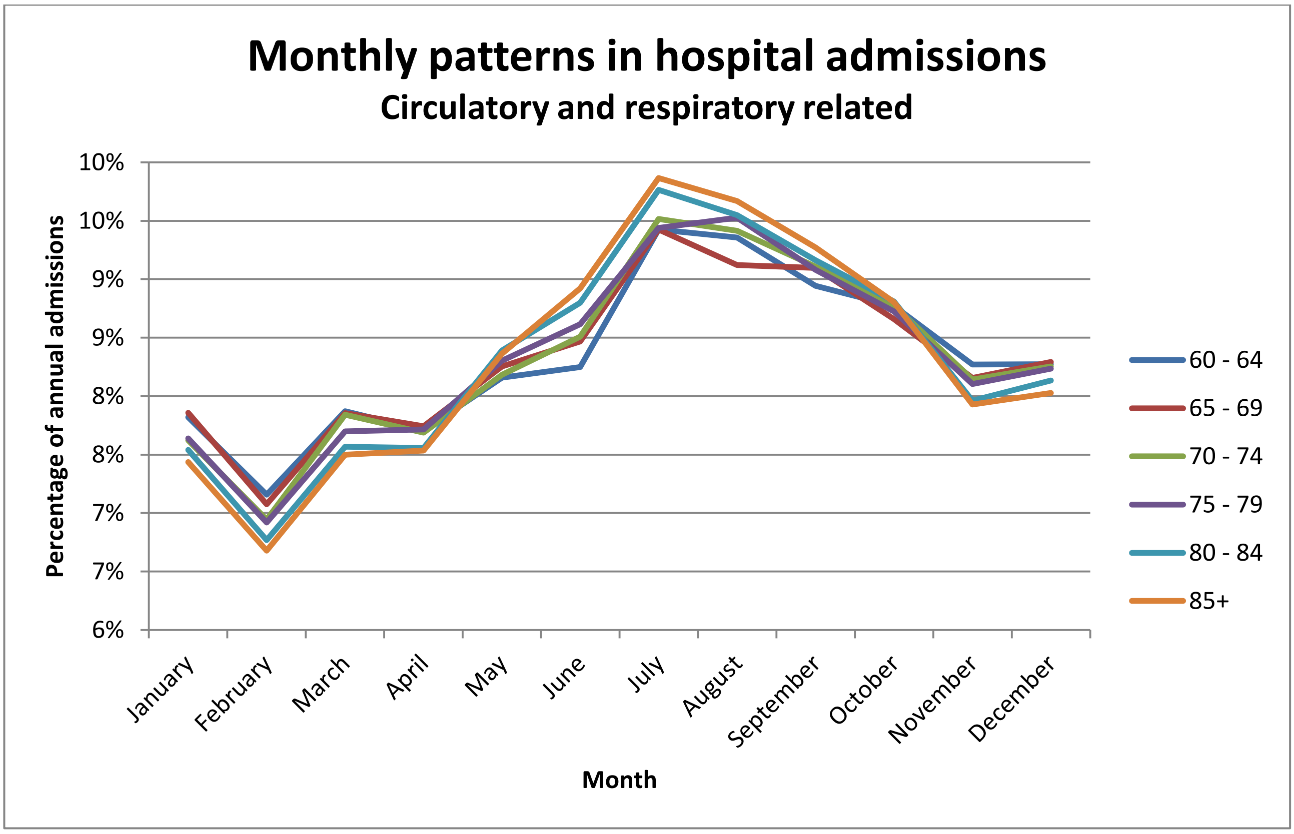

Figure 13:- Monthly hospital admissions as a percentage of annual admissions, by age group, for all circulatory and respiratory related admissions

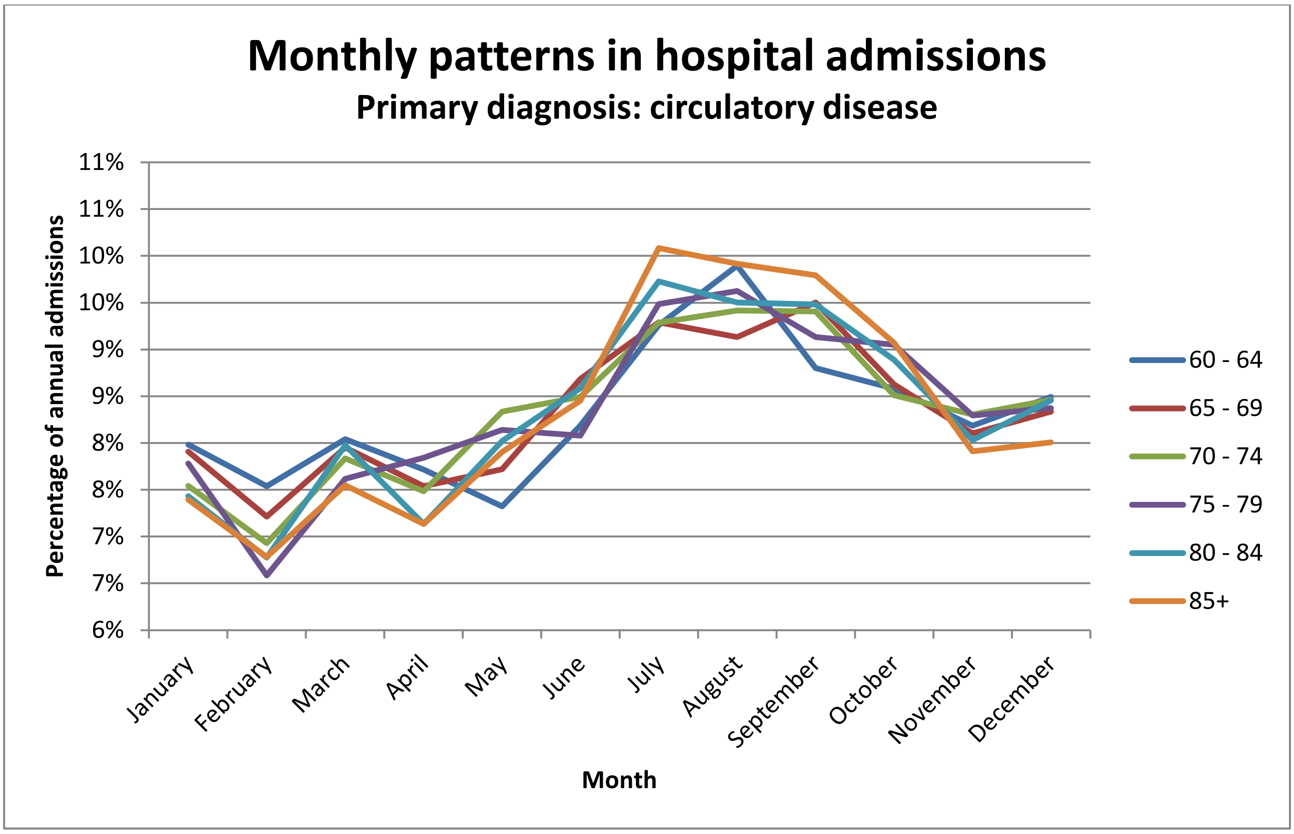

Figure 14:- Monthly hospital admissions as a percentage of annual admissions, by age group, for admissions with a primary diagnosis for circulatory disease

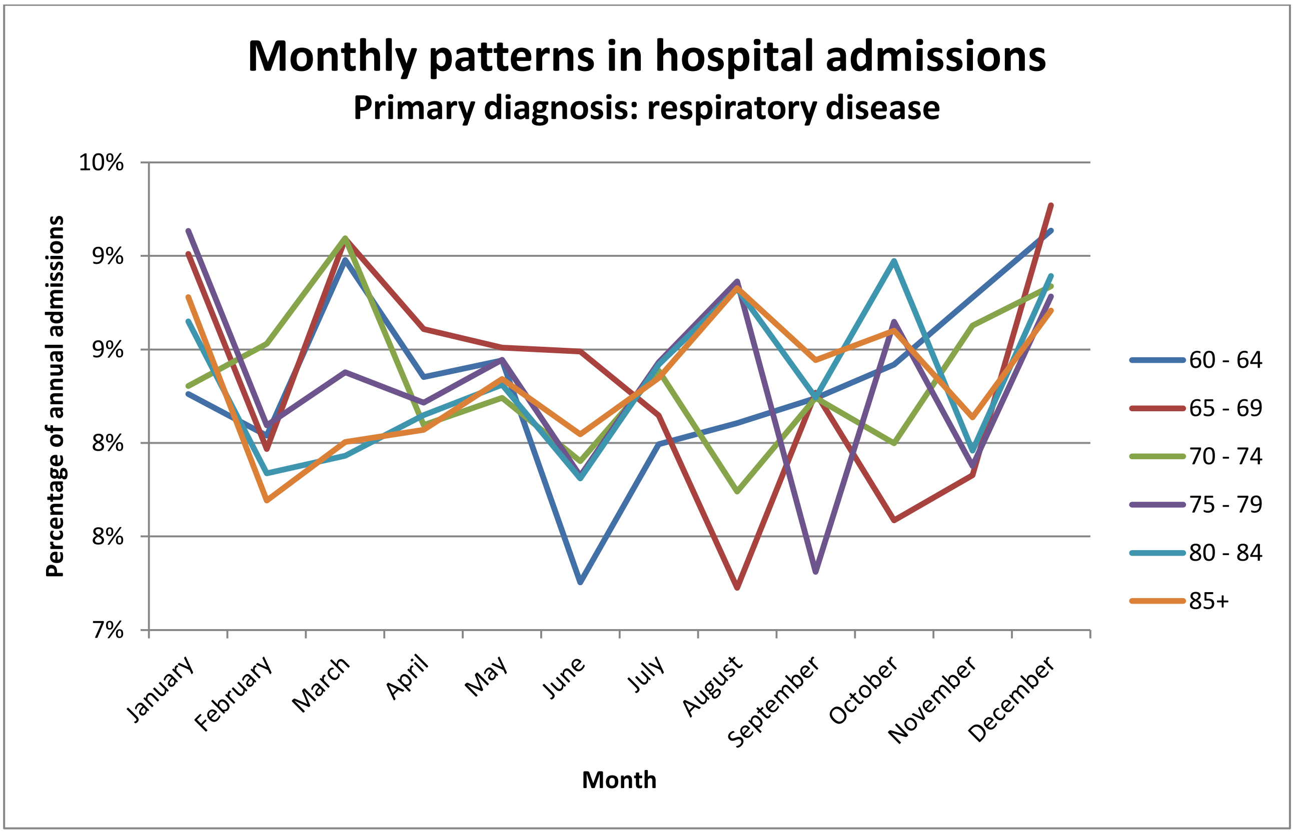

Figure 15:- Monthly hospital admissions as a percentage of annual admissions, by age group, for admissions with a primary diagnosis for respiratory disease

All of the eight main centres exhbit a similar monthly pattern in hospitalisation rates for all circulatory and respiratory admissions, as shown in Figure 16. Figure 17 and Figure 18 exhibit a similar pattern for circulatory and respiratory disease admissions respectively, albeit with greater variability than for all admissions in Figure 16.

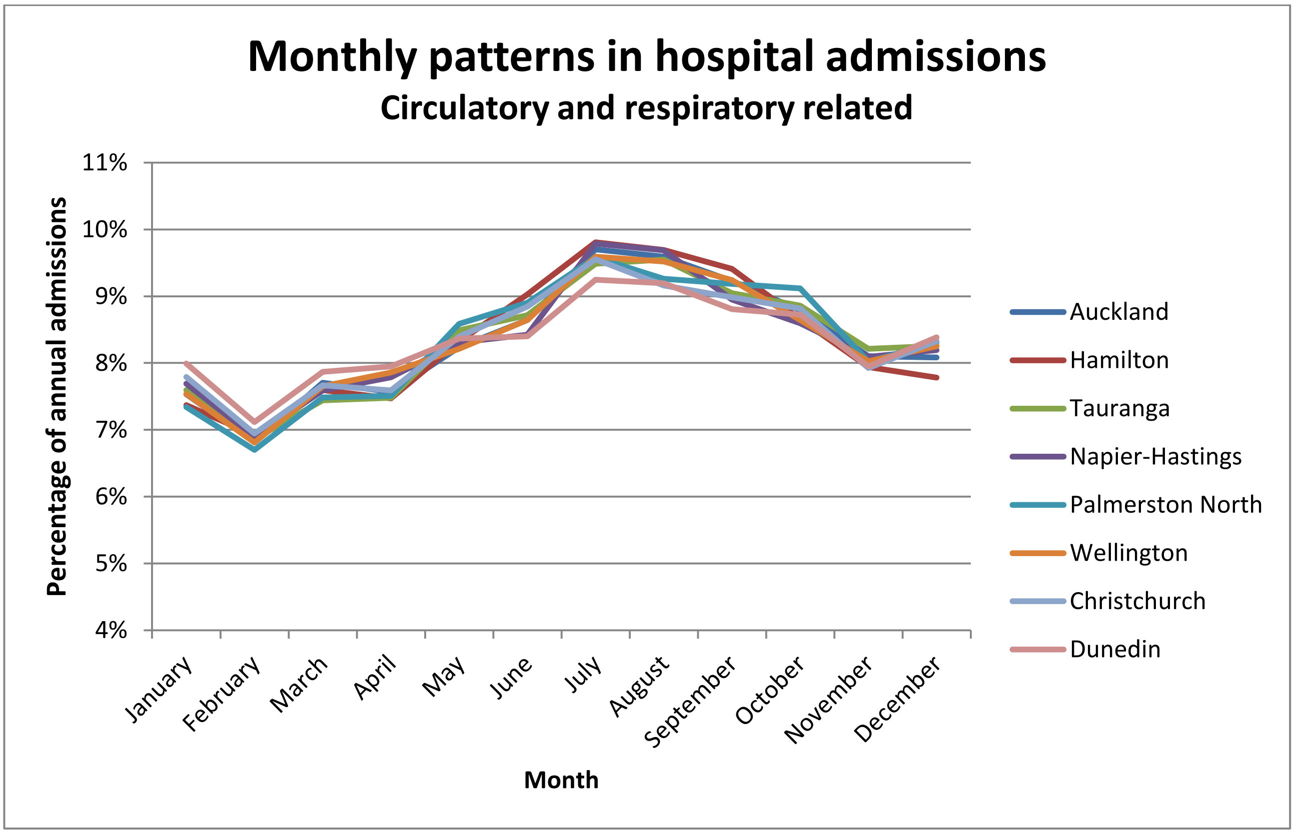

Figure 16: - Monthly hospital admissions as a percentage of annual admissions, by main centres, for all circulatory and respiratory related admissions

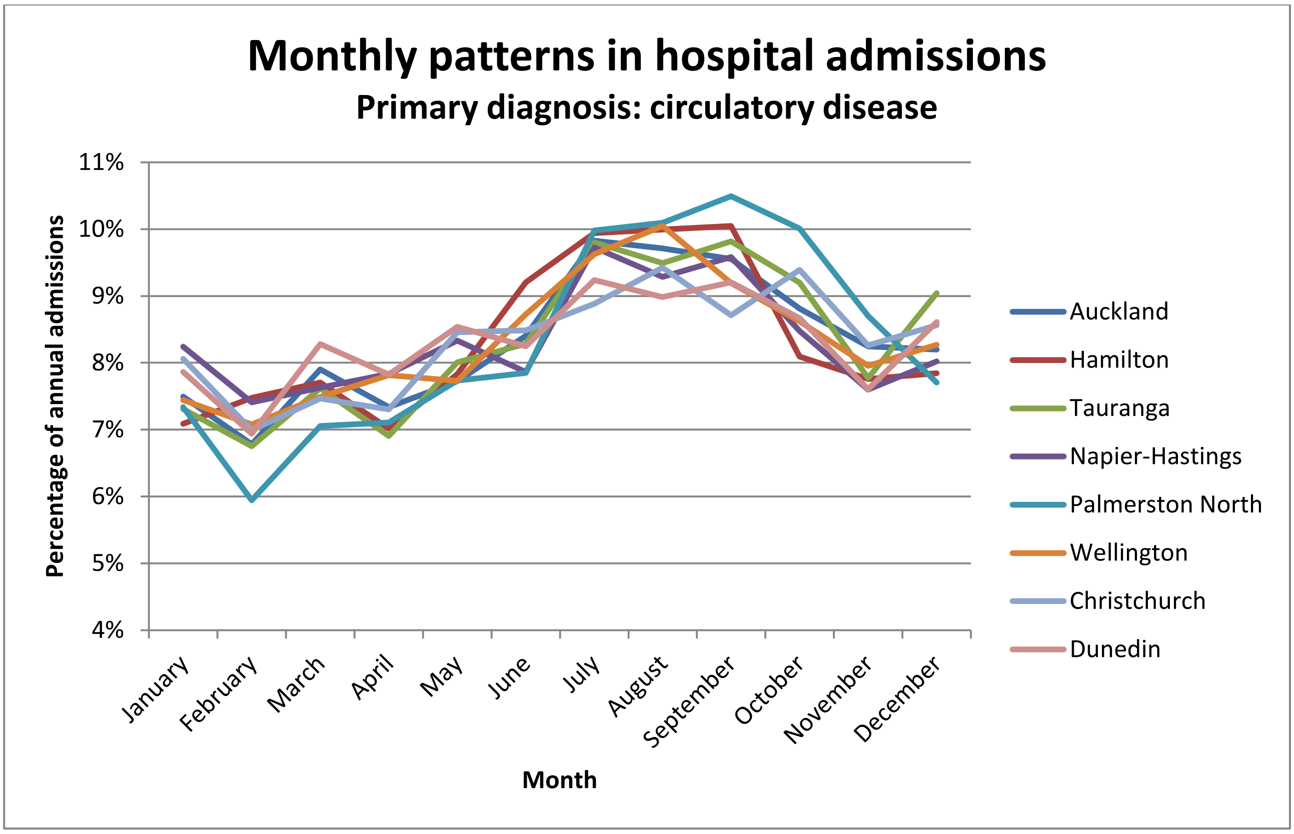

Figure 17:- Monthly hospital admissions as a percentage of annual admissions, by main centres, for admissions with a primary diagnosis for circulatory disease

