Preventable hospitalisations in Australia: understanding the impact of personal and health system factors using linked and longitudinal health data

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Preventable hospitalisations in Australia: understanding the impact of personal and health system factors using linked and longitudinal health data

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Preventable hospitalisations are used in Australia as a high-level indicator of health system performance, specifically the accessibility and quality of primary care. However, there are key gaps in understanding of how preventable hospitalisations relate to characteristics of patients and features of the health system, and surprisingly little evidence validating their use in Australia. In this thesis, new approaches to analysing longitudinal health data were applied to gain insights into the properties of this health performance indicator.

This thesis used linked questionnaire and longitudinal health data for a cohort of over 267,000 participants in the 45 and Up Study, Australia, containing detailed information on participants and their use of health services. Temporal patterns in use of primary care and other health services around preventable hospitalisation were explored using a visualisation of unit record health data. Predictors of preventable hospitalisation were identified using multilevel Poisson regression models, with variation partitioned between person- and geographic-levels. Through development of novel 'weighted-hospital service area networks', variation was further partitioned to the hospital-level.

Many patients admitted for preventable hospitalisation were found to have high levels of engagement with the health care system, both around the time of admission and compared to similar non-admitted patients. The supply of general practitioners explained only a small amount of geographic variation in preventable hospitalisation, while over one-third of variation was contributed by the sociodemographic and health characteristics of the population. Hospitals differed in their propensity to admit patients, with the greatest variability in smaller community hospitals, which account for a small proportion of admissions but contribute greatly to regional variation.

These findings show the preventable hospitalisation indicator in Australia should not be interpreted simply as a measure of the accessibility and quality of primary care. They suggest the most appropriate policy responses are long-term strategies to promote healthy living and targeted local interventions to efficiently manage the current burden of chronically ill patients. The findings demonstrate why caution should be used when adopting international health performance indicators, but also the benefits of using novel approaches to derive new information from linked and longitudinal data.

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Publications arising from this thesis

Publications from work contributing to this thesis

- Falster MO, Jorm LR, Douglas KA, Blyth FM, Elliott RF, Leyland AH. Sociodemographic and health characteristics, rather than primary care supply, are major drivers of geographic variation in preventable hospitalisations in Australia. *Medical Care* 2015; 53(5):436
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Publications under review or awaiting submission

- Falster MO, Jorm LR, Leyland AH. Using weighted hospital service area networks to explore variation in preventable hospitalization. Submitted to Health Services Research [under revision]
- Falster MO, Jorm LR, Leyland AH. Variation in hospitals' propensity to admit patients for preventable hospitalisation: results from a large population-based cohort. For submission to Medical Journal of Australia [awaiting submission]

Related co-authored publications on preventable hospitalisation

- Harrold TC, Randall DA, Falster MO, Lujic S, Jorm LR. The contribution of geography to disparities in preventable hospitalisations between Indigenous and non-Indigenous Australians. *PLoS ONE* 2014;9(5):e97892
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Abbreviations

- ABS Australian Bureau of Statistics
- ACI Agency for Clinical Information
- ACS Ambulatory care sensitive
- ACSQHC Australian Commission for Safety and Quality in Health Care
- AH&MRC Aboriginal Health and Medical Research Council
- AHC Avoidable hospital conditions
- AIHW Australian Institute for Health and Welfare
- AMI Acute myocardial infarction
- APDC Admitted Patients Data Collection
- APHID Assessing Preventable Hospitalisaiton InDicators Study
- ARIA+ Accessibility/Remoteness Index of Australia
- ARD Average relative deviation
- BHI Bureau of Health Information
- BMI Body mass index
- CHeReL Centre for Health Record Linkage
- CI Confidence interval
- COAG Council of Australian Governments
- COPD Chronic obstructive pulmonary disease
- ED Emergency department
- EDDC Emergency Department Data Collection
- FWE Fulltime workload equivalent
- GRAPHC Geographic and Resource Analysis in Primary Health Care
- GP General practitioner
- HSA Hospital service area
- HSAN Hospital service area network
- ICC Intraclass correlation coefficient
- ICD-9 International Statistical Classification of Diseases and Health Related Problems, 9th Revision, Clinical Modification
- ICD-9-CM International Statistical Classification of Diseases and Health Related Problems, 9th Revision, Clinical Modification
- ICD-10-AM International Statistical Classification of Diseases and Health Related Problems, 10th Revision, Australian Modification

- IHOPE Indigenous Health Outcome Patient Evaluation Study
- IRR Incidence rate ratio
- LHD Local Health District
- MeTeoR Metadata Online Registry
- MBS Medicare Benefits Schedule
- MCMC Markov chain Monte Carlo
- MLK Master linkage key
- NHA National Healthcare Agreement
- NHISSC National Health Information Standards and Statistics Committee
- NHMRC National Health and Medical Research Council
- NHPA National Health Performance Authority
- NHS National Health Service
- NSW New South Wales
- PCV Proportional change in variance
- PHSREC NSW Population and Health Services Research Ethics Committee
- RBDM Registry of Births, Deaths and Marriages
- SLA Statistical Local Area
- UK United Kingdom
- USA United States of America
- VPC Variance partitioning coefficient

Thesis abstract

Preventable hospitalisations are used in Australia as a high-level indicator of health system performance, specifically the accessibility and quality of primary care. However, there are key gaps in understanding of how preventable hospitalisations relate to characteristics of patients and features of the health system, and surprisingly little evidence validating their use in Australia. In this thesis, new approaches to analysing longitudinal health data were applied to gain insights into the properties of this health performance indicator.

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These findings show the preventable hospitalisation indicator in Australia should not be interpreted simply as a measure of the accessibility and quality of primary care. They suggest the most appropriate policy responses are long-term strategies to promote healthy living and targeted local interventions to efficiently manage the current burden of chronically ill patients. The findings demonstrate why caution should be used when adopting international health performance indicators, but also the benefits of using novel approaches to derive new information from linked and longitudinal data.

Chapter 1 Overview of thesis

Preventable hospitalisations are used internationally as a measure of health system performance. These hospitalisations include admissions for a variety of conditions, such as diabetes complications, angina, congestive heart failure and influenza, broadly considered able to be prevented through the provision of timely and effective primary and community care.

Initially developed in the US in the late 1980s and early 1990s, preventable hospitalisations are in common use worldwide because they are readily calculated using widely available hospital admissions data, yet indirectly capture information on the outcomes of primary care. In Australia, they are used as a high-level performance indicator of accessibility, effectiveness and safety of primary care in the in National Healthcare Agreement, and are reported at the local, state and federal levels.

However, there are key gaps and limitations in our understanding of preventable hospitalisations. Many factors beyond primary care, and beyond the potential influence of health policy makers, also influence admission. Despite over 25 years of research, understanding of the scope of this limitation remains poor, as very few studies are able to partition the contribution of these personal, contextual and health system factors to variation in admission. Furthermore, there has only been limited research in Australia, with almost all the evidence validating the indicator coming from the US – a country with a very different health care system. The extent to which the preventable hospitalisations indicator in Australia actually reflects what it purports to measure is not clear.

The availability of unique data linkages, and recent advances in health data science, provide an opportunity to explore and critically evaluate the variety of factors which drive variation in preventable hospitalisation in Australia, and to provide much-needed evidence on the validity of this leading health performance indicator.

1.1 Aims of the thesis

The overall aim of the thesis was to explore the appropriateness of preventable hospitalisations as a health performance indicator in Australia, through the utilisation of linked and longitudinal health data and new methodological approaches in health data science. More specifically, the analyses in this thesis aimed to address the following questions:

1) *How are patients admitted for a preventable hospitalisation using primary care services?*

Are patients accessing general practitioners in the period leading up to hospitalisations, and is this different to the rate of service use in the general population? Are there new ways of presenting such complex patterns of health service use?

2) *What are the relative contributions of primary care supply, and the health and demographic of the population, to geographic variation in preventable hospitalisation in Australia?*

   Is there evidence that preventable hospitalisations are a valid indicator of primary care supply? Can we overcome the ecological fallacies that exist in much of the literature using linked data and multilevel modelling?

3) *Do differences between hospitals contribute to variation in preventable hospitalisation?*

   How can we explore the contribution of hospitals to this population-level health outcome? Is there significant variation between hospitals, and what types of hospitals have higher rates of admission?

1.2 Outline of thesis

Four chapters of this thesis, formatted as research papers (Chapters 4-7), presenting original research. A further four chapters provide an outline of the thesis, background, methods, and discussion of results and implications for policy (Chapters 1-3, 8). As part of the publication process the research papers contain large amounts of online supplementary material; key tables and figures have been presented within the relevant thesis chapters, with complete copies of the original publication included in the Appendices.

Chapter 1 provides a brief overview of the thesis, broadly outlining the topic, aims, and structure.

Chapter 2 summarises the background to and context for this research. This includes an overview of the preventable hospitalisations indicator, including its history, development and use in policy; a review of the factors which drive variation in preventable hospitalisation, including primary care, patient, and hospital-level factors; and identification of new methods in health data science which have potential to deliver new insights into the properties of this health performance indicator.

Chapter 3 provides an overview of the methods used in this thesis. This includes a description of the study cohort, the various sources of data used, processes for data linkage, as well as the definition of exposures, outcomes and covariates. While analytic methods are described within

their respective chapters, this chapter also includes further information on the data visualisation and multilevel modelling techniques that have been used.

Chapter 4 explores how patients admitted for preventable hospitalisations are using health services around the time of preventable hospitalisation, using a novel visualisation of linked health data. This chapter has been published as: Falster MO, Jorm LR, Leyland AH. Visualising linked health data to explore health events around preventable hospitalisations in NSW Australia. *BMJ Open* 2016;6:e012031.

Chapter 5 investigates the relative contribution of primary care supply, and personal health and sociodemographic factors, to geographic variation in preventable hospitalisation. This chapter has been published as: Falster MO, Jorm LR, Douglas KA, Blyth FM, Elliott RF, Leyland AH. Sociodemographic and health characteristics, rather than primary care supply, are major drivers of geographic variation in preventable hospitalisations in Australia. *Medical Care* 2015; 53(5):436

Chapter 6 investigates a new method for exploring the potential contribution of hospitals to variation in preventable hospitalisation, analysed using 'weighted hospital service area networks' and multiple membership multilevel models. At the time of submission this paper was under revision: Falster MO, Jorm LR, Leyland AH. Using weighted hospital service area networks to explore variation in preventable hospitalization (under revision, Health Services Research).

Chapter 7 explores variation between hospitals in their propensity to admit patients for a preventable hospitalisation, using the methodology developed in Chapter 6, and in comparison to two 'marker' conditions: emergency admissions for acute myocardial infarction, and hip fracture.

Chapter 8 summarises the main findings from the thesis, discusses the implications both for policy and research, and describes the current dissemination and impact this research has already had on use of the preventable hospitalisations health performance indicator in Australia.

Appendices include codes used to define the preventable hospitalisations indicator, copies of the published manuscripts from Chapters 4 and 5, statistical appendices for analyses in Chapters 6 and 7, and copies of six additional publications on preventable hospitalisation I have published during my thesis. Of these publications, I was lead author on one report in the grey literature, and a contributing author on five academic publications. While these do not

contribute directly to my thesis, they supplement the thesis in further validating, exploring and guiding the use of the preventable hospitalisation indicator in Australia.

1.3 The role of the candidate

This thesis is embedded within the APHID (Assessing Preventable Hospitalisation InDicators) Study, a National Health and Medical Research Council (NHMRC) funded partnership project with partner organisations the Australian Commission on Safety and Quality in Health Care (ACSQHC), the Agency for Clinical Innovation (ACI), and the Bureau of Health Information (BHI). I completed my PhD in a dual-role as project co-ordinator of the APHID Study, in which I also managed the ethical requirements, data linkage process, data management, coordination of study reference group, dissemination to policy stakeholders, and additional student supervision.

For each of the research papers contributing to this thesis, I took the lead in developing the research questions, drafting analysis plans, performing statistical analyses, drafting the manuscript, incorporating feedback from co-authors, and managing the article submission, review and resubmission processes.

Chapter 2 Background

2.1 Introduction

Managing the health of the populations that they serve is one of the greatest policy priorities for governments everywhere. The Australian government spent over $161 billion on health in 2014-15, which represented 10% of the total economy.[1] Health expenditure has been increasing over time, both in real terms and as a proportion of the economy,[1] and with Australia's ageing population, demand for health services will continue to grow. As such, the Australian government has prioritised strategies for improving health outcomes for all Australians and ensuring the sustainability of the Australian health care system,[2] and methods to monitor and evaluate these strategies are needed.

To help meet this end, health performance indicators are used. A health performance indicator is a summary measure designed to describe a particular aspect of the healthcare system or the health of the population. Monitoring variation in these indicators, such as between small geographic areas, can be a powerful tool to help drive system change.[3] Creating a set of indicators allows organisations to set a strategic direction and define the scope for the system.[4] Reporting of performance against these indicators can improve the quality of care by providing incentives for change in the behaviours of providers of care, as well as engage consumers of these health services, including patient, their families and patient advocate Careful use and evaluation of health performance indicators can help bridge gaps between current and high-quality practices.[5]

A large number of health performance indicators are used in Australia, such as those reported in the Council of Australian Governments (COAG) National Healthcare Agreement (NHA),[2] and in higher-level strategic frameworks such as the National Health Performance Framework.[6] These indicators vary in scope, from measures of health such as life expectancy, smoking rates, infant mortality rates and incidence of cancers, to measures of the delivery of health services, such as patient satisfaction, waiting time for surgery, use of residential and community aged care facilities among the elderly, healthcare associated infections and survival of people diagnosed with notifiable conditions.

Rates of 'preventable hospitalisations' are a key health performance indicator in the NHA, used to address the objective 'Australians receive appropriate high quality and affordable primary and community health services'.[2] Preventable hospitalisations are those considered potentially

able to be prevented through timely and accessible quality primary and community based care, and based on the definition used in the NHA, were estimated to account for 6.2% of all hospital admissions in Australia in 2014-15.[7] Preventable hospitalisations are intuitively appealing as a health performance indicator, because they are easily identified in administrative hospital admissions data using a standardised set of hospital diagnosis codes, and reducing them could result both in improvements in the health of the population as well as in significant cost savings. As such, preventable hospitalisations are commonly reported by policy agencies at the local, state and federal levels, are used as a measure of disparities among vulnerable populations, and also as an outcome measure for evaluating new intervention programs and models of care.

Interpreting variation in preventable hospitalisations, however, can be difficult. Indicators should reflect factors that can be influenced by and are responsive to policy change.[4] However, many factors potentially influence preventable hospitalisations, making effective and policy responses difficult to identify and implement. There are key evidence gaps in our understanding of how preventable hospitalisations relate to the provision of primary care in Australia, as well as of the relative roles that other health system factors, and personal factors, play in driving admission. Given the considerable resources invested in reducing preventable hospitalisations in Australia, a clearer understanding of these gaps and limitations could improve the use of the performance indicator, and support better targeting of health policies and programs and monitoring of their results.

2.2 The context of the Australian health care system

Australia has a universal healthcare system with coverage through Medicare - Australia's national public health insurance scheme.[8] Medicare provides free or subsidised access to most medical services, including primary care and prescription pharmaceuticals, with general practitioners (GPs) acting as gatekeepers for some allied health services and subsidised specialist care. Medicare is funded by the Australian government, largely through taxation revenue.

The hospital sector includes a mixture of public and private hospital facilities. Public hospital facilities are run by the eight States and Territories which form the Federation of Australia, and are funded from a range of sources.[9] In 2012-13 this was primarily from the States and Territories (53%) and the Australian government (37%), with some additional non-government funding from health insurance funds (2%) and out-of-pocket payments by patients (3%).[1]

Private hospitals were largely funded by health insurance funds (48%) and out-of-pocket payments by patients (12%). Patients can choose to pay for private health insurance, which is optional, but complements the public system by offering choice of private hospitals, specialists in hospital, timing of procedures, and access to a range of ancillary services (e.g. dental, physiotherapy, optometry and podiatry services).

Most primary care is delivered by GPs, who are often self-employed and run their practice as a small business. Many GPs choose to work in small practices, however there has been a shift in recent years towards larger corporate practices, such as 'GP Superclinics' which often have greater levels of support, including practice nurses, allied health services and visiting specialists.[10, 11] Between 2005/06 and 2014/15 the proportion of GPs working solo or in small clinics (2-4 GPs) dropped from 48% to 31%, while the proportion working in large clinics (10 or more GPs) more than doubled from 13% to 29%.[12] There is great variation in the population distribution across Australia: 71% of the population resides in major cities, primarily located in coastal areas, with population densities usually over 100 people per square km (up to 15,100 in inner Sydney).[13] Conversely, just 2.2% of the population resides in remote or very remote areas, which comprises the majority of central Australia, with a population density usually below 0.1 people per square km.[13] These GP Superclinics are primarily located in regional areas[14] where there have traditionally been shortages in the medical workforce,[15] although there are also many large corporate clinics within metropolitan areas.

Patients are free to consult any GP at any practice, although most have some form of 'medical home' where they choose to receive most of their care. GPs charge patients on a fee-for-service basis, with Medicare reimbursing around 85-100% of the scheduled fee for ambulatory care. Fees are not regulated and doctors are free to charge above the scheduled fee, however many treat patients for the cost of the subsidy only so there is no out-of-pocket charge (referred to a 'bulk billing'). There are incentives to promote bulk billing for concession card holders (e.g. low-income patients), children, the elderly, as well as patients living in rural and remote areas. Over 74% of all Medicare services were bulk billed in 2009-10.[8]

Medicare also has a 'safety net', where once an annual threshold for out-of-pocket costs for medical services and pharmaceuticals has been exceeded, Medicare's contribution to the scheduled fee is increased for the remainder of the year to cover the gap in costs. There are lower thresholds for low-income families and individuals with concession cards.

There does remain however variation in access to health care. A recent report found that patients' experiences accessing health care services varied across Medicare Locals (large

organisational primary care catchments active between 2011 and 2014), with the average annual number of GP attendances ranging from 2.4 to 7.4 attendances per person, bulk billing rates ranging from 50% to 96% of all claims, and with 1% to 13% of adults reporting that they had delayed seeing a GP, or not seen a GP when they needed to, because of cost barriers in accessing care.[16]

2.3 Preventable hospitalisations

2.3.1 Use as a health performance indicator

Preventable hospitalisations are used internationally as a high-level health system performance indicator, and are also known variously as potentially preventable hospitalisations,[17] hospitalisations for ambulatory care sensitive (ACS) conditions,[18, 19] or potentially avoidable hospitalisations.[20, 21] The Australian indicator in the NHA is currently named 'selected potentially preventable hospitalisations', and is described as a measure of 'admissions to hospital that could have potentially been prevented through the provision of appropriate non-hospital health services',[22] although this definition has been refined during the course of this research.[23] While different terminology continues to be used both across and within countries, in some cases reflecting slightly different definitions and interpretations of the indicator,[21, 24] these indicators will be collectively referred to using the terminology 'preventable hospitalisations' in this thesis.

Preventable hospitalisations are identified using a defined set of hospital diagnosis and procedure codes for a defined set of conditions. Three broad categories of conditions are included in Australia: chronic, acute and vaccine-preventable conditions. Chronic conditions are those which may be preventable through lifestyle change, but can also be managed in a primary care setting to prevent health deterioration and hospitalisation. Acute conditions are those for which the conditions may not be preventable, but theoretically should not result in hospital if timely and adequate access to primary health care were received. Vaccine preventable conditions are those where the condition, and thus subsequent hospitalisations, may be preventable through vaccination.[25]

A full list of conditions according to the 2012 NHA is provided in Table 2.1, with their indicator specifications in Appendix 1.1. Past and current specifications of the preventable hospitalisations indicator as used in the NHA are detailed in the Australian Institute of Health and Welfare (AIHW) Metadata Online Registry (METeOR).[22, 23]

Reports on preventable hospitalisations typically compare population rates of preventable hospitalisation between geographic regions, usually as an age-standardised rate per capita, such as per 1,000 or 100,000 population. Crude rates of admission or total bed days are also sometimes reported as a measure of the burden of preventable hospitalisations in a population. Further stratification breaking down the indicator by condition or population subgroups (such as age or Aboriginal status) is sometimes provided as supplementary information identifying potential priorities for targeted action. Reporting of trends can also be provided, either to monitor for improvements or to identify emerging problem areas.

Table 2.1: Chronic, acute and vaccine preventable conditions included in the preventable hospitalisation indicator, according to the definition in the 2012 National Healthcare Agreement.

Chronic	Acute	Vaccine-preventable
▪ Asthma ▪ Congestive cardiac failure ▪ Diabetes complications ▪ Chronic obstructive pulmonary disease (COPD) ▪ Angina ▪ Iron deficiency anaemia ▪ Hypertension ▪ Nutritional deficiencies ▪ Rheumatic heart disease	▪ Dehydration and gastroenteritis ▪ Pyelonephritis ▪ Perforated/bleeding ulcer ▪ Cellulitis ▪ Pelvic inflammatory disease ▪ Ear, nose & throat infections ▪ Dental conditions ▪ Appendicitis with generalised peritonitis ▪ Convulsions and epilepsy ▪ Gangrene	▪ Influenza and pneumonia ▪ Other vaccine-preventable conditions

Examples of reporting of the preventable hospitalisation indicator in Australia include reports from the National Health Performance Authority (NHPA),[25] New South Wales (NSW) Ministry of Health,[26] AIHW[27, 28] Productivity Commission,[29] and the Atlas of Avoidable Hospitalisations in Australia.[30] Other countries similarly reporting the preventable hospitalisation indicator include the United Kingdom (UK),[31] United States of America (USA),[17, 32-35] Canada[18] and New Zealand.[36]

2.3.2 Early development of the indicator

The first specification for potentially preventable hospitalisations was developed in the USA in the late 1980s and early 1990s, where the indicator was used as a tool for identifying socio-economic and racial disparities in access to primary health care in New York City.[19] This set of 28 ACS conditions was derived through consensus by a panel of six internists and paediatricians expert in the provision of care to needy populations and the problems

associated with barriers in access to care. The study found substantially higher rates of admission for these ACS conditions in areas with lower household income, in contrast to 'marker conditions' (such as myocardial infarction) for which timely and effective outpatient care was not expected to have much influence. Rates of admission were even greater for poorer neighbourhoods where the population was predominantly black. It was concluded that higher rates of ACS conditions may reflect barriers in access to primary care, and that these ACS conditions could potentially be used as a 'yardstick' tool for planning and evaluation, showing the community's ability to meet the needs of the medically needy.[19]

While this was the first study to propose preventable hospitalisations as such a tool, there was a growing concurrent body of evidence on the association between such 'preventable' hospitalisations and access to care. Previous research in Washington D.C. found many uninsured patients reported difficulties accessing outpatient services,[37] with 38% of chronic disease patients reporting problems in accessing outpatient care for the condition that resulted in hospitalisation, and over 60% of these patients reporting the access problem as economic. Almost one-quarter of all hospital admissions in this uninsured population were considered preventable or avoidable given timely and appropriate primary care (judged by hospital quality assurance personnel), and this increased to 45% of admissions among chronic disease patients.[37]

A study in Maryland and Massachusetts found that rates of 12 'avoidable hospital conditions' (AHC) were higher among uninsured than privately insured patients, and this association largely remained after adjusting for the baseline rate of hospitalisation in an area (to account for other unmeasured factors such as patient demand and physician supply).[38] In this study, the 12 AHCs were selected using a literature review, clinical guidance from a panel of five general internists, and further critique and review from expert clinical consultants. The conditions were assessed according to criteria including consensus among previously published studies, the importance of the health problem, the clinical face validity of the condition reflecting problems related to outpatient care, and clarity in the coding and availability of the data.[38]

A further study examined small area variation in hospitalisation rates in California for five chronic conditions, and compared these rates to area-level aggregates of patients' self-reported difficulty accessing care, prevalence of chronic conditions, and propensity to seek care (from a patient telephone survey) as well as physician practice style (from a physician survey using the American Medical Association Masterfile).[39] There was an inverse association

between average self-reported access to care in an area and rates of preventable hospitalisations, and this finding remained after adjusting for both measures of patient and physician characteristics. However, caution was placed on the use of preventable hospitalisations as a planning and reporting tool, given the additional associations with demographic characteristics and insurance status. Furthermore, as this was an ecological study, further research was recommended to confirm the causal pathway between improvements in access to care and reduction in hospitalisation for these chronic conditions.[39]

Numerous studies have investigated preventable hospitalisations in the decades following these seminal works, analysing geographic patterns or trends in rates of admission, associations with the provision of primary care services, and associations with the demographic characteristics of the population. The current body of evidence around preventable hospitalisations is further discussed in Section 2.4.

2.3.3 Adoption of the indicator in Australia and internationally

Following the early studies in the USA, preventable hospitalisations were adopted in that country as a health performance indicator. In 1993 the US Institute of Medicine Committee on Monitoring Access to Personal Health Care Services recommended that preventable hospitalisations be implemented as two performance indicators: avoidable hospitalisations for chronic diseases, and avoidable hospitalisations for acute conditions.[40] These continue to be reported by health policy organisations in the USA, such as the Agency for Healthcare Research and Quality,[17, 32-35, 41] which has occasionally evaluated and refined conditions within the indicator according to their face validity, construct validity, precision, minimum bias, evidence of or potential for real-world application, and the ability to foster real quality improvement.[33, 41]

Preventable hospitalisations have also been adopted as a performance indicator by a number of other countries. In the UK they are reported as part of the National Health Service (NHS) Outcomes Framework[42] and have been the subject of targeted reports and policy investigations, such as by the Nuffield Trust and the Kings Fund.[31, 43, 44] In Canada this indicator is reported by the Canadian Institute for Health Information,[18] with further validation of data coding and research on the indicator by the Manitoba Centre for Health Policy.[45] In New Zealand the indicator is reported by the Health Quality and Safety Commission.[46]

In Australia the indicator was initially developed for performance monitoring in the Victorian Ambulatory Care Sensitive Conditions Study in 2001, using codes based on a selection of

conditions used in the international literature.[47] It was subsequently adopted by the NSW Ministry of Health in 2002 in their Report of the Chief Health Officer of NSW[30] and by the AIHW in 2003 in their Australian Hospital Statistics Report.[48] In 2008 preventable hospitalisations were recommended by the AIHW as a national performance indicator in the new agreements to replace the 2003-2008 Australian Health Care Agreements,[49] and subsequently adopted by the COAG in the NHA.[2, 50] The indicator is monitored and reported at the national level by the NHPA,[20, 25] and now continues to be reported by the AIHW in their Hospital Statistics Reports,[7] by the Productivity Commission,[29] and against the Aboriginal and Torres Strait Islander Health Performance Framework.[28] It is furthermore part of the Performance and Accountability Framework[6] – the reporting apparatus for the COAG National Health Reform Agreement which seeks to improve health care through reforms to the organisation, funding and delivery of health care services, and will be an area of focus for the newly established Primary Health Networks.[51, 52]

In effect, this reporting means that for many health jurisdictions their performance against the preventable hospitalisation indicator is intrinsically tied to health funding. For example, the Commonwealth's contribution to funding services to Local Health Districts (LHDs) in NSW, as part of the National Health Reform, is determined at the State-level according to negotiated annual activity levels and performance targets.[53] Preventable hospitalisations are one of the elements used to develop these activity targets,[53] and are subsequently part of the Service Agreements between NSW Health and LHDs outlining performance expectations for funding and support.[54]

Preventable hospitalisations are also used as an outcome measure for many new policies and programs. For example, preventable hospitalisations have been a key outcome in NSW in evaluating the introduction of a Chronic Disease Management Program[55] and the subsequent Integrated Care Strategy,[56] both designed to improve management of health conditions in the community and reduce reliance on acute care services. Similarly, reducing preventable hospitalisations is a key motivator for the new Commonwealth Health Care Homes[57] model of care, a reform in which medical practices take responsibility for coordinating the ongoing and comprehensive care of patients with chronic and complex conditions.

The specifications for the national preventable hospitalisations indicator in Australia were initially developed from those used in the Victorian Ambulatory Care Sensitive Conditions Study, and are now reviewed and occasionally revised by the National Health Information Standards and Statistics Committee (NHISSC) – a peak national committee for health

information, containing representatives from all states and territories, which oversees the development and endorsement of data standards, mandatory minimum data sets, and best practice data set specifications for the National Health Data Dictionary.[58] The Potentially Preventable Hospitalisations/Potentially Avoidable Deaths Working Group of the NHISSC undertakes this review, comprised of clinicians, policymakers and data experts, and aims to ensure that the measure remains relevant to Australian policy priorities, reliable in its measurement and comparable between regions and over time. These revisions include minor annual updates to account for changes in disease coding and classification, and occasional major reviews taking into account larger data quality issues and the current state of clinical care in the Australian health care system.

The current Australian indicator includes 21 conditions. Past and current specifications for the potentially preventable hospitalisation indicator as used in the Australian NHA are detailed in the AIHW METeOR.[22, 23]

2.3.4 Strengths as a health performance indicator

The main strength of the potentially preventable hospitalisations indicator is the ease with which it can be calculated using routinely collected hospital admission data. In many countries, including Australia, there are few data sources with wide population coverage that capture variation in the provision or quality of primary care, yet hospitalisation data are routinely collected and widely available to both policymakers and researchers. The potentially preventable hospitalisations indicator therefore presents an accessible means for exploring the interface between primary and secondary care.

As potentially preventable hospitalisations are identified using a standard set of diagnosis codes, they can readily be measured at various geographic levels across the healthcare system. Furthermore, it is relatively straightforward for a health jurisdiction or policy organisations to obtain further insight by disaggregating the indicator, to identify specific types of conditions (such as chronic diseases) or population subgroups (such as Indigenous people) which may identify priority areas for a targeted policy response.

2.3.5 Limitations as a health performance indicator

One of the biggest limitations in measuring and understanding preventable hospitalisations is the lack of consistency in definition. While the indicator is defined using a standardised set of diagnosis codes for a pre-specified set of conditions, the selection of these codes and

conditions can be very different between studies, countries, policy organisations, and over time.[17, 59] This can cause difficulties comparing statistics between jurisdictions and over time, as well as comparing results and conclusions between studies.

Some of these inconsistencies reflect technical differences necessitated by the use of different coding systems, such as the International Classification of Diseases (ICD) versions ICD-9, ICD-10 and ICD-10-AM (Australian Modification). Other differences reflect technical details of the way that the indicator is defined, such as whether planned admissions, hospital transfers, or admissions resulting in death are included. While some definitions exclude older patients over 65 years, as their admissions may be less 'preventable' given their, other definitions (such as those used in Australia) do not have an upper age limit, as the elderly population still reflect a large health care burden potentially amenable to improved care.

Notable differences also exist in the types of conditions included, which often relate to the differences in the scope of the indicator, which is designed to be the most relevant to the context and health system in which it is being used. While most indicators include a range of chronic and acute conditions, varying priorities for policy and research can instead lead to a focus on specific conditions (e.g. diabetes, heart failure)[32] or specific types of condition (e.g. chronic conditions).[24] Conversely, some versions of the indicator have an expanded scope, including admissions preventable through broader aspects of community care, such as mental health conditions.[21] A recent review found over 65 different conditions being used to define different versions of the indicator,[17] although a few conditions, such as congestive heart failure, asthma, diabetes, hypertension, cellulitis, chronic obstructive pulmonary disease (COPD), angina, dehydration, gastroenteritis, and ear, nose and throat infections, were commonly found within most indicator sets.[17, 59]

A key conceptual limitation is that not all of the hospitalisations captured by the indicator could actually have been prevented. For example, some admissions may reflect chronically ill or elderly patients who have received optimum management in a primary care setting, and for whom the admission is an inevitable consequence of eventual health deterioration. While this limitation is often reflected the indicator title, such as *potentially* preventable hospitalisations, or ambulatory care *sensitive* conditions, the lack of clarity about to what extent the outcome is actually modifiable remains problematic for a health performance indicator.

Furthermore, the role in which primary and community-based care can influence admission is varied, making it difficult for policymakers to respond to the indicator in a timely and appropriate manner. Some policy interventions to reduce preventable hospitalisations address

the organisation of health systems, such as incentives to increase equity in the distribution of GPs.[60] However interventions can also target clinical and self-management of conditions, such as chronic disease management and telemedicine programs,[43, 55, 61] as well as primary prevention at the population level, such as educational health promotion campaigns.[43, 61] Further strategies for reducing preventable hospitalisations include multidisciplinary interventions, such as integrated health and social care.[43, 62, 63] While the scope of the indicator is broadly considered to be a measure of primary and community care, admission may also be influenced by other health system factors, as well as the characteristics of patients themselves - some of which may be potentially amenable to change within the healthcare system (e.g. prevalence of chronic diseases), while others are not (e.g. income).

Good performance indicators should reflect factors which can be influenced by, and are responsive to, health policy change.[4, 64, 65] Given the range of potential intervention strategies for addressing preventable hospitalisations, that some strategies (such as primary prevention) aren't expected to drive change within a proximal timeframe, and that some drivers of admission may be beyond the reach of health policymakers altogether, a clearer understanding of the variety of factors that drive admission is needed to help guide the valid use of the preventable hospitalisations indicator.

2.4 Factors that drive variation in preventable hospitalisation

2.4.1 Evidence on the role of the primary care system

Preventable hospitalisations are often described as an indicator of access to, and quality of timely and effective primary care.[66] While a somewhat broad definition, this captures the breadth of hypothesised roles in which primary care can influence a patient's risk of admission. This definition is also supported by research investigating patients reported 'access to care'. Early seminal research on preventable hospitalisations, as previously discussed, found a strong ecological association between self-reported difficulties accessing care and rates of preventable hospitalisation, even after adjusting for the prevalence of chronic conditions and patterns of patient care seeking behaviour.[39] Similarly in Australia, the first research to explore geographic variation in preventable hospitalisation reported a significant inverse association between admission rates and self-rated access to care, as derived from a telephone survey.[67] However, this study only had 32 geographic units of observation, and the association disappeared after adjusting for the geographic remoteness of the region.

'Access to care', however, is a complex and multidimensional concept, and implicitly encompasses factors related to the volume and supply or services, geographic accessibility of services, organisational accommodation, affordability of care, acceptability of care to the patient, as well as interactions between these various dimensions.[68] More recent evidence on the potential role of primary care has tried to explore some of these elements separately.

Most research further unpacking the role of the primary care system has investigated the supply of primary care services. Given the geographically-based measurement of rates of hospitalisation, and the relative ease of accessing administrative workforce data, area-based measures of supply—such as the number of generalist or family physicians working in an area—have been most commonly used as these are both practical and conceptually appealing. Many studies have found inverse associations between the size of the primary care workforce and rates of preventable hospitalisation,[69-78] but results have been mixed.[79-84] Most of these studies have been from the USA, with only a few from other countries such as Switzerland,[75] Norway,[83] Sweden[76] and the United Kingdom (UK).[77] In some of these studies, associations were only evident within particular population subgroups, for example in Norway—a country with a universal health care system—where an inverse association between the supply of GP or long-term care services with unplanned medical admissions was found in the oldest age groups (85+ years) only.[83]

A few studies have further explored supply of primary care services through identifying the presence of community health care centres or public ambulatory clinics within a district, each finding lower rates of preventable hospitalisations in areas which have these facilities. [85-87]

A number of studies have used individual patient-level data to assess the characteristics of primary care supply at the patient level. Most assessed continuity of care, the provision of care by a regular provider or team of providers, as patients with a regular source of care are likely to receive better care coordination and have a greater sense of trust and satisfaction. These studies mostly found lower rates of preventable hospitalisation for patients with higher continuity of care,[88-92] although with some mixed findings,[93] varying effect sizes, and often limited adjustment for the patient demographic and health characteristics which might confound these relationships.

Other studies using individual patient-level data explored associations with the volume of services used, such as a study of older patients at the end of life which found higher levels of primary care service utilisation leading up to the last 6 months of life was associated with lower levels of health expenditure during the last 6 months of life, including lower rates of

preventable hospitalisations.[94] Other studies have found more complex associations. A study in Switzerland found that rates of preventable hospitalisations decreased for patients with a greater number of medical consultations, but this rate sharply increased after 19 medical consultations (in a six month period), representing likely differential preventive effects for the potentially sicker and very high use patients.[95]

One study in Canada, using patient-based longitudinal data, found that people living in lower income areas had higher levels of ambulatory care visits, higher rates of preventable hospitalisations, as well as more physician visits prior to hospitalisation than people in higher income areas.[84] Furthermore, there was a positive association between primary care utilisation and preventable hospitalisation for the most common types of preventable hospitalisation (e.g. asthma, angina, congestive heart failure, bacterial pneumonia, cellulitis) among all income quintiles, supporting their hypothesis that variation in preventable hospitalisation was more reflective of socio-economic gradients in health status than health care.

With regard to affordability of care, most of the evidence base comes from research identifying disparities in hospitalisation rates among socially disadvantaged populations as a proxy for affordability, such as areas with lower income[96-98] or with a greater proportion of racial minority groups.[99-102] A number of studies in the USA found higher levels of health insurance and managed care coverage was associated with lower rates of preventable hospitalisation,[38, 78, 103-108] particularly for elderly, ill and disadvantaged populations who traditionally have greater barriers accessing care.[103, 104] Conversely, one study found that increasing health insurance coverage among a previously uninsured population not only increased levels of primary care utilisation but also rates of preventable hospitalisation, possibly by increasing both patients' propensity to seek care and the accessibility of hospital facilities.[109]

These studies combined present a mixed evidence base for the association between primary care and preventable hospitalisations. While some findings broadly suggest higher access to primary care services are related with lower rates of hospitalisation, be it through increased supply, stronger provider and patient continuity, or the availability of health insurance, this is not consistent. Importantly, some of these inconsistencies appear to relate to differences between countries (e.g. with different types of health care systems) or differences between patient subgroups (e.g. patient age), suggesting the association is highly specific to both the patient needs and the models of care available for the study population.

2.4.2 Evidence on the role of individuals, their health and behaviour

The key role of patient characteristics in driving rates of preventable hospitalisation is a consistent finding in the research literature. Some of the earliest research studies used patient characteristics such as race or income as proxy measures for financial or social barriers in access to care, as has been previously discussed.[19, 38] However these studies also adjusted for characteristics of the population where possible, such as the prevalence of chronic conditions, and suggested further research was required to understand and control for the effect of patient characteristics.

Subsequent research has used two main types of approaches to explore the role of individual patient characteristics. The first approach has been to use aggregated patient level characteristics, such as disease prevalence, average income, racial composition of the population, or area-level deprivation, as ecological variables in analyses with geographic regions as the unit for analysis.[69, 73, 74, 76, 96] These ecological data are usually derived from census or administrative data sources, although in some studies more detailed patient demographics were collected in a patient survey and aggregated to the geographic level for analysis.[39, 67]

While this has been the most common approach, such aggregate measures are limited in interpretation as they are unable to account for co-linearity in population demographics, such as income, education and race, and prevalence of disease. These ecological measures are also subject to the 'ecological fallacy'[110, 111] inherent in inferring risk factors for individuals based on population-level information, where it is not known which members of the population actually had the outcome under investigation.

The second approach has been to analyse patient characteristics either at the patient level, or in population groups stratified by patient characteristics. Some studies have focused on a specific patient characteristic, such as socio-economic status (SES),[112] race,[101, 113, 114] multi-morbidity,[115-117] perceived stress[118] or healthy behaviours,[119] while other studies have explored a range of patient characteristics.[111, 120] More recent studies have used multilevel modelling, a statistical technique that allows data to sit at different hierarchical levels – such as patients living within their geographic area of residence, to better account for the mixture of person- and area-level exposures and outcomes being used in most analyses.[73, 75, 83, 121-123]

Such multilevel analyses overcome the ecological fallacy by allowing both patient-level characteristics and area-level characteristics of the health care system to be analysed at the patient- and area-levels accordingly. As such, in the past few years multilevel modelling has

become the standard methodological approach when investigating preventable hospitalisations. However, these studies mostly use only limited patient-level information, such as only that available through administrative data sets (e.g. age, sex, and prevalence of select chronic conditions). Multilevel modelling is discussed further in Sections 2.5.3 and 3.7.

Across both approaches, most evidence has emerged for the patient characteristics able to be identified using administrative data. There are some strong and consistent associations, with rates of preventable hospitalisations higher among males,[124, 125] older patients,[111, 124] patients with higher levels of multimorbidity,[115-117] lower level of socio-economic status,[96, 120, 122] and lower levels of health insurance[38, 103, 107] as well as among racial minority groups.[99-102, 114]

Few studies have investigated additional predisposing factors, such as health literacy or healthy behaviours (including smoking and drinking alcohol), and with inconsistent results.[66, 119, 124, 125] There is similarly limited evidence for additional factors which enable health service use, such as the role of social support and employment.[124] While there are also few studies that have directly assessed additional factors related to patient need, such as patients' perceived health, mental health and level of functioning, there is consistent moderate to strong evidence of an association between these measures of poorer patient health and higher rates of hospitalisation.[118, 125]

2.4.3 Evidence on the role of hospitals

There is only limited evidence of the potential role that health system factors, other than those related to primary care, play in preventable hospitalisation, and most of this evidence is in relation to hospital care. Hospitals have been hypothesised to play a key role in admission, with possible variations in hospital admission thresholds potentially influencing both a patient's risk of hospitalisation and subsequent geographic patterns of admission.[19]

Differences in a hospital's propensity to admit patients can arise from various mechanisms, such as differences in hospital capacity through the availability of beds and services[126, 127] as well as variation in physician preferences.[19, 128] Such factors have been found to explain much variation in general patterns of hospital utilisation,[129] but the evidence for preventable hospitalisations is not clear.[124] Only a few studies have explored the impact of hospital characteristics, mostly using geographically-based measures of supply, such as the number of beds per capita.[75, 78, 80, 107, 130] These studies relate to the well-established Roemer's law, the principle that the availability of hospital beds leads to higher levels of utilisation,[131] but the results of these studies have been mixed.

One study has explored more detailed characteristics of hospitals, finding that preventable hospitalisations increased not only with the number of acute hospital beds, but also for hospitals with higher rates of emergency department attendance and subsequent conversion to admission.[132] Anecdotal reports from GPs still suggest different types of hospitals may play a more direct role in choosing to admit patients, particularly in regional areas where travel times are large, access to other health services are poor, and doctors may be more likely to admit patients for observation.[133]

2.4.4 Gaps in knowledge

Preventable hospitalisations have been extensively studied over the past 20 years. At least 17 different literature reviews on preventable hospitalisations have been published, exploring variously predictors of admission,[33, 66, 82, 114, 124, 125, 134, 135] methods for identification,[17, 59, 136, 137] or different types health policy responses and interventions.[43, 61, 62, 124, 138, 139] Furthermore, exploration of geographic patterns of variation in preventable hospitalisation, or trends over time, have been explored in at least 11 different countries.[25, 26, 30, 31, 75, 81, 96, 101, 140-143] Despite this, considerable gaps in the knowledge base that underpin the use of this health performance indicator still remain.

First, while there has been much investigation into the many factors that drive geographic variation in preventable hospitalisation, there is surprisingly little understanding of the relative contribution of these factors to variation in the indicator. Health providers and policymakers should not be held accountable for factors beyond their control,[64, 65, 120] and while the literature identifies extraneous factors potentially influencing the indicator, adjustment for these factors is rarely performed. Knowing how much of the geographic variation in preventable hospitalisation is attributable to health system factors (primary care or otherwise), to potentially modifiable patient characteristics, or to non-modifiable socio-demographic characteristics, is essential to interpreting the indicator and understanding how—and to what extent—it is potentially amenable to change.

Only two studies have quantified the contribution of explanatory factors to geographic variation in admission, finding up to half the geographic variation being attributable to factors other than primary care.[64, 67] However, these studies used aggregated ecological measures of patient characteristics, subject to the ecological fallacy, and did not separate out the contribution of different factors to this variation.

A second gap is that only a limited range of measures of health care have been investigated. These are primarily ecological measures of health services readily accessible to researchers, such as primary care workforce statistics or hospital bed supply. Other patient-level measures of health care have been assessed, but are limited to those easily conceptualised and calculated using administrative data, such as the volume of services or continuity in provider of care.

While informative, 'access' is a complex construct and there remain many aspects of care which are poorly understood. Some of these, such as patient waiting times, affordability of care, quality of chronic disease management and variation in physician practice style, are difficult to measure and evaluate. Other aspects of care, such as complex patterns of patient interaction with the health care system, are recorded in administrative datasets but are difficult to quantify. Fresh data analytic approaches may offer new ways to fill this gap, such as how patients admitted for preventable hospitalisation are engaging with the broader health care system, which will enhance our understanding of the health performance indicator

Another key gap in knowledge is that much of the evidence base has come from the USA. Australia has a universal health care system with a safety net for the chronically ill and further subsided care for elderly and concessional patients. In contrast, the health care system in the USA has fragmented health insurance coverage from a mixture of private and public sources, with most private insurance provided through a patient's employer, and public insurance available through either Medicare (for patients aged 65 and over), Medicaid (for certain low-income populations) and military health care programs.[8] In 2010 almost 50 million residents were uninsured and 29 million residents were 'underinsured' – with high out-of-pocket expenses relative to their income.[8] While most insurance programs include some preventive and ambulatory care services, benefits vary according to the type of insurance package, and so there is considerable variation in access to and cost of care, particularly among low income and socially disadvantaged groups. Therefore, the applicability of the evidence base from the USA to the use of this performance indicator in Australia is questionable.

Only one Australian study, from the state of Victoria, has explored the association between primary care and preventable hospitalisation and this had limited statistical power, with only 32 geographical areas as the units of observation. It reported that associations with primary care supply did not remain after adjusting for the demographic and remoteness characteristics of the region.[67] For a performance indicator reported at the highest level of Australian government, a stronger evidence base is required.

2.5 New approaches and the potential to gain new insights

This thesis utilises novel approaches to data analytics to help derive new insights into preventable hospitalisations as a health performance indicator. These include: the use of linked cohort and longitudinal patient data; data visualisation; and multilevel modelling.

2.5.1 Linking longitudinal patient and administrative health datasets

Large amounts of information are routinely collected by governments, healthcare providers and insurers as people interact with various aspects of the healthcare system. For example, when patients are admitted to a hospital ward, visit a general practitioner, have a diagnostic test performed, or dispense a prescription for medication from a pharmacy, information on this transaction is recorded and stored in a centralised dataset. These longitudinal datasets are often referred to as administrative or routinely collected health data, as they have been collected as a by-product of standard operating procedure.

Administrative data sets are being leveraged for a number of purposes, including research, surveillance and program evaluation. Considered a source of 'big data' given the volume of information created (all interactions with the healthcare system), the velocity at which they are collected (continuously) and the variety of information collected from different sources, these data sources present a powerful means to evaluate the provision of health services in a real-world setting.

These sources of 'big data' have a number of advantages,[144] including whole of population coverage, a longitudinal structure with potential follow-up over a patient's life course, and their use is reasonably cost-effective because they have already been collected during the delivery of services. However, they also have several limitations. The data are usually generated on an event basis (e.g. at the time of hospitalisation), and do not contain any information for people who did not experience the event (e.g. people who were not admitted to hospital). Furthermore, limited information is often collected in these datasets, restricted to information relevant to the administrative function, and the quality and validity of this information can be variable.[145, 146] Most research on preventable hospitalisations has used administrative hospital data for analysis, and is subject to these limitations, such as limited information on patient demographics.

Data linkage is the bringing together of two or more datasets from different sources to create a new, richer dataset.[147] This process creates new opportunities for more complex research

and analysis, and as such development of large scale data linkage infrastructures are being prioritised across many countries, including Australia, to maximise the utility of administrative health data.[148, 149] The process of linkage can be deterministic, using a unique identifier such as social security number to connect records, or probabilistic, creating a 'linkage key' using a combination of identifying information such as name, address, and date of birth.[147] Data linkage is usually carried out by trusted third party organisations.

In this thesis, I use linked longitudinal health data from a variety of administrative sources, including hospital admissions, Medicare claims for primary care services, and mortality data, which is further linked to survey data from a large prospective cohort of more than one quarter of a million people. Bringing these datasets together creates a rich and complex data resource with comprehensive information on both the characteristics of the large study population, and how they have been interacting with the health care system.

2.5.2 Data visualisation

The sheer amount of data generated by the health care system can make it difficult to effectively comprehend and utilise the information these contain. However, the human perceptual system is highly sophisticated, specifically suited to spotting visual patterns of stimuli, and data visualisations are thus being used as an emerging tool to help us better see and understand information.[150]

There are many advantages in visualising data. It allows the viewer to explore concepts in the data in various ways, such as understanding both large-scale and small-scale features of the data, identifying outlying or problematic data points, observing emergent properties in the data that may not have been expected, or generating and exploring new hypotheses.[151] The strongest advantage however is that it provides the ability to comprehend huge amounts of information, or as Edward Tufte says in his seminal book *The Visual Display of Quantitative Information*, '*often the most effective way to describe, explore and summarize a set of numbers – even a very large set – is to look at pictures of those numbers'*.[152]

Several visualisation tools have been developed specifically for longitudinal health data. These typically present a visual timeline of health events for one or more patients over time,[150, 153-157] in which a visual representation of health events is placed on a continuous axis representing time. Different software package have differing capabilities to display these, such as the ability to centre patients' time on specific health events,[158] grouping patients with similar health trajectories,[156, 157] or as an interactive dashboard displaying further patient or clinical

characteristics.[155, 159] However, these tools exist largely in the domain of computer science, and have been developed primarily to aid patient monitoring, clinical decision making, and interactive data interrogation. Despite the potential, there are very few practical examples in the academic literature of such visualisations being used to explore, and generate new information from, large and complex health data.

In this thesis, I employ a custom data visualisation to explore temporal patterns in health service use around the time of preventable hospitalisation. While preventable hospitalisations are being used as an indicator of access to care, no study to date has explored if and how people have been using health services around the time of hospitalisation – a complex exploratory analysis that may only be possible using such innovative data analytic techniques.

2.5.3 Multilevel modelling

As previously discussed, many factors influence preventable hospitalisation. The indicator is typically measured as geographic rates of hospitalisation, and while some of these factors, such as remoteness, are inherently characteristics of geographies, other factors are at different levels of observation, such as individual health and socio-demographic characteristics, which sit at the person-level, or the characteristics of health services, such as GP clinics or hospitals, which sit at the level of these facilities.

Much of the research on preventable hospitalisations has used a single level of observation for analysis, for example either geographic regions or individual patients. These approaches typically transform other factors to the same level for analysis, such as aggregating patient characteristics at the regional level, or including a patient-level variable on the characteristics of the region they live in. However, these approaches also have limitations. As previously discussed, using aggregated population information is subject to a potential ecological fallacy,[110] in which inferences are made about individuals without actually knowing whether they had the outcome. Conversely, if there is clustering of patient-level information, but the clustered nature of the data is not accounted for in analysis, biased parameter standard errors and incorrect statistical inferences can result.[160]

Multilevel modelling is a statistical technique that structures data into different levels or hierarchies, and is increasingly being used in epidemiology, public health and health services research.[161] Also known as random effects modelling, mixed effect modelling or hierarchical modelling, this technique allows the data to sit at two or more levels for analysis, such as individual people nested within their geographic area of residence. This structure enables

analysis on both people and the context in which they live, providing both more accurate estimates for regression parameters at each level, and the ability to partition variation between these levels.

At the onset of the research presented in this thesis, no study had used multilevel modelling to explore preventable hospitalisations, but it has since become a standard analytic approach given the ability to combine both patient and health service characteristics.[73, 75, 83, 121-123] However, studies to date have been limited by their use of administrative data sets with limited patient-level information, and have mostly used multilevel modelling to adjust for clustered patient data, with little exploration of the variation which lies at each of these levels.

In this thesis, I use multilevel modelling to explore factors which drive variation in preventable hospitalisation at the patient-, geographic- and hospital-levels. Using the linked longitudinal health and patient survey data, this study is the first to use a comprehensive set of patient-level information. I also maximise the potential of multilevel models by exploring and quantifying variation at the various levels, including the development of novel multiple membership methods for attributing population variation to the hospital-level.

2.6 Theoretical framework

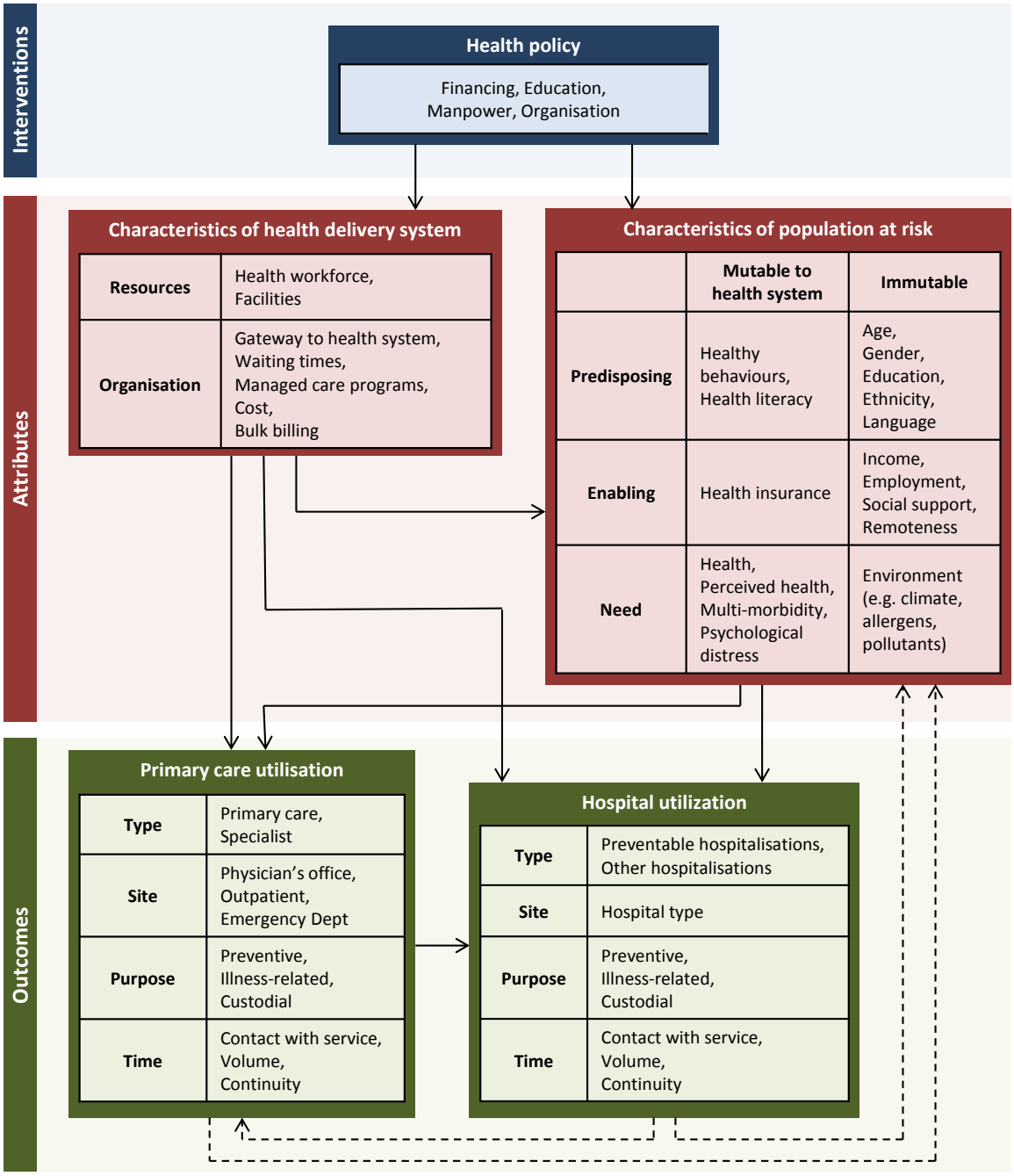
Figure 2.1 represents the theoretical framework used in this thesis for the interplay between social determinants of health, access to care and the utilisation of health services. It has been adapted from the conceptual framework for access to medical care developed by Aday and Andersen,[162] by grouping framework components as either interventions, attributes or outcomes, separating the utilisation of primary care and hospital services, and contextualising the contents of each component with relation to this research on preventable hospitalisations. Additional outcomes relating to consumer satisfaction are presented in the original conceptual framework,[162] but are not represented here as it has been little explored in the literature on preventable hospitalisations.

Under this framework, health policy can be developed to target access to medical care through either the characteristics of the health delivery system, or characteristics of the population at risk. Within the health system, policies can address the number and distribution of resources, as well as the organisation structures which influences barriers to, and quality of, care.

Characteristics of the population can be categorised as factors which predispose a patient to use services, factors which enable or facilitate use, as well as factors which reflect the patients'

health need.[163] Some of these characteristics are potentially mutable to change by the health care system, be it through population-based prevention strategies or health promotion in a primary care setting. However, most characteristics only have low or medium mutability in the short term, and can be difficult to modify, even in the long term.[164]

Figure 2.1: Conceptual framework for access to care and utilisation of health services*



** Adapted from Aday and Andersen, 1973*[162]

Both characteristics of the health delivery system and of the population influence realised access[165] in the utilization of health care services, which in this thesis can be categorised as either primary care services or hospital services. Each form of utilisation is characterised by the type of service provided, the site it is provided in, the purpose of the care, and the dimensions of time along which the care is provided.

The key hypothesis underpinning the use of preventable hospitalisations as a health performance indicator is that health policies targeting characteristics of the health delivery system will result in greater patient access to appropriate quality primary care services, subsequently reducing the number of preventable hospitalisations. Most research has explored this hypothesis by comparing patterns of primary care and hospital utilisation. The indicator is complicated by additional pathways which contribute to the outcome, including potential modification of mutable patient characteristics through direct health policy or by the health delivery system, characteristics of the delivery of hospital services, and patient characteristics immutable to change.

There may also be further interaction between components of the framework following health service utilisation, such as GP follow-up care following hospital discharge, and further impacts on patient characteristics (such as health, functional limitation) as a consequence of primary or hospital care. These are plausible mechanisms, but not hypothesised to play a large contributing role, and have been represented with dotted lines.

Chapter 3 Methods

3.1 Study cohort: The 45 and Up Study

The 45 and Up Study is a large scale prospective cohort of individuals aged 45 years and over in NSW, Australia.[166] The study has been developed to provide researchers with timely and reliable information on a wide range of exposures and outcomes of public health importance to the ageing population, and is managed by The Sax Institute in collaboration with major partner Cancer Council NSW, and partners the National Heart Foundation of Australia (NSW Division), NSW Ministry of Health, NSW Government Family & Community Services – Carers, Ageing and Disability Inclusion, and the Australian Red Cross Blood Service.

The study contains a total of 266,950 study participants, approximately 1 in 10 people aged 45 and over in NSW, and is the largest ongoing study of healthy aging in the Southern Hemisphere. Study participants were recruited over a three-year period, beginning in February 2006 and ending in December 2009. Participants were recruited through the Department of Human Services' Medicare (Australia's national universal health insurer) registration database, from which eligible individuals were randomly sampled, with individuals aged over 80 and people residing in rural areas oversampled by a factor of two. Sampled individuals were mailed an invitation to participate, including an information leaflet, a study questionnaire, consent form and reply paid envelope. Participants joined the study by returning the questionnaire and consent form, which included consent for long-term follow-up, and for their information to be linked with other sources of health-related information, such as hospital records, emergency department information, disease registers, and Medicare and general practice information. The study questionnaire was only available in English. Participants were also able to volunteer to join the study by contacting the study hotline and requesting an invitation pack.

The study response rate was 18%, which is lower than other comparable cohort studies, such as the Million Women Study[167] in the UK (response rate 53%) and the Australian Longitudinal Study on Women's Health (response rate between 37-56%)[168]. It is unlikely the study cohort is representative of the general population, and in comparison to the NSW Population Health Survey (response rate 59-64%) the 45 and Up Study cohort had similar prevalence estimates of age, sex, country of birth, highest level of education, fruit consumption and body mass index, but a lower prevalence of smoking, hypertension, diabetes, asthma, and high levels of psychological distress,[169] indicating a healthier cohort. However, the study is of considerable

size, and with the oversampled elderly and rural study population, has sufficient heterogeneity to allow for valid within-study comparisons.[170] For example, while prevalence estimates differed in comparison to the NSW Population Health Survey, patterns of exposure-outcome associations within each data source were found to be consistent.[169]

Data from the 45 and Up Study cohort is available as an open resource to researchers within Australia. Researchers can apply for access to the study data, which requires both scientific review and approval of a research proposal, and the payment of annual data licence and access fees. Over 90 research projects have used the 45 and Up Study data, on diverse topics such as cancer, cardiovascular health, physical activity, diabetes, mental health, and health service utilisation.

3.1.1 Access to the 45 and Up Study cohort through the APHID and GRAPHC Studies

This thesis uses data for participants in the 45 and Up Study linked with other longitudinal data sources, as obtained through the APHID Study.[171] The APHID Study is an NHMRC funded partnership project, in collaboration with the ACSQHC, ACI and BHI, which aims to validate preventable hospitalisations as a measure of health system performance in Australia. More specifically, the objectives of the APHID study are to: link questionnaire data from the 45 and Up Study to prospective data on use of primary care services, hospitalisations and deaths; analyse these data to establish the relationship between use of primary care services and preventable hospitalisations; establish the relationship between preventable hospitalisations and health outcomes for people with chronic conditions; and to conduct comparative analyses using data from Scottish Morbidity Records. While this thesis is embedded within the APHID Study, it does not seek to address all the study objectives. Data from the APHID Study are used in Chapters 4 and 5.

Some analyses in this thesis (Chapters 6 and 7) required additional geocoded information on study participants not available through APHID, and instead used data obtained through the GRAPHC (Geographic and Resource Analysis in Primary Health Care) Study.[172] The GRAPHC Study is a collaboration between the Australian National University and Western Sydney University, and aims to enhance the capacity of health services through the use of geographical information systems, tools, methods and data to support research into primary health care. The underlying data used in the GRAPHC Study are the same as those obtained through the APHID Study, although there are minor variations due to differences at the time of

data extraction, the current availability of linked data sources, and the current data linkage keys used for linking datasets.

3.2 Linked data sources

3.2.1 45 and Up Study baseline questionnaire data

At the time of study entry, participants in the 45 and Up Study completed a self-completed baseline questionnaire.[166] This included information on a variety of measures, including demographic and social characteristics, such as education, income, marital status, work, retirement, country of birth and social connectedness; personal health behaviours, including smoking, alcohol, physical activity, fruit and vegetable consumption, dietary information and sleep habits; and general health-related data, including disease and surgical history, family history of illnesses, medication, functional capacity, psychological distress, reproductive history, and incontinence. Different questionnaires were available for men and women, and copies of these questionnaires are available on the 45 and Up Study website (https://www.saxinstitute.org.au/our-work/45-up-study/questionnaires/).

Also provided with the 45 and Up Baseline questionnaire data is geocoded information on participant's area of residence. The participant's Statistical Local Area (SLA) of residence is derived from the participant's address, and is defined according to 2006 boundaries in the Australian Standard Geographical Classification.[173] Further information on participants' addresses are not routinely provided to researchers for issues of privacy and confidentiality.

The APHID and GRAPHC Study datasets differ with respect to two key pieces of information. The APHID Study contains an additional variable on whether the study participant identifies as Aboriginal or Torres Strait Islander (hereafter referred to as Aboriginal). The APHID Study sought additional approval for this variable to be released as Aboriginal people are known to have higher rates of preventable hospitalisation.[113]

On the other hand, the GRAPHC Study has additional geocoded information on study participants' area of residence at two smaller geographic levels: Postal Area and Census Collection District of residence. The GRAPHC study sought approval for use of these variables in order to better create geographic catchments of health service utilisation. The GRAPHC study data has been used in this thesis accordingly for analyses creating and analysing catchments of hospital service use (Chapters 6 and 7).

The 45 and Up Study is collecting a follow-up questionnaire from study participants, with the first wave of data collection beginning in 2012. This information was not available at the time of analysis and has not been used in this thesis.

3.2.2 Admitted Patient Data Collection

The NSW Admitted Patient Data Collection (APDC) is a census of all hospital separations (discharges, transfers and deaths) from all NSW public, private, psychiatric and repatriation hospitals in NSW, as well as public multi-purpose services, private day procedures and public nursing homes. The APDC data are recorded as episodes of care, which ends when a patient ends a period of stay in a hospital (e.g. discharge, transfer or death) or becomes a different type of patient within their stay. The dataset includes interstate hospitalisations of NSW residents, although as names and addresses are not included in these records, these hospitalisations are not included in linked data used for research.

The APDC contains information on the episode of care, diagnosis information coded according to the ICD-10-AM,[174] procedure information coded according to the Australian Classification of Health Interventions, as well as limited information on patient demographics.

3.2.3 Register of Births, Deaths and Marriages

The NSW Register of Births, Deaths and Marriages (RBDM) Mortality Data File contains fact of death information for all deaths of NSW residents. Further information on cause of death, while available for some years of follow-up, was not used in the research in this thesis.

3.2.4 Emergency Department Data Collection

The NSW Emergency Department Data Collection (EDDC) contains information on presentations to public emergency departments (EDs) in NSW. While there are around 150 EDs in NSW, the number of participating EDs has increased over time from around 46 in 1996 to around 90 in 2010. The larger EDs all currently participate in the EDDC, so this dataset captures a substantial proportion of ED presentations in NSW.[175]

The EDDC contains diagnosis information recorded by medical, nursing or clerical personnel at the point of care. The computer programs and diagnosis classifications used differ across EDs, and are coded according to the ICD-9-CM (Clinical Modification),[176] ICD-10-AM,[174] or SNOMED CT.[177]

3.2.5 Medicare Benefits Schedule

Medicare Benefits Schedule (MBS) claims data contain information on all claims for medical care subsidies processed by the Department of Human Services, including general consultations, diagnostic tests and pathology services. Only services attracting a subsidy are included in the MBS data, and so dental care, many allied health services, services rendered free-of-charge in recognised hospitals, or services that qualify for a benefit under the Department of Veterans' Affairs are not captured.

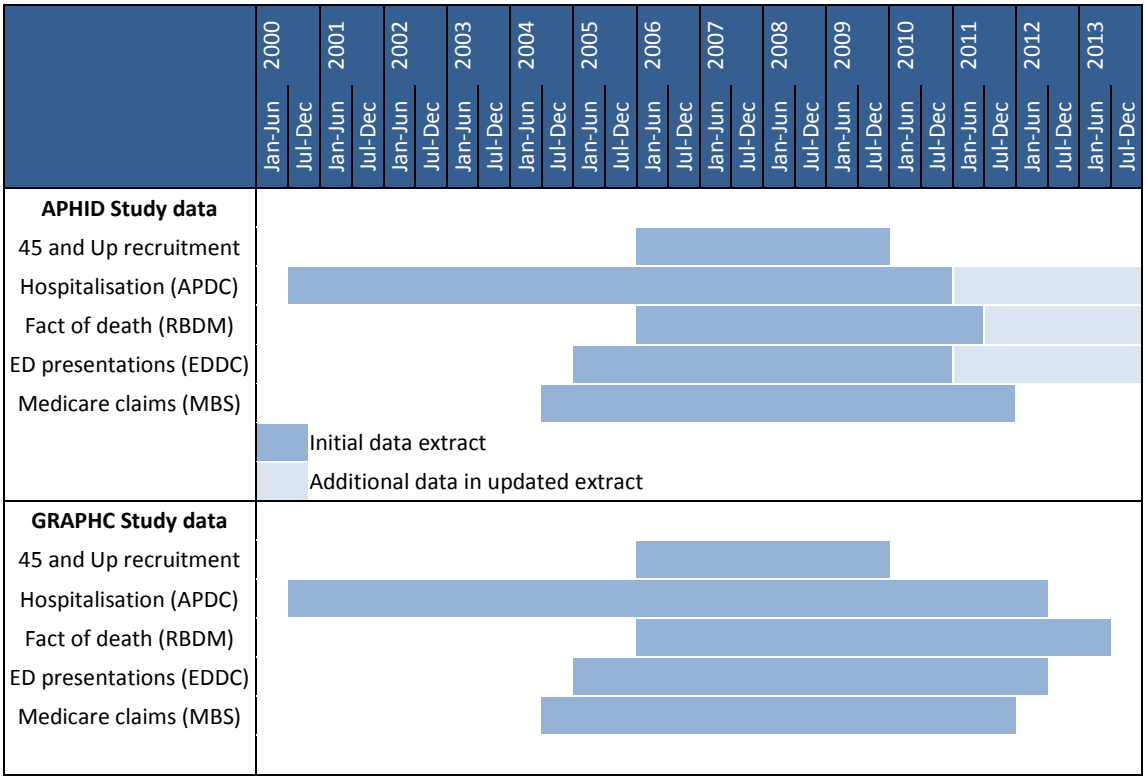
The MBS data contain information on the date, fee and benefit paid for the service, the type of service claimed, identified by an item code as well as an item category grouping similar professional services, and limited de-identified information on the provider of the service.

3.3 Data linkage

3.3.1 Linked data availability

Linked data extracts were obtained at three points in time throughout the course of this research. Different chapters in this thesis have therefore used data from these different extracts, to utilise either the most current or the most appropriate data for each project.

Figure 3.1: Availability of linked data within the APHID and GRAPHC Studies



A Gantt chart showing the availability of data within each study is provided in Figure 3.1. Data in the APHID Study were provided over two extracts: an initial data extract in 2012, and an update to select datasets held by the NSW Ministry of Health in 2014. This update provided an additional 2-3 years of follow-up data in the APDC, EDDC, and RBDM datasets. Data in the GRAPHC Study was provided in a single data extract in 2014.

The initial data extract in the APHID Study was used for the analysis in Chapter 5, and the updated data used for the analysis in Chapter 4. The GRAPHC Study data were used for the analyses in Chapters 6 and 7 (Table 3.1).

The 45 and Up Study maintains an active register of study participants, and at the time of data extraction data are provided for all participants currently active in the study (i.e. have not withdrawn). Thus, the number of study participants provided in each data extract differs according to the number of active participants provided by the 45 and Up Study at the time of the data extract.

Table 3.1: Number of records in each dataset within the APHID and GRAPHC Studies

Linked dataset	APHID Study - initial extract (Chapter 5)		APHID Study - updated extract (Chapter 4)		GRAPHC Study (Chapters 6,7)	
	Range	# records	Range	# records	Range	# records
45 and Up questionnaire	Feb 2006 – Dec 2009	267,091	Feb 2006 – Dec 2009	267,079	Feb 2006 – Dec 2009	267,112
APDC	Jul 2000 – Dec 2010	1,206,742	Jul 2000 – Dec 2013	1,761,178	Jul 2000 – Jun 2012	1,471,238
RBDM	Feb 2006 – Jun 2011	9,203	Feb 2006 – Dec 2013	18,430	Feb 2006 – Jun 2013	16,442
EDDC	Jan 2005 – Dec 2010	347,602	Jan 2005 – Dec 2013	586,131	Jan 2005 – Jun 2012	460,434
MBS	Jun 2004 – Dec 2011	46,203,507	Jul 2004 – Dec 2011	46,203,507	Jun 2004 – Dec 2011	46,012,650

3.3.2 Process of data linkage

Linked data in this project were obtained through two separate linkage processes.

The Sax Institute, which manages the 45 and Up Study, holds and manages both the 45 and Up Study baseline questionnaire and the linked MBS data from the Department of Human Services. Deterministic linkage between these datasets was performed by the Sax Institute using a unique Medicare person identifier.

Linkage of the 45 and Up Study cohort to the APDC, EDDC and the RBDM mortality data was performed by the NSW Centre for Health Record Linkage (CHeReL). The CHeReL is a trusted

third party organisation in the NSW Ministry of Health, which carries out linkage of health-related data in accordance with ethical, legal, privacy and confidentiality requirements. The CHeReL has a system of continuously updated links within and between core health-related datasets in NSW known as the Master Linkage Key (MLK). Each of the 45 and Up Study, APDC, EDDC and RBDM mortality data files are all included in the MLK.

Data linkage at CHeReL is performed probabilistically using commercially available ChoiceMaker software. Probabilistic linkage works by assigning a 'linkage weight' to each pair of records, based on the degree of match in personal information such as first name, surname, date of birth and address. A high linkage weight indicates the records likely match, while a low linkage weight indicates records likely do not match. Arbitrary cut-points in upper and lower linkage weights (indicating links and non-links) are chosen, reviewed and revised so both the false positive and false negative linkage rates are not above 0.5%. Following this, a clerical review of uncertain matches between these cut-points is undertaken. Quality assurance checks are regularly carried out on the MLK, and a manual clerical review on a sample of linkage records on the MLK in 2012 found a false positive linkage rate of 0.3% (http://www.cherel.org.au/quality-assurance).

De-identified data are provided to researchers, stripped of all personally identifying information, including name, date of birth, address and database IDs. A unique project person number, generated by CHeReL and attached to each dataset by the relevant data custodian, allows linkage of records within and across datasets. The project person number is unique to each study, so data sets from different studies, such as the APHID and GRAPHC Studies, cannot be linked together.

3.4 Defining exposures and outcomes

3.4.1 Preventable hospitalisations

Preventable hospitalisations were identified in the APDC hospitalisation data according to the indicator used in the Australian 2012 National Healthcare Agreement. [22] This comprises admissions for 21 different conditions (Table 2.1) broadly categorised as 'chronic', 'acute' and 'vaccine-preventable', and includes conditions such as diabetes complications, angina, asthma, and influenza. A full set of diagnosis and procedure codes used to define preventable hospitalisations according to the indicator definition is provided in Appendix 1.1.