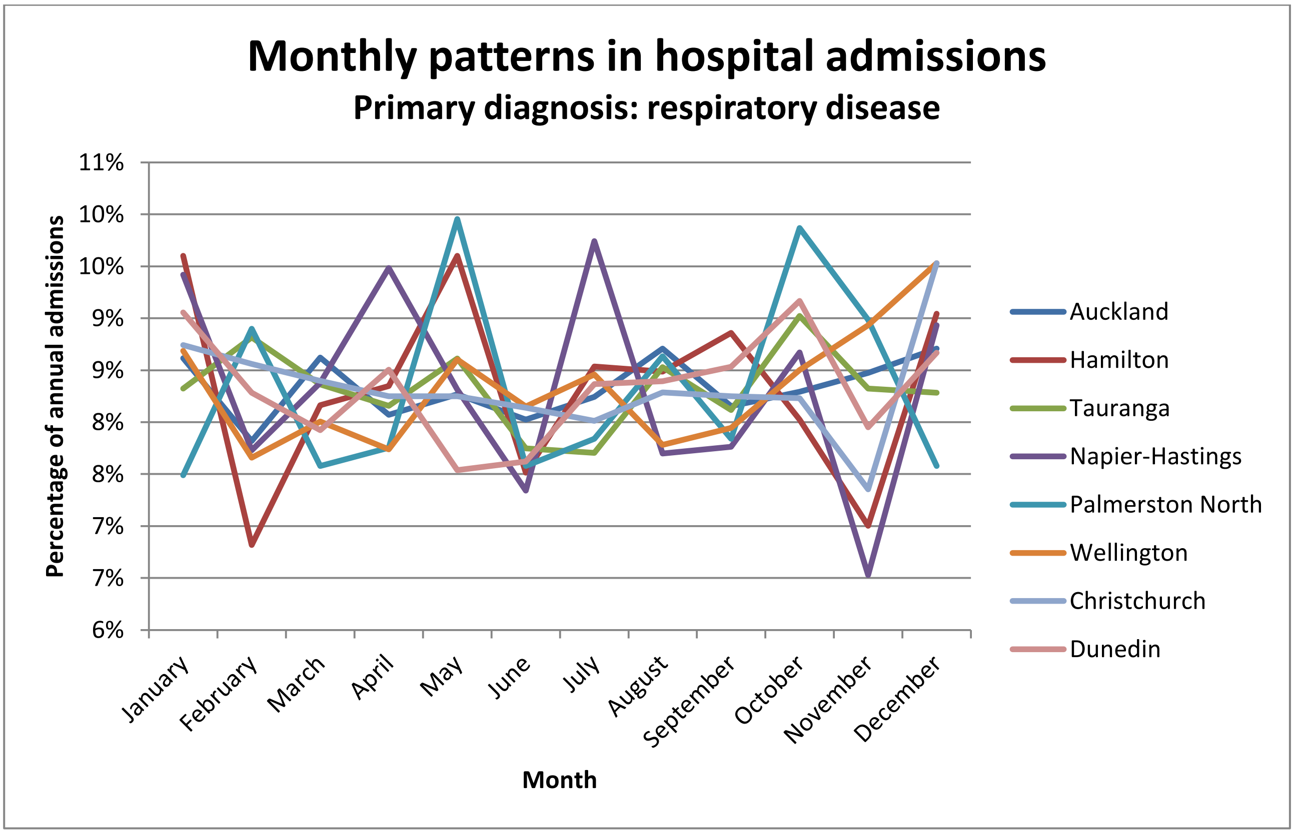

Figure 18:- Monthly hospital admissions as a percentage of annual admissions, by main centres, for admissions with a primary diagnosis for respiratory disease

The CSVH compares hospitalisation rates during the June to September period with rates for the of the year, with positive percentages representing the winter excess of hospitalisations. The CSVH is consistently positive for all admissions except one year in Dunedin (Figure 19) and predominantly positive for admissions with a primary diagnosis of circulatory disease (Figure 20); however admissions with a primary diagnosis of respiratory disease (Figure 21) exhibit some variability between positive and negative. The population weighted CSVH for all of New Zealand in the all admissions group is 15%. Admissions with a primary or secondary diagnosis for diseases associated with COPD, comprising of chronic bronchitis, emphysema, bronchiectasis and chronic airway obstruction, exhibited a 51% winter excess. This calculation does include some respiratory diseases that are not considered as COPD.

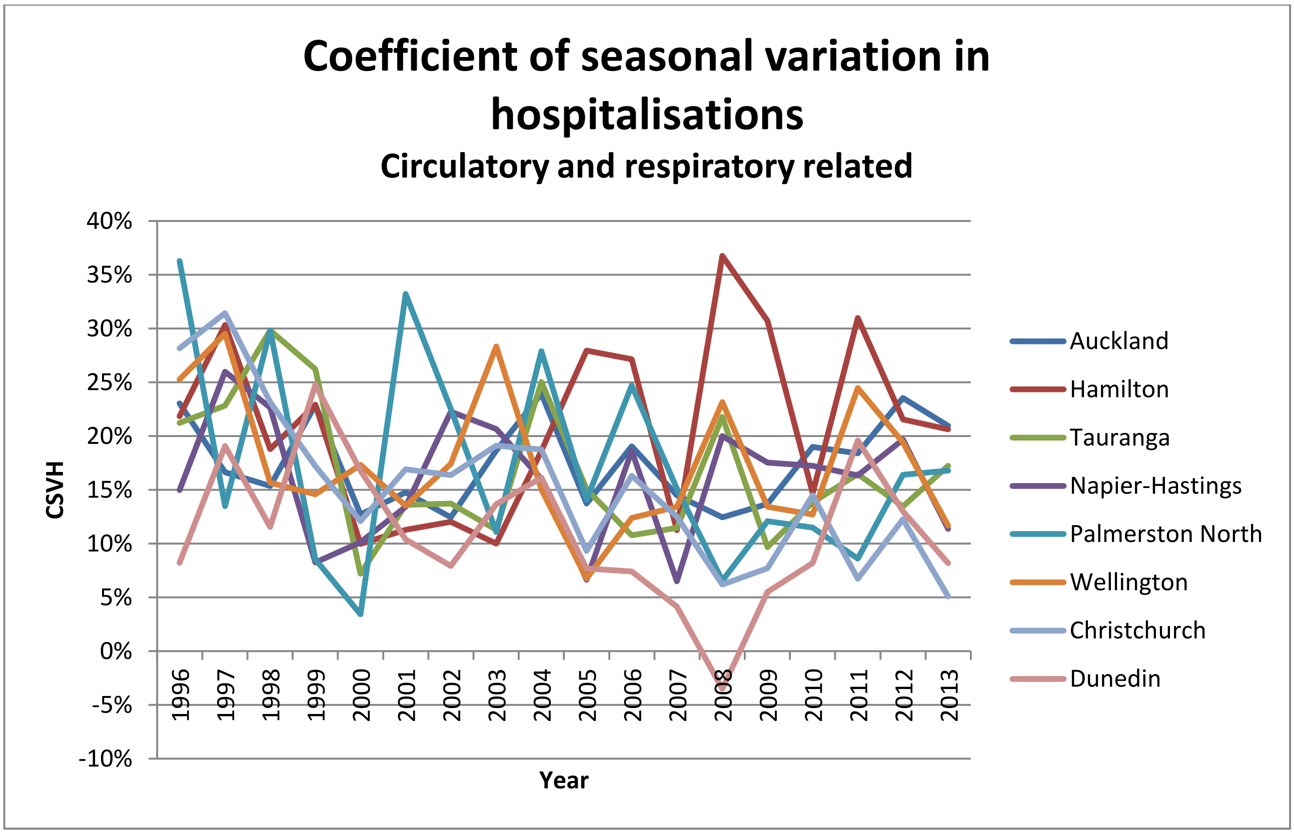

Figure 19:- Coefficient of seasonal variation in hospitalisations (CSVH) for each of eight main centres by year. For all circulatory and respiratory related admissions

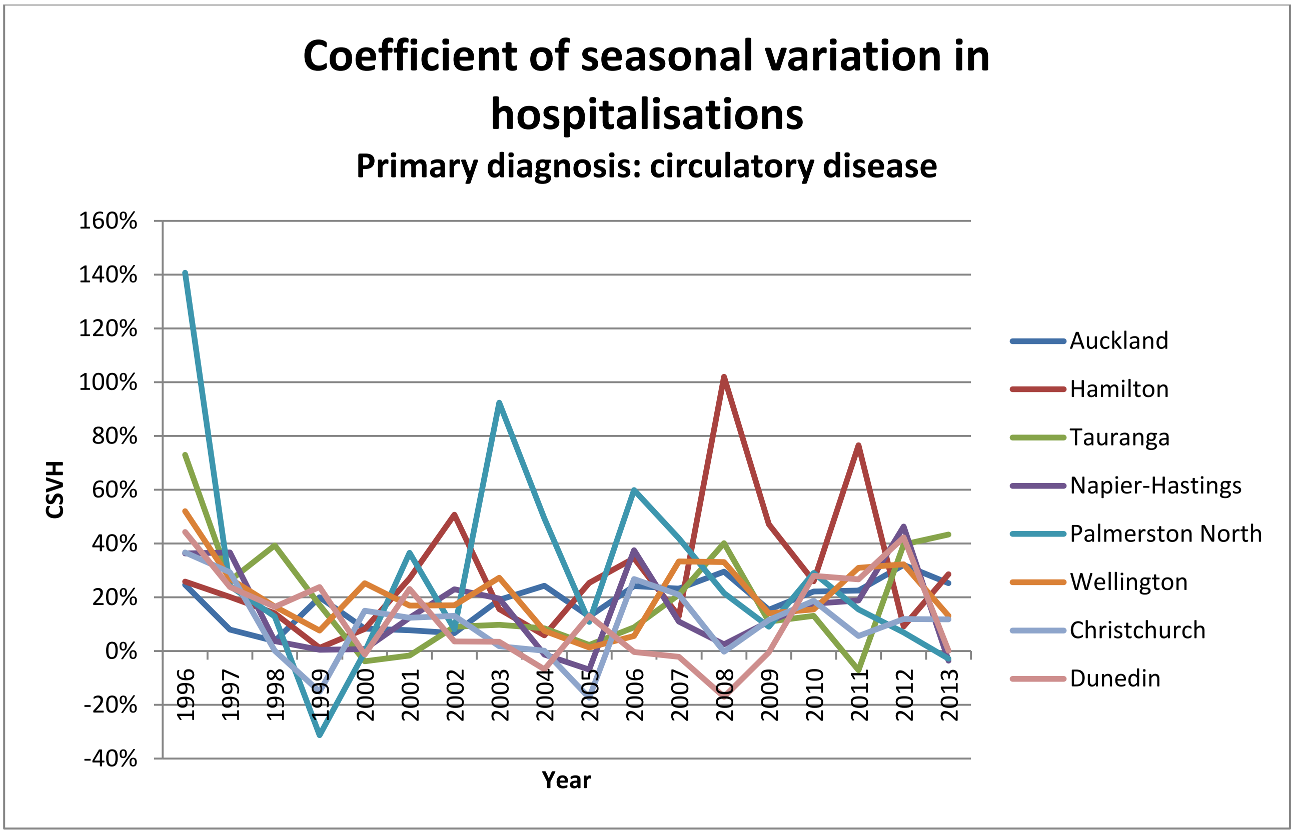

Figure 20:- Coefficient of seasonal variation in hospitalisations (CSVH) for each of eight main centres by year. For admissions with a primary diagnosis of circulatory disease

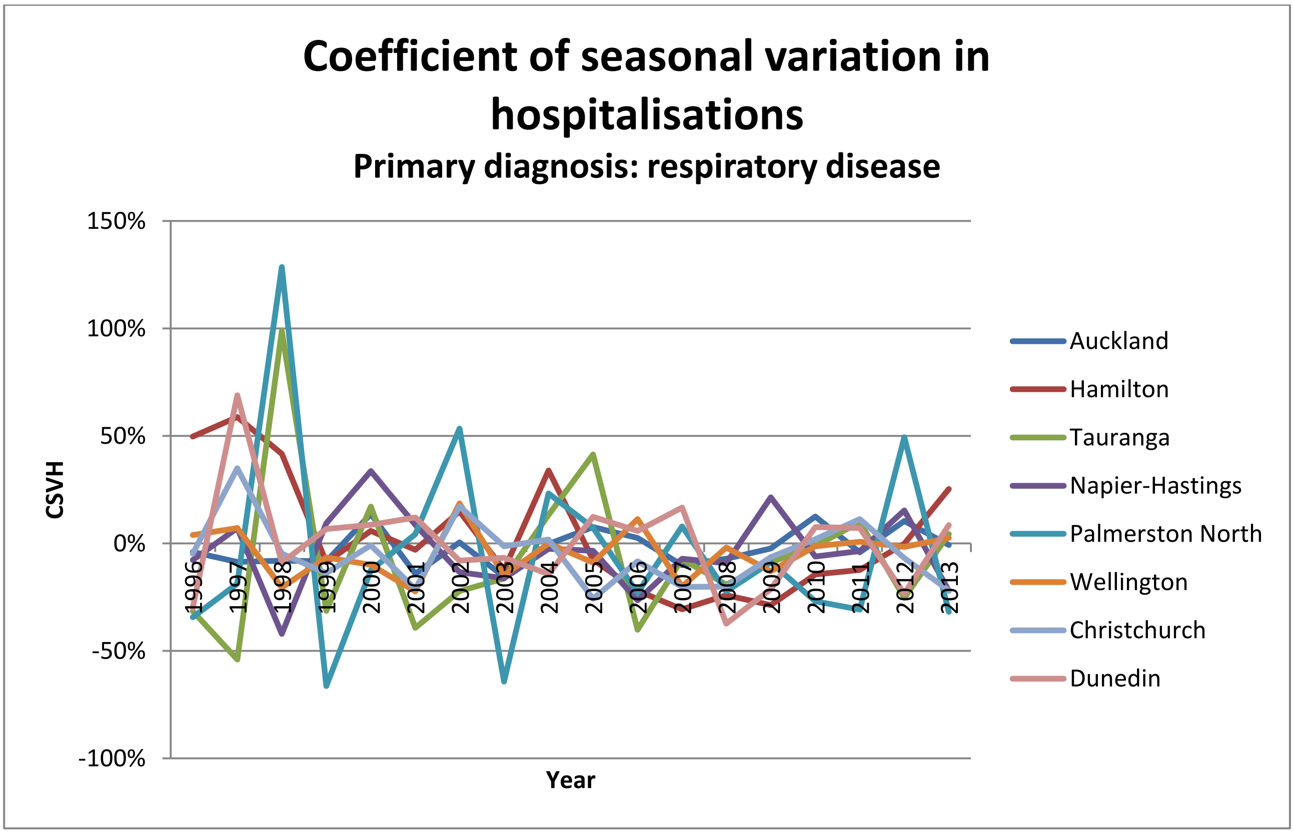

Figure 21:- Coefficient of seasonal variation in hospitalisations (CSVH) for each of eight main centres by year. For admissions with a primary diagnosis of respiratory disease

4.2.3 Daily patterns

Daily admission rates exhibited a normal distribution, as show in Figure 22 below, thus were modelled using a linear regression (Kutner, 2005). In order to assess the relationship between daily admission rates and cold spells, daily admission rates for each of the eight main centres were standardised by population (per 10,000) and modelled separately using each of the temperature indicators.

The regression equation is shown below, with B representing coefficients; hence B_1 is of particular interest as it quantifies the relationship between the temperature indicators and daily admission rates.

$$\textit{Daily admission rate per 10,000} = B_0 + B_1.\textit{temperature indicator}$$

The coefficient B_1 indicates the impact that a one unit increase in the temperature variables (i.e. one additional day with the temperature in the 1st or 10th percentile within a given period) on daily admission rates per 10,000 of population. In this circumstance, the F-statistic provides a comparative measure of explanatory power of the models, with higher F-statistics indicating that the variable provides greater explanatory power.