The APDC hospitalisation data includes a record for each episodes of care, of which there may be many for any period of stay in a hospital. As such, records for multiple episodes of care were reduced to a single hospital admission record, with type change separations, serial transfers and nested transfers all considered a continuation of the same episode of care. Characteristics of the admission (e.g. admission date, diagnoses, procedures, hospital) were identified by the first episode of care, but with the discharge date corresponding to the last episode of care within the period of stay. For Chapter 4, which describes longitudinal patterns of health service use rather than counts of admissions, transfers and type change separations were considered as separate episodes of care.

While there have been further annual revisions to the Australian preventable hospitalisations indicator during the course of the research presented in this thesis, the indicator definition used in this thesis has remained consistent. Many of the indicator changes reflect emerging issues around consistency in data capture and coding as new years of data become available. As the analyses primarily use data over a consistent period of follow-up, such updates were not necessary. This also allowed greater consistency in analysis across chapters.

3.4.2 Other types of health events

Chapters 4, 5 and 7 compare preventable hospitalisations with other health events, such as the use of other health services (e.g. GP and specialist consultations, ED presentations, deaths), as well as other 'marker' hospitalisations to compare and contrast results such as emergency admissions for hip fracture and acute myocardial infarction (AMI). These measures are detailed in Table 3.2, and further information for each type of health event is provided in the relevant chapter.

3.4.3 Personal characteristics

Self-reported characteristics of study participants were obtained the questionnaire that they completed at study entry. These variables were used in the analyses reported in Chapters 4-7, and are summarised in Table 3.3.

Table 3.2: Health events identified using linked administrative data

Dataset	Chapter	Health event	Definition
APDC	Chapters 6-7	All cause hospitalisations	All hospital admissions
APDC	Chapters 4 -7	Preventable hospitalisations	See Appendix 1.1
APDC	Chapter 4	Other 'non-preventable' hospitalisations	All hospital admissions which did not meet the criterion for being a preventable hospitalisation
APDC	Chapter 5	Emergency 'non-preventable' hospitalisations	All hospital admissions which did not meet the criterion for being a preventable hospitalisation, and with an 'emergency' admission status.
APDC	Chapter 7	Emergency acute myocardial infarction (AMI) hospitalisations	ICD-10 primary diagnosis code: I21, and with an 'emergency' admission status.
APDC	Chapter 7	Emergency hip fracture hospitalisations	ICD-10 primary diagnosis codes: S72.0, S72.1, S72.3, and with an 'emergency' admission status.
RBDM	Chapters 4-7	Deaths	All deaths in the RBDM mortality data file
MBS	Chapter 4	GP consultations	All claims in the MBS data with item group numbers 'A1' and 'A2'.
MBS	Chapter 4	Specialist consultations	MBS item codes: 85, 88, 94, 99-100, 102-152, 154-159, 288-289, 291-293, 296-297, 299-338, 342-353, 355-359, 361, 364, 366-367, 369-370, 384-389, 410-417, 501-503, 507, 511, 515, 519-520, 530, 532, 534, 536, 801, 803, 805, 807-809, 811, 813, 815, 820, 822-823, 825-826, 828, 830, 832, 834-835, 837-838, 851-852, 855, 857-858, 861, 864, 866, 871-872, 880, 887-893, 2799, 2801, 2806, 2814, 2820, 2824, 2832, 2840, 2946-2949, 2954, 2958, 2972-2978, 2984-3003, 3005, 3010, 3014-3015, 3018, 3023, 3028-3032, 3040, 3044, 3051-3055, 3062, 3069, 3074-3078, 3083, 3088, 3093, 5906-5912, 6004, 6007-6009, 6011-6016, 10801-10816, 17603-17690.
EDDC	Chapter 4	Emergency department presentations	All presentations to an emergency department in the EDDC data

Table 3.3: Person-level variables in the 45 and Up Study baseline questionnaire data

Variable	Description
Age	At the time of survey completion, categorised into 10 year age groups
Sex	As per Australian Medicare profile
Aboriginal or Torres Strait Islander status	Self-reported, categorised as: Aboriginal or Torres Strait Islander; non-Aboriginal or Torres Strait Islander
Highest education qualification	Self-reported, categorised as: did not complete high school; high school or equivalent; university or higher
Language other than English spoken at home	Self-reported language spoken at home (categorised as English only; any other)
Partnership status	Self-reported (categorised as: married or partnered; never married, separated, divorced or widowed)
Employment status	Self-reported, categorised as: not working/retires; part time; full time
Income	Self-reported annual household income
Private health insurance status	Self-reported of private health insurance, categorised as: private including basic hospital cover; private including extras (additional cover for ancillary non-hospital services); Department of Veterans' Affairs white or gold card; health care concession card; none.
Number of people can depend on	Self-reported, number of people you feel you can depend on living outside your home but within 1 hour travel. Categorised based on distribution of responses (0; 1-4; 5-10; 11+ people)
Number of healthy behaviours	Number of healthy behaviours,[178] of self-reported: non- smoking status; safe level of alcohol consumption (< 14 drinks per week); at least 2.5 hours of intensity-weighted physical activity per week;[179] and meeting daily dietary guidelines for fruit (2 serves) and vegetable (5 serves) consumption.[180]
Body Mass Index (BMI)	Calculated using self-reported height and weight. Categorised as: underweight (<18.5); healthy weight (18.5-25); overweight (25-30); and obese (30+).
Self-rated health	Self-reported, categorised as: excellent; very good; good; fair; poor
Multi-morbidity	Number of conditions, self-reported if a doctor has ever told you that you have: heart disease; high blood pressure; stroke; diabetes; blood clot; asthma; Parkinson's disease; and any cancer (except skin cancer)
Functional limitation	Self-reported, using the Medical Outcome Study physical functioning scale.[181] Categorised as: low distress, moderate distress; high distress; very high distress
Psychological distress	Self-reported, using the using the K10 Kessler Psychological Distress Scale.[182] Categorised as: low; moderate; high; and very high psychological distress.

3.4.4 Contextual information on health services and health service delivery

Further contextual information on geographic areas, health districts, and hospitals was identified from a variety of publicly available data sources. These are not considered 'linked' data as they do not pertain to a specific individual in the study, rather they characterises geographic areas or health services using publicly available information.

Geographic area

A number of variables were used to characterise geographic regions. Geographic remoteness was measured using the Accessibility/Remoteness Index of Australia (ARIA+).[173] Information on the density, composition, characteristics of and access to the health workforce from a variety of sources, including the 2006 Australian Census from the Australian Bureau of Statistics (ABS), the Australian Health Practitioner Regulation Agency Registration of Practitioners, the Health Landscape Australia tool from the Australian Primary Health Care Research Institute, the AIHW Medical Workforce Survey and the NSW Population Health Survey was explored. Each of these sources was subject to its own limitations, such as availability of data at the small area geographic level, representativeness of survey, and ability to characterise the health workforce. For example, simple headcounts of GPs do not account for the fact that different GPs work differing hours (e.g. full time or part time work) so provide different amounts of services, while many measures of full time equivalent (FTE) GPs using survey data often capture contracted work at the primary worksite, but not for multiple worksites, such as GPs who visit regional and remote communities.[183] Strengths and limitations of three different measures of workforce supply – headcounts, full time equivalent, and full time workload equivalent GPs, are presented in Table 3.4.

Only one measure of the primary care workforce was used in the final analyses for this thesis - the full time workload equivalent (FWE) number of GPs providing services in an area.[60, 183] This variable was chosen because it: (a) is conceptually appealing, representing the effective supply of primary care services in an area while taking into account patterns of part- and full-time work as well as multiple worksites of GPs; (b) unlike workforce surveys, is not subject to non-response bias, as it is derived using population-level data on claims for services; and (c) has been found to correlate reasonably well with other measures of the GP workforce.[183] FWE GPs were estimated using aggregate state-level data from the Department of Health and Ageing[184] and aggregate SLA-level data from the 2011 Social Health Atlas of Australia.[185] FWE GPs were calculated as the number of Medicare claims for GP services for residents of each SLA, divided

by the average number of claims per FWE GP in NSW. Population estimates were used as a population denominator to calculate the density of FWE GPs per 10,000 residents of each SLA.

Table 3.4: Area-level measures of the supply of GP services

	Headcounts of GPs	Full time equivalent GPs	Full time workload equivalent GPs
Concept	▪ Crude measure of number of GPs	▪ Measure of contracted hours	▪ Measure of the effective supply of GP services
Example data source	▪ Census ▪ Registrations ▪ Mailing lists ▪ Workforce survey	▪ Workforce survey	▪ Medicare claims data
Strengths	▪ Easy to calculate	▪ Accounts for mixture of full-time and part-time workforce	▪ Accounts for variable workloads and multiple worksites ▪ Population coverage
Limitations	▪ Does not account for variable working hours, or multiple worksites of GPs ▪ Data source may not be representative	▪ Data source may not be representative ▪ May not account for multiple worksites	▪ Needs to be indirectly derived from multiple data sources

Hospitals

Characteristics of hospitals in NSW, such as average number of available beds, bed occupancy rate, hospital staffing, and the proportion of admissions from emergency departments were sourced from the NSW Health Services Comparison Data Book 2008/2009.[186] This report is one of the only publicly available sources benchmarking hospital service characteristics across NSW, and is only available for public hospitals, with many characteristics (e.g. hospital bed occupancy rate) reported for the larger facilities only. While only a single report was used, this corresponded with the beginning of the follow-up period for most study participants. While a number of variables in this report were explored, only the average hospital bed occupancy rate was reported in Chapter 6. This chapter was largely methodological, and this variable was considered the most applicable to the existing literature on hospital characteristics and preventable hospitalisations.

An additional hospital characteristic, peer group of facility, was used in Chapter 7. This was obtained from the categorisation in the APDC. These values were checked against corresponding peer group values in the NSW Health Services Comparison Data Book.[186] While generally consistent, additional hospitals (and their corresponding peer group) were identified from later years of follow-up in the APDC, but not in the Health Services Comparison Data

Book, so this source was considered the most complete source of information. The definition and categorisation of hospital peer groups is in Appendix 1.2.

3.5 Data preparation

3.5.1 Data cleaning

Most of the person-level variables used in this thesis were from the 45 and Up baseline questionnaire data, which required extensive cleaning prior to use. First, all potential variables were checked against published expected counts[187] to ensure the data and formats provided were appropriate. Each variable was then coded and categorised meaningfully for analysis. This involved checking for outlying or inconsistent values, deciding whether to treat continuous variables (e.g. age, number of alcoholic drinks per day) in a continuous or categorical manner, and deciding on conceptually appropriate values that fit the distribution of the data (e.g. grouping income brackets, level of education). Variables representing more complex constructs, such as psychological distress using the K10 Scale[182] or level of functional limitation using the Medical Outcomes Study physical functioning scale[181] needed to be constructed according to the appropriate tool.

Data in each of the linked data sources were checked for duplicate records. Where patient demographic information was recorded (e.g. age, sex) it was checked for both internal consistency within the relevant dataset and consistency with the 45 an Up Study data; however data from the 45 and Up Study were considered the 'gold standard' and ultimately used for analysis. Linked mortality data provided a unique opportunity to assess the quality of data linkage, as study participants should not have other health records, or have entered the 45 and Up Study, after the date of death. Participants with such inconsistent dates were identified as having probable linkage errors.

3.6 Descriptive statistics

As a first step in each analysis, descriptive statistics were calculated. These were typically calculated as a crude number of events, or as a 'rate' by person year. Rates were calculated using the number of events for each person, divided by the person-years of follow-up time observed (e.g. from date of study entry to death or end of linked data, whichever came first).

3.6.1 Data visualisation

A custom data visualisation is used in this thesis to explore longitudinal patterns of health service use (Chapter 4). Data visualisations are an emerging tool for exploring and identifying underlying patterns in 'big data', and while guidelines exist on best practice principles for visualisation,[151, 188] there are few practical examples of their applied use in health services research.

A custom visualisation using standard analytic software (Stata) was developed, using the general structure of a timeline[150] while drawing off design principles of visualisation, vision and perception.[151, 188] For example, the purpose of the visualisation was to identify trends in health service use across individuals, and to compare these trends for similarities between types of health services. These comparisons were facilitated by juxtaposing health events on a similar scale; there were too many events for these to be superimposed, and the use of a common scale is known to be one of the most effective means of comparing the order and magnitude of items.[188]

Different colours were also used to help differentiate health events. Colours were identified from ColorBrewer 2.0 (http://colorbrewer2.org/), but specifically chosen to have similar luminance and saturation but differing hues. Major differences in the luminance and saturation of colours may result in different visual perceptions of the density of events (e.g. luminance influences the ability to detect edges, while events with greater saturation may be perceived as having a greater density of health events), while hues are considered to be one of the more effective means for differentiating between categorical attributes.[188]

The data visualisation contained data for a large number of study participants, with the scale exceeding the number of pixels used to produce the image. This size constraint limitation is a justification for interactive tools allowing a user to pan and zoom an image to fully explore the intricacies of the data.[151] However, ethical constraints on the publication of unit record data for individuals, as well as the practicalities of an academic publication, preclude such interactive visualisations being used. In line with the visualisation mantra '*overview first, zoom and filter, details on demand*',[189] static visualisations were chosen to portray an overview of the overarching trends in the data, with further details provided in supplementary descriptive statistics.

Similarly, while the interactive ability to filter and sort data is considered a key element of data visualisation,[150, 151, 154] this interactivity is not practicable for presenting information in a thesis or academic publication. These principles were however used to explore the data, which were

filtered into different populations (e.g. whole cohort, admitted patients, matched cohort of non-admitted patients), sorted by patient characteristics (e.g. number of hospitalisations, date of admission, length of stay, remoteness of residence, self-rated health) as well as zoomed in over different time scales (e.g. calendar year, 90-day period around admission). Various permutations of these configurations, revealing different insights into patterns of health service use, have been included in the chapter.

3.7 Statistical modelling

3.7.1 Multilevel modelling

The general structure of a multilevel model captures the effects of clustering by allowing both regression parameters and error terms to exist at different hierarchical levels. For example, an analysis might wish to include a variety of person-level variables (e.g. age, sex, health, education), as well as characteristics of the geographic area in which they live (e.g. remoteness, number of GPs working in area). In general linear terms, such a model can be expressed as:

$$Y_{ij} = \beta_0 + \sum_{p=1}^{P} \beta_p x_{pi} + \sum_{q=1}^{Q} \beta_q x_{qj} + u_j + e_i$$

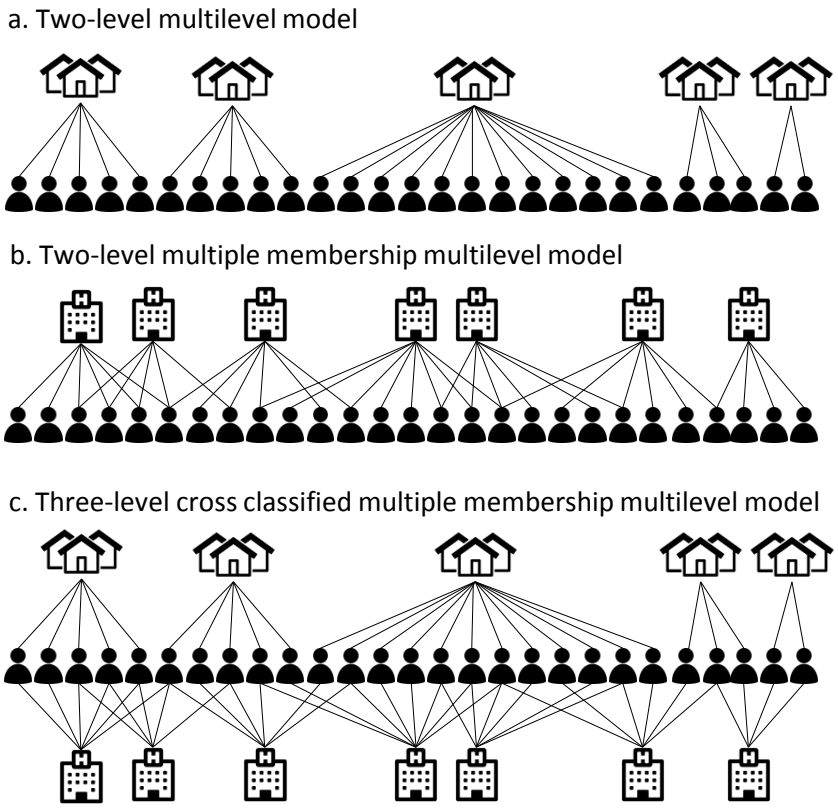
Where I people are clustered within J higher-level units (e.g. geographic areas of residence). Y_{ij} is the outcome, x_{pi} are the regression parameters for P person-level variables, and x_{qj} are the regression parameters for Q higher-level variables. β_0, β_p and β_q are the regression coefficients for the intercept, person-level and hospital-level parameters accordingly. e_i and u_j represent the residual variation at the person- and higher-levels, with e_i and u_j belonging to random distributions $e_i \sim N(0, \sigma_e^2)$ and $u_j \sim N(0, \sigma_u^2)$. Such a model can be generalised to GLMs for a range of outcomes, such as binary (e.g. whether a patient had a hospital admission) or counts (e.g. number of hospital admissions).

3.7.2 Models at different levels

The multilevel models used for the analyses presented in this thesis had several different hierarchical structures (Figure 3.2). The models used in Chapter 5 clustered study participants within their geographic area of residence, and had a standard two-level structure as described above. The models used in Chapter 6 clustered study participants within hospitals which

provide services to residents in the area, and used multiple membership multilevel models, which allowed participants to be clustered in more than one hospital. The models used in Chapters 6 and 7 clustered study participants in both in their geographic area of residence and the hospitals which provide services to residents in the area. As these two higher-levels were non-hierarchical (i.e. hospitals were not nested within a geographic region, nor were any regions unique to a hospital) a cross-classified multiple membership multilevel model was used.

Figure 3.2: Multilevel modelling data hierarchies used in this thesis, including information at the individual, geographic region and hospital levels



Multiple membership multilevel models[190, 191] allow data to be clustered in a hierarchical structure where a lower level unit, such as people, can be clustered in one or more higher level units, such as multiple teachers for students in a school, multiple nurses providing care to a patient, or in this case, multiple hospitals servicing a population. A multiple membership multilevel model extends the two-level approach above by allowing a weighted structure for each of the hospital-level components. A linear model with random intercepts can be written using classification notation[191] as:

$$Y_{ij} = \beta_0 + \left(\sum_{p=1}^{P} \beta_p x_{pi} + e_i \right) + \left(\sum_{r=1}^{R} \sum_{k=1}^{K} w_{k.i}^{(2)} \beta_q x_{qk}^{(2)} + \sum_{k=1}^{K} w_{k.i}^{(2)} u_k^{(2)} \right)$$

The superscript $^{(2)}$ indicates model components belonging to higher levels of classification (e.g. hospitals as the second level). Here, I people are clustered within K hospitals, with x_{qj} the regression parameters for R hospital-level variables, and u_k the residual variation at the hospital-level. To allow people to be clustered in more than one hospital, $w_{k.i}^{(2)}$ is the probability that person i will go to hospital k for their admission, with each hospital assigned a weight $\left(0 \leq w_{k.i}^{(2)} \leq 1\right)$ such that the sum of the weights equals one $\left(\sum_{k=1}^{K} w_{k.i}^{(2)} = 1\right)$. In this manner, people are proportionately clustered within all their potential hospital of admission, and the hospital-level parameters and random error terms become weighted averages of hospitals in the network. Where people are clustered within a single hospital, this simplifies to a regular two-level model structure.

The three-level model clustering study participants in both geographic area and hospital uses a cross-classified multiple membership multilevel model.[190-192] This model similarly includes regression parameters and residual error terms for the individual (level 1), geographic area (level 2) and weighted hospital (level 3) levels from the models above, although the higher levels are not nested in a hierarchical manner.

$$Y_{ij} = \beta_0 + \left(\sum_{p=1}^{P} \beta_p x_{pi} + e_i \right) + \left(\sum_{q=1}^{Q} \beta_q x_{qj}^{(2)} + u_j^{(2)} \right) + \left(\sum_{r=1}^{R} \sum_{k=1}^{K} w_{k.i}^{(3)} \beta_r x_{rk}^{(3)} + \sum_{k=1}^{K} w_{k.i}^{(3)} u_k^{(3)} \right)$$

3.7.3 Study Outcome

The study outcome, preventable hospitalisations, can be modelled and analysed in a number of ways (Table 3.5). This includes modelling as a binary outcome (ever/never having a hospitalisation) using a logistic model, time to first event using a Cox proportional hazards model, or a count of the number of hospitalisations using a Poisson model.

The Poisson model was chosen for three reasons. First, as participants had varying lengths of follow-up time, it incorporated the maximum amount of follow-up data. By using an offset of this exposure period the Poisson model models a 'rate' of admission, while a logistic approach would require similar exposure periods between participants (e.g. 2 years), and a Cox proportional hazards approach would be censored at first admission. Second, the Poisson approach accounts for multiple admissions for an individual. Finally, the Poisson approach best

corresponded with how the preventable hospitalisations is measured as a health performance indicate (rates of admission), aiding in the policy translation of results.

Table 3.5: Modelling approaches considered for analysing preventable hospitalisations

Outcome	Modelling approach(s)	Notes on implementation
▪ Ever had a preventable hospitalisation	▪ Logistic	▪ Simplest to implement ▪ Methodology well supported in the literature ▪ Doesn't account for multiple hospitalisations ▪ Doesn't utilise all follow-up data
▪ Time to first preventable hospitalisation	▪ Cox proportional hazards model	▪ Aligns the best with a cohort study design ▪ Utilises more, if not all follow-up data ▪ Doesn't account for multiple hospitalisations ▪ Difficult to implement the more complex multilevel models
▪ Number/rate of preventable hospitalisations	▪ Poisson ▪ Negative binomial ▪ Zero inflated Poisson	▪ Corresponds best with real world calculation and application ▪ Accounts for multiple hospitalisations ▪ Utilises all follow-up data ▪ Less support in literature for methods quantifying variation in multilevel models

A limitation of the Poisson approach is the assumption that the data fit a Poisson distribution. It is common for there to be some evidence of excess variation or 'overdispersion', with the variance of the crude rate (e.g. of hospital admission) being higher than the mean. In many cases this is dealt with by using a negative-binomial model, which has the same structure as a Poisson model but with an additional parameter to model the overdispersion. However, overdispersion may result not just from sources of random error, but also from unobserved systematic sources of variation, such as study participants' health, or clustering of people within geographic areas. It has been argued that fitting a model with an appropriate set of predictors which account for such sources of systematic variation may be more appropriate in accounting for overdispersion than the use of a negative-binomial model as a 'quick-fix' to adjust it away.[193] Given that a key aim of this research was to explore factors which contribute to variation in preventable hospitalisation, and that a comprehensive array of factors and hierarchical structures were available for analysis, the use of a Poisson model was considered more appropriate to address the aims of the thesis.

Similarly, some researchers have use a zero-inflated Poisson model to account for overdispersion when there are an excess number of zeros observed in the count data.[194] Such approaches often improve model fit, but assume a dual-state process is underlying the distribution of zeros and counts within the data.[195] This modelling approach was not further explored given the lack of a clear hypothesis justifying a two-stage mechanism, the

complicated nature of fitting multilevel zero-inflated models, and (as with negative-binomial models above) limitations in exploring sources of variation in models which include additional parameters to account for this residual variation.

3.7.4 Additional predictors and confounders

A range of covariates were explored or used for risk adjustment in this thesis. These include person-level variables, mostly identified from the 45 and Up Baseline questionnaire data, as well as area- and hospital-level variables characterising the area and/or health service. All covariates were selected according to the Andersen model of healthcare utilization,[163] in that they reflect factors which either predispose patients to use services (such as age, education, ethnicity), enable patients to use services (such as income, health insurance, availability of services), or reflect the patients' need for services (e.g. self-rated health, functional limitations). Incidence rate ratios (IRRs) and 95% confidence intervals (CIs) were calculated for each of the variables by exponentiating the regression parameters.

Missing values variables were treated as an additional variable category in all analyses. In Chapter 5 a 'complete case' sensitivity analysis was performed excluding participants with any missing values, with no notable change in the pattern of predictors or variation.

Care was taken when including covariates at higher (e.g. area, hospital) levels, as the number of units of observation at these levels were generally low (<300). Key exposure variables at these higher levels were usually included independently (Chapters 5-7), except when being used for risk adjustment purposes (Chapter 7).

Specification of the model structures used for the analyses in Chapters 5-7 have been provided in the relevant Statistical Appendices in Appendix 2.

3.7.5 Quantifying and explaining variation

The amount of residual variation between higher-level units (e.g. geographic areas, hospitals) in the multilevel analyses presented in this thesis was quantified using the variance of the random intercept parameter (σ^2). To explore and rank higher-level units (e.g. geographic areas, hospitals) in terms of their residual random effect, 'shrunken' residuals were extracted, which take into account a 'shrinkage' factor based on the estimated variance and size of the cluster.[196, 197]

One aim of the thesis was to explore sources of variation, and to assess how the inclusion of a variable explained variation at a particular level a proportional change in variance (PCV)[198] was calculated. The PCV compared the variance parameter between a base model (Model 1) and subsequent models (Model n) such that PCV=$(\sigma^2_{(Model1)}-\sigma^2_{(Modeln)})/\sigma^2_{(Model1)}$.

As the variance parameter can be difficult to interpret, higher-level variation was also quantified in a manner comparable to how IRRs were expressed for regression parameters in the model - as a median rate ratio (MRR).[199] The MRR for the variance σ_u^2 at a higher-level can be expressed as $MRR = \exp\left(0.95\sqrt{\sigma_u^2}\right)$, and can be interpreted as the median increase in rate of hospitalization if a person were to move from one cluster to another with a higher rate of hospitalization.

In Chapter 7 an alternate metric, the absolute relative deviation (ARD) was used.[200] The ARD is calculated using the higher-level residuals, and so allows quantification of the degree of variation between subgroups of higher-level units. The ARD was calculated as $ARD = \sum_{j=1}^{n}\left(n_j \times abs\left(\exp\left(u_j\right)-1\right)\right)/\sum_{j=1}^{n} n_j \times 100$, where n_j is the person-years of follow-up in higher level unit j, and u_j is the residual for higher level unit j from the multilevel model.

Further techniques for quantifying variation between levels are possible, such as a variance partitioning coefficient (VPC), otherwise known as the intraclass correlation coefficient (ICC), which quantifies the amount of residual variation at each level in the model.[192, 198] For example, in a two-level linear model with variance estimates at the individual $\left(\sigma_i^2\right)$ and area (σ_a^2) levels the proportion of variance at the area level would be calculated as $VPC = \sigma_a^2/\left(\sigma_a^2+\sigma_i^2\right)$. However, methods for calculating a VPC from Poisson models are not well supported in the literature. For logistic models, which use a logit link, the variance at the individual level is on a different scale (probability scale) to the variance at the higher-levels (logistic scale), and so transformation to a common scale is required.[199] One common solution for logistic models, known as the latent variable method,[192, 199] assumes the outcome is a latent continuous variable underling the binary outcome, and the people who have the outcome are those whose latent variable crosses a particular threshold. This allows the individual-level variance to be estimated as a function of the logistic distribution such that $\sigma_i^2 = \pi^2/3$. However, you cannot assume such a binary threshold when using a Poisson outcome on counts of hospitalisation, and so this method was not considered appropriate.

3.7.6 Statistical software

All data manipulation and preparation was performed in SAS versions 9.3 and 9.4. All multilevel models were run in specialised multilevel modelling software MLwiN[201] versions 2.25 and 2.35. All plots and figures were produced in Stata versions 12.0 and 14.1.

3.7.7 Assessing model convergence

Multilevel models in Chapter 5 were fitted using a second order penalised quasi-likelihood estimation procedure. Models for conditions with a small number of outcomes were not considered stable enough to be reported. Improvement in model fit over stepwise models was assessed using the proportion of residual variation being explained through additional variable inclusion in the model. Area-level residuals were checked to see if they fit a random distribution. Regression output from MLwiN was checked for consistency against comparable output from SAS (using 'GLIMMIX' procedure) and Stata (using 'xtmepoisson' command).

Multiple membership multilevel models in Chapters 6 and 7 were fitted using Markov chain Monte Carlo (MCMC) estimation, using 5000 burn-in samples and 20,000 iterations. Convergence of model parameters was assessed by visually monitoring chains of parameter trajectories.[202] Trace plots were examined for sufficient mixing among parameter estimates, with convergence assessed if the trace of parameter estimates approximated white noise. A smoothed histogram of the parameter estimates was also inspected, expected to approximate a normal distribution. Variance parameters were expected to have a skewed normal distribution with a longer right tail. Parameters which continued to show poor mixing, as well as correlation with the intercept parameter, were centred on their mean value.

Autocorrelation was visually assessed using the autocorrelation and partial autocorrelation functions. Accuracy was assessed using the Brooks-Draper diagnostic,[202] giving the estimated number of iterations to produce a mean estimate to 2 significant figures with accuracy of α=0.05. Where this value exceeded 20,000 (the base number of iterations), the number of iteration was increased to 100,000 and 250,000, if necessary, where consistency in parameter values, and changes in the Brooks-Draper diagnostic, were observed.

MCMC models were compared using the Deviance Information Criterion (DIC),[191] a likelihood-based measure which allows comparison between non-nested models. Models with a lower DIC were considered to be the models of better fit.

3.8 Ethics approval

Ethical approval for the 45 and Up Study was given by the University of New South Wales Research Ethics Committee. Ethical approval for the APHID Study was given by the NSW Population and Health Services Research Ethics Committee (PHSREC), the Aboriginal Health and Medical Research Council (AH&MRC) Research Ethics Committee, and the Western Sydney University Human Research Ethics Committee. Ethical approval for the GRAPHC Study was given by NSW PHSREC and the Western Sydney University Human Research Ethics Committee.

Chapter 4 Health service use around preventable hospitalisation

4.1 Background to chapter

While preventable hospitalisations are used as an indicator of access to and quality of primary care, there is surprisingly little information available on how patients are actually using health services, with most evidence coming from ecological measures of primary care supply. The objective of this chapter was to explore how patients admitted for a preventable hospitalisation were using health services around the time of admission, including the lead up to and following preventable hospitalisation, as well in comparison to the general population. To meet this objective, a novel method for visualising complex patterns in administrative health data was created.

This chapter uses data from the updated data extract in the APHID Study.

4.1.1 Publication details

This chapter has been published as:

- Falster MO, Jorm LR, Leyland AH. Visualising linked health data to explore health events around preventable hospitalisations in NSW Australia. *BMJ Open* 2016;6:e012031.

Please note that some online supplementary material from the publication has been presented within this chapter, and there has been minor edits to the labels of tables, figures and the online supplementary material to format this publication for the thesis. A copy of the final publication is included in Appendix 4.

4.2 Abstract

Objective

To explore patterns of health service use in the lead up to, and following, admission for a 'preventable' hospitalisation.

Setting

266,950 participants in the 45 and Up Study, NSW Australia

Methods

Linked data on hospital admissions, GP visits, and other health events were used to create visual representations of health service use. For each participant, health events were plotted against time, with different events juxtaposed using different markers and panels of data. Various visualisations were explored by patient characteristics, and compared to a cohort of non-admitted participants matched on socio-demographic and health characteristics. Health events were displayed over calendar year and in the 90 days surrounding first preventable hospitalisation.

Results

The visualisations revealed patterns of clustering of GP consultations in the lead up to, and following, preventable hospitalisation, with 14% of patients having a consultation on the day of admission, and 27% in the prior week. There was a clustering of deaths and other hospitalisations following discharge, particularly for patients with a long length of stay, suggesting patients may have been in a state of health deterioration. Specialist consultations were primarily clustered during the period of hospitalisation. Rates of all health events were higher in patients admitted for a preventable hospitalisation than the matched non-admitted cohort.

Conclusions

We did not find evidence of limited use of primary care services in the lead up to a preventable hospitalisation, rather people with preventable hospitalisations tended to have high levels of engagement with multiple elements of the healthcare system. As such preventable hospitalisations might be better used as a tool for identifying sicker patients for managed care programs. Visualising longitudinal health data was found to be a powerful strategy for

uncovering patterns of health service use, and such visualisations have potential to be more widely adopted in health services research.

Strengths and limitations of the study

- This is the first study to explore the temporal pattern of health events and health service use around preventable hospitalisations using large population-level data.
- Novel data visualisations allowed for efficient identification of health events before, during, and following preventable hospitalisation, as well as population level patterns of health service use.
- The visualisations are descriptive are not adjusted for patient factors such as age, sex and health status.
- The findings may not be generalizable to other healthcare systems, but the visualisations offer a novel approach that can be adopted for comparative research.

4.3 Introduction

Preventable hospitalisations have been adopted internationally as an indicator of timely and effective access to primary care services. Originally conceived in the late 1980's,[33] preventable hospitalisations, also known as ambulatory care sensitive or avoidable hospital admissions, comprise admissions for a set of diagnosis codes which are considered to be potentially preventable if the patient had access to quality primary care services. Intuitively appealing, these hospitalisations are reported by governments for performance measurement of the primary care system,[25, 32] and are used commonly in research as a health outcome measure. However, there has been surprisingly little research exploring the actual use of primary health care services around the time of hospitalisation, which requires linkage of primary care and hospital data for individuals.

As data on primary care are not always routinely collected, much of the research on preventable hospitalisations has been ecological, comparing population-based rates of hospitalisation to proxy measures of access, such as the supply of GP services in an area,[69, 73, 80, 203] the average number of available hospital beds,[75, 130] socio-economic characteristics of the population,[19] or perceived access to care.[39, 67] However, aggregated approaches may be subject to an ecological fallacy,[110] and there is a view that access can be more meaningfully explored through patient behaviour, or 'realised' access to care relative to need, rather than barriers that predispose or enable patients' access to services.[165]

The few studies with linked, person-level data on health service use have investigated the impact of provider continuity[89, 91] or the number of primary care consultations[94, 95] on rates of hospitalisation, broadly finding that people with more GP visits or with more visits to the regular provider of care had lower rates of preventable hospitalisation (with the exception of very high use patients). However, patients' use of primary care services differs greatly across countries and healthcare systems[8] and can be confounded by the disposition and need of a patient to use the services,[164] and there is growing debate on exactly what role GPs can take in further reducing rates of preventable hospitalisation.[60, 84, 112, 203, 204] Notably, there has been no exploration of the temporal pattern of primary care in the lead up to a preventable hospitalisation, which is important given many of these admissions are assumed to be avoidable if a person suffering an acute exacerbation could obtain care in a primary care setting.

Data visualisations are a promising method for exploring patterns of health events. Widely considered to be a powerful technique for investigating and identifying underlying patterns in 'big data',[188] a number of visualisation tools have been developed for longitudinal health data, typically presenting a visual timeline of health events for one or more patients over time.[150, 153-157] While there are a number of variations on this technique, such as centring patients' time on specific health events,[158] grouping patients with similar health trajectories,[156, 157] or as a dashboard displaying various clinical characteristics,[155, 159] these tools have not been widely utilised within health services research. This may be because the relevant software tools were developed to aid patient monitoring, clinical decision making, and interactive data interrogation, and so have limited capabilities for the varied and complex needs of researchers.[205, 206] An exploration of preventable hospitalisations, for example, would require combining different types of events (e.g. single day GP visits, multiple day hospital admissions) for large population-based cohorts, while adhering to ethical standards in maintaining the privacy of individual patients.[207] While no such visualisation tool currently exists, there is unfulfilled potential to create simple visualisations using more general visual analytic tools.

This study sought to explore the temporal pattern of health service use around preventable hospitalisations for participants in a large cohort of older adults in NSW Australia, using a novel data visualisation of trajectories of individual patient health service use.

4.4 Methods

4.4.1 Data sources

Linked health data were used within the APHID study, details of which have been published elsewhere.[171] Briefly, APHID includes participants from the Sax Institute's 45 and Up Study,[166] a prospective cohort of 266,950 men and women aged over 45 in NSW, Australia. Study participants were recruited from 2006-2009 through the Department of Human Services' Medicare system (Australia's national universal health insurer). At study entry participants completed a detailed questionnaire on their socio-demographic and health characteristics, and provided signed consent for long-term follow-up, including linkage to administrative health data sets.

For each study participant, linked data were obtained from a number of data sources. Hospitalisations were obtained from the NSW APDC, a census of all hospital separations (discharges, transfers and deaths) from all NSW public and private sector hospitals and day-procedure centres, with linked data available from 2000-2013. ED data were obtained from the NSW EDDC, which contains information on presentations to 80 EDs in NSW, capturing around 75% of all presentations to NSW EDs, with linked data from 2006-2013. Medicare-funded claims for GP and specialist medical practitioner consultations were obtained from the MBS, the country's universal health insurance scheme for subsidised medical care, with linked data from 2005-2011. Fact of death data were obtained from the NSW RBDM mortality data file, with linked data from 2006-2013.

Probabilistic data linkage of the APDC, EDDC and the RBDM mortality data was performed by the NSW Centre for Health Record Linkage (http://www.cherel.org.au/) using ChoiceMaker software; a manual clerical review on a sample of linkage records found a false positive linkage rate of 0.3%. Linkage of Medicare data was performed deterministically by the Sax Institute using a unique person identifier. Ethics approval for the 45 and Up Study was granted by the University of New South Wales Human Research Ethics Committee, and approval for the APHID study was granted by the NSW Population and Health Services Research, Aboriginal Health and Medical Research Council, and University of Western Sydney Research Ethics Committees.

4.4.2 Health events and health service use

Preventable hospitalisations were identified in the hospitalisation data according to the indicator used in the Australian 2012 National Healthcare Agreement. This comprises admissions for 21 different conditions broadly categorised as 'chronic', 'acute' and 'vaccine-preventable', and includes conditions such as diabetes complications, angina, asthma, and influenza (Appendix 1.1).[22]

A range of other types of health events were identified in the linked health data, including claims for GP or specialist medical practitioner services from the MBS data, all presentations to an ED from the EDDC data, all other hospitalisations from the APDC data, and all deaths from the RBDM mortality data file. The criteria for identifying each type of event are provided in Table 3.2.

All preventable hospitalisations for study participants were identified during a snapshot time-window, 1st January to 31st December 2010, for which linked data from all data sources were available. To explore events surrounding preventable hospitalisations, records for GP consultations, ED presentations, all other hospitalisations, specialist consultations, and deaths were extracted for an extended period around this time-window, 1st July 2009 to 30th June 2011.

4.4.3 Visualising longitudinal health data

The visualisations presented unit record data using static timelines,[150] with each row on the y-axis representing a person, and each point on the x-axis representing a point in time. Single date events, such as a health consultation, disease notification, or death were represented by a point or symbol at that moment in time. Interval events, such as a hospital stay, were represented by a line indicating the length of the event.

To bring structure to the figures so that patterns were easier to identify, each type of health event was plotted using a different colour and on a separate vertical panel. Patients on the y-axis were sorted according to features of their preventable hospitalisations, including whether they were admitted or not, the number of hospitalisations, date of first hospitalisation and length of hospital stay, as well as their personal characteristics, such as remoteness of area of residence or self-rated health. Time on the x-axis was displayed either centred on the date of first admission, or spread over the calendar year. A variety of plots were produced, varying the time scale (calendar time, 90 day period surrounding first admission), or the order in which

participants were displayed. The plots were interpreted by looking for visual patterns in the position, density or clustering of the health events.

In order to compare patterns of health events to the general population, relative to the need and disposition to use health services, a propensity-matched sub-cohort of participants who had not been admitted for a preventable hospitalisation was also identified. This cohort was matched to the admitted cohort on a range of socio-demographic (e.g. age, sex, geographic remoteness of residence,[173] income, education) and health (e.g. body mass index, self-rated health, multi-morbidities, functional limitations) characteristics using a 'greedy' matching algorithm.[208]

All data manipulation was performed in SAS v9.3, while all figures were produced in Stata 12.0. An example of data structure and Stata syntax for producing a plot are provided in Appendix 4.

4.5 Results

Of the 266,950 study participants, 1.7% (n=4,717) died prior to 2010, leaving 262,233 participants for analysis. Of these, 8,715 were admitted for a preventable hospitalisation in 2010, of whom 78% were admitted for a preventable hospitalisation once, 16% were admitted twice, 3% were admitted three times, and 3% were admitted four or more times. 63% of preventable hospitalisations were for chronic, 35% for acute and 2% for vaccine-preventable conditions, with patients admitted for chronic conditions tending to have on average more hospitalisations per person (Table 4.1).

Figure 4.1 presents a plot of health events for all persons admitted for a preventable hospitalisation in 2010, with time centred on the 90 days before and after the first date of admission. Patients are sorted by their total number of preventable hospitalisations and length of stay, so that the preventable hospitalisations form a 'funnel' shape. At the time of admission, there is a clear corresponding 'shadow' of GP consultations and ED presentations, indicating that many patients used these services in the lead-up to admission. Subsequent descriptive statistics (Table 4.2) found that 14.5% of patients had a GP consultation on the day of admission, with 27.4% of patients having at least one further GP consultation in the week leading up to the day of admission, and 64.8% in the prior month. Almost half (48.9%) of patients presented to an ED on the day of admission.

Table 4.1: Breakdown of preventable hospitalisations of 45 and Up Study participants in 2010 by type of condition

Category of preventable hospitalisation	Hospitalisations		
	Total admissions	Admitted patients	Average # admissions per patient
Preventable hospitalisation			
All preventable hospitalisations	11,645	8,715	1.3
Chronic conditions			
All chronic	7,351	5,228	1.4
Diabetes complications	1,911	1,429	1.3
Angina	1,703	1,364	1.2
COPD	1,576	986	1.6
Congestive cardiac failure	1,237	945	1.3
Iron deficiency anaemia	734	633	1.2
Asthma	190	159	1.2
Hypertension	164	154	1.1
Rheumatic heart disease	60	47	1.3
Nutritional deficiencies	6	4	1.5
Acute conditions			
All acute	4,103	3,614	1.1
Dehydration & gastroenteritis	1,118	1,061	1.1
Pyelonephritis	1,048	911	1.2
Cellulitis	873	739	1.2
Dental conditions	487	464	1.0
Convulsions & epilepsy	239	198	1.2
Ear, nose, throat infections	141	138	1.0
Perforated/bleeding ulcer	103	100	1.0
Gangrene	57	52	1.1
Pelvic inflammatory disease	19	17	1.1
Appendicitis	18	17	1.1
Vaccine-preventable conditions			
All vaccine-preventable	221	179	1.2
Influenza & pneumonia	198	160	1.2
Other vaccine-preventable	24	20	1.2

There was a similar ‘shadow’ indicating increased levels of GP visits, other hospitalisations and deaths in the period immediately following discharge, particularly for patients with a longer length of stay (Figure 4.1). Rates of death in the broader period following discharge similarly appeared to increase for patients with a longer length of stay.

Figure 4.1: Health events in the 90 days leading up to, and following, first preventable hospitalisation, with patients sorted by their number of preventable hospitalisations in 2010 and length of hospital stay

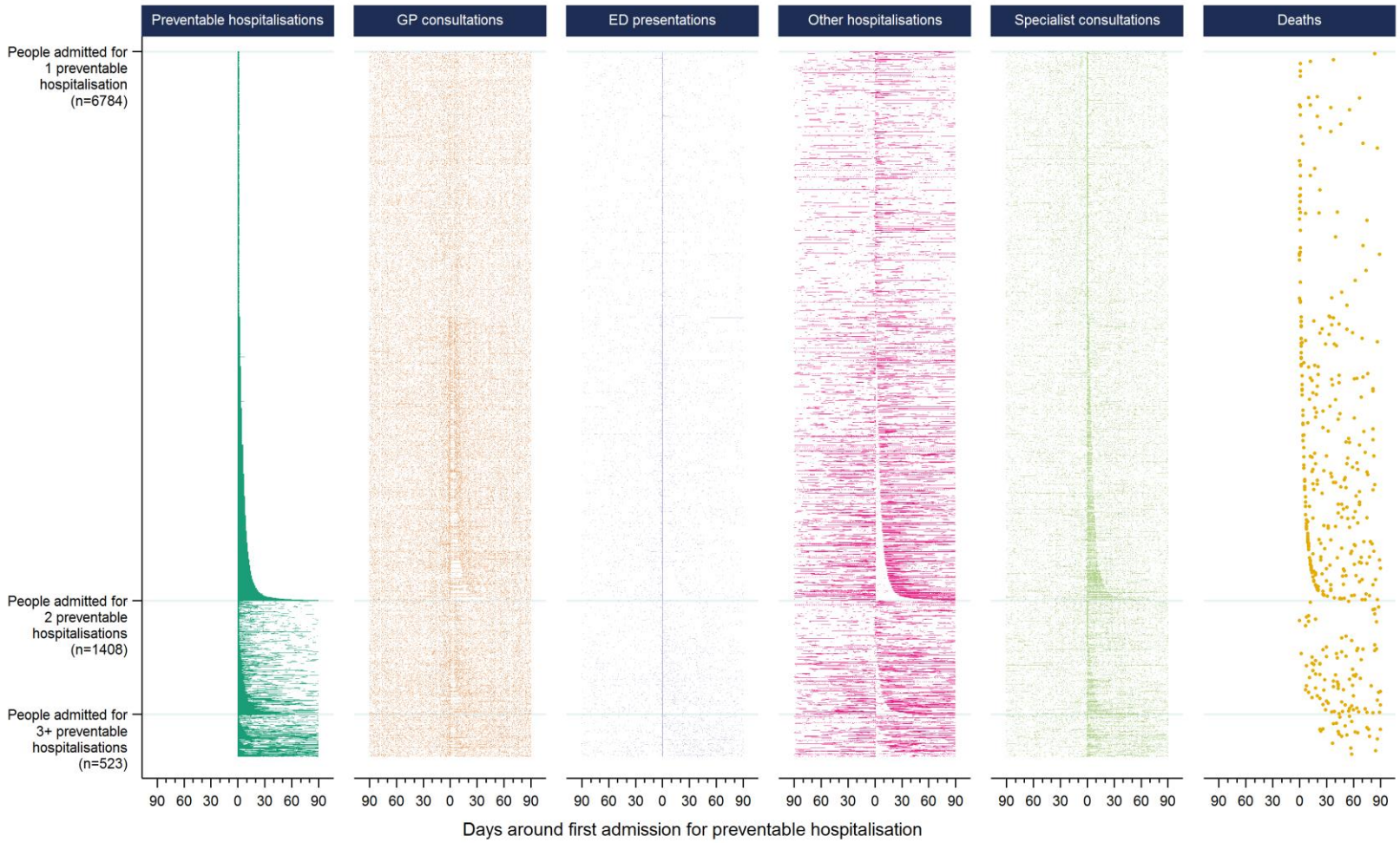


Figure 4.2: Health events in participants admitted for preventable hospitalisation in 2010, and a demographically-matched cohort of non-admitted participants

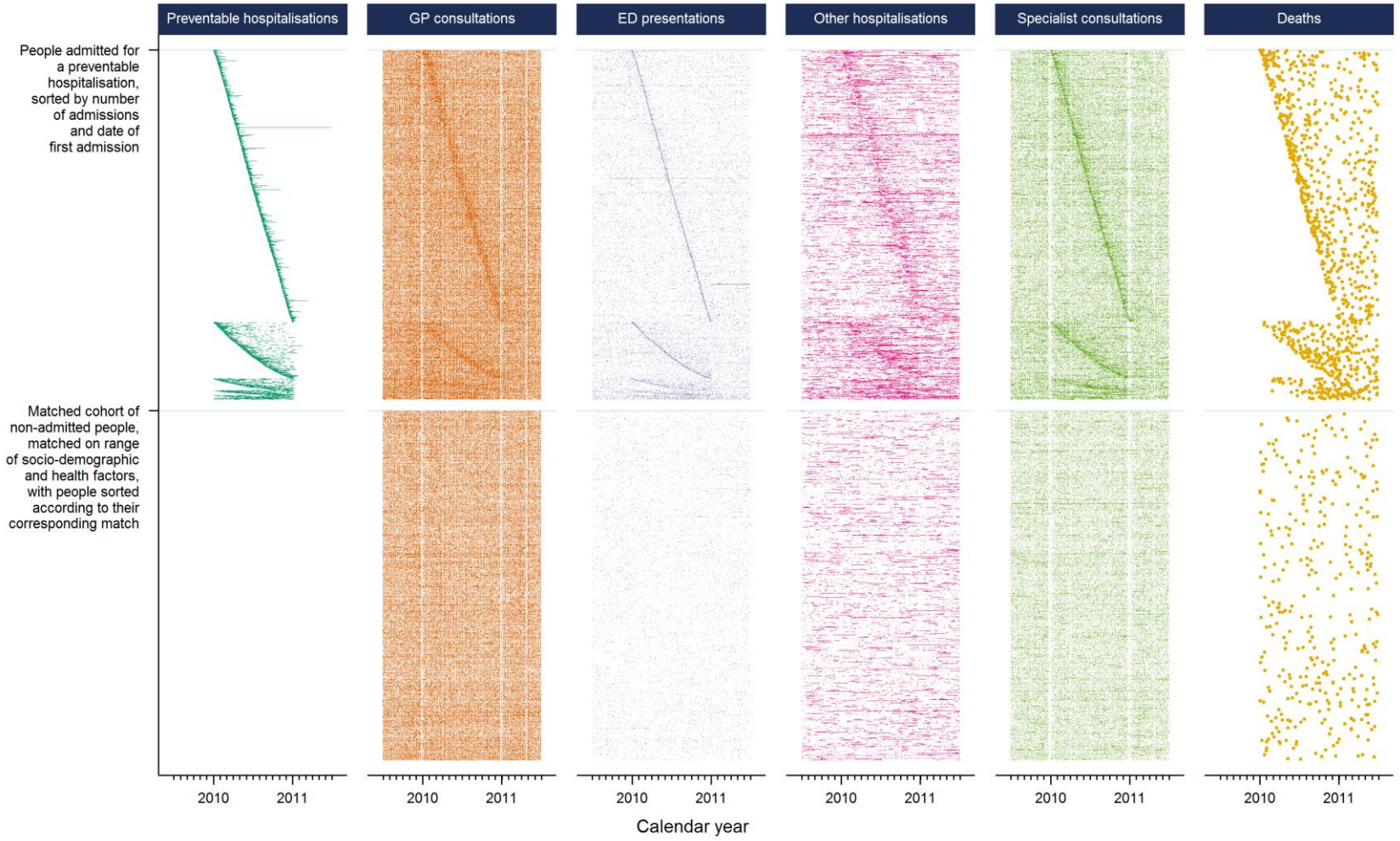


Table 4.2: Health events in the 3 months preceding and following first preventable hospitalisation

Type of health event/health service use	Same day	Cumulative % of admitted patients with health event in period surrounding[a] first preventable hospitalisation			
		1 day	1 week	1 month	3 months
Prior to day of first admission					
GP consultation	14.5%	6.8%	27.4%	64.8%	87.2%
ED presentation	48.9%	2.4%	5.4%	11.4%	20.3%
Other hospitalisation	0.8%	0.8%	3.9%	12.0%	23.1%
Specialist consultation	26.2%	2.6%	12.5%	37.9%	60.1%
Following day of first discharge					
Preventable hospitalisation	0.6%	0.5%	2.3%	7.1%	12.7%
GP consultation	6.9%	7.3%	37.0%	72.3%	87.7%
ED presentation	6.2%	1.0%	4.4%	12.3%	23.1%
Other hospitalisation	1.2%	0.9%	4.5%	14.1%	27.9%
Specialist consultation	26.6%	4.2%	13.4%	41.6%	64.7%
Deaths	1.5%	0.1%	0.3%	1.4%	3.9%

[a] *Does not include health events on the days of preventable hospitalsiation.*

Specialist medical practitioner consultations appeared to be largely provided during the period of hospitalisation (Figure 4.1), although 12.5% of patients had a specialist consultation in the week prior, and 37.9% in the month prior to hospitalisation (Table 4.2). In total, 30.4% and 75.3% of patients used either GP or specialist services in the week and month prior to hospitalisation, respectively (Table 4.3).

Table 4.3: Interaction between GP and specialist consultations in the period leading up to first preventable hospitalisation

Type of health event/health service use	Cumulative % of admitted patients with health event in period prior to day of first preventable hospitalisation			
	1 day	1 week	1 month	3 months
Prior to day of first admission				
GP consultation only	6.6%	23.9%	37.4%	30.7%
Specialist consultation only	2.5%	8.9%	10.5%	3.5%
Both GP and specialist consultation	0.1%	3.6%	27.4%	56.5%
Neither GP or specialist consultation	90.7%	63.6%	24.7%	9.2%

To determine if health events and service use were different among admitted patients to the general population, Figure 4.2 plots health service over calendar year for study participants admitted for a preventable hospitalisation, and the matched cohort of study participants not admitted for a preventable hospitalisation. Admitted patients were sorted by their total number of preventable hospitalisations and the date of first admission, so that preventable hospitalisations form the shape of a line. The non-admitted participants were sorted according

to their corresponding match. The two cohorts were very similar across socio-demographic and health characteristics at the time of study entry (Appendix 4).

There are visible vertical 'gaps' in Figure 2 among claims for GP and specialist consultations over calendar years, corresponding to weekends and holiday periods (e.g. Christmas, Easter) where many healthcare professionals (and patients) are on leave. As with Figure 4.1, there is a corresponding 'shadow' among all health events occurring around the time of a preventable hospitalisation. Across the whole calendar year, the density of health events appears to be greater for admitted patients than their matched non-admitted peers. Subsequent descriptive statistics (Table 4.4) found the rate of health events in the admitted patients was more than twice that of the matched non-admitted participants for all type of events except GP (around 30% higher) and specialist (around 85% higher) consultations. There was a slight increase in the density of all health events for patients with a greater number of preventable hospitalisations.

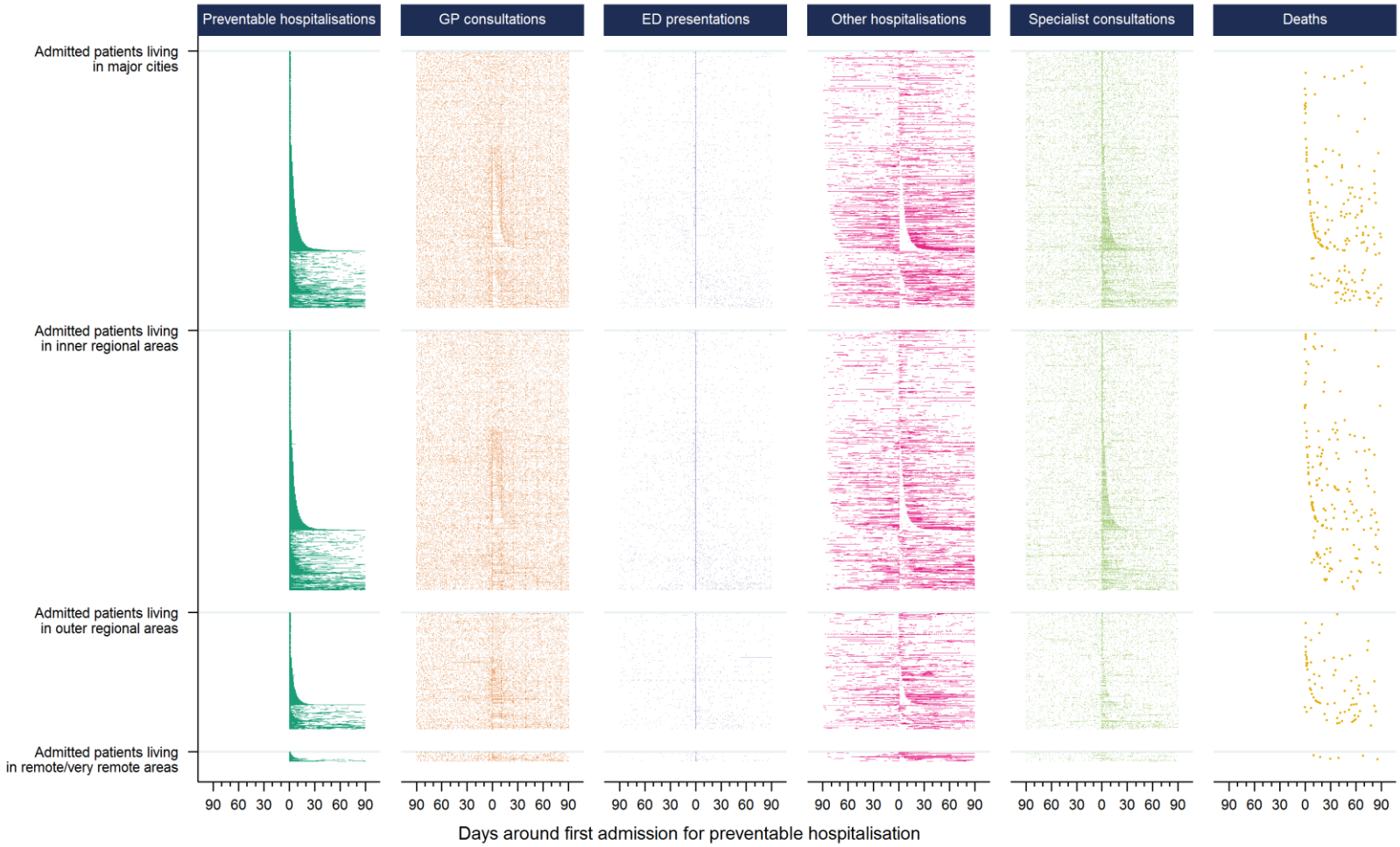
Table 4.4: Rates of health events per person-year[a] for study participants admitted with a preventable hospitalisation during 2010, as well as an age, sex, and geographic remoteness matched cohort of study participants not admitted for a preventable hospitalisation

Type of health event/service use	Participants admitted with preventable hospitalisation					Matched[b] non-admitted cohort (n=8,715)
	Total (n=8,715)	By number of admissions				
		1 (n=6,784)	2 (n=1,408)	3 (n=299)	4+ (n=224)	
GP consultations	13.1	12.5	14.7	17.0	17.4	9.7
ED presentations	1.3	1.1	1.7	2.2	3.8	0.4
Other hospitalisations	2.1	1.9	2.3	3.3	5.9	0.8
Specialist consultations	6.8	6.2	8.4	10.6	12.3	3.7
Deaths	0.08	0.07	0.12	0.15	0.23	0.03

[a] For GP consultations, ED presentations, other hospitalisations and specialist consultations, an observation period from, 1 July 2009 to 30 June 2011 or death (whichever came first). For deaths, an observation period from 1 January 2010 to 30 June 2011 or death (whichever came first), as only study participants alive at 1 January 2010 were considered for analysis.

[b] Study participants not admitted for a preventable hospitalisation in 2010, propensity matched to participants admitted for a preventable hospitalisation by age (in 10 year age groups), sex, remoteness of residence, education, marital status, language spoken at home, Aboriginal or Torres Strait Islander status, employment status, household income, private health insurance, number of people can depend on, BMI, self-rated health, multimorbidity, functional limitations, and psychological distress (Appendix 4).

Figure 4.3: Patterns of health events and health service use in the 90 days leading up to and following first admission for a preventable hosptialisation, with patients sorted by the remoteness of hteir geographic area of residence, number of preventable hospitalisations in 2010 and length of hospital stay



Additional plots display all study participants sorted by their self-reported health status (Appendix 4); and all admitted patients sorted by the remoteness of their area of residence (Figure 4.3). These plots show a gradient of increased levels of service use with poorer self-rated health, and that many residents in regional areas, but not major cities, have GP consultations during the period of their hospitalisation, respectively.

4.6 Discussion

This study was the first to explore the temporal pattern of health events in the periods preceding and following preventable hospitalisation, and in doing so created novel visualisations of trajectories of individual patient health service use. We found that participants admitted for a preventable hospitalisation did not show evidence of limited access to primary care, rather they tended to have high levels of engagement with the healthcare system, with higher rates of health events and service use than non-admitted patients, and a clustering of other health events at the time of preventable hospitalisation.

Only a very few studies, none from Australia, have had linked data on both a persons' use of primary care services and preventable hospitalisations with which to compare our results,[84, 91, 94, 95] but our findings are consistent with the view that preventable hospitalisations may be more reflective of gradients of health than of poor access to health care.[84, 112, 203] Australia has a universal health care system with GPs as gatekeepers to specialist care, and use of services may be more reflective of need than in the US, the setting for much of the previous research on preventable hospitalisations. Health-related factors have been found to be some of the strongest and most consistent drivers of preventable hospitalisation,[125, 203] and the clustering of other hospitalisations and deaths following discharge indicate many patients might be in a state of health deterioration. Indeed, participants admitted for a preventable hospitalisation had twice the number of annual GP visits (13.1 per year) compared to the Australian average (6.5)[8] and around 30% more GP consultations than people from the same study population with similar socio-economic status and health characteristics (9.8). With similarly higher rates of ED presentations and specialist consultations, this elevated pattern of realised access to services is likely to indicate greater health need beyond the factors used for propensity matching.

These findings support strategies for reducing the overall health care burden by targeting patients with high levels of health service use, such as through managed care programs.[209] Integrated care programs involving coordination between healthcare providers for patients

with complex needs have been found to be effective in reducing hospitalisations.[210, 211] The current findings that almost two-thirds of patients had visited a GP in the month leading up to admission, that many patients, especially in rural areas, had GP consultations during their hospitalisation, and that many patients had specialist visits both in the lead-up to and during their hospitalisation, suggest these admissions may have been a considered part of their care. Furthermore, the clustering of multiple health events, particularly other hospitalisations, around the time of preventable hospitalisation indicates poor specificity should the indicator be interpreted as an isolated 'preventable' health event. By visualising patterns of health service use, the visualisations in this study offer a useful starting point for identifying classes of high use individuals, rather than specific types of hospitalisations, for targeted policy intervention.

While claims based measures of GP and specialist use give an indication of patients realised access to services, they are limited in their ability to unpack further dimensions around access to, or quality of, care. For example, 14% of admitted patients had seen a GP on the same day as their preventable hospitalisation, but the current data did not allow temporal sequencing of events on the day of admission, such as referrals by a GP or admissions through an ED. Accordingly, we could not determine whether these visits were the direct antecedents of the admission, or could perhaps have been opportunities for it to be prevented through timely provision of care. Patients may face a number of barriers, such as waiting times and cost, that in Australia are often not proportional to patients' need.[16] However, data on service use is an integral part of understanding patients' access to health care,[16] and studies further integrating patient and doctor experiences and measures of health need[212] will help consolidate our understanding of the true 'preventability' of these admissions.

The elements used here for creating the visual trajectories of individual patient health service use have been well explored within the literature. Timelines have been used to plot longitudinal health events in a number of ways, as point events or intervals, and for individual patients[155, 158] or clustered groups.[156, 157] Filtering, ordering, and aligning people and events are known to help add structure to help identify underlying patterns of the data,[158, 188] and similarly colouring, juxtaposing and superimposing different items is known to be an effective means for comparing and contrasting groups.[188] However, no visualisation tool has combined these elements in a manner which allows the flexible presentation of large-scale data on patterns of health service use. This is not surprising, given the current visualisation tools are more oriented towards clinical information for patient management, and there is great

diversity in the size, shape or format of the administrative data that are used for health services research.

Although a range of software platforms are available for producing custom visual analytics, the plots in this study present a simple approach to visualisation using longitudinal data that is an accessible 'first step' for researchers. They were created using standard statistical software, could be created in a range of other software packages, and could be used for studies exploring, for example, pathways of patient admissions, transfers and referrals; disparities in health service use; outcomes following surgery or hospitalisation; or adherence to pharmacotherapy or treatment protocols. However, one limitation is that considerable thought needs to go into the construction of the plots. Choosing the right structure, such as a juxtaposed or superimposed plots, as well as characteristics of the data items, such as point, line and symbol size, hue and luminance are important to ensure accurate visual comparisons are made. Good guidance exists to help with these choices.[150, 188] Consideration should also be made to the size of the plot, and whether the number of pixels available will be sufficient to present the quantity of information required. In this study, large amounts of information were presented in a comparably small image, allowing clear identification of overarching patterns in the data yet protecting individual privacy because data trajectories of individual patients are almost impossible to identify. While for many researchers the benefits of a customised visualisation may be outweighed by the usability and support of off-the-shelf interactive software tools, these plots are technically feasible within a range of software packages and easier adoption in the future may come through users sharing metadata and syntax, such as in that provided in Appendix 4, or the adaption of software tools targeted towards more flexible displays of longitudinal health data.

A limitation of the study is that participants in the 45 and Up Study are older and potentially healthier than the general population,[166] and with a low study participation rate (18%), there may be concerns about generalisability. However, persons aged 45 years and above represent a clinically meaningful population, contributing two-thirds of preventable hospitalisations in Australia, and with the highest rates of admission.[30] While previous research has found internal risk estimates from the 45 and Up Study to be comparable to those from population health surveys,[169] and there is sufficient heterogeneity between study participants to allow for valid within-cohort comparisons, the visualisations in this study were descriptive and largely unadjusted. However, the core strength of these visualisations is that they allow interrogation of the data not possible using standard epidemiological methods, and it is difficult to conceive

a more effective method for exploring the complex pattern of health events before, during, and following preventable hospitalisation.

4.7 Conclusion

This study did not find evidence that preventable hospitalisations reflected limited use of primary care services, rather admitted patients tended to have high levels of engagement with multiple elements of the healthcare system. Preventable hospitalisations in Australia may therefore be more useful as a tool for identifying sicker patients for managed care programs, which can improve the quality, coordination and timeliness of care received, rather than as an indicator of supply of primary care. Visualising longitudinal health data was found to be a powerful strategy for uncovering patterns of health service use, and while technically possible, is underutilised within health services research. Such visualisations have potential to be more widely adopted.

Chapter 5 Factors influencing geographic variation in hospitalisation

5.1 Background to chapter

Much of the existing literature validating preventable hospitalisations as an indicator of primary care has compared geographic rates of preventable hospitalisation with the supply of primary care services in the area. However, various factors potentially contribute to rates of admission, but most studies have had only limited exploration of the role of patient characteristics.

The objective of this chapter was to investigate the relative contribution of primary care supply and personal socio-demographic and health characteristics to geographic variation in preventable hospitalisation.

This chapter uses data from the APHID Study. A statistical appendix includes model specifications, not included in manuscript for publication (Appendix 2.1).

5.1.1 Publication details

This chapter has been published as:

- Falster MO, Jorm LR, Douglas KA, Blyth FM, Elliott RF, Leyland AH. Sociodemographic and health characteristics, rather than primary care supply, are major drivers of geographic variation in preventable hospitalisations in Australia. Medical Care 2015; 53(5):436

Please note that some online supplementary material from the publication has been presented within this chapter, and there has been minor edits to the labels of tables, figures and the online supplementary material to format this publication for the thesis. A copy of the final publication is included in Appendix 4.

5.2 Abstract

Background

Geographic rates of preventable hospitalisation are used internationally as an indicator of accessibility and quality of primary care. Much research has correlated the indicator with the supply of primary care services, yet multiple other factors may influence these admissions.

Objective

To quantify the relative contributions of the supply of GPs and personal socio-demographic and health characteristics, to geographic variation in preventable hospitalisation.

Methods

Self-reported questionnaire data for 267,091 participants in the 45 and Up Study, Australia, were linked with administrative hospital data to identify preventable hospitalisations. Multilevel Poisson models, with participants clustered in their geographic area of residence, were used to explore factors which explain geographic variation in hospitalisation.

Results

GP supply, measured as full-time workload equivalents, was not a significant predictor of preventable hospitalisation, and explained only a small amount (2.9%) of the geographic variation in hospitalisation rates. Conversely, more than one third (36.9%) of variation was driven by the socio-demographic composition, health and behaviours of the population. These personal characteristics explained a greater amount of the variation for chronic conditions (37.5%) than acute (15.5%) or vaccine-preventable conditions (2.4%).

Conclusions

Personal socio-demographic and health characteristics, rather than GP supply, are major drivers of preventable hospitalisation. Their contribution varies according to condition, and if used for performance comparison purposes, geographic rates of preventable hospitalisation should be reported according to individual condition or potential pathways for intervention.

5.3 Introduction

Preventable hospitalisations (also known as hospitalisations for ‘ambulatory care sensitive conditions’, ‘potentially avoidable hospitalisations’ and ‘potentially preventable hospitalisations’) are those considered to be preventable through timely access to quality

primary and preventive care.[19, 32, 66] Rates of preventable hospitalisation are reported internationally as an indicator of health system performance and, in Australia, are used to guide the allocation of health service resources.[2, 20] Typically, this reporting involves comparing rates of preventable hospitalisations between geographic or health administrative areas,[20, 30] with the underlying rationale that variation in admission rates is related to the accessibility or quality of primary care, based on measures such as the density of the GP workforce,[69, 73, 78] perceived availability of health services,[39, 67] the presence of community health centres,[85] or having a regular source of care.[89, 91]

Health system performance indicators should reflect factors that can be influenced by, and are responsive to, health policy change.[4, 64] Policy interventions to reduce preventable hospitalisations usually address health care systems, such as incentives to increase equity in the distribution of GPs.[60, 213] However multiple factors influence variation in preventable hospitalisation, and interventions can also target clinical and self-management of conditions (such as chronic disease management and telemedicine programs) and primary prevention at population-level (such as health promotion campaigns). Accordingly, the valid use and interpretation of preventable hospitalisation as a measure of health system performance requires an understanding of the relative contributions of personal and health care factors,[64] particularly because more proximal interventions would be expected to drive change more quickly than those operating through primary prevention.

Most attempts to explore the multiple factors that drive preventable hospitalisations have used an ecological approach, analysing area-based measures such as disease prevalence, average income, racial composition of the population or area-level deprivation.[39, 69, 79, 80, 84] Interpretation of such analyses can be limited because they are subject to 'ecological fallacy' by inferring risk factors for individuals based on population-level information, while it is not known which members of the population were actually hospitalised.[110, 111] Few studies of preventable hospitalisation have collected detailed socio-demographic or health data for individuals, and these have used these data only to construct aggregate area-level variables,[39, 67] or else did not explore the role of personal characteristics in driving geographic variation in admission.[70, 111, 119]

Multilevel modelling, a statistical technique that structures data into hierarchies, such as individuals nested within their geographic area of residence, can estimate the relative contributions of factors at each of these levels to the total variation in an outcome.[161] While multilevel modelling has increasingly been used to explore personal and contextual drivers of

preventable hospitalisations, analyses to date have been limited by the use of administrative hospital[75, 83, 130] or US Medicare claims[73] data, which did not include detailed information about individual patients.

This study used multilevel modelling and detailed person-level data from a large-scale cohort study linked to routinely collected health data to investigate the relative contributions of the supply of GP services, relative to the contribution of personal socio-demographic, health and behavioural characteristics, to geographic variation in preventable hospitalisations.

5.4 Methods

5.4.1 Study population

This observational cohort study used data from the APHID study, details of which have been published elsewhere.[171] Briefly, APHID includes participants from the Sax Institute's 45 and Up Study,[166] a prospective cohort of over 267,000 men and women aged over 45 in NSW, Australia. Study participants were recruited from 2006-2009 through Medicare Australia (Australia's national universal health insurer), and joined the study by completing a self-administered questionnaire, including information on demographic characteristics, indicators of socioeconomic status, self-reported health, number and type of co-morbidities and behavioural risk factors. Participants also provided consent for long-term follow-up, including linkage to administrative health data sets.

Self-reported survey data for 45 and Up Study participants were linked with hospital admissions data from the NSW APDC, a census of all hospital separations (discharges, transfers and deaths) from all NSW public and private sector hospitals and day-procedure centres, and mortality data from the NSW RBDM mortality data file, which contains fact-of-death information on death registrations within Australia. Probabilistic data linkage was performed by the NSW Centre for Health Record Linkage (http://www.cherel.org.au/) using ChoiceMaker software. A manual clerical review on a sample of linkage records found a false positive linkage rate of 0.3%.

Ethics approval for the 45 and Up Study was granted by the University of New South Wales Human Research Ethics Committee, and approval for the APHID study was granted by the NSW Population and Health Services Research, Aboriginal Health & Medical Research Council, and University of Western Sydney Research Ethics Committees.

5.4.2 Preventable hospitalisations

Preventable hospitalisations were identified using the linked APDC hospital admissions data and defined according to the preventable hospitalisation indicator in the Australian 2012 National Healthcare Agreement.[22] This indicator is composed of admissions for 21 conditions, broadly categorised as 'chronic', 'acute' and 'vaccine-preventable' (Appendix 1.1). To assess whether hospitalisations for these conditions differed from other hospitalisations, an additional category of 'non-preventable' hospitalisations was defined as all emergency hospitalisations not included in the preventable hospitalisation indicator.

Table 5.1: Person- and area-level covariates used in models predicting rates of preventable hospitalisation

Category	Variables	Included as covariate in Model:			
		1	2	3	4
Baseline demographics (person-level)	Age, sex	X	X	X	X
Health system factors (area-level)	Full time workload equivalent general practitioners per 10,000 residents	-	X	X	X
Socio-demographic factors (person-level)	Aboriginal or Torres Strait Islander status, highest education qualification, language other than English spoken at home, marital status, employment status, annual household income, private health insurance, and number of people can depend on.	-	-	X	X
Health and behavioural factors (person-level)	Number of healthy behaviours (of smoking, exercise, diet and alcohol consumption), body mass index, Self-rated health, number of co-morbidities, functional limitation, and psychological distress.	-	-	-	X

5.4.3 Personal-level variables

Self-reported information from the 45 and Up Study baseline survey was used to identify characteristics of the study participants (Table 5.1). Socio-demographic characteristics included age, sex, Aboriginal or Torres Strait Islander status, annual household income, highest level of education, speaking a language other than English at home, marital status, health insurance status, and number of people outside their home they can depend on. Health and behavioural characteristics included body mass index (using self-reported height and weight), self-reported health status, level of functional limitation (using the Medical Outcomes Study physical functioning scale), level of psychological distress (using the K10 Scale), number of co-morbidities (heart disease, high blood pressure, stroke, diabetes, blood clot, asthma, Parkinson's disease, and any cancer except skin cancer), and a positive health behaviour

score[178] calculated as the total number of the following reported behaviours: non-smoking status, safe level of alcohol consumption (<14 drinks per week), at least 2.5 hours of intensity-weighted physical activity per week, and meeting daily dietary guidelines for fruit (2 serves) and vegetable (5 serves) consumption.

5.4.4 Geographic-level variables

Geographic areas of residence were identified from the 45 and Up Study using SLAs, one of the smallest geographic units available in the Australian Standard Geographical Classification.[173] SLAs were defined using boundaries from the 2006 Australian Census. The 199 SLAs differ in size and population across the state due to variation in remoteness from urban centres (Figures 5.1 and 5.2), with mean population 33,883 (range 357 to 138,322).[214]

The number of FWE GPs within each SLA, measured the effective supply of primary care services.[60, 183] It was estimated using aggregate state-level data from the Department of Health and Ageing[184] and aggregate SLA-level data from the 2011 Social Health Atlas of Australia.[185] FWE GPs were calculated as the number of Medicare claims for GP services for residents of each SLA, divided by the average number of claims per FWE GP in NSW. Population estimates were used to calculate the density of FWE GPs per 10,000 residents of each SLA, and divided into quintiles. A sensitivity analysis treated FWE GPs as population-weighted quintiles, and produced similar results (data not shown).

5.4.5 Statistical methods:

Multilevel Poisson models were used to analyse rates of preventable hospitalisation, with individuals as the unit of analysis. Counts of the number of preventable hospitalisations for each individual were taken between the date of study entry and the end of follow-up through the linked hospital data (30th December 2010), or death, whichever came first. The log of the follow-up time was used as an offset. Individuals were clustered in their geographic area of residence (SLA) using a random intercept parameter, which allowed the baseline risk of admission to vary between these geographic areas. Separate analyses were run for the three major categories of preventable admission, and where numbers allowed, the individual conditions.

Figure 5.1: Distribution of density of full time workload equivalent general practitioners per 10,000 residents across Statistical Local Areas (SLAs) in NSW

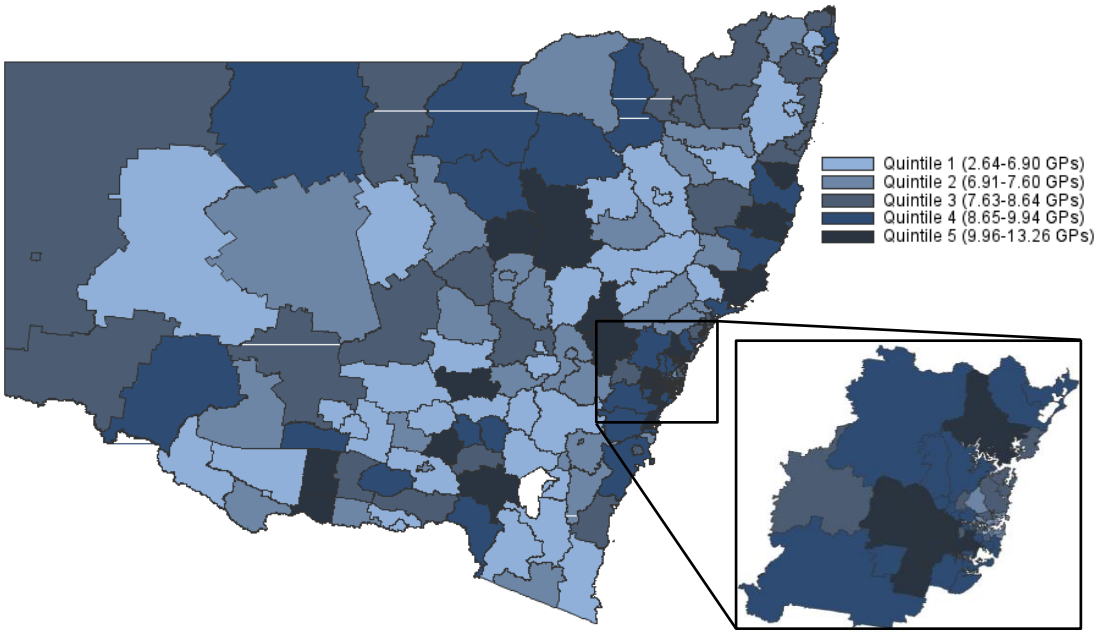
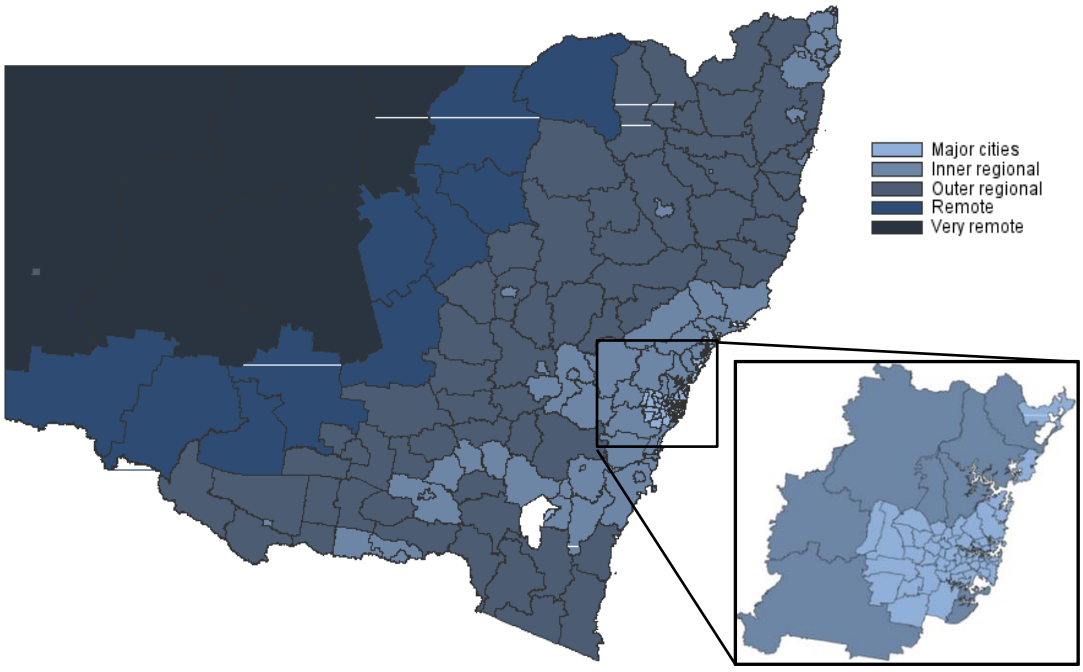


Figure 5.2: Distribution of remoteness categories across SLAs in NSW, using remoteness categories from the Accessibility/Remoteness Index of Australia (ARIA+).



Geographic variation in risk of preventable hospitalisation was first quantified using multilevel models adjusted for age and sex (Model 1). The variance (σ^2) of the random intercept parameter for the SLAs was used to quantify the amount of variation in the risk of admission between geographic areas.[198]

Quintiles of the density of FWE GPs were added to the model as an area-level covariate (Model 2). Subsequent models (Table 5.1) sequentially added person-level confounders, starting with socio-demographic variables considered to be non-modifiable and largely outside the scope of health policy action (Model 3), followed by health and behavioural characteristics considered potentially amenable to health interventions targeting populations or individuals (Model 4). os IRRs and 95% CIs were calculated for each of the variables by exponentiating the regression parameters. The amount of geographic variation in admission (from Model 1) which was explained by the variables in each subsequent model (Model n), was calculated as the PCV,[198] where $PCV=(\sigma^2_{(Model1)}-\sigma^2_{(Modeln)})/\sigma^2_{(Model1)}$.

Missing values were treated as additional categories; incidence rate ratios for these 'missing' categories are reported in Appendix 4. A sensitivity analysis excluding (n=90,678) persons with missing data on any variable found no notable changes in the patterns of individual-level predictors of admission or changes in area level variation between models (data not shown). All models used a 2nd order penalised quasi-likelihood estimation procedure, and all analyses were performed in SAS 9.3 and MLwiN 2.25. Model specifications are presented in Appendix 2.1.

5.5 Results:

Of the N=267,091 45 and Up Study participants, 1.6% (n=4,336) were excluded because their age or geographic area of residence was unknown, they resided outside of NSW, or had incompatible dates for records in the linked data (e.g. death prior to study entry), leaving n=262,755 for analysis (Table 5.2) over an average of 2.8 years of follow-up between 2006-2010. At the area-level, the rate of FWE GPs ranged from 2.6 to 13.3 per 10,000 residents (Figure 5.2).

Of the study participants, n=20,009 (7.6%) participants had a preventable hospitalisation, with n=14,525 having one, n=3,425 having two, and n=2,059 having three or more admissions, giving a total of 30,553 hospitalisations. More participants had preventable hospitalisations for chronic conditions than for acute or vaccine preventable conditions (Table 5.3), and the mean number of admissions per admitted person was greater for the chronic than for the acute or vaccine-preventable conditions (mean of 1.6, 1.2 and 1.1 admissions per year respectively).

Table 5.2: Cohort characteristics, and average rate of preventable hospitalisations per 100 person-years of follow-up

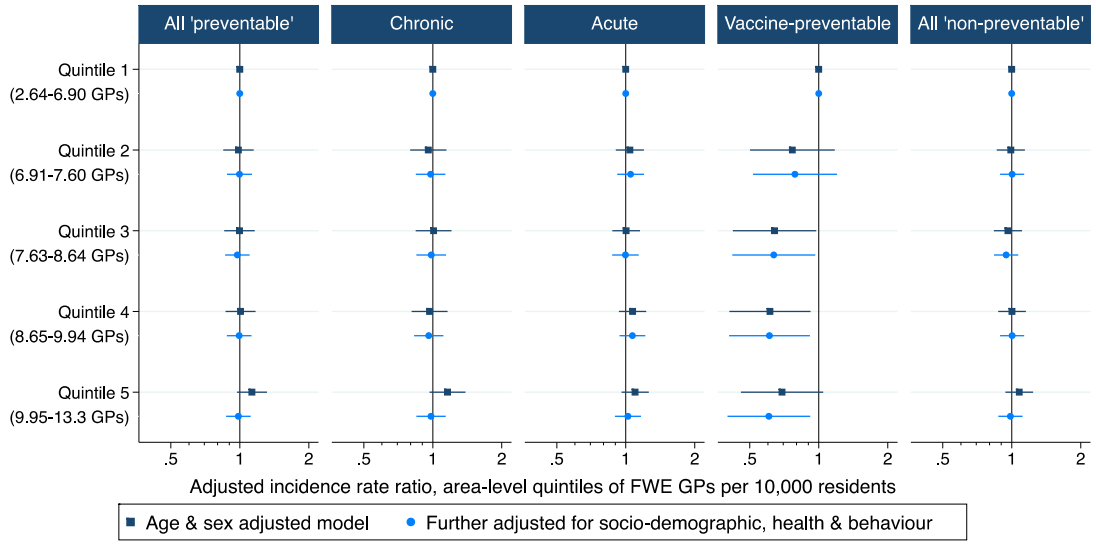
	Persons	Rate[a] of preventable hospitalisation
Total cohort	262,755	4.2
Age		
45-54 years	76,265	1.5
55-64 years	84,402	2.6
65-74 years	57,441	5.2
75-84 years	36,534	10.0
85+ years	8,113	14.4
Gender		
Males	121,813	4.9
Females	140,942	3.5
Aboriginal status		
Non-Aboriginal	256,181	4.1
Aboriginal	1,910	9.1
Household income		
<$10,000	14,705	7.7
$10,000 - $29,999	62,328	6.3
$30,000 - $49,999	39,774	3.1
$50,000-$69,000	27,381	2.2
$70,000 or above	61,556	1.5
Healthy behaviours		
0 behaviours	2,126	5.1
1 positive behaviours	22,194	5.8
2 positive behaviours	92,552	5.1
3 positive behaviours	112,939	3.4
4 positive behaviours	32,944	3.0
Self-rated health		
Excellent	38,153	1.2
Very good	93,583	2.0
Good	85,735	4.2
Fair	30,448	10.6
Poor	5,564	23.3
Number of comorbidities		
None	107,122	1.7
1 comorbidity	91,984	3.2
2 comorbidities	44,139	7.3
3+ comorbidities	19,510	15.2
Density of FWE GPs [b]		
Quintile 1 (2.64 – 6.90)	31,664	3.8
Quintile 2 (6.91 – 7.60)	42,961	4.1
Quintile 3 (7.63 – 8.64)	57,672	4.1
Quintile 4 (8.65 – 9.94)	76,508	4.2
Quintile 5 (9.95 – 13.3)	53,950	4.6

[a] Rate of hospitalisations per 100 person-years, from time of study entry to end of linked hospital data (31st December 2010) or death, whichever came first. Participants were recruited from 2006 to 2009, with an average follow-up time of 2.8 years.

[b] Full-time workload equivalent (FWE) generalist practitioners (GPs) per 10,000 residents in each Statistical Local Area (SLA).

There was significant variation between areas in the age- and sex-adjusted rate of preventable hospitalisation (σ^2=0.103, p<0.001). The amount of variation differed across major categories of conditions (Table 5.3), and was greater for admissions for vaccine-preventable (σ^2=0.328, p=0.003), than for chronic (σ^2=0.144, p<0.001) or acute (σ^2=0.058, p<0.001) conditions, although vaccine-preventable conditions had a larger standard error due to the low number of events.

Figure 5.3: Association between quintiles of the density of full time workload equivalent (FWE) general practitioners (GPs) per capita within Statistical Local Areas, with the rate of preventable and 'non-preventable' hospitalisations, from multilevel Poisson models adjusted for age and sex, and further adjusted for personal socio-demographic, health and behavioural characteristics



The inclusion of area-level FWE GPs in the model (Table 5.3) explained little of the area-level variation in preventable hospitalisation (PCV=2.9%), and the rate of preventable hospitalisation was not significantly related to area-level quintiles of FWE GPs in either an age-sex adjusted model, or models further adjusted for personal socio-demographic or health characteristics (Figure 5.3). Similarly, no clear trend was evident across major categories of preventable hospitalisation (Figure 5.3) and most individual conditions (Figure 5.4). There was an inverse association between quintiles of FWE GPs and rate of hospitalisations for vaccine preventable conditions (primarily influenza and pneumonia), and a higher rate of hospitalisation in the upper quintiles for dental conditions, although confidence intervals for these estimates were wide.

Figure 5.4: Association between density of full time workload equivalent (FWE) general practitioners (GPs) per capita within Statistical Local Areas, with the rate of preventable and 'non-preventable' hospitalisations, from multilevel Poisson models adjusted for age and sex, and further adjusted for personal socio-demographic, health and behavioural characteristics.

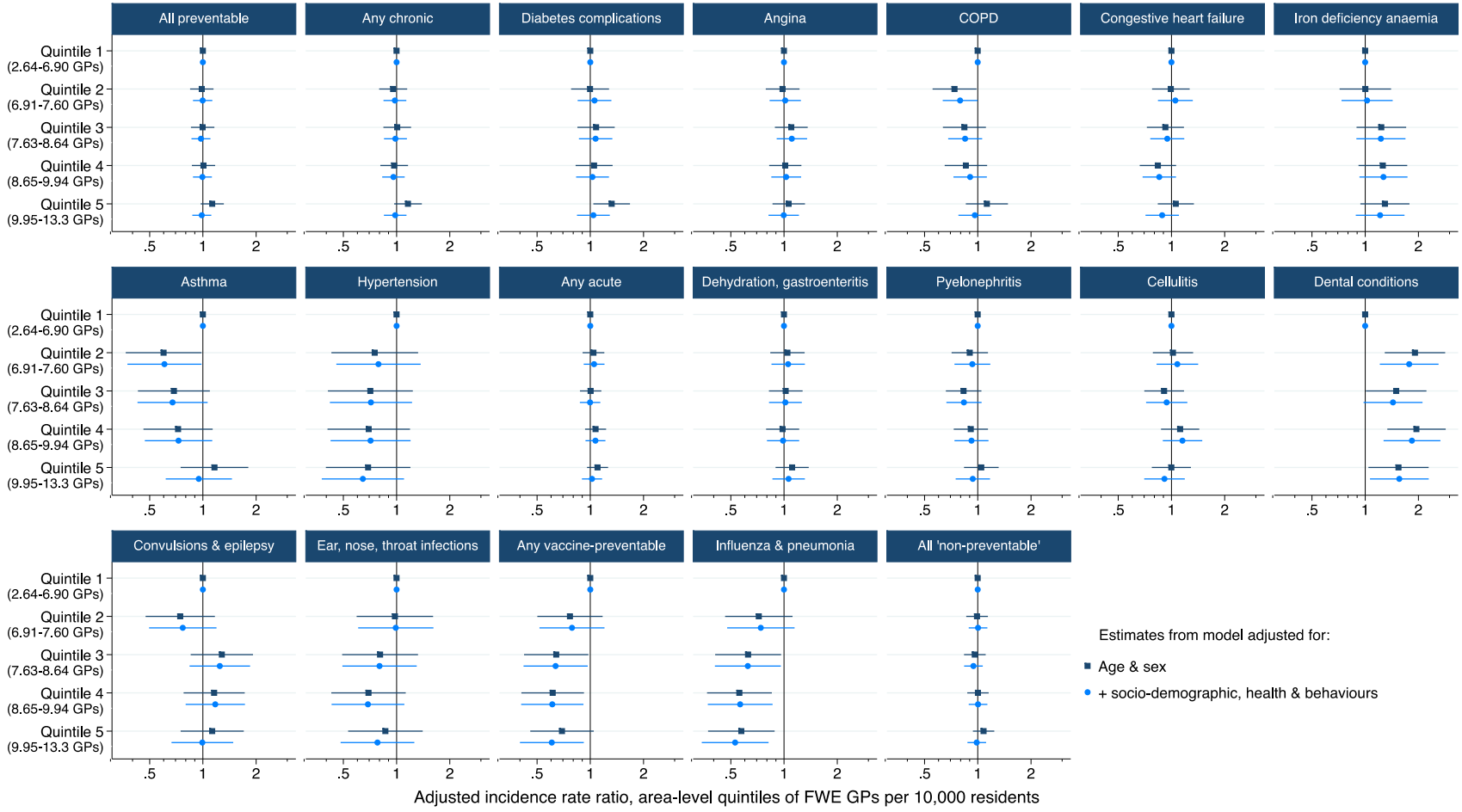


Table 5.3: Area level variance, σ^2, across 199 Statistical Local Areas in rate of preventable hospitalisations, and the proportional change in area-level variance (PCV) between an age and sex adjusted multilevel Poisson model (Model 1) with additional models sequentially adjusted for general practitioner workforce supply (Model 2), socio-demographic factors (Model 3), and health and behavioural factors (Model 4).

Category of preventable hospitalisation	Hospitalisations			Area level variance σ^2, and standard error (SE) of σ^2, in adjusted rate of admission						
	Total admissions	Admitted patients	Average # admissions per patient	Model 1	Model 2		Model 3		Model 4	
				σ^2 (SE of σ^2)	σ^2 (SE of σ^2)	PCV	σ^2 (SE of σ^2)	PCV	σ^2 (SE of σ^2)	PCV
Preventable hospitalisation										
All preventable hospitalisations	30,553	20,009	1.5	0.103 (0.012)	0.100 (0.011)	2.9%	0.076 (0.009)	26.2%	0.062 (0.007)	39.8%
Chronic conditions										
All chronic	20,022	12,297	1.6	0.144 (0.017)	0.139 (0.016)	3.5%	0.105 (0.013)	27.1%	0.085 (0.011)	41.0%
Diabetes complications	7,090	4,291	1.7	0.227 (0.029)	0.219 (0.028)	3.5%	0.179 (0.024)	21.1%	0.161 (0.022)	29.1%
Angina	4,162	3,375	1.2	0.126 (0.020)	0.125 (0.020)	0.8%	0.107 (0.018)	15.1%	0.097 (0.017)	23.0%
COPD	3,944	2,109	1.9	0.299 (0.040)	0.273 (0.037)	8.7%	0.176 (0.026)	41.1%	0.139 (0.022)	53.5%
Congestive cardiac failure	2,893	2,067	1.4	0.154 (0.026)	0.146 (0.025)	5.2%	0.128 (0.022)	16.9%	0.108 (0.020)	29.9%
Iron deficiency anaemia	1,829	1,445	1.3	0.252 (0.043)	0.246 (0.043)	2.4%	0.237 (0.042)	6.0%	0.239 (0.042)	5.2%
Asthma	536	410	1.3	0.475 (0.101)	0.403 (0.091)	15.2%	0.376 (0.088)	20.8%	0.361 (0.085)	24.0%
Hypertension	421	387	1.1	0.692 (0.139)	0.657 (0.135)	5.1%	0.604 (0.128)	12.7%	0.588 (0.125)	15.0%
Rheumatic heart disease	99	89	1.1	-	-	-	-	-	-	-
Nutritional deficiencies	6	6	1.0	-	-	-	-	-	-	-
Acute conditions										
All acute	10,066	8,591	1.2	0.058 (0.009)	0.057 (0.009)	1.7%	0.052 (0.008)	10.3%	0.048 (0.008)	17.2%
Dehydration & gastroenteritis	2,999	2,794	1.1	0.119 (0.021)	0.117 (0.021)	1.7%	0.110 (0.020)	7.6%	0.105 (0.019)	11.8%
Pyelonephritis	2,328	2,015	1.2	0.117 (0.023)	0.109 (0.022)	6.8%	0.107 (0.021)	8.5%	0.102 (0.021)	12.8%
Cellulitis	1,957	1,612	1.2	0.138 (0.027)	0.132 (0.027)	4.3%	0.138 (0.028)	0.0%	0.150 (0.029)	-8.7%
Dental conditions	1,299	1,210	1.1	0.335 (0.060)	0.302 (0.056)	9.9%	0.278 (0.053)	17.0%	0.274 (0.052)	18.2%
Convulsions & epilepsy	563	429	1.3	0.212 (0.061)	0.202 (0.060)	4.7%	0.170 (0.055)	19.8%	0.171 (0.055)	19.3%
Ear, nose, throat infections	390	380	1.0	0.395 (0.102)	0.357 (0.097)	9.6%	0.339 (0.095)	14.2%	0.328 (0.093)	17.0%

Category of preventable hospitalisation	Hospitalisations			Area level variance σ^2, and standard error (SE) of σ^2, in adjusted rate of admission						
	Total admissions	Admitted patients	Average # admissions per patient	Model 1	Model 2		Model 3		Model 4	
				σ^2 (SE of σ^2)	σ^2 (SE of σ^2)	PCV	σ^2 (SE of σ^2)	PCV	σ^2 (SE of σ^2)	PCV
Perforated/bleeding ulcer	242	232	1.0	-	-	-	-	-	-	-
Appendicitis	129	103	1.3	-	-	-	-	-	-	-
Pelvic inflammatory disease	90	86	1.0	-	-	-	-	-	-	-
Gangrene	72	72	1.0	-	-	-	-	-	-	-
Vaccine-preventable conditions										
All vaccine-preventable	570	508	1.1	0.328 (0.078)	0.296 (0.074)	9.8%	0.292 (0.073)	11.0%	0.288 (0.072)	12.2%
Influenza & pneumonia	514	462	1.1	0.358 (0.086)	0.311 (0.080)	13.1%	0.307 (0.079)	14.2%	0.306 (0.079)	14.5%
Other vaccine-preventable	57	47	1.2	-	-	-	-	-	-	-
'Non-preventable' emergency										
All 'non-preventable'	75,421	45,282	1.7	0.095 (0.010)	0.093 (0.010)	2.1%	0.073 (0.008)	23.2%	0.068 (0.007)	28.4%

The addition of person-level socio-demographic characteristics to the model (Table 5.3) explained an additional 23.3% of area-level variation in preventable hospitalisations (PCV=26.2%), while a further 13.6% was explained by the addition of person-level health and behavioural characteristics (PCV=39.8%). Combined, these person-level characteristics explained 36.9% of the area-level variation in preventable hospitalisations, with this proportion being greater for admissions for chronic (37.5%) than for acute (15.5%) or vaccine-preventable (2.4%) conditions. Among individual causes, person-level characteristics explained the greatest area-level variation for COPD (44.8%), diabetes (25.6%), congestive cardiac failure (24.7%) and angina (22.2%), the four most common chronic causes of preventable admissions. However, small numbers of admissions for the less common causes limited the extent to which cause-specific comparisons could be drawn.

Most person-level variables in the fully adjusted model were found to be significant predictors of preventable hospitalisation (Figure 5.5). Overall, admission rates were highest for participants who were older, had poorer self-reported health, greater functional limitation, greater number of co-morbidities, or were Aboriginal or Torres Strait Islander. Admission rates were lower for females, participants who were employed, had higher levels of income, or reported greater numbers of positive health behaviours. Predictors of admission differed slightly between the major categories of preventable hospitalisation, with the higher rate of admissions associated with older age and poorer health being most pronounced for chronic conditions, and a slightly different pattern of association for acute admissions among females and participants who speak a language other than English at home.

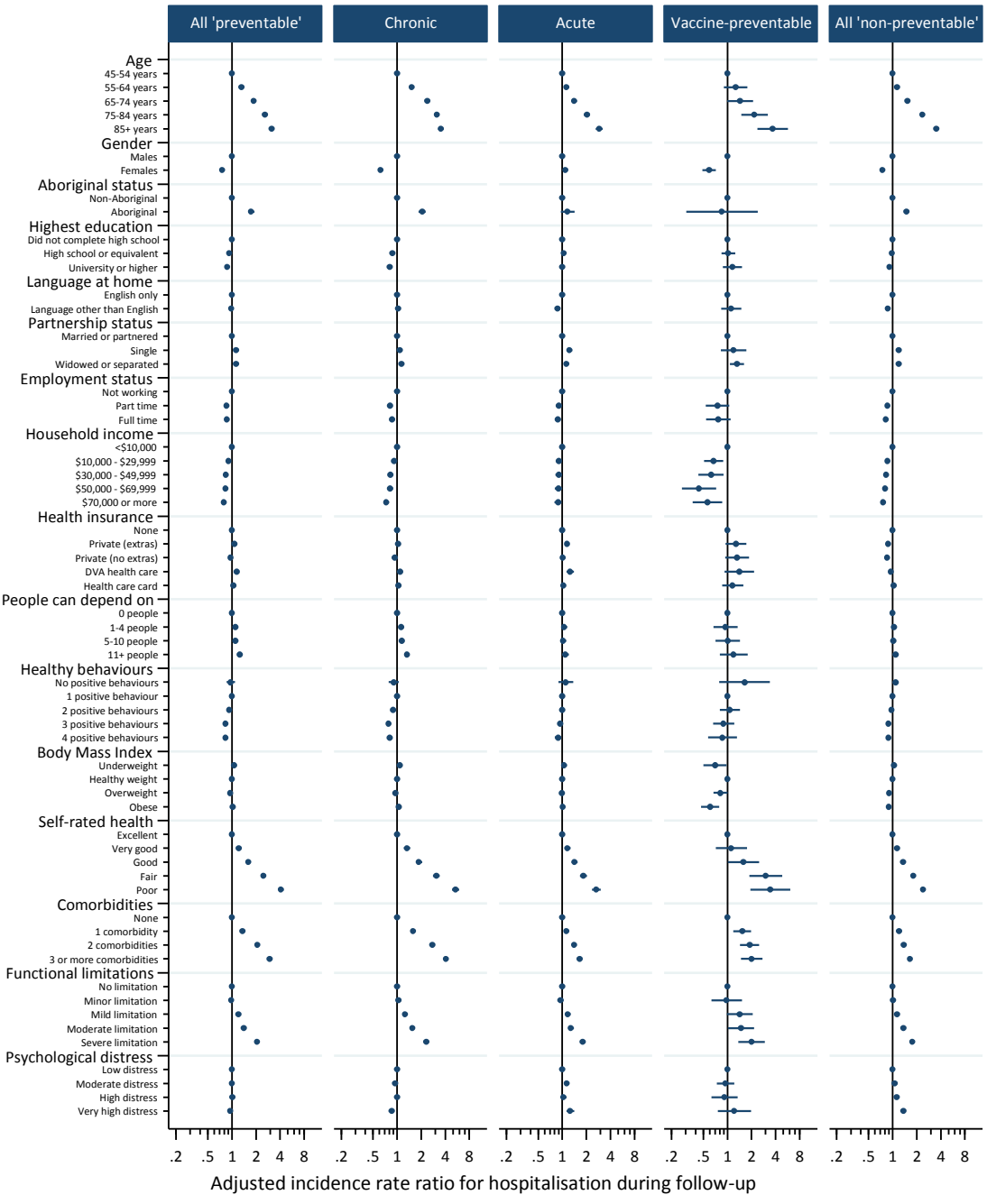
Study participants had 75,421 ‘non-preventable‘ emergency hospitalisations during the corresponding period. There was significant area-level variation in rates of ‘non-preventable’ hospitalisation (σ^2=0.095, p<0.001), of which 2.1% was explained by the inclusion of FWE GPs in the model, and a further 26.3% by the socio-demographic, health and behavioural characteristics of the population (Table 5.3). As for preventable hospitalisations, there was no significant association between rates of ‘non-preventable’ hospitalisation and area-level quintile of FWE GPs (Figure 5.3).

5.6 Discussion

This study was the first to use detailed person-level data to assess how both the supply of GP services and the composition of the population influences geographic variation in preventable hospitalisations - a key consideration in the valid use of preventable hospitalisations as a

health system performance indicator. We found that supply of GP services explained only a small amount (2.9%) of the geographic variation in rates of preventable hospitalisation, and that these rates did not vary significantly according to quintiles of GP supply, but that more than one third (36.9%) of geographic variation in preventable hospitalisations was driven by personal socio-demographic and health characteristics.

Figure 5.5: Incidence rate ratios (IRRs) for person-level predictors of preventable hospitalisation, in multilevel Poisson models simultaneously adjusted for all person-level variables and area-level quintiles of full time workload equivalent GPs



The lack of a significant association between the supply of GP services and preventable hospitalisations was unexpected, because much of the literature has demonstrated inverse associations.[69, 72, 73, 78] However, results have been inconsistent,[79, 80, 83, 84] and much of the research has used practitioner headcount measures or self-rated access to care rather than more objective measures of effective supply. Most of the existing research was done in the US with few studies in Australia.[67] Australia has a higher number of annual physician visits per capita (6.5) than the US (3.9), UK (5.0) and Canada (5.5), with a 'safety net' scheme to improve access to health care services for low-income groups, and targeted interventions to reduce health disparities for more vulnerable populations.[8] It may be that current strategies to improve access to GPs have been effective, with fewer barriers to accessing care than in countries such as the US, and the use of primary care services in Australia may be more reflective of the underlying health need of the population. While previous ecological-level research in Australia found an inverse association between full-time equivalent (FTE) GPs and preventable hospitalisations,[67] this association disappeared after adjusting for socio-demographic and health characteristics of areas.

This study instead indicated that preventable hospitalisations may be more representative of gradients in health than in health care.[84] Prior research has found that up to half the variation in preventable hospitalisation between areas was attributed to factors other than accessibility of primary care, such as socio-demographic, health or hospital service factors,[64, 67] although interpretation of these findings was limited by the use of aggregate area-level measures of risk exposure, or a small sample sizes for geographic areas. Many studies have adjusted for socio-demographic or health characteristics, and such adjustment is recommended for the standard reporting of the indicator.[33] This study shows that care should be taken to unpack, not just adjust for, the contribution of these factors, as good performance measures should be both attributable and responsive to policy change,[4] and such adjustment may actually mask the most important drivers of admission.

Few prior studies have detailed person-level data with which to investigate person-level predictors of hospitalisation,[70, 111] with much of the evidence coming from aggregate ecological analyses or analyses on specific conditions.[33, 66, 124] Our findings with regard to the demographic characteristics of the population are consistent with the literature, with higher rates of preventable hospitalisation among men, older persons and Aboriginal or Torres Strait Islander people.[111, 124, 215] Similarly, the inverse associations between markers of socioeconomic status—such as income, education, and employment—are consistent with strong associations reported in the literature, as are the higher rates among participants with poorer self-rated

health, greater number of co-morbidities, and higher levels of functional limitation.[66, 111, 124, 125] Fewer studies have investigated the role of social support, health behaviours, and mental health, and the findings have been less consistent.[124, 125, 178]

While it is well understood that chronic, acute and vaccine-preventable conditions in the indicator relate to primary care in different ways,[66] only some reporting systems stratify their results accordingly.[30, 32] It is argued there may be insufficient events to analyse conditions separately,[33] and that the use of condition-specific indicators can lead to 'tunnel vision' with a concentration of performance efforts around those conditions being monitored.[130] This study found the contribution of various factors to geographic variation in preventable hospitalisation varied markedly according to condition, and vaccine-preventable conditions alone appeared to have an inverse association with GP supply. Conversely, the high-volume chronic conditions – diabetes complications, COPD, congestive cardiac failure and angina – were most strongly driven by the socio-demographic and health characteristics of the population. Our finding that area-level supply of primary care services and person-level socio-demographic factors made similar contributions to geographic variation in 'preventable' and 'non-preventable' hospitalisations casts further doubt on the value of the aggregate indicator. Where possible we suggest that it is desirable to separate the indicator according to conditions that present different pathways for intervention.

Our findings do not downplay the potential role of primary care, and the broader health system, in reducing rates of unnecessary hospitalisation for chronic conditions. However, they point to the need for further work to identify effective interventions and appropriate performance measures for these. While social determinants of health may be targeted through long-term primary prevention, the responsiveness of these strategies may be low and influenced by factors outside of the health system. Admissions for chronic conditions may be more amenable to disease management and strategies to improve the quality of care, because multi-morbid patients require complex case management, patient adherence to guidelines is often poor,[33] and medication-related hospitalisations for people with chronic disease are common.[216, 217] Quality of care may also be improved by focussing on the primary care system more broadly, not just GP care, such as support of pharmacist and physician assistants for check-ups, diagnoses, and repeat prescriptions.[60]

The core strengths of this study include the availability of detailed person-level information with linked hospital admissions data, and the use of multilevel modelling to examine how population composition influences geographic variation in admission. Reliable area-level data

that are representative of the population, such as disease prevalence, can be difficult to obtain,[218] and while a number of studies have had either detailed person-level data,[70, 111] or used multilevel modelling to incorporate individual factors into small-area analyses of preventable admission,[73, 83, 130] this is the first study to our knowledge to incorporate both. This study is also one of the few to present results stratified by both major categories and individual conditions[30, 33, 64, 67, 84] that are included in the indicator. This is especially useful because a number of versions of the indicator have been used over time and in different jurisdictions,[30, 59] hindering direct comparisons between these different aggregate indicators.

A limitation of this study is that participants in the 45 and Up Study are older and potentially healthier than the general population[166], and given the low participation rate (18%) there may be concerns about generalisability. However, persons aged 45 years and over have the highest rate of preventable admissions per capita, and contribute two-thirds of preventable hospitalisations in Australia[30]. As it is a healthier cohort, participants may be more likely to access primary care services. However, internal relative risk estimates from the 45 and Up Study have found to be comparable to those from population health surveys,[169] and the large sample size provides substantial heterogeneity to allow for valid within-cohort comparisons.[170] Another potential limitation of the study was its reliance on the FWE GP measure as a sole measure of GP supply. However, the use of FWE GPs accounted for multiple worksites and differing caseloads of GPs in regional and rural areas, and is theoretically preferable to headcounts as a measure of realised access to primary care services.[60] The study was also unable to account for all potential drivers of admission, such as variations in hospital characteristics, which would require assigning potential pools of patients to their likely hospital(s) of admission.[131] Residual over dispersion in the model may have also resulted in less accurate variance estimates and confidence intervals.

This study has confirmed that personal characteristics are major drivers of preventable hospitalisation, and importantly, the contribution of these factors varies according to condition. In the Australian setting at least, variations in GP supply explain little of the geographic variation in rates of preventable hospitalisation. Our findings suggest the need for caution in the international adoption of health system performance indicators that have largely been developed and tested within the US healthcare system. International comparative work using similar individual-level data and multilevel modelling methods will potentially shed light on how the use and interpretation of this performance indicator may vary across countries and according to health system characteristics.

Chapter 6 Developing a method for exploring hospital variation

6.1 Background to chapter

Hospitals are hypothesised to influence rates of preventable hospitalisations, with differences in hospital characteristics, such as the availability of beds and services, influencing the propensity to admit patients. Exploration of this effect however is difficult, as rates of preventable hospitalisations are a population-level outcome, but hospitals do not have a clear patient catchment allowing data to be analysed at the hospital-level. The objective of this chapter was to develop a method for attributing population variation in preventable hospitalisation to the potential role of hospitals.

This chapter uses data from the GRAPHC Study. A statistical appendix includes additional online supplementary material, model specifications, and further information on the parameter convergence from statistical models in this chapter, not included in manuscript for publication (Appendix 2.3).

6.1.1 Publication details

This chapter is currently under revision at the journal Health Services Research, initially submitted in June 2016:

- Falster MO, Jorm LR, Leyland AH. Using weighted hospital service area networks to explore variation in preventable hospitalization. Submitted to Health Services Research [under revision]

Please note that some online supplementary material from the publication has been presented within this chapter, and there has been minor edits to the labels of tables, figures and the online supplementary material to format this publication for the thesis.

6.2 Abstract

Objective

Demonstrate the use of multiple membership multilevel models, which cluster patients in a weighted network of hospitals, for exploring between-hospital variation in preventable hospitalizations.

Data sources

Linked survey and hospital admission data for a cohort of 267,014 people aged over 45 in NSW, Australia.

Study design

Patterns of patient flow were used to create weighted hospital service area networks (weighted-HSANs) to 79 large public hospitals of admission. Multiple membership multilevel models on rates of preventable hospitalization clustering participants on weighted-HSANs, were contrasted with models clustering on 72 hospital service areas (HSAs) that assigned participants to a discrete geographic region.

Principal findings

Between-hospital variation in rates of preventable hospitalization was more than two times greater when modelled using weighted-HSANs rather than HSAs. Use of weighted-HSANs permitted identification of small hospitals with particularly high rates of admission, and influenced performance ranking of hospitals, particularly those with a broadly distributed patient base. There was no significant association with hospital bed occupancy.

Conclusion

Multiple membership multilevel models can analytically capture information lost on patient attribution when creating discrete health care catchments. Weighted-HSANs have broad potential application in health services research, and can be used across methods for creating patient catchments.

6.3 Introduction

Both policymakers and health researchers seek to quantify variation in health service use, expenditure, and outcomes. For policymakers, attributing such variation to responsible organisations, such as hospitals or health districts, can create networks of accountability,[219]

and through performance monitoring, have the power to drive health care reform.[220] For researchers, quantifying variation allows identification of factors which influence health outcomes, and can facilitate the development of new metrics for performance and targeted intervention strategies to meet specific health goals.

Central to this process is the ability to analyse data at a level at which variation is meaningful. For example, 'preventable' hospitalizations are internationally used as an indicator of access to and quality of primary care,[25, 32] and population variation in preventable hospitalization is often partitioned into geographic 'primary care service areas' reflecting natural markets of primary care supply.[73, 81] However preventable hospitalizations can also be influenced by other health system factors, such as hospitals - which may have a different propensity to admit patients based on factors including the availability of beds.[127, 131] This hypothesis remains poorly explored, as such analyses require attributing population variation in admission to the hospital-level, and the few studies which have explored these associations[75, 78, 80, 107, 130, 132] mostly used ecological measures of hospital services at the geographic level. Defining hospitals' patient catchments to capture hospital-level variation poses particular difficulties, as patients may not have a designated hospital for admission, administrative data cannot determine a patient's likely hospital where they have not had an admission, and in most health systems choice of hospital is driven not only by geographic proximity but by provider and patient choice, as well as financial factors such as private health insurance arrangements.

A variety of methods have been developed to create hospital patient catchments, often referred to as 'hospital service areas' or HSAs.[221, 222] Typically, this involves locating hospitals within geographic regions, then aggregating these regions into larger geographic catchments in which the plurality of patient admissions are to hospitals within the catchment. Alternate methods use different algorithms on patient flows and plurality of residence;[132, 221-223] spatial analysis on distance to hospitals;[86, 224, 225] hospital cluster analysis on patterns of patient utilisation and geography;[226, 227] projected need based on patterns of outpatient service use;[131] or network analyses built on patterns of physician or hospital referrals.[228-231]

HSAs are widely used and accepted within health service research and for policy evaluation, and while the purpose of HSAs is often to create clean geographic boundaries of patient catchments for health service planning, most of these methods have the limitation that patient loyalty to the assigned HSA is often quite low, with the HSAs typically capturing between 50%-80% of hospital admissions for their population.[223, 229, 230, 232] This is a major conceptual difficulty with HSAs, as they are supposed to represent discrete health care markets, yet

patients are receiving care from a variety of additional sources.[223, 233] Ignoring this can lead to misattribution of variation and potentially bias parameter estimates and statistical inferences.[191, 234] Furthermore, the use of catchments containing multiple hospitals limits the ability to attribute variation to specific hospitals,[131] which may be needed to investigate specific hospital characteristics (rather than geographic aggregates of resources), or to produce hospital performance rankings, such as through league tables.[235] The use of larger catchments, such as Hospital Referral Regions containing several HSAs and even more facilities limits the ability to evaluate specific hospital even further.[223]

One method for dealing with such uncertainty is the use of multiple membership multilevel models.[190, 191] Developed within education and social sciences, multiple membership multilevel models allow data to be clustered in a hierarchical structure where a lower level unit, such as people, can be clustered in one or more higher level units, such as multiple teachers for students in a school, multiple nurses providing care to a patient, or in this case, multiple hospitals servicing a population. While conceptually appealing, the multiple membership modelling approach has not been widely utilised in health services research. To the authors' knowledge, such an approach has not been used in the analysis of HSAs, but could potentially address the major limitations by capturing the uncertainty around patient loyalty and allowing population variation to be correctly attributed to specific hospitals.

In this study we demonstrate the use of multiple membership multilevel models for exploring between-hospital variation in rates of preventable hospitalization in NSW, Australia. Using these models we quantify and visualise variation between hospitals in rates of preventable hospitalization and assess their association with a measure of the availability of hospital beds. These results are contrasted to a more traditional approach clustering patients in a single HSA.

6.4 Methods

6.4.1 Multiple membership multilevel models

The general structure of a multilevel model captures the effects of clustering by allowing both regression parameters and error terms to exist at different hierarchical levels. For example, an analysis might wish to look at a variety of person-level variables (e.g. age, sex, health, education), as well as higher-level variables of the health system (e.g. type of hospital, bed availability). In general terms, such a model could be expressed as:

$$Y_{ij} = \beta_0 + \sum_{p=1}^{P} \beta_p x_{pi} + \sum_{q=1}^{Q} \beta_q x_{qj} + u_j + e_i$$

Where I people are clustered within J hospitals or HSAs. Y_{ij} is the outcome, x_{pi} are the regression parameters for P person-level variables, and x_{qj} are the regression parameters for Q hospital-level variables. β_0, β_p and β_q are the regression coefficients for the intercept, person-level and hospital-level parameters accordingly. e_i and u_j represent the residual variation at the person- and hospital-levels, with e_i and u_j belonging to random distributions $e_{ij} \sim N(0, \sigma_e^2)$ and $u_j \sim N(0, \sigma_u^2)$. Such a model could be extended to generalised linear models for a range of outcomes, such as binary (e.g. whether a patient had a hospital admission) or counts (e.g. number of hospital admissions).

A multiple membership multilevel model extends this approach by allowing a weighted structure for each of the hospital-level components. A linear model with random intercepts can be written as:

$$Y_{ij} = \beta_0 + \sum_{p=1}^{P} \beta_p x_{pi} + \sum_{q=1}^{Q} \sum_{j=1}^{J} w_{j.i}^{(2)} \beta_q x_{qj}^{(2)} + \sum_{j=1}^{J} w_{j.i}^{(2)} u_j^{(2)} + e_i$$

The superscript $^{(2)}$ in this classification notation[191] indicates model components belonging to the second level of classification (i.e. hospitals), and should further levels be included these would be indicated by further superscripts $^{(3)}$, $^{(4)}$, etc. Here, $w_{j.i}^{(2)}$ is the probability that person i will go to hospital j for their admission, with each hospital assigned a weight $\left(0 \leq w_{j.i}^{(2)} \leq 1\right)$ such that the sum of the weights for person i equals one $\left(\sum_{j=1}^{J} w_{j.i}^{(2)} = 1\right)$. In this manner, people are proportionately clustered within all their potential hospital of admission, and the hospital-level parameters and random error terms become weighted averages of hospitals in the network. Where people are clustered within a single hospital, this simplifies to the regular two-level model above.

6.4.2 Variation in preventable hospitalization

Study population

Data used for this analysis were obtained from The Sax Institute's 45 and Up Study,[166] a prospective cohort of 267,014 residents of NSW, Australia aged 45 and over. Participants were recruited between 2006 and 2009 through the Medicare Australia (Australia's national universal health insurer) enrolment data base, where at study entry participants completed a

detailed questionnaire containing self-reported information on their health, socio-demographic characteristics and risk factor behaviour. Participants also provided consent for long-term follow-up, including linkage with administrative health data sets.

For each study participant, linked data extracts were obtained for hospital admissions from the NSW APDC, a census of all hospital separations (discharges, transfers and deaths) from all NSW public and private hospitals and day-procedure centres, as well as mortality data from the NSW RBDM, which contains fact-of-death information on death registrations within Australia. Probabilistic data linkage between datasets was performed by a third party, the NSW Centre for Health Record Linkage (http://www.cherel.org.au/), using Choicemaker software. A manual clerical review on a sample of linked records in the Master Linkage Key found a false-positive linkage rate of 0.3%. Linked hospital data were available for the period 2000-2011, and mortality data from 2006-2011.

Participants were excluded if they had an unknown age, area of residence, or had inconsistent records possibly indicating incorrect linkage (e.g. death before date of study entry). Ethics approval for the 45 and Up Study was given by the University of New South Wales Human Research Ethics Committee, and ethics approval for this study was given by the NSW Population and Health Services Research Ethics Committee and the University of Western Sydney Research Ethics Committee.

Hospitalizations and weighted hospital service area networks

Records used for this analysis were all hospitalizations during the period of follow-up, from the date of participants' study entry (between 2006-2009) until death or the end of linked data (31/12/2011), whichever came first. Analyses were restricted to admissions to principal, major and district public hospitals (peer groups A1-C2, see Appendix 1.2), as private hospitals in Australia have different types of patients with different patterns of care, and smaller facilities such as community hospitals, psychiatric facilities, nursing homes and rehabilitation centres are often not considered in hospital performance benchmarking and comparisons.[186, 236] Changes of type of care within a hospital (e.g. from acute care to palliative care, and transfers between hospitals, were considered a continuation of the same episode of care.

Weighted hospital service area networks (weighted-HSANs) were created using patterns of patient flow for all-cause hospitalizations. Participants were grouped by their area of residence, in this case Postal Areas, of which there are over 600 in NSW. Participants were then allocated to all hospitals of admission among participants in their postal area, with the weighting corresponding to the proportional distribution of admissions between hospitals. To

assign participants to just a single HSA, all residents of a postal area were allocated to the most common hospital of admission. Not all hospitals had a corresponding HSA population, as some did not provide the plurality of services for any postal area.

As an outcome, a count of all 'preventable' hospitalizations for each study participant during their follow-up period was identified in the hospital claims data according to the definition in the Australian 2012 National Healthcare Agreement.[22] The indicator is composed of admissions for 21 conditions, broadly categorised as chronic, acute and vaccine-preventable (Appendix 1.1), and is currently used as a high level health system performance indicator within Australia.

Hospital data from the same period of time were used for creating weighted-HSANs and HSAs based on patient flow, and for counting preventable hospitalizations, as catchments defined during a performance evaluation period have been found to better reflect actual patterns of service utilisation than a prospective attribution.[237]

Hospital- and person-level characteristics

Hospital bed occupancy rate was identified from hospital benchmarking reports for 2008/2009,[186] which corresponds to the early period of follow-up for most study participants. It was calculated as the proportion of occupied bed days to the number of available bed days for the period, and can exceed 100% for some hospitals with a high number of same day admissions where a single bed is used to treat more than one patient. For the models clustering participants in a weighted-HSAN, a weighted average hospital bed occupancy rate for all hospitals in a network was calculated using the weighting distribution of the weighted-HSAN.

Person-level socio-demographic and health characteristics were obtained from the self-reported survey completed at entry into the 45 and Up Study, including age, sex, marital status, highest level of education, household income, employment, language spoken at home, health insurance status, number of people can depend on, body mass index, multi-morbidity, number of healthy behaviours, self-rated health, functional limitation, and psychological distress (Table 3.3).

Statistical analyses

Multilevel Poisson models were used to model 'rates' of preventable hospitalization, with counts of the number of hospitalizations per person during the follow-up period as the outcome and the log of the follow-up time as an offset. All models were adjusted for self-reported personal socio-demographic and health characteristics as fixed effects, so the models

were exploring residual variation potentially attributable to the health care system. These variables were included in the analysis as they reflect predisposing, need and access related factors for health service use,[163] and have previously been found to be associated with preventable hospitalization.[203]

Models were run hierarchically clustering participants in weighted-HSANs, with between-hospital variation quantified as the variance of the hospital-level random-intercept parameter σ_u^2 and as a median rate ratio (MRR),[238] such that $MRR = \exp\left(0.95\sqrt{\sigma_u^2}\right)$. The MRR can be interpreted as the median increase in rate of hospitalization if a person were to move from one hospital cluster to another with a higher rate of hospitalization. To compare this variation to other levels of geographic disaggregation, models were also run hierarchically clustering participants in either HSAs; SLAs, another small level geographic unit; cross-classified models clustering people in both a SLA and HSA; and cross-classified multiple membership models clustering people in both a SLA and weighted-HSANs. SLA boundaries are unrelated to postal areas, and were chosen for analysis as they are used for indicator performance measurement and evaluation. Postal areas are a smaller geographic unit allowing more granularity in defining HSAs and the weighted-HSANs.

To rank hospitals with higher- or lower- than average rates of admission, the median and 95% credible intervals were obtained from the posterior distribution of the hospital-level residuals, which take into account a 'shrinkage' factor based on the estimated variance and size of the hospital cluster.[196, 197] The ranking of hospitals after adjusting for person-level characteristics from a model clustering people in weighted-HSANs was compared to rankings from a model clustering people in a single HSA.

Hospital bed occupancy was then included in the models, as a continuous variable, re-scaled so that one unit change represents a 10% change in hospital bed occupancy rate, centred on the group mean value. A PCV[199] was used to see how much of the between-hospital variation was explained by this variable, calculated as the proportional difference between the hospital-level random-intercept parameter σ_u^2 after including hospital bed occupancy in the model. Changes in model fit were assessed using the deviance information criteria (DIC).

All data preparation was performed in SAS v9.3, and all modelling was performed in MLwiN 2.25, using MCMC estimation with inference based on 20,000 samples following a burn-in of 5,000. Model specifications are presented in Appendix 2.2. Trajectories of stored parameter estimates were visually checked for irregular distributions and convergence to a unimodal distribution.

6.5 Results

There were 267,014 study participants, of which n=78 were excluded for having unknown age, unknown area of residence in NSW or incompatible dates in the linked data. The remaining 266,936 participants had an average follow-up of 3.7 years, and resided within 612 different postal areas, each containing between 1 to 4,166 participants. n=82,553 participants (31%) had one or more all-cause hospitalizations to a major public hospital during follow-up, for a total of n=267,032 admissions to 79 different hospitals. Participants in 19 postal areas did not have any hospitalizations during the period of follow-up; the 174 participants residing in these areas were excluded, leaving 266,762 in 593 areas for analysis (Table 6.1).

Table 6.1: Demographic distribution of study participants and number of hospitalizations to major public hospitals

	Study population		Number of hospitalizations*			
			All cause		'Preventable'	
	N	% of N	n	% of N	N	% of N
Total (N)	266,762	100	267,032	100	26,728	100
Age						
45-64	163,596	61.3	94,112	35.2	7,651	28.6
65-84	94,913	35.6	154,959	58.0	16,099	60.2
85+	8,253	3.1	17,961	6.7	2,978	11.1
Sex						
Male	123,740	46.4	148,985	55.8	14,678	54.9
Female	143,022	53.6	118,047	44.2	12,050	45.1
Multimorbidity†						
No conditions	108,978	40.9	54,567	20.4	4,488	16.8
1 condition	93,358	35.0	88,140	33.0	7,261	27.2
2 conditions	44,697	16.8	69,834	26.2	7,905	29.6
3+ conditions	19,729	7.4	54,491	20.4	7,074	26.5
Self-rated health						
Excellent/very good	133,871	50.2	58,636	22.0	4,965	18.6
Good	86,928	32.6	88,475	33.1	8,467	31.7
Fair / poor	36,552	13.7	103,923	38.9	11,524	43.1
Missing/unknown	9,411	3.5	15,998	6.0	1,772	6.6

** Hospitalizations to public hospitals, from participants' time of study entry (between 2006-2009) to death or end of linked data (end 2011), whichever came first (average of 3.7 years of follow-up). † Self-reported conditions, of heart disease, high blood pressure, stroke, diabetes, blood clot, asthma, Parkinson's disease, and any cancer except skin cancer.*

Within each postal area, participants were admitted to a mean of 15 different hospitals (range 1-56), which formed the basis of the weighting for the HSAN (Table 6.2). Figure 6.1 shows the proportion of admissions within the 593 postal areas which were to the most common, second

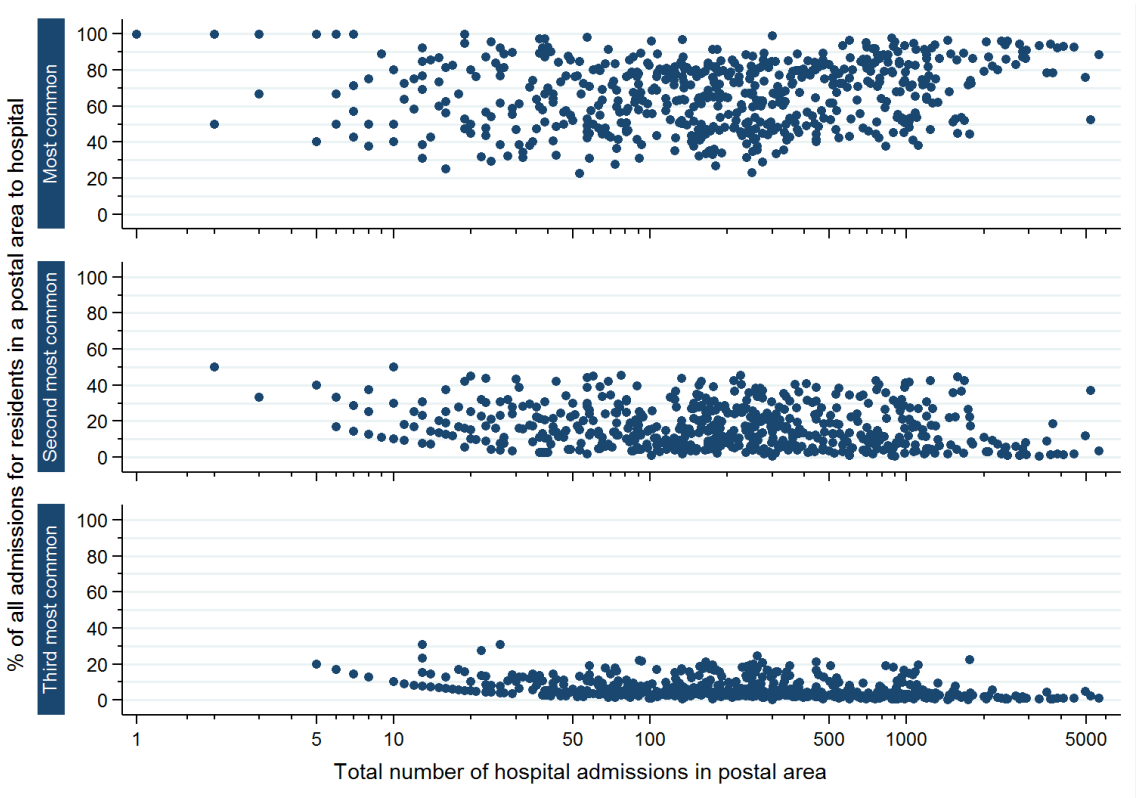
most common or third most common hospital of admission. On average, the most common hospital accounted for 67% of admissions in a postal area, although in almost a quarter of postal areas (24%) this hospital accounted for no more than half of all admissions. The second most common hospital of admission accounted for an average of 17% of admissions in a postal area, although in 11% of postal areas it accounted for more than one third of all admissions.

Table 6.2: Characteristics of weighting structure between study participants, postal areas, hospital service areas (HSAs), and weighted hospital service area networks (weighted-HSANs)

	Mean	Interquartile range	Min-max
Postal areas (n=593)			
Number of study participants	451.4	82 - 561	1 – 4166
Number of all cause hospitalisations	450.3	63 – 518	1 – 5642
Number of public hospitals of admission	14.8	8 – 20	1 – 56
% all cause hospitalisations to the:			
Most common hospital	66.6	50.8 – 81.3	22.6 – 100.0
Second most common hospital	17.0	7.1 – 25.0	0.3 – 50.0
Third most common hospital	6.5	2.5 – 9.1	0.3 – 30.8
Hospital Service Areas (n=72)			
Study patient catchment size	3705.0	1160 - 5798	12 – 12,801
Postal areas included	8.2	3 - 12	1 - 27
Market share index (%)	69.2	64.0 - 86.7	0.2 – 97.5
Hospitals, from weighted-HSANs (n=79)			
Weighted study patient catchment size	3376.7	973 – 5720	277 – 13,227
Total postal areas serviced	110.9	50 – 136	17 – 377
where hospital weight >5%	18.7	8 – 22	1 – 73
where hospital weight >10%	13.9	6 – 17	0 – 57
where hospital weight >20%	10.3	4 – 14	0 – 44
where hospital weight >50%	5.7	1 – 10	0 – 26
Study participants (n=266,762)			
Number of hospitals in weighted-HSAN	25.6	15 - 34	1 – 56
% weighting which is to the:			
Most common hospital	70.4	53.7 – 85.0	22.6 – 100
Second most common hospital	14.3	4.5 – 22.2	0 – 50.0
Third most common hospital	4.8	1.6 – 5.7	0 – 30.8

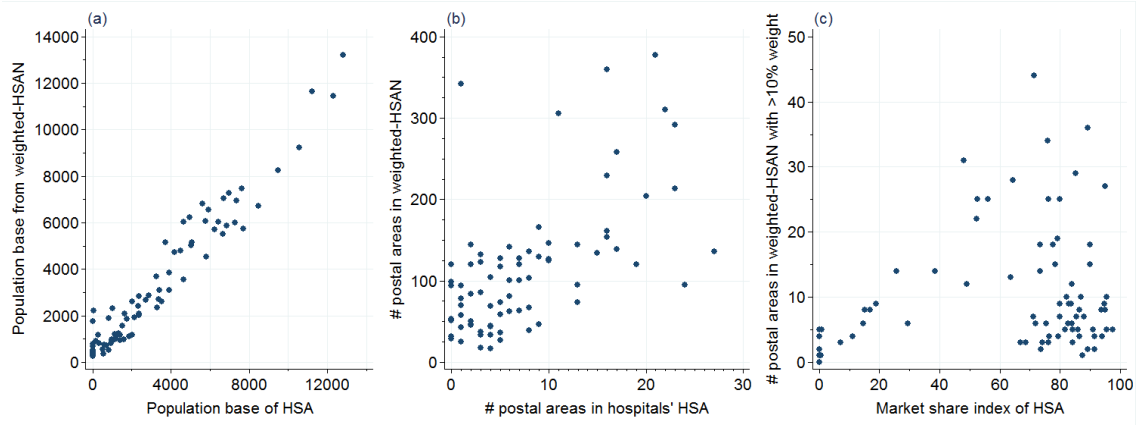
Aggregating postal areas into HSAs based on the most common hospital of admission resulted in 72 HSAs from the total of 79 major hospitals. HSAs each comprised of a mean of 8 postal areas, and contained a mean of 3,705 study participants (Table 6.2). After applying the weighting structure from postal areas to the study population, participants were each clustered within a mean of 26 hospitals within their weighted-HSAN, with the most common hospital of admission accounting for a mean 70.4% of the weighting.

Figure 6.1: Proportion of all cause hospitalizations for study participants in 593 postal areas in NSW Australia, which are to the most common, second most common and third most common hospitals of admission



There was broad correlation between the size of the population base for HSAs and corresponding hospitals from weighted-HSAN, although hospitals drew their population from a much larger number of postal areas when using a weighted-HSAN (Figure 6.2). While many hospitals had a market share index (the proportion of admissions which are from within their catchment) from their HSA over 70%, there were a number of outlying hospitals for which this was poor (Figure 6.2). Further comparisons of characteristics of hospitals from using HSAs and weighted-HSANs are in Appendix 2.2.1.

Figure 6.2: Characteristics of hospitals when analysed using an HSA or weighted-HSAN, including (a) population base, (b) postal areas used to construct patient catchments, and (c) market share index of HSA and number of postal areas making meaningful contribution to weighted-HSAN



6.5.1 Hospital variation in preventable hospitalization

During follow-up, there were 26,728 preventable hospitalizations among 16,999 (6.3%) study participants. After adjusting for personal socio-demographic and health characteristics, there was significant residual variation between hospitals in rates of preventable hospitalizations (Table 6.3), such that a person moving to another hospital network with a higher rate of admission would face a median 41% increase in their rate of hospitalization (MRR: 1.41, 95% CIs: 1.31-1.54). The amount of residual variation which sat in models clustered on weighted-HSANs (σ^2=0.130) was over two times as high as models clustered on HSAs (σ^2=0.059). However, the variation between SLAs (σ^2=0.291) was much greater than for either weighted-HSANs or HSAs, and models including SLA consequently had a lower DIC (Supplementary File 1). When people were additionally clustered within SLAs, there were similar amounts of variation between hospitals in a weighted-HSAN (σ^2=0.234) and SLAs (σ^2=0.234), but less variation between HSAs (σ^2=0.089) than between SLAs (σ^2=0.230). These cross-classified approaches resulted in the lowest DIC (Table 6.4).

Comparison of the residual random effect of hospitals (Figure 6.3) show there is much variation between hospitals in their residual rate of hospitalization, with many hospitals having significantly lower- or higher than average rates of admission. The ranking of hospitals using weighted-HSANs was notably different to the ranking of HSAs based on the primary hospital of admission. For example, one hospital had relatively low residual rates of preventable hospitalisation in the weighted-HSAN model but average rates when modelled as a HSA. This

hospital is an acute facility in a major city (Sydney) with one small postal area forming its HSA (43 people). However, it was the second most common hospital of admission in 19 postal areas, and serviced participants from a total of 342 postal areas, although it only accounted for a large proportion of admissions (>10%) in 4 of these. With a weighted-HSAN patient catchment of 2227 people, the HSA represented only 0.2% of this hospital's admissions from the study population.

Table 6.3: Random intercept variance parameters from models on rates of preventable hospitalisation,* with study participants hierarchically clustered within weighted hospital service area networks (weighted-HSAN), hospital service areas (HSA), and/or statistical local areas (SLA)

Model structure, persons clustered within:	Variance estimate (and SE of variance)		
	Hospitals in weighted-HSAN (n=79)	Hospital service area (n=72)	Statistical local area (n=173)
Weighted-hospital service area network†	0.130 (0.032)	-	-
Hospital service area (HSA) ‡	-	0.059 (0.012)	-
Statistical local area (SLA) ‡	-	-	0.291 (0.039)
Both weighted-HSAN and SLA §	0.234 (0.061)	-	0.234 (0.061)
Both HSA and SLA¶	-	0.089 (0.022)	0.230 (0.033)

** Multilevel Poisson models, adjusted for socio-demographic and health characteristics of study participants. †Two-level multiple membership multilevel model. ‡Two-level multilevel model § Three-level cross-classified multiple membership multilevel model. ¶ Three-level cross-classified multilevel model*

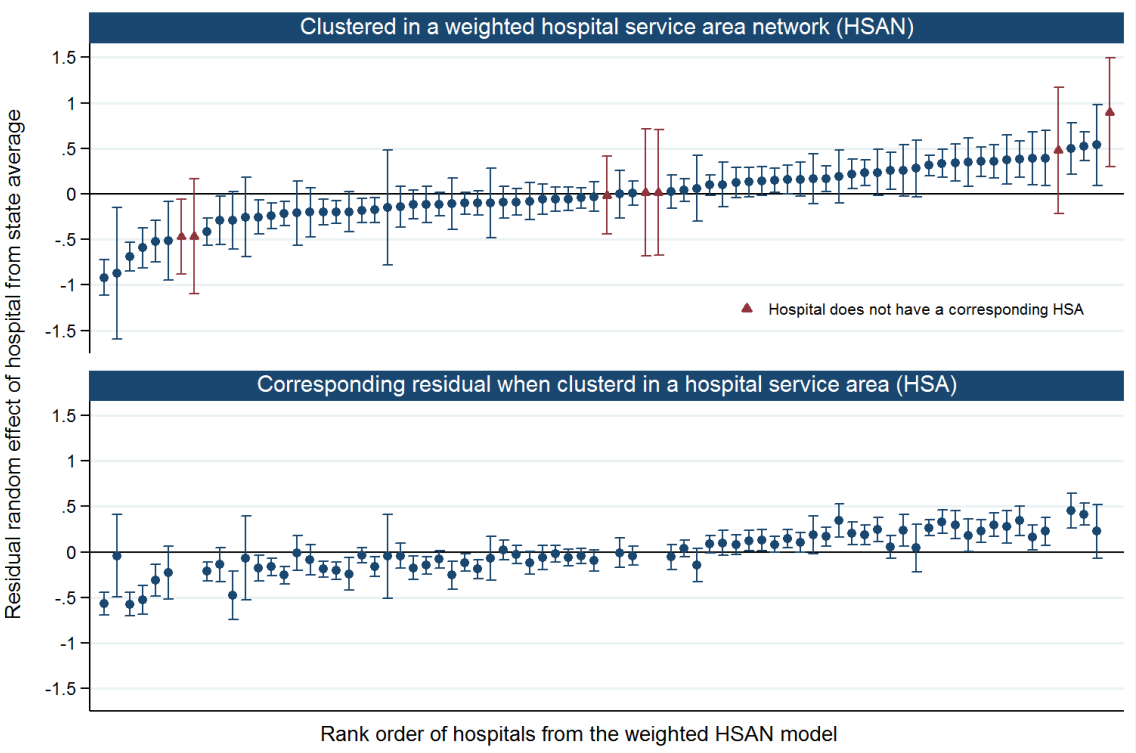
Table 6.4: Deviance information criterion statistic sequentially adjusting for (1) age and sex, (2) further personal socio-demographic and health characteristics, and (3) hospital bed occupancy

Model structure, persons clustered within	Deviance information criterion (DIC)		
	Age and sex	+ socio-demographic and health	+ hospital bed occupancy
Weighted-HSAN	183167.0	159985.4	159984.9
HSA	183323.0	159908.5	159910.5
SLA	181432.1	158424.8	-
Weighted-HSAN and SLA	181086.9	158190.4	158190.8
HSA and SLA	181165.2	158198.4	158196.0
No random intercept	185452.5	160854.6	-

The weighted-HSAN model also identified residuals for an additional 7 hospitals that did not form the basis for any corresponding HSA (Figure 6.3). For example, the hospital with the highest residual rates of preventable hospitalization did not have a corresponding HSA; it was a smaller district hospital within 30 minutes' drive to a large base hospital. Its population base

was drawn from 29 postal areas, including 4 postal areas where it was the second most common hospital of admission and accounted for between 8-26% of admissions. Conversely, the two additional hospitals in the centre of the figure were specialised acute hospitals with small weighted populations (277 and 348 people) drawn from a large number of postal areas (99 and 120 respectively) from which they were at most the 3rd or 4th most common hospital of admission.

Figure 6.3: Ranking of hospitals based on residual hospital-level random effects in rates of preventable hospitalizations* with participants clustered using a weighted-HSAN, and corresponding values with participants clustered using a single HSA



** Two level multilevel Poisson model, adjusted for socio-demographic and health characteristics of study participants.*

6.5.2 Hospital bed occupancy and preventable hospitalization

In models clustered on a weighted-HSAN, there was no significant association between a 10% increase in hospital bed occupancy rate and preventable hospitalizations (IRR: 1.01, 95% CIs: 0.96-1.07). This result was similar when clustering people in the leading hospital of a HSA, and was not impacted by the additional clustering of people within an SLA (Table 6.5).

Table 6.5: Incidence rate ratio (IRR) for preventable hospitalization from a 10% increase in average hospital bed occupancy rate, from models* with study participants hierarchically clustered within either weighted hospital service area networks (weighted-HSAN) or hospital service areas (HSA), and statistical local areas (SLA).

Model structure, persons hierarchically clustered within	Incidence rate ratio	
	IRR	(95% CIs)
Weighted-hospital service area network (HSAN) †	1.01	(0.96 – 1.07)
Hospital service area (HSA) ‡	1.00	(0.96 – 1.04)
Both weighted-HSAN and statistical local area (SLA) §	0.98	(0.90 – 1.07)
Both HSA and SLA¶	1.02	(0.96 – 1.08)

** Multilevel Poisson models, adjusted for socio-demographic and health characteristics of study participants. †Two-level multiple membership multilevel model. ‡ Two-level multilevel model § Three-level cross-classified multiple membership multilevel model. ¶ Three-level cross-classified multilevel model*

Across all models, the inclusion of the bed occupancy variable had only minor impacts on the between-hospital or between HSA variation (PCV<2.5%) and the model DIC (Tables 6.4 and 6.6). In contrast, the personal health and sociodemographic factors included in the model had already explained 65% and 44% of the between HSAN and between HSA variation accordingly and had major impacts on the DIC (Tables 6.4 and 6.6). Incidence rate ratios for all person-level variables were almost identical in analyses using weighted-HSANs or HSAs (Appendix 2.2.1).

Table 6.6: Proportional change in between-hospital, HSA or SLA level variance after sequentially adjusting for (1) age and sex, (2) further personal socio-demographic and health characteristics, and (3) hospital bed occupancy

Model structure, persons clustered within	Variance parameter (and SE of variance)			Proportional change in variance parameter from prior model		
	(1) Age and sex	(2) + socio-demographic and health	(3) + hospital bed occupancy	(1)	(2)	(3)
Two level models						
Weighted-HSAN	0.367 (0.084)	0.130 (0.032)	0.132 (0.032)	-	64.6%	-1.5%
HSA	0.105 (0.020)	0.059 (0.012)	0.059 (0.012)	-	43.8%	0.0%
SLA	0.325 (0.042)	0.291 (0.039)	-	-	10.5%	-
Three level models						
Weighted-HSAN and SLA						
Weighted-HSAN	0.393 (0.096)	0.234 (0.061)	0.230 (0.062)	-	40.5%	1.7%
SLA	0.316 (0.046)	0.270 (0.040)	0.273 (0.041)	-	14.6%	-1.1%
HSA and SLA						
HSA	0.091 (0.023)	0.089 (0.022)	0.091 (0.022)	-	2.2%	-2.2%
SLA	0.282 (0.040)	0.230 (0.033)	0.231 (0.033)	-	18.4%	-0.4%

6.6 Discussion

In this study we demonstrated the novel use of weighted hospital service area networks and multiple membership multilevel models to explore how variation in a population-level outcome could be attributed to hospitals. In our analysis on rates of preventable hospitalisation we found more than twice the variation between hospitals compared to a more traditional approach using HSAs. This variation captures information usually lost through assigning a population to discrete patient catchments. Weighted-HSANs produced notably different results for some hospitals, such as those with a broadly distributed patient base, and identified smaller hospitals which would otherwise not be considered. Additionally, they allow assessment of specific hospital characteristics (such as bed occupancy), as opposed to the geographically-based measures commonly explored. The multiple membership models have a clear application within health services research for analysing variation between hospitals, or other health services without clear patient attribution, particularly as they can be applied using an extension of current popular methodologies.

6.6.1 Hospital variation in preventable hospitalisation

Variation in hospital practice has long been hypothesised to be a contributing factor to the preventable hospitalisations health performance indicator, but there has been almost no quantification of this effect. While one study estimated hospital-based rates of admission using a projected patient catchment from the distribution of admissions in age- and sex-stratified groups, it was unable to attribute variation to both the patient- and hospital-levels.[132]

Using weighted-HSANs, the current study found no association between hospital bed occupancy and preventable hospitalization. This was surprising, given the well-established Roemer's law, i.e. that the availability of hospital beds leads to higher levels of utilisation.[127, 131, 239] We used a measure of bed availability attributable to hospitals (occupancy rate), different to the more geographic measures usually explored in the literature (beds per capita), which may explain some of this finding. However, in previous studies exploring preventable hospitalizations and number of beds or inpatient bed-days per capita, many[75, 78, 80, 130] but not all[107, 132] found no significant associations. It may be that a more nuanced exploration of features related to hospital capacity, such as the presence of an emergency department or the role of the hospital in the community, is required, and the weighted-HSANs method now allows such hypotheses to be explored.