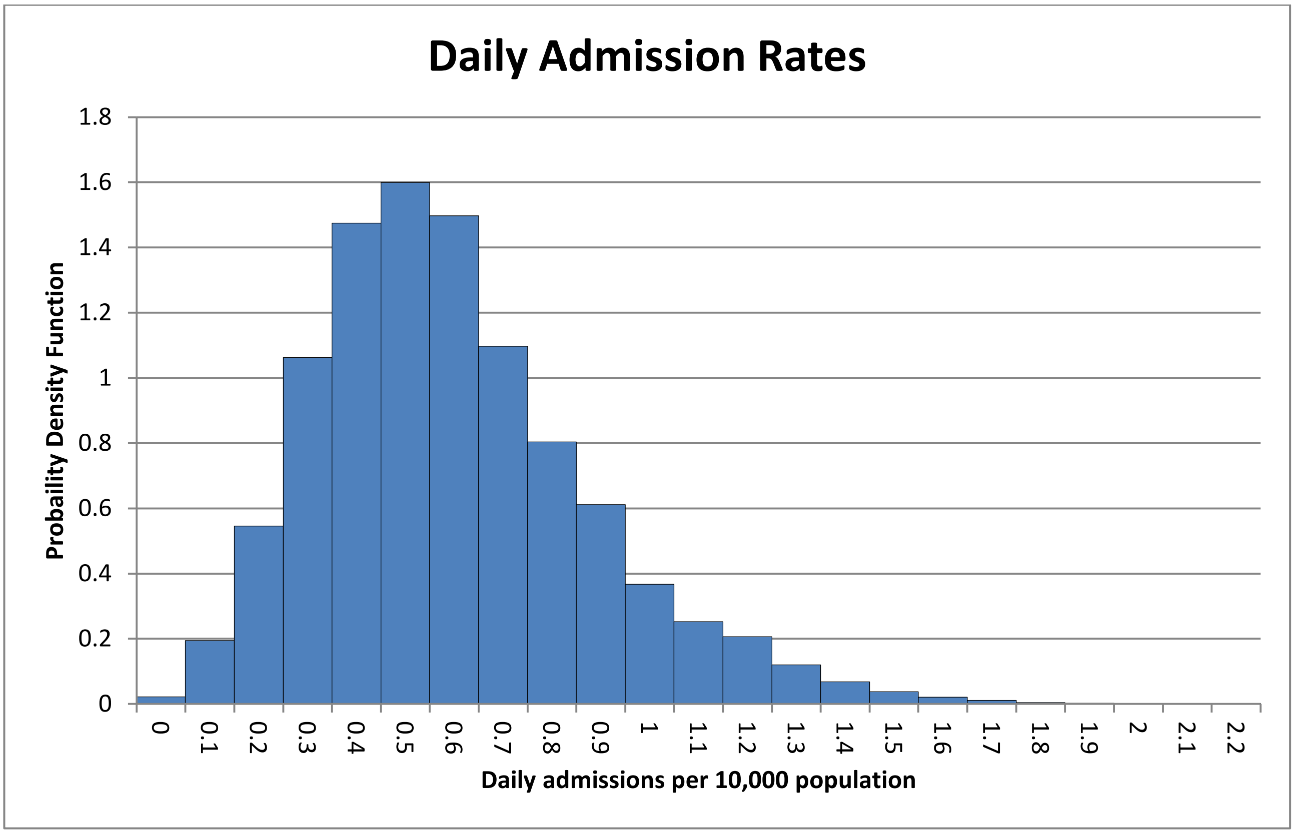

Figure 22:- Histogram of daily admission rates for all respiratory and circulatory related admissions

For all respiratory and circulatory related admissions, Table 11 shows that the number of days with minimum temperatures in the 10th percentile in the period 1-28 and 21-28 days prior are positively correlated with admission rates and are statistically significant at a 99% confidence level. Each additional 10th percentile day in the 1-28 days prior is associated with an increase in daily admission rates of 0.0018 admissions per 10,000 of population. Each additional 10th percentile day in the 21-28 days prior is associated with an increase in daily admission rates of 0.0053 admissions per 10,000 of population. The winter period of June-September is associated with an increase in admission rates of 0.097 per 10,000 of population compared to the remainder of the year.

Table 11:- Summary of linear regression models relating temperature variables to daily admission rates per 10,000 of population, for all respiratory and circulatory related admissions

Temperature variable	***Coefficient***	***t-value***	***F-statistic***
10th percentile on day of admission	-0.00194	-0.483	0.234
1st percentile on day of admission	0.00054	0.088	0.008
10th percentile days in 7 days prior	0.00016	0.135	0.018
10th percentile days in 14 days prior	0.00107	1.337	1.786
10th percentile days in 21 days prior	0.00093	1.456	2.121
10th percentile days in 28 days prior	**0.00178****	**3.244**	**10.520**
1st percentile days in 7 days prior	-0.00276	-1.324	1.752
1st percentile days in 14 days prior	-0.00041	-0.282	0.080
1st percentile days in 21 days prior	-0.00049	-0.419	0.175
1st percentile days in 28 days prior	0.00052	0.515	0.265
10th percentile days 7-14 days prior	0.00217	1.816	3.297
10th percentile days 14-21 days prior	0.00087	0.725	0.526
10th percentile days 21-28 days prior	**0.00527*****	**4.376**	**19.150**
1st percentile days 7-14 days prior	0.00175	0.837	0.700
1st percentile days 14-21 days prior	-0.00081	-0.386	0.149
1st percentile days 21-28 days prior	0.00380	1.809	3.272
Admission during June-September	**0.09793*****	**38.380**	**1473**
** significant at 5%; ** significant at 1%; *** significant at 0.1%*			

For all admissions with a primary diagnosis of circulatory disease, Table 12 shows that the number of days with minimum temperatures in the 1st and 10th percentile in the period 1-7 days prior are negatively correlated with admission rates, and are statistically significant at a 95% confidence level. Each additional 1st percentile day in the 1-7 days prior is associated with a decrease in daily admission rates of 0.0014 per 10,000 of population. Each additional 10th percentile day in the 1-7 days prior is associated with a decrease in daily admission rates of 0.0009 per 10,000 of population. The winter period of June-September is associated with higher admission rates of 0.008 per 10,000 compared to the remainder of the year.

Table 12:- Summary of linear regression models relating temperature variables to daily admission rates per 10,000 of population, for admissions with a primary diagnosis of circulatory disease

Temperature variable	*Coefficient*	*t-value*	*F-statistic*
10th percentile on day of admission	-0.00145	-1.259	1.584
1st percentile on day of admission	-0.00347	-1.958	3.833
10th percentile days in 7 days prior	**-0.00086***	**-2.525**	**6.377**
10th percentile days in 14 days prior	-0.00026	-1.140	1.299
10th percentile days in 21 days prior	-0.00028	-1.533	2.351
10th percentile days in 28 days prior	-0.00018	-1.132	1.282
1st percentile days in 7 days prior	**-0.00140***	**-2.361**	**5.573**
1st percentile days in 14 days prior	-0.00015	-0.364	0.133
1st percentile days in 21 days prior	-0.00041	-1.244	1.549
1st percentile days in 28 days prior	-0.00029	-1.017	1.035
10th percentile days 7-14 days prior	0.64440	0.803	0.000
10th percentile days 14-21 days prior	-0.00040	-1.169	1.367
10th percentile days 21-28 days prior	0.00013	0.390	0.152
1st percentile days 7-14 days prior	0.00106	1.765	3.115
1st percentile days 14-21 days prior	-0.00105	-1.747	3.052
1st percentile days 21-28 days prior	0.00004	0.067	0.005
Admission during June-September	**0.00842*****	**11.460**	**131.300**
** significant at 5%; ** significant at 1%; *** significant at 0.1%*			

For all admissions with a primary diagnosis of respiratory disease, Table 13 shows that the number of days with minimum temperatures in the 1st and 10th percentile in the period 14-21 days prior are negatively correlated with admission rates, and are statistically significant at a 95% confidence level. Each additional 1st percentile day in the 14-21 days prior is associated with a decrease in daily admission rates of 0.0013 per 10,000 of population. Each additional 10th percentile day in the 14-21 days prior is associated with a decrease in daily admission rates of 0.0007 per 10,000 of population. Each additional 1st percentile day in period 1-28 days prior to admission is associated with a decrease in daily admission rates of 0.0005 per 10,000 of population. The winter period of June-September is not associated with any significant differences in admission rates compared to the remainder of the year.

Table 13:- Summary of linear regression models relating temperature variables to daily admission rates per 10,000 of population, for admissions with a primary diagnosis of respiratory disease

Temperature variable	***Coefficient***	***t-value***	***F-statistic***
10th percentile on day of admission	0.00150	1.426	2.033
1st percentile on day of admission	0.00066	0.407	0.166
10th percentile days in 7 days prior	0.00015	0.474	0.225
10th percentile days in 14 days prior	0.00022	1.029	1.060
10th percentile days in 21 days prior	-0.00007	-0.411	0.169
10th percentile days in 28 days prior	-0.00006	-0.388	0.151
1st percentile days in 7 days prior	-0.00015	-0.281	0.079
1st percentile days in 14 days prior	-0.00017	-0.446	0.199
1st percentile days in 21 days prior	-0.00051	-1.730	2.993
1st percentile days in 28 days prior	**-0.00053***	**-2.070**	**4.286**
10th percentile days 7-14 days prior	0.00033	1.049	1.101
10th percentile days 14-21 days prior	**-0.00071***	**-2.287**	**5.229**
10th percentile days 21-28 days prior	-0.00003	-0.081	0.007
1st percentile days 7-14 days prior	-0.00021	-0.399	0.159
1st percentile days 14-21 days prior	**-0.00134***	**-2.485**	**6.173**
1st percentile days 21-28 days prior	-0.00067	-1.249	1.560
Admission during June-September	-0.00094	-1.373	1.886
** significant at 5%; ** significant at 1%; *** significant at 0.1%*			

4.2.4 Spatial patterns

The best predictor for each of the three admission groups, as indicated by the highest F-statistic in Table 11, Table 12 and Table 13 was used in a separate regression for each of eight main centres. Table 14 shows significant variation in coefficients between the main centres, with Auckland, Tauranga and Christchurch experiencing a statistically significant relationship between daily admission rates for all circulatory and respiratory related admissions and the number of 10th percentile days between 21 and 28 days prior, with a positive relationship. For admissions with a primary diagnosis for circulatory disease, Auckland, Napier-Hastings and Christchurch experienced a significant relationship between the number of days in the 10th percentile in the 7 days prior and admission rates, with a negative relationship. For admissions with a primary diagnosis for respiratory disease, Auckland and Christchurch experienced a significant relationship between the number of 1st percentile days in the 14-21 days prior and admission rates, with a negative relationship.

Table 14: - Summary of linear regression models relating temperature variables to daily admission rates per 10,000 of population, for each of the eight main centres and three diagnosis groups

	All circulatory and respiratory related admissions		***Admissions with a primary diagnosis for circulatory disease***		***Admissions with a primary diagnosis for respiratory disease***	
	10th percentile days 21-28 days prior		***10th percentile days in the 7 days prior***		***1st percentile days 14-21 days prior***	
	Coefficient	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*
Auckland	**0.003692***	**2.351**	**-0.00073***	**-2.511**	**-0.0006***	**-2.098**
Hamilton	0.003414	1.212	-0.00085	-0.927	-0.00217	-1.794
Tauranga	**0.008385***	**2.319**	-0.00039	-0.329	-0.00204	-1.27
Napier-Hastings	0.003276	0.984	**-0.00205***	**-2.305**	-0.00158	-1.182
Palmerston North	0.004131	1.149	-0.00144	-1.038	-0.00297	-1.378
Wellington	0.001974	0.859	0.000665	1.457	-0.00015	-0.28
Christchurch	**0.004216***	**2.048**	**-0.00139****	**-2.879**	**-0.00117***	**-1.976**
Dunedin	0.0013	0.345	-0.00073	-0.669	-0.00111	-0.657
** significant at 5%; ** significant at 1%; *** significant at 0.1%*						

4.2.5 *Socioeconomic deprivation*

Socioeconomic deprivation, as measured by NZDep did not appear related the monthly pattern of admissions with insignificant differences in admissions between NZDep deciles across all (Figure 23), circulatory (Figure 24) and respiratory (Figure 25) admissions, although circulatory and respiratory diseases exhibited greater variability.

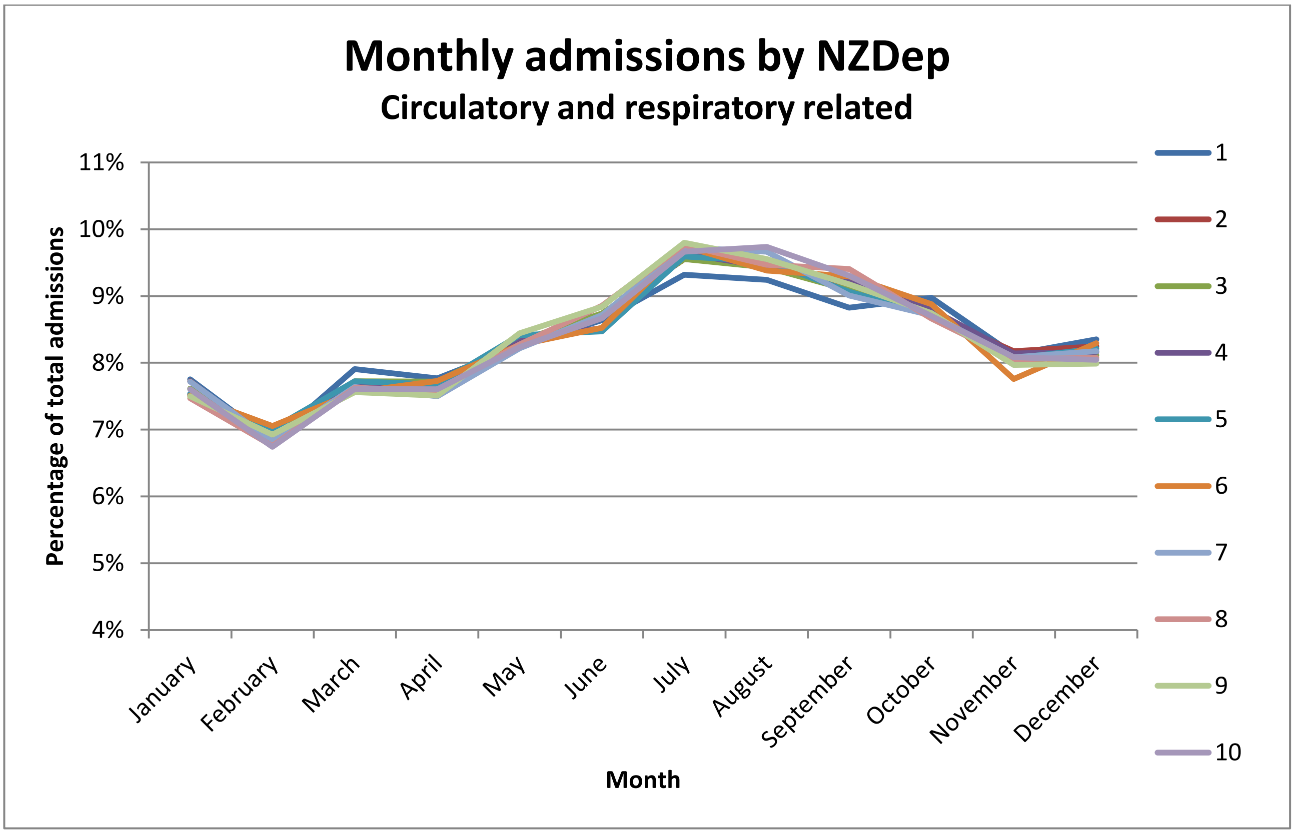

Figure 23:- Monthly admissions as a percentage of annual admissions, by NZDep socioeconomic deprivation deciles. For all circulatory and respiratory related admissions

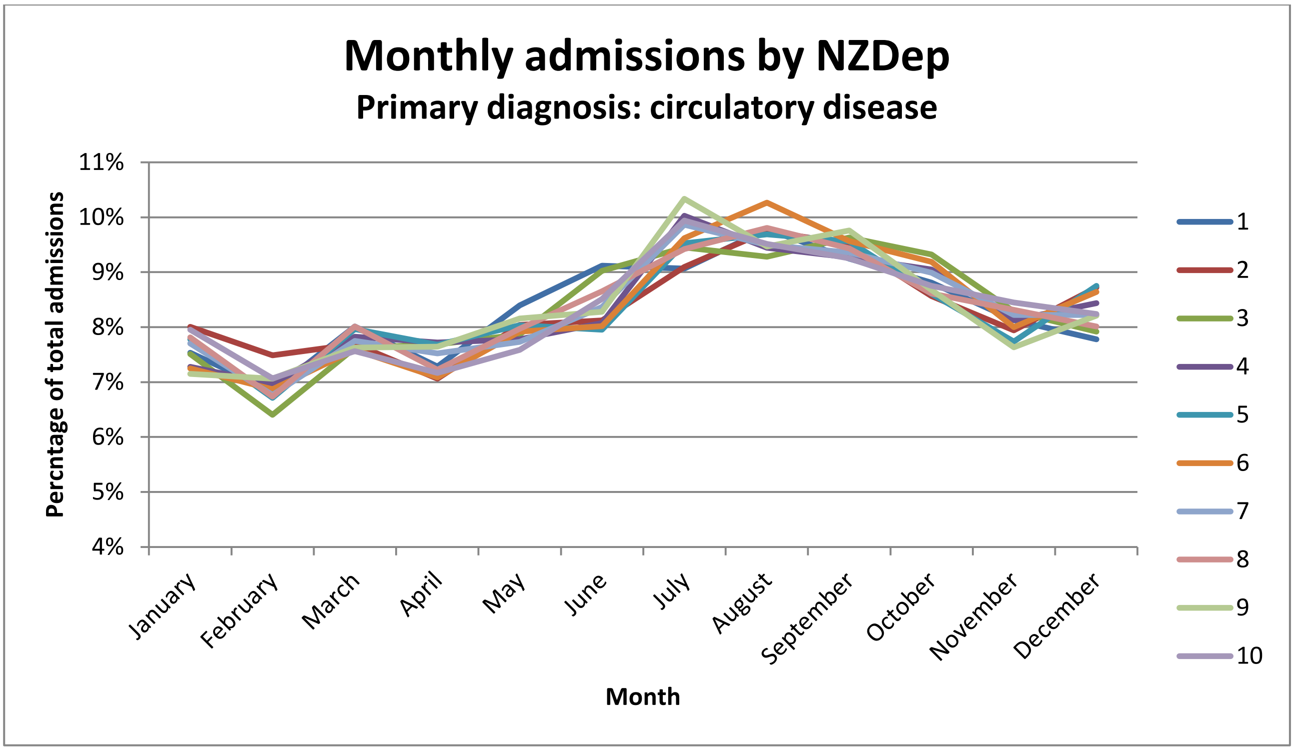

Figure 24:- Monthly admissions as a percentage of annual admissions, by NZDep socioeconomic deprivation deciles. For admissions with a primary diagnosis of circulatory disease