Results from this Australian study may be most comparable to other countries with a universal health care system. Variation was explored between large public hospitals in NSW, which are those used for standardised reporting of hospital performance, but there may be further uncaptured variation between private or smaller community hospitals. The results may also be sensitive to methods used for determining hospital weights, and residual over-dispersion in the model may have resulted in less accurate variance estimates and CIs.

6.6.2 Weighted hospital service area networks

The use of weighted-HSANs and multiple membership multilevel models has broader potential applications in health services research. While multiple membership multilevel models have been used on patient populations with known patterns of care, such as patients receiving care from multiple facilities, this approach has not previously been applied to investigate population-level outcomes where prospective providers of care are unknown. For example, these methods could be used to investigate how availability of regional hospital birthing facilities impacts maternal choices on delivery, whether hospital-based outpatient services reduce patient admissions, or if the presence of an emergency department results in differing levels of discretionary hospitalisations.

One advantage of the multiple membership modelling approach is the ability to assess exposures and explore residual variation at the hospital level. While HSAs allow this to some extent, their geographic nature and aggregation of facilities limits more detailed exploration. In this analysis, we identified outlying hospitals that would be all but invisible to standard analytic approaches.

Given the range of potential methods for creating patient catchments, results may be sensitive to the choice of method used. Geographically-based methods often have the difficulty of allocating both the patient population and the exposure (e.g. number of hospital beds) to distinct geographic regions using the same pattern of patient flows, potentially inducing an artificial correlation.[131] The current analysis partially overcame this difficulty by using an exposure already attributed to hospitals (bed occupancy), and an outcome (preventable hospitalizations) different to the services determining the weighting structure (all cause hospitalization).

While many HSAs did have a high market share, our analysis also demonstrates that patient catchments for some services may be poorly defined, such as the outlying hospital with a small HSA but a broadly distributed patient base. It was for these facilities that the use of the

weighted-HSANs had the largest impact. While further refinement of HSAs may improve accuracy of some patient catchments, there will remain some regions which are meaningfully serviced by multiple facilities, and some facilities which meaningfully service a broad population. This is a constant limitation of HSAs. Manual revision of HSAs use considerable resources, such as those constructed for the Dartmouth Atlas,[221] and it is not always practicable for such boundaries to be reconstructed, with many existing boundaries continuing to be used even if the current services underpinning these catchments have changed.

While multiple membership multilevel models lose the advantages of a clean and discrete population base, more recent methods for creating HSAs have been moving towards capturing 'natural' patterns of health service use for a more robust evaluation of services, as well as automated methods for HSA construction,[240] and the use of multiple membership models seem a logical evolution. A key strength of the multiple membership analytic approach is that it could potentially be used across a range of alternative methods for constructing patient catchments. For example, networks of patients, physicians and hospital referrals could use patterns of referrals to create a weighting structure, much like the patterns of hospital patient flow used in this analysis. Implementation would require using information on the probabilistic allocation of patients to hospitals from within each respective algorithm, usually produced but discarded following allocation, to create the weighting structure for the hospital networks.

A limitation is that multiple membership multilevel models can be complex, and currently require specialised multilevel modelling software. The capacity of statistical software to handle complex hierarchical structures however has been improving. A further limitation is that while the multiple membership models use a weighting structure to allocate participants within a hospital network, the outcome (in this case, number of preventable hospitalizations) is not classified according to hospital of admission, although such practice is standard in population-based analyses on admission rates.

6.7 Conclusion

The needs of researchers and health policymakers to capture service-level variation and create accountable care organisations must be met with statistical methods that fully utilise available information. The use of weighted hospital service area networks and multiple membership multilevel models directly address the uncertainty inherent in patient catchments used for analysing and evaluating hospital performance, and this study found more than two times the variation in preventable hospitalization than a standard approach using hospital service areas.

By bringing the analysis back to the level of the hospital, this approach will also enable health researchers to explore associations between population health service use and outcomes with a wider range of hospital characteristics.

Chapter 7 Hospital variation in propensity to admit patients

7.1 Background to chapter

Chapter 5 explored the relative contribution of personal sociodemographic factors and primary care supply to geographic variation in preventable hospitalisation, and Chapter 6 developed a method to further partition variation to the hospital-level. The objective of this chapter was to bring together these approaches, to assess if different types of public hospitals had a different propensity to admit patients for preventable hospitalisation after adjusting for both patient- and area-level characteristics.

This chapter uses data from the GRAPHC Study. A statistical appendix includes further information on model specifications, and parameter convergence from statistical models in this chapter, not included in manuscript for publication (Appendix 2.3).

7.1.1 Publication details

This chapter has been prepared for submission to the Medical Journal of Australia. As it uses the methodology developed in Chapter 6, submission is dependent on acceptance of the corresponding manuscript for publication. At the time of submission, reviewers' feedback for the methodology in Chapter 6 has been positive, focused on the types of information presented, with no suggested modifications to the structure or implementation of the method.

- Falster MO, Jorm LR, Leyland AH. Variation in hospitals' propensity to admit patients for preventable hospitalisation: results from a large population-based cohort. For submission to Medical Journal of Australia [awaiting submission]

Please note that minor edits to the labels of tables, figure and online supplementary material have been made in this chapter to format the submitted manuscript for the thesis.

7.2 Abstract

Objectives

To quantify between-hospital variation in preventable hospitalisations in New South Wales, Australia, according to hospital category.

Design, setting and participants

Self-reported survey data for 266,826 participants in the 45 and Up Study (2006-2009) were linked with hospital records (to end 2011). Between-hospital variation in admissions was quantified using multiple membership multilevel Poisson models, adjusted for personal socio-demographic, health and area-level contextual characteristics.

Outcomes

Admissions to public hospitals during the follow-up period for preventable hospitalisations, and two 'marker' conditions: emergency admissions for AMI and hip fracture.

Results

There was significant between-hospital variation in preventable hospitalisation after adjusting for patient and area characteristics, with hospitals varying on average 26% from the mean. People serviced by community (IRR:1.06; 95% CIs:1.02-1.10), and to a lesser extent multipurpose (IRR:1.05; 95% CIs:1.01-1.09) hospitals had higher rates of preventable hospitalisation and there was greater between-hospital variation in these categories of hospital than in larger hospitals. There was comparatively little between-hospital variation for AMI and hip fracture, regardless of hospital category.

Conclusions

Differences in hospital admission practice contribute to geographic variation in rates of preventable hospitalisation in Australia, in particular reflecting the different roles played by community and multipurpose hospitals compared with major and principal referral hospitals.

Summary of significance

The known: Preventable hospitalisations are widely used as an indicator of the accessibility and quality of primary care. The contribution of hospitals to variation in this indicator is unknown.

The new: For similar patients, rates of preventable admission vary significantly according to hospital, and this variation is greatest among smaller facilities. Community and multipurpose hospitals comprise the majority of admissions in rural and remote areas, and some of these facilities have the highest rates of preventable hospitalisation.

The implications: Hospitals play a role in preventable hospitalisations, and this health performance indicator should not be interpreted simply as a measure of the accessibility and quality of primary care.

7.3 Introduction

Preventable hospitalisations are a widely used, yet contentious, health performance indicator. They are used as a measure of the accessibility and quality of primary care in the Australian National Healthcare Agreement,[22] and reported as population rates by geographic area, with significant variation across Australia.[25, 241] With preventable hospitalisations accounting for 6.2% of all hospitalisations in 2014/15,[7] reducing these represents significant potential cost savings to the healthcare system.

Interpreting the indicator, however, is difficult, with growing evidence that a range of factors beyond primary care, such as the health and sociodemographic characteristics of the population, also drive admission rates.[124, 203] As such, recent policy responses are stressing the need for localised, rather than generic, strategies for reducing preventable hospitalisation - tailored to current models of care in a district as well as the needs and characteristics of the population.[25, 241]

One health system factor which remains poorly understood is the potential role of hospitals. Differences in a hospitals' propensity to admit patients arise from various mechanisms, such as variations in physician preferences[128] and in hospital capacity through the availability of beds and services.[126, 127, 129] However evidence on the role hospitals play for preventable hospitalisations is limited, and comes almost exclusively from international studies.[124] Higher rates have been reported in UK hospitals that convert more emergency department presentations into admissions,[132] and some areas in the USA[107] with more hospital beds per capita – although the latter finding has not been consistent.[75, 78, 80, 130] Anecdotal reports suggest that different types of hospitals may play a more direct role in choosing to admit patients for observation, particularly in regional areas where travel times are large and access to other health services are poor.[133]

The aim of this study was to quantify between-hospital variation in preventable hospitalisations in New South Wales, Australia, according to hospital category.

7.4 Methods

Study population

This study included participants in The Sax Institute's 45 and Up Study,[166] a prospective cohort of 267,014 residents of NSW, Australia aged 45 and over. Eligible participants were randomly selected between 2006 and 2009 through the Medicare Australia enrolment data base. At study entry participants completed a detailed questionnaire containing information on their health and socio-demographic characteristics, and provided consent for long-term follow-up, including linkage with administrative health data sets.

For each study participant, linked data on hospital admissions (between 2000-2011) and deaths (between 2006-2011) were obtained from the NSW APDC, a census of all hospital separations (discharges, transfers and deaths) from all NSW public and private hospitals and day-procedure centres, and the NSW RBDM mortality data file, respectively. Data linkage was performed probabilistically by the NSW Centre for Health Record Linkage (http://www.cherel.org.au/). Participants were excluded if they had an unknown age, area of residence, or had inconsistent records possibly indicating incorrect linkage (e.g. death before date of study entry).

Ethics approval for the 45 and Up Study was given by the University of New South Wales Human Research Ethics Committee, and ethics approval for this study was given by the NSW Population and Health Services Research Ethics Committee and the University of Western Sydney Research Ethics Committee.

Hospitalisations, outcomes and exposures

Hospital outcomes were identified using the linked hospital admissions data, from the time of participants' entry into the study (between 2006-2009) until death or the end of linked data (31/12/2011), whichever came first. Hospital admissions were restricted to public hospitals only. Transfers and type change separations were considered a continuation of the same episode of care.

Preventable hospitalisations were identified according to the 'selected potentially preventable hospitalisations' indicator in the National Healthcare Agreement,[22] a composite measure of

hospital admissions for 21 conditions. Two additional outcomes, for which hospital admission was unlikely to be influenced by discretionary patterns of care, were used as 'marker' conditions: emergency admissions for AMI, and emergency admissions for hip fracture.[242] Hospital diagnosis and procedure codes used to identify outcomes are provided in Appendix 1.1. Sensitivity analyses tested a recently suggested modification to the preventable hospitalisations indicator, categorising preventable hospitalisations as short (<= 2 days length of stay [LOS]) and long (3+ days LOS), on the basis that shorter admissions may be more amenable to secondary prevention.[243]

All person-level information was derived from the self-reported survey completed at study entry, including participants' age, sex, education, marital status, annual household income, employment, language spoken at home, health insurance status, level of social support, body mass index, healthy behaviours, multi-morbidity, functional limitation, self-rated health and psychological distress. These variables reflect patients' predisposition and need to use health services,[163] with most previously found to be associated with preventable hospitalisation.[203] All variables were treated as categorical, with missing values as an additional category.[203]

Area-level information was assigned according to the SLA of patient residence. Geographic remoteness was derived from the Accessibility/Remoteness Index of Australia,[173] and the rate FWE GPs in the area was estimated using aggregated Medicare claims data.[183, 203]

Hospital category was classified according to hospital peer group, a categorisation used for benchmarking and reporting that groups similar hospitals by the types of services provided. Peer groups are defined using several criteria, including size, specialisation, non-acute activity, role, and geographic location.[186] For this analysis, peer groups were collapsed into six broad categories reflecting major differences in the size, role and location of facilities: principal, major metropolitan, major non-metropolitan, district, community and multipurpose hospitals, the latter containing a mix of primarily multipurpose and sub-acute hospitals - smaller facilities which provide integrated acute health, nursing home, hostel, community health and aged care services, or non-specialised sub-acute services, as negotiated between the community, service providers, and relevant departmental agencies (Appendix 1.2).

Statistical methods

Between-hospital variation in admission was analysed using cross classified multiple membership multilevel Poisson models.[191] All models used the number of hospitalisations as an outcome and the log of the follow up time as an offset, so as to model 'rates' of admission,

and were adjusted for participants' socio-demographic and health characteristics and the geographic remoteness and supply of GP services in their area of residence, so that the remaining residual variation was potentially attributable to hospitals.

Multilevel models allow for variation to be partitioned to various 'levels' for analysis, and these models clustered study participants in both their geographic area of residence (SLA) and all potential hospitals of admission. Because a patient could be admitted to any number of hospitals, this clustering was performed using a weighted network of all hospitals servicing the population, the weighting determined by patterns of patient flow for all-cause admissions at the level of the postal-area (see Chapter 6).

From these models, hospital-level IRRs were derived – which measure the ratio to which each hospital deviates from the state average, taking into account the factors included in the model, as well as the size of the cluster through a 'shrinkage' factor.[196] The size of the spread of this deviation was measured using a random intercept (σ^2) from the multilevel model, as well as the ARD - which quantifies, on average, how much these adjusted hospitalisation rates differ from the total adjusted hospitalisation rate.[200]

Model specifications are presented in Appendix 2.3. IRRs for different hospital types were derived by further including the hospital category in the model, and taking the exponential of these parameter estimates. All analyses were performed in SAS9.4 and MLwiN v2.35.

7.5 Results

Of 267,014 participants in the linked dataset, n=119 were excluded for having unknown area of residence (postcode or SLA) or incompatible dates in the linked data. Participants in 16 postal areas did not have any hospitalizations during follow-up; the 69 participants residing in these areas were also excluded as they were unable to be weighted to any hospital in the multilevel model, leaving 266,826 for analysis, with an average follow-up of 3.7 years between 2006 and 2011. Mean age, self-reported health and multi-morbidity of study participants were broadly consistent across remoteness categories (Table 7.1), although participants in remote areas were slightly younger, with poorer health and a higher number of comorbidities.

The majority of the 30,264 preventable hospitalisations during follow-up were to principal hospitals (31%) with only a small proportion to community (9.1%) and multipurpose (2.6%) facilities (Table 7.1). However, this pattern was inverted for participants in remote and outer regional areas, with the majority of admissions in these areas to community (24.6%) and

district hospitals (37.4%). A similar pattern was observed in the 3,167 emergency AMI and 1,550 emergency hip fracture admissions, although with fewer admissions overall to district, community and multipurpose hospitals (data not shown)

Table 7.1: Cohort characteristics at baseline, and number of preventable hospitalisations during follow-up, by remoteness of area of residence

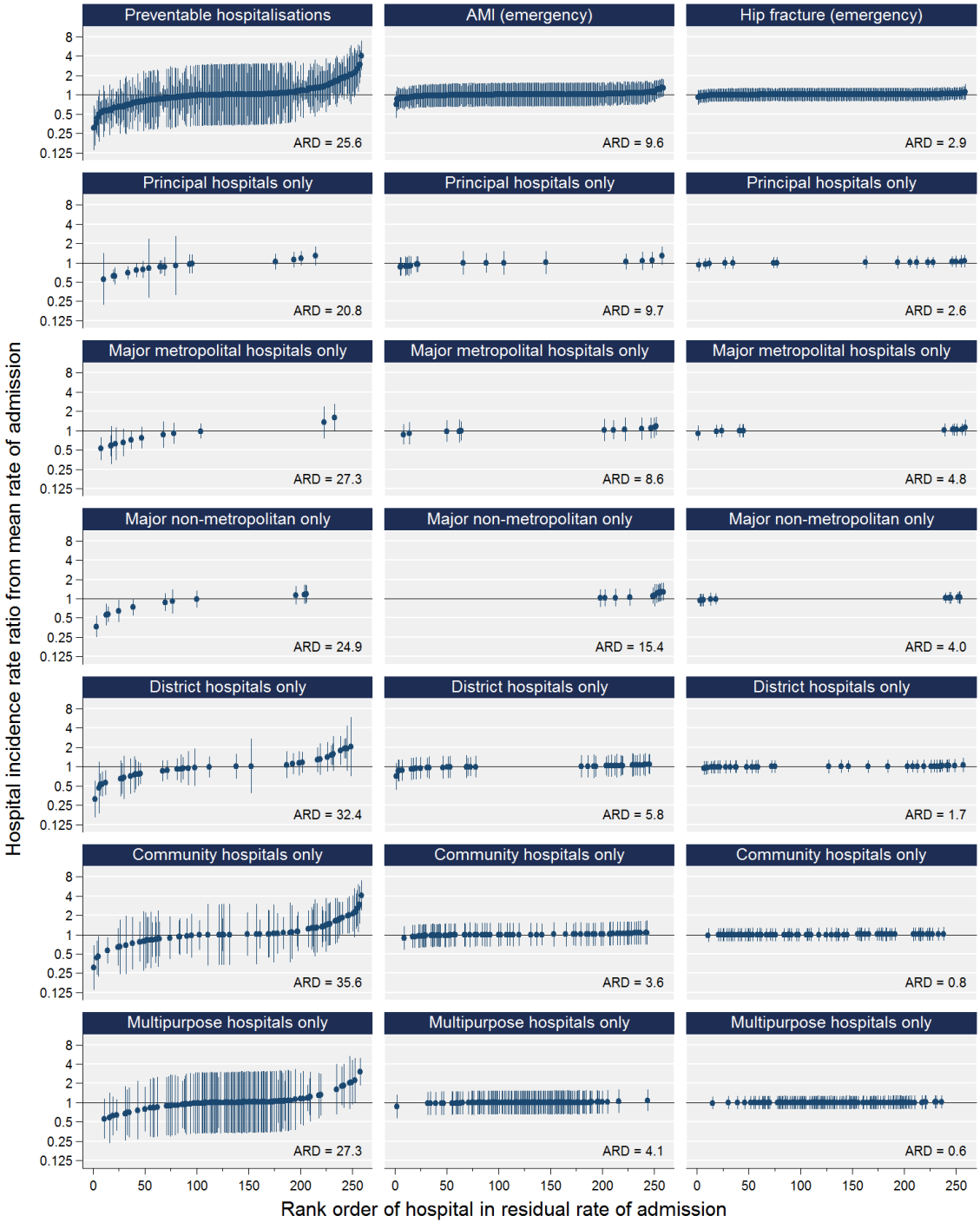
	Total	By remoteness category of residence			
		Major cities	Inner regional	Outer regional	Remote
Cohort characteristics					
N	266,826	119,496	94,568	47,438	5,324
Age (mean)	62.7	63.4	62.4	62.2	60.7
Age (IQR)	53.6-70.4	53.6-71.9	53.8-69.7	53.7-69.4	52.0-67.8
% Female	53.6	52.4	54.7	54.3	55.5
% fair/poor self-rated health	13.7	13.9	13.4	13.7	16.1
% with >3 comorbidities	7.4	7.3	7.5	7.2	8.0
Preventable hospitalisations					
Number of admissions	30,264	12,512	10,161	6512	1079
Admissions to hospital type (%)					
- Principal	9398 (31.0)	7506 (60.0)	1600 (15.7)	255 (3.9)	37 (3.4)
- Major metropolitan	4172 (13.8)	3321 (26.5)	787 (7.7)	61 (0.9)	3 (0.3)
- Major non-metropolitan	6443 (21.3)	560 (4.5)	3933 (38.7)	1872 (28.7)	78 (7.2)
- District	6715 (22.2)	804 (6.4)	3070 (30.2)	2468 (37.9)	373 (34.6)
- Community	2760 (9.1)	278 (2.2)	611 (6.1)	1491 (22.9)	380 (35.2)
- Multipurpose	776 (2.6)	43 (0.3)	160 (1.6)	365 (5.6)	208 (19.3)

Multilevel models adjusted for personal socio-demographic and health characteristics, as well as remoteness and supply of GP services of the area of residence, found significant variation between hospitals in preventable hospitalisation, such that each hospital deviated on average 26% from the mean adjusted rate of admission (σ^2=0.312; SE=0.059; ARD=25.6). This variation was less pronounced for emergency admissions for AMI (σ^2=0.047; SE=0.026; ARD=9.6) and was not significant for hip fracture (σ^2=0.015; SE=0.017; ARD=2.9)

Figure 7.1 show hospital-level IRRs from the multilevel model, which indicate how each hospital differs from the state average after adjusting for the various factors in the model. There was considerable variation in preventable hospitalisation, with 7% of hospitals having a significantly higher or lower than average adjusted rate of admission. When stratified by type of hospital, the greatest variation was seen in community, district and multipurpose hospitals, with community hospitals in particular including many of the facilities with the highest levels of preventable hospitalisation – up to 4 times the average rate of admission. There were no

hospitals with significant deviations from the mean for emergency AMI or hip fracture admissions, although several major non-metropolitan hospitals tended to have higher levels of emergency AMI admissions.

Figure 7.1: Hospital ranking and incidence rate ratio from the mean adjusted rate of admission, with average relative deviation (ARD) of all hospitals from the mean, overall and stratified by hospital category for preventable hospitalisations and emergency admissions for acute myocardial infarction (AMI) and hip fracture



ARDs stratified by hospital category (Figure 7.1) corroborated these results, with community hospitals having the highest levels of variation in preventable hospitalisation (average 36% difference from the mean), and principal hospitals varying the least (average 21% difference from the mean). There was less variation between all hospital types for emergency AMI or hip fracture admissions than preventable hospitalisations, although conversely for these admissions the highest levels of variation were seen among principal, major metropolitan, and major non-metropolitan hospitals.

Table 7.2: Incidence rate ratio (IRR) for preventable hospitalisation and emergency admissions for acute myocardial infarction (AMI) and hip fracture, overall and stratified by hospital category

	Incidence rate ratio	
	IRR	(95% CIs)
Preventable hospitalisations	-	-
Principal	1.00	(ref)
Major metropolitan	0.99	(0.95 – 1.03)
Major non-metropolitan	1.01	(0.97 – 1.04)
District	1.02	(0.99 – 1.06)
Community	1.06	(1.02 – 1.10)
Multipurpose	1.05	(1.01 – 1.09)
AMI (emergency)	-	-
Principal	1.00	(ref)
Major metropolitan	1.02	(0.99 – 1.05)
Major non-metropolitan	1.04	(1.02 – 1.07)
District	1.00	(0.97 – 1.03)
Community	0.97	(0.93 – 1.01)
Multipurpose	0.93	(0.88 – 0.99)
Hip fracture (emergency)	-	-
Principal	1.00	(ref)
Major metropolitan	1.02	(0.99 – 1.05)
Major non-metropolitan	0.99	(0.96 – 1.02)
District	0.99	(0.96 – 1.02)
Community	0.96	(0.91 – 1.01)
Multipurpose	1.02	(0.94 – 1.09)

The inclusion of hospital category in the regression models (Table 7.2) showed significantly higher rates of preventable hospitalisations among people serviced by community (IRR:1.06; 95% CIs:1.02-1.10) and multipurpose (IRR:1.05; 95% CIs:1.01-1.09) than principal hospitals. For emergency AMI admissions, there was significantly higher rates in people serviced by major non-metropolitan (IRR:1.04; 95% CIs:1.02-1.07), and lower rates among people serviced by multipurpose facilities (IRR:0.93; 95% CIs:0.88-0.99).

A sensitivity analysis categorising preventable hospitalisations as short or long stay admissions (Table 7.3) found differing patterns of variation by length of stay, with the significantly higher rates of admission for community and multipurpose hospitals restricted to short-stay preventable hospitalisations only.

Table 7.3: Average relative deviation (ARD) and Incidence rate ratio (IRR) by hospital category for rates of preventable hospitalisation, separated as short-stay (0-2 days length of stay) and long-stay (>2 days length of stay) admissions

	Short stay (0-2 days length of stay)			Long stay (>2 days length of stay)		
	ARD	IRR	(95% CIs)	ARD	IRR	(95% CIs)
Principal	17.9	1.00	(ref)	14.6	1.00	(ref)
Major metropolitan	25.5	0.99	(0.95 – 1.02)	25.9	1.00	(0.97 – 1.03)
Major non-metropolitan	22.7	1.02	(0.98 – 1.05)	11.3	0.99	(0.96 – 1.02)
District	30.4	1.02	(0.99 – 1.05)	24.3	0.98	(0.95 – 1.00)
Community	17.5	1.04	(1.01 – 1.07)	25.7	1.02	(0.99 – 1.05)
Multipurpose	24.3	1.04	(1.00 – 1.08)	11.6	0.99	(0.95– 1.03)

7.6 Discussion

This study found significant variation in preventable hospitalisation, after adjustment for patient and geographic factors, between public hospitals. This was most marked for community hospitals—which varied on average 36% from the mean—and to a lesser extent multipurpose facilities. Similar variation was not observed for other less discretionary marker conditions, major hospitals servicing regional areas, or admissions with a longer length of stay, indicating varying propensity to admit patients for preventable hospitalisations among these smaller facilities. While admissions to community and multipurpose hospitals represented only a small burden (12%) of all preventable hospitalisations, they made up 55% of admissions in remote areas. Accordingly, these differences in admission practices are likely to play an important role in driving geographic variation in the preventable hospitalisations performance indicator, where remote regions have both high variability, with over a five-fold variation in rates of preventable hospitalisations, but also the consistently highest rates of admission across Australia.[25]

There is very little evidence about how hospital characteristics influence rates of preventable hospitalisations in Australia. One study of major hospitals in NSW reported up to 11-fold and 7-fold variations, between hospitals in the proportion of all medical admissions that were for congestive heart failure and chronic obstructive pulmonary disease, respectively.[244] Earlier work from the current team, focussed on major hospitals only, found no association between

preventable hospitalisations and hospital bed occupancy rates (Chapter 6). Importantly, this previous analysis excluded community or multipurpose hospitals, which were the facilities in this study with the strongest patterns of variation.

The differing patterns found according to hospital category points to the varying roles of these facilities in serving their communities. While it is difficult to assess causes for variation in the context of this analysis, higher rates of preventable hospitalisations may represent greater integration of primary care and hospital services in some facilities, particularly in small regional and remote areas, while for other facilities it may represent differences in discretionary admission thresholds. Thus, interpretation of the indicator is dependent on localised knowledge on the services provided. The high rates of AMI admissions seen among major non-metropolitan hospitals also suggest that local factors are at play, including the purposeful diversion of these patients to hospitals better equipped for complex cardiac care.

These results are the first to provide evidence of a hospital-level difference in propensity to admit patients for preventable hospitalisations in Australia, and align with growing evidence that this indicator represents reflects factors more than access to and quality of primary care, including the sociodemographic and health characteristics of the population.[203] The implications for performance measurement are clear: interpretation of the indicator is complex, and factors along the care continuum influence variation in admission rates. Use of the indicator for purposes beyond its original intent—as a yardstick measure of health system performance[19]—need to be approached with caution.

The strength of this study lies in the use of a large cohort with detailed survey and linked health data. Much inference on preventable hospitalisation is limited either by unmeasured confounders or the use of ecological measures of patient demographics, and estimation of hospital effects can be difficult given the lack of a discrete population denominator. The use of cross-classified multiple membership multilevel models make this one of the only studies to perform appropriate modelling for each of patient-, area- and hospital-level effects. Limitations include that the results may be sensitive to different patient weighting structures, although the measures of patient flow used are consistent with widely accepted methods for constructing hospital patient catchments in the US.[221] There also remains unexplained hospital variation in this analysis, with limited data on hospital characteristics, so the impact of more complex models of care, such as integrated care programs have yet to be explored. Furthermore, given features of the study design, including the older age of the study population (45 and over) and the low response rate (18%) there may be limited generalisability

of results. However, the considerable size and heterogeneity of the study mean inferences from within-cohort comparisons remain valid.[169, 170]

7.7 Conclusion

Differences in hospital admission practice contribute to geographic variation in rates of preventable hospitalisation in Australia, in particular reflecting the different roles played by community and multipurpose hospitals compared with major and principal referral hospitals in regional and remote areas. The preventable hospitalisations health performance indicator should not be interpreted simply as a measure of the accessibility and quality of primary care services.

Chapter 8 Discussion

8.1 Review of background and aims

Preventable hospitalisations are used in Australia as a high-level performance indicator of the primary health care system. They are widely used by health policymakers, to compare performance of health jurisdictions,[25] to set benchmarks and track performance of health systems over time,[26] to measure health disparities among vulnerable populations,[28] and to evaluate the impact of implementing new models of care.[55]

However, there is surprisingly little evidence supporting the use of preventable hospitalisations in Australia. Most of the research validating the indicator has come from the USA – a country with considerable barriers to accessing primary care - such as costs, health insurance coverage and inequities in the distribution of ambulatory care services.[8] Australia has a universal health care system with higher subsidies for the elderly and low income families and a 'safety net' for patients with high medical expenditure,[8] and it is questionable whether evidence from the USA will be generalizable to an Australian setting.

Furthermore, there are key gaps in our broader understanding of how preventable hospitalisations relate to primary care. Many additional factors potentially influence admission, such as the health of the population, their predisposition to seek care, healthy behaviours, distance from services, and the capacity and propensity of hospitals to admit patients for different types of conditions. Some of these factors are amenable to intervention - such as through long-term preventive strategies, while others are immutable to the healthcare system. The independent contribution of various factors to geographic variation in the indicator is unknown, but needed for policymakers to target interventions, and evidence on the role of many factors, such as hospital care, is weak.[124] Indeed much of the research over the past 20 years have used similar study designs, analysing ecological measures of primary care supply, patient characteristics and hospital capacity, which provide limited inferences on factors at the different patient-, area- and hospital- levels.

This thesis sought to use new methodological approaches to analysing longitudinal health data to gain new insights in the appropriateness of the preventable hospitalisation health performance indicator in Australia.

The key aims were to address the following questions:

1) How are patients admitted for a preventable hospitalisation using primary care services? Are patients accessing general practitioners in the period leading up to hospitalisations, and is this different to the rate of service use in the general population? Are there new ways of presenting such complex patterns of health service use?
2) What are the relative contributions of primary care supply, and the health and demographic of the population, to geographic variation in preventable hospitalisation in Australia? Is there evidence that preventable hospitalisations are a valid indicator of primary care supply? Can we overcome the ecological fallacies that exist in much of the literature using linked data and multilevel modelling?
3) Do differences between hospitals contribute to variation in preventable hospitalisation? How can we explore the contribution of hospitals to this population-level health outcome? Is there significant variation between hospitals, and what types of hospitals have higher rates of admission?

8.2 Summary of main findings

8.2.1 How admitted patients are using primary care services

The research presented in Chapter 4 used a visualisation of patient unit record data to explore the use of health services around preventable hospitalisations. This showed that many patients admitted for a preventable hospitalisation saw GPs around the time of admission, with 14% of patients consulting a GP on the day of admission, and 27% of patients in the week prior. This pattern was more evident in patients with a longer length of stay, where patients also had more deaths and readmission for other types of hospitalisation following discharge, suggesting that these patients may have been sicker at the time of their hospitalisation.

Interestingly, this pattern also varied across remoteness categories, with many patients in remote areas having GP consultations during the time of hospitalisation. This is reflective of the different roles of hospitals in rural areas, where many GPs may have formal appointments at their local hospital. With greater travel time for accessing services these physicians may potentially be more likely to admit a patient for observation.[133]

Patients admitted for a preventable hospitalisation were also found to have higher rates of GP consultations (mean of 13.1 visits per year) compared to a cohort matched on baseline patient health, demographics and remoteness from services (mean of 9.7 visits per year). This was also

more than twice the mean rate of annual physician visits in Australian (6.5) and more than four times that in the USA (3.9).[8]

These results suggest that patients admitted for a preventable hospitalisation were highly engaged with the healthcare system, likely to be sicker, and in some cases the admission may have been a result of coordinated care. As Australia is a country with a universal healthcare system, this indicates that patterns in the use of GP services may be more reflective of patient need, than variation in barriers to accessing care.

This interpretation is supported by a supplementary paper I co-authored during the course of the thesis research (Appendix 3.2), which found no association between rates of preventable hospitalisations in the last 6 months of life with baseline levels of GP utilisation in the preceding year.[245] This was in stark contrast to a comparable US study on elderly patients,[94] which found an inverse association, and remarkably different distribution in the baseline use of primary healthcare services – with 38% of patients having none and 21% of patients had 6 or more primary care consultations in the year leading up to the end of life period, compared with 22% and 42% of patients respectively in our study.

The data visualisation used in Chapter 4 was a novel approach for both exploring preventable hospitalisations and for visualising health data. Few studies have explored patient-level use of health services, either as the number of primary care consultations[84, 94, 95] or measures of continuity of care,[88-93] but no previous studies have explored the temporal proximity of primary care to preventable hospitalisation, nor the range of additional health services used, such as specialist consultations, emergency department presentations, and other types of hospitalisation. It is difficult to conceptualise how many of the additional insights obtained, such as the use of GP services during the time of preventable hospitalisation in regional and remote areas, or the high levels of readmission for other hospitalisations following discharge for preventable hospitalisation (highlighting the non-specificity of the indicator), could be as efficiently obtained using traditional epidemiological approaches.

Furthermore, the visualisation developed was a novel approach to visualising timelines of patient-level health data. While a variety of visualisation tools and software packages are available, these are often limited in capacity, lacking the flexibility to adapt to the varied needs of health researchers - such as the need to plot both point (e.g. GP consultation) and interval (e.g. hospitalisation) events. While the visualisation framework in Chapter 4 is not comparable as a software tool, and lacks important features such as interactivity, example syntax and metadata for producing such plots is provided (Appendix 4), and it is one of the only examples

of visual timelines actually being used in research, with most of the visualisation literature focused on developing, user testing and reviewing software tools. This chapter is therefore an important translational bridge, demonstrating how this new approach can be used to gain new and practical insights.

8.2.2 The relative contribution of patient characteristics and primary care supply to geographic variation in hospitalisation

The research presented in Chapter 5 used linked patient survey and administrative hospitalisation data, along with multilevel modelling, to explore factors that explained geographic variation in preventable hospitalisation. I found that only a small proportion (2.9%) was explained by the supply of primary care services, while over one third (36.9%) was explained by the sociodemographic and health characteristics of the population. This pattern varied between types of preventable hospitalisation, with sociodemographic and health characteristics explaining more of the geographic variation for chronic conditions (37.5%) – particularly COPD (44.8%), diabetes (25.6%), congestive cardiac failure (24.7%) and angina (22.2%), but little of the geographic variation for acute (15.5%) or vaccine-preventable conditions (2.4%).

Surprisingly there was no association between the area-level supply of primary care services with rates of preventable hospitalisation. The strongest predictors of admission were instead patients' age, self-rated health, multimorbidity and functional limitation. This pattern of results was not only the case for all subtypes of preventable hospitalisation, but also for a comparison outcome of all 'non-preventable' hospitalisations.

These results are complemented by the supplementary co-authored papers in Appendix 3.1, which highlight the potential beneficial role of long term health promotion, with an estimated 29% of preventable hospitalisations potentially able to be averted if our study population all undertook a number of positive healthy behaviours, and reduction in smokers' risk of hospitalisation for COPD within 5 years of quitting smoking.

The analysis design in Chapter 5 filled an important gap in the research in preventable hospitalisations. In using a novel linkage of comprehensive patient survey and longitudinal health data for a large cohort, and analysing using a multilevel model, this was the first study to explore how patient characteristics influence geographic variation in preventable hospitalisation, using data and methods appropriate to the patient- and area-level factors under investigation.

8.2.3 Hospital variation in propensity to admit patients

In Chapters 6 and 7 I developed and applied a new method, weighted-hospital service area networks, for attributing population variation in preventable hospitalisations to the hospital-level using multiple membership multilevel models. I found significant variation between hospitals in rates of preventable hospitalisation, which varied on average 26% from the mean rate of admission. The most variation was found between smaller types of facilities, such as community and multipurpose hospitals, and many of these facilities also had the highest residual rates of hospitalisation, even after adjusting for patient health, geographic remoteness and the supply of GP services in the area. Very little between-hospital variation was found for two comparison conditions: emergency admissions for AMI and hip fracture.

Community and multipurpose facilities are generally small and not usually subject to benchmark reporting and evaluation in Australia. However, while these facilities only accounted for 12.5% of all preventable hospitalisations, this increased to 54.5% of admissions for people living in remote and very remote regions. Anecdotal evidence has previously suggested some facilities in regional areas may have a higher propensity to admit patients for observation, where travel times are large and there is more limited access to services for patients.[133] The greater variation found between these facilities, as well as the higher rates of admission, suggest that these differences in hospitals' propensity to admit patients may be contributing to geographic patterns of preventable hospitalisation.

This interpretation of results is consistent with analyses in Chapter 4, which found that many patients in remote areas had GP consultations during the time of their preventable hospitalisation. With many GPs in regional areas also having formal appointments within local hospitals, these results do suggest that hospitals are playing a different role within these regional communities in responding to the health needs of the population.

The analysis in Chapter 6 also explored the association of preventable hospitalisation with average hospital bed occupancy rate, as a measure of the availability of hospital resources. While no significant association was found, this analysis was restricted to the larger public hospitals where benchmarking data are available. The findings from this chapter are consistent with those in Chapter 7, with potential discretionary admission practices as a result of capacity likely to be a more important factor in the smaller community and multipurpose facilities.

Through the use of a new analytic approach, weighted hospital service area networks, the analyses in Chapters 6 and 7 are some of the first to explore the role of specific hospital

characteristics in driving variation in preventable hospitalisation. Almost all of the prior evidence had explored geographic aggregations of hospital resources, such as the number of beds per capita,[75, 78, 80, 107, 130] although one UK study has explored hospital characteristics through the creation of projected population denominators.[132] While multiple membership multilevel models are not a new statistical methodology, the application to analysing population hospital catchments is a novel approach, and one that has great potential to uncover further insights on how features of the health system can influence rates of preventable hospitalisations.

8.3 Implications for policy and practice

8.3.1 Preventable hospitalisations as a health performance indicator in Australia

The results presented in this thesis indicate that the preventable hospitalisation indicator in Australia cannot be interpreted simply as a measure of the accessibility of primary care. A variety of factors across the care continuum influenced admission for preventable hospitalisation, including patient demographics not mutable to health system intervention, patient health characteristics potentially amenable to long-term interventions, as well as variation in hospitals' propensity to admit patients. Given that many of these factors had stronger associations with preventable hospitalisation than primary care supply, and accounted for more geographic variation, these are not just confounders, but some of the primary drivers of variation of this health performance indicator.

This is not to say that primary care does not play a potential role, rather doing 'more of the same', such as increasing physician supply, is unlikely to address the factors underlying preventable hospitalisations.[60, 84] The higher levels of health service utilisation in Australia, compared to the USA, as well as the higher levels of utilisation among admitted patients compared to non-admitted patients, suggests that this utilisation may be more reflective of patterns of patient need. If additional barriers to accessing primary care were introduced in Australia, such reduction in patient safety-nets, bulk-billing practice, GP incentives to service rural and remote areas, or an increase in patient co-payments, then the disparities observed in countries like the USA, which doesn't have a universal health care system, may start to be observed.

Primary care may also play a role through the timeliness or quality of services provided. The data used in this thesis did not allow detailed evaluation of this dimension of primary care. If many admitted patients are already engaged with healthcare services, improvements in the quality or efficiency of care, such as through the use of chronic disease management plans, integrated care programs or patient-centric medical homes, could reduce the total burden of care for patients with chronic conditions.[43, 62] Evaluation of the effectiveness of such programs was, however, outside the scope of this thesis.

How then should policymakers in Australia use and respond to the preventable hospitalisations indicator? While the complexities in interpretation mean it arguably should not be used for monitoring health system performance, the fact it is intuitively appealing, easy to calculate, and already embedded in Australia's health performance and accountability framework,[6, 23] means it will likely remain a 'zombie indicator'[246] that continues to be used, despite evidence to the contrary.

If so, it is important that the indicator is interpreted according to its original intent – as a yardstick measure of health system performance.[19] The indicator has been broadly adopted in Australia for a variety of purposes, such as an outcome measure for evaluating chronic disease management programs,[55] but it is unlikely to be highly responsive to any single form of intervention. More recent reports on preventable hospitalisations have stressed the need for localised, rather than generic, strategies that are tailored to current models of care in a district as well as the needs and characteristics of the population,[25, 241] and the results of this thesis support this interpretation.

Utility of the indicator can also be enhanced through stratified reporting, and inclusion of supplementary statistics, to help guide priorities of local policymakers. For example, stratifying the indicator by major conditions, or conditions with similar pathways for intervention, can help inform where the largest burden of preventable hospitalisations lies in a population, and better identification of clear best practice guidelines for managing these specific conditions.

New data sources on primary care are now becoming available, and can give a clearer indication of how specific elements of care vary. For example, a report from the NHPA on Australian's experiences with primary health care[16] combined patient survey and Medicare claims data to explore geographic variation in waiting times, cost barriers, and utilisation of GP, dental professional, medical specialist and pharmaceutical care. Similarly, MBS and PBS claims data are increasingly being used to monitor trends in specific types of health services,[185, 247] adherence to best practice guidelines[194, 248] and hospitalisations which may have been

prevented through medication-related issues,[217] while practitioner registration, mailing list and survey data are being used to monitor the distribution of the health workfoce.[12, 183, 249, 250] Developing new indicators from such data sources, linked to specific practices and intervention strategies, has great potential to better inform the performance of the Australian health care system.

8.3.2 International adoption of performance indicators from different healthcare systems

While the results of this thesis are specific to the Australian health care system, the findings have relevance to the use of preventable hospitalisations around the world. Preventable hospitalisations are currently used as a measure of health system performance in the USA,[17, 32-35] UK,[31, 65] Canada[18] and New Zealand,[36] with further research coming out of Switzerland,[75] Norway,[83] Sweden[76], Finland,[143] Italy,[130] Denmark,[118, 142, 251] Spain,[142, 252, 253] Portugal,[142] Germany,[254, 255] France,[141] Slovenia,[142] Brazil,[256] Singapore[101] and Taiwan.[88, 90, 122] However, the vast majority of research validating the indicator has come from the USA.[19, 38, 39, 69, 73, 78, 85, 104, 109]

This thesis found that preventable hospitalisations in Australia were not a particularly good measure of the accessibility of primary care, partially because Australia has a very different healthcare system to the USA, resulting in vastly different patterns in healthcare utilisation, with the indicator primarily reflecting the varied patient and health system factors which all play a role in driving admission. Similarly, evidence supporting the preventable hospitalisations indicator from other health care systems, while limited, has been mixed.[64, 65, 84, 253] This is likely to reflect further variation between countries in the balance of factors which enable and inhibit health service use.

Preventable hospitalisations have been monitored in Australia for over 10 years, but with little change in performance over time.[7] Meanwhile, considerable administrative, workforce and strategic resources have been spent in monitoring and responding to the indicator. This use of resources has been of questionable value given the few practical insights relevant to the healthcare system that have been generate through this activity.

These results highlight why policymakers should be cautious in adopting international health performance indicators from different healthcare systems, particularly one as complex as preventable hospitalisations. Care should be taken to critically review how generalizable the existing evidence is to the system under evaluation, what aspects of care are likely to be

reflected, and how responsive the indicator is expected to be to policy interventions, given the context, population, and resources available.

8.4 Dissemination and policy impact

I have presented results from this thesis at a number of academic conferences, including internationally at the International Population Health Data Network Conferences in 2014 (Vancouver) and 2016 (Swansea), the Scottish Health Informatics Program Conference in 2013 (St Andrews), The Farr Institute International Conference in 2015 (St Andrews) and the C9-GO8 Forum on Big Data in China (Nanjing) in 2015. In Australia and New Zealand I have presented results at the Health Services and Policy Research Conferences in 2013 (Wellington) and 2015 (Melbourne) and the Annual 45 and Up Study Collaborators Meetings in 2012, 2013, 2014 and 2016 (all in Sydney), including a plenary in 2015.

8.4.1 Presentations to policy stakeholders

At the onset of the APHID Study, a policy reference group was established, comprising study investigators, members from APHID Study partner organisations, such as the ACSQHC, BHI and ACI, nominated policy stakeholders from the AIHW, NHPA, Department of Health and Ageing, NSW Ministry of Health, Clinical Excellence Commission and GP NSW, as well as nominated researchers from Australian National University, UNSW, University of Sydney and Western Sydney University. Preliminary analysis plans and study results were presented to this reference group over two meetings in 2012 and 2013, to help prioritise policy relevant objectives, analyses and publications from the study.

I coordinated a policy forum in November 2014, presenting results from Chapter 5, as well as preliminary results from Chapters 4, 6 and 7 to an audience of over 60 participants. In addition to the reference group, this included stakeholders from Western Sydney, South Eastern Sydney, Central Coast and Mid North Coast Local Health Districts, Blacktown and Westmead hospitals, representatives from various initiatives within the NSW Ministry of Health including integrated health, chronic care, disability, injury and pain management, as well as additional primary care researchers from UNSW, University of Sydney and Monash University.

In response to strong policy interest in the study, I have also given a number of invited presentations to policy organisations and committees. Similar to the reference group and policy forum, these presentations included the objectives of the study, preliminary and final results from Chapters 4-7, as well as an opportunity for feedback on policy priorities for

research. Between 2012-2016, this has included two seminars each for the NHPA, ACSQHC, and ACI, separate presentations to the ACSQHC Primary Care Committee and ACI Research Sub-Committee, as well as talks for the AIHW, BHI and Sydney Local Health District Public Health Observatory.

The outcome of these presentations has been to connect the study findings with the relevant policy stakeholders, both those developing and reporting the preventable hospitalisation indicator, as well as service-level staff tasked with implementing policies to reduce preventable hospitalisations. While study results are being cited in relevant policy documents, such as a discussion paper on risk stratification by the ACI,[209] a baseline needs assessment of the Capital Primary Health Network,[257] and a review of care programs for reducing preventable hospitalisations by the Primary Health Care Research & Information Service,[258] the larger impact has been through subsequent advisory roles and committee memberships as a result of this active community engagement.

8.4.2 Commonwealth advisory groups and committees

During 2012-2014 I was invited to participate in the NHISSC Potentially Preventable Hospitalisations/Potentially Avoidable Deaths Working Group. This working group was tasked with revising the national standards for reporting of the preventable hospitalisation indicator, and participation in the group allowed me to both present my research, and participate in discussions on the definition, scope and purpose of inclusion of each of the conditions within the indicator.

During 2014-2015 I was invited to participate in the NHPA Potentially Avoidable Hospitalisations Advisory Committee. This committee was tasked with providing advice on the measurement and interpretation of results and key messages for their 2015 report on potentially preventable hospitalisations.[25] During participation in this committee I provided advice on measurement of the preventable hospitalisations indicator, data quality issues, types of data reporting and useful statistics, as well as interpretation of results. In addition to committee membership, I provided additional advice on potential supplementary analyses for the report, including additional analyses using Medicare data, and a possible commissioned exploration of preventable hospitalisations at the end of life using APHID Study data.

In 2016 national reporting of the preventable hospitalisations indicator was moved to the ACSQHC. During 2016 I was invited to participate in the ACSQHC Potentially Preventable Hospitalisations Topic Expert Group for the upcoming Australian Atlas of Healthcare Variation

2.0. As with the NHPA, I provided advice on the measurement, interpretation and supporting literature around interventions for this health performance indicator. At the time of thesis submission, this report has not yet been published.

The outcome of participation in these advisory groups has been to help influence the manner in which the indicator is reported and interpreted in Australia. For example, results in Chapter 5 suggests a broader role of the health care system in preventing unnecessary hospitalisations for chronic diseases, including long-term primary prevention, chronic disease management strategies, and support of non-GP care such as pharmacists and physician assistants. In more recent years the description of the indicator metadata has been updated to reflect a more nuanced interpretation of the potential range of health services which can influence admission, being revised from '*admissions to hospital that could have potentially been prevented through the provision of appropriate non-hospital health services',*[22] to '*admission to hospital for a condition where the hospitalisation could have potentially been prevented through the provision of appropriate individualised preventative health interventions and early disease management usually delivered in primary care and community-based care settings (including by general practitioners, medical specialists, dentists, nurses and allied health professionals).'*[23]

Similarly, a key recommendation in Chapter 5 is for stratified reporting of individual conditions or groups of conditions according to potential pathways for intervention. This recommendation was adopted by the NHPA in their 2015 report,[25] which included separate reporting for the five most common conditions which together accounted for over 60% of bed days for preventable hospitalisations. This stratified reporting is set to continue in the upcoming ACSQHC Australian Atlas for Healthcare Variation 2.0.

8.4.3 Interpretive guide

In 2016 I was commissioned by the ACSQHC to draft an interpretive guide for the preventable hospitalisations indicator, in response to reported difficulties in accurately interpreting the indicator from the NHISSC. These guides were primarily for a health professional audience, with utility for service level staff but also targeted to Boards and CEOs of Primary Health Networks, for whom preventable hospitalisations were likely to be a headline performance measure.

The drafted interpretive guide included an overview of preventable hospitalisations, evolution of how it has been used as a health performance indicator in Australia, strengths and

limitations of the indicator, additional data sources informing the provision of primary care, and facilitated examples of how reported information can be interpreted – including comparisons between geographic regions, breakdown by conditions and population subgroups, and trends over time. The caveats in interpretation of the indicator identified in Chapter 5 are directly referenced, and some of the content of Section 2.3 of this thesis has been adapted for this guide.

The published guide is included in Appendix 3.4. The outcome of this work is that the results of this thesis will directly guide the use and interpretation of the preventable hospitalisations indicator across health jurisdictions, and at the highest level of government reporting, in Australia.

8.5 Strengths and limitations

The core strengths of this study come from the novel data set, facilitated through data linkage, bringing together detailed person-level information with linked longitudinal data on hospital admissions, mortality, GP and specialist use, as well as characteristics of hospitals and the areas in which patients live.

First, much inference on preventable hospitalisation is limited either by unmeasured confounders or the use of ecological measures of patient demographics. The linked data allowed me to appropriately adjust for patient characteristics in all chapters of this thesis, be it through the use of propensity matching (Chapter 4) or the inclusion of patient-level characteristics in multilevel models (Chapters 5-7). The resulting models in Chapter 7, which use cross-classified multiple membership multilevel models, with study participants clustered in both their area of residence and network of hospitals servicing their area, form possibly the most comprehensive analysis to date on preventable hospitalisations, incorporating factors at each of the patient-, area- and hospital-levels.

Second, the availability of linked data also facilitated the use of new analytic approaches, a key strength which has been previously discussed. Through taking a fresh approach, employing powerful analytic techniques from computer science and statistics rarely used in health services research, the research presented in this thesis delivered new insights into preventable hospitalisations, be it patient trajectories of health service use around preventable hospitalisation, the contribution of patient characteristics to geographic variation in admission, or the degree of variation between hospitals.

However, the use of new analytic approaches also posed challenges, because there were few published studies with which to compare results. Further methodological development may be needed, such as comparison of different weighting structures in the weighted-HSANs. Furthermore, considerable space in the publications from Chapters 4 and 6 were by necessity dedicated to describing these methods, limiting the extent to which their application to preventable hospitalisations could be discussed.

The results in specific chapters may also be sensitive to the methods used for analysis. For example, comparisons between patients admitted for a preventable hospitalisation with a matched non-admitted cohort may differ using a different set of variables for propensity matching; there may be residual overdispersion as a result of using Poisson regression models in Chapters 5 -7; and analyses on hospital variation in Chapters 6 and 7 may be sensitive to different methods for constructing weighted-HSANs. Furthermore, there may be errors in the probabilistic data linkage process, although strict quality assurance methods are used at the NSW CHeReL to ensure low rates of both false-positive and false-negative linkages.[259]

A further limitation of this study is the generalisability of results. As it used an Australian cohort, the results are not necessarily applicable to other health care systems. Participants in the 45 and Up Study are also an older and potentially healthier cohort than the general population[166], and given the low participation rate (18%), are unlikely to be a representative sample of all Australians. However, persons aged 45 years and over have the highest rate of preventable admissions per capita, and contribute two-thirds of preventable hospitalisations in Australia.[30] Internal relative risk estimates from the 45 and Up Study have also been found to be comparable to those from population health surveys,[169] and the large sample size provides substantial heterogeneity, so that any within-cohort comparisons should remain valid.[170]

Finally, there are further characteristics of patients and health systems that are likely to affect preventable hospitalisation that were not explored in this thesis. As has been noted in the literature, 'no single study has been able to deal with all possible types of care which might affect hospitalization',[84] and there remain further characteristics, particularly of the health care system, yet to be explored. This includes the quality and timeliness of primary care, the impact of care coordination and continuity of care, use of specialists by patients with chronic disease, and administrative and structural hospital characteristics which influence patient admissions and conversion from emergency department to hospital care. A better understanding of these health system factors, and how they relate to different types of preventable hospitalisations, will help inform pathways for policymakers to best respond to

the indicator. However, the research presented here has addressed key features of the health system as identified in the literature, and offers methods for which some of these further characteristics can now be explored.

8.6 Implications for further research

This thesis adds to the growing literature on factors which influence variation in preventable hospitalisation. While the results are contextual to the Australian healthcare system, they add to the mixed evidence on the applicability of the indicator from international studies, such as from Canada,[84] the UK[64] and Spain[253, 260] – all countries with a universal health care system.[8] Given the growing use of the preventable hospitalisations indicator, and the need for contextual evidence for different healthcare systems discussed above, the results of this thesis stress the need for further international comparative research, to help inform the potential generalisability across countries and health care systems.

The findings presented in this thesis also suggest that where preventable hospitalisations are being investigated, there is an important need to further unpack results to better inform where and how policymakers can respond to the indicator. Significant variation was found in the contribution of personal characteristics, between conditions in the indicator, and between hospitals, even of the same type. Research articles which focus on a single association, for example, an association between primary care supply and preventable hospitalisations, adjusting for but not exploring how patient sociodemographic and health characteristics relate to geographic variation,[73] may be missing potentially useful information. For example, a moderate association with primary care supply may be 'significant', but if other patient or health system factors account for a much larger proportion of variation, then it does not follow that the indictor will still be a particularly useful or responsive measure of primary care supply.

Finally, this thesis demonstrates two new methodological approaches for analysis, methods which can similarly be adopted by other studies to generate new insights on preventable hospitalisations, or other health outcomes. The novel data visualisation is replicable using standard statistical software, with example metadata and syntax provided in the publication (Appendix 4), and should be possible using various types of longitudinal health data across various countries and types of data collection. This method provided both a way to analyse temporal patterns of health utilisation around a specific health event (e.g. preventable hospitalisation), but also an intuitive and visual way to compare baseline levels of health service utilisation between population groups.

The weighted-HSAN analytic approach similarly facilitated new insights, allowing variation to be partitioned to individual hospitals, rather than aggregated geographies of multiple facilities. Given this approach is an analytic extension for existing methodologies creating patient catchments of health facilities, it can also be incorporated into many existing data infrastructures and bodies of research. While hospital service areas in the USA continue to be used for research and have not been updated for many years,[223] the emergence of new automated programs for deriving patient catchments of hospitals,[240] and a shift towards catchments that better reflect patient's use of services rather than designated geographies,[229] may provide new international opportunities for this method to be utilised.

8.7 Conclusions

The preventable hospitalisations indicator in Australia should not be interpreted simply as a measure of the accessibility of primary care services. Through linking longitudinal health data for a large population cohort, and using novel multilevel modelling and data visualisation techniques, the research presented in this thesis found that many patients admitted for preventable hospitalisation had higher levels of engagement with the healthcare system, and factors other than primary care–such as patient sociodemographic and health characteristics, and variation in the propensity for smaller regional hospitals to admit patients for care–accounted for much of the variation in admission.

These findings point to the difficult and complex array of factors which drive preventable hospitalisations, and how these will vary between healthcare systems with differing barriers and enablers for care. Caution should be used when adopting international health performance indicators from different healthcare systems, and in Australia policy responses for reducing preventable hospitalisations require localised, rather than generic, strategies tailored to current models of care in a district as well as the needs and characteristics of the population. The results of this thesis also point to the benefits of using novel approaches for deriving new insights, having extracted new types of information, and overcoming limitations inherent in over 25 years of international research on preventable hospitalisations.

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Appendix 1 Codes and definitions

Appendix 1.1 Preventable hospitalisations

The codes below are according to the 2012 definition of potentially preventable hospitalisations, as in the National Healthcare Agreement.

Category	ICD-10-AM diagnosis and procedure codes
Chronic	
Angina	I20, I24.0, I24.8, I24.9 as principal diagnosis only, exclude cases with procedure codes not in blocks [1820] to [2016]
Asthma	J45, J46 as principal diagnosis only
Chronic obstructive pulmonary disease (COPD)	J20, J41, J42, J43, J44, J47 as principal diagnosis only, J20 only with additional diagnoses of J41, J42, J43,J44, J47
Congestive cardiac failure	I50, I11.0, J81 as principal diagnosis only, exclude cases with the following procedure codes: 33172-00, 35304-00, 35305-00, 35310-02, 35310-00, 38281-11, 38281-07, 38278-01, 38278-00, 38281-02, 38281-01, 38281-00, 38256-00, 38278-03, 38284-00, 38284-02, 38521-09, 38270-01, 38456-19, 38456-15, 38456-12, 38456-11, 38456-10, 38456-07, 38456-01, 38470-00, 38475-00, 38480-02, 38480-01, 38480-00, 38488-06, 38488-04, 38489-04, 38488-02, 38489-03, 38487-00, 38489-02, 38488-00, 38489-00, 38490-00, 38493-00, 38497-04, 38497-03, 38497-02, 38497-01, 38497-00, 38500-00, 38503-00, 38505-00, 38521-04, 38606-00, 38612-00, 38615-00, 38653-00, 38700-02, 38700-00, 38739-00, 38742-02, 38742-00, 38745-00, 38751-02, 38751-00, 38757-02, 38757-01, 38757-00, 90204-00, 90205-00, 90219-00, 90224-00, 90214-00, 90214-02.
Diabetes complications	E10–E14.9 as principal diagnoses, and E10–E14.9 as additional diagnoses where the principal diagnosis was: hypersmolarity (E87.0), acidosis (E87.2), transient ischaemic attack (G45), nerve disorders and neuropathies (G50–G64), cataracts and lens disorders (H25–H28), retinal disorders (H30–H36), glaucoma (H40–H42), myocardial infarction (I21–I22), other coronary heart diseases (I20, I23–I25), heart failure (I50), stroke and sequelae (I60–I64, I69.0–I69.4), peripheral vascular disease (I70–I74), gingivitis and periodontal disease (K05), kidney diseases including end-stage renal disease (N00–N29), and renal dialysis (Z49)
Hypertension	I10, I11.9 as principal diagnosis only, exclude cases with procedure codes according to the list of procedures excluded from the Congestive cardiac failure category above.
Iron deficiency anaemia	D50.1, D50.8, D50.9 as principal diagnosis only.
Nutritional deficiencies	E40, E41, E42, E43, E55.0, E64.3 as principal diagnosis only.
Rheumatic heart disease	I00 to I09 as principal diagnosis only. (Note: includes acute rheumatic fever)
Acute	
Appendicitis with generalised peritonitis	K35.0 in any diagnosis field

Category	ICD-10-AM diagnosis and procedure codes
Cellulitis	L03, L04, L08, L88, L98.0, L98.3 as principal diagnosis only, exclude cases with any procedure except those in blocks 1820 to 2016 or if procedure is 30216-02, 30676-00, 30223-02, 30064-00, 34527-01, 34527-00, 90661-00 and this is the only listed procedure
Convulsions and epilepsy	G40, G41, O15, R56 as principal diagnosis only
Dehydration and gastroenteritis	A09.9, E86, K52.2, K52.8, K52.9 as principal diagnosis only.
Dental conditions	K02, K03, K04, K05, K06, K08, K09.8, K09.9, K12, K13 as principal diagnosis only.
Ear, nose and throat infections	H66, H67, J02, J03, J06, J31.2 as principal diagnosis only.
Gangrene	R02 in any diagnosis field
Pelvic inflammatory disease	N70, N73, N74 as principal diagnosis only.
Perforated/bleeding ulcer	K25.0, K25.1, K25.2, K25.4, K25.5, K25.6, K26.0, K26.1, K26.2, K26.4, K26.5, K26.6, K27.0, K27.1, K27.2, K27.4, K27.5, K27.6, K28.0, K28.1, K28.2, K28.4, K28.5, K28.6 as principal diagnosis only.
Pyelonephritis	N10, N11, N12, N13.6, N39.0 as principal diagnosis only.
Vaccine-preventable	
Influenza and pneumonia	J10, J11, J13, J14, J15.3, J15.4, J15.7, J15.9, J16.8, J18.1, J18.8 in any diagnosis field, excludes cases with additional diagnosis of D57 (sickle-cell disorders) and people under 2 months
Other vaccine-preventable conditions	A35, A36, A37, A80, B05, B06, B16.1, B16.9, B18.0, B18.1, B26, G00.0, M01.4 in any diagnosis field

Appendix 1.2 Hospital peer group

Hospital Peer Group	Description
Principal	
A1a Principal Referral Group A	Acute hospitals, treating 25,000 or more acute casemix weighted separations per annum, with an average cost weight greater than 1 and having more than 1 specialty service.
A1b Principal Referral Group B	Acute hospitals, treating 25,000 or more acute casemix weighted separations per annum, with an average cost weight greater than 1 and 1 or fewer specialty services.
A2 Paediatric Specialist	Establishments where the primary role is to provide specialist acute care services for children.
A3 Ungrouped Acute	Establishments whose primary role is the provision of acute services of a specialised nature for which there is insufficient peers to form additional peer groups.
Major metropolitan	
B1 Major Metropolitan:	Acute hospitals, treating 10,000 or more acute casemix weighted separations per annum, but having less than 25,000 acute casemix weighted separations or an average casemix weight of less than 1.
Major non-metropolitan	
B2 Major Non-Metropolitan:	Acute hospitals treating 10,000 or more acute casemix weighted separations per annum that are located in rural areas providing acute specialist and referral services for a catchment population from a large geographical area.
District	
C1 District Group 1	Acute hospitals, treating 5,000 or more, but less than 10,000 acute casemix weighted separations per annum.
C2 District Group 2	Acute hospitals, treating 2,000 or more, but less than 5,000 acute casemix weighted separations per annum, plus acute hospitals treating less than 2,000 acute casemix weighted separations per annum but with more than 2,000 separations per annum.
Community	
D1a Community Acute with Surgery	Acute hospitals, treating less than 2,000 acute casemix weighted separations per annum, and less than 2,000 acute separations per annum, with less than 40% nonacute and outlier bed days of total bed days and greater than 2% of their acute weighted separations being surgical.
D1b Community Acute without Surgery	Acute hospitals, treating less than 2,000 acute casemix weighted separations per annum, and less than 2,000 acute separations per annum, with less than 40% nonacute and outlier bed days of total bed days, and less than 2% of their acute weighted separations being surgical.
D2 Community Non-Acute	Non-acute hospitals, treating less than 2,000 acute casemix weighted separations per annum, and less than 2,000 acute separations per annum, with more than 40% nonacute and outlier bed days of total bed days.
Multi-purpose	
F1 Psychiatric	Establishments devoted primarily to the treatment and care of inpatients with psychiatric, mental or behavioural disorders. Centres of non-acute treatment of drug dependence, developmental and intellectual disability are not included here. This group also excludes institutions mainly providing living quarters or day care.

Hospital Peer Group	Description
F2 Nursing Homes	Establishments which provide long-term care involving regular base nursing care to chronically ill, frail, disabled or convalescent persons or senile inpatients. They must be approved by the Commonwealth Department of Health and Family Services and /or licensed by the State, or controlled by government departments.
F3 Multi-Purpose Services	Multi-Purpose Services (MPSs) which provide integrated acute health, nursing home, hostel, community health and aged care services under one organisational structure, as agreed between the Commonwealth and State Governments. MPSs provide a range of services which are negotiated with the community, the service providers and the relevant Departments.
F4 Sub Acute	Establishments that primarily provide sub-acute services, but are not specialist palliative care or specialist rehabilitation establishments.
F5 Palliative Care	Establishments with a specific function of providing palliative care to terminally ill patients.
F6 Rehabilitation	Establishments with a primary role in providing services to persons with an impairment, disability or handicap where the primary goal is improvement in functional status.
F7 Mothercraft	Establishments where the primary role is to help mothers acquire mothercraft skills in an inpatient setting.
F8 Ungrouped Non-Acute	Establishments whose primary role is the provision of non-acute services, but for which there are insufficient peers to form an addition peer group. Limited comparisons can be made within this peer group and with other non-acute facilities.

Appendix 2 Statistical appendices

Appendix 2.1 Statistical appendix for Chapter 5

This statistical appendix includes additional information on model specification for analyses presented within this chapter. These were not included in the online supplementary material for the publication.

The model specification for the multilevel Poisson model on preventable hospitalisations, clustered within Statistical Local Area, adjusted for patient-level baseline demographics, is below.

$$\text{pphc0}_{ij} \sim \text{Poisson}(\pi_{ij})$$
$$\log(\pi_{ij}) = \text{offs}_{ij} + \beta_{0j}\text{cons} + \beta_1\text{agebase\_grpc\_1}_{ij} + \beta_2\text{agebase\_grpc\_2}_{ij} + \beta_3\text{agebase\_grpc\_3}_{ij} + \beta_4\text{agebase\_grpc\_4}_{ij} + \beta_5\text{sex\_45up\_2}_{ij}$$
$$\beta_{0j} = \beta_0 + u_{0j}$$
$$\begin{bmatrix} u_{0j} \end{bmatrix} \sim \text{N}(0,\ \Omega_u)\ :\ \Omega_u = \begin{bmatrix} \sigma^2_{u0} \end{bmatrix}$$
$$\text{var}(\text{pphc0}_{ij}|\pi_{ij}) = \pi_{ij}$$

The model specification for the multilevel Poisson model on preventable hospitalisations, clustered within Statistical Local Area, adjusted for patient-level baseline demographics and area-level FWE GPs, is below.

$$\text{pphc0}_{ij} \sim \text{Poisson}(\pi_{ij})$$
$$\log(\pi_{ij}) = \text{offs}_{ij} + \beta_{0j}\text{cons} + \beta_1\text{agebase\_grpc\_1}_{ij} + \beta_2\text{agebase\_grpc\_2}_{ij} + \beta_3\text{agebase\_grpc\_3}_{ij} + \beta_4\text{agebase\_grpc\_4}_{ij} + \beta_5\text{sex\_45up\_2}_{ij} + \beta_6\text{gp\_fwe\_qt\_2}_j + \beta_7\text{gp\_fwe\_qt\_3}_j + \beta_8\text{gp\_fwe\_qt\_4}_j + \beta_9\text{gp\_fwe\_qt\_5}_j$$
$$\beta_{0j} = \beta_0 + u_{0j}$$
$$\begin{bmatrix} u_{0j} \end{bmatrix} \sim \text{N}(0,\ \Omega_u)\ :\ \Omega_u = \begin{bmatrix} \sigma^2_{u0} \end{bmatrix}$$
$$\text{var}(\text{pphc0}_{ij}|\pi_{ij}) = \pi_{ij}$$

The model specification for the multilevel Poisson model on preventable hospitalisations, clustered within Statistical Local Area, adjusted for patient-level baseline demographics, socio-demographic factors and area-level FWE GPs, is below.

$$\text{pphc0}_{ij} \sim \text{Poisson}(\pi_{ij})$$
$$\log(\pi_{ij}) = \text{offs}_{ij} + \beta_{0j}\text{cons} + \beta_1\text{agebase\_grpc\_1}_{ij} + \beta_2\text{agebase\_grpc\_2}_{ij} + \beta_3\text{agebase\_grpc\_3}_{ij} + \beta_4\text{agebase\_grpc\_4}_{ij} + \beta_5\text{sex\_45up\_2}_{ij} + \beta_6\text{gp\_fwe\_qt\_2}_j + \beta_7\text{gp\_fwe\_qt\_3}_j + \beta_8\text{gp\_fwe\_qt\_4}_j + \beta_9\text{gp\_fwe\_qt\_5}_j + \beta_{10}\text{educ\_1}_{ij} + \beta_{11}\text{educ\_2}_{ij} + \beta_{12}\text{educ\_9}_{ij} + \beta_{13}\text{language\_1}_{ij} + \beta_{14}\text{marital\_b\_0}_{ij} + \beta_{15}\text{marital\_b\_2}_{ij} + \beta_{16}\text{marital\_b\_9}_{ij} + \beta_{17}\text{atsi2\_1}_{ij} + \beta_{18}\text{atsi2\_9}_{ij} + \beta_{19}\text{income\_b\_1}_{ij} + \beta_{20}\text{income\_b\_2}_{ij} + \beta_{21}\text{income\_b\_3}_{ij} + \beta_{22}\text{income\_b\_4}_{ij} + \beta_{23}\text{income\_b\_8}_{ij} + \beta_{24}\text{income\_b\_9}_{ij} + \beta_{25}\text{workstat\_2}_{ij} + \beta_{26}\text{workstat\_3}_{ij} + \beta_{27}\text{workstat\_9}_{ij} + \beta_{28}\text{phi\_1}_{ij} + \beta_{29}\text{phi\_2}_{ij} + \beta_{30}\text{phi\_3}_{ij} + \beta_{31}\text{phi\_4}_{ij} + \beta_{32}\text{ppldepend2\_1}_{ij} + \beta_{33}\text{ppldepend2\_2}_{ij} + \beta_{34}\text{ppldepend2\_3}_{ij} + \beta_{35}\text{ppldepend2\_9}_{ij}$$
$$\beta_{0j} = \beta_0 + u_{0j}$$
$$\begin{bmatrix} u_{0j} \end{bmatrix} \sim \text{N}(0,\ \Omega_u)\ :\ \Omega_u = \begin{bmatrix} \sigma^2_{u0} \end{bmatrix}$$
$$\text{var}(\text{pphc0}_{ij}|\pi_{ij}) = \pi_{ij}$$

The model specification for the multilevel Poisson model on preventable hospitalisations, clustered within Statistical Local Area, adjusted for patient-level baseline demographics, socio-demographic, health and behavioural factors, and area-level FWE GPs, is below.

$$\text{pphc0}_{ij} \sim \text{Poisson}(\pi_{ij})$$

$$\begin{aligned}\log(\pi_{ij}) = \text{offs}_{ij} &+ \beta_{0j}\text{cons} + \beta_1\text{agebase\_grpc\_1}_{ij} + \beta_2\text{agebase\_grpc\_2}_{ij} + \beta_3\text{agebase\_grpc\_3}_{ij} + \beta_4\text{agebase\_grpc\_4}_{ij} + \beta_5\text{sex\_45up\_2}_{ij} + \\ &\beta_6\text{gp\_fwe\_qt\_2}_{j} + \beta_7\text{gp\_fwe\_qt\_3}_{j} + \beta_8\text{gp\_fwe\_qt\_4}_{j} + \beta_9\text{gp\_fwe\_qt\_5}_{j} + \beta_{10}\text{educ\_1}_{ij} + \beta_{11}\text{educ\_2}_{ij} + \beta_{12}\text{educ\_9}_{ij} + \beta_{13}\text{language\_1}_{ij} + \\ &\beta_{14}\text{marital\_b\_0}_{ij} + \beta_{15}\text{marital\_b\_2}_{ij} + \beta_{16}\text{marital\_b\_9}_{ij} + \beta_{17}\text{atsi2\_1}_{ij} + \beta_{18}\text{atsi2\_9}_{ij} + \beta_{19}\text{income\_b\_1}_{ij} + \beta_{20}\text{income\_b\_2}_{ij} + \\ &\beta_{21}\text{income\_b\_3}_{ij} + \beta_{22}\text{income\_b\_4}_{ij} + \beta_{23}\text{income\_b\_8}_{ij} + \beta_{24}\text{income\_b\_9}_{ij} + \beta_{25}\text{workstat\_2}_{ij} + \beta_{26}\text{workstat\_3}_{ij} + \beta_{27}\text{workstat\_9}_{ij} + \\ &\beta_{28}\text{phi\_1}_{ij} + \beta_{29}\text{phi\_2}_{ij} + \beta_{30}\text{phi\_3}_{ij} + \beta_{31}\text{phi\_4}_{ij} + \beta_{32}\text{ppldepend2\_1}_{ij} + \beta_{33}\text{ppldepend2\_2}_{ij} + \beta_{34}\text{ppldepend2\_3}_{ij} + \beta_{35}\text{ppldepend2\_9}_{ij} + \\ &\beta_{36}\text{hbs\_0}_{ij} + \beta_{37}\text{hbs\_2}_{ij} + \beta_{38}\text{hbs\_3}_{ij} + \beta_{39}\text{hbs\_4}_{ij} + \beta_{40}\text{bmi\_cat\_0}_{ij} + \beta_{41}\text{bmi\_cat\_2}_{ij} + \beta_{42}\text{bmi\_cat\_3}_{ij} + \beta_{43}\text{bmi\_cat\_9}_{ij} + \\ &\beta_{44}\text{sr\_health\_1}_{ij} + \beta_{45}\text{sr\_health\_2}_{ij} + \beta_{46}\text{sr\_health\_3}_{ij} + \beta_{47}\text{sr\_health\_4}_{ij} + \beta_{48}\text{sr\_health\_9}_{ij} + \beta_{49}\text{sr\_comorb1\_cat\_1}_{ij} + \\ &\beta_{50}\text{sr\_comorb1\_cat\_2}_{ij} + \beta_{51}\text{sr\_comorb1\_cat\_3}_{ij} + \beta_{52}\text{mos\_cat\_1}_{ij} + \beta_{53}\text{mos\_cat\_2}_{ij} + \beta_{54}\text{mos\_cat\_3}_{ij} + \beta_{55}\text{mos\_cat\_4}_{ij} + \\ &\beta_{56}\text{mos\_cat\_9}_{ij} + \beta_{57}\text{k10cat\_2}_{ij} + \beta_{58}\text{k10cat\_3}_{ij} + \beta_{59}\text{k10cat\_4}_{ij} + \beta_{60}\text{k10cat\_9}_{ij}\end{aligned}$$

$$\beta_{0j} = \beta_0 + u_{0j}$$

$$\begin{bmatrix} u_{0j} \end{bmatrix} \sim \text{N}(0,\ \Omega_u)\ :\ \Omega_u = \begin{bmatrix} \sigma^2_{u\,0} \end{bmatrix}$$

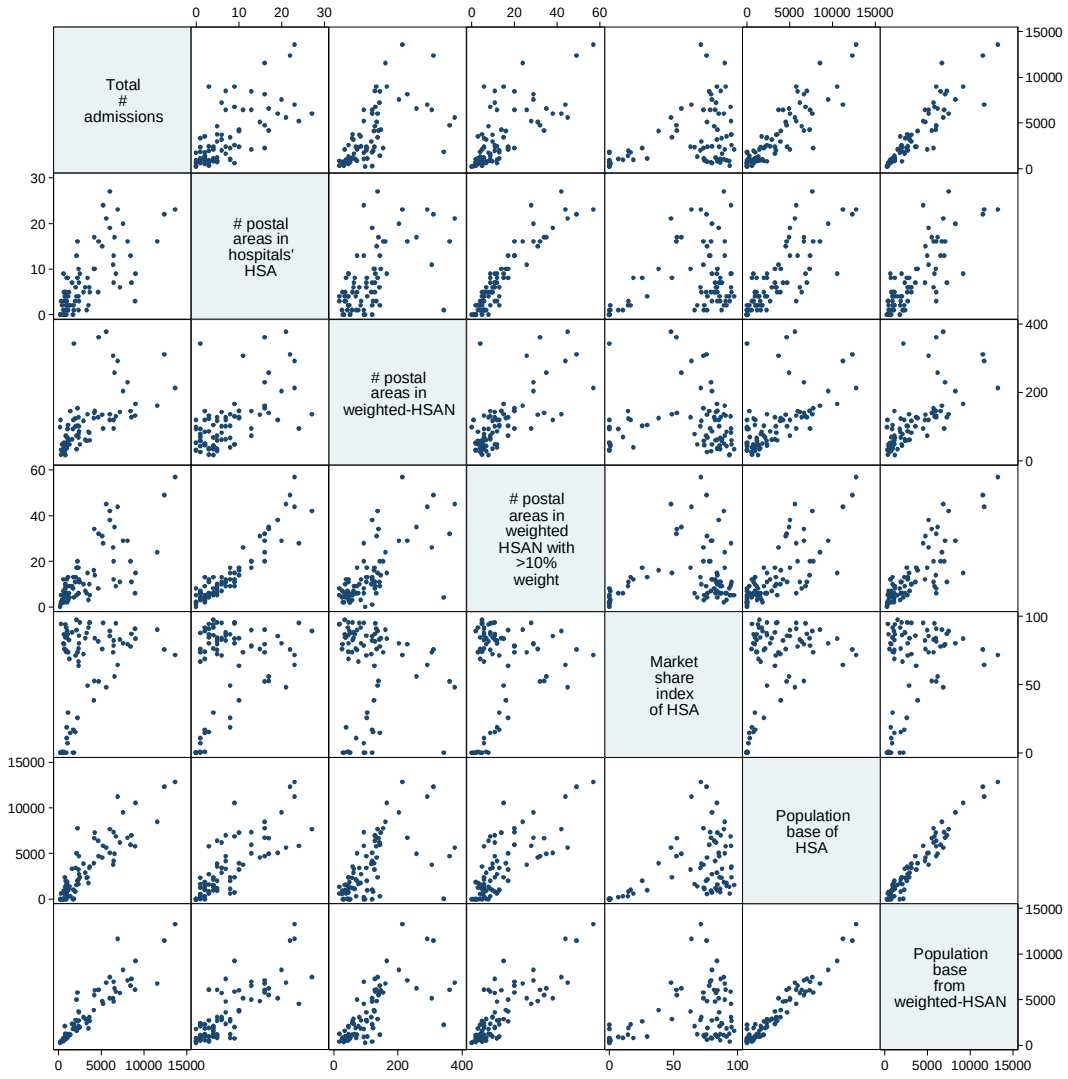
$$\text{var}(\text{pphc0}_{ij}|\pi_{ij}) = \pi_{ij}$$

Appendix 2.2 Statistical appendix for Chapter 6

This statistical appendix includes additional online supplementary material, submitted with the corresponding publication but not presented within the research chapter, as well as additional model specifications and diagnostics not intended for publication. Some of these diagnostics were requested by reviewers, and have been included in this thesis to provide information on parameter convergence for key results reported in this chapter.

Appendix 2.2.1 Additional online supplementary material

Supplementary Figure A2.1: Correlation between hospital-level characteristics from patient populations constructed using a hospital service area (HSA) and weighted-hospital service area network (weighted-HSAN)



Supplementary Table A2.2: Incidence rate ratios (IRRs) from multilevel models clustering participants in hospitals using either weighted hospital service area networks (weighted-HSAN) or hospital service areas (HSA)

	Clustered in weighted-HSAN		Clustered in HSA	
	IRR	(95% CIs)	IRR	(95% CIs)
Hospital bed occupancy (per 10% increase)				
Average across weighted-HSAN	1.01	(0.96 - 1.07)	-	-
Primary hospital of HSA	-	-	1.00	(0.96 - 1.04)
Age				
45-54 years	1.00	(ref)	1.00	(ref)
55-64 years	1.20	(1.15 - 1.26)	1.19	(1.14 - 1.26)
65-74 years	1.68	(1.60 - 1.77)	1.66	(1.57 - 1.76)
75-84 years	2.49	(2.36 - 2.62)	2.45	(2.32 - 2.60)
85+ years	3.29	(3.09 - 3.50)	3.23	(3.02 - 3.46)
Gender				
Male	1.00	(ref)	1.00	(ref)
Female	0.71	(0.69 - 0.73)	0.70	(0.69 - 0.72)
Highest education				
Did not complete high school	1.00	(ref)	1.00	(ref)
High school or equivalent	0.94	(0.91 - 0.96)	0.93	(0.91 - 0.96)
University or higher	0.87	(0.83 - 0.91)	0.86	(0.82 - 0.90)
Unknown/missing	1.13	(1.06 - 1.20)	1.13	(1.06 - 1.20)
Partnership status				
Married or partnered	1.00	(ref)	1.00	(ref)
Single	1.18	(1.13 - 1.24)	1.17	(1.12 - 1.23)
Widowed or separated	1.16	(1.13 - 1.19)	1.16	(1.13 - 1.19)
Unknown/missing	1.26	(1.11 - 1.43)	1.26	(1.11 - 1.43)
Household income				
<$10,000	1.00	(ref)	1.00	(ref)
$10,000 - $29,999	0.88	(0.85 - 0.92)	0.88	(0.85 - 0.92)
$30,000 - $49,999	0.80	(0.76 - 0.85)	0.80	(0.76 - 0.85)
$50,000 - $69,999	0.75	(0.70 - 0.81)	0.75	(0.70 - 0.80)
$70,000 or more	0.65	(0.60 - 0.70)	0.64	(0.60 - 0.69)
Rather not say	0.92	(0.88 - 0.97)	0.92	(0.88 - 0.96)
Unknown/missing	1.13	(1.07 - 1.19)	1.12	(1.07 - 1.18)
Employment status				
Not working	1.00	(ref)	1.00	(ref)
Part time	0.81	(0.77 - 0.85)	0.81	(0.77 - 0.85)
Full time	0.82	(0.78 - 0.87)	0.82	(0.78 - 0.87)
Unknown/missing	0.92	(0.84 - 1.01)	0.92	(0.84 - 1.01)
Language spoken at home				
English only	1.00	(ref)	1.00	(ref)
Other	0.91	(0.87 - 0.95)	0.90	(0.87 - 0.94)
Health insurance status				
None	1.00	(ref)	1.00	(ref)
Private (extras)	1.04	(0.99 - 1.08)	1.04	(1.00 - 1.09)

	Clustered in weighted-HSAN		Clustered in HSA	
	IRR	(95% CIs)	IRR	(95% CIs)
Private (no extras)	1.28	(1.20 - 1.35)	1.28	(1.20 - 1.35)
DVA health care	1.62	(1.56 - 1.67)	1.63	(1.57 - 1.68)
Health care card	1.51	(1.46 - 1.57)	1.52	(1.46 - 1.58)
Number of people can depend on				
0 people	1.00	(ref)	1.00	(ref)
1-4 people	1.07	(1.02 - 1.13)	1.07	(1.02 - 1.12)
5-10 people	1.05	(1.00 - 1.10)	1.04	(0.99 - 1.10)
11+ people	1.18	(1.11 - 1.25)	1.18	(1.11 - 1.25)
Unknown/missing	1.13	(1.05 - 1.20)	1.12	(1.05 - 1.20)
Health behaviours [a]				
No positive behaviours	0.88	(0.78 - 0.99)	0.87	(0.78 - 0.98)
1 positive behaviour	1.00	(ref)	1.00	(ref)
2 positive behaviours	0.88	(0.84 - 0.91)	0.87	(0.84 - 0.91)
3 positive behaviours	0.77	(0.74 - 0.80)	0.76	(0.73 - 0.80)
4 positive behaviours	0.75	(0.71 - 0.79)	0.75	(0.71 - 0.79)
Body Mass Index				
Underweight	1.14	(1.10 - 1.19)	1.14	(1.09 - 1.19)
Healthy weight	1.00	(ref)	1.00	(ref)
Overweight	0.94	(0.91 - 0.97)	0.94	(0.91 - 0.97)
Obese	1.00	(0.96 - 1.03)	1.00	(0.96 - 1.03)
Unknown/missing	1.22	(1.10 - 1.34)	1.22	(1.10 - 1.34)
Self-rated health				
Excellent	1.00	(ref)	1.00	(ref)
Very good	1.23	(1.13 - 1.33)	1.22	(1.14 - 1.31)
Good	1.64	(1.51 - 1.78)	1.63	(1.52 - 1.75)
Fair	2.64	(2.42 - 2.88)	2.62	(2.43 - 2.82)
Poor	4.18	(3.81 - 4.60)	4.15	(3.81 - 4.51)
Unknown/missing	2.35	(2.13 - 2.58)	2.33	(2.14 - 2.54)
Number of morbidities [b]				
None	1.00	(ref)	1.00	(ref)
1 morbidity	1.33	(1.28 - 1.38)	1.33	(1.28 - 1.38)
2 morbidities	2.01	(1.93 - 2.09)	2.01	(1.93 - 2.09)
3+ morbidities	2.74	(2.62 - 2.86)	2.74	(2.63 - 2.86)
Functional limitations [c]				
No limitation	1.00	(ref)	1.00	(ref)
Minor limitation	1.02	(0.95 - 1.09)	1.02	(0.95 - 1.09)
Mild limitation	1.24	(1.17 - 1.32)	1.24	(1.17 - 1.32)
Moderate limitation	1.55	(1.46 - 1.65)	1.55	(1.47 - 1.64)
Severe limitation	2.35	(2.21 - 2.50)	2.36	(2.22 - 2.50)
Unknown/missing	1.70	(1.60 - 1.81)	1.70	(1.60 - 1.81)
Psychological distress [d]				
Low distress	1.00	(ref)	1.00	(ref)
Moderate distress	1.02	(0.98 - 1.05)	1.02	(0.98 - 1.05)
High distress	0.95	(0.91 - 1.00)	0.95	(0.90 - 1.00)
Very high distress	0.99	(0.93 - 1.05)	0.98	(0.92 - 1.05)
Unknown/missing	1.12	(1.06 - 1.19)	1.12	(1.06 - 1.19)

	Clustered in weighted-HSAN		Clustered in HSA	
	IRR	(95% CIs)	IRR	(95% CIs)
Variance				
Weighted-HSAN / HSA (SE)	0.132	(0.032)	0.059	(0.012)
Units of analysis				
Level 1 (people)	266,762	-	266,762	-
Level 2 (hospitals/HSAs)	79	-	72	-

[a] *Healthy behaviours, of non-smoking status, safe level of alcohol consumption (<14 drinks per week), at least 2.5 hours of intensity-weighted physical activity per week, and meeting dietary guidelines for daily fruit (2 serves) and vegetable (5 serves) consumption*

[b] *Of self-reported heart disease, high blood pressure, stroke, diabetes, blood clot, asthma, Parkinson's disease, and any cancer except skin cancer.*

[c] *Measured using the Medical Outcome Study physical functioning scale.*

[d] *Measured using the K10 scale.*

Appendix 2.2.2 Model specification

The model specification for the multiple membership multilevel Poisson model on preventable hospitalisations, adjusted for patient-level characteristics, clustered within a weighted-hospital service area network, is below.

$$\text{pphc0}_i \sim \text{Poisson}(\pi_i)$$

$$\begin{aligned}\log(\pi_i) = \text{offs}_i + \beta_{0i}\text{cons}_i + \beta_1\text{agebase\_grpc\_1}_i + \beta_2\text{agebase\_grpc\_2}_i + \beta_3\text{agebase\_grpc\_3}_i + \beta_4\text{agebase\_grpc\_4}_i + \beta_5\text{sex\_45up\_2}_i + \beta_6\text{educ\_1}_i + \\ \beta_7\text{educ\_2}_i + \beta_8\text{educ\_9}_i + \beta_9\text{marital\_b\_0}_i + \beta_{10}\text{marital\_b\_2}_i + \beta_{11}\text{marital\_b\_9}_i + \beta_{12}\text{income\_b\_1}_i + \beta_{13}\text{income\_b\_2}_i + \beta_{14}\text{income\_b\_3}_i + \\ \beta_{15}\text{income\_b\_4}_i + \beta_{16}\text{income\_b\_8}_i + \beta_{17}\text{income\_b\_9}_i + \beta_{18}\text{workstat\_2}_i + \beta_{19}\text{workstat\_3}_i + \beta_{20}\text{workstat\_9}_i + \beta_{21}\text{hbs\_0}_i + \beta_{22}\text{hbs\_2}_i + \\ \beta_{23}\text{hbs\_3}_i + \beta_{24}\text{hbs\_4}_i + \beta_{25}\text{bmi\_cat\_0}_i + \beta_{26}\text{bmi\_cat\_2}_i + \beta_{27}\text{bmi\_cat\_3}_i + \beta_{28}\text{bmi\_cat\_9}_i + \beta_{29}\text{sr\_health\_1}_i + \beta_{30}\text{sr\_health\_2}_i + \\ \beta_{31}\text{sr\_health\_3}_i + \beta_{32}\text{sr\_health\_4}_i + \beta_{33}\text{sr\_health\_9}_i + \beta_{34}\text{sr\_comorb1\_cat\_1}_i + \beta_{35}\text{sr\_comorb1\_cat\_2}_i + \beta_{36}\text{sr\_comorb1\_cat\_3}_i + \\ \beta_{37}\text{mos\_cat\_1}_i + \beta_{38}\text{mos\_cat\_2}_i + \beta_{39}\text{mos\_cat\_3}_i + \beta_{40}\text{mos\_cat\_4}_i + \beta_{41}\text{mos\_cat\_9}_i + \beta_{42}\text{k10cat\_2}_i + \beta_{43}\text{k10cat\_3}_i + \beta_{44}\text{k10cat\_4}_i + \\ \beta_{45}\text{k10cat\_9}_i + \beta_{46}\text{language\_1}_i + \beta_{47}\text{phi\_2}_i + \beta_{48}\text{phi\_3}_i + \beta_{49}\text{phi\_4}_i + \beta_{50}\text{phi\_5}_i + \beta_{51}\text{ppldepend2\_1}_i + \beta_{52}\text{ppldepend2\_2}_i + \\ \beta_{53}\text{ppldepend2\_3}_i + \beta_{54}\text{ppldepend2\_9}_i\end{aligned}$$

$$\beta_{0i} = \beta_0 + \sum_{j \in hos1(i)} w_{i,j}^{(2)} u_{0j}^{(2)}$$

$$\left[u_{0,hos1(i)}^{(2)}\right] \sim \text{N}(0,\ \Omega_u^{(2)}) \ :\ \Omega_u^{(2)} = \left[\Omega_{u0,0}^{(2)}\right]$$

$$\text{var}(\text{pphc0}_i | \pi_i) = \pi_i$$

The model specification for the multiple membership multilevel Poisson model on preventable hospitalisations, adjusted for patient-level characteristics as well as average hospital bed occupancy rate (centred on group mean value), clustered within a weighted-hospital service area network, is below.

$$\text{pphc0}_i \sim \text{Poisson}(\pi_i)$$

$$\begin{aligned}\log(\pi_i) = \text{offs}_i + \beta_{0i}\text{cons}_i + \beta_1\text{agebase\_grpc\_1}_i + \beta_2\text{agebase\_grpc\_2}_i + \beta_3\text{agebase\_grpc\_3}_i + \beta_4\text{agebase\_grpc\_4}_i + \beta_5\text{sex\_45up\_2}_i + \\ \beta_6(\text{occ10\_ave-gm})_i + \beta_7\text{educ\_1}_i + \beta_8\text{educ\_2}_i + \beta_9\text{educ\_9}_i + \beta_{10}\text{marital\_b\_0}_i + \beta_{11}\text{marital\_b\_2}_i + \beta_{12}\text{marital\_b\_9}_i + \\ \beta_{13}\text{income\_b\_1}_i + \beta_{14}\text{income\_b\_2}_i + \beta_{15}\text{income\_b\_3}_i + \beta_{16}\text{income\_b\_4}_i + \beta_{17}\text{income\_b\_8}_i + \beta_{18}\text{income\_b\_9}_i + \beta_{19}\text{workstat\_2}_i + \\ \beta_{20}\text{workstat\_3}_i + \beta_{21}\text{workstat\_9}_i + \beta_{22}\text{hbs\_0}_i + \beta_{23}\text{hbs\_2}_i + \beta_{24}\text{hbs\_3}_i + \beta_{25}\text{hbs\_4}_i + \beta_{26}\text{bmi\_cat\_0}_i + \beta_{27}\text{bmi\_cat\_2}_i + \\ \beta_{28}\text{bmi\_cat\_3}_i + \beta_{29}\text{bmi\_cat\_9}_i + \beta_{30}\text{sr\_health\_1}_i + \beta_{31}\text{sr\_health\_2}_i + \beta_{32}\text{sr\_health\_3}_i + \beta_{33}\text{sr\_health\_4}_i + \beta_{34}\text{sr\_health\_9}_i + \\ \beta_{35}\text{sr\_comorb1\_cat\_1}_i + \beta_{36}\text{sr\_comorb1\_cat\_2}_i + \beta_{37}\text{sr\_comorb1\_cat\_3}_i + \beta_{38}\text{mos\_cat\_1}_i + \beta_{39}\text{mos\_cat\_2}_i + \beta_{40}\text{mos\_cat\_3}_i + \\ \beta_{41}\text{mos\_cat\_4}_i + \beta_{42}\text{mos\_cat\_9}_i + \beta_{43}\text{k10cat\_2}_i + \beta_{44}\text{k10cat\_3}_i + \beta_{45}\text{k10cat\_4}_i + \beta_{46}\text{k10cat\_9}_i + \beta_{47}\text{language\_1}_i + \beta_{48}\text{phi\_2}_i + \\ \beta_{49}\text{phi\_3}_i + \beta_{50}\text{phi\_4}_i + \beta_{51}\text{phi\_5}_i + \beta_{52}\text{ppldepend2\_1}_i + \beta_{53}\text{ppldepend2\_2}_i + \beta_{54}\text{ppldepend2\_3}_i + \beta_{55}\text{ppldepend2\_9}_i\end{aligned}$$

$$\beta_{0i} = \beta_0 + \sum_{j \in hos1(i)} w_{i,j}^{(2)} u_{0j}^{(2)}$$

$$\left[u_{0,hos1(i)}^{(2)}\right] \sim \text{N}(0,\ \Omega_u^{(2)}) \ :\ \Omega_u^{(2)} = \left[\Omega_{u0,0}^{(2)}\right]$$

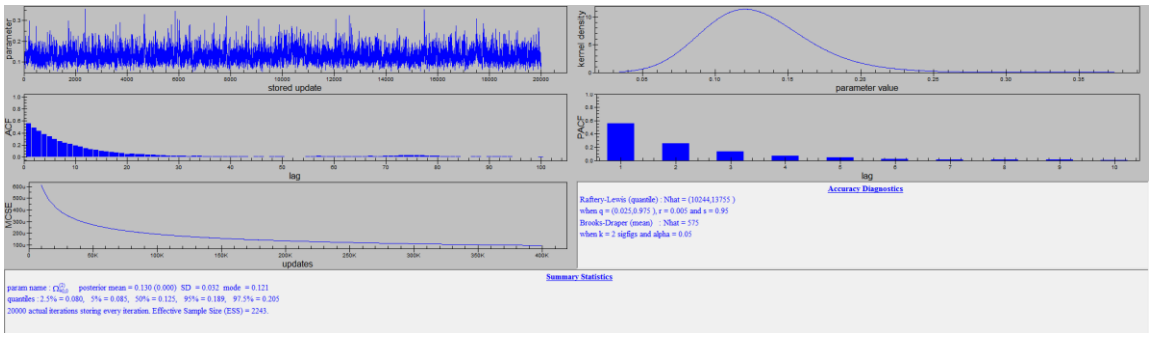
$$\text{var}(\text{pphc0}_i | \pi_i) = \pi_i$$

Appendix 2.2.3 Model diagnostics

Convergence of hospital-level random intercept variance parameter

Inspection of the diagnostics for the hospital-level random intercept parameter (Supplementary Figure A2.2), in a two-level model adjusted for patient characteristics, found reasonable convergence of the parameter, with parameter trajectories approximating noise, a smoothed histogram indicator convergence on a single value (with a slightly skewed normal distribution with a longer right tail – expected for a variance parameter[202]), limited evidence of autocorrelation, and a low Brooks-Draper (mean) Nhat statistic (575). These diagnostics all indicated good convergence of this parameter.

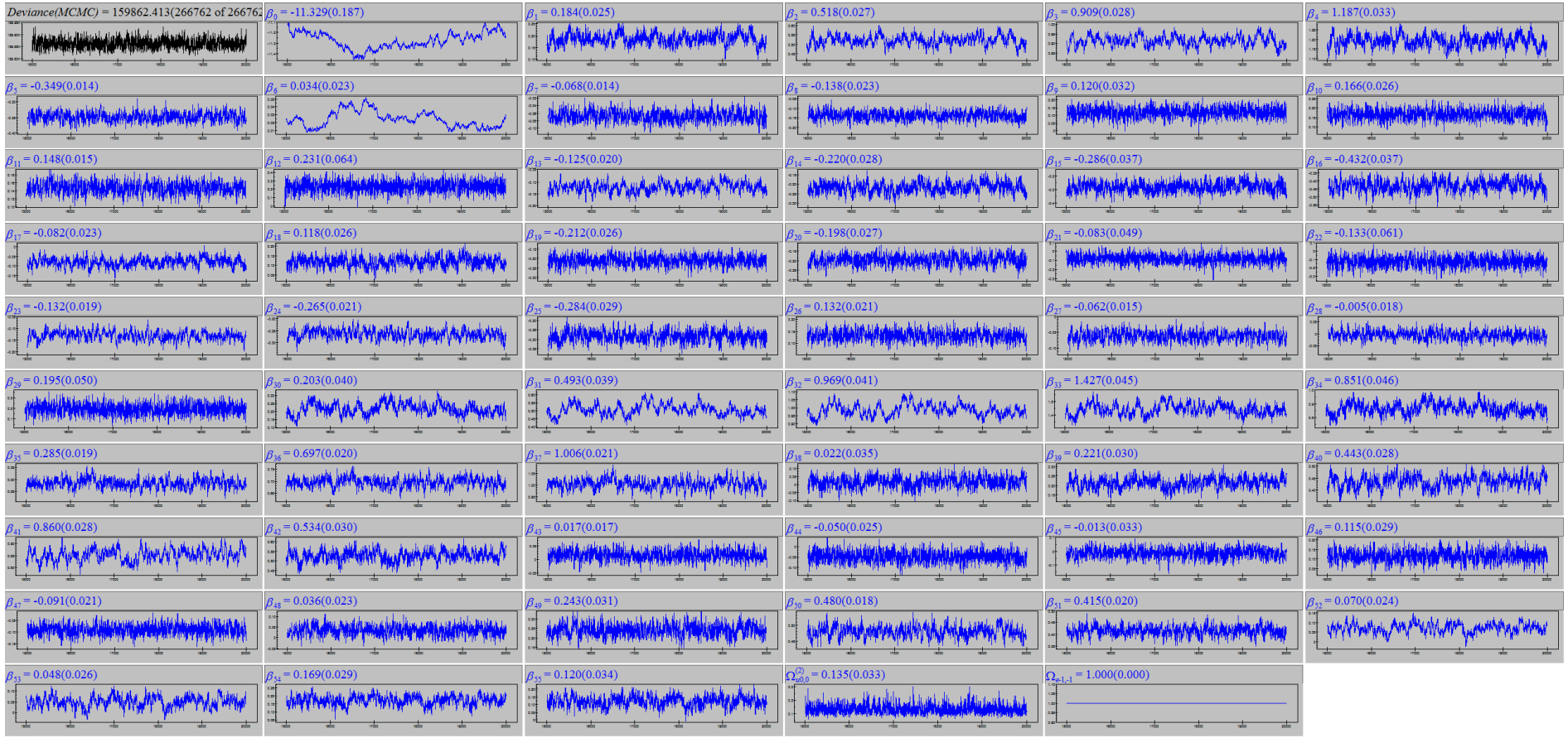
Supplementary Figure A2.2: Diagnostics for hospital-level random intercept variance parameter, from model fit with 20,000 samples following a burn-in of 5,000.



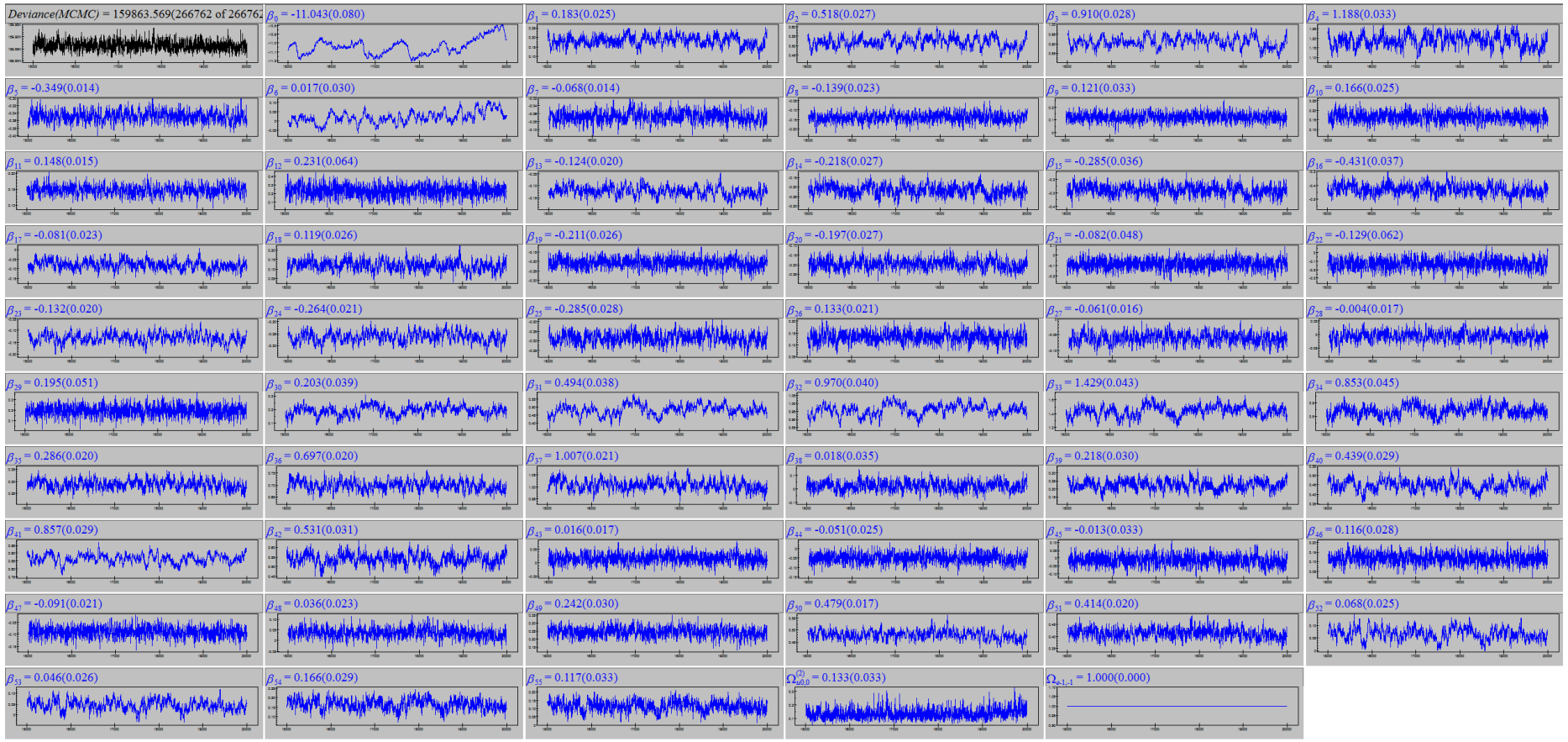
Convergence of average hospital bed occupancy parameter

Analysis of parameter trajectories from initial model two-level model, including all person-level covariates as well as average hospital bed occupancy rate (Supplementary Figure A2.3), revealed two parameters which did not convergence but appeared to have an inverse association: the fixed effect intercept (β_0), and the parameter for hospital bed occupancy rate (β_6).

Supplementary Figure A2.3: Trajectories for all parameters in two-level model, adjusted for patient-level characteristics and hospital bed occupancy rate

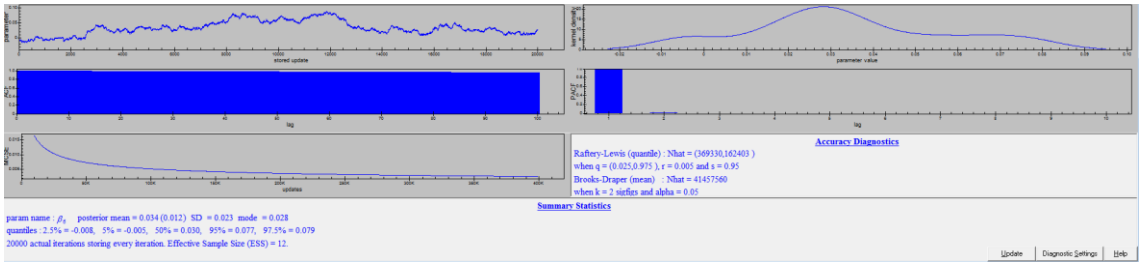


Supplementary Figure A2.4: Trajectories for all parameters in two-level model, adjusted for patient-level characteristics and hospital bed occupancy rate (centred on mean value)



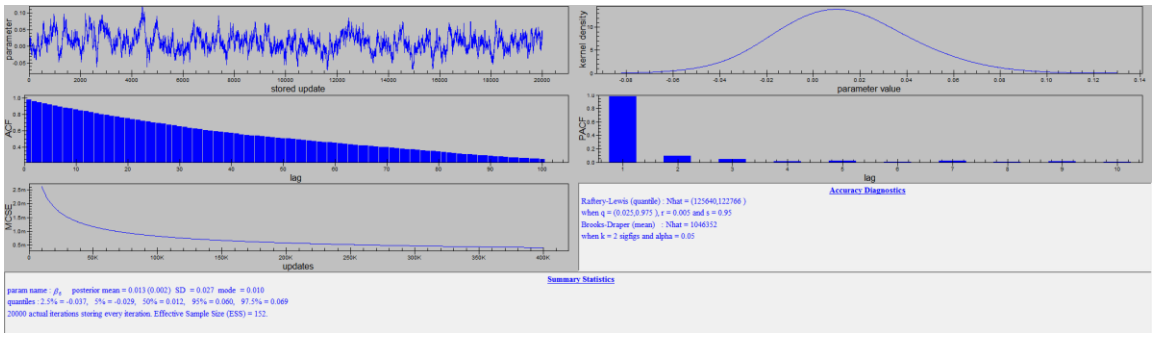
Closer inspection of diagnostics for the hospital bed occupancy parameter (Supplementary Figure A2.5) revealed the parameter did not have clear convergence on a single parameter value, and a very high lag indicating autocorrelation.

Supplementary Figure A2.5: Diagnostics for hospital bed occupancy parameter (not centred), from model fit with 20,000 samples following a burn-in of 5,000.



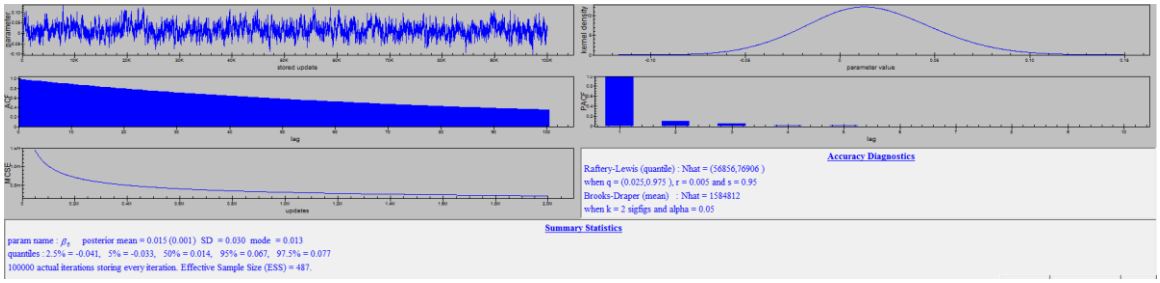
Revision of the hospital bed occupancy rate variable, centred on the mean value, resolved this issue with apparent convergence of both parameters (Supplementary Figure A2.4). Further inspection of diagnostics for the hospital bed occupancy rate (Supplementary Figure A2.6) revealed some evidence of autocorrelation, and a high Brooks-Draper (mean) Nhat statistic (1,046,352). The Brooks-Draper diagnostic gives the estimated number of iterations to produce a mean estimate to 2 significant figures with accuracy of α=0.05, and indicated further iterations in the model may be needed.

Supplementary Figure A2.6: Diagnostics for hospital bed occupancy variable, centred on the mean value, from model fit with 20,000 samples following a burn-in of 5,000.

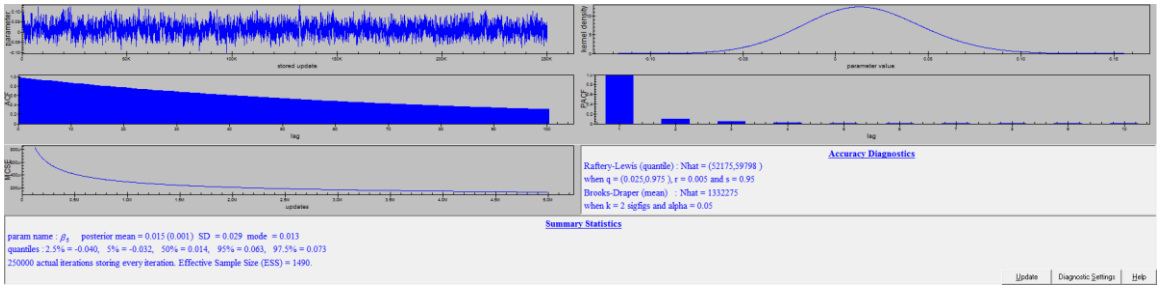


Subsequent models increased the number of samples up to 100,000 and 250,000 iterations (Supplementary Figures A2.7, A2.8), and found consistent parameter estimates for this variable, although continued evidence for autocorrelation. Given the consistency, I felt that further increasing the number of iterations appeared to have limited benefit, while introducing significant practical computational constraints (each model taking several days to run).

Supplementary Figure A2.7: Diagnostics for hospital bed occupancy variable, from model fit with 100,000 samples following a burn-in of 5,000.



Supplementary Figure A2.8: Diagnostics for hospital bed occupancy variable, from model fit with 250,000 samples following a burn-in of 5,000.



Appendix 2.3 Statistical appendix for Chapter 7

As with Appendix 2.2, the following material is not included in the corresponding publication for this chapter. As the models used were complex, this statistical appendix has been provided to give further information on model specification and parameter convergence for key results reported in this chapter.

Appendix 2.3.1 Model specification

The model specification for the cross-classified multiple membership multilevel Poisson model on preventable hospitalisations, adjusted for patient- and area-level characteristics, clustered within Statistical Local Areas and a weighted-hospital service area network, is below.

$$\text{pphc0}_i \sim \text{Poisson}(\pi_i)$$

$$\begin{aligned}\log(\pi_i) = \text{offs}_i + \beta_{0i}\text{cons}_i + \beta_1\text{agebase\_grpc\_1}_i + \beta_2\text{agebase\_grpc\_2}_i + \beta_3\text{agebase\_grpc\_3}_i + \beta_4\text{agebase\_grpc\_4}_i + \beta_5\text{sex\_45up\_2}_i + \beta_6\text{educ\_1}_i + \\ \beta_7\text{educ\_2}_i + \beta_8\text{educ\_9}_i + \beta_9\text{marital\_b\_0}_i + \beta_{10}\text{marital\_b\_2}_i + \beta_{11}\text{marital\_b\_9}_i + \beta_{12}\text{income\_b\_1}_i + \beta_{13}\text{income\_b\_2}_i + \\ \beta_{14}\text{income\_b\_3}_i + \beta_{15}\text{income\_b\_4}_i + \beta_{16}\text{income\_b\_8}_i + \beta_{17}\text{income\_b\_9}_i + \beta_{18}\text{workstat\_2}_i + \beta_{19}\text{workstat\_3}_i + \beta_{20}\text{workstat\_9}_i + \\ \beta_{21}\text{hbs\_0}_i + \beta_{22}\text{hbs\_2}_i + \beta_{23}\text{hbs\_3}_i + \beta_{24}\text{hbs\_4}_i + \beta_{25}\text{bmi\_cat\_0}_i + \beta_{26}\text{bmi\_cat\_2}_i + \beta_{27}\text{bmi\_cat\_3}_i + \beta_{28}\text{bmi\_cat\_9}_i + \beta_{29}\text{sr\_health\_1}_i + \\ \beta_{30}\text{sr\_health\_2}_i + \beta_{31}\text{sr\_health\_3}_i + \beta_{32}\text{sr\_health\_4}_i + \beta_{33}\text{sr\_health\_9}_i + \beta_{34}\text{sr\_comorb1\_cat\_1}_i + \beta_{35}\text{sr\_comorb1\_cat\_2}_i + \\ \beta_{36}\text{sr\_comorb1\_cat\_3}_i + \beta_{37}\text{mos\_cat\_1}_i + \beta_{38}\text{mos\_cat\_2}_i + \beta_{39}\text{mos\_cat\_3}_i + \beta_{40}\text{mos\_cat\_4}_i + \beta_{41}\text{mos\_cat\_9}_i + \beta_{42}\text{k10cat\_2}_i + \\ \beta_{43}\text{k10cat\_3}_i + \beta_{44}\text{k10cat\_4}_i + \beta_{45}\text{k10cat\_9}_i + \beta_{46}\text{language\_1}_i + \beta_{47}\text{phi\_2}_i + \beta_{48}\text{phi\_3}_i + \beta_{48}\text{phi\_4}_i + \beta_{50}\text{phi\_5}_i + \beta_{51}\text{ppldepend2\_1}_i + \\ \beta_{52}\text{ppldepend2\_2}_i + \beta_{53}\text{ppldepend2\_3}_i + \beta_{54}\text{ppldepend2\_9}_i + \beta_{55}\text{aria\_group2\_2}_i + \beta_{56}\text{aria\_group2\_3}_i + \beta_{57}\text{aria\_group2\_4}_i + \\ \beta_{58}\text{gp\_fwe\_qt\_2}_i + \beta_{59}\text{gp\_fwe\_qt\_3}_i + \beta_{60}\text{gp\_fwe\_qt\_4}_i + \beta_{61}\text{gp\_fwe\_qt\_5}_i\end{aligned}$$

$$\beta_{0i} = \beta_0 + \sum_{j \in hos1(i)} w^{(3)}_{i,j} u^{(3)}_{0j} + u^{(2)}_{0,slacode(i)}$$

$$\left[u^{(3)}_{0,hos1(i)}\right] \sim \text{N}(0,\ \Omega^{(3)}_u)\ :\ \Omega^{(3)}_u = \left[\Omega^{(3)}_{u0,0}\right]$$

$$\left[u^{(2)}_{0,slacode(i)}\right] \sim \text{N}(0,\ \Omega^{(2)}_u)\ :\ \Omega^{(2)}_u = \left[\Omega^{(2)}_{u0,0}\right]$$

$$\text{var}(\text{pphc0}_i|\pi_i) = \pi_i$$

The model specification for the cross-classified multiple membership multilevel Poisson model on preventable hospitalisations, adjusted for patient- and area-level characteristics as well as hospital peer group (centred on group mean value), clustered within Statistical Local Areas and a weighted-hospital service area network, is below.

$$\text{pphc0}_i \sim \text{Poisson}(\pi_i)$$

$$\begin{aligned}\log(\pi_i) = \text{offs}_i + \beta_{0i}\text{cons}_i + \beta_1\text{agebase\_grpc\_1}_i + \beta_2\text{agebase\_grpc\_2}_i + \beta_3\text{agebase\_grpc\_3}_i + \beta_4\text{agebase\_grpc\_4}_i + \beta_5\text{sex\_45up\_2}_i + \\ \beta_6(\text{hospeer10\_ave2-gm})_i + \beta_7(\text{hospeer10\_ave3-gm})_i + \beta_8(\text{hospeer10\_ave4-gm})_i + \beta_9(\text{hospeer10\_ave5-gm})_i + \\ \beta_{10}(\text{hospeer10\_ave6-gm})_i + \beta_{11}\text{educ\_1}_i + \beta_{12}\text{educ\_2}_i + \beta_{13}\text{educ\_9}_i + \beta_{14}\text{marital\_b\_0}_i + \beta_{15}\text{marital\_b\_2}_i + \beta_{16}\text{marital\_b\_9}_i + \\ \beta_{17}\text{income\_b\_1}_i + \beta_{18}\text{income\_b\_2}_i + \beta_{19}\text{income\_b\_3}_i + \beta_{20}\text{income\_b\_4}_i + \beta_{21}\text{income\_b\_8}_i + \beta_{22}\text{income\_b\_9}_i + \beta_{23}\text{workstat\_2}_i + \\ \beta_{24}\text{workstat\_3}_i + \beta_{25}\text{workstat\_9}_i + \beta_{26}\text{hbs\_0}_i + \beta_{27}\text{hbs\_2}_i + \beta_{28}\text{hbs\_3}_i + \beta_{29}\text{hbs\_4}_i + \beta_{30}\text{bmi\_cat\_0}_i + \beta_{31}\text{bmi\_cat\_2}_i + \beta_{33}\text{bmi\_cat\_3}_i + \\ \beta_{33}\text{bmi\_cat\_9}_i + \beta_{34}\text{sr\_health\_1}_i + \beta_{35}\text{sr\_health\_2}_i + \beta_{36}\text{sr\_health\_3}_i + \beta_{37}\text{sr\_health\_4}_i + \beta_{38}\text{sr\_health\_9}_i + \beta_{39}\text{sr\_comorb1\_cat\_1}_i + \\ \beta_{40}\text{sr\_comorb1\_cat\_2}_i + \beta_{41}\text{sr\_comorb1\_cat\_3}_i + \beta_{42}\text{mos\_cat\_1}_i + \beta_{43}\text{mos\_cat\_2}_i + \beta_{44}\text{mos\_cat\_3}_i + \beta_{45}\text{mos\_cat\_4}_i + \\ \beta_{46}\text{mos\_cat\_9}_i + \beta_{47}\text{k10cat\_2}_i + \beta_{48}\text{k10cat\_3}_i + \beta_{49}\text{k10cat\_4}_i + \beta_{50}\text{k10cat\_9}_i + \beta_{51}\text{language\_1}_i + \beta_{52}\text{phi\_2}_i + \beta_{53}\text{phi\_3}_i + \beta_{54}\text{phi\_4}_i + \\ \beta_{53}\text{phi\_5}_i + \beta_{56}\text{ppldepend2\_1}_i + \beta_{57}\text{ppldepend2\_2}_i + \beta_{58}\text{ppldepend2\_3}_i + \beta_{59}\text{ppldepend2\_9}_i + \beta_{60}\text{aria\_group2\_2}_i + \\ \beta_{61}\text{aria\_group2\_3}_i + \beta_{62}\text{aria\_group2\_4}_i + \beta_{63}\text{gp\_fwe\_qt\_2}_i + \beta_{64}\text{gp\_fwe\_qt\_3}_i + \beta_{65}\text{gp\_fwe\_qt\_4}_i + \beta_{66}\text{gp\_fwe\_qt\_5}_i\end{aligned}$$

$$\beta_{0i} = \beta_0 + \sum_{j \in hos1(i)} w^{(3)}_{i,j} u^{(3)}_{0j} + u^{(2)}_{0,slacode(i)}$$

$$\left[u^{(3)}_{0,hos1(i)}\right] \sim \text{N}(0,\ \Omega^{(3)}_u)\ :\ \Omega^{(3)}_u = \left[\Omega^{(3)}_{u0,0}\right]$$

$$\left[u^{(2)}_{0,slacode(i)}\right] \sim \text{N}(0,\ \Omega^{(2)}_u)\ :\ \Omega^{(2)}_u = \left[\Omega^{(2)}_{u0,0}\right]$$

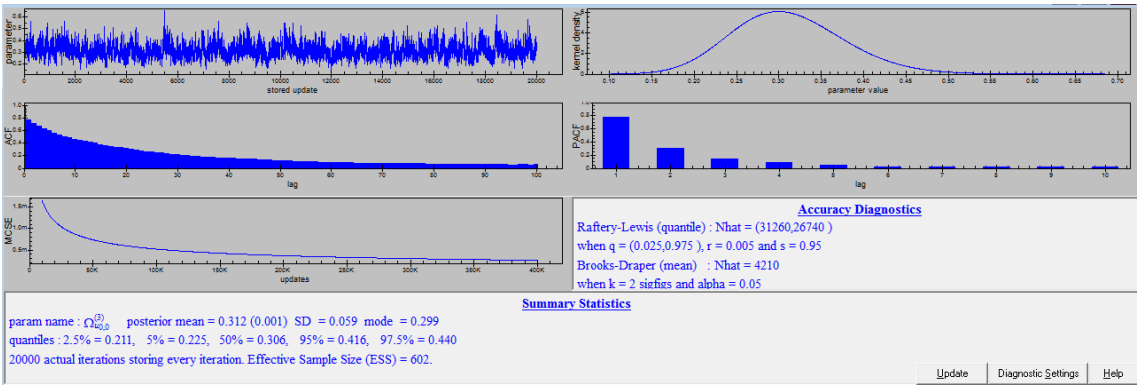
$$\text{var}(\text{pphc0}_i|\pi_i) = \pi_i$$

Appendix 2.3.2 Model diagnostics

Convergence of hospital-level random intercept variance parameter

Inspection of the diagnostics for the hospital-level random intercept parameter (Supplementary Figure 2.9), in a three--level model, with patients clustered in their area of residence and a weighted-hospital service area network, adjusted for patient and area-level characteristics, found reasonable convergence of the parameter, with parameter trajectories approximating noise, a smoothed histogram indicator convergence on a single value (with a slightly skewed normal distribution with a longer right tail – expected for a variance parameter[202]), limited evidence of autocorrelation, and a low Brooks-Draper (mean) Nhat statistic (4210). These diagnostics all indicated good convergence of this parameter.

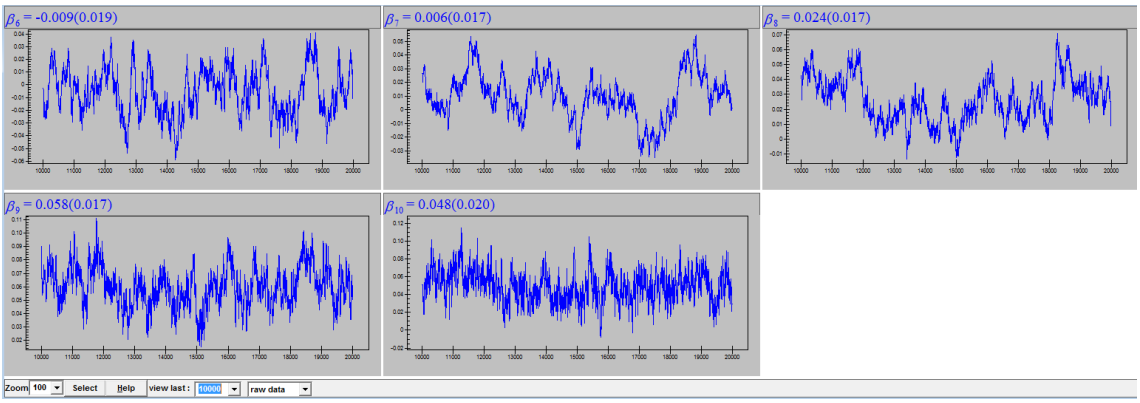
Supplementary Figure A2.9: Diagnostics for hospital-level random intercept variance parameter, from model fit with 20,000 samples following a burn-in of 5,000



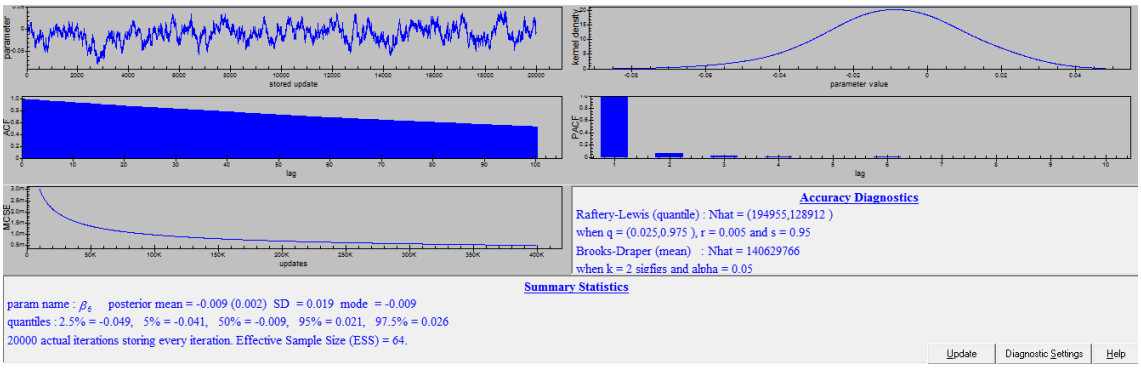
Convergence of hospital category parameters

Analysis of parameter trajectories from a model further including hospital category revealed reasonable mixing among all parameters (Supplementary Figure A2.10). However, as in Appendix 2.2.3, while these parameters all had apparent convergence on a single value (Supplementary Figures A2.11 – A2.15), there was some evidence of autocorrelation, and high Brooks-Draper statistics (e.g. 263,955,958) indicating further iterations may be needed.

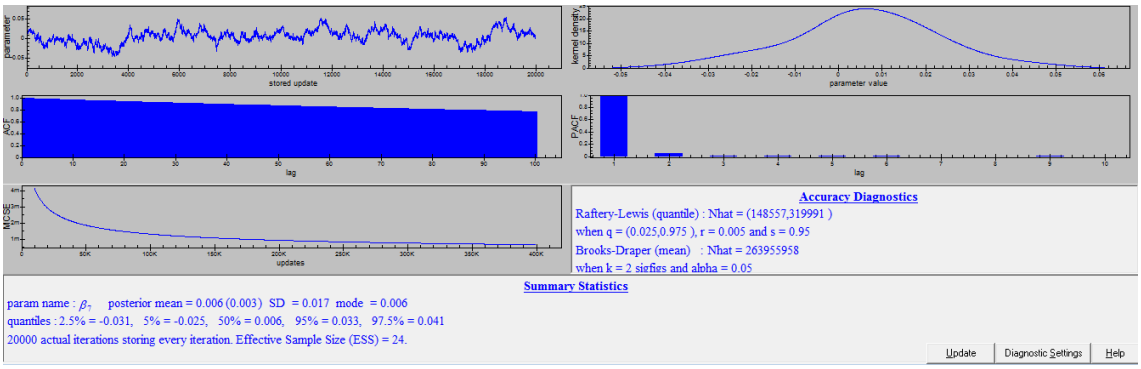
Supplementary Figure A2.10: Trajectories of hospital category parameters, 20,000 samples following a burn-in of 5,000



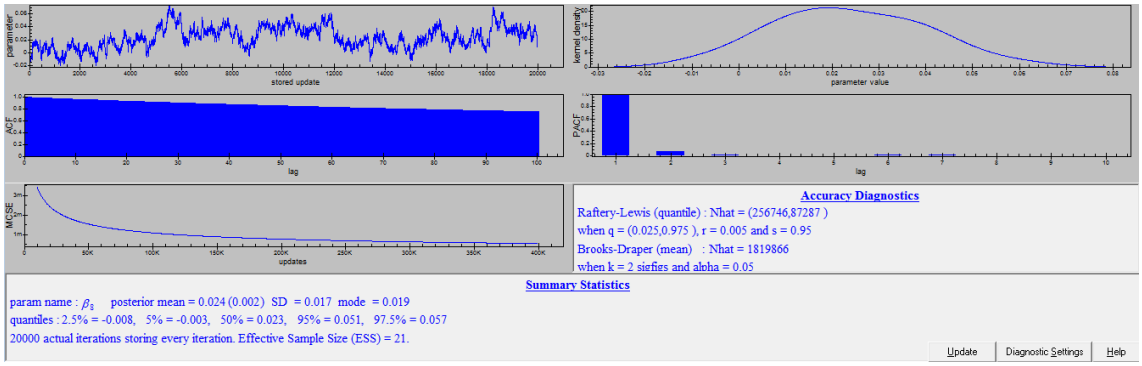
Supplementary Figure A2.11: Diagnostics of major metropolitan hospital category parameter, 20,000 samples following a burn-in of 5,000



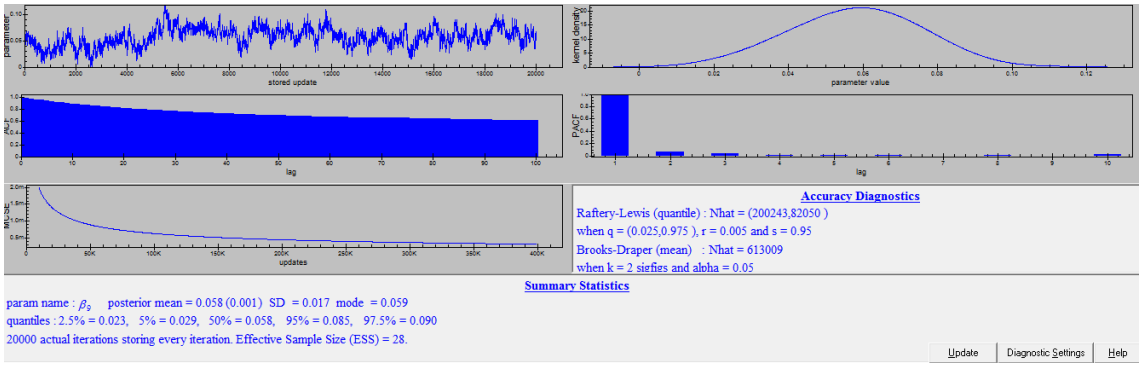
Supplementary Figure A2.12: Diagnostics of major non-metropolitan hospital category parameter, 20,000 samples following a burn-in of 5,000



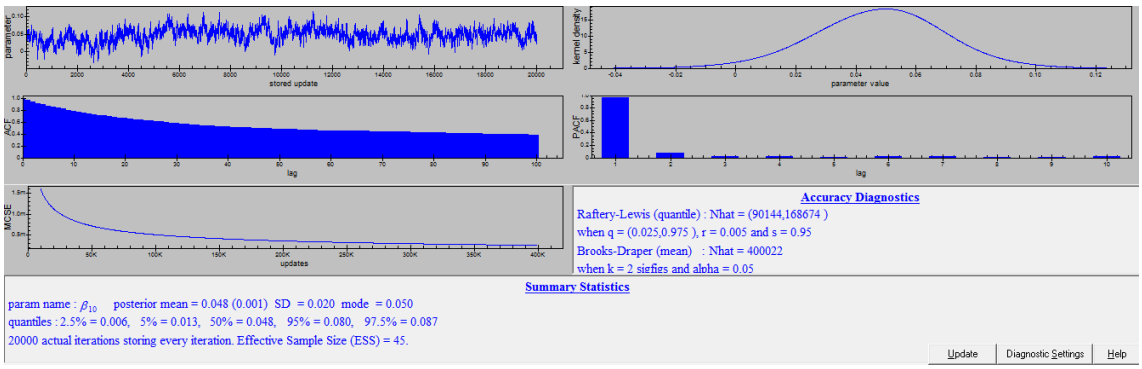
Supplementary Figure A2.13: Diagnostics of district hospital category parameter, 20,000 samples following a burn-in of 5,000



Supplementary Figure A2.14: Diagnostics of community hospital category parameter, 20,000 samples following a burn-in of 5,000

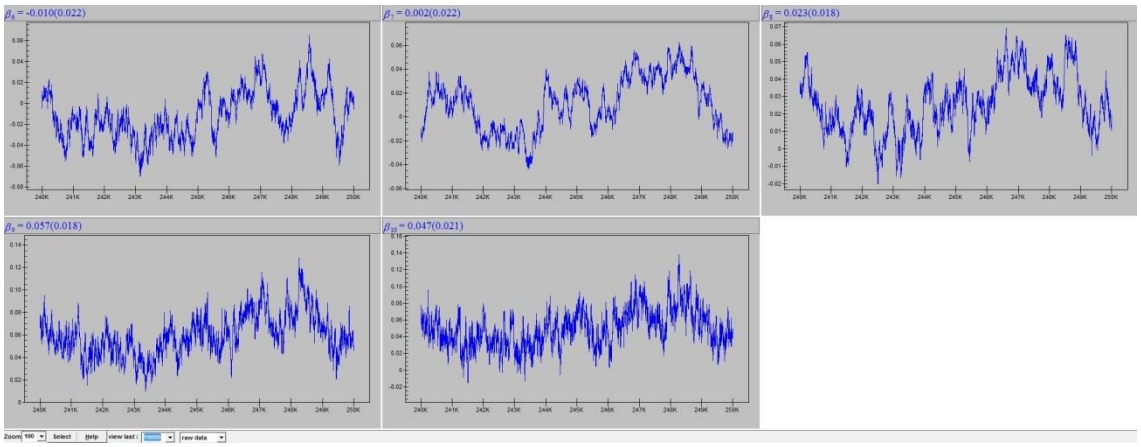


Supplementary Figure A2.15: Diagnostics of multipurpose hospital category parameter, 20,000 samples following a burn-in of 5,000

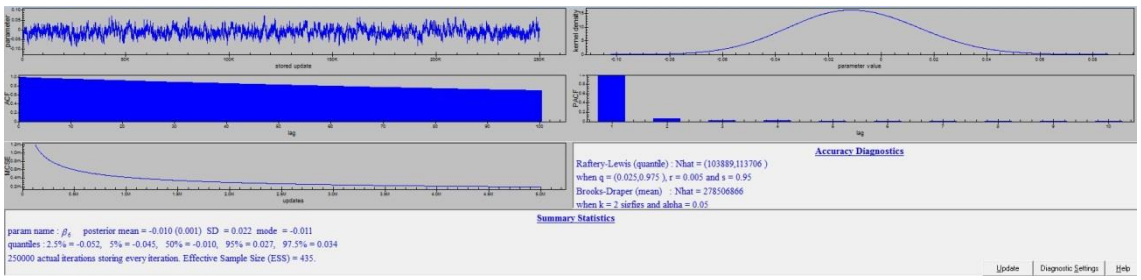


As in Appendix 2.2.3, updating the model to have 250,000 iterations did not result in notable changes to the mixing of parameters (Supplementary Figure A2.16), nor to the parameter estimates (Supplementary Figures A2.17 – A2.21), although there was continued evidence for autocorrelation. Given the consistency, I felt that further increasing the number of iterations appeared to have limited benefit, while introducing significant practical computational constraints (each model taking several days to run).

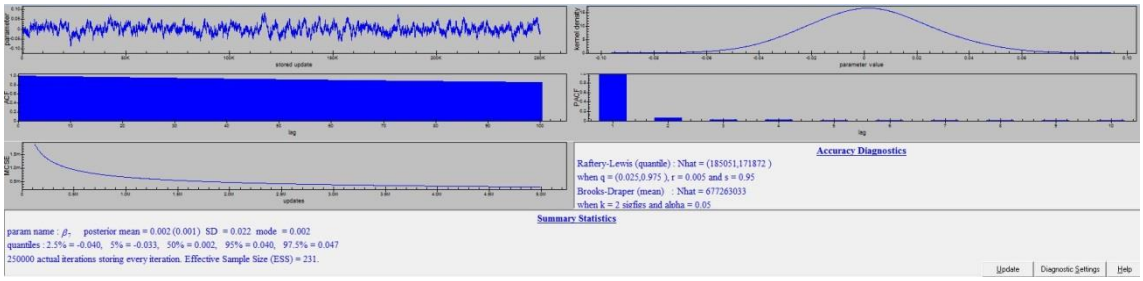
Supplementary Figure A2.16: Trajectories of hospital category parameters, 250,000 samples following a burn-in of 5,000



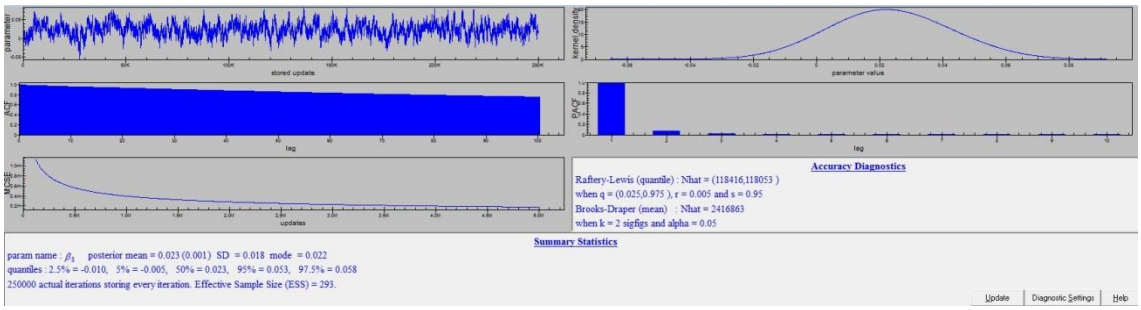
Supplementary Figure A2.17: Diagnostics of major metropolitan hospital category parameter, 250,000 samples following a burn-in of 5,000



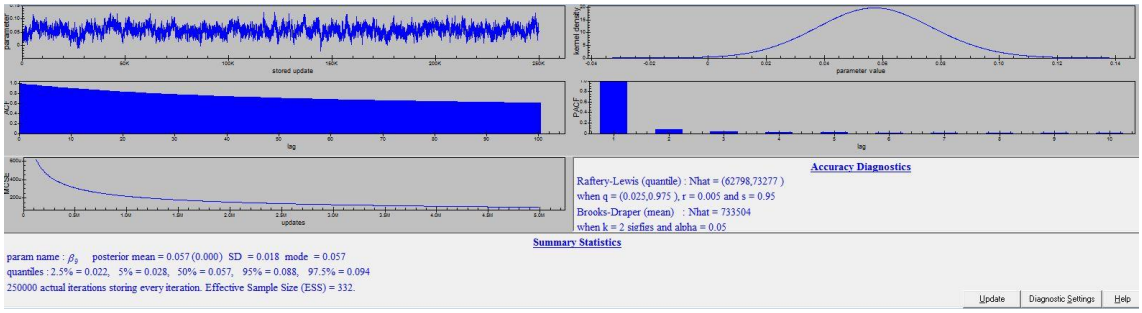
Supplementary Figure A2.18: Diagnostics of major non-metropolitan hospital category parameter, 250,000 samples following a burn-in of 5,000



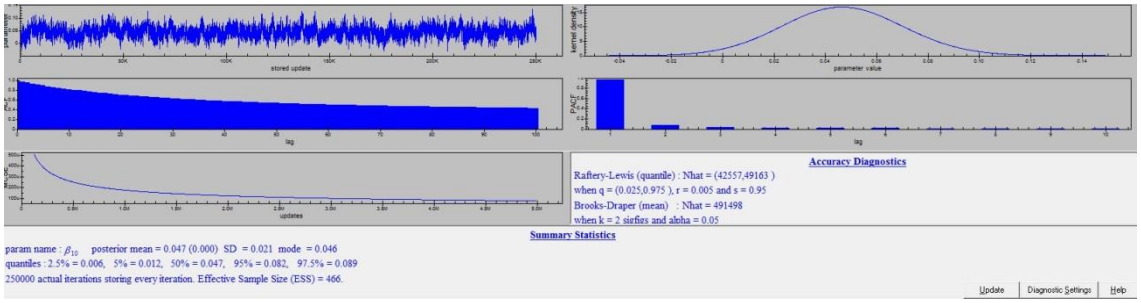
Supplementary Figure A2.19: Diagnostics of district hospital category parameter, 250,000 samples following a burn-in of 5,000



Supplementary Figure A2.20: Diagnostics of community hospital category parameter, 250,000 samples following a burn-in of 5,000



Supplementary Figure A2.21: Diagnostics of multipurpose hospital category parameter, 250,000 samples following a burn-in of 5,000



Appendix 3 Additional publications

During the tenure of this thesis I collaborated on additional publications on preventable hospitalisations. I played a collaborative role in five of these publications, contributing advice on the design, statistical analysis and interpretation of results, as well as contributed to the drafting of the manuscripts. I furthermore drafted an interpretive guide to the preventable hospitalisations indicator, commissioned by the Australian Commission for Safety and Quality for Health Care, for publication in the grey literature.

While these are not a direct part of my thesis, they do supplement the analyses, results and interpretation of findings in an Australian policy context. This appendix briefly discusses the key findings, and provides copies, of these additional publications.

Appendix 3.1 Further impacts of patient characteristics

- Tran B, Falster MO, Douglas K, Blyth F, Jorm LR. Health behaviours and potentially preventable hospitalisations: a prospective study of older Australian adults. *PLoS ONE* 2014;9(4):e93111
- Tran B, Falster MO, Douglas K, Blyth F, Jorm LR. Smoking and potentially preventable hospitalisation: the benefit of smoking cessation in older ages. *Drug and Alcohol Dependence* 2015; 150:85

Two publications assessed in greater detail how specific patient characteristics influence rates of preventable hospitalisation, specifically healthy behaviours, and patient smoking. Both studies used data from the APHID Study.

The first publication assessed the relationship between healthy behaviours and preventable hospitalisations.[178] There had been little research investigating the impact of specific healthy behaviours,[124] such as smoking, drinking, diet and exercise, which influence patients' disposition to use health services. This paper created a 'healthy behaviour' index score using a number of self-reported patient characteristics from the 45 and Up Study baseline questionnaire data, including: patients non-smoking status; low-to-moderate alcohol consumption (<14 standard alcoholic drinks per week), sufficient physical activity (≥2.5 hrs physical activity per week), sufficient fruit and vegetable intake (>2 servings of fruit and >5 servings of vegetables per day), healthy sitting time (<8 hours per day), and healthy sleeping time (≥7 hrs sleeping time per day). The association of these behaviours with preventable

hospitalisation was analysed using a Cox proportional hazards model, on time from study entry to first admission for a preventable hospitalisation.

This study found that patients who were non-smokers, had sufficient physical activity, and healthy sitting and sleeping time had a lower risk of preventable hospitalisation, and that his risk decreased with each additional healthy behaviour. An estimated 29% of preventable hospitalisations could be prevented if our study population undertook all positive health behaviours, highlighting the important role of health promotion in reducing preventable hospitalisations. A modified version of this healthy behaviour score is used as a descriptive characteristics and covariate in Chapters 4-7 of this thesis.

The second publication further interrogated how patient risk of preventable hospitalisation for select chronic conditions (diabetes complications, CHF, COPD and angina) varied according to smoking status.[261] Patients' smoking history was obtained from the 45 and Up baseline questionnaire data, including information on their duration, intensity (cigarettes per day) and cumulative dose (number of pack-years of tobacco exposure) of smoking, as well as time since quitting for ex-smokers.

This study found patients who were smokers had higher risk of hospitalisation for any of the conditions, and that there was a strong dose-response relationship with smoking duration, intensity, and cumulative dose. However, for people who had quit smoking, the excess risk of hospitalisation for COPD was reduced within 5 years of quitting, with the excess risk for all other conditions reduced within 15 years. Thus even among the older adults observed in our study cohort, quitting smoking could still benefit patients' in reducing their risk of preventable hospitalisation.

While these papers are intrinsically related, they both point to the potential benefit of long-term health promotion strategies in potentially reducing the future burden of preventable hospitalisations.

Appendix 3.2 Preventable hospitalisations at the end of life

- Tran B, Falster MO, Girosi F, Jorm L. Relationship between use of general practice and healthcare costs at the end of life: a data linkage study in New South Wales, Australia. *BMJ Open*. 2016 Jan 7;6(1):e009410.

This publication explored whether higher levels of primary care utilisation leading up to the end-of-life period resulted in lower levels of health expenditure at the end of life.[245] Using data from the APHID Study, including linked hospitalisation, fact of death, emergency department and Medicare claims data, as well as linked pharmaceutical claims in the Pharmaceutical Benefits Scheme dataset not analysed in this thesis, healthcare expenditure in the last 6 months of life was calculated and stratified according to quintiles of GP service utilisation in the preceding 12 months.

This study found there was no significant association between hospital expenditure in the last 6 months of life – both overall and separately for preventable hospitalisations - with quintiles of GP use in the preceding year. However, there was a significant linear association with Medicare expenditure in the last 6 months of life – which includes not only subsidies for GP consultations, but also specialist services, diagnostic services, and pharmaceutical dispensations.

Appendix 3.3 Disparities between Aboriginal and non-Aboriginal people

- Harrold TC, Randall DA, Falster MO, Lujic S, Jorm LR. The contribution of geography to disparities in preventable hospitalisations between Indigenous and non-Indigenous Australians. *PLoS ONE* 2014;9(5):e97892
- Falster K, Banks E, Lujic S, Falster M, Lynch J, Zwi K, *et al*. Inequalities in pediatric avoidable hospitalizations between Aboriginal and non-Aboriginal children in Australia: a population data linkage study. *BMC Pediatrics* 2016; 16(1):169

Aboriginal people in Australia experience profound disadvantage across a range of indicators, including life expectancy, child mortality, employment and education. In 2007 the Council of Australian Governments pledged to 'close the gap' in Indigenous health,[262] and preventable hospitalisations are used as one of the tools for measuring the effectiveness of the health care system.[28] These two publications explored variation in disparities in rates of preventable hospitalisation between Aboriginal and non-Aboriginal people, across geographic regions in NSW, and among infants and children. They used data from the Indigenous Health Outcome Patient Evaluation (IHOPE) Study, a study which investigated a range of health disparities between Aboriginal and non-Aboriginal people in NSW using population-level linked hospital and mortality data.

The first publication explored the disparities in rates of preventable hospitalisation between Aboriginal and non-Aboriginal people by conditions and across geographic regions of NSW.[215] It found that Aboriginal people had more than twice the rate or preventable hospitalisations as non-Aboriginal people, and the size of this disparity varied considerably between conditions – with the largest disparities for some of the more common chronic conditions such as diabetes complications and COPD. The size of the disparity also varied considerably between geographic regions, and areas with both high rates of preventable hospitalisation and a high disparity between Aboriginal and non-Aboriginal people were identified.

The second publication explored disparities between Aboriginal and non-Aboriginal people using new measures of ACS and 'avoidable' hospitalisations, specifically developed for use in the paediatric population.[263] This revised indicator is necessary, given poor access to primary care is likely to result in different types of admissions for children than the chronic conditions which make up the bulk of the traditional indicator. This study found substantial inequalities in both ACS and avoidable hospitalisations, in contrast to no significant disparity within a set of 'non-avoidable' hospitalisations. Both the rates of hospitalisation, and the size of the inequality, was greatest for ACS admissions in Aboriginal children under 2 years of age, highlighting the critical need for access to early interventions in primary care to help narrow the gap in health disadvantage.

Appendix 3.4 A guide to the preventable hospitalisations indicator

- Falster M, and Jorm L. A guide to the potentially preventable hospitalisations indicator in Australia*. Centre for Big Data Research in Health, University of New South Wales in consultation with Australian Commission on Safety and Quality in Health Care and Australian Institute of Health and Welfare*: Sydney; 2017

As discussed in Section 8.4.3, I was commissioned by the ACSQHC to draft an interpretive guide for the preventable hospitalisations indicator, in response to reported difficulties in accurately interpreting the indicator. These guides are targeted to a health professional audience, including Boards and CEOs of Primary Health Networks. The drafted interpretive guide included an overview of preventable hospitalisations, evolution of how it has been used as a health performance indicator in Australia, strengths and limitations of the indicator, additional data sources informing the provision of primary care, and facilitated examples of how reported information on the indicator can be interpreted.

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PLOS ONE

Health Behaviours and Potentially Preventable Hospitalisation: A Prospective Study of Older Australian Adults

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Abstract

Objective: Several studies have demonstrated the effects of health behaviours on risk of chronic diseases and mortality, but none have investigated their contribution to potentially preventable hospitalisation (PPH). We aimed to quantify the effects on risk of PPH of six health behaviours: smoking; alcohol consumption; physical activity; fruit and vegetables consumption; sitting time; and sleeping time.