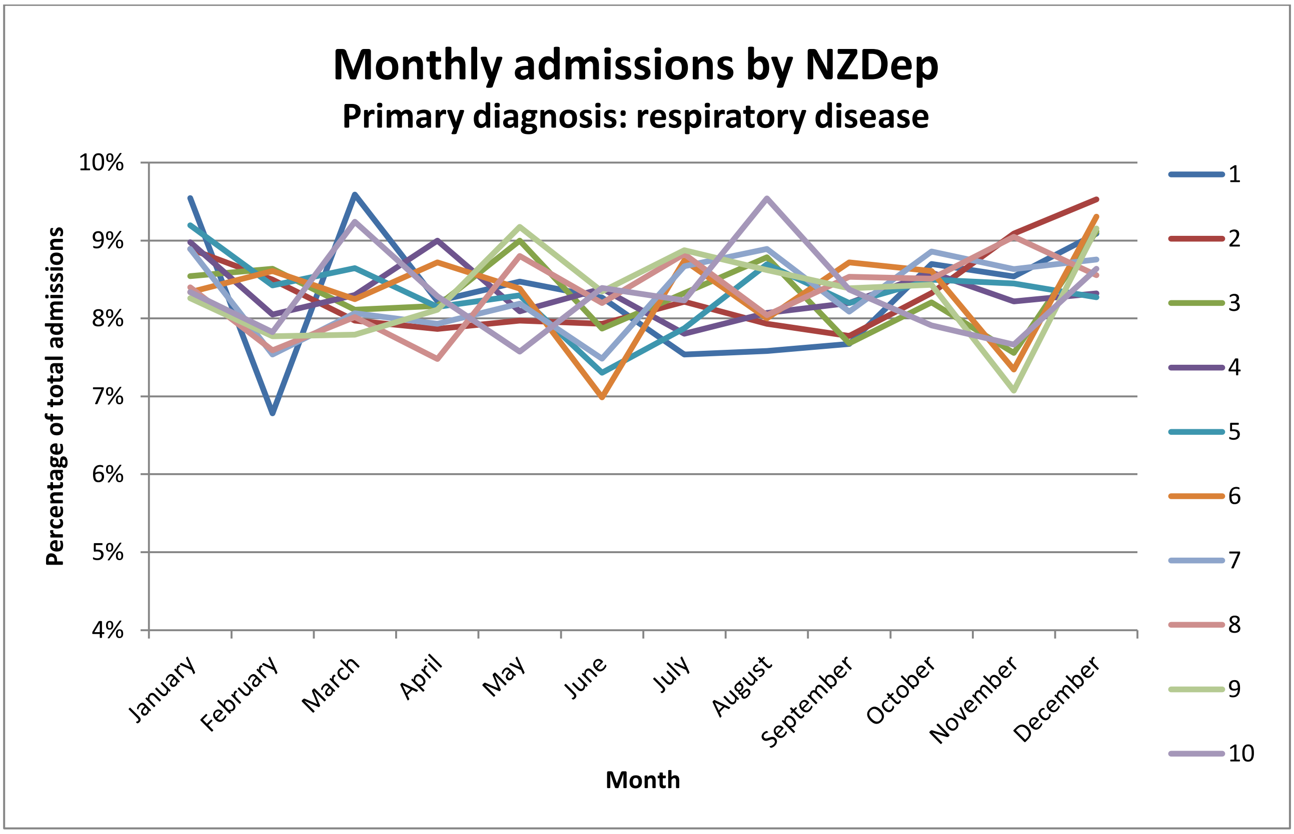

Figure 25:- Monthly admissions as a percentage of annual admissions, by NZDep socioeconomic deprivation deciles. For admissions with a primary diagnosis of respiratory disease

4.3 Length of admission

4.3.1 Overview

Mean length of admission has fallen significantly over the 18 years included in the dataset in all eight main centres, for the all (Figure 26), circulatory (Figure 27) and respiratory (Figure 28) diagnosis groups. For the all diagnosis group, the mean length of admission for New Zealand as a whole in 1996 was 8.0 days, which dropped to 5.5 days in 2013. For circulatory primary diagnoses, mean length of admission fell from 7.8 to 5.9 days and for respiratory primary diagnosis from 8.2 to 5.5 days over the same period.

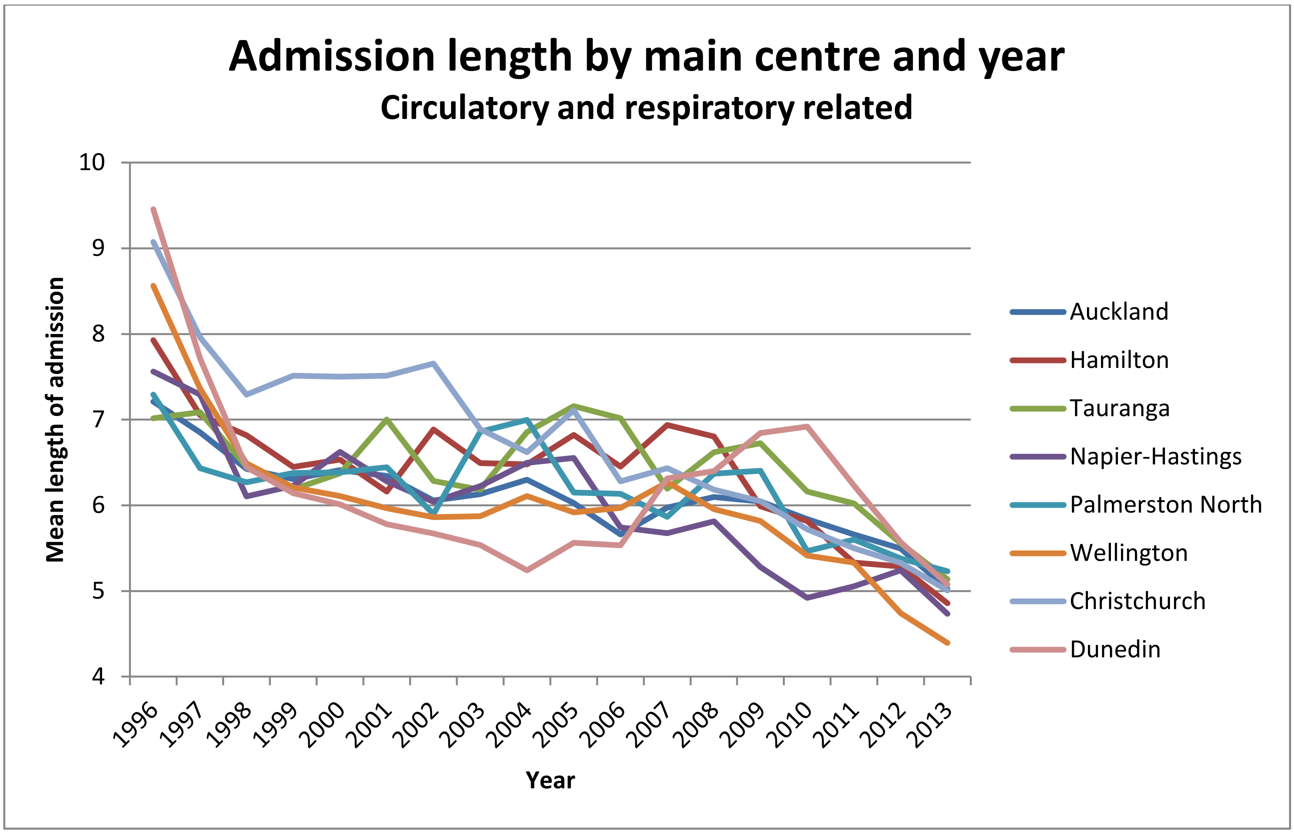

Figure 26:- Mean length of admission by each of eight main centres and year, for all circulatory and respiratory related admissions

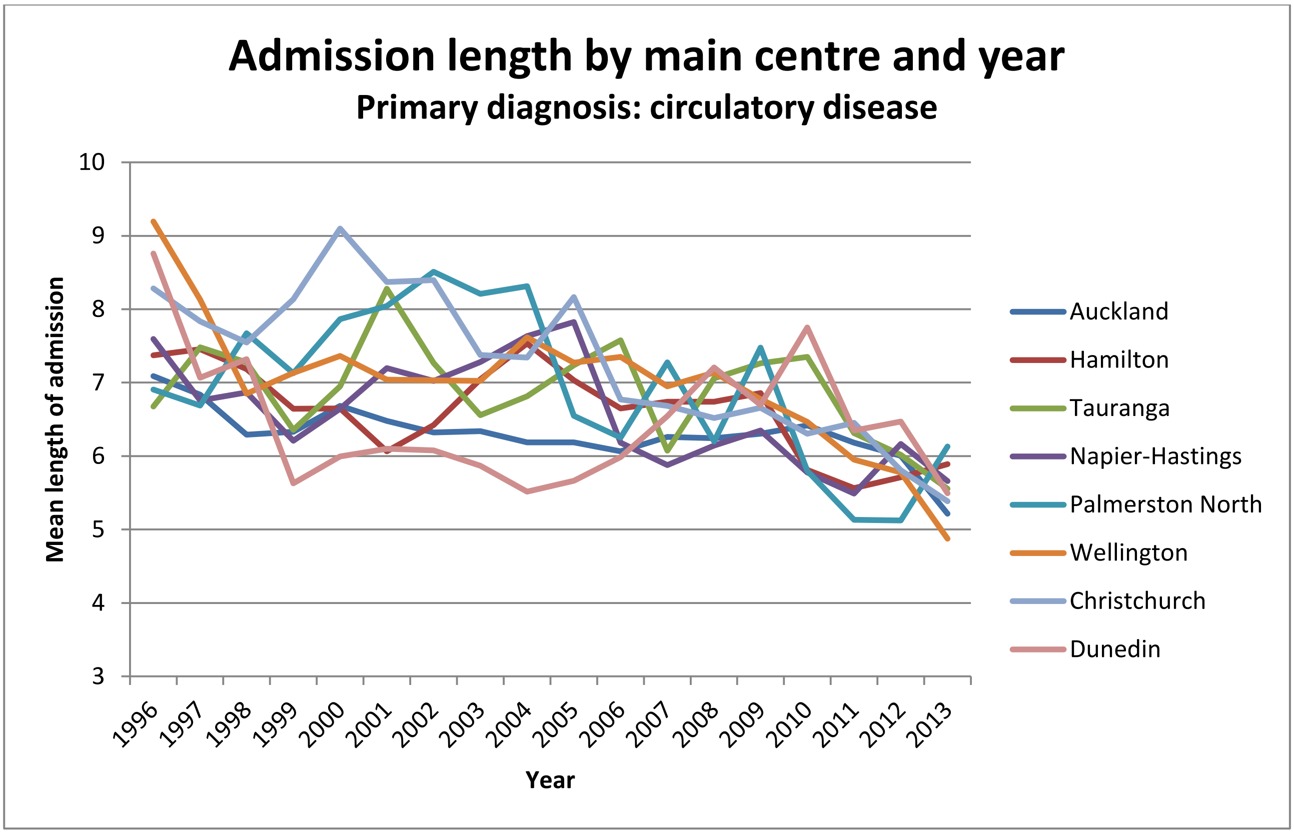

Figure 27:- Mean length of admission by each of eight main centres and year, for admissions with a primary diagnosis for circulatory disease

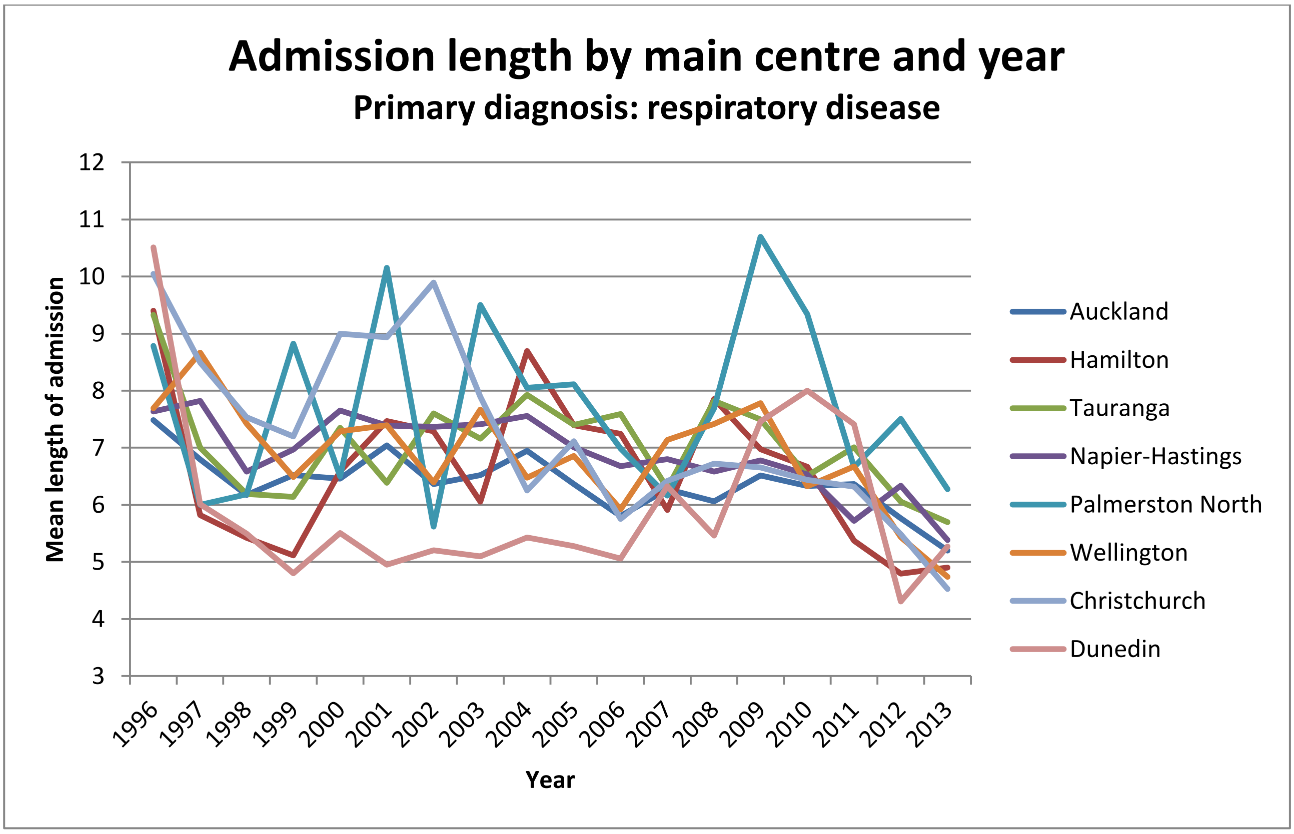

Figure 28:- Mean length of admission by each of eight main centres and year, for admissions with a primary diagnosis for respiratory disease

Mean length of stay consistently increases with age for the all diagnosis group, as shown in Figure 29 with a higher mean length of admission for each successive age group. The mean length of stay for patients aged 85 years and over is 21% higher than those aged 60-64 years. The relationship between length of stay and age is less consistent for the circulatory (Figure 30) and respiratory (Figure 31) disease primary diagnosis groups; however there is still a general increase in length of admission with age.