Design/Setting: Prospective observational study in New South Wales, Australia.

Subjects: 267,006 men and women aged 45 years and over.

Outcome Measures: PPH admissions and mortality during follow-up according to individual positive health behaviours (non-smoking, $<$14 alcoholic drinks per week, $\geq$2.5 hours of physical activity per week, $\geq$2 servings of fruit and 5 servings of vegetables per day, $<$8 hours sitting and $\geq$7 hours sleeping per day) and the total number of these behaviours.

Results: During an average of 3 years follow-up, 20971 (8%) participants had at least one PPH admission. After adjusting for potential confounders, participants who reported all six positive health behaviours at baseline had 46% lower risk of PPH admission (95% CI 0.48–0.61), compared to those who reported having only one of these behaviours. Based on these risk estimates, approximately 29% of PPH admissions in Australians aged 45 years and over were attributable to not adhering to the six health behaviours. Estimates were similar for acute, chronic and vaccine-preventable categories of PPH admissions.

Conclusions: Individual and combined positive health behaviours were associated with lower risk of PPH admission. These findings suggest that there is a significant opportunity to reduce PPH by promoting healthy behaviours.

Citation: Tran B, Falster MO, Douglas K, Blyth F, Jorm LR (2014) Health Behaviours and Potentially Preventable Hospitalisation: A Prospective Study of Older Australian Adults. PLoS ONE 9(4): e93111. doi:10.1371/journal.pone.0093111

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Introduction

Potentially preventable hospitalisation (PPH, also termed avoidable or ambulatory care sensitive hospitalisation), defined on the basis of a set of diagnoses relating to chronic, acute and vaccine-preventable conditions [1], has been adopted by health systems internationally as an indicator of access to and quality of primary care [2–6]. However, there has been little attention to the mechanisms by which primary care may prevent these admissions, and the potential contributions of primary and secondary prevention [7].

Longitudinal studies from around the world have demonstrated that positive health behaviours, including non-smoking, low or moderate alcohol use, being physically active, and consumption of fruit and vegetables, are associated with reduced risk of chronic diseases [8,9] and mortality [10–13]. Recently, evidence from observational studies has suggested that prolonged sitting time [14,15] and short sleep duration [16,17] increase the risk of mortality. However, there has been no comprehensive examination of the impact of health behaviours on the risk of PPH.

Much research on PPH has focused on socio-demographic or structural factors which moderate access to and quality of primary care, as well as the density of general practitioners, perceived availability of health services, presence of community health centres, and continuity in health service provision [18]. Previous studies have shown that demographic characteristics of participants such as older age, ethnic background, rural residential location and poor health status were associated with increased risk of PPH [19,20].

Using individual-level data from a large prospective cohort study, linked to hospital morbidity and death data, we aimed to (i) quantify the individual and combined effects of six health

behaviours (smoking, alcohol consumption, physical activity, fruit and vegetables consumption, sitting and sleeping time) on risk of PPH; and (ii) compare the magnitudes of these effects according to category of PPH admission.

Methods

Participants

This was part of the Assessing Preventable Hospitalisation InDicators (APHID) study [1]. APHID uses linked survey and administrative data for participants in the Sax Institute's 45 and Up Study, a prospective cohort of over 267000 men and women aged 45 years and above and resident in New South Wales (NSW), Australia [21]. Participants were randomly sampled from the database of the national health insurance scheme (Medicare Australia). Participants entered the study by completing a mailed self-administered questionnaire at baseline (between February 2006 and April 2009) and providing written consent for long-term follow-up and linkage of their health information to a range of routine health databases. People residing in non-urban areas and those aged 80 years and over were oversampled. The overall response rate for the 45 and Up Study is estimated to be 18% and the study included about 10% of the NSW population aged 45 and over.

Data collection

Exposure and confounding variables used in this analysis were derived from self-reported data from the 45 and Up Study baseline questionnaire (available at https://www.saxinstitute.org.au/our-work/45-up-study/), apart from the measure of remoteness of residence, which was assigned according to the mean score of Accessibility Remoteness Index of Australia Plus (ARIA+) for the Postal Area of the participant's address [22]. History of chronic conditions was obtained from responses to the questions "Has a doctor ever told you have melanoma/prostate cancer/breast cancer/other cancer/heart disease/stroke/diabetes/asthma" and "In the last month, have you been treated for osteoarthritis?" Other variables were classified according to the groupings in **Table 1**, with an additional category for missing values.

Because similar factors may influence both individuals' health behaviours and their disposition, capacity, and need to use health services and therefore risk of hospitalisation, a number of confounders were considered in the analysis [23]. These included sex, age (grouped into 5-year categories), educational level (did not complete high school, high school or equivalent, University or higher), marital status (single, married or partnered, windowed or separated), language spoken at home (English, language other than English), annual household income (<$10,000, $10,000–$29,999, $30,000–$49,999, $50,000–$69,999, $70,000 or more, and "I would rather not answer the question") and their health insurance status (private health insurance with or without extras, Department of Veterans Affairs card, health care card, and none).

Current smoking status was based on responses to the questions: "Have you ever been a regular smoker?", and (if yes) "Are you a regular smoker now?" Alcohol consumption was classified using responses to the question "How many alcoholic drinks do you have each week?" To adjust for under-reporting, alcohol consumption per week among drinkers was inflated by a factor of 9% [24]. Physical activity was assessed using the Active Australia Questionnaire [25] which elicits the number of hours and sessions of moderate and vigorous physical activity and walking per week. We weighted vigorous physical activity by a factor of two [25]. Information on fruit and vegetables intake was collected using the questions: "How many serves of vegetables/fruit or glasses of fruit juice do you usually eat/have each day?" Sitting and sleeping time were assessed using the questions: "How many hours in each 24-hour day do you usually spend sitting/sleeping (including at night and naps)?"

For each of the six health behaviours, we generated a binary exposure variable indicating "positive" health behaviour, according to national guidelines and the findings of previous studies: current non-smoking, consuming less than 14 alcoholic drinks per week ("low-to-moderate alcohol intake") [26], doing more than 2.5 hours of intensity-weighted physical activity over at least 5 sessions per week ("sufficient physical activity") [27], consuming at least 5 servings of vegetables and 2 servings of fruit per day ("sufficient fruit and vegetables intake") [28], having less than 8 hours of sitting per day ("healthy sitting time") [14] and 7 hours or more of sleeping per day ("healthy sleeping time") [16].

We ascertained PPH admissions using linked hospital morbidity data, which captures all separations from public and private sector hospitals, based on the ICD10-AM diagnosis codes specified in the 2012 Australian National Healthcare Agreement PPH indicator [29] and categorised into chronic, acute and vaccine-preventable conditions (**Table S1**). All-cause mortality was ascertained from death registrations. Data were linked by the Centre for Health Record Linkage (http://www.cherel.org.au/) using probabilistic record linkage methods and commercially available software.

Statistical analysis

Participants were followed from the date of recruitment to the date of first PPH admission or death, or December 2010 (the last date to which hospital data were available), whichever occurred first. Cox proportional hazards models with age as the underlying time variable [30] were used to estimate age- and sex- adjusted and multivariate adjusted hazard ratios (HRs) and 95% confidence intervals (CI) for PPH admission, overall and by category, according to individual positive health behaviours and the total number of these behaviours. One positive health behaviour was used as the reference category for the number of positive health behaviours because very few participants reported none of these behaviours. Other variables included in the fully adjusted models were: level of education, marital status, household income, remoteness, language other than English spoken at home, private health insurance, history of chronic diseases and PPH admission in the 12 months prior to study entry. Trend tests were assessed by fitting the number of positive health behaviours as a continuous term. We repeated similar analyses with all-cause mortality as the outcome in order to compare the magnitude of effects. To investigate the potential impacts of missing data and reverse causation, respectively, we ran models that included only participants with data available for all six health behaviours, and excluding participants who had PPH admissions or died in the first 12 months of follow-up. The point estimates were essentially unaltered (data not shown).

We calculated the population attributable risk (PAF) for all six positive health behaviours using the formula: $PAF_{combined} = 1-\Pi(1-PAF_i)$ [31] where PAF_i was calculated from the formula $PAF_i = \frac{P_i(HR_i-1)}{1+P_i(HR_i-1)}$ [32] with HR_i was adjusted HR and P_i was national prevalence data for Australian adults: non-smoking: 84% [33]; low-to-moderate alcohol intake: 81% [33]; sufficient physical activity: 33% [33]; sufficient fruit and vegetables intake: 6% [33]; healthy sitting time: 67% [34]; healthy sleeping time: 36% [16]. 95% confidence intervals for the combined PAFs were derived using a substitution method [35]. Analyses were performed using SAS version 9.3.

Table 1. Characteristics of participants according to number of positive health behaviours.

	Number of positive health behaviours						
	0	**1**	**2**	**3**	**4**	**5**	**6**
N (% of total)	229 (0.1)	2816 (1.0)	16198 (6.1)	51457 (19.3)	91194 (34.2)	81963 (30.7)	23149 (8.7)
Gender							
Male	162 (70.7)	1672 (59.4)	9244 (57.1)	27875 (54.2)	45206 (49.6)	33561 (41.0)	6135 (26.5)
Female	67 (29.3)	1144 (40.6)	6954 (42.9)	23582 (45.8)	45988 (50.4)	48402 (59.0)	17014 (73.5)
Age, years							
45–50	50 (21.8)	437 (15.5)	2325 (14.3)	7353 (14.3)	12249 (13.4)	10173 (12.4)	2318 (10.0)
50–54	48 (21.0)	486 (17.3)	2770 (17.1)	8678 (16.9)	14928 (16.4)	12734 (15.5)	3336 (14.4)
55–59	52 (22.7)	475 (16.9)	2647 (16.3)	8695 (16.9)	15592 (17.1)	13998 (17.1)	4044 (17.5)
60–64	24 (10.5)	380 (13.5)	2154 (13.3)	7059 (13.7)	13384 (14.7)	13279 (16.2)	4089 (17.7)
65–69	16 (7.0)	259 (9.2)	1630 (10.1)	5504 (10.7)	11256 (12.3)	11400 (13.9)	3635 (15.7)
70–74	8 (3.5)	228 (8.1)	1274 (7.9)	4062 (7.9)	8324 (9.1)	7980 (9.7)	2501 (10.8)
75–79	10 (4.4)	202 (7.2)	1087 (6.7)	3418 (6.6)	6145 (6.7)	5510 (6.7)	1613 (7.0)
80+	21 (9.2)	349 (12.4)	2311 (14.3)	6688 (13.0)	9316 (10.2)	6889 (8.4)	1613 (7.0)
Education							
Did not complete high school	121 (52.8)	1282 (45.5)	6420 (39.6)	18214 (35.4)	29909 (32.8)	26212 (32.0)	7916 (34.2)
High school or equivalent	72 (31.5)	997 (35.4)	6224 (38.4)	20712 (40.2)	38085 (41.8)	35136 (42.9)	9694 (41.9)
University or higher	22 (9.6)	338 (12.0)	3005 (18.6)	11470 (22.3)	21815 (23.9)	19594 (23.9)	5302 (22.9)
Missing	14 (6.1)	199 (7.1)	549 (3.4)	1061 (2.1)	1385 (1.5)	1021 (1.2)	237 (1.0)
Marital status							
Single	45 (19.6)	337 (12.0)	1322 (8.1)	3447 (6.7)	5172 (5.7)	3946 (4.8)	915 (4.0)
Married or partnered	103 (45.0)	1564 (55.5)	10397 (64.2)	36161 (70.3)	67919 (74.5)	63544 (77.5)	18398 (79.5)
Widowed or separated	75 (32.8)	869 (30.9)	4336 (26.8)	11468 (22.3)	17527 (19.2)	14090 (17.2)	3754 (16.2)
Missing	6 (2.6)	46 (1.6)	143 (0.9)	381 (0.7)	576 (0.6)	383 (0.5)	82 (0.3)
Household income							
<$10,000	28 (12.2)	305 (10.8)	1322 (8.2)	3214 (6.3)	4895 (5.4)	4117 (5.0)	1054 (4.5)
$10,000–$29,999	50 (21.8)	662 (23.5)	3718 (22.9)	11796 (22.9)	21123 (23.2)	19989 (24.4)	5853 (25.3)
$30,000–$49,999	26 (11.4)	313 (11.1)	1905 (11.8)	6987 (13.6)	13931 (15.3)	13155 (16.0)	6064 (17.6)
$50,000–$69,999	9 (3.9)	234 (8.3)	1462 (9.0)	5212 (10.1)	9612 (10.5)	8900 (10.9)	2433 (10.5)
$70,000 or more	34 (14.9)	487 (17.3)	3685 (22.7)	12910 (25.1)	22542 (24.7)	18466 (22.5)	4672 (20.2)
Prefer not to answer	39 (17.0)	428 (15.2)	2491 (15.4)	7997 (15.5)	14529 (15.9)	13986 (17.1)	4425 (19.1)
Missing	43 (18.8)	387 (13.7)	1615 (10.0)	3341 (6.5)	4562 (5.0)	3350 (4.1)	648 (2.8)
Remoteness							
Major cities	101 (44.1)	1314 (46.7)	7840 (48.4)	24712 (48.0)	41760 (45.8)	34901 (42.6)	8917 (38.5)
Inner regional	79 (34.5)	948 (33.7)	5280 (32.6)	17184 (33.4)	31766 (34.8)	30223 (36.9)	9092 (39.3)
Outer regional	40 (17.5)	477 (16.9)	2687 (16.6)	8485 (16.5)	15848 (17.4)	15261 (18.6)	4706 (20.3)
Remote/Very remote	8 (3.5)	75 (2.6)	389 (2.4)	1067 (2.1)	1800 (2.0)	1555 (1.9)	430 (1.9)
Missing	1 (0.4)	2 (0.1)	2 (0.01)	9 (0.02)	20 (0.02)	23 (0.03)	4 (0.02)
Language spoken at home							
English only	196 (85.6)	2430 (86.3)	14366 (88.7)	45980 (89.4)	82185 (90.1)	74659 (91.1)	21723 (93.8)
Language other than English	33 (14.4)	385 (13.7)	1832 (11.3)	5477 (10.6)	9009 (9.9)	7302 (8.9)	1426 (6.2)
Missing	0	1 (0.04)	0	0	0	2 (0.0)	0
Private health insurance							
Private (extras)	55 (24.0)	856 (30.4)	6481 (40.0)	23766 (46.2)	45220 (49.6)	42180 (51.5)	12340 (53.3)
Private (no extras)	13 (5.7)	241 (8.6)	1780 (11.0)	6818 (13.3)	13247 (14.5)	12492 (15.2)	3679 (15.9)
DVA health care	6 (2.6)	69 (2.4)	414 (2.6)	1141 (2.2)	1730 (1.9)	1180 (1.4)	271 (1.2)
Health care card	92 (40.2)	859 (30.5)	4019 (24.8)	10243 (19.9)	15684 (17.2)	13158 (16.1)	3650 (15.8)
None	63 (27.5)	791 (28.1)	3504 (21.6)	9489 (18.4)	15313 (16.8)	12953 (15.8)	3209 (13.8)

Table 1. Cont.

	Number of positive health behaviours						
	0	**1**	**2**	**3**	**4**	**5**	**6**
History of chronic diseases*							
No	145 (63.3)	1722 (61.2)	9615 (59.4)	31105 (60.5)	56666 (62.1)	51919 (63.3)	14457 (62.5)
Yes	84 (36.7)	1094 (38.8)	6583 (40.6)	20352 (39.5)	34528 (37.9)	30044 (36.7)	8692 (37.5)
Prior PPH admission							
No	219 (95.6)	2700 (95.9)	15468 (95.5)	49490 (96.2)	88569 (97.1)	79910 (97.5)	22628 (97.8)
Yes	10 (4.4)	116 (4.1)	730 (4.5)	1967 (3.8)	2625 (2.9)	2053 (2.5)	521 (2.2)

*Including melanoma, prostate/breast cancer and other cancers but not including non-melanoma skin cancer, heart disease, stroke, diabetes, asthma and osteoarthritis. Prior PPH was defined as any preventable hospitalisation which occurred 12 months prior to the study entry. Positive health behaviours were defined as current non-smoking, consuming less than 14 alcohol drinks per week, doing more than 2.5 hours of physical activity per week, consuming at least 5 servings of vegetables and 2 serving of fruit per day, having less than 8 hours of sitting per 24 hours and 7 hours or more of sleeping per 24 hours.
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Ethical approval

Ethics approval for the APHID study was obtained from the NSW Population and Health Services Research Ethics Committee, Aboriginal Health and Medical Research Council of NSW Ethics Committee, and the University of Western Sydney Ethics Committee. The conduct of the 45 and Up Study was approved by the University of New South Wales Human Research Ethics Committee.

Table 2. Risk of potentially preventable hospitalisation (PPH) for individual health behaviours.

Health behaviour	Cohort N (% of total)	Any PPH admission		
		PPH admission (% of N)	**Age and sex adjusted HR (95% CI)**	**Multivariable adjusted HR* (95% CI)**
All participants				
Non-smoking	246267 (92.8)	19218 (7.8)	0.64 (0.61–0.68)	0.74 (0.69–0.78)
<14 alcohol drinks per week	212201 (81.2)	16958 (8.0)	1.23 (1.18–1.27)	1.12 (1.08–1.17)
≥2.5 hrs physical activity per week	179616 (67.3)	11247 (6.3)	0.64 (0.62–0.65)	0.74 (0.71–0.76)
≥2 servings of fruit and 5 servings of vegetables per day	59894 (23.5)	4511 (7.5)	0.96 (0.92–0.99)	0.99 (0.96–1.03)
<8 hrs sitting time per 24 hrs	184752 (74.1)	13645 (7.4)	0.82 (0.80–0.85)	0.86 (0.83–0.89)
≥7 hrs sleeping time per 24 hrs	220338 (84.3)	16522 (7.5)	0.85 (0.82–0.86)	0.94 (0.90–0.97)
Men				
Non-smoking	113679 (92.4)	10094 (8.9)	0.67 (0.63–0.72)	0.78 (0.72–0.85)
<14 alcohol drinks per week	87031 (71.5)	8172 (9.4)	1.21 (1.16–1.26)	1.11 (1.06–1.17)
≥2.5 hrs physical activity per week	82974 (67.0)	6080 (7.3)	0.63 (0.61–0.66)	0.73 (0.70–0.77)
≥2 servings of fruit and 5 servings of vegetables per day	18986 (16.2)	1794 (9.5)	1.02 (0.96–1.07)	1.01 (0.96–1.07)
<8 hrs sitting time per 24 hrs	83396 (71.5)	7161 (8.6)	0.84 (0.80–0.87)	0.86 (0.82–0.91)
≥7 hrs sleeping time per 24 hrs	103158 (85.0)	8893 (8.6)	0.82 (0.78–0.87)	0.91 (0.86–0.97)
Women				
Non-smoking	132588 (93.2)	9124 (6.9)	0.61 (0.57–0.66)	0.69 (0.63–0.75)
<14 alcohol drinks per week	125170 (89.7)	8786 (7.0)	1.29 (1.19–1.39)	1.15 (1.06–1.25)
≥2.5 hrs physical activity per week	96642 (67.5)	5167 (5.4)	0.63 (0.61–0.66)	0.74 (0.71–0.78)
≥2 servings of fruit and 5 servings of vegetables per day	40908 (29.7)	2717 (6.6)	0.92 (0.88–0.96)	0.98 (0.93–1.03)
<8 hrs sitting time per 24 hrs	101356 (76.5)	6484 (6.4)	0.81 (0.77–0.85)	0.86 (0.82–0.91)
≥7 hrs sleeping time per 24 hrs	117180 (83.6)	7629 (6.5)	0.88 (0.84–0.92)	0.95 (0.90–1.01)

PPH: potentially preventable hospitalisation.
*Adjusted for age, sex, education, marital status, income, remoteness, language other than English, private health insurance, history of chronic diseases, prior PPH admission and mutually adjusted for other health behaviours.
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Table 3. Risk of potentially preventable hospitalisation (PPH) by number of positive health behaviours.

Number of positive health behaviours	Cohort N (% of total)	Any PPH admission		
		PPH admission (% of N)	Age and sex adjusted HR (95% CI)	Multivariate adjusted HR* (95% CI)
All participants				
0	229 (0.1)	34 (14.8)	1.36 (0.96–1.93)	1.13 (0.80–1.61)
1	2816 (1.0)	365 (13.0)	1.00	1.00
2	16198 (6.1)	1822 (11.2)	0.82 (0.73–0.92	0.84 (0.75–0.94)
3	51457 (19.3)	5009 (9.7)	0.71 (0.64–0.79)	0.76 (0.69–0.85)
4	91194 (34.1)	7029 (7.7)	0.57 (0.51–0.63)	0.64 (0.58–0.72)
5	81963 (30.7)	5323 (6.5)	0.49 (0.44–0.54)	0.57 (0.51–0.63)
6	23149 (8.7)	1389 (6.0)	0.46 (0.41–0.52)	0.54 (0.48–0.61)
Test for trend			p<0.0001	p<0.0001
Men				
0	162 (0.1)	23 (14.2)	1.42 (0.92–2.19)	1.11 (0.72–1.71)
1	1672 (1.3)	200 (12.0)	1.00	1.00
2	9244 (7.5)	1049 (11.3)	0.87 (0.75–1.02)	0.94 (0.81–1.09)
3	27875 (22.5)	2793 (10.0)	0.74 (0.64–0.86)	0.83 (0.72–0.96)
4	45206 (36.5)	3837 (8.5)	0.60 (0.52–0.69)	0.70 (0.61–0.81)
5	33561 (27.1)	2629 (7.8)	0.52 (0.45–0.60)	0.63 (0.54–0.72)
6	6135 (5.0)	504 (8.2)	0.52 (0.44–0.61)	0.62 (0.52–0.73)
Test for trend			p<0.0001	p<0.0001
Women				
0	67 (0.1)	11 (16.4)	1.34 (0.73–2.47)	1.31 (0.71–2.41)
1	1144 (0.8)	165 (14.4)	1.00	1.00
2	6954 (4.9)	773 (11.1)	0.75 (0.63–0.89)	0.72 (0.61–0.85)
3	23582 (16.5)	2216 (9.4)	0.67 (0.60–0.78)	0.68 (0.58–0.80)
4	45988 (32.1)	3192 (6.9)	0.53 (0.45–0.62)	0.57 (0.49–0.67)
5	48402 (33.8)	2694 (5.6)	0.44 (0.38–0.52)	0.50 (0.42–0.58)
6	17014 (11.9)	885 (5.2)	0.41 (0.35–0.49)	0.47 (0.40–0.56)
Test for trend			p<0.0001	p<0.0001

Positive health behaviours were defined as current non-smoking, consuming less than 14 alcohol drinks per week, doing more than 2.5 hours of physical activity per week, consuming at least 5 servings of vegetables and 2 serving of fruit per day, having less than 8 hours of sitting per 24 hours and 7 hours or more of sleeping per 24 hours.

*Adjusted for age, sex, education, marital status, income, remoteness, language other than English, private health insurance, history of chronic diseases and prior PPH admission.

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Data sharing statement

The APHID study dataset has been constructed with the permission of each of the custodians of the respective source datasets and with specific ethical approval. The dataset could potentially be made available to other researchers if they obtain the necessary approvals. More information about these approvals is available from the authors on request.

Results

Of the 267,031 participants in the 45 and Up Study in the dataset supplied for these analyses, 25 were excluded because they had inconsistent linked records, leaving 267,006 persons for analysis, with mean age at baseline 63 years (standard deviation 11 years).

Characteristics of participants according to number of health behaviours are shown in **Table 1**. Nearly 9% of participants reported undertaking all six of the positive health behaviours, while only 0.1% reported undertaking none of them. Women had on average more positive health behaviours than men (4.3 versus 3.9, P<0.001), and a greater proportion of women than men undertook all six positive health behaviours (73.5% versus 26.5%).

During an average of 2.7 years follow-up (interquartile range 2.3–2.9), 20971 (7.9%) participants had at least one PPH admission: 12971 (4.9%) for chronic, 8968 (3.4%) for acute and 585 (0.2%) for vaccine-preventable conditions. In the fully-adjusted model, non-smoking, sufficient physical activity, healthy sitting time and healthy sleeping time were all associated with reduced risk of PPH admission (**Table 2**). Low-to-moderate alcohol intake was associated with a higher risk of PPH admission. There was no significant association between sufficient fruit and vegetables intake and risk of PPH. Results were similar when stratified by gender, although in women the association between sufficient fruit and vegetables intake and lower risk of PPH admission attained borderline statistical significance (**Table 2**).

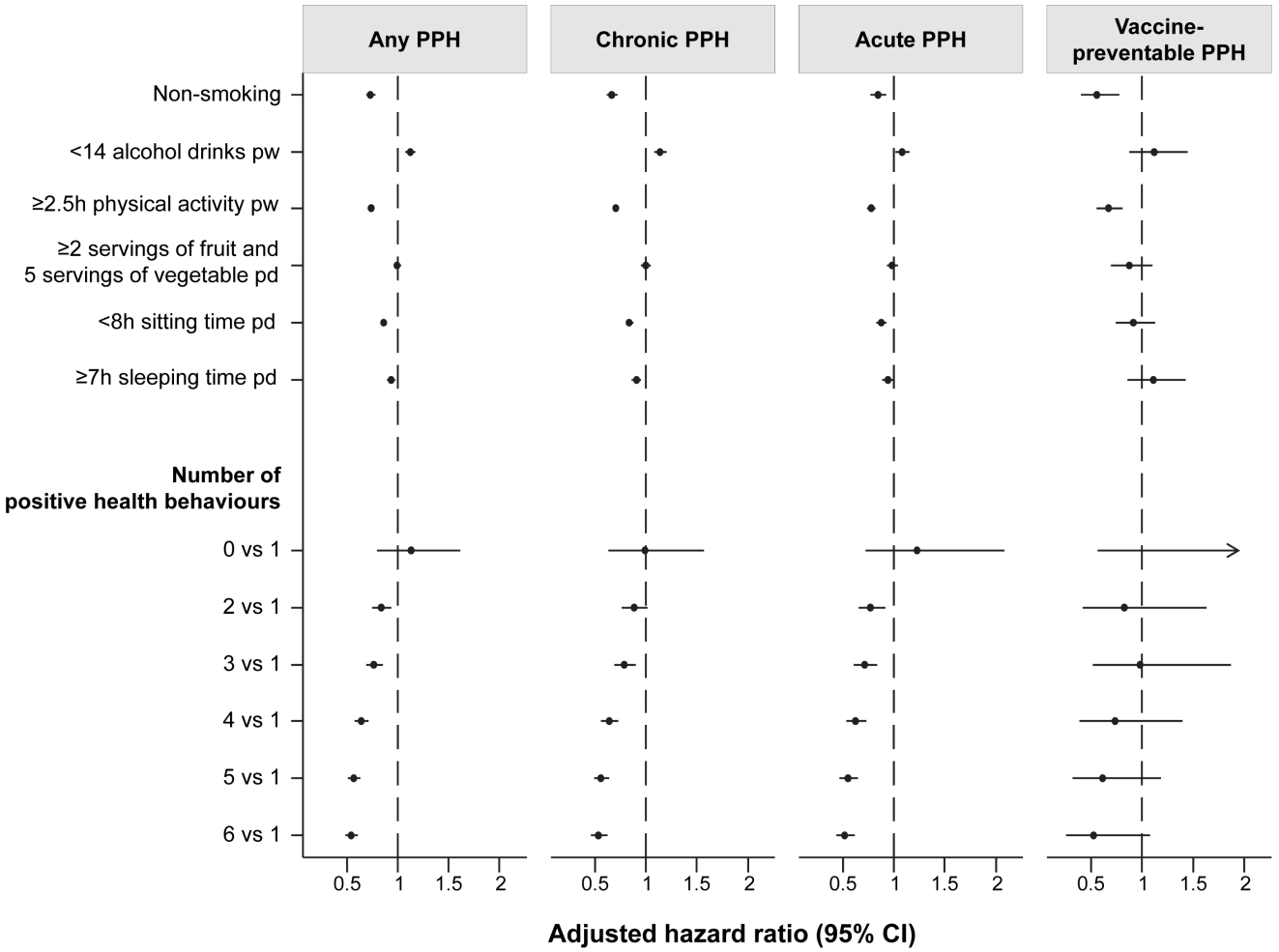

Figure 1. Risk of chronic, acute, and vaccine-preventable hospitalisations according to individual and combine of health behaviours. Hazard ratios (95% CI) estimated for the effect of each positive health behaviour on risk of PPH admission were adjusted for age, sex, education, marital status, income, remoteness, language other than English, private health insurance, history of chronic diseases, prior PPH admission and mutually adjusted for other health behaviours. Hazards ratios (95% CI) estimated for the effect of number of positive health behaviours on risk of PPH admission were adjusted for age, sex, education, marital status, income, remoteness, language other than English, private health insurance, history of chronic diseases and prior PPH admission.
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The risk of PPH admission during follow-up was significantly lower among participants reporting greater numbers of positive health behaviours: those reporting more than two positive health behaviours had between 16 and 46% lower risk of PPH admission compared with those reporting one health behaviour (**Table 3**). Results were similar when stratified by gender. Tests for trend showed a significant inverse linear association between number of positive health behaviours and risk of PPH admission, in all participants and in gender-specific analyses (**Table 3**).

Analyses stratified by category of PPH condition showed an inverse association between number of positive health behaviours and PPHs due to chronic, acute and vaccine-preventable conditions (P-trend all <0.001), although the estimates of PPHs due to vaccine-preventable conditions had wide confidence intervals (**Figure 1**).

Three per cent of participants died from any cause during follow up (N = 9133). Non-smoking, sufficient physical activity and healthy sitting time were individually associated with 27–44% lower risk of mortality in the fully adjusted model. No significant reduction was observed for low-to-moderate alcohol intake, sufficient fruit and vegetables intake or healthy sleeping time (**Table S2**). Mortality risk decreased linearly with increasing numbers of positive health behaviours. Those reporting more than two positive health behaviours had between 27–67% lower risk of death compared to those reporting one behaviour (**Table S3**). Results for mortality risk were similar when stratified by gender.

The estimated proportion of PPH admissions among Australian adults that were attributable to not undertaking the six positive health behaviours was 29% (95% CI 28%–31%) (35% (95% CI 34%–36%) of chronic PPH admissions, 25% (95% CI 24%–26%) of acute PPH admissions, and 37% (37%–38%) of vaccine-preventable PPH admissions). The comparable figure for all-cause mortality was 47% (95% CI 46%–48%).

Discussion

In this large prospective study of people aged 45 years and over, we found that the risk of PPH admission decreased with increasing number of reported positive health behaviours (non-smoking, low-to-moderate alcohol consumption, sufficient physical activity,

sufficient fruit and vegetables intake, healthy sitting time and healthy sleeping time). The magnitude of the association between these behaviours and PPH admission was similar for chronic, acute and vaccine-preventable PPH conditions. We estimated that approximately 29% of PPH admissions among Australian adults could be prevented if everyone undertook all six of these positive health behaviours. To our knowledge this is the first quantification of the relationship between individual and combined health behaviours and PPH admission.

Our findings with regard to mortality risk in relation to smoking status, physical activity and diet were congruent with those of previous longitudinal studies [10,11,13,14,16], and with previous studies in the 45 and Up Study population exploring sitting time [14] and sleeping time [16] The magnitude of the associations between similar sets of combined positive health behaviours and mortality risk in previous studies ranged from 42% [13] to 55% [36], consistent with our estimated 47% risk reduction for six compared with one positive behaviours.

However, there are few existing analyses of the association between health behaviours and PPH admission with which to compare with our results [7]. Previous studies have shown an association between obesity and higher risk of hospitalisation [37–39], both overall and for diabetes complications [40], and obesity is associated with sedentary lifestyle [41] and an unhealthy diet [42]. Other studies have clearly shown that smoking is associated with higher risk of hospitalisation for chronic obstructive pulmonary disease [43] and asthma [44]. Reduction in risk of hospitalisation for vaccine-preventable PPH conditions in association with positive health behaviours might at first appear to be counter-intuitive. However, many of these hospitalisations are for complications of influenza, which are more common in smokers and people with chronic comorbidities [45,46].

Our results suggest that low-to-moderate alcohol consumption is associated with increased risk of PPH admissions, and this is not consistent with previous findings for mortality [10–12]. Measurement of alcohol consumption in older people is problematic [47] and our measure had some shortcomings. Participants were asked to report recent alcohol consumption, rather than lifetime consumption. Observational studies on recent alcohol consumption have found an inverse association with some conditions [48,49]; whereas others measuring lifetime alcohol consumption have suggested a positive association [50]. One possible explanation for these discrepant findings could be that those participants with underlying medical conditions might have drunk more alcohol in their early life then reduced their intake in response to their disease diagnosis [48]. We inflated our measure of alcohol consumption by a factor of 9% to account for under-reporting [24], but it remains possible that measurement error in this population was more substantial than this [51].

Again, we had no previous estimates for the population proportion of PPH admissions that may be attributable to positive health behaviours with which to compare our findings. The estimated PAF for mortality in our study for the six health behaviours combined (47%) comparable to those previously reported for similar sets of health behaviours [11,12,36,52], suggesting that PAF estimates generated from the 45 and Up Study are consistent with those from other cohorts internationally.

Strengths of our study included the longitudinal study design, the large sample size, the availability of data about a wide range of lifestyle factors and potential confounders, and comprehensive linkage to other health databases for ascertainment of outcomes [21]. The self-reported nature of the 45 and Up Study questionnaire introduces the potential for error in our measures of health behaviours, although the physical activity scale [25] and measure of sitting time [53] have previously been validated. However, the prospective design of the study and the independent ascertainment of outcomes through data linkage minimised the likelihood that such error was systematic and therefore introduced bias into our findings.

There was a relatively low participation rate in the 45 and Up Study (18%), raising a concern about the generalizability of our findings. A previous analysis that compared the 45 and Up Study cohort to a 'representative' population health survey found the subjects in both studies to be similar in terms of age, sex, remoteness of residence, country of birth, education, fruit consumption and obesity, but that participants in the 45 and Up Study had a lower prevalence of smoking, and higher rates of private health insurance, than the survey respondents. However, relative risk estimates relating to smoking and fruit consumption (among other variables) calculated using data from the two studies were very similar [54]. The large sample size in the 45 and Up Study provides substantial heterogeneity, and in these circumstances risk estimates calculated from internal comparisons within a cohort should remain valid [55].

We used a relatively short follow up period, and it is possible that people with illnesses likely to lead to PPH admission may have modified their health behaviours. Such reverse causation could result in a bias towards the null where individuals actively modify their behaviour in response to illness (e.g. by giving up smoking), but bias could operate in the opposite direction if illness itself influences the behaviour (e.g. by reducing capacity to undertake physical activity). However, we controlled for history of chronic disease and prior PPH in our models, and our results were unchanged when we excluded participants who had PPH admissions or died in the first 12 months of follow up.

The most important caveat with regard to our findings (and all previous studies exploring the relationship between health behaviours and mortality risk) is the potential for the observed associations to be influenced by residual confounding. We controlled for a wide range of confounding variables, but the potential remains for unmeasured "latent" variables such as health literacy, healthcare-seeking behaviour, compliance with health advice and risk-taking propensity to contribute to the observed associations. We would suggest that use of the number of positive health behaviours as an overall measure of "healthy behaviour" has advantages over approaches that use the individual component variables, because it does not make or invite assumptions about the independence or unique causal roles of specific health behaviours.

Our results provide novel evidence for the potential protective effect of positive health behaviours on PPH admission. They suggest that one of the key ways that primary care can contribute to reducing these admissions is through effective primary and secondary preventive interventions that modify individual behaviours and reduce risk. The results also indicate that effective population-level primary prevention strategies are likely to contribute to reducing the health system burden of PPH as these are currently conceptualised. Thus PPH should be viewed as a performance measure not just for primary care, but for the prevention system more broadly.

Supporting Information

Table S1 Conditions included in the Australian National Healthcare Agreement potentially preventable hospitalisations performance indicator.
(DOCX)

Table S2 Risk of mortality for individual health behaviours.
(DOCX)

Table S3 Risk of mortality by number of positive health behaviours.
(DOCX)

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Author Contributions

Conceived and designed the experiments: LJ. Performed the experiments: LJ. Analyzed the data: BT MF. Wrote the paper: BT MF KD FB LJ.

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Smoking and potentially preventable hospitalisation: The benefit of smoking cessation in older ages

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ABSTRACT

Aims: Reducing preventable hospitalisation is a priority for health systems worldwide. This study sought to quantify the contribution of smoking to preventable hospitalisation in older adults and the potential benefits of smoking cessation.
Methods: Self-reported smoking data for 267,010 Australian men and women aged 45+ years linked with administrative hospital data were analysed using Cox's models to estimate the effects on risk of hospitalisation for congestive heart failure (CHF), diabetes complications, chronic obstructive pulmonary disease (COPD) and angina. The impacts of smoking and quitting smoking were also quantified using risk advancement periods (RAP).
Results: The cohort included 7% current smokers, 36% former smokers and 57% never smokers. During an average follow-up of 2.7 years, 4% of participants had at least one hospitalisation for any of the study conditions (0.8% for CHF, 1.7% for diabetes complications, 0.8% for COPD and 1.4% for angina). Compared to never smokers, the adjusted hazard ratio for hospitalisation for any of the conditions for current smokers was 1.89 (95% CI 1.75–2.03), and the RAP was 3.8 years. There were strong dose-response relationships between smoking duration, smoking intensity and cumulative smoking dose on hospitalisation risk. The excess risk of hospitalisation and RAP for COPD was reduced within 5 years of smoking cessation across all age groups, but risk reduction for other conditions was only observed after 15 years.
Conclusion: Smoking is associated with increased risk of preventable hospitalisation for chronic conditions in older adults and smoking cessation, even at older ages, reduces this risk.

1. Introduction

Preventable hospitalisations are those that might be avoided through prevention and management in primary care, and rates of these admissions are used internationally as an indicator of health system performance (Jorm et al., 2012). Preventable hospitalisations account for around 10% of total hospital stays and total hospital expenditure (Stranges and Stocks, 2008), and reducing them is a priority for health systems worldwide (Muenchberger and Kendall, 2010).

The chronic conditions included in commonly used definitions of preventable hospitalisation include congestive heart failure (CHF), diabetes complications, chronic obstructive pulmonary disease (COPD) and angina, all of which are smoking-related. Accordingly, there is clear potential to reduce the rate of these hospitalisations through interventions to promote smoking cessation (Jackson et al., 2001). The majority of preventable hospitalisations for chronic conditions occur among people aged 65 years and over (Stranges and Stocks, 2008). While it has been clearly demonstrated that quitting smoking at age 60 years or older reduces the risk of mortality from all causes and many smoking-related causes (Gellert et al., 2012; He et al., 2014), few population-based studies have quantified the benefits of "late" quitting for preventable hospitalisation outcomes. Existing studies of the relationship between smoking and preventable hospitalisation in older populations have been restricted to specific patient groups (Godtfredsen et al., 2002; Shah et al., 2010), have presented combined mortality and morbidity endpoints (Gellert et al., 2013b), or have not stratified according to age at quitting (Baumeister et al., 2007).

In this study, data from a large prospective cohort of Australian men and women aged 45 years and over, linked with hospital morbidity data were used to: (1) quantify the effects of smoking on

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risk of preventable hospitalisation (expressed both as hazard ratios [HRs] and risk advancement periods [RAP]) for CHF, diabetes complications, COPD and angina; (2) investigate the contributions of smoking duration and smoking intensity to these risks; and (3) investigate the impact of quitting smoking at older ages on risk of preventable hospitalisation.

2. Methods

2.1. Participants

This analysis was part of the Assessing Preventable Hospitalisation InDicators (APHID) study (Jorm et al., 2012). APHID uses linked survey and administrative data for participants in the Sax Institute's 45 and Up Study, a prospective cohort of 267,091 men and women aged 45 years and over and resident in New South Wales (NSW), Australia (Banks et al., 2008). Participants were randomly sampled from the database of the national health insurance scheme (Medicare Australia). Participants entered the study by completing a mailed self-administered questionnaire at study entry (between February, 2006 and April, 2009) and providing written consent for long-term follow-up and linkage of their health information to a range of routine health databases. People residing in non-urban areas and those aged 80 years and over were oversampled. The overall response rate for the 45 and Up Study is estimated to be 18% and the study included about 10% of the NSW population aged 45 and over.

2.2. Data collection

2.2.1. Social-demographic data. Exposure and confounding variables used in this analysis were derived from self-reported data from the 45 and Up Study baseline questionnaire collected at study entry (available at https://www.saxinstitute.org.au/our-work/45-up-study/), apart from the measure of remoteness of residence, which was assigned according to the mean score of Accessibility Remoteness Index of Australia Plus (ARIA+) for the Postal Area of the participant's address (AIHW, 2004).

Socio-demographic data included participants' educational level (did not complete high school, high school or equivalent, University or higher), marital status (single, married or partnered, windowed or separated), language spoken at home (English, language other than English), annual household income (<$10,000, $10,000–$29,999, $30,000–$49,999, $50,000–$69,999, $70,000 or more, and 'I would rather not answer the question'), and health insurance status (private health insurance with or without extras, Department of Veterans Affairs card, health care card, and none). Participants' self-reported weight (kg) and height (cm) without shoes were used to calculate body mass index (BMI, kg/m^2), which was classified into groups according to WHO categorisation: 'underweight' $\leq$18.5 kg/m^2, 'healthy weight' <18.5–25 kg/m^2, 'overweight' 25.1–30 kg/m^2, and 'obese' >30 kg/m^2.

A score was generated for participants' number of positive health behaviours based on meeting recommendations for five behaviours (less than 14 alcohol drinks per week, more than 2.5 h of intensity-weighted physical activity over at least 5 sessions per week, at least 2 servings of fruit and 5 servings of vegetables per day, less than 8 h of sitting and not less than 7 h sleeping time per day) (Tran et al., 2014).

2.2.2. Smoking history and derivation of smoking variables. Current smoking status was based on responses to the questions "Have you ever been a regular smoker?", and (if yes) "Are you a regular smoker now?" Current and former smokers were asked further detailed questions about their smoking history, including the age at which they started smoking regularly, the age at which they stopped smoking regularly (for former smokers) and the average number of cigarettes or pipes/cigars they smoked each day.

Smoking duration was defined as the difference between starting age and either quitting age (former smokers) or current age (current smokers). Smoking intensity was calculated as the number of cigarettes and pipes/cigars smoked each day. Cumulative number of pack-years of tobacco exposure was derived by dividing the number of cigarettes and pipes/cigars smokes average each day by 20 and multiplying by the total number of years smoked. Time since quitting smoking was calculated as the difference between the age at which former smokers had stopped smoking regularly and their current age. For categorical analyses, each of the above smoking measures was categorised into quartiles. Participants with missing smoking data were excluded from the analyses.

2.2.3. Outcomes. Incident preventable hospitalisations for CHF, diabetes complications, COPD and angina were ascertained using linked hospital morbidity data, which captures all separations from public and private sector hospitals in NSW, based on the ICD10-AM diagnosis codes specified in the 2012 Australian National Healthcare Agreement potentially preventable hospitalisation indicator (NHA, 2012). Hospital morbidity data and death registration records were linked to the baseline data from the 45 and Up Study by the Centre for Health Record Linkage (http://www.cherel.org.au/) using probabilistic record linkage methods and commercially available software.

2.2.4. Statistical analysis. Participants were followed from the date of recruitment to either the date of first hospitalisation for each of the study conditions (CHF, diabetes complications, COPD and angina) or death or 30 December, 2010 (the last date to which hospital data were available), whichever occurred first. Separate analyses were run for each smoking variable (smoking status, smoking duration, smoking intensity, cumulative smoking dose and time since quitting smoking) and for each condition.

All participants were included in analyses of the association between smoking and preventable hospitalisation, with never-smokers as the reference group, except for analyses of time since quitting, where current smokers were used as the reference group. Cox proportional hazards models with age as the underlying time variable (Thiebaut and Benichou, 2004) were used to estimate hazard ratios (HRs) and 95% confidence intervals (CIs) for risk of hospitalisation. To assess the dose-response relationship between smoking variables and risk of hospitalisation, smoking duration (per 10 years), smoking intensity (per 10 cigarettes/day), cumulative dose (per 10 pack-years) or time since quitting (per 10 years) were included in models among ever-smokers only.

A number of variables were considered to influence both smoking and the risk of hospitalisation (Tran et al., 2014). In this analysis, we included age, sex, level of education, marital status, household income, speaking a language other than English at home, private health insurance status and remoteness of residence as social-demographic characteristics; and body mass index, number of positive health behaviours and prior admission in the 12 months prior to study entry as health and behavioural characteristics of the study participants. For present and former smokers who did not report the number of cigarettes smoked per day ($N = 1475$, 1.3% of the population who reported ever smoking), median values for smoking intensity in the population were assigned (20 cigarettes per day for men and 15 cigarettes per day for women). This imputation had negligible impacts on the overall risk estimates.

Point estimates of risk advancement periods (RAP) for each smoking variable were derived from multivariable Cox models as the ratio of the regression coefficients for smoking exposure (by category) to the regression coefficient for age (as a continuous variable). Confidence intervals for RAP were calculated using variance and covariance estimates for regression coefficients (Brenner et al., 1993). Values of RAP describe how much sooner a given risk of hospitalisation is reached among exposed than among unexposed individuals: positive RAPs suggest the risk will be advanced to younger ages, whereas negative RAPs suggest the risk will be postponed to older ages (Liese et al., 2000).

To study the relative importance of smoking intensity and smoking duration on risk of hospitalisation, effect modification analysis was conducted for the effect of smoking intensity (median cut-off: 15 cigarettes per day) and duration of smoking (median cut-off: 25 years). RAPs for time since quitting smoking were also estimated according to strata of age at study entry (<65, 65–74 and $\geq$75 years).

To assess the potential impact on our estimates of quitting smoking in response to a recent diagnosis of the study conditions or other smoking-related diseases ("sick-quitter bias"; Sargent et al., 2012), sensitivity analyses were performed that combined former smokers who had quit less than 5 years ago with current smokers.

All analyses were performed using Stata 12.0. A significance level of $P < 0.05$ was used for all comparisons.

3. Results

Of the 267,091 participants in the 45 and Up Study, 60 participants were excluded because of missing date of study entry and a further 21 were excluded because of possible inconsistent linkage, leaving 267,010 eligible participants included in this analysis. The mean age of participants was 63 years (standard deviation 11 years). Women comprised nearly 54% of the cohort.

Over an average of 2.7 years follow-up (interquartile range: 2.3–2.9 years), 11,035 (4.1%) participants were admitted to hospital at least once for any of the study conditions (0.8% for congestive heart failure, 1.7% for diabetes complications, 0.8% for COPD and 1.4% for angina) (Table 1). There were significant differences between participants who were hospitalised and those who were not in terms of age, gender, BMI, level of education, marital status, household income, private health insurance, number of positive health behaviours and a history of preventable hospitalisation for the same condition in the past 12 months (Table 1). Residents of remote areas were more likely than those living in metropolitan areas to be hospitalised for CHF or COPD; but this was not observed for diabetes complications or angina. People who spoke a language other than English were more likely than English-speakers to be admitted for CHF and diabetes complications, but not for COPD and angina (Table 1).

Table 1
Characteristics of participants at study entry, and number of persons admitted for preventable hospitalisation during follow-up.

	Cohort *N* (% of total)	Any study hospitalisation (% of *N*)	Congestive heart failure (% of *N*)	Diabetes complications (% of *N*)	Chronic obstructive pulmonary disease (% of *N*)	Angina (% of *N*)
N	267,010	11,035 (4.1)	2230 (0.8)	4509 (1.7)	2210 (0.8)	3738 (1.4)
Age (y)						
45–54	77,873 (29.2)	745 (1.0)	57 (0.1)	313 (0.4)	114 (0.2)	334 (0.4)
55–64	85,873 (32.2)	2085 (2.4)	159 (0.2)	866 (1.0)	370 (0.4)	929 (1.1)
65–74	58,079 (21.8)	3279 (5.7)	448 (0.8)	1485 (2.6)	626 (1.1)	1232 (2.1)
75–84	36,909 (13.8)	3831 (10.4)	1014 (2.8)	1548 (4.2)	844 (2.3)	1066 (2.9)
85+	8264 (3.1)	1095 (13.3)	552 (6.7)	297 (3.6)	256 (3.1)	177 (2.1)
P value		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Gender						
Male	123,856 (46.4)	6764 (5.5)	1348 (1.1)	2807 (2.3)	1254 (1.0)	2470 (2.0)
Female	143,154 (53.6)	4271 (3.0)	882 (0.6)	1702 (1.2)	956 (0.7)	1268 (0.9)
P value		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
BMI						
Underweight	21,137 (7.9)	1145 (5.4)	261 (1.2)	430 (2.0)	312 (1.5)	303 (1.4)
Healthy weight	91,452 (34.3)	2976 (3.3)	687 (0.8)	878 (1.0)	778 (0.9)	972 (1.1)
Overweight	96,955 (36.3)	3811 (3.9)	719 (0.7)	1529 (1.6)	621 (0.6)	1486 (1.5)
Obese	55,001 (20.6)	2927 (5.3)	529 (1.0)	1592 (2.9)	454 (0.8)	931 (1.7)
Missing	2465 (0.9)	176 (7.1)	34 (1.4)	80 (3.3)	45 (1.8)	46 (1.9)
P value		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Level of education						
Did not complete high school	90,077 (33.7)	4992 (5.5)	1093 (1.2)	2057 (2.3)	1144 (1.3)	1492 (1.7)
High school or equivalent	110,921 (41.5)	4318 (3.9)	824 (0.7)	1771 (1.6)	794 (0.7)	1567 (1.4)
University or higher	61,546 (23.1)	1371 (2.2)	206 (0.3)	535 (0.9)	186 (0.3)	603 (1.0)
Missing	4466 (1.7)	354 (7.9)	107 (2.4)	146 (3.3)	86 (1.9)	76 (1.7)
P value		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Marital status						
Single	15,184 (5.7)	591 (3.9)	117 (0.8)	272 (1.8)	144 (1.0)	145 (1.0)
Married or partnered	198,088 (74.2)	7201 (3.6)	1236 (0.6)	2964 (1.5)	1252 (0.6)	2762 (1.4)
Widowed or separated	52,121 (19.5)	3167 (6.1)	859 (1.7)	1247 (2.4)	796 (1.5)	806 (1.6)
Missing	1617 (0.6)	76 (4.7)	18 (1.1)	26 (1.6)	18 (1.1)	25 (1.6)
P value		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Household income						
<$10,000	14,936 (5.6)	1202 (8.1)	275 (1.8)	543 (3.6)	301 (2.0)	306 (2.1)
$10,000–$29,999	63,192 (23.7)	4072 (6.4)	869 (1.4)	1688 (2.7)	898 (1.4)	1245 (2.0)
$30,000–$49,999	40,381 (15.1)	1289 (3.2)	199 (0.5)	503 (1.3)	204 (0.5)	541 (1.3)
$50,000–$69,999	27,862 (10.4)	603 (2.2)	87 (0.3)	230 (0.8)	79 (0.3)	273 (1.0)
$70,000 or more	62,796 (23.5)	829 (1.3)	80 (0.1)	304 (0.5)	63 (0.1)	447 (0.7)
Prefer not to answer	43,895 (16.4)	1955 (4.5)	412 (0.9)	796 (1.8)	388 (0.9)	652 (1.5)
Missing	13,948 (5.2)	1085 (7.8)	308 (2.2)	445 (3.2)	277 (2.0)	274 (2.0)
P value		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Remoteness						
Major cities	119,546 (44.8)	4968 (4.2)	1070 (0.9)	2073 (1.7)	912 (0.8)	1635 (1.4)
Inner regional	94,575 (35.4)	3856 (4.1)	708 (0.8)	1590 (1.7)	789 (0.8)	1340 (1.4)
Outer regional	47,504 (17.8)	1947 (4.1)	399 (0.8)	745 (1.6)	433 (0.9)	671 (1.4)
Remote/very remote	5324 (2.0)	263 (4.9)	52 (1.0)	101 (1.9)	76 (1.4)	92 (1.7)
Missing	61 (0.02)	1 (1.6)	1 (1.6)	0	0	0
P value		0.02	0.002	0.07	<0.0001	0.15
Language spoken at home						
English	241,543 (90.5)	9905 (4.1)	1963 (0.8)	3924 (1.6)	2051 (0.9)	3399 (1.4)
Other	25,464 (9.5)	1129 (4.4)	267 (1.1)	585 (2.3)	158 (0.6)	339 (1.3)
Missing	3	1 (33.3)	0	0	1 (33.3)	0
P value		0.01	<0.0001	<0.0001	0.0001	0.33
Private health insurance						
Private (extras)	130,898 (49.0)	3914 (3.0)	641 (0.5)	1595 (1.2)	505 (0.4)	1600 (1.2)
Private (no extras)	38,271 (14.3)	1433 (3.7)	276 (0.7)	565 (1.5)	228 (0.6)	571 (1.5)
DVA health care	4811 (1.8)	655 (13.6)	221 (4.6)	232 (4.8)	161 (3.4)	158 (3.3)
Health care card	47,707 (17.9)	3516 (7.4)	765 (1.6)	1505 (3.2)	961 (2.0)	950 (2.0)
None	45,323 (17.0)	1517 (3.4)	327 (0.7)	612 (1.4)	355 (0.8)	459 (1.0)
P value		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Number of positive health behaviours						
0	1392 (0.5)	110 (7.9)	36 (2.6)	36 (2.6)	35 (2.5)	18 (1.3)
1	12,838 (4.8)	913 (7.1)	222 (1.7)	367 (2.9)	254 (2.0)	238 (1.9)
2	48,694 (18.2)	2741 (5.6)	652 (1.3)	1129 (2.3)	636 (1.3)	796 (1.6)
3	93,745 (35.1)	3792 (4.1)	767 (0.8)	1529 (1.6)	798 (0.9)	1284 (1.4)
4	86,352 (32.3)	2794 (3.2)	455 (0.5)	1157 (1.3)	411 (0.5)	1115 (1.3)
5	23,989 (9.0)	685 (2.9)	98 (0.4)	291 (1.2)	76 (0.3)	287 (1.2)
P value		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Table 1 (*Continued*)

	Cohort *N* (% of total)	Any study hospitalisation (% of *N*)	Congestive heart failure (% of *N*)	Diabetes complications (% of *N*)	Chronic obstructive pulmonary disease (% of *N*)	Angina (% of *N*)
Prior admission						
No	262,473 (98.3)	9354 (3.6)	2047 (0.8)	3718 (1.4)	1838 (0.7)	3472 (1.3)
Yes	4537 (1.7)	1681 (37.1)	183 (32.4)	791 (34.7)	372 (49.1)	266 (17.5)
P value		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Smoking status						
Never smokers	152,145 (57.2)	4871 (3.2)	1083 (0.7)	2153 (1.4)	467 (0.3)	1788 (1.2)
Former smokers	94,585 (35.6)	5197 (5.5)	1026 (1.1)	2045 (2.2)	1345 (1.4)	1690 (1.8)
Current smokers	19,194 (7.2)	893 (4.7)	102 (0.5)	284 (1.5)	373 (1.9)	239 (1.3)

P values were estimated excluding missing category.

Seven per cent of all participants were current smokers, 36% were former smokers and 57% were never smokers (Table 1). Characteristics of participants at baseline by smoking status were shown in Supplementary Table S1. Current smokers (4.7%) and former smokers (5.5%) were significantly ($P < 0.0001$) more likely to be hospitalised for any of the study conditions than never smokers (3.2%). Multivariable Cox regression showed that the greatest elevation in risk of hospitalisation among current smokers compared with never smokers was for COPD (HR 6.81, 95% CI 5.87–7.89), with HRs for the other conditions ranging from 1.25 to 1.41 (Fig. 1 and Table S2). Risk advancement periods of 17.7, 6.7, 2.9 and 0.8 years were found among current smokers compared to never smokers for COPD, CHF, angina and diabetes complications, respectively (Table S2). There were clear dose-response relationships between smoking duration, intensity and cumulative smoking and increased risk of hospitalisation among people with history of smoking for any of the study conditions, and for each individual condition (Table S2).

Compared to current smokers, every 10 years increasing time since quitting smoking was associated with a 16% decreased risk of hospitalisation for any of the study condition s (HR 0.84, 95% CI 0.82–0.86; Table S2). Analyses by time since quitting showed that smoking cessation for 5–14, 15–24 and 25 or more years was associated with a reduction in risk of hospitalisation for any of the study conditions of 3%, 15% and 40%, respectively (Fig. 1 and Table S2). The corresponding RAPs were −0.2, −1.8 and −3.3 years (Table S2). The risk estimates for participants who had quit smoking less than 5 years ago were not significantly different to those for current smokers. Similar results were observed for each individual condition (Fig. 1 and Table S2).

Estimates of risk advancement periods (RAPs) for time since quitting smoking stratified by age at study entry are shown in Fig. 2.

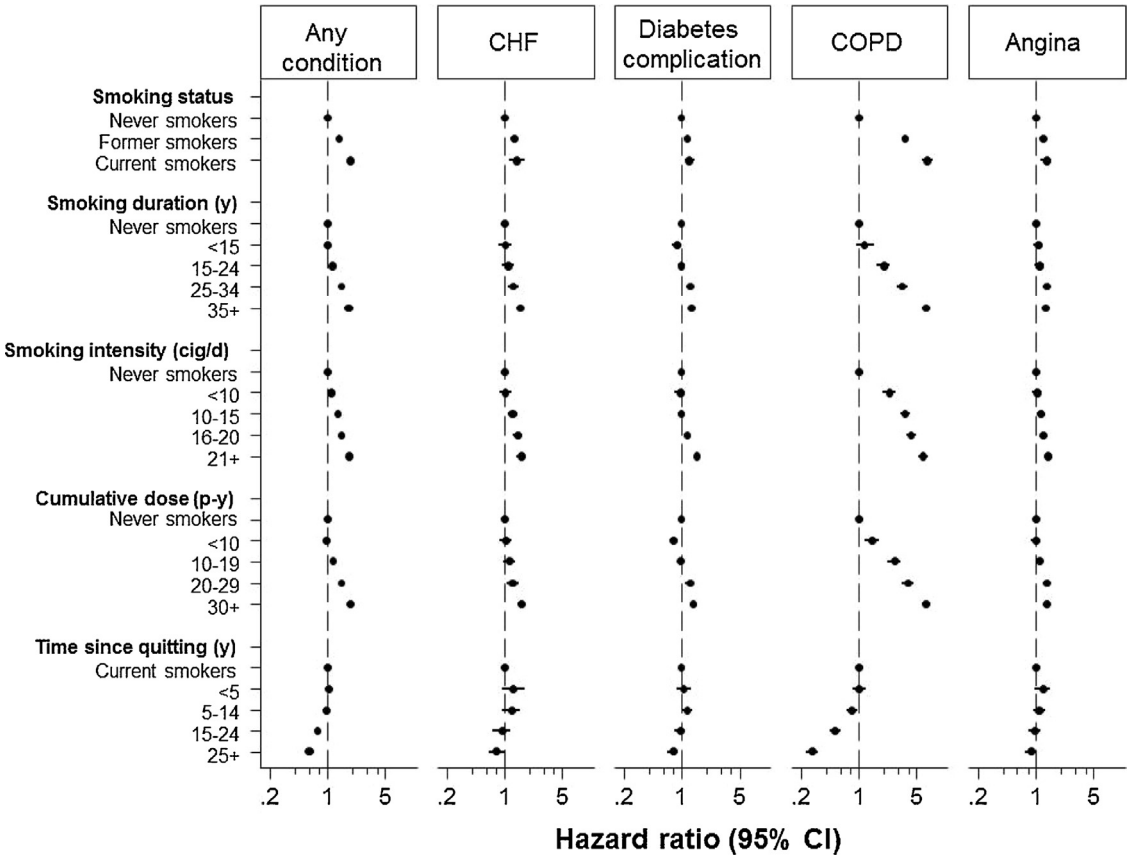

Fig. 1. Hazard ratios (HR) and 95% confidence intervals (CI) for the association between smoking and risks of preventable hospitalisation. Estimates of HR compared to never smokers (except time since quitting where the estimates were compared to current smokers) were adjusted for age, sex, BMI, education, marital status, household income, remoteness of residence, language other than English, private health insurance, number of positive health behaviours, and prior admission in the past 12 months. CHF: congestive heart failure; COPD: chronic obstructive pulmonary disease.

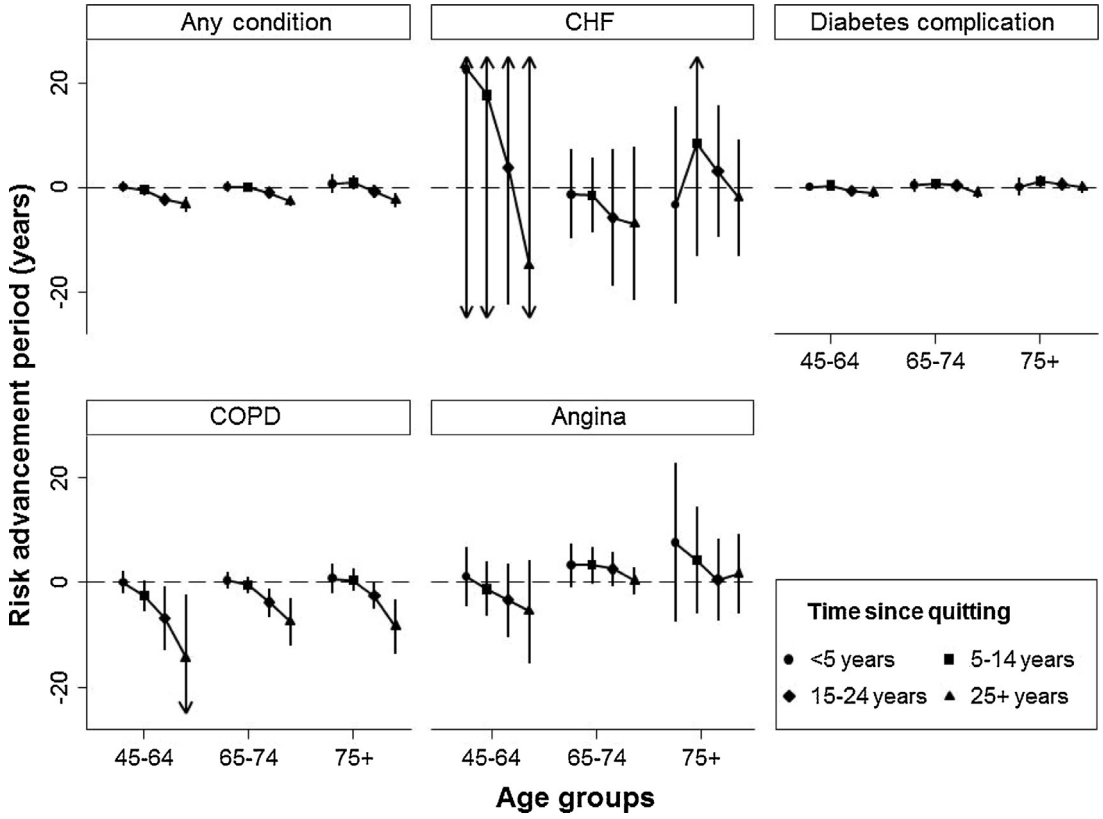

Fig. 2. Risk advancement periods (RAPs) of time since quitting smoking (<5, 5–14, 15–24 and ≥25 years) and risks of preventable hospitalisation stratified by age at study entry (45–64, 65–74 and ≥75 years). Estimates of RAPs compared to current smokers for any study conditions, congestive heart failure (CHF), diabetes complications, chronic obstructive pulmonary disease (COPD) and angina were adjusted for age, sex, BMI, education, marital status, household income, remoteness of residence, language other than English, private health insurance, number of positive health behaviours, and prior admission in the past 12 months.

Compared to current smokers, there was a decreasing trend in RAPs with time since quitting for any of the study conditions and for COPD. For CHF, diabetes complications and angina, the estimates of RAPs for time since quitting smoking were non-significant with wide confidence intervals across all age groups (Fig. 2).

Sensitivity analyses combining former smokers who had quit less than 5 years ago with current smokers did not significantly change the results (data not shown).

There was an additive effect of smoking duration and smoking intensity on risk of hospitalisation. Among those who had smoked for 25 years or longer, the risk of hospitalisation for any of the study conditions was significantly higher in those who smoked more than 15 cigarettes per day (HR = 1.90, 95% CI 1.75–2.06), compared to those who smoked less than 15 cigarettes per day (HR = 1.49, 95% CI 1.36–1.63; Table S3). Similar trends were observed for all individual conditions (Table S3).

4. Discussion

In this large population-based cohort of Australian men and women aged 45 years and over, we found that cigarette smoking substantially increased the risk of preventable hospitalisation for chronic conditions. Current smoking increased hospitalisation risk almost 7-fold for COPD, and by 25–41% for diabetes complications, angina and CHF. Prolonged smoking duration was associated with increased risk of hospitalisation, and this was exacerbated by heavy smoking intensity. For example, among smokers who had been smoking for 25 years or more, those who smoked more than 15 cigarettes a day had a more than 4-fold increased risk of hospitalisation for COPD, compared with a 2.9-fold increased risk for those who smoked less than 15 cigarettes per day. Time since quitting smoking was associated with decreasing risk of hospitalisation and risk advancement periods (RAP), for the study conditions combined and for each individual condition. Quitting smoking at any age was associated with reduced RAPs for the study conditions combined and for COPD. The excess risk of hospitalisation and RAP for COPD was reduced within 5 years of smoking, but risk reduction for other conditions was only observed after 15 years.

To the best of our knowledge, this was the first investigation to examine the effect of time since quitting smoking and hospitalisations for a range of chronic diseases that are included in the commonly used rubric of 'preventable' hospitalisation, and to provide estimates of RAPs for these outcomes. Our results for factors related to smoking were broadly consistent with previous findings for specific patient cohorts including those with index admissions for COPD (Godtfredsen et al., 2002) and myocardial infarction (Shah et al., 2010). Our finding that the excess risk of preventable hospitalisation, especially for COPD, decreased among smokers who quit more than 5 years previously, even among older quitters, was also similar to findings from Germany with regard to excess risk of cardiovascular outcomes (Gellert et al., 2013b) and mortality (Gellert et al., 2013a). Taken together, these findings indicate that some of the smoking-related risk advancement for chronic disease can be reversed within a short time following cessation and that the beneficial effects of smoking cessation for some conditions are independent of age.

Patterns of association for other variables in our data with regard to the demographic characteristics of the population are consistent with literature, such as higher rates of preventable hospitalisation among men and older participants (Culler et al., 1998; Katteri et al., 2013). Similarly, the inverse associations between markers of socioeconomic status (Blustein et al., 1998; Katteri et al., 2013),

such as income and education are also consistent with existing literature; as are the higher rates among remote residents (Ansari et al., 2012; Katteri et al., 2013) and those with fewer positive health behaviours (Russell et al., 2001; Tran et al., 2014). Although other Australian studies have reported that rates of hospitalisation overall, and of preventable hospitalisation (Correa-Velez et al., 2007; Singh and de Looper, 2002), were lower in overseas-born groups, these did not provide a detailed breakdown by individual condition. Our finding that rates of admission among people speaking a language other than English were higher for some conditions (congestive heart failure and diabetes complications) and lower or not different for others (COPD and angina) indicates that influences such as genetic predisposition, language skills and cultural background (Freund et al., 2013) may impact differently on various smoking-related conditions.

Our study had several strengths. Firstly, it used data from a large-scale cohort study that captured detailed data on several dimensions of smoking exposure, and a wide range of known and potential confounding and mediating factors. Secondly, the longitudinal design of the study with the independent ascertainment of incident hospitalisation helped to minimise the potential impact of recall bias. Finally, the inclusion of large numbers of older adults allowed precise estimation of age-specific risks and RAPs, and therefore of the potential benefits of quitting smoking even among the very old.

Nevertheless, this analysis also had some limitations. The use of self-reported data could result in potential misclassification of smoking exposure, and measures of changes in smoking behaviour, such as smoking intensity, over time were not available. The 45 and Up Study had a low response rate (18%), reflecting the trend towards declining participation rates in cohort studies and other epidemiological studies (Morton et al., 2006). However, this response rate was greater than that achieved by the UK Biobank (5–10%), a comparable contemporary cohort study which like the 45 and Up Study had a focus on achieving a large, diverse participant base for valid estimation of risk associations (Manolio et al., 2012).

Consistent with a "healthy cohort effect", the prevalence of current smoking (7%) in the 45 and Up Study was lower than that reported in the NSW Health Survey (12%), the most comparable population survey, which had a response rate of 60% (Barr et al., 2008). Although the possibility of bias cannot be ruled out, previous analysis showed that risk estimates for a range of exposure-outcome relationships calculated from the 45 and Study were consistent with those calculated from the NSW Health Survey (Mealing et al., 2010).

Although a number of potential confounders were controlled for in the analyses, the possibility of residual confounding by imperfect measurement or unmeasured confounders cannot be ruled out. The sensitivity analyses combining recent quitters with current smokers produced similar results to the main analyses, suggesting that the effects of quitting in response to recent disease diagnosis did not substantially bias the risk estimates downwards.

In summary, findings showed that smoking was associated with increased risk of preventable hospitalisation for CHF, diabetes complications, COPD and angina in people aged 45 years and over, and there were dose-response relationships between smoking intensity, smoking duration and cumulative smoking and these risks. The excess risk of preventable hospitalisations from these causes combined, and specifically for COPD, was reduced within 5–14 years by quitting smoking even at older ages. These findings indicate that promotion of smoking cessation is a key mechanism whereby primary care services, and the prevention system more broadly, can act to reduce preventable hospitalisation for chronic disease and the consequent health system and societal costs.

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Contributors

BT conducted the data analyses and drafted the manuscript. MF extracted data for analysis, assisted with statistical methods and data presentation, and reviewed and edited the manuscript. LJ conceived, designed and managed the study, obtained funding, reviewed and edited the manuscript and provided overall supervision. All authors reviewed and approved the final manuscript.

Conflict of interest

The authors have declared that no competing interests exist.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.drugalcdep.2015.02.028.

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BMJ Open

Relationship between use of general practice and healthcare costs at the end of life: a data linkage study in New South Wales, Australia

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ABSTRACT

Objective: This analysis investigated the relationships between healthcare expenditures in the last 6 months of life and use of general practitioner (GP) services in the preceding 12-month period among older residents of New South Wales, Australia.

Methods: Questionnaire data (2006–2009) for more than 260 000 people aged 45 years and over were linked to individual hospital and death records and cost data. For 14 819 participants who died during follow-up, generalised linear mixed models were used to explore the relationships between costs of hospital, emergency department (ED) and Medicare-funded outpatient and pharmaceutical services in the last 6 months of life, and quintile of GP use in the 18–7 months before death. Analyses were adjusted for age at death, sex, educational level, language, private health insurance, household income, self-reported health status, functional limitation, psychological distress, number of comorbidities and geographic clustering.

Results: Almost 85% of decedents had at least one hospitalisation in the last 6 months, and the mean (median) of total cost for each person in this period was $A20 453 (14 835). There was no significant difference in the hospital cost, including cost for preventable hospitalisations in the last 6 months of life, across quintiles of GP use in the 18–7 months before death. Participants in the lowest quintile of GP use incurred more ED costs, but ED costs were similar across the other quintiles of GP use. Costs for Medicare-funded outpatient services and pharmaceuticals increased steeply according to quintile of GP use.

Conclusions: In the Australian setting, there was no association between use of GP services in the 18–7 months before death and hospital costs in the last 6 months, but there was significant association with higher costs for outpatient services and pharmaceuticals. However, there was some indication that limited GP access might be associated with increased ED use at end of life.

Strengths and limitations of this study

- This is a large-scale study to explore the longitudinal relationship between use of primary services and healthcare expenditures at the end of life, using detailed individual-level information about potential confounders and health service use.
- This study includes costs for inpatient, emergency department, outpatient services and pharmaceuticals.
- Limitations include the use of administrative claims data containing only limited information about quality of primary care services and cause of death. The use of self-reported data for covariates at baseline may also introduce some bias.

INTRODUCTION

The costs of healthcare rise dramatically at the end of life, especially in developed countries.[1 2] Most of these costs are spent caring for older people, such that in Australia almost 9% of total hospital expenditure is attributable to care for people aged 65 years and over in their last year of life, which is estimated to be about 5% of the total health budget.[3] These high costs could at least, in part, reflect unnecessary and expensive treatments for those at the end of life.[4]

The high costs of healthcare at the end of life have focused attention on how these costs might be contained, with better end-of-life care delivered, through provision of primary, community and palliative care services.[5] However, little information exists about the potential to reduce end-of-life costs through better management in primary care in the lead-up to end of life. A study of almost 80 000 deceased Medicare beneficiaries aged 66 years and over in the USA found that greater numbers of visits to primary care physicians in the year prior to the 6-month end-of-life period were associated with lower total healthcare costs at the end of life, and with fewer preventable hospitalisations for congestive heart failure and chronic

obstructive pulmonary disease.[6] The applicability of these findings to a country such as Australia, where the government provides universal health coverage for its citizens and there is no charge for treatment at public hospitals, is unknown.

In a system with greater access to publically funded healthcare, such as Australia, it is possible that those who use more primary care services prior to the end of life might also use more care at the end of life. Therefore, this study investigated the relationship between healthcare expenditures in the last 6 months of life and use of general practitioner (GP) services in the 18–7 months before death, using data from a large cohort of older residents of New South Wales (NSW), Australia.