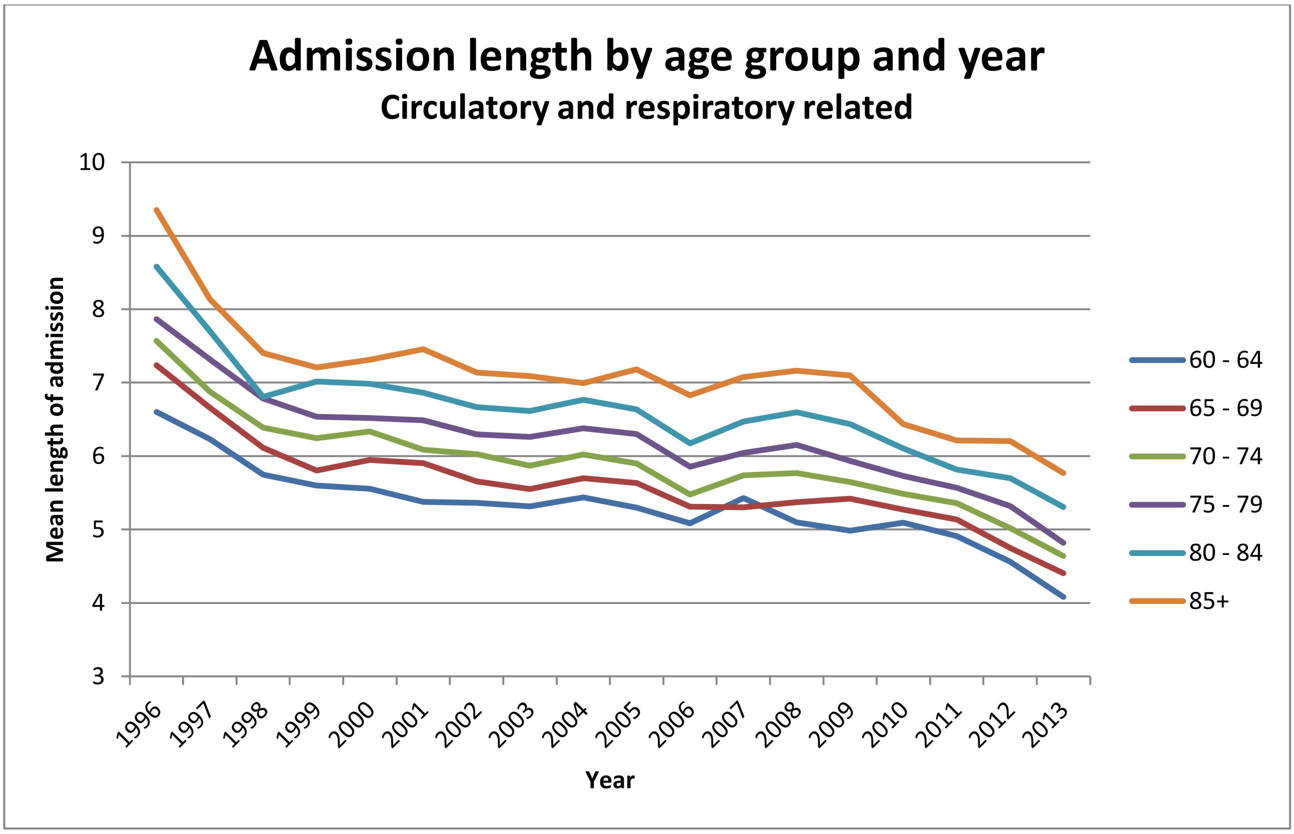

Figure 29:- Mean length of admission by age group and year, for all circulatory and respiratory related admissions

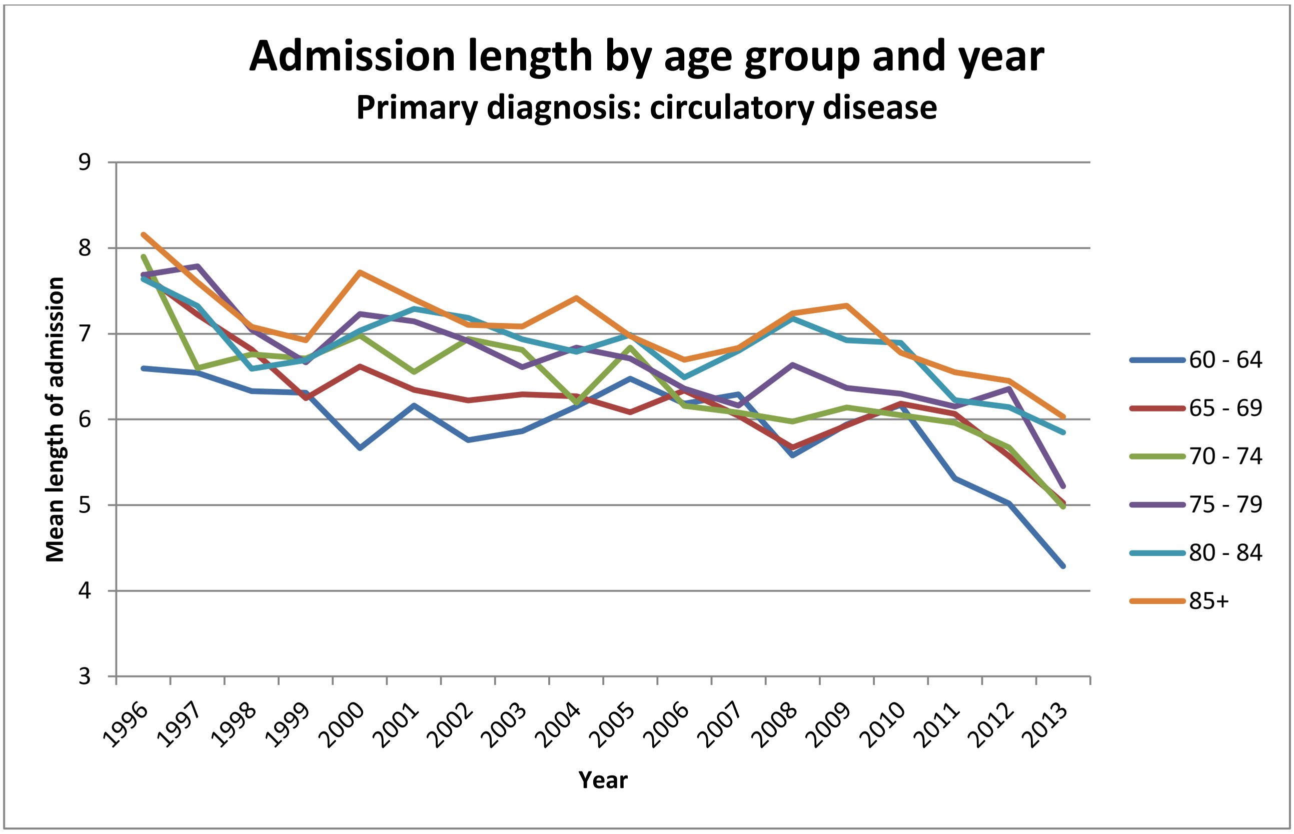

Figure 30:- Mean length of admission by age group and year, for admissions with a primary diagnosis of circulatory disease

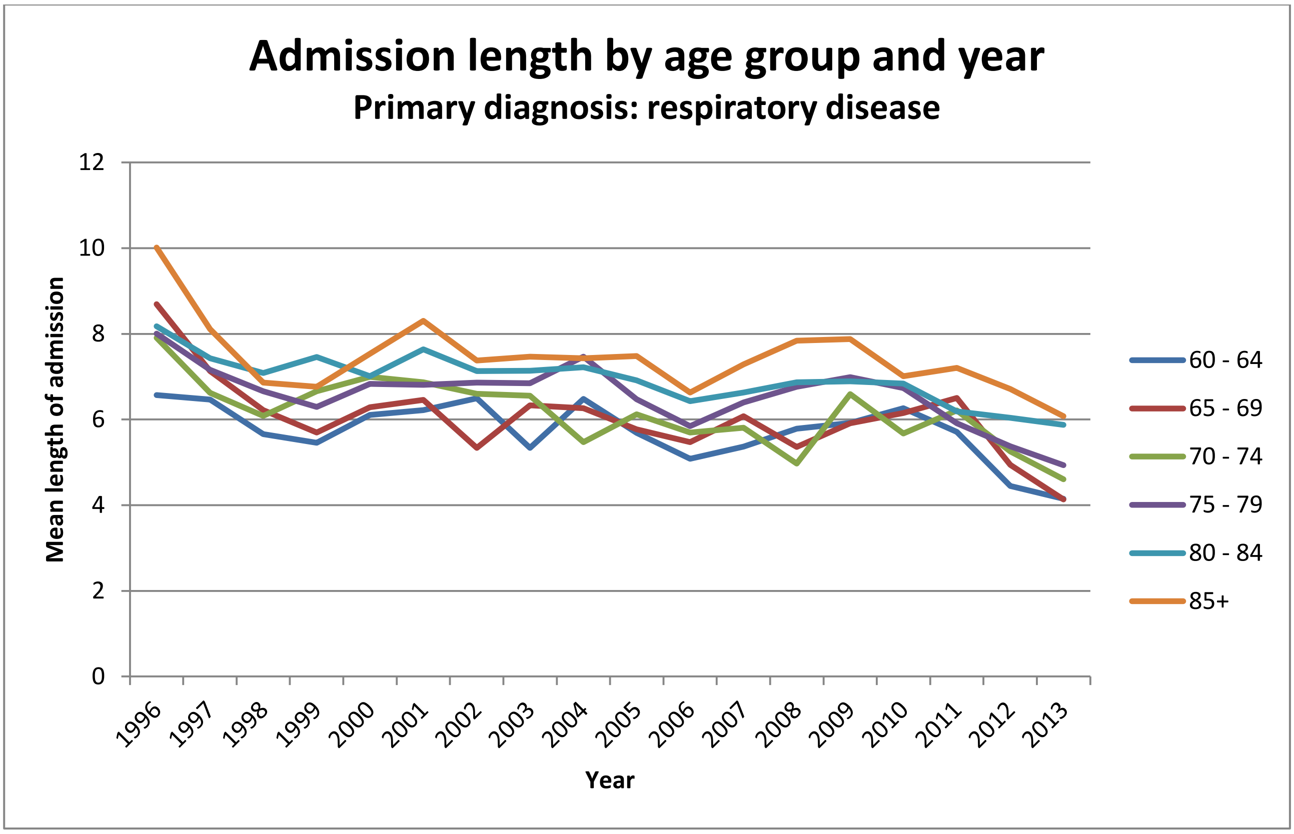

Figure 31:- Mean length of admission by age group and year, for admissions with a primary diagnosis of respiratory disease

Within the all circulatory and respiratory related diagnosis group, mean length of admission varies significantly by primary diagnosis, as shown for 18 ICD diagnosis groups in Figure 32 below. Admissions with a primary diagnosis of a mental disorder experience the longest length of admission, with a mean of 15 days. Diseases of the sense organs and cases not attributed to a specific disease (symptoms, signs and ill-defined conditions) experienced the shortest admission lengths, both with an average of less than four days. Disease of the circulatory and respiratory systems both exhibit admission lengths approximately in the middle of the range shown.

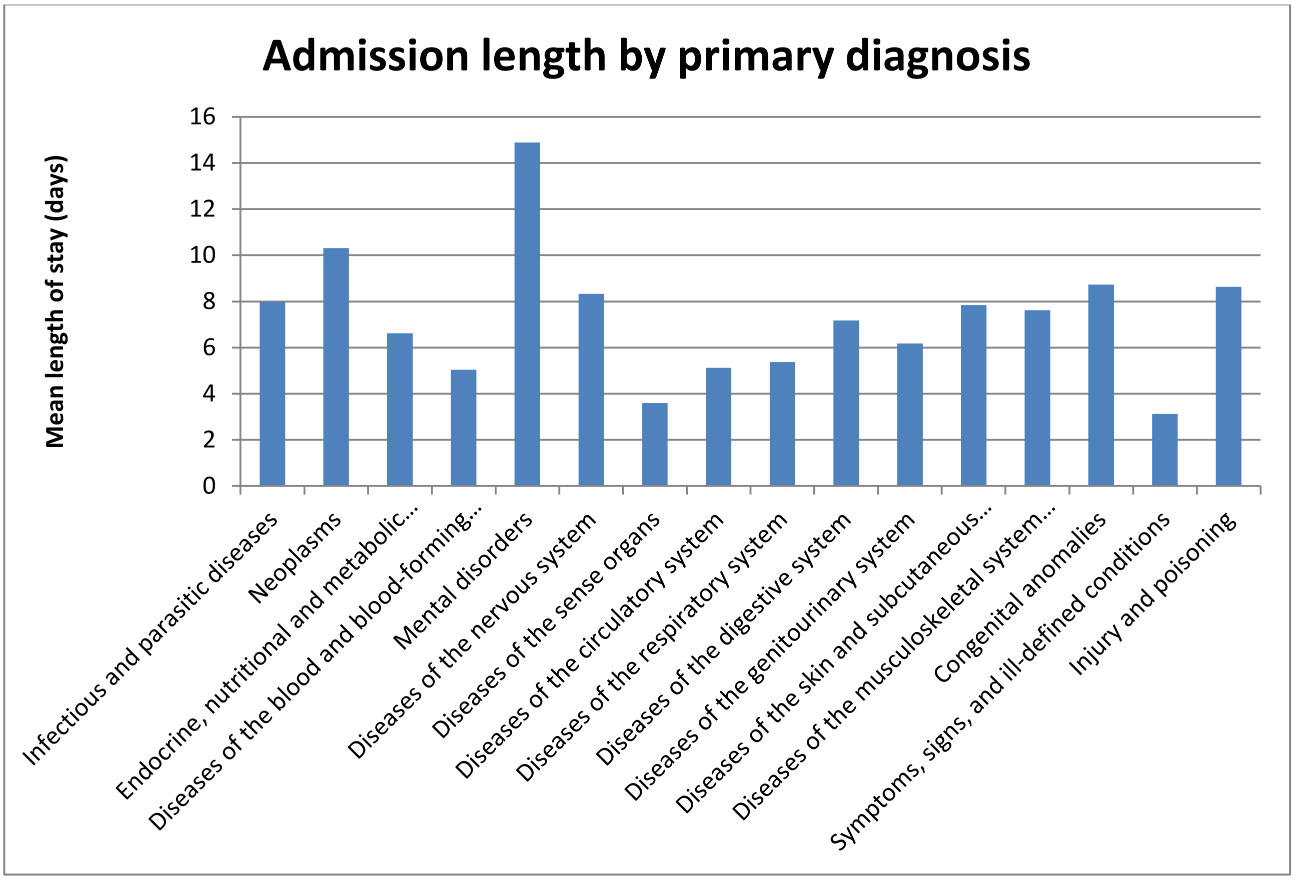

Figure 32:- Mean length of stay for each of 16 ICD primary diagnosis groups, for the all circulatory and respiratory related diagnosis group.

4.3.2 Seasonality and temperature

The effect of seasonality and temperature was investigated through several methods, comparing the mean length of admission between months and seasons, and relating temperature indicators to admission lengths. The mean length of admission varies throughout the year for all three diagnosis groups; however there is no clear pattern to this variation, as seen in Figure 33. Throughout the year, mean length of admission for primary diagnoses of circulatory and respiratory disease is higher than for the circulatory and respiratory related diagnosis groups. The mean length of admission varied little between seasons. The mean length for all admissions was 6.1 days in both winter and non-winter months; for circulatory admissions the mean was 6.4 days in winter and 6.6 days outside winter months; and for respiratory admissions the mean was 6.6 days in winter and 6.5 days in non-winter. This is a crude indicator and will not reflect changes in the demographic profile of patients admitted between seasons.

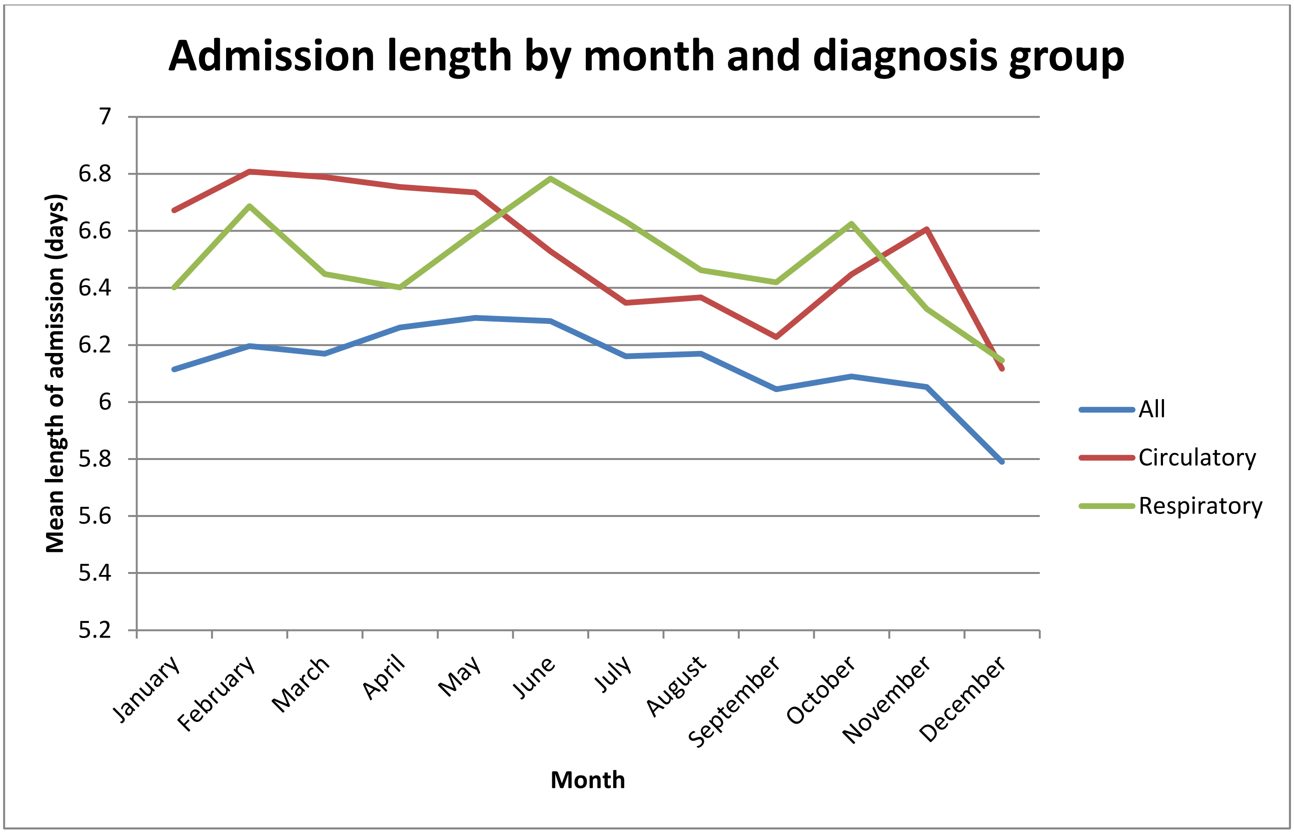

Figure 33:- Mean length of admission by month and diagnosis

The length of admission variable exhibits a negative binomial distribution, as shown in Figure 34 with the probability density decaying as the length of admission increases from a modal value of one day. Given this distribution, length of admission was modelled using a zero-truncated negative binomial regression (Hilbe, 2007).

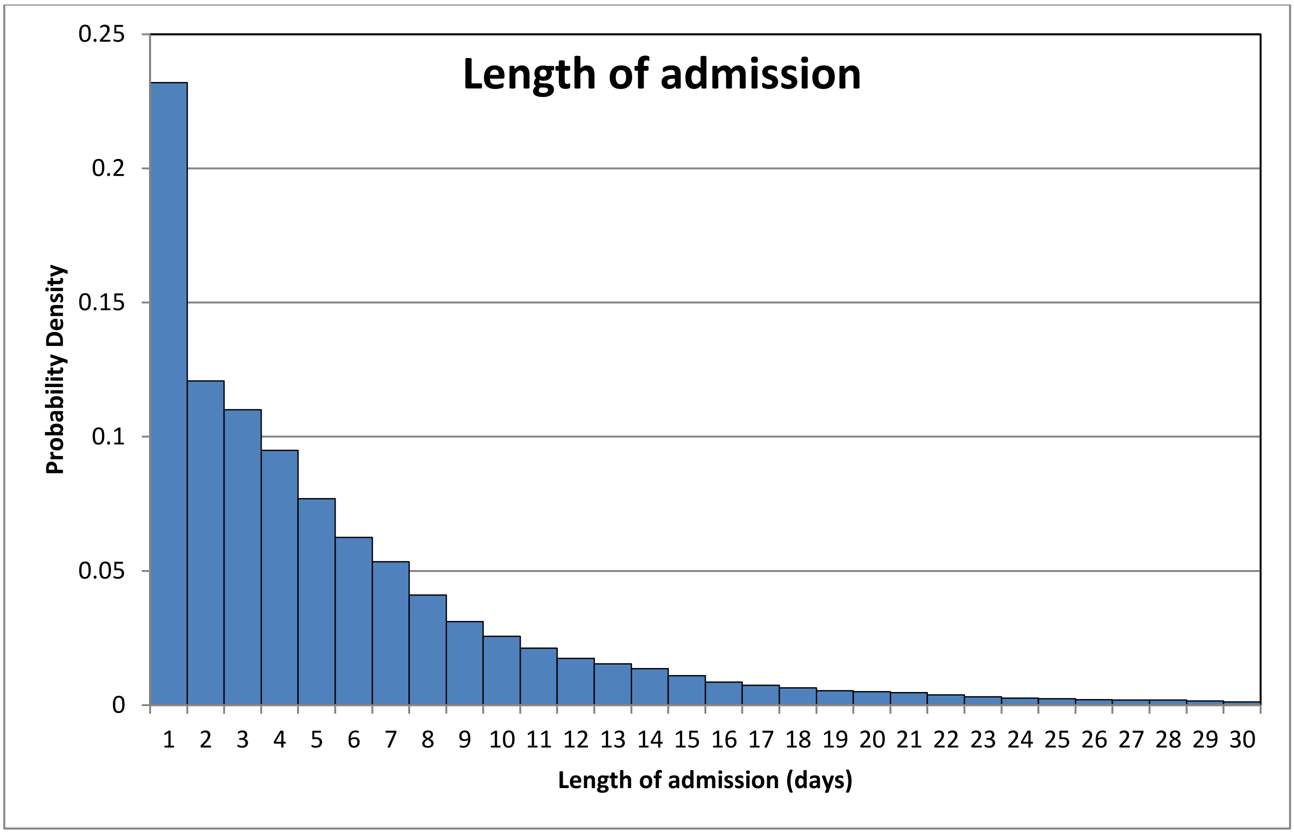

Figure 34:- Length of admission in days, shown in a probability density histogram. Note that the length of admission axis is truncated at 30 days; this variable extends to a maximum of 120 days

In order to assess the relationship between length of admission and cold spells, the length of each admission in the dataset was modelled separately using each of the temperature indicators whilst controlling for patient age, the NZDep socioeconomic deprivation score for the patient's neighbourhood, and Maori or Pacific Island ethnicity. The regression equation is shown below, with B representing coefficients; hence B_1 is of particular interest as it quantifies the relationship between the temperature indicators and length of hospitalisation.

$$\textit{Length of hospital admission} = B_0 + B_1.\textit{temperature indicator} + B_2.\textit{patient age} + B_3.\textit{NZDep score} + B_4.\textit{Maori ethnicity} + B_5.\textit{Pacific Island ethnicity}$$

The coefficient B_1 indicates the impact that a one unit increase in the temperature variables (i.e. one additional day with the temperature in the 1st or 10th percentile within a given period) on the length of admission measured in days. Z-values indicate the significance of each temperature indicator, with values greater than 1.96 indicating that the variable is statistically significant at a 95% confidence level. The Akaike information criterion (AIC) value provides a relative estimate of information loss for each of the models, with lower AIC scores representing a model of greater quality. For each of the three diagnosis groups, the model with the lowest AIC score was used for subsequent analysis of the relationship between length of admission and ethnicity and NZDep.

For all respiratory and circulatory related admissions, Table 15 shows the relationship between temperature and admission duration, with the effects of patient age, NZDep score and ethnicity isolated. All measures of low minimum temperatures on the day of admission and 1-28 days prior are associated with longer admission durations at statistically significant 95% confidence level. The number of 1st percentile days up to 21 days prior to admission is associated with an increase in the length of admission by over 0.01 days on average. Admissions on days with 1st percentile temperatures are 0.026 days longer on average.

Table 15:- Summary of negative binomial regression models relating temperature variables to length of hospital admission, for all respiratory and circulatory related admissions. Patient characteristics including age, NZDep score and ethnicity are controlled for.

Temperature Indicator	*Coefficient*	*Z-value*	*Log-likelihood*	*AIC*
10th percentile on day of admission	0.01540***	4.969	-4326456	8652926
1st percentile on day of admission	0.02592***	5.498	-4326453	8652920
10th percentile days in 7 days prior	0.00766***	8.410	-4325868	8651750
10th percentile days in 14 days prior	0.00667***	10.826	-4325104	8650222
10th percentile days in 21 days prior	0.00622***	12.644	-4323968	8647950
10th percentile days in 28 days prior	0.00540***	12.767	-4322074	8644162
1st percentile days in 7 days prior	0.01336***	8.650	-4325866	8651746
1st percentile days in 14 days prior	0.01117***	10.562	-4325107	8650228
1st percentile days in 21 days prior	0.01083***	12.765	-4323966	8647946
1st percentile days in 28 days prior	0.00950***	13.022	-4322070	8644154
10th percentile days 7-14 days prior	0.00699***	7.700	-4325133	8650280
10th percentile days 14-21 days prior	0.00689***	7.563	-4324019	8648052
10th percentile days 21-28 days prior	0.00399***	4.408	-4322145	8644304
1st percentile days 7-14 days prior	0.01110***	7.199	-4325137	8650288
1st percentile days 14-21 days prior	0.01315***	8.506	-4324011	8648036
1st percentile days 21-28 days prior	0.00836***	5.439	-4322140	8644294
Admission during June-September	0.00637**	3.159	-4352195	8704404
** significant at 5%; ** significant at 1%; *** significant at 0.1%*				

The highest quality model for the all circulatory and respiratory related diagnosis group, as indicated by the lowest AIC score in Table 15, incorporated the 1st percentile days in 28 days prior temperature indicator, and is summarised in Table 16 below. This indicates that admission duration increases with patient age, and is lower amongst patients that identify with Maori or Pacific Island ethnicity, with both results statistically significant.

Table 16:- Detailed analysis of negative binomial regression of admission duration, for all circulatory and respiratory disease related admissions

Explanatory variable	***Coefficient***	***Z-value***
NZDep	-0.00055	-1.500
Age	**0.00924*****	**81.034**
Ethnicity - Maori	**-0.03997*****	**-10.705**
Ethnicity - Pacific Islander	**-0.10772*****	**-20.961**
1st percentile days 1-28 days prior	**0.00950*****	**13.019**
** significant at 5%; ** significant at 1%; *** significant at 0.1%*		

For circulatory disease admissions, Table 17 shows the relationship between temperature and admission duration, with the effects of patient age, NZDep score and ethnicity isolated. All of the cumulative 1^{st} and 10^{th} percentile indicators are significantly associated with admission duration, with the 1^{st} percentile indicators exhibiting coefficients approximately twice that of the 1^{st} percentile indicators. A one day increase in the number of 1^{st} percentile days in the period 1-7 days prior to admission is associated with a 0.02 day increase in the length of admission. The four-month winter period is associated with 0.04 day shorter admissions. Both the 10^{th} and 1^{st} percentile 7-14 day prior to admission indicators are significantly related to admission duration.

Table 17:- Summary of negative binomial regression models relating temperature variables to length of hospital admission, for all circulatory admissions. Patient characteristics including age, NZDep score and ethnicity are controlled for.

Temperature Indicator	*Coefficient*	*Z-value*	*Log-likelihood*	*AIC*
10th percentile on day of admission	**0.03235*** **	**3.514**	**-439546**	**879106**
1st percentile on day of admission	**0.03014***	**2.153**	**-439550**	**879113**
10th percentile days in 7 days prior	**0.00987*** **	**3.682**	**-439511**	**879035**
10th percentile days in 14 days prior	**0.00730*** **	**4.016**	**-439406**	**878826**
10th percentile days in 21 days prior	**0.00505*** **	**3.470**	**-439307**	**878627**
10th percentile days in 28 days prior	**0.00354** **	**2.824**	**-439124**	**878262**
1st percentile days in 7 days prior	**0.01825*** **	**4.008**	**-439509**	**879032**
1st percentile days in 14 days prior	**0.01494*** **	**4.793**	**-439402**	**878819**
1st percentile days in 21 days prior	**0.01197*** **	**4.778**	**-439301**	**878616**
1st percentile days in 28 days prior	**0.00811*** **	**3.768**	**-439121**	**878255**
10th percentile days 7-14 days prior	**0.00636***	**2.376**	**-439411**	**878836**
10th percentile days 14-21 days prior	0.00131	0.484	-439313	878639
10th percentile days 21-28 days prior	-0.00083	-0.311	-439128	878270
1st percentile days 7-14 days prior	**0.01493*** **	**3.294**	**-439409**	**878831**
1st percentile days 14-21 days prior	0.00861	1.880	-439311	878636
1st percentile days 21-28 days prior	-0.00219	-0.482	-439128	878269
Admission during June-September	**-0.04081*** **	**-6.876**	**-442120**	**884254**
** significant at 5%; ** significant at 1%; *** significant at 0.1%*				

The highest quality model for the primary diagnosis of circulatory disease group, as indicated by the lowest AIC score in Table 17, incorporated the 1st percentile days in 28 days prior temperature indicator. This model is summarised in Table 18 below, indicating that circulatory disease patients identifying with Maori or Pacific Island ethnicities experience shorter admissions than other ethnicities. Admission duration increases with the age of the patient, and is statistically significant.

Table 18:- Detailed analysis of negative binomial regression model of admission duration, for primary diagnosis of circulatory disease.

Explanatory variable	*Coefficient*	*Z-value*
NZDep	**-0.00498*****	**-4.628**
Age	**0.00245*****	**7.342**
Ethnicity - Maori	**-0.09984*****	**-9.079**
Ethnicity - Pacific Islander	**-0.24573*****	**-17.571**
1st percentile days 1-28 days prior	**0.00811*****	**3.757**
** significant at 5%; ** significant at 1%; *** significant at 0.1%*		

For respiratory disease admissions, Table 19 shows the relationship between temperature and admission duration, with the effects of patient age, NZDep score and ethnicity isolated. All of the cumulative 10th percentile indicators are significantly associated with admission duration, with a one day increase in the number of 10th percentile days in the period 1-7 days prior to admission associated with a 0.01 day increase in the length of admission. A one day increase in the number of 10th percentile days in the period 7-14 days prior to admissions is also associated with a 0.01 day increase in the length of admission. The four-month winter period is associated with 0.03 day longer admissions. The 1st percentile days in the 1-7 days prior to admission indicator is the only 1st percentile indicator significantly associated with length of admission.

Table 19:- Summary of negative binomial regression models relating temperature variables to length of hospital admission, for all respiratory admissions. Patient characteristics including age, NZDep score and ethnicity are controlled for.

Temperature Indicator	*Coefficient*	*Z-value*	*Log-likelihood*	*AIC*
10th percentile on day of admission	0.01218	0.937	-167577	335167
1st percentile on day of admission	**0.04106***	**2.072**	**-167575**	**335164**
10th percentile days in 7 days prior	**0.01138****	**3.011**	**-167559**	**335132**
10th percentile days in 14 days prior	**0.00514***	**2.015**	**-167517**	**335048**
10th percentile days in 21 days prior	**0.00638****	**3.120**	**-167483**	**334981**
10th percentile days in 28 days prior	**0.00516****	**2.945**	**-167396**	**334806**
1st percentile days in 7 days prior	**0.01311***	**2.034**	**-167561**	**335137**
1st percentile days in 14 days prior	0.00735	1.670	-167517	335049
1st percentile days in 21 days prior	0.00379	1.075	-167488	334989
1st percentile days in 28 days prior	0.00414	1.379	-167399	334813
10th percentile days 7-14 days prior	0.00012	0.032	-167519	335052
10th percentile days 14-21 days prior	**0.01071****	**2.813**	**-167484**	**334983**
10th percentile days 21-28 days prior	0.00233	0.618	-167400	334814
1st percentile days 7-14 days prior	0.00431	0.682	-167519	335051
1st percentile days 14-21 days prior	-0.00287	-0.446	-167488	334990
1st percentile days 21-28 days prior	0.00773	1.220	-167400	334813
Admission during June-September	**0.02976*****	**3.461**	**-168551**	**337115**
** significant at 5%; ** significant at 1%; *** significant at 0.1%*				

The highest quality model for the primary diagnosis of respiratory disease group, as indicated by the lowest AIC score in Table 19, incorporated the 10th percentile days in 28 days prior temperature indicator. This model is summarised in Table 20 below, and indicates that respiratory disease patients identifying with Maori or Pacific Island ethnicity experience shorter admissions than other ethnicities, and is statistically significant. Admission duration increases with the age of the patient, and is statistically significant.

Table 20:- Detailed analysis of negative binomial regression of admission duration, for primary diagnosis of respiratory disease

Explanatory variable	***Coefficient***	***Z-value***
NZDep	-0.00267	-1.759
Age	**0.00728*** **	**15.481**
Ethnicity - Maori	**-0.03197***	**-2.217**
Ethnicity - Pacific Islander	**-0.11863*** **	**-6.410**
10th percentile days 1-28 days prior	**0.00516** **	**2.945**
** significant at 5%; ** significant at 1%; *** significant at 0.1%*		

4.3.3 Spatiality

The highest quality model for each of the three diagnosis groups, as indicated by the lowest AIC score in Table 15, Table 17 and Table 19 was applied to admission duration for each of the eight main centres separately. For all circulatory and respiratory related admissions, Table 21 shows that seven of the eight main centres experienced a statistically significant relationship between admission duration and the number of 1st percentile days in the 28 days prior, with Christchurch experiencing the greatest magnitude of increase. For admissions with a primary diagnosis for circulatory disease, Wellington and Dunedin admission durations experienced a statistically significant relationship with 1st percentile days in the 28 days prior, with similar magnitudes. For admissions with a primary diagnosis for respiratory disease, Auckland and Dunedin admission durations experienced a statistically significant relationship with the number of 10th percentile days in the 28 days prior; with the magnitude in Dunedin approximately double that of Auckland.

Table 21:- Summary of negative binomial regression models relating temperature variables to length of hospital admission, for all three admission groups and all eight main centres. Patient characteristics including age, NZDep score and ethnicity are controlled.

	All circulatory and respiratory related admissions		*Admissions with a primary diagnosis for circulatory disease*		*Admissions with a primary diagnosis for respiratory disease*	
	1st percentile days in the 28 days prior		*1st percentile days in the 28 days prior*		*10th percentile days in the 28 days prior*	
	Coefficient	*Z-value*	*Coefficient*	*Z-value*	*Coefficient*	*Z-value*
Auckland	**0.00276***	**2.054**	0.00587	1.523	**0.00872****	**2.879**
Hamilton	0.00571	1.281	0.00773	0.555	0.01919	1.696
Tauranga	**0.00905***	**-2.175**	0.01230	1.027	-0.00743	-0.826
Napier-Hastings	**0.01903*****	**5.277**	0.00842	0.778	0.01454	1.880
Palmerston North	**0.01284***	**2.130**	-0.00455	-0.251	0.01129	0.693
Wellington	**0.01696*****	**5.673**	**0.02844****	**3.054**	0.00871	1.168
Christchurch	**0.02101*****	**7.849**	0.00586	0.734	-0.00727	-1.169
Dunedin	**0.01347*****	**3.306**	**0.02402***	**2.092**	**-0.01575***	**-1.977**

** significant at 5%; ** significant at 1%; *** significant at 0.1%*

4.3.4 Socioeconomic Deprivation

The relationship between length of admission and socioeconomic deprivation, as measured by the area-level NZDep Index and length of stay was investigated in two ways, first crudely in graphical form, then by regression analysis. Figure 35 shows the crude relationship between length of admission and the NZDep measure of socioeconomic deprivation, with an overall trend of patients from the least deprived areas staying in hospital longer than those from the most deprived areas, although this varies significantly between the highest and lowest deciles. Figure 36 illustrates that socioeconomic variation does not have factor into the monthly variation of length of admission, whilst showing the broad pattern of individuals from more deprived areas experiencing shorter admissions. The coefficient on NZDep in a regression analysis of length of admission, allows for the effect of individual factors, including age and ethnicity, and temperature indicators, to be controlled for. As shown in Table 16, there is no significant relationship between the NZDep score of a patient's residence and their length of admission for all circulatory and respiratory related admissions. Table 18 indicates that for admissions with a primary diagnosis of circulatory disease, patients from areas with higher socioeconomic deprivation experience shorter admissions on average, with a decrease of 0.005 nights per increase in NZDep decile, which is statistically significant. For admissions with a primary diagnosis for respiratory disease, Table 20 shows that there is no statistically significant relationship between admission duration and the NZDep decile of the patient's residence.