METHODS

Participants

This analysis was nested within the Assessing Preventable Hospitalisation InDicators (APHID) study.[7] APHID uses linked survey and administrative data for participants in the Sax Institute's 45 and Up Study, a prospective cohort of 266 950 men and women aged 45 years and over, and residents in NSW, Australia.[8] Participants entered the study by completing a mailed self-administered questionnaire at study entry (between February 2006 and April 2009), and providing written consent for long-term follow-up and linkage of their health information to a range of routine health databases. People residing in non-urban areas, and those aged 80 years and over, were oversampled. The overall response rate for the 45 and Up Study was estimated to be 18%, and the study included about 10% of the NSW population aged 45 years and over.

Data sources

NSW Registry of Births, Deaths and Marriages

The NSW Registry of Births, Deaths and Marriages (RBDM) captures details of all deaths registered in NSW. In this analysis, we used death registrations for participants in the 45 and Up Study who died, up to 31 December 2011. Cause of death was not available at the time of this analysis.

NSW Admitted Patient Data Collection

The Admitted Patient Data Collection (APDC) is a routinely collected census of hospital separations (discharges, transfers and deaths) from all NSW public and private sector hospitals and day procedure centres. The APDC data used in this analysis related to all separations for the 45 and Up Study participants in the last 6 months of life (hereafter referred to as 'end of life').[6]

NSW Emergency Department Data Collection

The Emergency Department Data Collection (EDDC) provides information about patient presentations to the emergency departments (ED) of urban and large regional public hospitals across NSW which cover almost 90% of all ED visits in the state. Data used in this analysis were those presentations for the 45 and Up Study participants in the end of life.

Medicare and Pharmaceutical Benefits Scheme

Medicare is the country's universal health insurance scheme and administers claims for subsidised medical care including GP consultations under the Medical Benefits Schedule (MBS) and for pharmaceutical products under the Pharmaceutical Benefits Scheme (PBS). Only services attracting subsidy are included in Medicare data. Dental care, many allied health services and prescription medicines that cost less than specific copayment thresholds are not captured.

'GP visits' were identified as all unreferred attendances by GPs, medical practitioners or practice nurses (on behalf of a medical practitioner) in the 18–7 months prior to death. This included general consultations (at consultation rooms or residential aged care facilities, in working or after hours), telehealth, management of chronic diseases, and selected psychological services.[9 10] Quintiles of GP visits were generated based on the distribution of GP visits for all participants in the 18–7 months before death. All data from the MBS and PBS, except for claims of in-hospital services in the MBS, were used to calculate expenditures for outpatient healthcare and pharmaceutical services in the last 6 months of life. MBS services were further categorised into 'Specialist' services based on broad type of service item codes.[11]

Data linkage

Linkage of RBDM and APDC data was performed by the Centre for Health Record Linkage (CHeReL) (http://www.cherel.org.au) using probabilistic record linkage methods and commercially available software (ChoiceMaker; ChoiceMaker Technologies Inc). CHeReL quality assurance data show false-positive and false-negative rates for data linkage of 0.4% and <0.1%, respectively. Linkage of MBS and PBS data was performed by the Sax Institute, using a unique identifying number that was provided to the Commonwealth Department of Human Services.

Eligibility criteria

The 45 and Up Study participants who died <12 months after study entry were excluded from the analysis to ensure that baseline data reflected health prior to, rather than during, the end-of-life period. Moreover, participants who held a Department of Veterans' Affairs (DVA) healthcare card were excluded, because Medicare data does not capture all services provided to these cardholders. Those having no claims to the Medicare system during the entire linkage (from June 2004 to December 2011) were also excluded.

Variables

Sociodemographic and health characteristics of participants were derived from the self-reported baseline

questionnaire of the 45 and Up Study (available at https://www.saxinstitute.org.au/our-work/45-up-study/). These included age, sex, educational level, language spoken at home, health insurance status and annual household income. Health characteristics collected included self-reported health status, level of functional limitation,[12] level of psychological distress,[13] and number of comorbidities (heart disease, high blood pressure, stroke, diabetes, blood clot, asthma, Parkinson's disease and any cancer except skin cancer). Geographic area of residence was classified according to Statistical Local Areas (SLAs)[14] defined using boundaries from the 2006 Australian Census.

Outcomes

The outcomes examined, all for the last 6 months of life, were (1) hospital costs for all inpatient services including hospital costs for 'preventable' hospitalisations (see online supplementary table S1) (classified using the International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification diagnosis codes specified in the 2012 Australian National Healthcare Agreement indicator 'Selected potentially preventable hospitalisation');[15] (2) total ED costs; (3) total MBS costs, including costs for GP and specialist consultations; (4) total PBS costs and (5) total costs, the sum of (1)–(4). Hospital costs were assigned to each inpatient episode using the Australian Refined Diagnosis-Related Group-specific average cost reported in the National Hospital Cost Data Collection[16] for the specific year of admission. Cost for each ED presentation was estimated using visit type, triage category and separation mode.[17] Costs for MBS and PBS were the sum of all subsidies paid by Medicare for each decedent. All expenditures were converted to 2012 Australian dollars using the consumer price index (CPI) for all groups.[18]

Statistical analysis

Sociodemographic and health characteristics of decedents were summarised using simple descriptive statistics and compared across quintiles of GP use using Pearson's χ^2 statistics. Differences in the average of health service use including number of admissions, ED presentations, number of claims and bed days, number of MBS services and all PBS items in the last 6 months of life by quintile of GP visits in the 18–7 months before death was tested using the non-parametric Wilcoxon-Mann-Whitney tests. Mean total healthcare costs, and separate costs for all hospitalisations including preventable hospitalisations, ED presentations, MBS and PBS, were estimated using generalised linear mixed models with a log link and gamma distribution. A sensitivity analysis was used to test if there was an association between quintile of GP visits in the 18–7 months before death and number of claims, or MBS cost provided for each GP visit in the last 6 months of life. Furthermore, to explore the potential impacts of changes in health status after baseline, a sensitivity analysis was performed restricted to decedents who died between 12 and 24 months after study entry.

The covariates included in the models for estimating healthcare costs were age at death, sex, educational level, language other than English spoken at home, private health insurance, annual household income, self-reported health status, functional limitation, psychological distress and number of comorbidities. Participants were clustered within geographic areas using a random intercept across the SLA of residence (N=192).

To investigate the effects of baseline health status on healthcare expenditures in the 6 months before death, stratified analyses according to number of comorbidities (none, 1, 2 and more than 3) and self-reported health status (excellent/very good/good vs fair/poor) were performed. Stratified analysis according to age at death (<75 vs ≥75 years) was performed to examine whether the relationship between GP use and costs varied with age.

Stata statistical software (V.12.2, StataCorp LP) with gllamm package[19 20] was used to perform multivariate analyses of cost and quintiles of GP services utilisation; and SAS statistical software (V.9.3, SAS Institute Inc) for all other analyses. All analyses tests were two-sided, and p value <0.05 was considered statistically significant.

RESULTS

Characteristics of decedent participants

The analysis included 14 819 participants in the 45 and Up Study who died during follow-up, after excluding those who were holders of a DVA healthcare card (N=1271), died <12 months after study entry (N=2106), or had possibly inconsistent linkage (N=120). Average follow-up time from study entry to death for decedents in this cohort was approximately 3.6 years (range 1–7.8 years). The average age at study entry and death was 76 years (range 45–106) and 79 years (range 45–108 years), respectively. Women comprised 40% of total decedents.

Decedents had, on average, 6.4 GP visits (median 4, range 0–137) in the 18–7 months before death. In this period, 22% of decedents had no GP visit, 14% had 1–2 visits, 21% had 3–5 visits, 22% had 6–10 visits and 20% had more than 10 visits. Decedents in the upper quintile of GP visits were significantly older, were more likely to report poor health status, and had higher levels of functional limitation at baseline (table 1) compared to decedents in the bottom quintile. There were no associations between other sociodemographic or health characteristics and different groups of GP use (table 1).

In this decedent cohort, there were a total of 39 008 hospital admissions for any cause in the last 6 months of life, of which 5198 (13%) were classified as preventable hospitalisations. On average, each decedent had 2.6 hospital admissions (median 2) during the 6 months before death and 0.35 preventable hospitalisations (median 0)

Table 1 Baseline characteristics of decedents by quintile of GP visits in the 18–7 months before death

	Total decedent cohort	Quintile of GP visits				
		0	1–2	3–5	6–10	11+
N	14 819	3282 (22.2)	2139 (14.4)	3130 (21.1)	3246 (21.9)	3022 (20.4)
Age at death (years)						
45–54	371 (2.5)	63 (1.9)	56 (2.6)	90 (2.9)	85 (2.6)	77 (2.5)
55–64	1363 (9.2)	261 (8.0)	198 (9.3)	311 (9.9)	307 (9.5)	286 (9.5)
65–74	2771 (18.7)	594 (18.1)	398 (18.6)	580 (18.5)	614 (18.9)	585 (19.4)
75–84	5135 (34.7)	1031 (31.4)	762 (35.6)	1119 (35.8)	1151 (35.5)	1072 (35.5)
85+	5179 (34.9)	1333 (40.6)	725 (33.9)	1030 (32.9)	1089 (33.5)	1002 (33.2)
p Value		ref	**<0.001**	**<0.001**	**<0.001**	**<0.001**
Sex						
Male	8875 (59.9)	1922 (58.6)	1299 (60.7)	1877 (60.0)	1961 (60.4)	1816 (60.1)
Female	5944 (40.1)	1360 (41.4)	840 (39.3)	1253 (40.0)	1285 (39.6)	1206 (39.9)
p Value		ref	0.11	0.25	0.13	0.22
Language						
English	13 290 (89.7)	2946 (89.8)	1917 (89.6)	2809 (89.7)	2904 (89.5)	2714 (89.8)
Other	1527 (10.3)	335 (10.2)	221 (10.3)	321 (10.3)	342 (10.5)	308 (10.2)
Missing	2 (0.0)	1 (0.0)	1 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)
p Value		ref	0.88	0.95	0.67	0.98
Education						
Did not complete high school	6418 (43.3)	1416 (43.1)	932 (43.6)	1360 (43.5)	1420 (43.7)	1290 (42.7)
High school/apprenticeship	5817 (39.3)	1278 (38.9)	847 (39.6)	1236 (39.5)	1267 (39.0)	1189 (39.3)
University or higher	1997 (13.5)	465 (14.2)	278 (13.0)	416 (13.3)	429 (13.2)	409 (13.5)
Missing	587 (4.0)	123 (3.7)	82 (3.8)	118 (3.8)	130 (4.0)	134 (4.4)
p Value		ref	0.47	0.59	0.55	0.77
Remoteness						
Major cities	7345 (49.6)	1650 (50.3)	1062 (49.6)	1555 (49.7)	1615 (49.8)	1463 (48.4)
Inner regional	4780 (32.3)	1044 (31.8)	710 (33.2)	1000 (31.9)	1051 (32.4)	975 (32.3)
Outer regional	2433 (16.4)	541 (16.5)	343 (16.0)	516 (16.5)	508 (15.7)	525 (17.4)
Remote/very remote	257 (1.7)	46 (1.4)	24 (1.1)	57 (1.8)	72 (2.2)	58 (1.9)
Missing	4 (0.0)	1 (0.0)	0 (0.0)	2 (0.1)	0 (0.0)	1 (0.0)
p Value		ref	0.61	0.60	0.07	0.21
Private health insurance						
Private extras	5277 (35.6)	1204 (36.7)	765 (35.8)	1093 (34.9)	1158 (35.7)	1057 (35.0)
Private no extras	2093 (14.1)	455 (13.9)	319 (14.9)	434 (13.9)	448 (13.8)	437 (14.5)
Healthcare card	5092 (34.4)	1087 (33.1)	713 (33.3)	1092 (34.9)	1134 (34.9)	1066 (35.3)
None	2357 (15.9)	536 (16.3)	342 (16.0)	511 (16.3)	506 (15.6)	462 (15.3)
p Value		ref	0.70	0.41	0.46	0.18
Household annual income ($A)						
<10 000	1553 (10.5)	313 (9.5)	226 (10.6)	331 (10.6)	345 (10.6)	338 (11.2)
10 000–29 999	5612 (37.9)	1236 (37.7)	827 (38.7)	1176 (37.6)	1241 (38.2)	1132 (37.5)
30 000–49 999	1620 (10.9)	400 (12.2)	217 (10.1)	344 (11.0)	351 (10.8)	308 (10.2)
50 000–69 999	728 (4.9)	162 (4.9)	98 (4.6)	171 (5.5)	137 (4.2)	160 (5.3)
70 000 or more	978 (6.6)	210 (6.4)	153 (7.2)	196 (6.3)	215 (6.6)	204 (6.8)
Prefer not to answer	2705 (18.3)	610 (18.6)	392 (18.3)	574 (18.3)	589 (18.1)	540 (17.9)
Missing	1623 (11.0)	351 (10.7)	226 (10.6)	338 (10.8)	368 (11.3)	340 (11.3)
p Value		ref	0.16	0.46	0.24	0.06
Self-reported health status						
Excellent	701 (4.7)	164 (5.0)	76 (3.6)	157 (5.0)	162 (5.0)	142 (4.7)
Very good	2856 (19.3)	687 (20.9)	429 (20.1)	570 (18.2)	649 (20.0)	521 (17.2)
Good	5243 (35.4)	1252 (38.1)	768 (35.9)	1095 (35.0)	1060 (32.7)	1068 (35.3)
Fair	3879 (26.2)	787 (24.0)	557 (26.0)	853 (27.3)	881 (27.1)	801 (26.5)
Poor	1183 (8.0)	211 (6.4)	159 (7.4)	257 (8.2)	274 (8.4)	282 (9.3)
Missing	957 (6.5)	181 (5.5)	150 (7.0)	198 (6.3)	220 (6.8)	208 (6.9)
p Value		ref	**0.02**	**<0.001**	**<0.001**	**<0.001**
Number of comorbidities						
None	2857 (19.3)	660 (20.1)	400 (18.7)	599 (19.1)	623 (19.2)	575 (19.0)
1	4853 (32.7)	1097 (33.4)	700 (32.7)	1044 (33.4)	1062 (32.7)	950 (31.4)

Continued

Table 1 Continued

	Total decedent cohort	Quintile of GP visits				
		0	1–2	3–5	6–10	11+
2	4122 (27.8)	878 (26.8)	595 (27.8)	842 (26.9)	918 (28.3)	889 (29.4)
3 or more	2987 (20.2)	647 (19.7)	444 (20.8)	645 (20.6)	643 (19.8)	608 (20.1)
p Value		ref	0.43	0.70	0.51	0.07
Functional limitation						
No limitation	1305 (8.8)	322 (9.8)	201 (9.4)	273 (8.7)	285 (8.8)	224 (7.4)
Minor limitation	942 (6.4)	217 (6.6)	135 (6.3)	184 (5.9)	221 (6.8)	185 (6.1)
Mild limitation	1748 (11.8)	410 (12.5)	259 (12.1)	388 (12.4)	378 (11.6)	313 (10.4)
Moderate limitation	2890 (19.5)	672 (20.5)	414 (19.4)	573 (18.3)	625 (19.3)	606 (20.1)
Severe limitation	5867 (39.6)	1201 (36.6)	814 (38.1)	1285 (41.1)	1289 (39.7)	1278 (42.3)
Missing	2067 (13.9)	460 (14.0)	316 (14.8)	427 (13.6)	448 (13.8)	416 (13.8)
p Value		ref	0.73	**0.004**	0.08	**<0.001**
Psychological distress						
Low distress	10 553 (71.2)	2392 (72.9)	1535 (71.8)	2190 (70.0)	2299 (70.8)	2137 (70.7)
Moderate distress	2099 (14.2)	442 (13.5)	284 (13.3)	467 (14.9)	455 (14.0)	451 (14.9)
High distress	848 (5.7)	172 (5.2)	118 (5.5)	183 (5.8)	203 (6.3)	172 (5.7)
Very high distress	386 (2.6)	87 (2.7)	63 (2.9)	85 (2.7)	74 (2.3)	77 (2.5)
Missing	933 (6.3)	189 (5.8)	139 (6.5)	205 (6.5)	215 (6.6)	185 (6.1)
p Value		ref	0.86	0.15	0.17	0.26

Numbers in parenthesis represent the proportion of decedent in the specified quintile. p Values were estimated excluding missing records.
GP, general practitioner. Bold values indicate a statistically significant difference at $p<0.05$.

(table 2). Almost 85% of decedents (N=12 563) had at least one hospitalisation in this period, and 24% (N=3619) had at least one preventable hospitalisation, while approximately 75% (N=11 117) had at least one presentation to ED. There was a significant increase in the average number of hospital admissions and bed days in the upper quintiles of GP use compared to the lowest for preventable hospitalisations (table 2). By contrast, the average number of ED presentations was higher in the lowest quintile of GP use compared to the other quintiles. There was a strong and positive association between numbers of MBS and PBS claims in the last 6 months of life and quintile of GP visits in the 18–7 months before death (table 2). The positive association was also observed even if we took into account number of claims by number of GP visits in order to capture the intensity of services provided for each visit (data not shown).

Healthcare costs

Expenditures were right skewed with the mean (median; IQR) for the total healthcare cost in the last 6 months being $A20 453 (14 835; 6224–27 806). Mean (median, IQR) costs for all hospitalisations, preventable hospitalisations, ED presentation, MBS and PBS in this period for each decedent were $A18 753 (12 950; 4981–25 805), $A3151 (0; 0–0), $A971 (751; 211–1397), $A415 (83; 0–529), and $A313 (0; 0–295), respectively. The average cost for GP services per person was twice as much as for specialist services (table 3). Expenditure on hospital services accounted for the majority (79%) of total healthcare costs in the last 6 months of life, with ED visits (9%), MBS claims (8%) and PBS claims (4%) making much smaller contributions.

There was no significant trend in the unadjusted or adjusted hospital cost (p value for trend=0.14 or 0.33, respectively), and cost for preventable hospitalisations (p value for trend=0.42 or 0.08, respectively) at the 6 months before death across quintiles of GP visits (table 3 and figure 1). However, there was a significant inverse trend between increasing GP visits and adjusted ED cost (p value for trend=0.02), driven by greater use of ED services in the lowest quintile of GP use compared with the other quintiles (table 3 and figure 1). There was a steep increase in MBS and PBS costs according to number of GP visits (p value for trend <0.001). Separate analyses for MBS costs for GP consultations, specialist consultations and all other claims showed similar patterns (table 3). The association was also observed for MBS cost per each GP visit. Overall, there was a significant positive association between quintile of GP visits and total healthcare cost, with this result driven by the costs for outpatient services and pharmaceuticals rather than hospital costs.

Stratified analyses according to number of comorbidities and self-reported health status showed no differences between strata or compared to the unstratified results (see online supplementary table S2). Stratified analysis by age at death showed patterns similar to the main analysis, with significant trends of increasing MBS costs with increasing quintiles of GP visits in both age groups, but no significant increase in hospital cost (see online supplementary table S2). Sensitivity analysis restricting to the subset of decedents who died in the

Table 2 Average usage of healthcare services in the last 6 months of life, by quintile of GP visits in the 18–7 months before death

	Average usage of healthcare service for the decedent cohort	Average usage of healthcare service by quintile of GP visit, mean (median)				
		0	1–2	3–5	6–10	11+
Hospital bed days						
All hospital admissions	22.02 (14)	21.41 (13)	21.55 (14)	21.97 (14)	22.30 (15)	22.76 (14)
p Value		ref	0.37	0.10	**0.03**	**0.01**
Preventable hospitalisations	3.21 (0)	3.26 (0)	3.17 (0)	3.03 (0)	3.26 (0)	3.32 (0)
p Value		ref	0.37	0.98	0.85	0.50
Number of hospital admissions						
All hospital admissions	2.63 (2)	2.53 (2)	2.49 (2)	2.65 (2)	2.58 (2)	2.88 (2)
p Value		ref	0.28	**0.04**	**0.04**	**<0.001**
Preventable hospitalisations	0.35 (0)	0.35 (0)	0.35 (0)	0.35 (0)	0.35 (0)	0.35 (0)
p Value		ref	0.34	0.95	0.92	0.46
Number of ED presentations	1.67 (1)	1.74 (1)	1.65 (1)	1.63 (1)	1.65 (1)	1.66 (1)
p Value		ref	**0.03**	**0.004**	**0.002**	**0.006**
Number of MBS claims						
#All claims	7.14 (2)	0.45 (0)	2.93 (0)	5.33 (3)	9.00 (7)	17.28 (14)
p Value		ref	**<0.001**	**<0.001**	**<0.001**	**<0.001**
# GP	2.52 (1)	0.12 (0)	0.88 (0)	1.74 (1)	3.04 (2)	6.54 (6)
p Value		ref	**<0.001**	**<0.001**	**<0.001**	**<0.001**
# Specialist	0.61 (0)	0.03 (0)	0.21 (0)	0.48 (0)	0.80 (0)	1.45 (1)
p Value		ref	**<0.001**	**<0.001**	**<0.001**	**<0.001**
# All other	4.02 (0)	0.30 (0)	1.85 (0)	3.11 (1)	5.16 (3)	9.29 (6)
Value		ref	**<0.001**	**<0.001**	**<0.001**	**<0.001**
Number of PBS claims	6.35 (0)	0.16 (0)	1.35 (0)	3.54 (0)	8.02 (2)	17.73 (13)
p Value		ref	**<0.001**	**<0.001**	**<0.001**	**<0.001**

ED, emergency department; GP, general practitioner; MBS, Medical Benefits Schedule; PBS, Pharmaceutical Benefits Scheme. Bold values indicate a statistically significant difference at $p<0.05$.

12–24 months after study entry (n=2615) showed a similar pattern of increasing outpatient healthcare cost with increasing quintiles of GP visits, and no significant association for hospital cost (see online supplementary table S3).

DISCUSSION

This analysis showed that greater use of GP services in the 18–7 months before death was associated with greater total healthcare costs at the 6 months before death, with this result driven by the costs for outpatient services and pharmaceuticals. There was no association between GP use in the 18–7 months before death and hospital inpatient costs in the last 6 months of life.

These findings, to the best of our knowledge, contrast starkly with results from the only previous study that has directly addressed this issue, in a large sample of US Medicare beneficiaries,[6] which found an inverse relationship between GP use and total costs. A striking difference between the two studies was probably due to the different patterns of GP use: in this study, 42% of decedents had at least six GP visits or more in the 18–7 months before death, compared with only 22% of the US decedents.[6] This is, however, consistent with the overall higher number of annual GP visits per capita in Australia (6.5) versus in the USA (3.9).[21] Such a large gap in healthcare usage levels may reflect differences in the design, generosity and accessibility of the US and Australian healthcare system, which may explain the discrepant results. In the USA, unlike in Australia, limitations in access to care may mean that patients who would benefit from GP care are not receiving it, exacerbating ill-health in the end-of-life period.

The potential for preventive care to avert end-of-life hospital costs would be expected to be greatest for those admissions that are considered to be preventable through primary care. About 13% hospitalisations in the last 6 months of life in our analysis met the current Australian definition for a preventable hospitalisation, as used nationally to monitor primary care performance. However, the absence of a relationship between quintile of GP visits and costs, either for all hospital costs or preventable hospitalisations, suggests that if GPs have a role in preventing these hospitalisations, it is likely to lie much earlier in life and in the causal pathways for these conditions, consistent with findings regarding the key roles of patient sociodemographic factors and adverse health-related behaviours.[22 23]

Findings of positive association between GP visits and total costs in this study suggested that hospital care at the end of life could reflect the 'real' need for

Table 3 Mean healthcare expenditure ($A) and its 95% CI in the last 6 months of life, by quintile of GP visits in the 18–7 months before death

	Mean healthcare expenditure (95% CI) for the decedent cohort	Mean healthcare expenditure (95% CI) by quintile of GP visits					
		0	1–2	3–5	6–10	11+	p Value for trend
Total healthcare costs							
Unadjusted	20 453 (20 439 to 20 466)	19 413 (18 713 to 20 113)	19 742 (18 860 to 20 624)	20 355 (19 603 to 21 106)	20 740 (19 988 to 21 492)	21 877 (21 055 to 22 699)	<0.001
Adjusted	20 495 (20 427 to 20 562)	19 333 (19 195 to 19 471)	19 782 (19 615 to 19 948)	20 314 (20 175 to 20 453)	20 891 (20 751 to 21 030)	22 022 (21 867 to 22 177)	**<0.001**
All hospital admissions							
Unadjusted	18 753 (18 749 to 18 757)	18 363 (17 658 to 19 068)	18 535 (17 654 to 19 416)	18 893 (18 150 to 19 635)	18 811 (18 085 to 19 537)	19 124 (18 359 to –19 889)	0.14
Adjusted	18 792 (18 728 to 18 856)	18 303 (18 165 to 18 441)	18 585 (18 420 to 18 750)	18 857 (18 721 to 18 993)	18 956 (18 823 to 19 090)	19 226 (19 084 to 19 369)	0.33
Preventable hospitalisation							
Unadjusted	3151 (3150 to 3152)	3224 (2911 to 3537)	3281 (2887 to 3676)	3083 (2777 to 3390)	3121 (2817 to 3426)	3082 (2771 to 3394)	0.42
Adjusted	3190 (3163 to 3217)	3302 (3242 to 3361)	3242 (3166 to 3319)	3160 (3102 to 3218)	3160 (3104 to 3215)	3096 (3039 to 3154)	0.08
All ED presentations							
Unadjusted	971 (971 to 972)	1017 (982 to 1051)	952 (912 to 992)	951 (918 to 984)	961 (928 to 994)	967 (933 to 1002)	0.06
Adjusted	973 (970 to 975)	1018 (1013 to 1024)	951 (945 to 957)	951 (946 to 957)	964 (958 to 969)	971 (965 to 977)	**0.02**
All MBS claims							
Unadjusted	415 (410 to 421)	24.4 (21.8 to 27.1)	171 (149 to 195)	318 (283 to 353)	531 (473 to 589)	988 (876 to 1099)	<0.001
Adjusted	428 (422 to 434)	22.5 (22.4 to 22.7)	173 (172 to 175)	327 (325 to 330)	542 (538 to 546)	1030 (1022 to 1038)	**<0.001**
GP MBS claims							
Unadjusted	124 (123 to 126)	6.5 (5.9 to 7.1)	47.3 (41.7 to 52.9)	87.6 (79.0 to 96.2)	152 (137 to 167)	315 (283 to 346)	<0.001
Adjusted	127 (125 to 129)	6.1 (6.1 to 6.2)	47.5 (47.1 to 47.8)	88.8 (88.2 to 89.5)	154 (153 to 155)	325 (322 to 327)	**<0.001**
Specialist MBS claims							
Unadjusted	65.2 (64.4 to 66.0)	3.2 (2.7 to 3.7)	25.5 (20.2 to 30.7)	55.6 (46.1 to 65.1)	86.7 (72.2 to 101.2)	148 (122 to 173)	<0.001
Adjusted	69.9 (68.9 to 71.0)	2.6 (2.6 to 2.6)	26.2 (25.9 to 26.6)	58.6 (57.9 to 59.3)	94.6 (93.5 to 95.7)	159 (157 to 161)	**<0.001**
All other MBS claims							
Unadjusted	226 (223 to 229)	14.7 (12.7 to 16.8)	98.8 (81.9 to 115.7)	175 (150 to 199)	293 (252 to 333)	525 (450 to 601)	<0.001
Adjusted	235 (232 to 238)	13.3 (13.2 to 13.4)	99.8 (98.8 to 100.8)	183 (182 to 185)	300 (298 to 303)	555 (550 to 559)	**<0.001**
All PBS claims							
Unadjusted	313 (308 to 318)	8.3 (6.7 to 10.0)	83.1 (62.5 to 103.7)	193 (154 to 233)	437 (349 to 525)	798 (631 to 964)	<0.001
Adjusted	328 (323 to 333)	7.4 (7.3 to 7.4)	85.2 (84.0 to 86.3)	201 (199 to 204)	452 (447 to 457)	845 (835 to 855)	**<0.001**

Values were adjusted mean of costs either unadjusted or adjusted for age at death (10-year groups), sex, language, education, private health insurance, number of comorbidities, self-reported health status, functional limitation, psychological distress and random effect of statistical local area. p Values for trend were estimated for each comparison using the lowest quintile as a reference group. Bold values indicate a statistically significant difference at p<0.05.
ED, emergency department; MBS, Medical Benefits Schedule; PBS, Pharmaceutical Benefits Scheme.

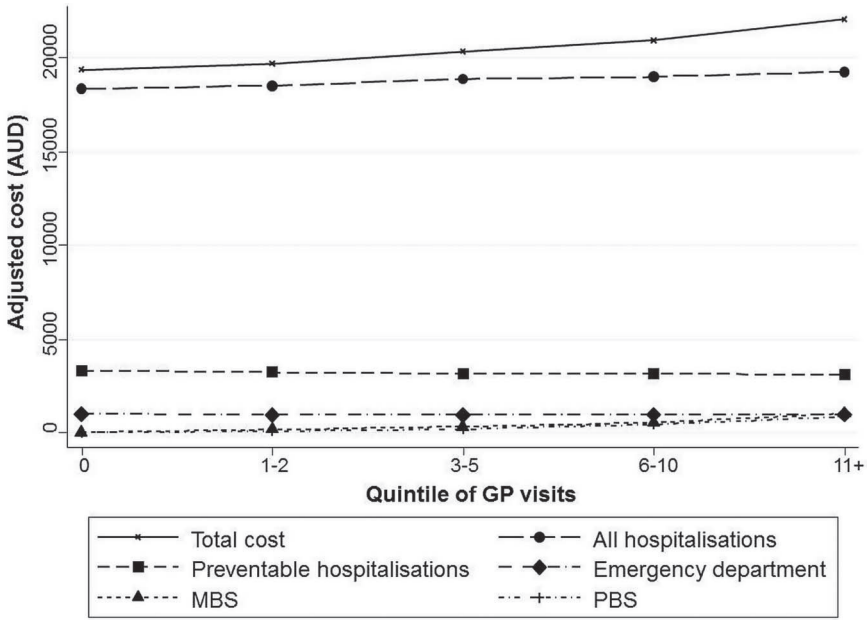

Figure 1 Adjusted* mean healthcare expenditures in the last 6 months of life, by quintile of GP visits in the 18–7 months before death. *Adjusted for age at death (10-year groups), sex, language, education, private health insurance, number of comorbidities, self-reported health status, functional limitation, psychological distress and random effect of statistical local area. AUD, Australian dollar; GP, general practitioner; MBS, Medical Benefits Schedule; PBS, Pharmaceutical Benefits Scheme.

multidisciplinary care for those with deteriorating health and high risk of mortality, rather than admissions that could be avoided. Thus, where preventable hospitalisation is used as a performance indicator for primary care, it may be appropriate to consider excluding admissions at the end of life.

There was no existing study of the relationship between GP visits and ED cost at the end of life with which to compare with our results. We could find only one study for patients with cancer at the end of life suggesting that a greater level of continuity of care with their primary care provider was associated with fewer presentations to ED and thus lower cost.[24] We found that decedents who used no GP services in the lead up to end of life had more ED visits at the end of life. These decedents, who were older on average than others, may have included a greater proportion of residents of residential aged care, for whom there is growing concern that current delivery of GP services is not optimal.[25]

Greater usage of GP services in the 18–7 months before death was associated with higher use of pharmaceutical and outpatient services, including GP and specialist visits, in the last 6 months of life. This association is consistent with patterns of healthcare expenditure in the general population.[26] Only 53% of decedents in this cohort visited their GP in the last 6 months of life period, compared with 75% who had at least one ED presentation and 85% who had at least one hospital admission. These findings reflect the current predominant organisation of end-of-life care in Australia, where 54% of people die in hospital.[27]

Indeed, although most Australians express a wish to die at home, few do so.[27] Only about 15% of Australians aged 65 years and over die at home, compared with about 30% in countries including New Zealand, the USA, Ireland and France.[28] International studies have indicated that home-based palliative care for those at the end of life is effective in delivering better outcomes including increased patient satisfaction and lower costs,[29 30] and there is substantial potential to further develop these models of care in Australia.

This study had several strengths. It used detailed questionnaire data from a large prospective cohort study, with comprehensive ascertainment of healthcare utilisation and costs from administrative databases, eliminating the potential for recall bias. While previous Australian studies of end-of-life healthcare costs have reported only hospital costs,[3 31 32] this study captured inpatient, ED, outpatient services and pharmaceuticals costs. Nonetheless, only Medicare-subsidised outpatient expenditures were included, and costs for non-admitted community-based services, such as home-based palliative care not provided by GPs, or dispensing of non-subsided pharmaceuticals, were not captured. This might reduce the generalisability of the findings to other populations with different healthcare systems. In addition, the incompleteness of data collection for presentations to all EDs in NSW may have resulted in underestimation of ED costs. Moreover, measures of comorbidities and health status used baseline questionnaire data, so did not reflect incident conditions or deteriorating health during follow-up.

This study was restricted to decedent participants of the 45 and Up Study, raising a concern regarding the generalisability of these findings to other populations. The 45 and Up Study had a low response rate (18%), reflecting the trend towards declining participation rates in cohort and other epidemiological studies such as the UK Biobank (5–10%), a comparable study focussing on achieving a large, diverse cohort of participants.[33] However, relative risk estimates from the 45 and Up Study have been shown to be comparable with those from population health surveys,[34] and the large sample

size provides substantial heterogeneity to support valid within-cohort comparisons.

The association between GP visits in the 18–7 months before death and use of healthcare services in the following 6 months is likely to reflect the influences of health seeking behaviour and access to healthcare, as well as need for healthcare. Although these factors could not be fully partitioned out in the current analyses, they did control for positive health behaviours (a proxy measure of health seeking behaviour) and clustering by geographic area (a surrogate for access to care).

This study found that in the Australian setting, greater use of GP services in the lead up to end of life had no impact on hospital costs in the 6-month end-of-life period, but was associated with higher costs for outpatient services, pharmaceuticals and overall total healthcare cost. There was some indication that limited GP access might increase ED use at end of life. The findings do not preclude a key role for GP care in containing end-of-life costs, for example, through discussion of end-of life treatment preferences and advance care planning, delivering care in residential aged-care settings, and participating in home-based palliative care.

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Contributors BT conducted the data analyses and drafted the manuscript. MOF extracted data for analysis, assisted with statistical methods and data presentation, reviewed and edited the manuscript. FG advised on the statistical methods, assisted with data interpretation and edited the manuscript. LJ conceived, designed and managed the study, obtained funding, reviewed and edited the manuscript and provided overall supervision. BT, MOF and LJ have full access to the data. All authors reviewed and approved the final manuscript.

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Competing interests None declared.

Patient consent Obtained.

Ethics approval Ethics approval for the APHID study was obtained from the NSW Population and Health Services Research Ethics Committee, Aboriginal Health and Medical Research Council of NSW Ethics Committee, and the University of Western Sydney Ethics Committee. The conduct of the 45 and Up Study was approved by the University of New South Wales Human Research Ethics Committee.

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The Contribution of Geography to Disparities in Preventable Hospitalisations between Indigenous and Non-Indigenous Australians

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Abstract

Objectives: To quantify the independent roles of geography and Indigenous status in explaining disparities in Potentially Preventable Hospital (PPH) admissions between Indigenous and non-Indigenous Australians.

Design, setting and participants: Analysis of linked hospital admission data for New South Wales (NSW), Australia, for the period July 1 2003 to June 30 2008.

Main outcome measures: Age-standardised admission rates, and rate ratios adjusted for age, sex and Statistical Local Area (SLA) of residence using multilevel models.

Results: PPH diagnoses accounted for 987,604 admissions in NSW over the study period, of which 3.7% were for Indigenous people. The age-standardised PPH admission rate was 76.5 and 27.3 per 1,000 for Indigenous and non-Indigenous people respectively. PPH admission rates in Indigenous people were 2.16 times higher than in non-Indigenous people of the same age group and sex who lived in the same SLA. The largest disparities in PPH admission rates were seen for diabetes complications, chronic obstructive pulmonary disease and rheumatic heart disease. Both rates of PPH admission in Indigenous people, and the disparity in rates between Indigenous than non-Indigenous people, varied significantly by SLA, with greater disparities seen in regional and remote areas than in major cities.

Conclusions: Higher rates of PPH admission among Indigenous people are not simply a function of their greater likelihood of living in rural and remote areas. The very considerable geographic variation in the disparity in rates of PPH admission between Indigenous and non-Indigenous people indicates that there is potential to reduce unwarranted variation by characterising outlying areas which contribute the most to this disparity.

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Introduction

There is overwhelming evidence that Indigenous Australians, like indigenous peoples worldwide, suffer profound health disadvantage. The life expectancy of Indigenous Australians at birth is around 11.5 years lower for males and 9.7 years lower for females, compared with non-Indigenous Australians [1]. Much of the gap between Indigenous and non-Indigenous Australians is driven by cardiovascular disease, diabetes and related complications, such as renal failure [2]. Similar ethnic disparities for these conditions have been observed in other countries, such as New Zealand [3], the United States of America [4–7] and Canada [8].

The concept of the "potentially preventable hospitalisation" (PPH) provides policymakers and health care managers with a framework to identify admissions that may have been prevented if timely and adequate care was available to that individual outside of the hospital system [9]. PPHs are identified using a set of admission diagnosis and procedure codes and are broadly grouped into acute, chronic or vaccine preventable PPH. Rates of PPH admissions, by Indigenous status, are reported by both state and federal governments [10–14] and are a key performance indicator specified in the National Healthcare Agreement (NHA), with the aim of reducing PPH admissions to 8.5% of total admissions by 2014–15 [15]. This routine reporting consistently shows that age-adjusted rates of PPH admission are much higher in Indigenous than non-Indigenous Australians, but the magnitude of the differential varies with jurisdiction, from about three-fold in New South Wales (NSW) [11] and Queensland [10] to four-fold in the Northern Territory [9]. Much higher rates of PPH admission are also reported among residents of rural and remote areas [14]. Because Indigenous people make up a greater proportion of the population in rural areas, where admission rates tend to be higher, it is possible that some of the disparity is driven by the differential distribution of the Indigenous population.

Further, evidence from other countries indicates that ethnicity and rurality both contribute to disparities in health care, with rural

ethnic minorities experiencing poorer access to health care [16]. Importantly, existing analyses have not quantified the independent roles of geography and Indigenous status in explaining differences in rates of PPH admission between Indigenous and non-Indigenous Australians. Nor have they explored how much this disparity varies among local areas, an essential step in identifying strategies to reduce unwarranted variation.

Our study aimed to address these knowledge gaps.

Methods

Ethics approval

Approval for the study was given by the NSW Population and Health Services Research Ethics Committee, the Aboriginal Health and Medical Research Council of NSW Ethics Committee, and the University of Western Sydney Human Research Ethics Committee.

Study design

Observational study using linked hospital admission records.

Population

New South Wales (NSW) is the largest state in the Commonwealth of Australia, with a population of 6,663,402 in 2006, and includes both highly urbanised and rural areas. While Indigenous Australians represent only 2.3% of the total population of NSW, 23% of all Indigenous people living in Australia reside in NSW [17]. NSW is comprised of 199 Statistical Local Areas (SLAs) with an average population 35,906 people (range: 364–141,686) and an average spatial area 4,027 km^2 (range: 4–93,284 km^2) [18]. SLA was the finest level of geography at which population estimates were available for the study period [18].

Data

The NSW Admitted Patients Data Collection (APDC) includes information about all separations (discharges, transfers and deaths) from NSW public and private hospitals and day procedure centres. Diagnoses are coded using the International Classification of Diseases and Related Problems, Australian Modification (ICD-10-AM), and procedures are coded using the Australian Classification of Health Interventions Sixth Edition [19].

APDC data were available for the period 1 July 2003 to 30 June 2008. As NSW did not have a unique patient identifier available during the study period, hospital separations associated with the same individual were identified using probabilistic methods by the NSW Centre for Health Record Linkage [20]. Probabilistic matching was performed by the Centre for Health Record Linkage using key personal identifier variables, such as date of birth, first name, last name, sex and residential address to form probability weights for the likelihood of a particular hospital admission being associated with one person. The Centre for Health Record Linkage uses the software package ChoiceMaker, which can adjust for data entry errors, incomplete and missing data [21]. In addition to automated linkage, the CHeReL also conducts a manual clerical review on a sample of records in order to audit linkage quality. False positive and false negative rates for data linkage are 0.4% and less than 0.1%, respectively.

Indigenous people are known to be under-identified in the APDC [22], however there is evidence to indicate that the level of identification improved during the time period of this study [23,24]. Hence, taking this information into account, an admission was reported as being for an Indigenous person on the basis of the status recorded on their most recent hospital record. This approach increased the number of PPH admissions reported as Indigenous by 5.4%.

We derived synthetic Indigenous population estimates for NSW SLAs using a combination of age- and sex-specific estimates of the total population for SLAs, age- and sex-specific estimates of the Indigenous population for NSW, and the estimated proportion of the population of each SLA that was Indigenous, from the 2006 Australian Census [25,26]. We estimated the non-Indigenous population by subtracting Indigenous population estimates from the total population.

We identified PPH admissions according to the 2012 NHA performance indicator: Selected potentially preventable hospitalisations [27]. We aggregated the number of PPH admissions by broad PPH grouping and specific condition by strata based on financial year, 10-year age-group (from 0–9 to 80+), sex, Indigenous status and SLA, and then combined these with the estimated population counts. SLAs were grouped into four remoteness categories (major cities, inner regional, outer regional, remote) based on their average Accessibility/Remoteness Index of Australia Plus (ARIA+) score in 2006 [28]. The ARIA+ score measures the remoteness of a point based on the physical road distance to the nearest urban centre in each of five size classes, with the score ranging from 0 (highly accessible) to 15 (high remoteness). ARIA scores are spatially interpolated for a range of different geographical units in order to provide scores for a geographical area. The index excludes socio-economic factors from its calculation [28].

Statistical analysis

We calculated directly age-standardised admission rates for all PPH conditions and the broad PPH groupings, using events from the hospital data as the numerator and population from the synthetic population estimates as the denominator. The rates were standardised to the 2001 Australian Standard Population [29]. We also calculated average length of stay (ALOS), with the numerator the total number of bed days for each PPH admission and the denominator the total number of PPH admissions.

We used multilevel Poisson models to compare admission rates between Indigenous and non-Indigenous people. All models were adjusted for age group and sex, with the exception of the pelvic inflammatory disease condition-specific model which was only adjusted for age-group, and all models included a random intercept for the SLA of residence. Variation at the SLA level (τ^2) was expressed as a median rate ratio, which was the median of the rate ratios of pair-wise comparisons of people with identical characteristics taken from randomly chosen SLAs. We also added a random slope for Indigenous status to see whether there was significant variation across areas in the Indigenous to non-Indigenous admission rate ratio. Using area-level "shrunken" residuals from the multilevel models that borrow information from the average to stabilise estimates [30], we estimated PPH admission rates by Indigenous status, and the rate ratio of Indigenous to non-Indigenous admissions, in each SLA. All models included the log of the population as an offset. Strata with no people were excluded.

We used negative binomial multilevel models to compare differences in ALOS between Indigenous and non- Indigenous people. All models were adjusted for age group and sex and included a random intercept for SLA of residence and the log of the number of admissions as an offset. Strata with no admissions were excluded.

Model outputs included adjusted rate ratios (aRR) with their 95% confidence intervals (CI). All analyses were carried out using SAS 9.3 [31] and MLwiN 2.25 [32].

Results

Over the 5-year study period, PPH diagnoses accounted for 987,604 admissions in NSW. Of these, 36,430 (3.7%) were for Indigenous people. The majority of admissions were for chronic conditions (57%), followed by acute (41%) and vaccine preventable conditions (2.4%), with this distribution being similar for Indigenous and non-Indigenous people (Table 1).

The overall age-standardised rate of PPH admissions for Indigenous people was 76.5 per 1 000, compared with 27.3 for non-Indigenous people (Table 1), a ratio of 2.80. Indigenous people experienced significantly higher age-standardised rates of admission for most PPH conditions, with the exception of appendicitis, pelvic inflammatory disease and nutritional deficiencies (Table 1).

Figure 1 presents Indigenous to non-Indigenous rate ratios, adjusted for age, sex and geographic clustering by including a random intercept for SLA in multilevel models. After adjusting for geographic clustering the magnitude of the Indigenous to non-Indigenous overall PPH aRR decreased from 2.58 (95% CI 2.55–2.60) to 2.16 (95% CI 2.14–2.19), indicating that PPH admission rates in Indigenous people were 2.16 times higher than in non-Indigenous people of the same age group and sex who lived in the same SLA. This indicated that geographic clustering accounted for only some of the observed disparity. Significantly higher rates of PPH admissions for Indigenous people were found for all PPH conditions with the exception of nutritional deficiencies (for which numbers were very small) (Figure 1). The SLA-level variation was equivalent to a median rate ratio of 1.50; in other words, for any population group defined by age, sex and Indigenous status from two randomly chosen areas, PPH admissions in one area were on average 50% higher than in the other area.

After adjusting for age, sex and SLA, the largest disparities in PPH admission rates were seen for diabetes complications (aRR = 5.07, 95% CI 4.97–5.17), COPD (aRR = 4.07, 95% CI 3.92–4.22), rheumatic heart disease (aRR = 3.78, 95% CI 3.11–4.59), other vaccine preventable (aRR = 2.94, 95% CI 2.55–3.40) and congestive cardiac failure (aRR = 2.71, 95% CI 2.55–2.88) (Figure 1).

Rates of PPH admission varied markedly according to SLA ($p < 0.001$) (from the random intercept model) and the rate ratio of Indigenous to non-Indigenous admissions also varied significantly ($p<0.001$) (from the random intercept and random slope model). Figure 2 plots the variation in Indigenous to non-Indigenous rates of PPH admission by SLA and remoteness category, and highlights SLAs where the age- and sex-adjusted Indigenous rate of PPH admission was higher than the state average for Indigenous people as well as being higher than the adjusted non-Indigenous rate in that area. Figure S1 plots the variation in Indigenous to non-Indigenous rate ratios of PPH admission by SLA on a map of NSW. It shows that rates of PPH admission were higher in Indigenous than non-Indigenous people in the vast majority of SLAs, with greater disparities seen in regional and remote areas than in major cities. More than 30 SLAs, mainly in regional areas, had both higher than average Indigenous rates of PPH admissions and higher than average disparities in rates between Indigenous and non-Indigenous people. These "high rate, high disparity" SLAs are shown in Table 2. Three SLAs, Hay, Junee and Lithgow (C), had both lower than average Indigenous rates of PPH admissions and lower than average disparities in rates between Indigenous and non-Indigenous people. Both Junee and Lithgow (C) are inner regional areas, while Hay is a remote area according to the ARIA+ remoteness classification.

Average length of stay for PPH admissions in Indigenous people was slightly longer than for non-Indigenous people of the same age group and sex who lived in the same SLA (aRR 1.05, 95% CI 1.02–1.08), with this difference being statistically significant for acute (aRR 1.08, 95% CI 1.05–1.12) and chronic (aRR 1.04, 95% CI 1.01–1.08) but not vaccine-preventable (aRR 1.00, 95% CI 0.86–1.16) conditions. Including a random slope term for Indigenous status did not markedly alter our estimates of the disparity in Indigenous and non-Indigenous average length of stay (not shown).

Discussion

Ours was the first study to our knowledge to explore the independent roles of geography and Indigenous status in explaining differences in rates of PPH admission between Indigenous and non-Indigenous people. Our results demonstrated unequivocally that higher rates of PPH admission among Indigenous people are not simply a function of their greater likelihood of living in rural and remote areas where rates of PPH admissions are higher [14]. The slightly longer length of PPH hospital stays for Indigenous than non-Indigenous patients who lived in the same SLA suggested that it was unlikely that a "lower threshold" for admission of Indigenous patients was a major contributor to the observed disparities. However, longer stays could reflect lesser availability of assistance with care at home or in the community, as well as greater disease severity. Further, it is possible that longer stays may also reflect differences in hospital discharge practices or the types of hospitals that Indigenous and non-Indigenous people seek treatment from.

Our age-standardised rates of hospitalisation for PPH diagnoses in Indigenous people in NSW (76.5 admissions per 1,000) were lower than those reported for Indigenous people in the Northern Territory (110 per 1,000) in the years 1998–99 to 2005–06 [9], while the rates for non-Indigenous people were similar in both studies (27.3 and 27.8 per 1,000 respectively). Likely explanations include higher incidence and prevalence of PPH conditions in the NT Indigenous population, differences in the prevalence of behavioural risk factors that contribute to the risk of developing specific PPH conditions, differences between the jurisdictions in the provision and accessibility of primary health care and hospital services, and possibly better identification of Indigenous people in NT hospital data [22]. However, audits of NSW hospital data found that about 88% of admissions were correctly recorded in 2007 and that 91% in 2010 were correctly identified in NSW public hospitals [22,23]. Also, we enhanced the reporting of Indigenous status by using the most recent hospital record for each individual.

We found that after adjusting for age, sex and SLA of residence, rates of PPH admission in Indigenous people were significantly higher than those in non-Indigenous people across almost all conditions included in the PPH indicator. However, diabetes complications contributed around one-third of all PPH admissions in Indigenous people, and were also responsible for the largest disparity, with the rate of these admissions for Indigenous people being more than five times higher than for non-Indigenous people of the same age group, sex and SLA of residence. Large ethnic disparities in potentially avoidable hospitalisations for diabetes were also evident between New Zealand Māori and people of European descent [3], and African Americans and non-Hispanic Whites in the United States of America (USA) [4,5]. Our finding reinforces the importance of tackling the determinants of diabetes, and better diabetes management, as key priorities for improving the health of Indigenous Australians.

Table 1. Number of admissions and age-standardised admission rate by Indigenous status, NSW, 2003/04 to 2007/08.

	Indigenous				Non-Indigenous			
	n	%	ASR	(95% CI)	n	%	ASR	(95% CI)
Acute conditions	15044	41.30%	21.97	(21.51–22.43)	385300	40.50%	11.4	(11.37–11.44)
Appendicitis with generalised peritonitis	153	0.40%	0.17	(0.14–0.20)	4938	0.50%	0.15	(0.15–0.15)
Cellulitis	1870	5.10%	3.04	(2.86–3.22)	51459	5.40%	1.48	(1.47–1.49)
Convulsions and epilepsy	3777	10.40%	5.57	(5.36–5.78)	51346	5.40%	1.56	(1.55–1.58)
Dental conditions	2545	7.00%	2.58	(2.46–2.69)	67049	7.00%	2.06	(2.05–2.08)
Ear Nose and Throat conditions	2933	8.10%	2.84	(2.71–2.97)	50118	5.30%	1.56	(1.55–1.58)
Gangrene	116	0.30%	0.29	(0.23–0.36)	5067	0.50%	0.14	(0.14–0.15)
Dehydration and gastroenteritis	1281	3.50%	2.59	(2.41–2.77)	69784	7.30%	2.01	(2.00–2.03)
Pelvic inflammatory disease	284	0.80%	0.39	(0.35–0.44)	7489	0.80%	0.46	(0.45–0.47)
Perforated/bleeding ulcers	158	0.40%	0.4	(0.33–0.48)	8037	0.80%	0.22	(0.22–0.23)
Pyelonephritis	1930	5.30%	4.12	(3.87–4.37)	70191	7.40%	1.99	(1.98–2.00)
Chronic conditions	20688	56.80%	53.5	(52.65–54.36)	546973	57.50%	15.38	(15.34–15.42)
Angina	2018	5.50%	5.49	(5.22–5.77)	97683	10.30%	2.73	(2.71–2.74)
Asthma	3062	8.40%	3.77	(3.60–3.93)	60097	6.30%	1.87	(1.85–1.88)
Congestive cardiac failure	1078	3.00%	4.01	(3.73–4.30)	67257	7.10%	1.81	(1.79–1.82)
COPD	3125	8.60%	10.65	(10.23–11.08)	91535	9.60%	2.52	(2.50–2.54)
Diabetes complications	11824	32.50%	31.5	(30.86–32.14)	228072	24.00%	6.38	(6.35–6.40)
Hypertension	318	0.90%	0.79	(0.69–0.90)	10554	1.10%	0.29	(0.29–0.30)
Iron deficiency anaemia	455	1.20%	1.24	(1.11–1.38)	30461	3.20%	0.86	(0.85–0.87)
Nutritional deficiencies	5	0.00%	0.01	(0.00–0.01)	192	0.00%	0.01	(0.00–0.01)
Rheumatic heart disease	124	0.30%	0.2	(0.16–0.25)	2851	0.30%	0.08	(0.08–0.08)
Vaccine preventable conditions	882	2.40%	1.51	(1.39–1.65)	23040	2.40%	0.67	(0.66–0.68)
Influenza and pneumonia	682	1.90%	1.22	(1.10–1.34)	18429	1.90%	0.53	(0.53–0.54)
Other vaccine-preventable	201	0.60%	0.3	(0.26–0.35)	4635	0.50%	0.14	(0.13–0.14)
Overall	36430	100%	76.48	(75.51–77.46)	951174	100%	27.34	(27.29–27.40)

Note: ASR, age standardised rate per 1000 population; CI, confidence interval. With the exception of pelvic inflammatory disease and nutritional deficiencies, all rates were statistically significantly higher for Indigenous Australians ($p<0.05$).

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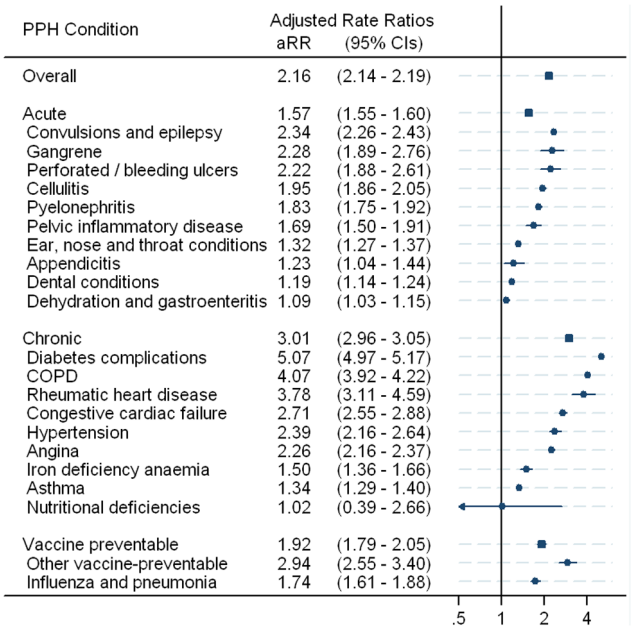

Figure 1. Adjusted admission rate ratio for selected PPH conditions, for Indigenous people compared with non-Indigenous people, 2003/04 to 2007/08, after adjustment for age group, sex and area of residence.
doi:10.1371/journal.pone.0097892.g001

We found that there was very considerable geographic variation in the disparity in rates of PPH admission between Indigenous and non-Indigenous people in NSW, presenting the potential to reduce disparities by characterising and targeting the sources of this variation. We identified more than 30 "high rate, high disparity" SLAs in NSW, mainly in regional areas, as well as three "low rate, low disparity" SLAs. However, using administrative hospital data alone, we were unable to identify the relative contributions of such factors as differences in underlying disease prevalence, disease severity, access to quality care, and admission practices to these variations in admission rates. While studies of ambulatory care-sensitive hospitalisations in the USA were able to account for underlying disease prevalence in their estimates of ethnic disparities [4,5], these did not examine ethnic disparities according to small geographical areas.

We could not identify other studies that investigated how ethnic disparities in potentially preventable hospitalisation varied with geography. Findings for disparities in mortality have varied between settings. Studies in New Zealand have reported relatively little variation in disparities between New Zealand Māori and European/other populations in life expectancy [33] and mortality [34] at the District Health Board level. Research in Massachusetts, USA [35] reported substantial variations in disparities in mortality between Black and White populations at the Census Tract level, while this variation was not found using similar methods for the more urbanised population of Los Angeles [36]. These contrasting findings emphasise the importance of methods that are able to account for both the person and their place, such as multilevel modelling, in studies of ethnic disparities in health [16,34].

A possible artefactual contributor to geographic variation in our study was inconsistency in the numerator (hospital admission) and denominator (population census) data that were used to calculate admission rates. For example, high mobility of Indigenous people [37] between their main rural place of residence and inner Sydney might contribute to the high PPH admission rates observed in Sydney South SLA.

Linkage of hospital data to other population-based data such as large-scale health survey data, disease registers or Medicare claims would go some way towards addressing the limitations of our study, by ensuring consistency between numerator and denominator data, and providing more detailed information about patient risk factors. Unfortunately such linkages are not presently available as part of the current National Aboriginal and Torres Strait Islander Health Survey, and processes for access to linked Medicare and other Commonwealth data for research, while currently being revised [38], are very difficult to navigate.

Although we urgently need more information to characterise the sources of geographic variation in PPH admission rates, evidence is starting to emerge about the types of interventions that might be successful in tackling these variations. These include chronic disease management interventions that place an emphasis on the Chronic Care Model [39], recall and reminder systems for people with diabetes [40], ensuring that Indigenous people have

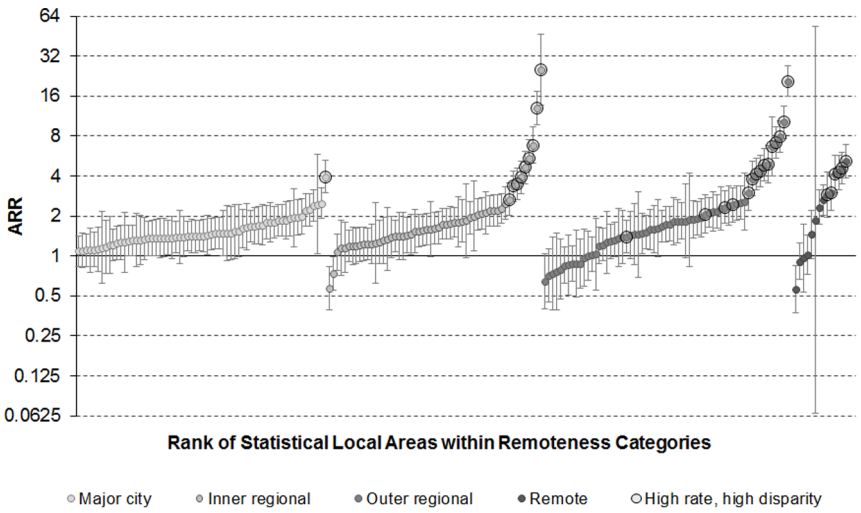

Figure 2. Indigenous to non-Indigenous PPH admission rate ratio by Statistical Local Area and remoteness categories, 2003/04 to 2007/08, adjusted for age group and sex.
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Table 2. "High rate, high disparity" Statistical Local Areas.

Remoteness Area	Statistical Local Areas
Major cities	Sydney - South
Inner regional	Clarence Valley (A) - Grafton, Wagga Wagga - Part A, Wagga Wagga - Part B, Lismore - Part A, Armidale Dumaresq - City, Ballina, Richmond Valley - Balance, Byron, Richmond Valley - Casino
Outer regional	Warrumbungle Shire, Tumut, Griffith, Gilgandra, Narrabri, Tenterfield, Armidale Dumaresq - Balance, Eurobodalla, Kyogle, Inverell - Part B, Broken Hill, Nambucca, Narrandera, Wellington, Bega Valley, Kempsey, Murrumbidgee
Remote/Very Remote	Balranald, Brewarrina, Central Darling, Bourke, Carrathool, Walgett, Lachlan, Coonamble, Warren

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access to culturally appropriate health care services designed to meet their specific needs [41] and the application of continuous quality improvement principles to Indigenous primary health care services, such as in the Healthy for Life program [42].

Repeating our analyses using linked hospital data for the whole of Australia, when available, will allow exploration of inter-jurisdictional differences. It will also open up possibilities for applying novel evaluation methods using "natural experiments" [43] to identify the features of current programs and services that are associated with lower rates of potentially preventable hospitalisation among Indigenous Australians.

Supporting Information

Figure S1 Map of Indigenous to non-Indigenous PPH admission rate ratio by Statistical Local Area, 2003/04 to 2007/08, adjusted for age group and sex.
(TIF)

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Author Contributions

Conceived and designed the experiments: TCH DR MOF SL LJ. Analyzed the data: TCH DR. Wrote the paper: TCH DR MOF SL LJ.

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RESEARCH ARTICLE Open Access

Inequalities in pediatric avoidable hospitalizations between Aboriginal and non-Aboriginal children in Australia: a population data linkage study

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Abstract

Background: Australian Aboriginal children experience a disproportionate burden of social and health disadvantage. Avoidable hospitalizations present a potentially modifiable health gap that can be targeted and monitored using population data. This study quantifies inequalities in pediatric avoidable hospitalizations between Australian Aboriginal and non-Aboriginal children.

Methods: This statewide population-based cohort study included 1 121 440 children born in New South Wales, Australia, between 1 July 2000 and 31 December 2012, including 35 609 Aboriginal children. Using linked hospital data from 1 July 2000 to 31 December 2013, we identified pediatric avoidable, ambulatory care sensitive and non-avoidable hospitalization rates for Aboriginal and non-Aboriginal children. Absolute and relative inequalities between Aboriginal and non-Aboriginal children were measured as rate differences and rate ratios, respectively. Individual-level covariates included age, sex, low birth weight and/or prematurity, and private health insurance/patient status. Area-level covariates included remoteness of residence and area socioeconomic disadvantage.

Results: There were 365 386 potentially avoidable hospitalizations observed over the study period, most commonly for respiratory and infectious conditions; Aboriginal children were admitted more frequently for all conditions. Avoidable hospitalization rates were 90.1/1000 person-years (95 % CI, 88.9–91.4) in Aboriginal children and 44.9/1000 person-years (44.8–45.1) in non-Aboriginal children (age and sex adjusted rate ratio = 1.7 (1.7–1.7)). Rate differences and rate ratios declined with age from 94/1000 person-years and 1.9, respectively, for children aged <2 years to 5/1000 person-years and 1.8, respectively, for ages 12- < 14 years. Findings were similar for the subset of ambulatory care sensitive hospitalizations, but in contrast, non-avoidable hospitalization rates were almost identical in Aboriginal (10.1/1000 person-years, (9.6–10.5)) and non-Aboriginal children (9.6/1000 person-years (9.6–9.7)).

Conclusions: We observed substantial inequalities in avoidable hospitalizations between Aboriginal and non-Aboriginal children regardless of where they lived, particularly among young children. Policy measures that reduce inequities in the circumstances in which children grow and develop, and improved access to early intervention in primary care, have potential to narrow this gap.

Keywords: Indigenous health, Avoidable hospitalisations, Preventable hospitalisations, Child health, Inequalities

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Background

It is well established that Australian Aboriginal children start life with a disproportionate burden of social and health disadvantage [1–3]. The early life disadvantage experienced by Aboriginal children is a precursor to adverse outcomes later in life. Aboriginal Australians experience worse health, development, education and employment outcomes than non-Aboriginal Australians through child- and adult-hood [1, 2, 4–7]. There is an identified need for better evidence for targeting and evaluating the impact of policy, programs and services on closing modifiable health gaps during early childhood [8].

Routinely collected population data can provide unique insights into the magnitude and nature of health problems affecting large numbers of people, as well as making visible the experience of smaller sub-populations. Rates of avoidable hospitalization were originally conceived as an indicator of access to quality out-of-hospital care [9]. These indicators use routinely collected hospital data and usually include a set of diagnosis and procedure codes for conditions that are considered amendable to non-hospital interventions. Like many countries, Australian government agencies routinely report on avoidable hospitalizations for a range of acute, chronic and vaccine-preventable conditions [10]. However, when it comes to children, the Australian indicator may have limited relevance because it includes a number of predominantly adult diseases [10].

The United States Agency for Healthcare Research and Quality first published a set of 'Pediatric Quality Indicators' to identify hospitalizations in children that may be avoidable via changes at the health system or provider level in 2006 [11]. More recently, a pediatric avoidable hospitalization indicator was developed in New Zealand that reframed the concept of 'avoidable' to include conditions that might be influenced not only by primary care, but also broader policy measures, such as provision of affordable and quality housing, childcare and income support [12]. This broader definition of avoidable hospitalizations is useful because it avoids potentially unfair and unrealistic expectations about the extent to which reductions in hospitalizations might be achieved through primary care alone [12].

To our knowledge, Australian children have been included in few studies of avoidable hospitalizations to date [13–17], and only two have provided a breakdown by Aboriginal status [16, 17]. A study of aggregate hospital separation data from five de-identified Australian states and territories in 1993–94 reported higher rates of hospitalization for select child-relevant ambulatory care sensitive conditions in Aboriginal compared with non-Aboriginal children [17]. Aboriginal 0–14 year old children were also found to have higher avoidable hospitalization rates than their non-Aboriginal peers in the Northern Territory in 1998–2006, although a pediatric indicator was not used [16]. Moreover, rates were mostly reported for broad age groups, which is problematic because pediatric avoidable hospitalization rates are highest in the first two years of life [18]. Because of the identified need to target and monitor modifiable health gaps between Australian Aboriginal and non-Aboriginal children, we aim to quantify inequalities in pediatric avoidable hospitalizations between Aboriginal and non-Aboriginal children in the most populous state of Australia, New South Wales (NSW), by applying a pediatric avoidable hospitalization indicator to linked hospital data for children born between July 2000 and December 2012.

Methods

Data sources

We used hospital data from the NSW Admitted Patients Data Collection, which includes records of all separations from public and private hospitals and day procedure centers in NSW. Each record represents an episode of care that ends when a patient is transferred to another type of care, discharged from hospital, or dies. Patient demographics and multiple diagnoses and procedures are recorded for each separation. Diagnoses are coded according to the Australian modification of the International Statistical Classification of Diseases and Related Problems 10th Revision (ICD-10-AM) [19] and procedures according to the Australian Classification of Health Interventions [19]. We also used death registration data from the NSW Register of Births, Deaths and Marriages to ascertain children who died during the study period. Approval to link and use these data was obtained from the relevant data custodians (NSW Ministry of Health and NSW Register of Births, Deaths and Marriages) prior to seeking ethical approval.

Data were linked by the NSW Centre for Health Record Linkage using probabilistic methods that match identifiers common to the records being linked (e.g. name, sex, date of birth, address) [20]. Only a de-identified unique project person number and information about hospitalizations and/or deaths that occurred between 1 July 2000 and 31 December 2013 were released to the researchers.

Setting

NSW is Australia's most populous state. The 2006 Australian Census, which is the approximate mid-point for this study period, estimated approximately 6.8 million residents in NSW, including almost 150 000 (2.2 %) Aboriginal and/or Torres Strait Islander people [21]. Henceforth, we refer to Aboriginal and/or Torres Strait Islander people as 'Aboriginal' because Torres Strait Islander people accounted for 0.1 % of the NSW population in 2006 [21]. In 2006, 73 % of the NSW population lived in a major city, 27 % lived in regional areas, and less than 1 % lived in remote areas [21]. In contrast, 43 % of the NSW Aboriginal population lived in a major city in

2006, 52 % lived in regional areas, and 5 % lived in remote areas [21].

Australia's universal public health insurance scheme (Medicare) covers the cost of necessary health care to individuals admitted as public patients in public hospitals [22]. The Medicare Benefits Schedule sets fees for medical services provided in primary care settings; however, there is variation in the amount and method in which patients are charged for these services. General practitioners (GPs) can directly bill Medicare for services provided (known as 'bulk billing'), in which case the patient incurs no cost. GPs also have the option to charge the patient the Medicare Benefits Schedule fee, and the patient may seek reimbursement from Medicare. The GP is also entitled to charge more than the Medicare Benefits Schedule fee, in which case the patient incurs the cost of the 'gap' between the charged amount and the Medicare Benefits Schedule fee.

Study population

Children and their records were included in this analysis if they were born in a NSW hospital between 1 July 2000 and 31 December 2012, and their area of residence was within the state of NSW ($n = 1\ 124\ 717$). We defined birth admissions as hospital records with a 'live born infant' ICD-10-AM diagnosis code (i.e. Z38) or a date of birth within the hospital admission and separation dates. From this group, 3277 children were excluded because: their sex was coded as indeterminate or missing ($n = 34$); there were discrepancies in their date of birth, admission and/or separation date on their birth record ($n = 289$); or they died before 29 days of age ($n = 2954$). A total of 1 121 440 children were included in this analysis (Table 1).

Analysis variables

Our main outcome was pediatric potentially avoidable hospitalizations, as defined by Andersen et al. [12]. We also report ambulatory care sensitive and non-avoidable hospitalizations [12]. We used the primary diagnosis to identify avoidable, ambulatory care sensitive or non-avoidable hospitalizations (Additional file 1: Table S1). Admissions occurring before children were 29 days old were excluded. Hospitalizations for vaccine preventable diseases were classified as avoidable if the child's age was greater than or equal to the recommended immunisation age for each condition in NSW [23]. Admissions for which the emergency status was coded as 'planned' were excluded from the count of avoidable hospitalizations, except for dental conditions, because most planned admissions are unlikely to be avoidable.

The following individual- and area-level covariates were in the hospital data: Aboriginality; age; sex; low birth weight (<2500 g) and/or prematurity (<37 weeks gestation); private health insurance/patient status; remoteness of residence, measured by the Accessibility/Remoteness Index of Australia Plus (ARIA+) [24]; and area socioeconomic disadvantage, measured by the Australian Bureau of Statistics Socioeconomic Indexes for Areas (SEIFA) [25]. The child's Aboriginality recorded in the hospital data is based on the response to the question 'Is this child of Aboriginal or Torres Strait Islander origin?', which is asked directly of the mother at birth, and of a parent or guardian at admission for children aged less than 15 years. Although the number of Aboriginal people identified in hospital data increases with the use of multiple record algorithms [26–28], we assigned Aboriginality from the birth record to avoid introducing misclassification bias whereby more frequently hospitalized children have more opportunity to be recorded as Aboriginal, either correctly or in error. For the same reason, we assigned other variables from the birth admission. We calculated the child's age on admission as the difference between their dates of birth and admission.

Data analysis

We calculated person-years of follow-up for each child from the date they were 29 days old until 31 December 2013, or their date of death. We estimated admission rates (ARs) per 1000 person-years by dividing the number of admissions by the person-years accumulated, and multiplying by 1000. We calculated 95 % confidence intervals (CIs) assuming a Poisson distribution of events. Rate differences were calculated by subtracting the AR for non-Aboriginal children from the AR for Aboriginal children. Aboriginal to non-Aboriginal admission rate ratios (ARRs) for each outcome and age group were calculated by dividing the Aboriginal AR by the non-Aboriginal AR. We calculated the proportion of avoidable hospital admissions that occurred outside of standard general medical practice hours (i.e. 08:00–18:00) [29].

To account for differences in age and sex, negative binomial models were used to estimate adjusted ARRs for Aboriginal to non-Aboriginal children for each outcome and condition, modeling the number of hospitalizations as an outcome (using a log link), and including terms for age (in two year age groups), sex and Aboriginal status, with the log of the person-years of follow-up as an offset (Model 1). To account for clustering within geographic statistical local areas (henceforth, 'areas'), a random intercept term was added to the model, which allowed the baseline admission rate to vary between areas, creating a multi-level model (Model 2). In the multilevel model, we then explored whether any of the inequality in study outcomes reflected differences between Aboriginal and non-Aboriginal children in terms of other measured covariates (Model 3). To test whether the effect of covariates on each outcome were the same for Aboriginal and non-Aboriginal children, we tested interaction terms between Aboriginal status and each covariate in

Table 1 Characteristics and person years of follow-up time (2000–2013) for Aboriginal and non-Aboriginal children in a population cohort born between July 2000 and December 2012 in New South Wales, Australia

	Non-Aboriginal			Aboriginal		
	N	%	Person years	*N*	%	Person years
Total	1,085,831	100	7,681,406	35,609	100	223,190
Birth year						
Jul 2000–Dec 2004	367,542	34	4,125,434	9,047	25	100,296
Jan 2005–Dec 2008	353,945	33	2,466,933	11,607	33	79,332
Jan 2009–Dec 2012	364,344	34	1,089,040	14,955	42	43,562
Contribution of follow-up to age group[a]						
Less than 2 years	-	-	2,123,515	-	-	68,971
2–4 years	-	-	1,802,906	-	-	55,189
4–6 years	-	-	1,440,318	-	-	41,123
6–8 years	-	-	1,081,702	-	-	28,451
8–10 years	-	-	736,009	-	-	18,066
10–12 years	-	-	406,279	-	-	9,431
12–13 years	-	-	90,678	-	-	1,959
Sex						
Female	527,500	49	3,729,845	17,251	48	108,591
Male	558,331	51	3,951,561	18,358	52	114,599
Low birth weight and/or premature birth						
No	1,017,508	94	7,212,029	32,039	90	201,599
Yes	68,323	6	469,377	3,570	10	21,591
Private patient and/or health insurance						
No	702,362	65	5,049,008	34,531	97	217,477
Yes	383,469	35	2,632,399	1,078	3	5,713
Geographical remoteness						
Major city	730,967	67	5,105,713	10,238	29	64,754
Inner regional	262,887	24	1,899,768	13,231	37	79,583
Outer regional	84,425	8	617,719	8,837	25	56,053
Remote/Very remote	7,552	1	58,205	3,303	9	22,800
Area-level socio-economic disadvantage[b]						
First quintile (Most disadvantaged)	199,716	18	1,443,310	16,719	47	107,615
Second quintile	235,069	22	1,669,550	9,746	27	59,739
Third quintile	219,196	20	1,560,849	6,210	17	37,857
Fourth quintile	225,527	21	1,569,176	2,344	7	14,415
Fifth quintile (Least disadvantaged)	206,323	19	1,438,522	590	2	3,564

[a]Children contribute person years of follow-up from the date they are 29 days old until their death or the end of the study period (December 31, 2013). Many of the children contribute person years of follow-up to more than one age group during the study period; [b]Socio-economic indices for Areas (SEIFA) Index of Relative Socio-Economic Advantage and Disadvantage based on the child's statistical local area of residence at birth

multilevel models adjusted for age, sex, and variation in rates between areas (by including a random intercept term for areas).