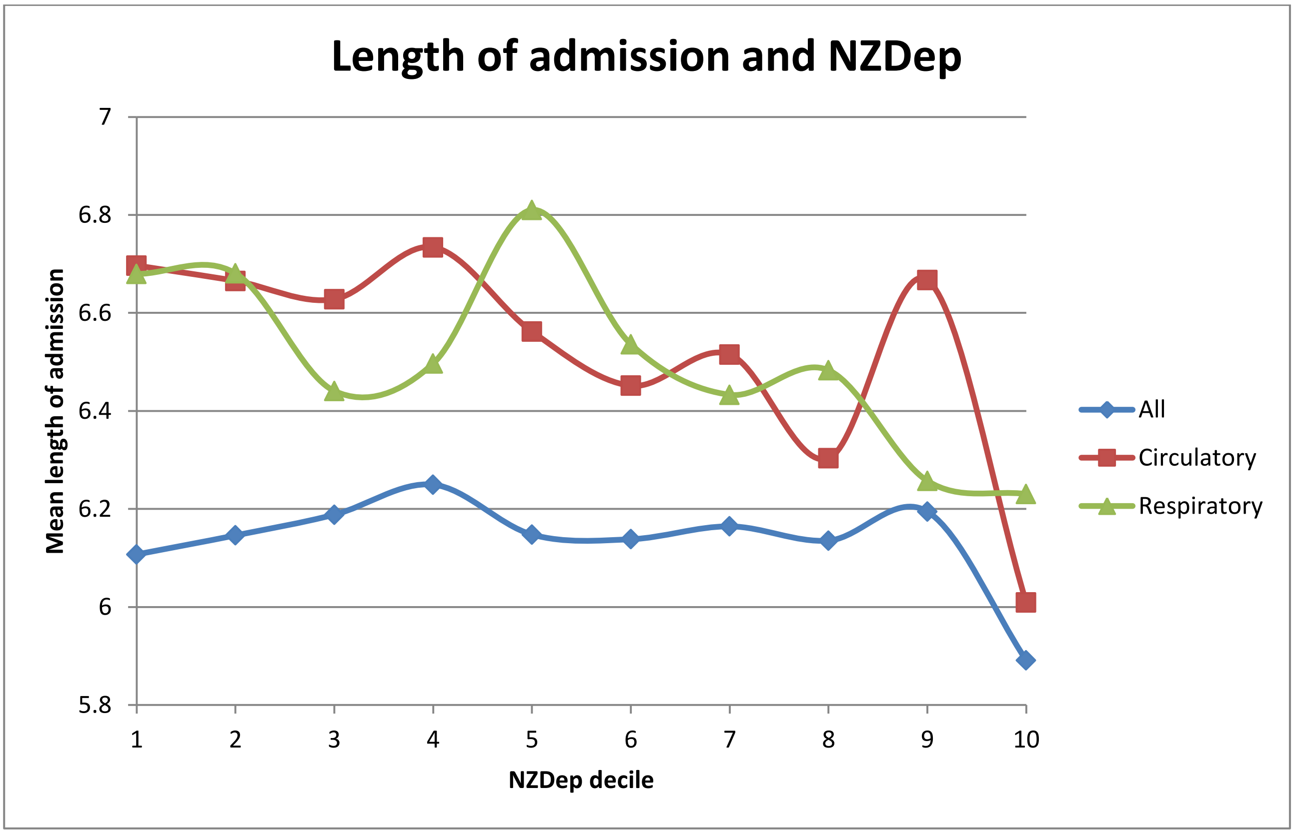

Figure 35:- Graph of mean length of hospital admission for three admission groups, by NZDep socioeconomic deprivation deciles

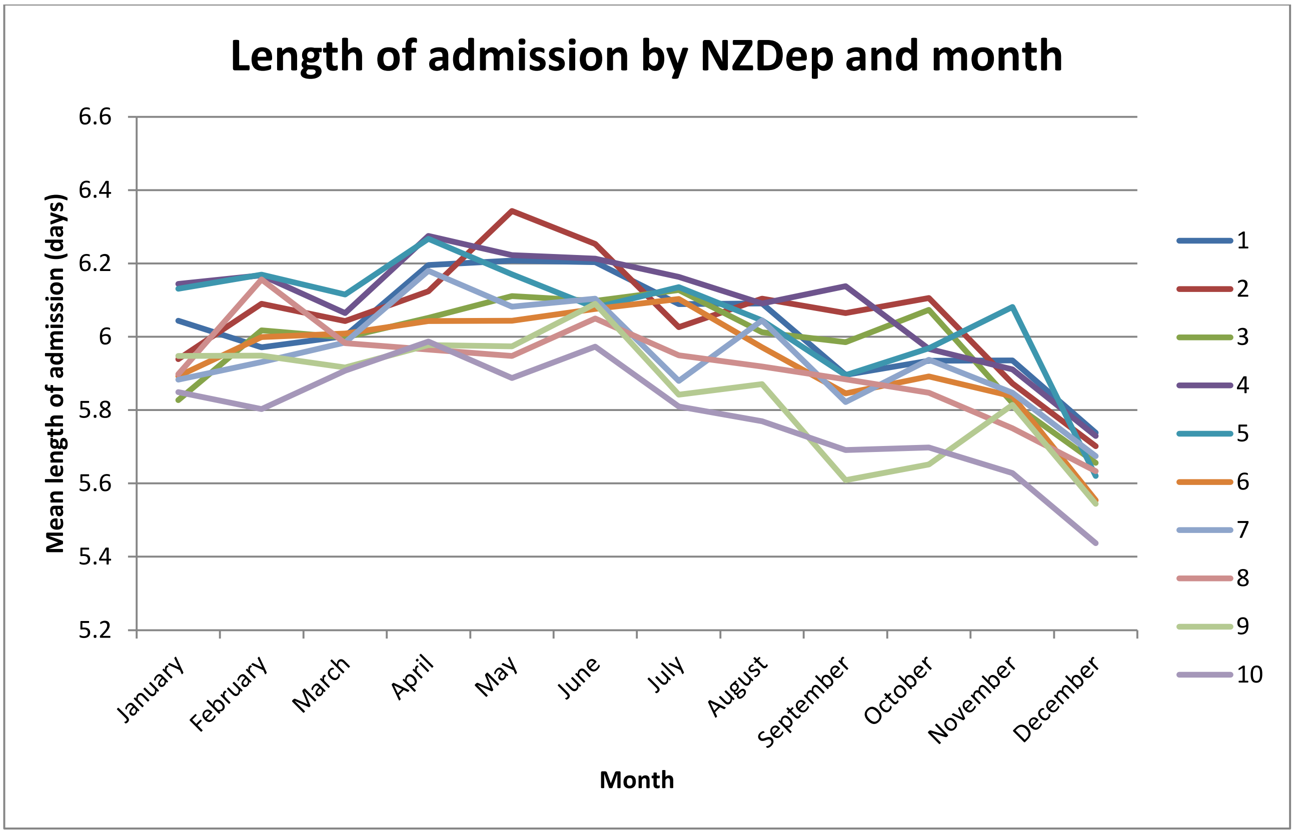

Figure 36:- Graph of mean length of hospital admission by NZDep socioeconomic deprivation deciles and month of admission

5 Discussion

Unnecessary hospital admissions represent a considerable burden on both patients and the resources of the public health sector. Building a greater understanding of the demographic, temporal and climatic factors that are associated with hospital admission rates and durations will enable opportunities for preventative public health interventions to reduce this burden. Direct correlations and detailed regression results are considered together to understand the magnitude, sensitivity and spatial variation of hospital admissions in New Zealand. These findings are contextualised through discussion of international literature and New Zealand statistics. The demographic characteristics of patients have a significant association with their likelihood of admission and length of stay. The covariance of circulatory and respiratory diseases are strongly responsive to season, hence they are commonly the focus of EWMb and EWM studies (Bull & Morton, 1978; Davie et al., 2007; World Health Organization, 1985). Analysis has confirmed this responsiveness to season, although the effect of season is distinctly different on each of the three diagnosis groups. The association between admission rates and cold spells was more varied, and this relationship varied across New Zealand.

5.1 Demography

Healthcare demand was shown to vary significantly between demographics, with covariance between age, ethnicity and socioeconomic deprivation complicating the underlying relationship. Distinct patterns of healthcare demand were related to age despite the dataset representing only the population over the age of 60. While all age groups over the age of 60 experience a higher rate of hospitalisations than younger age groups (Ministry of Health, 2011), there is a distinctly higher rate of hospital admissions for those over the age of 80. Older aged patients experience a greater length of admission on average, for both circulatory and respiratory disease, and this pattern has endured over time despite overall decreases in the mean length of admission. Broad relationships between age, ethnicity and socioeconomic deprivation with admission rates and duration echoed the findings of previous studies in New Zealand (Davie et al., 2007; Ministry of Health, 2011).

Age is closely associated with ethnicity and socioeconomic deprivation, as those identifying with Maori, Pacific Island and Asian ethnicities are younger on average than their European counterparts. Pacific and Maori ethnicities tend to experience shorter life expectancy than other ethnic groups due to lifestyle factors, with high rates of smoking and obesity underlying the disparity in life expectancy (Dachs et al., 2008). Patients identifying with Maori ethnicity in the dataset will have average life expectancies of less than 80, with a 6-year life expectancy disparity between Maori and non-Maori persisting (Timutimu, 2011). As a result of this disparity, older age admissions, particularly ages 80 and over are overrepresented by those identifying with European ethnicity. Moreover, Maori and Pacific Islanders are more likely than Europeans to reside in more socioeconomically deprived areas, as shown in Figure 37. Ultimately, this means that patients aged 80 and over are more likely to be both European and from a low deprivation area.

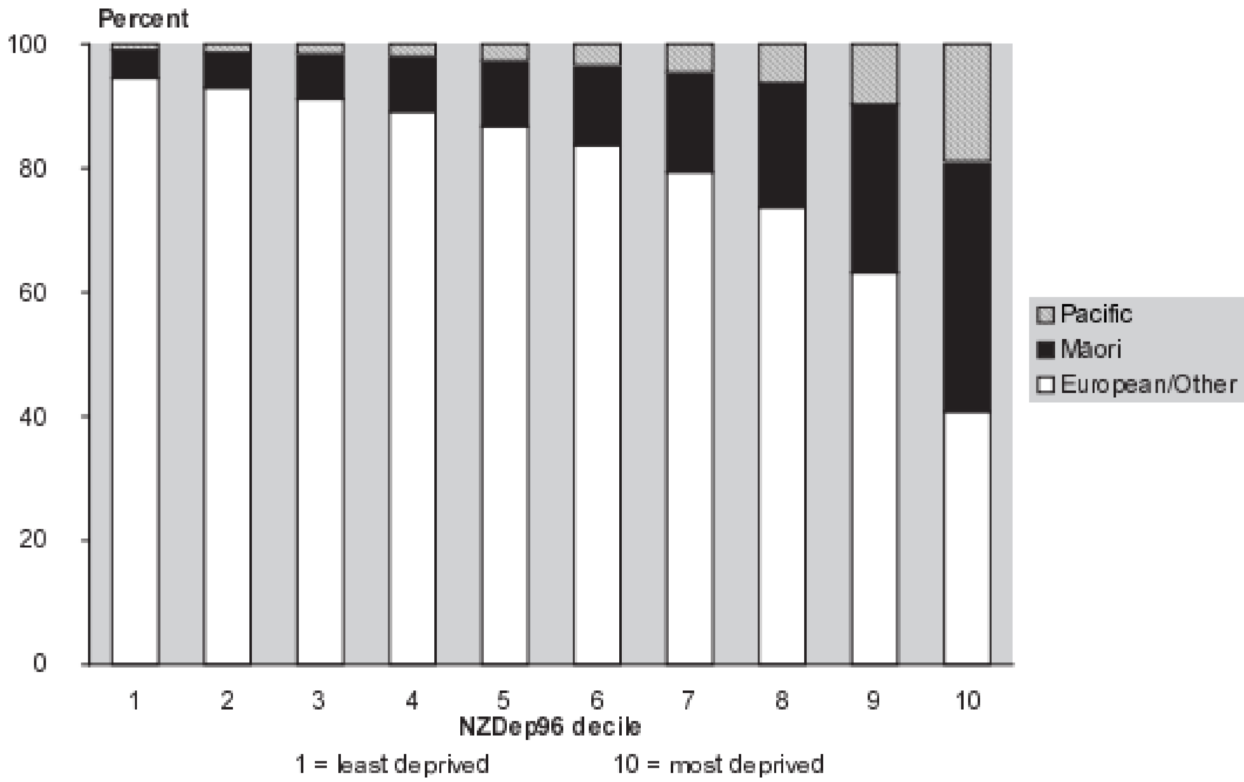

Figure 37:- Proportion of each deprivation decile that is Maori, Pacific or European/Other ethnicity, 1996 (Howden-Chapman, 2000, p. 15)

Figure 38 illustrates the relationship between NZDep and life expectancy at a meshblock level, with those from lower socioeconomic groups typically experiencing shorter life expectancies, although this gradient becomes weaker as age increases, as the cumulative effect of earlier life stages becomes the dominant factor driving health status (Howden-Chapman, 2000; Public Health Intelligence, 2001). Ethnicity has a life-long influence on health, whereas NZDep only reflects the health influence of the patient's current neighbourhood. This was exhibited in regression analysis of admission rates, with ethnicity explaining a greater degree of variation in admission rates and duration than NZDep. Both higher deprivation and Maori or Pacific ethnicity were associated with shorter admissions. Given that regression analysis controls for the effect on age on admission duration, with older patients typically admitted for longer periods, the shorter admissions experienced by Maori, Pacific Islanders and otherwise economically deprived patients is not solely due to the younger population in these groups.

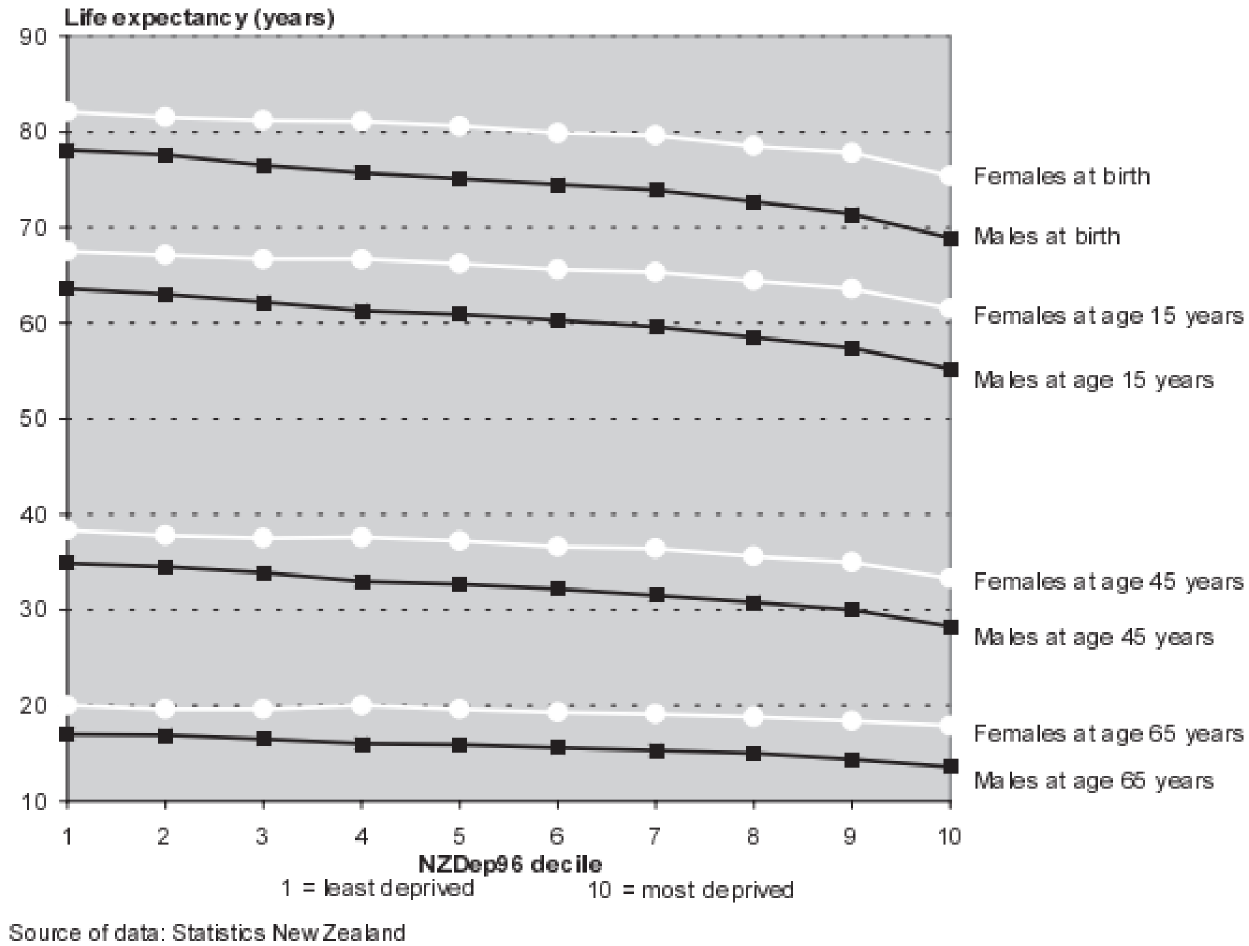

Figure 38:- Life expectancy at four ages, by deprivation decile, for the total New Zealand population, 1995-97 (Howden-Chapman, 2000, p. 22)

Patients identifying with Maori or Pacific Island ethnicity experienced shorter admissions on average than other groups; this was statistically significant for all three diagnosis groups, even with patient age controlled for. Patients from more socioeconomically deprived areas also experienced shorter admissions, even with ethnicity and age controlled for. This finding has been documented in other studies (Ministry of Health, 2011) and it has been suggested that this is due to cultural differences, with Maori finding hospitals unfamiliar and overwhelming, preferring to recover at home with family (Denise Wilson, 2012).

In this analysis, NZDep scores at a CAU level were analysed together with patient characteristics. CAU vary in size, exhibiting a median size of 2000 residents in the 2006 Census (Statistics New Zealand, 2012). Application of small area measures of deprivation may give rise to the ecological fallacy, as inferences about individuals are made from aggregated data which reflects neighbourhood composition, not a direct measure an individual. Best practice is to mitigate this risk through the use of the smallest spatial units possible (Howden-Chapman, 2000), however the spatial location of patients in this dataset was not available at a lower level such as meshblock scale. Small-scale spatial phenomena with high variance can exhibit a much lower variance when measured at a coarser scale (Schuurman, Bell, Dunn, & Oliver, 2007). It is conceivable that variation in socioeconomic deprivation at a meshblock scale will have been masked by a CAU scale measures, and thus the explanatory power and statistical significance will be diminished.

Demographic factors can also influence the vulnerability of an individual to external factors such as season and temperature. The population over the age of 80 appears to be more vulnerable to the effects of the winter season than the rest of the population, with this group experiencing a more pronounced peak of circulatory admissions during winter than younger age groups. NZDep does not appear to influence vulnerability to the winter season, with crude graphical analysis in Figure 36 demonstrating that NZDep is not related to monthly admission variation. This confirms the findings of a meta-study which noted little evidence of a relationship between socioeconomic deprivation and EWMb and EWM (Telfar-Barnard, Baker, Hales, & Howden-Chapman, 2008), whilst bringing into question evidence that suggests a greater risk of winter mortality among those on low incomes and/or who are renting their residence, both of which are factors in the NZDep index (Hales, Blakely, Foster, Baker, & Howden-Chapman, 2012; Salmond, Crampton, & Atkinson, 2007).

5.2 Long term changes

Mean length of admission has fallen over the 18 years of data analysed, for all 18 diagnosis groups in the ICD-9 classification system for diseases and health problems. This finding is consistent with a concerted drive across the publicly-funded health sector to reduce costs through higher bed utilisation (Malcolm, 2007), which results in reduced admission lengths. This can be broken down further into a strong fall towards 2000, followed by a plateauing throughout the 2000s, and another strong fall in the 2010s. This appears to be concordant with a conservative government, with the New Zealand National Party holding power between 1990 and 1999, and from 2008 to the present time (Gibbons, 2011). There does not appear to be a corresponding effect on ASR, which suggests that measures to reduce the length of hospital admissions have not resulted in patients presenting at hospitals more frequently, although this does not take into account any impact on quality of life and mortality outcomes.

There is no clear trend in ASR over the 18 years analysed, although rates have varied considerably between years. The age standardisation process takes into account the age distribution of the underlying population; hence ageing of New Zealand's population has offset the increase in crude admission rates over this period. These changes have also manifested as a gradual increase in the average age at admission of 1.36 years over the 18 years of the dataset analysed. Over the same period, the mean age of the population of 60 has fallen slightly by 0.15 years even as the median age for the total population has increased by four years (Statistics New Zealand, 2013c). This provides some evidence for Fries (1980) compression of morbidity hypothesis, which suggests that the period of morbidity prior to death can be reduced if the onset of chronic illness is delayed by more than life expectancy increases. As the mean age of admission for patients over the age of 60 has increased faster than the mean age of the population over 60, this shows that the onset of illness has been delayed by more than the population ageing, thus the period of morbidity prior to death has been compressed at a population level. However, no overall conclusion can be drawn from this as further information about quality of life and a broader would be needed.

5.3 Seasonality and temperature

The concept of EWMb has been well established both in New Zealand (Davie et al., 2007) and elsewhere (Healy, 2003), and the mechanism of the relationship between morbidity and season has commonly been attributed to low temperatures, although this has not been conclusively proven (Mercer, 2003). The aim of developing a series of cold temperature indicators was to improve the understanding of causality. Season was again shown to have a strong relationship with hospital admission rates and duration for most subsets of the data. The winter season was associated with higher admission rates for all three diagnosis groups with the exception of respiratory disease, and lower admissions for all three groups except circulatory disease. The association with cold temperature indicators was mixed.

Season, as indicated with a binary indicator for the winter season, appears to explain daily admission rates better than temperature indicators. This is despite monthly admission rates showing a gradual rise from an annual trough in February up to a July peak, without a clear seasonal demarcation. The overall magnitude of EWH for the all diagnosis group of 15% was consistent with the magnitude of EWM of 18% as found by Davie et al. (2007) in their earlier study of all-cause mortality in New Zealand, which ranks above the median of 15 developed countries summarised in Table 1. It should be noted that this study has only analysed admissions related to circulatory and respiratory disease, which although representing the most vulnerable disease to winter, are not an overall measure of EWMb. The all and circulatory diagnosis groups both exhibit significantly higher winter admissions, although for some centres, particular years experienced lower winter admissions than the rest of the year. Respiratory admissions varied widely and did not show any seasonal pattern.

COPD, a subset of respiratory disease, exhibits a distinctly different seasonal pattern to respiratory disease as a whole. COPD patients from areas of high socioeconomic deprivation are typically admitted for longer than those from areas of low deprivation (Agboado et al., 2012); this runs counter to the general relationship between socioeconomic deprivation and admission duration (Ministry of Health, 2011). COPD represents a significant burden of disease, as the fourth ranked cause of death in New Zealand and requiring considerable healthcare resources to manage (Broad & Jackson, 2003). However, without an exclusive definition of the disease based on ICD classification system for disease, temporal patterns can only be approximated from the NMDS dataset (Joshi, 2008). With a CSVH of 51% for COPD associated respiratory diseases, this provides evidence that COPD is highly seasonal, despite a coefficient of approximately zero for respiratory diseases as a whole. This suggests a lack of seasonality in many of the non-COPD respiratory disease, and that COPD may show a stronger relationship with temperature indices than respiratory diseases as a whole. An association between COPD exacerbations or deaths and temperature variation has been established in studies outside New Zealand, so this area warrants further investigation (Barnes, Drazen, & Rennard, 2008; Donaldson & Wedzicha, 2014; Song et al., 2008).

Season does not appear to have a crude relationship with length of admission, however regression analysis controlling for patient characteristics shows a greater length of stay during the winter season for the all and respiratory diagnosis groups, and shorter length of stay for patients with a primary diagnosis of circulatory disease. This demonstrates that the demographic profile of patients admitted varies significantly throughout the year. The NZDep decile of patients admitted has been shown to be constant throughout the year so age and/or ethnicity must be changing throughout the year. It has been established that patients aged 80 and over are more likely to be admitted than younger age groups, in general and particularly during winter (Davie et al., 2007; Ministry of Health, 2011). Elderly age groups also tend to be admitted for longer, with the joint implication that a considerable increase in healthcare resources is needed during winter.

Admission duration was generally more responsive to cold spells than admission rates, with longer admissions for the all diagnosis group associated with cold spells prior to admission, measured by all of the cold spell indicators. Temperature indicators showed little relationship with admission rates, although a weak but statistically significant relationship for some main centres. The set of cold spell indicators was designed to understand the relationship between hospital admission rates and durations in relation to the severity of cold spell; the lag period for cold spells to affect admissions; and whether the effect is cumulative in nature. Differentiating between the 1st and 10th percentile cold spell indicators provides an understanding of the effect of cold spell severity. Temperatures within the coldest 10% appear to be more significant predictors of admission duration for respiratory disease, however admission rates respond weakly to both levels of severity.

Admission rates for the all diagnosis group only respond to 10^{th} percentile cold spells. Admission duration of the all diagnosis group and circulatory group responded to both levels of severity.

The lag period takes into account the time between a cold spell and an acute admission presenting at hospital. The incidence of cold spells up to 28 days prior to admission is weakly related to both admission rates and duration, for the all diagnosis group and respiratory diagnosis group. Cold spells between 14 and 21 days prior to admission were related significantly to respiratory admission rates and duration. Both admission rates and duration for circulatory disease are most strongly related to cold spells up to 7 days prior to admission, including on the day of admission.

To understand any cumulative effect of cold spells, two types of lagged cold spell indicators were employed. Indicators measuring the total number of cold spells prior to admission, that is the 1-7, 1-14, 1-21 and 1-28 day indicators, take into account the cumulative effect of cold spells on admissions. The indicators measuring the effect of cold spells in a specific period prior to admission, that is 7-14, 14-21, and 21-28 days prior to admission, provide a counterfactual to the cumulative indicator by measuring the lag period for an effect to become apparent after a cold spell. Length of admission for circulatory and respiratory disease exhibited a greater response to the cumulative cold spell indicators, whereas the all diagnosis group responded similarly to both the cumulative and specific lag period indicators. Admission rates for the all diagnosis group exhibited an increase 21-28 days after cold spells, which suggests that there is no cumulative effect. Circulatory and respiratory admission rates, which are both subsets of the all diagnosis group, tended to fall after cold spells, up to 7 days later for circulatory disease and 14-21 days later for respiratory disease. This is difficult to reconcile, as the all diagnosis group exhibits the opposite relationship with temperature, and the winter season is associated with higher admissions for circulatory disease. Cold temperatures have been established as a factor for cardiovascular diseases (Donaldson & Keatinge, 2002; Fares, 2013), a subset of circulatory disease. The lack of explanatory power for cold spell indicators suggests that they do not capture the facet of cold temperatures that affects circulatory disease, and potentially a different form of cold temperature indicators may yield a significant relationship.

For some subsets of the data, despite a strong association with the winter season, there was no consistent relationship with any of the temperature variables. This may be explained by an inadequacy of the temperature variables to capture the aspects of climate that affect health or behavioural patterns that are associated with the winter season but not cold spells in particular. It is not possible to identify seasonal behaviours from this analysis, although it is clear that only a small portion of seasonal variation is explained by cold spell indicators, and thus seasonal factors not quantified in this study are influencing admission rates and duration. A number of studies have suggested that winter behavioural changes contribute towards EWMb, however such changes are difficult to quantify (Cannell et al., 2006; Donaldson & Keatinge, 2002; Fares, 2013)

The temperature indicators developed were based on the hypothesised impact of cold spells on admissions, but were developed without an understanding of the underlying causal methods, so may not be the best measures to understand the underlying relationship. Other permutations of weather indices may provide a greater understanding of this relationship. The weather records associated with each patient are based on those recorded at the nearest weather station from the CliFlo database to their residential address, which does induce some inaccuracy. Climatic variations on a regional scale may mean that the temperature records are not representative of the climate experienced by the patient.

Global climate change is expected to induce more frequent weather extremes in future, including cold spells (Solomon et al., 2007). An increase in the frequency and severity of cold spells in New Zealand may increase the magnitude of EWMb, thus an understanding of this phenomenon may become more important in future.

5.4 Spatial patterns

Admission rates varied across New Zealand, with distinct differences across the eight main centres persisting over the 18 years analysed for all three diagnosis groups. Despite distinct differences in admission rates and climate, there was little significant variation in the monthly pattern of admissions between centres, as admission rates exhibited a weak relationship with temperature indices overall. The relationship between admission duration and temperature indices showed significant variation between main centres; however the magnitude of this relationship was small.

The variation in ASR of hospital admissions across New Zealand is expected due to differences in climate and population. Variation in the age distribution of population is controlled for in the age standardisation process, however differences in ethnicity and socioeconomic deprivation have been found to affect admission rates at an individual level, thus variations in population composition between the main centres that is not controlled for will likely influence overall admission rates. It is best practice to age standardise rates separately for each ethnic group (Harraway, 1993), however annual population estimates were insufficient for this purpose. Socioeconomic deprivation ranges across New Zealand, with generally higher levels of deprivation in North Island cities compared to South Island cities (White, 2008). Ethnicity follows a similar pattern, with the greatest concentration of people identifying with Pacific Island ethnicity residing in Auckland, and a greater proportion of those identifying with Maori ethnicity residing in the North Island (Statistics New Zealand, 2013c).

The excess of winter hospital admissions showed year-to-year volatility without any spatial pattern between main centres, echoing a prior study of EWM in New Zealand which found no spatial differences across four regions (Davie et al., 2007). This means that at a broad level, there is no discernible spatial pattern of EWMb or EWM in New Zealand despite a demonstrable temperature gradient. When comparing specific cold spell indicators with admission rates, only Auckland and Christchurch exhibited a consistent statistically significant relationship which may be due to these centres housing large population groups which reduces variance. Nonetheless, the magnitude of these relationships is such that the presence of a cold spell in preceding days is associated with an increase in admissions of less than one patient across the three diagnosis groups, even in the largest population centre, Auckland. Across all centres, the direction of relationship remained consistent, albeit with a small magnitude, associating cold spells with an increase in admissions for the all diagnosis group and a decrease in admissions for the circulatory and respiratory primary diagnosis group.

Admission duration exhibited a stronger and more significant relationship cold spell indicators compared to admission rates, and accordingly more significant relationships at a sub-national level. Within the seven main centres with a significant relationship, the variation in magnitude between them was modest, despite the strong temperature gradient between the centres. Admission duration for patients with circulatory and respiratory related diagnoses was positively related with cold spells; however the circulatory and respiratory primary diagnosis groups exhibited positive and negative directions, limiting any overall conclusion. Nonetheless, the magnitude of this relationship implies that a cold spell in the preceding days would only increase total bed stay-nights by less than one, limiting the usefulness of cold spell indicators in forecasting demand for healthcare services.

5.5 Directions for future research

This research has provided a greater understanding of EWH and patterns of admissions of the elderly in New Zealand. However, the causal mechanism underlying some of these associations is unclear, and warrants further investigation in three areas. It would be worthwhile to investigate the relationship between COPD exacerbations and cold weather indicators, given the significant impact of COPD exacerbations on quality of life and public healthcare resources. An understanding of these factors may guide enhanced preventative measures to reduce or mitigate exacerbations. This would require a dataset with an exclusive definition of COPD. Significant evidence was found to show that patients identifying with Maori or Pacific Island ethnicity and those from areas of high socioeconomic deprivation experienced shorter hospital admissions than other patients, even with patient age controlled for. Investigating the mechanisms underlying this relationship and the resulting outcomes would be worthwhile, as shorter admissions may adversely affect the quality of care and recovery, resulting in an inequity of health outcomes. This could be investigated in a micro scale study using patient case studies. Some association has been found between hospital admission and duration and the winter season, but an inconsistent relationship with temperature indicators was found. Further investigation into non-climatic factors associated with the winter season, such as time spent indoors or other seasonal behaviours, may yield an understand of how mitigation strategies or modifiable behaviours could reduce the winter excess of hospitalisations, and by association, mortality.

5.6 Research implications

This research has provided an enhanced understanding of the contributors to EWMb in New Zealand through analysis of factors associated with hospital admissions. Acute hospital admissions represent the most severe component of morbidity in a population, so although the presence of cold spells was only associated with minor increases in admission rates or durations, these cold spells may be associated with a higher incidence of less severe morbidity in the community. Preventative public health strategies targeting groups with particular vulnerabilities to morbidity will likely reduce the incidence of morbidity by a far greater magnitude than has been measured in this study through hospital admissions. This research has shown that elderly of all ages are more vulnerable to circulatory and respiratory morbidity during the winter season, especially those over the age of 80. EWH do vary in magnitude throughout New Zealand; nonetheless the phenomenon is ubiquitous and public health interventions are therefore justified in all regions.

6 Conclusion

Through investigation of hospital admissions in New Zealand over 18 years, a greater understanding of the magnitude of EWMb and the relationship with demographic, spatial, temporal and climatic factors has been gained. It has been demonstrated that the impact of cold spells on EWH varies widely, although the winter season is associated with a significant increase in hospital admission rates and durations. Understanding patterns in admission rates and duration is beneficial for resource planning in a hospital; these results show that despite significant correlations, the magnitude of the relationship means that for New Zealand hospitals, cold spells are unlikely to induce noticeable increases in demand. The winter season and cold spells are likely associated with increases in minor illness, which if targeted with mitigation strategies, could improve quality of life. It has been established that socioeconomic deprivation does not affect winter vulnerability to the winter season for circulatory and respiratory disease. Patients over the age of 80 throughout the New Zealand are particularly vulnerable to the effects of winter. These patterns have been demonstrated across New Zealand despite considerable climatic variation, and therefore strategies to mitigate EWMb may be effective throughout the entire country and result in quality of life improvements through reduction of morbidity.

Several directions for future research have been identified. Socioeconomic deprivation and Maori or Pacific Island ethnicities have been associated with shorter hospital admissions; this phenomenon deserves investigation. The magnitude of EWH for COPD is estimated to be 51%, so research into COPD exacerbations in winter may have great potential in reducing healthcare demand and improving quality of life. Investigating behavioural changes associated with the winter season may improve understanding of EWM and inform preventative strategies. It has been established that the magnitude of EWMb in New Zealand is substantial and therefore improving our understanding of the phenomenon may be beneficial for individuals and the public health system.

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