We used SAS 9.3 [30], MLwiN 2.25 [31], and R 2.15.0 for analyses [32]. Multilevel modeling in MLwiN used generalized least squares (IGLS) estimation and a 2nd order PQL approximation.

Results

We identified 365 386 potentially avoidable hospitalizations among the 1 121 440 children born between 1 July 2000 and 31 December 2012, who were followed from birth until 31 December 2013 (Additional file 1: Table S2). Of these, 243 643 hospitalizations were considered ambulatory care sensitive. The avoidable hospitalization rate was 90.1 per

1000 person-years (95 % CI, 88.9–91.4) in Aboriginal children compared with 44.9 per 1000 person-years (95 % CI, 44.8–45.1) in non-Aboriginal children (Additional file 1: Table S2). The ambulatory care sensitive hospitalization rate was 56.7 (95 % CI, 55.7–57.7) and 30.1 (95 % CI, 29.9–30.2) per 1000 person-years in Aboriginal and non-Aboriginal children, respectively. Of the ambulatory care sensitive hospitalizations, 56 % and 57 % of admissions occurred outside standard general practice hours for Aboriginal and non-Aboriginal children, respectively. The non-avoidable hospitalization rate was 10.1 (95 % CI, 9.6–10.5) and 9.6 (95 % CI, 9.6–9.7) per 1000 person years in Aboriginal and non-Aboriginal children.

The five most common causes of avoidable hospitalization among Aboriginal children in the cohort were acute bronchiolitis (AR, 20.3; 95 % CI, 19.7–20.9), gastroenteritis (AR, 12.2; 95 % CI, 11.7–12.7), asthma (AR, 10.8; 95 % CI, 10.3–11.2), dental conditions (AR, 9.4; 95 % CI, 9.0–9.8), and acute upper respiratory tract infections (URTIs) (AR, 9.3; 8.9–9.7) (Fig. 1). Four of the five most common causes were the same for non-Aboriginal children, but with lower rates: gastroenteritis (AR, 7.8; 95 % CI, 7.8–7.9), asthma (AR, 7.3; 95 % CI, 7.2–7.4), acute bronchiolitis (AR, 6.5; 95 % CI, 6.5–6.6), acute URTIs (AR, 4.6; 95 % CI 4.6–4.7) and viral infection of unspecified site (AR, 3.8; 95 % CI 3.7–3.8) (Fig. 1). The conditions with the greatest Aboriginal to non-Aboriginal rate difference were acute bronchiolitis (RD, 13.8), dental (RD, 5.7), acute URTIs (RD, 4.7), gastroenteritis (RD, 4.4) and skin infections (4.2) (Additional file 1: Table S2).

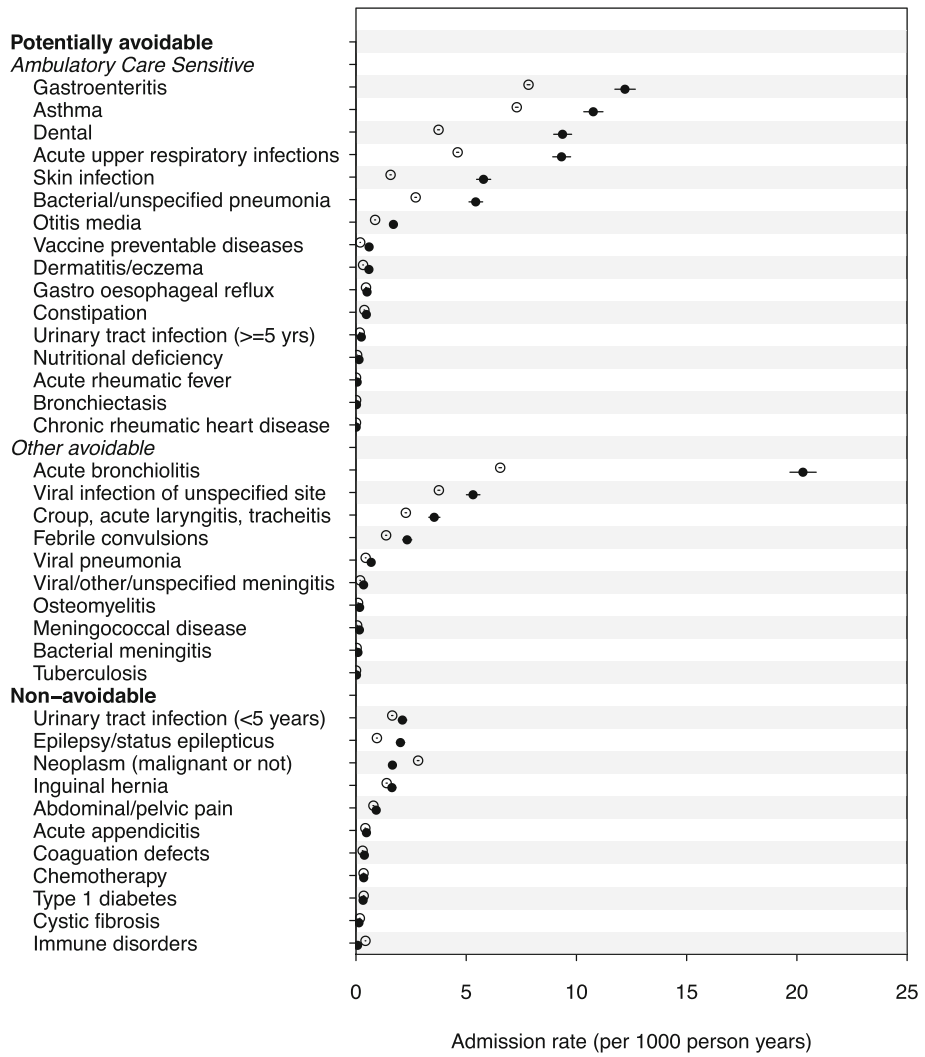

Fig. 1 Title: Admission rates for potentially avoidable and non-avoidable hospitalizations (2000–2013) in a population cohort of Aboriginal and non-Aboriginal children born 2000–2012, New South Wales, Australia. Legend: closed circles, Aboriginal; open circles, non-Aboriginal; Error bars (through circles) are 95 % confidence intervals. Sorted by Aboriginal admission rates in descending order. Admission rates, rate differences, rate ratios and 95 % confidence intervals are shown in Additional file 1: Table S2

For Aboriginal and non-Aboriginal children, avoidable hospitalization rates were highest among those aged less than two years (179.9 and 85.7 per 1000 person-years, respectively) and decreased to less than 10 per 1000 person-years among children aged 12 to <14 years (Fig. 2). Among children less than two years of age, Aboriginal children were 1.9 times more likely to be admitted for an avoidable hospitalization than non-Aboriginal children, and the rate difference was 94.1 per 1000 person-years (Fig. 2, Table 2). The rate difference between Aboriginal and non-Aboriginal children declined to 5.3 per 1000 person-years by 12 to <14 years of age.

Aboriginal children had higher avoidable hospitalization rates across all categories of sex, low birth weight/prematurity, private health insurance/patient status and remoteness or disadvantage of the area where children started life (Fig. 3). In particular, the relative difference in avoidable hospitalizations between those living in remote areas versus major cities was greater for Aboriginal versus non-Aboriginal children; compared with non-Aboriginal children living in major cities (ARR, 1.0; reference group), Aboriginal children living in remote areas and major cities were 2.2 (95 % CI, 1.9–2.6) and 1.5 (95 % CI, 1.4–1.5) times more likely to be admitted for an avoidable hospitalization, respectively (Fig. 4). In contrast, non-Aboriginal children living in remote areas were 1.1 (95 % CI, 1.0–1.3) times more likely to be admitted for an avoidable hospitalization than non-Aboriginal children living in major cities.

After adjusting for differences in age and sex (Model 1), Aboriginal children were 1.7 times as likely to have an avoidable hospitalization as non-Aboriginal children in the cohort (Table 3). When variation in admission rates between areas was also accounted for (Model 2), the Aboriginal to non-Aboriginal admission rate ratio for avoidable hospitalizations was 1.6 (95 % CI, 1.6–1.6). After accounting for differences in individual- and area-level characteristics (Model 3), the Aboriginal to non-Aboriginal admission rate ratio was 1.6 (95 % CI, 1.6–1.7). The magnitude of the inequality was similar for the subset of ambulatory care sensitive hospitalizations, after adjustment for age and sex (ARR, 1.7; 95 % CI, 1.7–1.8), and after inclusion of random intercept and adjustment for all covariates (ARR,1.6; 95 % CI, 1.6–1.6) (Table 3). In contrast, Aboriginal children were marginally less likely to be admitted for a non-avoidable hospitalization than non-Aboriginal children (Table 3; ARR, 0.9; 95 % C, 0.8–1.0) after adjustment for age, sex and variation in admission rates between areas.

Discussion

We found that avoidable hospitalization rates were almost double in Aboriginal compared with non-Aboriginal children less than two years of age, and the absolute difference in rates was 94 per 1000 person-years. Although the absolute and relative inequalities were present across all ages, the absolute difference in rates between Aboriginal and non-Aboriginal children declined to 5 per 1000 person-years by 12 to <14 years of age. Respiratory and infectious conditions were the most common reasons for avoidable hospitalizations in all children, although Aboriginal children were admitted more frequently for all conditions. We also found that the impact of living in more remote and disadvantaged areas on a child's risk of avoidable hospitalization was greater for Aboriginal children.

To our knowledge, this is the first Australian study to reveal that avoidable hospitalizations are highest in children in the first two years of life and decrease among older children, consistent with findings in New Zealand [18].

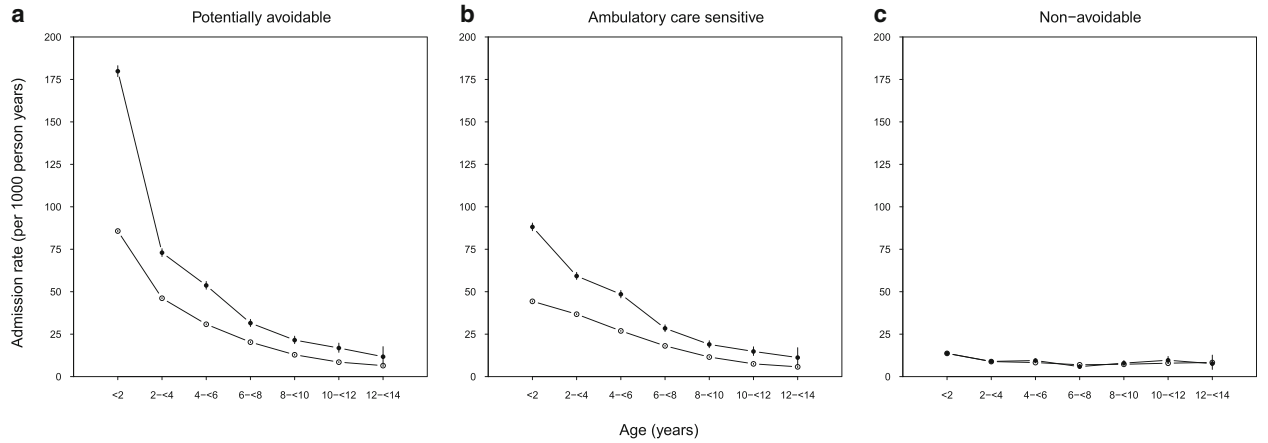

Fig. 2 Title: Age-specific admission rates for potentially avoidable, ambulatory care sensitive and non-avoidable hospitalizations (2000–2013) in a population cohort of Aboriginal and non-Aboriginal children born 2000–2012, New South Wales, Australia. Legend: closed circles, Aboriginal; open circles, non-Aboriginal. Error bars (through circles) are 95 % confidence intervals

Table 2 Age-specific Aboriginal to non-Aboriginal rate differences and rate ratios for potentially avoidable, ambulatory care sensitive and non-avoidable hospitalisations (2000–2013) in a population cohort of Aboriginal and non-Aboriginal children born between July 2000 and December 2012 in New South Wales, Australia

Age group	Potentially avoidable			Ambulatory care sensitive			Non-avoidable		
	Rate difference (RD)	Rate ratio (RR) (95 % CI)		RD	RR (95 % CI)		RD	RR (95 % CI)	
0–< 2 years	94.1	1.9	(1.8–1.9)	43.79	1.9	(1.8–1.9)	- < 0.1	0.8	(0.7–0.9)
2–< 4 years	26.8	1.5	(1.5–1.6)	22.49	1.6	(1.5–1.6)	<0.1	0.8	(0.7–0.9)
4–< 6 years	22.9	1.7	(1.6–1.8)	21.58	1.8	(1.7–1.9)	1.2	1.0	(0.7–1.4)
6–< 8 years	11.3	1.5	(1.4–1.6)	10.31	1.6	(1.4–1.7)	−1.1	0.9	(0.6–1.2)
8–< 10 years	8.7	1.7	(1.5–1.9)	7.45	1.6	(1.5–1.8)	0.7	1.1	(0.9–1.3)
10–< 12 years	8.3	2.0	(1.7–2.3)	7.32	2.0	(1.6–2.3)	1.7	1.2	(0.9–1.6)
12–< 14 years	5.3	1.8	(1.2–2.8)	5.46	2.0	(1.3–3.0)	−0.7	1.0	(0.6–1.6)

CI confidence interval, *RD* rate difference, *RR* rate ratio

For the first time, we demonstrated that absolute differences in avoidable hospitalizations between Aboriginal and non-Aboriginal children were greatest in children less than two years, while the magnitude of the relative inequality was similar across age groups. In most contexts, both the absolute and relative differences between two groups matter [33]. That the relative inequality is similar across age groups suggests there is a general problem that requires a systemic approach. On the other hand, the greater absolute differences in avoidable hospitalizations between Aboriginal and non-Aboriginal children less than two years of age indicate there may be scope to reduce avoidable hospitalizations via targeted prevention and early intervention measures that reduce disease burden and improve access to treatment for common childhood conditions.

Respiratory and infectious conditions were the most common reasons for avoidable hospitalization among all children in the cohort, with Aboriginal children more likely to be admitted for all conditions. These findings are consistent with other Australian data on common conditions resulting in pediatric emergency department presentations [34] and higher hospitalization rates for respiratory diseases [35–39] and gastroenteritis [38, 40–42] among Aboriginal children in Western Australia. Although we were unable to ascertain the burden of these conditions outside of the

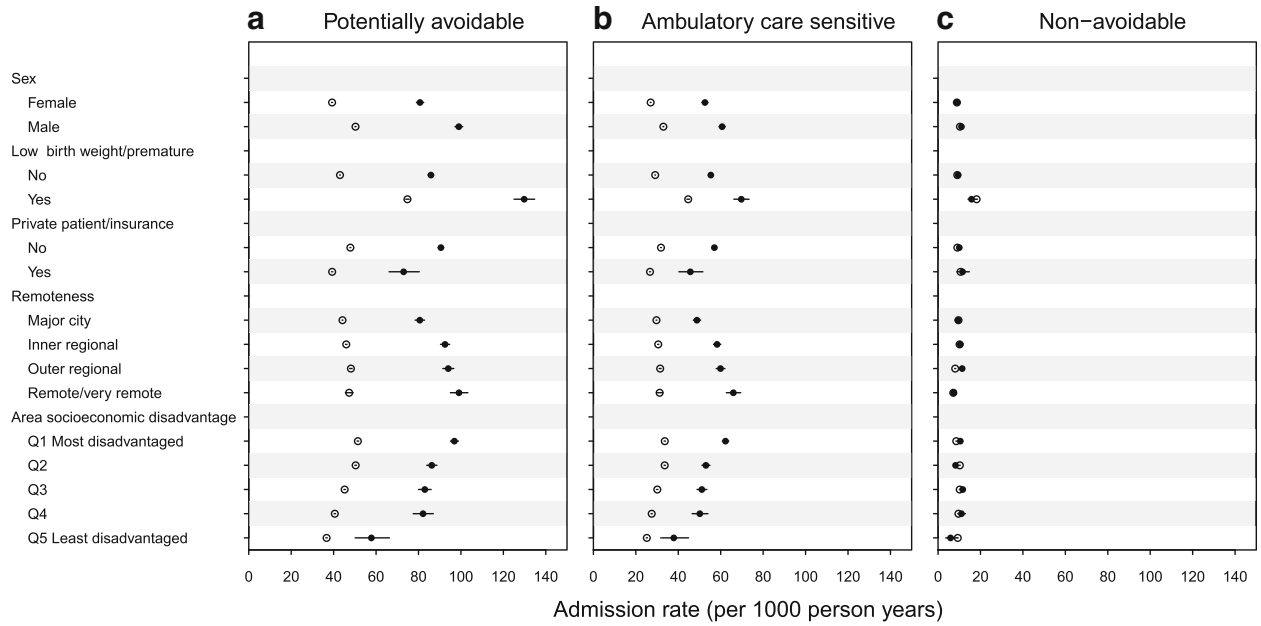

Fig. 3 Title: Admission rates for (**a**) potentially avoidable, (**b**) ambulatory care sensitive and (**c**) non-avoidable hospitalizations (2000–2013) by individual- and area-level characteristics in a population cohort of Aboriginal and non-Aboriginal children born 2000–2012, New South Wales, Australia. Legend: closed circles, Aboriginal; open circles, non-Aboriginal. Error bars (through circles) are 95 % confidence intervals

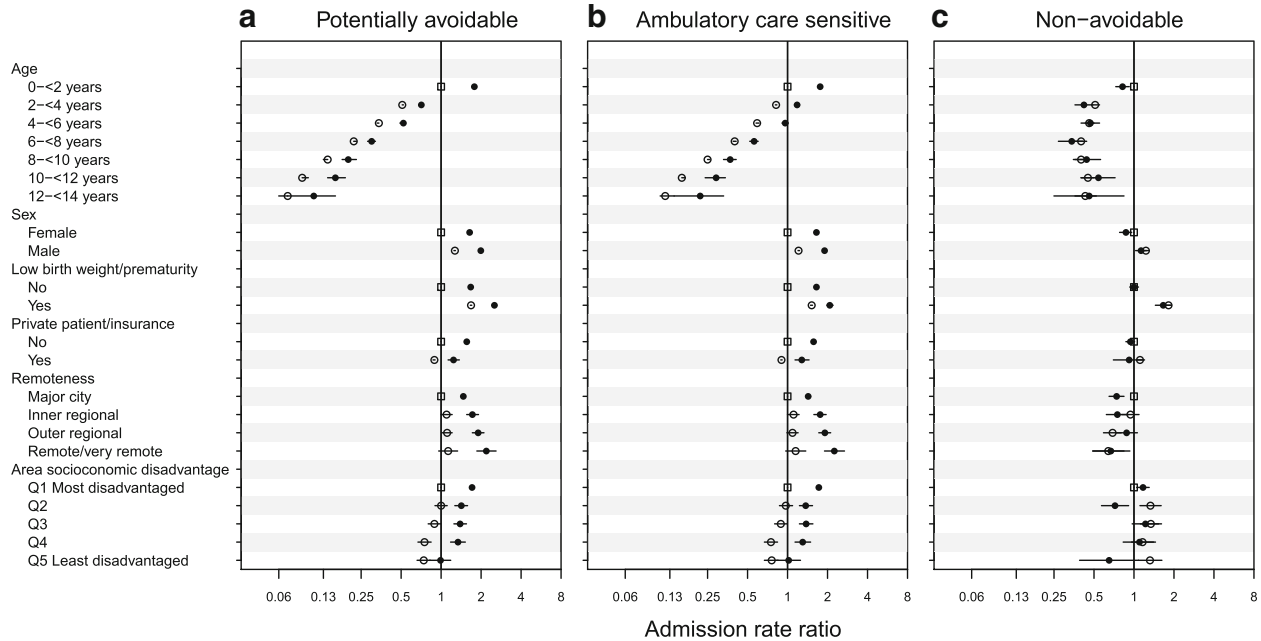

Fig. 4 Title: Admission rate ratios for (**a**) potentially avoidable, (**b**) ambulatory care sensitive, and (**c**) non-avoidable hospitalizations for interactions between individual- and area-level characteristics and Aboriginal status from multilevel negative binomial models with a random intercept for Statistical Local Area, adjusted for age and sex. Rate ratios are relative to the reference group. Legend: closed circles, Aboriginal; open circles, non-Aboriginal; open square, non-Aboriginal reference group. Error bars (through symbols) are 95 % confidence intervals

hospital setting, other studies have previously reported a high burden of respiratory diseases [43–46], skin infections [47] and otitis media [48–50] in Aboriginal children, particularly in remote communities. Moreover, some important exposures associated with respiratory and infectious conditions, such as smoking [51, 52] and poor housing conditions [53], are known to be common in Aboriginal families [54–56] and associated with poverty. Dental conditions were also a common cause of avoidable hospitalization for Aboriginal children. Previous studies have also documented poor dental health in Aboriginal communities [57–59], as well as higher rates of hospitalization for dental conditions among Aboriginal children in Western Australia [60, 61].

The remoteness or disadvantage of the area where a child lives has previously been associated with avoidable hospitalizations in children in the Australian state of

Table 3 Aboriginal to non-Aboriginal admission rate ratios from multilevel models for potentially avoidable, ambulatory care sensitive and non-avoidable hospitalisations (July 2000 to December 2013) in a population cohort of children born between July 2000 and December 2012 in New South Wales, Australia

Model	Variables and random effects added to the model:	Aboriginal to non-Aboriginal Rate Ratio	95 % confidence interval	
Potentially avoidable hospitalisations				
1	Age and sex	1.73	1.71	1.75
2	Model 1 + random intercept for area	1.60	1.58	1.62
3	Model 2 + individual[a]- and area[b]-level characteristics	1.60	1.58	1.61
Ambulatory care sensitive hospitalisations				
1	Age and sex	1.74	1.72	1.77
2	Model 1 + random intercept for area	1.60	1.58	1.62
3	Model 2 + individual[a]- and area[b]-level characteristics	1.57	1.55	1.59
Non-avoidable hospitalisations				
1	Age and sex	0.89	0.81	0.97
2	Model 1 + random intercept for area	0.90	0.82	0.97
3	Model 2 + individual[a]- and area[b]-level characteristics	1.03	0.96	1.10

[a]Low birth weight/prematurity and private health insurance/patient status; [b]geographical remoteness and area socio-economic disadvantage

Victoria [13, 14] and New Zealand [18]. What this study shows is that living in more remote or disadvantaged areas has a greater impact on a child's risk of avoidable hospitalization if they are Aboriginal. Aboriginal families living in remote and disadvantaged areas experience a disproportionate burden of the determinants of poor child health (e.g. overcrowded housing [54]). Barriers to accessing primary care for Aboriginal families – including some that may disproportionately impact on those living in remote and disadvantaged areas – have previously been identified, including: the physical availability of health services (which are clustered in major cities and more advantaged areas), transport, flexible service delivery, affordability, and the cultural acceptability and appropriateness of health services [62]. Health literacy, physician behaviour and hospital admission practices may also impact on whether a child is admitted to hospital.

Because Australia's universal health insurance scheme (Medicare) covers the cost of necessary health care provided to public patients admitted to public hospitals [22], costs associated with hospitalisation should not have been a determinant of rates of avoidable hospitalisation in this study. However, families may incur costs for seeking GP care because Australian GPs have the option to charge patients more than the Medicare Benefits Schedule fee. During the study period, NSW patients paid an out-of-pocket 'gap' payment for 14–24 % of all GP visits [63]. Therefore, costs associated with GP services may deter some families from seeking primary health care for their children in a timely manner.

Use of population data in this study conferred the advantage of a large cohort; this enabled us to reliably quantify the magnitude of the inequality in avoidable hospitalizations between Aboriginal and non-Aboriginal children in narrow age bands for the first time, which is important for guiding policy. Importantly, it has also made visible the health experience of Aboriginal children, a small and disadvantaged sub-population. Other strengths of the study include the length of follow-up for children born earlier in the study period and minimal loss to follow-up (children account for a small proportion of the 3 % of people who migrate outside of NSW each year [64, 65]).

Potential limitations of the outcome measure must be considered. The extent to which the avoidable hospitalizations identified in this study were truly avoidable is unknown. Recent research suggests that socio-demographic and health factors explain more of the geographic variation in adult avoidable hospitalizations than general practitioner supply [66], and our main outcome measure was not focused on primary care as the sole strategy for reducing avoidable hospitalizations. However, we found similar inequalities for avoidable hospitalizations and the subset of ambulatory care sensitive hospitalizations. Despite living in the same area, Aboriginal and non-Aboriginal children may not realise equal access to available primary care services, for reasons including transport difficulties and cultural barriers [62]. In this study, more than half the ambulatory care sensitive hospitalizations occurred outside office hours. From our data, we were unable to determine whether these admissions were for severe and rapid onset illness that would have resulted in hospitalization under any circumstances, or whether improved access to primary care in the days and hours prior to hospitalization might have prevented some of these hospitalizations.

A limitation of using routinely collected hospital data is the under-recording of Aboriginal status [26, 67–69]. These errors are not randomly distributed across hospitals and areas; past audits have shown Aboriginal status has been recorded more accurately in remote areas and that recording of Aboriginal status has improved over time [68, 69]. We aimed to minimize bias introduced in this study by deriving both the numerator and the denominator from the hospital data, rather than deriving the denominator from census data. Another shortcoming is the limited set of covariates available in the data. Private health insurance/patient status was the only individual-level indicator of socioeconomic advantage in the data, and only 3 % of Aboriginal children had private health insurance or were admitted as a private patient compared with 35 % of non-Aboriginal children. The higher proportion of Aboriginal children with low birth weight and/or prematurity in this cohort likely reflects a greater burden of socioeconomic disadvantage among Aboriginal children, but measures such as household income and parent education level were not available. As such, our modeling shows the effect of Aboriginality combined with other unmeasured covariates.

Conclusions

In an equitable world, there should be no difference in avoidable hospitalizations between Aboriginal and non-Aboriginal children. We observed substantial inequalities in these hospitalizations between Aboriginal and non-Aboriginal children regardless of where they lived, but particularly among very young children. An important question is: How can we close this gap? Broad policy measures that aim to reduce inequities in the circumstances in which children grow and develop (e.g. better quality and affordable housing) may impact on the incidence of common childhood conditions in Aboriginal children, including hospitalization for these conditions [12, 70]. Increased access to early intervention in primary care, particularly for young Aboriginal children, and those living in remote and disadvantaged areas, may also impact on avoidable hospitalizations. Finally, this study provides a novel source of baseline population data to inform the future impact of policies and interventions on existing inequalities.

Additional file

Additional file 1: Table S1. (ICD-10-AM codes) and **Table S2.** (Potentially avoidable, ambulatory care sensitive and non-avoidable hospitalisation admission rates). **Table S1.** title "List of ICD-10-AM codes used to identify potentially avoidable, ambulatory care sensitive and non-avoidable hospitalisations (adapted from Andersen et al., 2012)", and **Table S2.** title "Potentially avoidable, ambulatory care sensitive and non-avoidable hospitalisation admission rates (2000–2013) in a population cohort of Aboriginal and non-Aboriginal children born between July 2000 and December 2012 in New South Wales, Australia". (DOCX 61 kb)

Abbreviations

ARRs: Admission rate ratios; ARs: Admission rates; CIs: Confidence intervals; ICD-10-AM: International Statistical Classification of Diseases and Related Problems 10th Revision; NSW: New South Wales

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Availability of data and materials

The datasets supporting the conclusions of this article are available from the Ministry of Health and the Register of Births, Deaths and Marriages, New South Wales (NSW), Australia. The NSW Centre for Health Record Linkage linked the datasets for this study. These data are available to researchers on request and subject to approval from the relevant data custodians and ethics committees, as outlined on the NSW Centre for Health Record Linkage website (http://www.cherel.org.au/).

Authors' contributions

LJ and KF had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. LJ and SE contributed to the conception and design of the Indigenous Health Outcomes Patient Evaluation (IHOPE) study. LJ initiated the IHOPE study and supervised all analyses. KF designed and conducted the statistical analysis for this sub-study, and drafted the manuscript, with input from all authors. SL, MF and AL contributed statistical expertise for this sub-study. All authors contributed to the interpretation of findings, providing feedback on drafts of the manuscript and approved the final draft.

Competing interests

The authors declare that they have no competing interests.

Consent for publication

No applicable.

Ethics approval and consent to participate

Ethics approval was obtained from the NSW Population and Health Services Research Ethics Committee (Ref no. 2009/03/141), Aboriginal Health and Medical Research Council of NSW Ethics Committee (Ref no. 684/09), and the University of Western Sydney (Ref no. H7304), and Australian National University Human Research Ethics Committees (Ref no. 2015/506). For this statewide population data linkage study, the need to obtain consent from individuals to participate in the study was waived by the reviewing ethics committees. Approval to link and use these data was obtained from the relevant data custodians (NSW Ministry of Health and NSW Register of Births, Deaths and Marriages) prior to seeking ethical approval.

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65. Australian Bureau of Statistics. Australian Demographic Statistics. ABS Catalogue No. 3101.0 Table 4. Estimated Resident Population, States and Territories. Canberra: Australian Bureau of Statistics; 2012.
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Appendix 4 Published manuscripts from this thesis

Appendix 4.1 Published manuscript for Chapter 4

- Falster MO, Jorm LR, Leyland AH. Visualising linked health data to explore health events around preventable hospitalisations in NSW Australia. *BMJ Open* 2016;6:e012031.

The following documents are included in this appendix:

- Published manuscript
- Online supplementary file 1
- Online supplementary file 2
- Online supplementary file 3

Appendix 4.2 Published manuscript for Chapter 5

- Falster MO, Jorm LR, Douglas KA, Blyth FM, Elliott RF, Leyland AH. Sociodemographic and health characteristics, rather than primary care supply, are major drivers of geographic variation in preventable hospitalisations in Australia. *Medical Care* 2015; 53(5):436

The following documents are included in this appendix:

- Published manuscript
- Online supplementary file 1

BMJ Open

Visualising linked health data to explore health events around preventable hospitalisations in NSW Australia

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ABSTRACT

Objective: To explore patterns of health service use in the lead-up to, and following, admission for a 'preventable' hospitalisation.

Setting: 266 950 participants in the 45 and Up Study, New South Wales (NSW) Australia

Methods: Linked data on hospital admissions, general practitioner (GP) visits and other health events were used to create visual representations of health service use. For each participant, health events were plotted against time, with different events juxtaposed using different markers and panels of data. Various visualisations were explored by patient characteristics, and compared with a cohort of non-admitted participants matched on sociodemographic and health characteristics. Health events were displayed over calendar year and in the 90 days surrounding first preventable hospitalisation.

Results: The visualisations revealed patterns of clustering of GP consultations in the lead-up to, and following, preventable hospitalisation, with 14% of patients having a consultation on the day of admission and 27% in the prior week. There was a clustering of deaths and other hospitalisations following discharge, particularly for patients with a long length of stay, suggesting patients may have been in a state of health deterioration. Specialist consultations were primarily clustered during the period of hospitalisation. Rates of all health events were higher in patients admitted for a preventable hospitalisation than the matched non-admitted cohort.

Conclusions: We did not find evidence of limited use of primary care services in the lead-up to a preventable hospitalisation, rather people with preventable hospitalisations tended to have high levels of engagement with multiple elements of the healthcare system. As such, preventable hospitalisations might be better used as a tool for identifying sicker patients for managed care programmes. Visualising longitudinal health data was found to be a powerful strategy for uncovering patterns of health service use, and such visualisations have potential to be more widely adopted in health services research.

Strengths and limitations of this study

- This is the first study to explore the temporal pattern of health events and health service use around preventable hospitalisations using large population-level data.
- Novel data visualisations allowed for efficient identification of health events before, during, and following preventable hospitalisation, as well as population-level patterns of health service use.
- The visualisations are descriptive are not adjusted for patient factors such as age, sex and health status.
- The findings may not be generalisable to other healthcare systems, but the visualisations offer a novel approach that can be adopted for comparative research.

INTRODUCTION

Preventable hospitalisations have been adopted internationally as an indicator of timely and effective access to primary care services. Originally conceived in the late 1980s,[1] preventable hospitalisations, also known as ambulatory care sensitive or avoidable hospital admissions, comprise admissions for a set of diagnosis codes which are considered to be potentially preventable if the patient had access to quality primary care services. Intuitively appealing, these hospitalisations are reported by governments for performance measurement of the primary care system,[2 3] and are used commonly in research as a health outcome measure. However, there has been surprisingly little research exploring the actual use of primary healthcare services around the time of hospitalisation, which requires linkage of primary care and hospital data for individuals.

As data on primary care are not always routinely collected, much of the research on preventable hospitalisations has been ecological, comparing population-based rates of hospitalisation to proxy measures of access, such as the supply of general practitioner (GP) services in an area,[4–7] the average number of available hospital beds,[8 9] socioeconomic characteristics of the population[10] or perceived access to care.[11 12] However, aggregated approaches may be subject to an

ecological fallacy,[13] and there is a view that access can be more meaningfully explored through patient behaviour, or 'realised' access to care relative to need, rather than barriers that predispose or enable patients' access to services.[14]

The few studies with linked, person-level data on health service use have investigated the impact of provider continuity[15 16] or the number of primary care consultations[17 18] on rates of hospitalisation, broadly finding that people with more GP visits or with more visits to the regular provider of care had lower rates of preventable hospitalisation (with the exception of very high use patients). However, patients' use of primary care services differs greatly across countries and healthcare systems,[19] and can be confounded by the disposition and need of a patient to use the services,[20] and there is growing debate on exactly what role GPs can take in further reducing rates of preventable hospitalisation.[4 21–24] Notably, there has been no exploration of the temporal pattern of primary care in the lead-up to a preventable hospitalisation, which is important, given many of these admissions are assumed to be avoidable if a person suffering an acute exacerbation could obtain care in a primary care setting.

Data visualisations are a promising method for exploring patterns of health events. Widely considered to be a powerful technique for investigating and identifying underlying patterns in 'big data',[25] a number of visualisation tools have been developed for longitudinal health data, typically presenting a visual timeline of health events for one or more patients over time.[26–31] While there are a number of variations on this technique, such as centring patients' time on specific health events,[32] grouping patients with similar health trajectories,[30 31] or as a dashboard displaying various clinical characteristics,[29 33] these tools have not been widely used within health services research. This may be because the relevant software tools were developed to aid patient monitoring, clinical decision-making and interactive data interrogation, and so have limited capabilities for the varied and complex needs of researchers.[34 35] An exploration of preventable hospitalisations, for example, would require combining different types of events (eg, single-day GP visits, multiple-day hospital admissions) for large population-based cohorts, while adhering to ethical standards in maintaining the privacy of individual patients.[36] While no such visualisation tool currently exists, there is unfulfilled potential to create simple visualisations using more general visual analytic tools.

This study sought to explore the temporal pattern of health service use around preventable hospitalisations for participants in a large cohort of older adults in New South Wales (NSW) Australia, using a novel data visualisation of trajectories of individual patient health service use.

METHODS

Data sources

Linked health data were used within the Assessing Preventable Hospitalisation InDicators (APHID) study, details of which have been published elsewhere.[37] Briefly, APHID includes participants from the Sax Institute's 45 and Up Study,[38] a prospective cohort of 266 950 men and women aged over 45 in NSW, Australia. Study participants were recruited from 2006 to 2009 through the Department of Human Services' Medicare system (Australia's national universal health insurer). At study, entry participants completed a detailed questionnaire on their sociodemographic and health characteristics, and provided signed consent for long-term follow-up, including linkage to administrative health data sets.

For each study participant, linked data were obtained from a number of data sources. Hospitalisations were obtained from the NSW Admitted Patient Data Collection (APDC), a census of all hospital separations (discharges, transfers and deaths) from all NSW public and private sector hospitals and day procedure centres, with linked data available from 2000 to 2013. Emergency department (ED) data were obtained from the NSW Emergency Department Data Collection (EDDC), which contains information on presentations to 80 EDs in NSW, capturing around 75% of all presentations to NSW EDs, with linked data from 2006 to 2013. Medicare-funded claims for GP and specialist medical practitioner consultations were obtained from the Medical Benefits Schedule (MBS), the country's universal health insurance scheme for subsidised medical care, with linked data from 2005 to 2011. Fact of death data were obtained from the NSW Registry of Births, Deaths and Marriages (RBDM) mortality data file, with linked data from 2006 to 2013.

Probabilistic data linkage of the APDC, EDDC and the RBDM mortality data was performed by the NSW Centre for Health Record Linkage (http://www.cherel.org.au/) using ChoiceMaker software; a manual clerical review on a sample of linkage records found a false positive linkage rate of 0.3%. Linkage of Medicare data was performed deterministically by the Sax Institute using a unique person identifier. Ethics approval for the 45 and Up Study was granted by the University of New South Wales Human Research Ethics Committee, and approval for the APHID study was granted by the NSW Population and Health Services Research, Aboriginal Health and Medical Research Council and University of Western Sydney Research Ethics Committees.

Health events and health service use

Preventable hospitalisations were identified in the hospitalisation data according to the indicator used in the Australian 2012 National Healthcare Agreement. This comprises admissions for 21 different conditions broadly categorised as 'chronic', 'acute' and 'vaccine-preventable', and includes conditions such as diabetes complications, angina, asthma and influenza (see online supplementary file 1).[39]

A range of other types of health events were identified in the linked health data, including claims for GP or

specialist medical practitioner services from the MBS data, all presentations to an ED from the EDDC data, all other hospitalisations from the APDC data and all deaths from the RBDM mortality data file. The criteria for identifying each type of event are provided in online supplementary file 1.

All preventable hospitalisations for study participants were identified during a snapshot time window, 1 January to 31 December 2010, for which linked data from all data sources were available. To explore events surrounding preventable hospitalisations, records for GP consultations, ED presentations, all other hospitalisations, specialist consultations and deaths were extracted for an extended period around this time window, 1 July 2009–30 June 2011.

Visualising longitudinal health data

The visualisations presented unit record data using static timelines,[28] with each row on the y-axis representing a person and each point on the x-axis representing a point in time. Single date events, such as a health consultation, disease notification or death, were represented by a point or symbol at that moment in time. Interval events, such as a hospital stay, were represented by a line indicating the length of the event.

To bring structure to the figures so that patterns were easier to identify, each type of health event was plotted using a different colour and on a separate vertical panel. Patients on the y-axis were sorted according to features of their preventable hospitalisations, including whether they were admitted or not, the number of hospitalisations, date of first hospitalisation and length of hospital stay, as well as their personal characteristics, such as remoteness of area of residence or self-rated health. Time on the x-axis was displayed either centred on the date of first admission or spread over the calendar year. A variety of plots were produced, varying the time scale (calendar time, 90-day period surrounding first admission), or the order in which participants were displayed. The plots were interpreted by looking for visual patterns in the position, density or clustering of the health events.

In order to compare patterns of health events to the general population, relative to the need and disposition to use health services, a propensity-matched subcohort of participants who had not been admitted for a preventable hospitalisation was also identified. This cohort was matched to the admitted cohort on a range of sociodemographic (eg, age, sex, geographic remoteness of residence,[40] income, education) and health (eg, body mass index (BMI), self-rated health, multimorbidities, functional limitations) characteristics using a 'greedy' matching algorithm.[41]

All data manipulation was performed in SAS V.9.3, while all figures were produced in Stata V.12.0. An example of data structure and Stata syntax for producing a plot are provided in online supplementary file 2.

RESULTS

Of the 266 950 study participants, 1.7% (n=4717) died prior to 2010, leaving 262 233 participants for analysis. Of these, 8715 were admitted for a preventable hospitalisation in 2010, of whom 78% were admitted for a preventable hospitalisation once, 16% were admitted twice, 3% were admitted thrice and 3% were admitted four or more times. 63% of preventable hospitalisations were for chronic, 35% for acute and 2% for vaccine-preventable conditions, with patients admitted for chronic conditions tending to have on average more hospitalisations per person (see online supplementary file 3).

Figure 1 presents a plot of health events for all persons admitted for a preventable hospitalisation in 2010, with time centred on the 90 days before and after the first date of admission. Patients are sorted by their total number of preventable hospitalisations and length of stay, so that the preventable hospitalisations form a 'funnel' shape. At the time of admission, there is a clear corresponding 'shadow' of GP consultations and ED presentations, indicating that many patients used these services in the lead-up to admission. Subsequent descriptive statistics (table 1) found that 14.5% of patients had a GP consultation on the day of admission, with 27.4% of patients having at least one further GP consultation in the week leading up to the day of admission and 64.8% in the prior month. Almost half (48.9%) of patients had presented to an ED on the day of admission.

There was a similar 'shadow' indicating increased levels of GP visits, other hospitalisations and deaths in the period immediately following discharge, particularly for patients with a longer length of stay (figure 1). Rates of death in the broader period following discharge similarly appeared to increase for patients with a longer length of stay.

Specialist medical practitioner consultations appeared to be largely provided during the period of hospitalisation (figure 1), although 12.5% of patients had a specialist consultation in the week prior, and 37.9% in the month prior to hospitalisation (table 1). In total, 30.4% and 75.3% of patients used either GP or specialist services in the week and month prior to hospitalisation, respectively (see online supplementary file 3).

To determine if health events and service use were different among admitted patients to the general population, figure 2 plots health service over calendar year for study participants admitted for a preventable hospitalisation and the matched cohort of study participants not admitted for a preventable hospitalisation. Admitted patients were sorted by their total number of preventable hospitalisations and the date of first admission, so that preventable hospitalisations form the shape of a line. The non-admitted participants were sorted according to their corresponding match. The two cohorts were very similar across sociodemographic and health characteristics at the time of study entry (see online supplementary file 3).

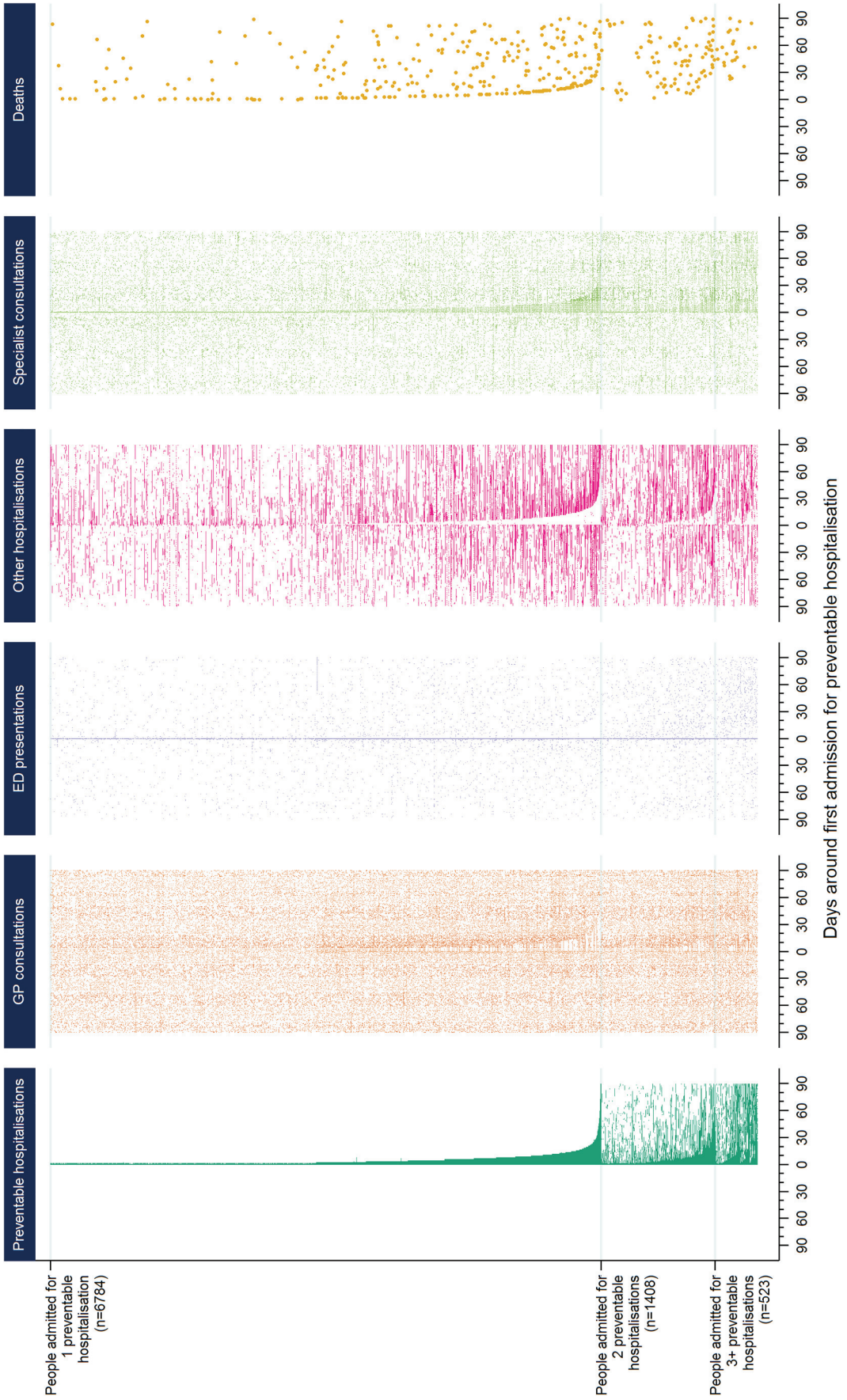

Figure 1 Health events in the 90 days leading up to, and following, first preventable hospitalisation, with patients sorted by their number of preventable hospitalisations in 2010 and length of hospital stay. ED, emergency department; GP, general practitioner.

Table 1 Health events in the 3 months preceding and following first preventable hospitalisation

Type of health event/health service use	Same day (%)	Cumulative % of admitted patients with health event in period surrounding* first preventable hospitalisation			
		1 day	1 week	1 month	3 months
Prior to day of first admission					
GP consultation	14.5	6.8	27.4	64.8	87.2
ED presentation	48.9	2.4	5.4	11.4	20.3
Other hospitalisation	0.8	0.8	3.9	12.0	23.1
Specialist consultation	26.2	2.6	12.5	37.9	60.1
Following day of first discharge					
Preventable hospitalisation	0.6	0.5	2.3	7.1	12.7
GP consultation	6.9	7.3	37.0	72.3	87.7
ED presentation	6.2	1.0	4.4	12.3	23.1
Other hospitalisation	1.2	0.9	4.5	14.1	27.9
Specialist consultation	26.6	4.2	13.4	41.6	64.7
Deaths	1.5	0.1	0.3	1.4	3.9

*Does not include health events on the days of preventable hospitalisation.
ED, emergency department; GP, general practitioner.

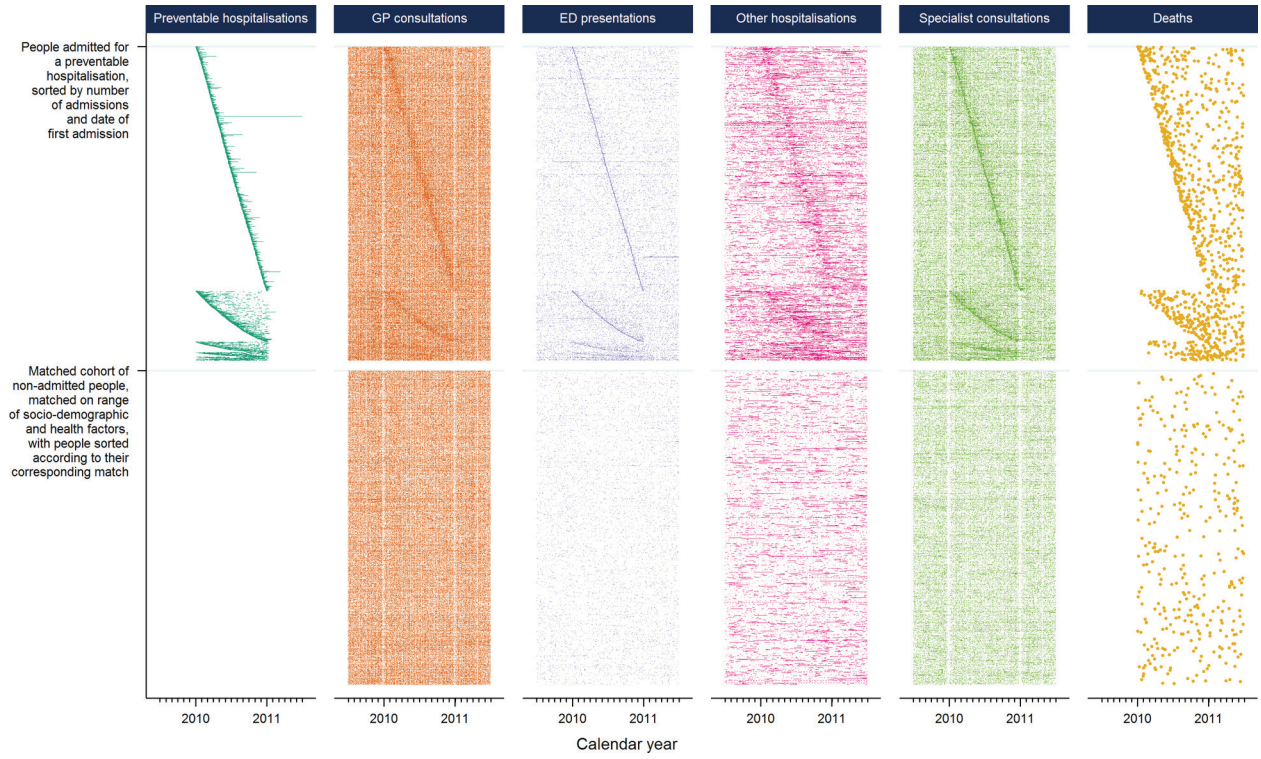

Figure 2 Health events in participants admitted for preventable hospitalisation in 2010, and a demographically matched cohort of non-admitted participants. ED, emergency department; GP, general practitioner.

There are visible vertical 'gaps' in figure 2 among claims for GP and specialist consultations over calendar years, corresponding to weekends and holiday periods (eg, Christmas, Easter), where many healthcare professionals (and patients) are on leave. As with figure 1, there is a corresponding 'shadow' among all health events occurring around the time of a preventable hospitalisation. Across the whole calendar year, the density of health events appears to be greater for admitted patients than their matched non-admitted peers. Subsequent descriptive statistics (table 2) found the rate of health events in the admitted patients was more than twice that of the matched non-admitted participants for all type of events except GP (around 30% higher) and specialist (around 85% higher) consultations. There was a slight increase in the density of all health events for patients with a greater number of preventable hospitalisations.

Table 2 Rates of health events per person-year* for study participants admitted with a preventable hospitalisation during 2010, as well as a demographically matched cohort of study participants not admitted for a preventable hospitalisation

	Participants admitted with preventable hospitalisation					
		By number of admissions				
Type of health event/ service use	Total (n=8715)	1 (n=6784)	2 (n=1408)	3 (n=299)	4+ (n=224)	Matched† non-admitted cohort (n=8715)
GP consultations	13.1	12.5	14.7	17.0	17.4	9.7
ED presentations	1.3	1.1	1.7	2.2	3.8	0.4
Other hospitalisations	2.1	1.9	2.3	3.3	5.9	0.8
Specialist consultations	6.8	6.2	8.4	10.6	12.3	3.7
Deaths	0.08	0.07	0.12	0.15	0.23	0.03

*For GP consultations, ED presentations, other hospitalisations and specialist consultations, an observation period from 1 July 2009 to 30 June 2011 or death (whichever came first). For deaths, an observation period from 1 January 2010 to 30 June 2011 or death (whichever came first), as only study participants alive at 1 January 2010 were considered for analysis.
†Study participants not admitted for a preventable hospitalisation in 2010, propensity matched to participants admitted for a preventable hospitalisation by age (in 10-year age groups), sex, remoteness of residence, education, marital status, language spoken at home, Aboriginal or Torres Strait Islander status, employment status, household income, private health insurance, number of people can depend on, BMI, self-rated health, multimorbidity, functional limitations and psychological distress (see online supplementary file 2).
BMI, body mass index; ED, emergency department; GP, general practitioner.

Additional plots are provided in online supplementary file 3, including all study participants sorted by their self-reported health status, and all admitted patients sorted by the remoteness of their area of residence. These plots show a gradient of increased levels of service use with poorer self-rated health and that many residents in regional areas, but not major cities, have GP consultations during the period of their hospitalisation.

DISCUSSION

This study was the first to explore the temporal pattern of health events in the periods preceding and following preventable hospitalisation, and in doing so created novel visualisations of trajectories of individual patient health service use. We found that participants admitted for a preventable hospitalisation did not show evidence of limited access to primary care, rather they tended to have high levels of engagement with the healthcare system, with higher rates of health events and service use than non-admitted patients, and a clustering of other health events at the time of preventable hospitalisation.

Only a very few studies, none from Australia, have had linked data on a persons' use of primary care services and preventable hospitalisations with which to compare our results,[15 17 18 23] but our findings are consistent with the view that preventable hospitalisations may be more reflective of gradients of health than of poor access to healthcare.[4 23 24] Australia has a universal healthcare system with GPs as gatekeepers to specialist care, and use of services may be more reflective of need than in the USA, the setting for much of the previous research on preventable hospitalisations. Health-related factors have been found to be some of the strongest and most consistent drivers of preventable hospitalisation,[4 42] and the clustering of other hospitalisations and deaths following discharge indicate many patients might be in a state of health deterioration. Indeed, participants admitted for a preventable hospitalisation had twice the number of annual GP visits (13.1 per year) compared with the Australian average (6.5)[19] and around 30% more GP consultations than people from the same study population with similar socioeconomic status and health characteristics (9.8). With similarly higher rates of ED presentations and specialist consultations, this elevated pattern of realised access to services is likely to indicate greater health need beyond the factors used for propensity matching.

These findings support strategies for reducing the overall healthcare burden by targeting patients with high levels of health service use, such as through managed care programmes.[43] Integrated care programmes involving coordination between healthcare providers for patients with complex needs have been found to be effective in reducing hospitalisations.[44 45] The current findings that almost two-third of patients had visited a GP in the month leading up to admission, that many patients, especially in rural areas, had GP consultations during their hospitalisation, and that many patients had specialist visits in the lead-up to and during their hospitalisation, suggest these admissions may have been a considered part of their care. Furthermore, the clustering of health events, particularly other hospitalisations, around the time of preventable hospitalisation indicates poor specificity should the indicator be interpreted as an isolated 'preventable' health event. By visualising patterns of health service use, the visualisations in this study offer a useful starting point for identifying classes of high use individuals, rather than specific types of hospitalisations, for targeted policy intervention.

While claim-based measures of GP and specialist use give an indication of patients' realised access to services, they are limited in their ability to unpack further dimensions around access to, or quality of, care. For example,

14% of admitted patients had seen a GP on the same day as their preventable hospitalisation, but the current data did not allow temporal sequencing of events on the day of admission, such as referrals by a GP or admissions through an ED. Accordingly, we could not determine whether these visits were the direct antecedents of the admission, or could perhaps have been opportunities for it to be prevented through timely provision of care. Patients may face a number of barriers, such as waiting times and cost, that in Australia are often not proportional to patients' need.[46] However, data on service use are an integral part of understanding patients' access to healthcare,[46] and studies further integrating patient and doctor experiences and measures of health need[47] will help consolidate our understanding of the true 'preventability' of these admissions.

The elements used here for creating the visual trajectories of individual patient health service use have been well explored within the literature. Timelines have been used to plot longitudinal health events in a number of ways, as point events or intervals, and for individual patients[29 32] or clustered groups.[30 31] Filtering, ordering, and aligning people and events are known to help add structure to help identify underlying patterns of the data,[25 32] and similarly colouring, juxtaposing and superimposing different items is known to be an effective means for comparing and contrasting groups.[25] However, no visualisation tool has combined these elements in a manner which allows the flexible presentation of large-scale data on patterns of health service use. This is not surprising, given the current visualisation tools are more oriented towards clinical information for patient management, and there is great diversity in the size, shape or format of the administrative data that are used for health services research.

Although a range of software platforms are available for producing custom visual analytics, the plots in this study present a simple approach to visualisation using longitudinal data that is an accessible 'first step' for researchers. They were created using standard statistical software, could be created in a range of other software packages, and could be used for studies exploring, for example, pathways of patient admissions, transfers and referrals; disparities in health service use; outcomes following surgery or hospitalisation; or adherence to pharmacotherapy or treatment protocols. However, one limitation is that considerable thought needs to go into the construction of the plots. Choosing the right structure, such as a juxtaposed or superimposed plots, as well as characteristics of the data items, such as point, line and symbol size, hue and luminance are important to ensure accurate visual comparisons are made. Good guidance exists to help with these choices.[25 28] Consideration should also be made to the size of the plot, and whether the number of pixels available will be sufficient to present the quantity of information required. In this study, large amounts of information were presented in a comparably small image, allowing clear identification of overarching patterns in the data, yet protecting individual privacy because data trajectories of individual patients are almost impossible to identify. While for many researchers the benefits of a customised visualisation may be outweighed by the usability and support of off-the-shelf interactive software tools, these plots are technically feasible within a range of software packages and easier adoption in the future may come through users sharing metadata and syntax, such as in that provided in online supplementary file 2, or the adaption of software tools targeted towards more flexible displays of longitudinal health data.

A limitation of the study is that participants in the 45 and Up Study are older and potentially healthier than the general population,[38] and with a low study participation rate (18%), there may be concerns about generalisability. However, persons aged 45 years and above represent a clinically meaningful population, contributing two-thirds of preventable hospitalisations in Australia, and with the highest rates of admission.[48] While previous research has found internal risk estimates from the 45 and Up Study to be comparable with those from population health surveys,[49] and there is sufficient heterogeneity between study participants to allow for valid within-cohort comparisons, the visualisations in this study were descriptive and largely unadjusted. However, the core strength of these visualisations is that they allow interrogation of the data not possible using standard epidemiological methods, and it is difficult to conceive a more effective method for exploring the complex pattern of health events before, during and following preventable hospitalisation.

CONCLUSION

This study did not find evidence that preventable hospitalisations reflected limited use of primary care services, rather admitted patients tended to have high levels of engagement with multiple elements of the healthcare system. Preventable hospitalisations in Australia may therefore be more useful as a tool for identifying sicker patients for managed care programmes, which can improve the quality, coordination and timeliness of care received, rather than as an indicator of supply of primary care. Visualising longitudinal health data was found to be a powerful strategy for uncovering patterns of health service use, and while technically possible, is underutilised within health services research. Such visualisations have potential to be more widely adopted.

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Contributors MOF conceived the project, performed data analysis, designed the visualisation and drafted the manuscript. LRJ and AHL provided guidance and interpretation. All three authors edited, reviewed and approved the final manuscript. LRJ conceived the APHID study.

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Competing interests None declared.

Ethics approval NSW Population and Health Services Research Ethics Committee.

Data sharing statement The data set used for this study was constructed from pre-existing source data sets (routinely collected data and the 45 and Up Study) with the permission from the custodians of each of these data sets and with specific ethical approval. The data set could potentially be made available to other researchers if they obtain the necessary approvals. Further information on this process can be obtained from the 45 and Up Study (45andUp.research@saxinstitute.org.au) and the NSW Centre for Health Record Linkage (cherel.mail@moh.health.nsw.gov.au).

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Supplementary File 1: Codes used to define health events

Preventable hospitalisations

Preventable hospitalisations were identified in the NSW APDC hospitalisation data according to conditions included in the Australian 2012 National Healthcare Agreement.

Category	ICD-10-AM diagnosis and procedure codes
Chronic	
Angina	I20, I24.0, I24.8, I24.9 as principal diagnosis only, exclude cases with procedure codes not in blocks [1820] to [2016]
Asthma	J45, J46 as principal diagnosis only
Chronic obstructive pulmonary disease (COPD)	J20, J41, J42, J43, J44, J47 as principal diagnosis only, J20 only with additional diagnoses of J41, J42, J43,J44, J47
Congestive cardiac failure	I50, I11.0, J81 as principal diagnosis only, exclude cases with the following procedure codes: 33172-00, 35304-00, 35305-00, 35310-02, 35310-00, 38281-11, 38281-07, 38278-01, 38278-00, 38281-02, 38281-01, 38281-00, 38256-00, 38278-03, 38284-00, 38284-02, 38521-09, 38270-01, 38456-19, 38456-15, 38456-12, 38456-11, 38456-10, 38456-07, 38456-01, 38470-00, 38475-00, 38480-02, 38480-01, 38480-00, 38488-06, 38488-04, 38489-04, 38488-02, 38489-03, 38487-00, 38489-02, 38488-00, 38489-00, 38490-00, 38493-00, 38497-04, 38497-03, 38497-02, 38497-01, 38497-00, 38500-00, 38503-00, 38505-00, 38521-04, 38606-00, 38612-00, 38615-00, 38653-00, 38700-02, 38700-00, 38739-00, 38742-02, 38742-00, 38745-00, 38751-02, 38751-00, 38757-02, 38757-01, 38757-00, 90204-00, 90205-00, 90219-00, 90224-00, 90214-00, 90214-02.
Diabetes complications	E10–E14.9 as principal diagnoses, and E10–E14.9 as additional diagnoses where the principal diagnosis was: hypersmolarity (E87.0), acidosis (E87.2), transient ischaemic attack (G45), nerve disorders and neuropathies (G50–G64), cataracts and lens disorders (H25–H28), retinal disorders (H30–H36), glaucoma (H40–H42), myocardial infarction (I21–I22), other coronary heart diseases (I20, I23–I25), heart failure (I50), stroke and sequelae (I60–I64, I69.0–I69.4), peripheral vascular disease (I70–I74), gingivitis and periodontal disease (K05), kidney diseases including end-stage renal disease (N00–N29), and renal dialysis (Z49)
Hypertension	I10, I11.9 as principal diagnosis only, exclude cases with procedure codes according to the list of procedures excluded from the Congestive cardiac failure category above.
Iron deficiency anaemia	D50.1, D50.8, D50.9 as principal diagnosis only.
Nutritional deficiencies	E40, E41, E42, E43, E55.0, E64.3 as principal diagnosis only.
Rheumatic heart disease	I00 to I09 as principal diagnosis only. (Note: includes acute rheumatic fever)
Acute	
Appendicitis with generalised peritonitis	K35.0 in any diagnosis field
Cellulitis	L03, L04, L08, L88, L98.0, L98.3 as principal diagnosis only, exclude cases with any procedure except those in blocks 1820 to 2016 or if procedure is 30216-02, 30676-00, 30223-02, 30064-00, 34527-01, 34527-00, 90661-00 and this is the only listed procedure
Convulsions and epilepsy	G40, G41, O15, R56 as principal diagnosis only
Dehydration and gastroenteritis	A09.9, E86, K52.2, K52.8, K52.9 as principal diagnosis only.
Dental conditions	K02, K03, K04, K05, K06, K08, K09.8, K09.9, K12, K13 as principal diagnosis only.
Ear, nose and throat infections	H66, H67, J02, J03, J06, J31.2 as principal diagnosis only.
Gangrene	R02 in any diagnosis field
Pelvic inflammatory disease	N70, N73, N74 as principal diagnosis only.

Perforated/bleeding ulcer	K25.0, K25.1, K25.2, K25.4, K25.5, K25.6, K26.0, K26.1, K26.2, K26.4, K26.5, K26.6, K27.0, K27.1, K27.2, K27.4, K27.5, K27.6, K28.0, K28.1, K28.2, K28.4, K28.5, K28.6 as principal diagnosis only.
Pyelonephritis	N10, N11, N12, N13.6, N39.0 as principal diagnosis only.
Vaccine-preventable	
Influenza and pneumonia	J10, J11, J13, J14, J15.3, J15.4, J15.7, J15.9, J16.8, J18.1, J18.8 in any diagnosis field, excludes cases with additional diagnosis of D57 (sickle-cell disorders) and people under 2 months
Other vaccine-preventable conditions	A35, A36, A37, A80, B05, B06, B16.1, B16.9, B18.0, B18.1, B26, G00.0, M01.4 in any diagnosis field

General Practitioner (GP) consultations

Consultations with a General Practitioner were identified as all claims in the linked MBS data within item groups A1 & A2, and included claims provided in-hospital.

Emergency Department (ED) presentations

Presentations to an Emergency Department were identified using all records in the EDDC data.

"Other" hospitalisations

All "other" hospitalisations were identified as all records in the NSW APDC hospitalisation data which did not meet the above criteria for a preventable hospitalisation.

Specialist consultations

Specialist consultations were identified in the linked MBS data according to the Broad Type of Service category for "Specialist attendances", and includes services provided in hospital. The item codes used to identify claims were: 85, 88, 94, 99-100, 102-152, 154-159, 288-289, 291-293, 296-297, 299-338, 342-353, 355-359, 361, 364, 366-367, 369-370, 384-389, 410-417, 501-503, 507, 511, 515, 519-520, 530, 532, 534, 536, 801, 803, 805, 807-809, 811, 813, 815, 820, 822-823, 825-826, 828, 830, 832, 834-835, 837-838, 851-852, 855, 857-858, 861, 864, 866, 871-872, 880, 887-893, 2799, 2801, 2806, 2814, 2820, 2824, 2832, 2840, 2946-2949, 2954, 2958, 2972-2978, 2984-3003, 3005, 3010, 3014-3015, 3018, 3023, 3028-3032, 3040, 3044, 3051-3055, 3062, 3069, 3074-3078, 3083, 3088, 3093, 5906-5912, 6004, 6007-6009, 6011-6016, 10801-10816, 17603-17690.

Deaths

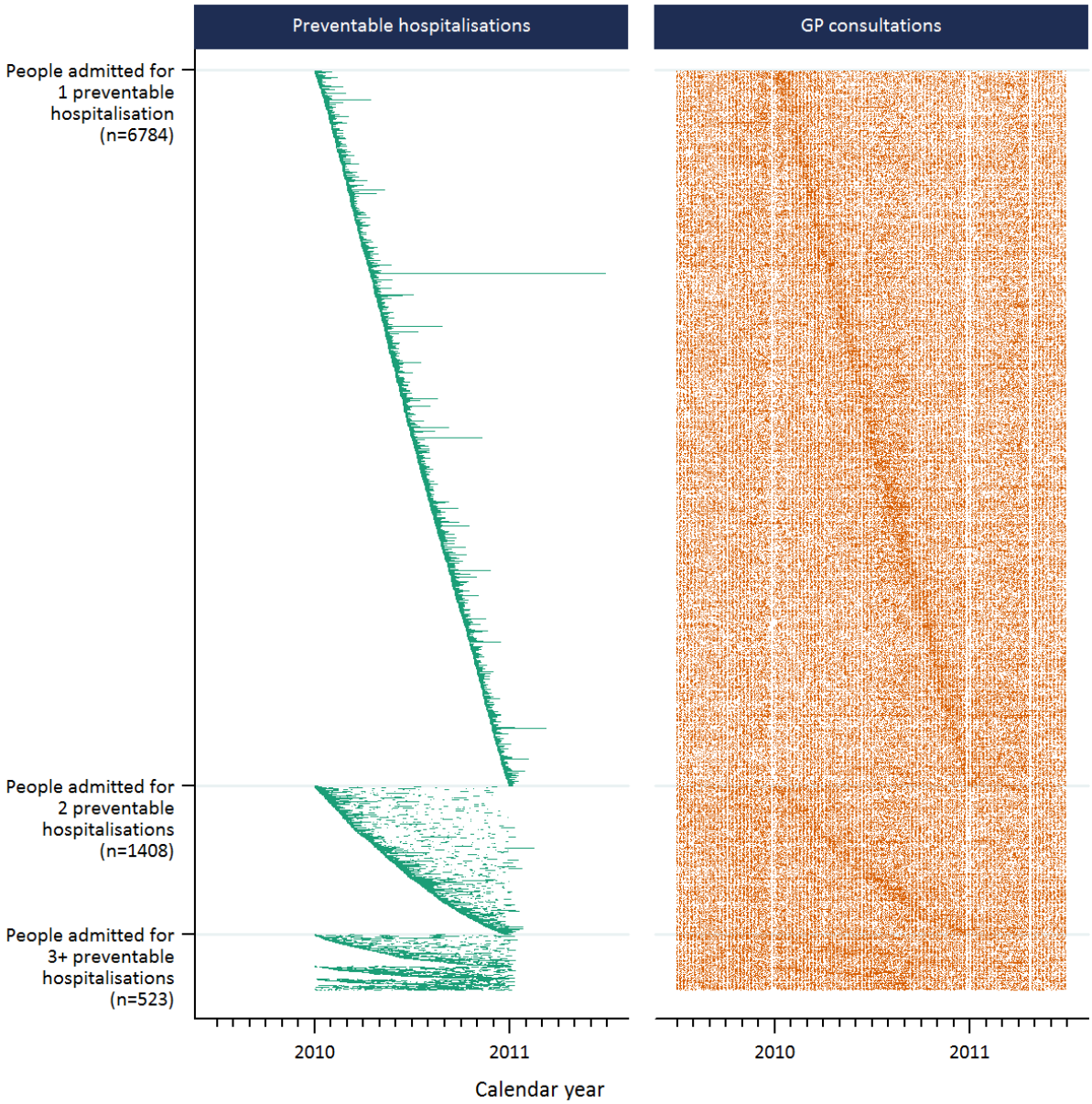
All deaths on the linked NSW Registry of Births, Deaths and Marriages (RBDM) were included.

Supplementary File 2: Example of data structure and Stata code for producing trajectories of individual patient health service use

This file contains sample Stata code, and an example of the underlying data structure, which has been used to produce a custom visualisation on preventable hospitalisations and GP consultations.

Supplementary Figure 2.1:

Trajectory of individual patient health service use comparing patterns of admission for preventable hospitalisations to consultations with general practitioners (GP) for participants in the 45 and Up Study



Example Stata syntax to produce trajectories of individual patient health service use

The Stata syntax used for producing Supplementary Figure 2.1 is presented below. Please note that this syntax is not designed to be directly applicable to other datasets, but provides an example of how such a plot can be constructed

Stata syntax	Notes on syntax
twoway ///	▪ 'Twoway' command creates overlaid plots of numerical data over an x-and y-axis
/* Spike plot presenting lines for preventable hospitalisations */ ///	▪ Horizontal spike from start to end date of hospitalisation, using a very thin line with a custom colour
(rspike hos_start hos_end yorder1 , lcolor("27 158 119") lwidth(vvvthin) horizontal) ///	
/* Scatter plot presenting dots for GP consultations */ ///	▪ Scatter plot of date of GP visit, using a tiny point with a custom colour
(scatter yorder1 consult_date, msymbol(point) mcolor("217 95 2") msize(tiny)) ///	
if datatype ==”Preventable hospitalisation” | datatype==”GP consultation” , ///	▪ Restrict data to just the health events needed for the plot
/* Stratify data into separate vertical panels */ ///	▪ Stratify on 'datasource' variable (contains identifier for different health events) in 1 row of panels.
by(datasource, rows(1)) ///	
subtitle(, size(vsmall) color(white) margin(small) ///	Formatting of panel heading text.
box fcolor(dknavy) lcolor(dknavy)) ///	Formatting of panel heading box.
/* Y-axis title, labels, ticks etc */ ///	▪ Y-axis labelling can be customised as desired.
ytitle(, size(zero) color(white)) yscale(reverse) ///	In this plot, no title for the y-axis is presented.
ylabel(1 6790 8198 , labsize(zero) angle(horizontal) ticks) ///	The 'major' y-axis labels have been used to create tick marks and grid lines for the main groupings.
ymtick(1 "People admitted for" 201 "1 preventable" 400 "hospitalisation" ///	
601 "(n=7202)" 6790 "People admitted for" 6990 "2 preventable" 7190 ///	The 'minor' y-axis labels have been used to create labels for the major groupings. The values used to create the labels start at the major groupings and increase incrementally by 200 (chosen arbitrarily through trial/error to look neat).
hospitalisations" 7390 "(n=1137)" 8198 "People admitted for" 8398 ///	
"3+ preventable" 8598 "hospitalisations" 8798 "(n=378)" , ///	
labels angle(horizontal) labgap(vsmall) ticks tlcolor(black) tlength(zero)) ///	
/* X-axis title, labels, ticks etc */ ///	▪ X-axis labelling can be customised as desired.
xtitle(Calendar year) xtitle(, size(vsmall)) ///	Tick marks on the x-axis correspond to date values in the data. In this case, all the dates variables are centred on 01Jan2010 - which has a numerical value of 0 (so 02Jan2010 has a value of 1, etc)
xlabel(0 "2010" 365 "2011" , labsize(vsmall)) ///	
xmtick(/*-182.5 182.5 547.5*/ -182.5(30.4375) 547.5) ///	
/* Other plot formatting characteristics */ ///	▪ Other plot formatting characteristics, such as plot size and background/outline colours. Note that as the plot has been stratified over panels of events, some of these characteristics will need to be placed within a 'by' statement.
xsize(20) ysize(20) ///	
by(, note(, size(zero) color(white)) ///	
graphregion(margin(tiny) fcolor(white) lcolor(white) ifcolor(white) ilcolor(white)) ///	
legend(off))	

Example data structure used to produce trajectories of individual patient health service use

The following table is a mock-up, using fictional data, of the dataset used to produce Supplementary Figure 2.1 above. The dataset included linked data for 266,950 people from 4 different administrative datasets – hospitalisations, emergency department (ED) visits, Medicare claims, and deaths. The table contains a combination of patient-level metadata, merged with an appended set of cleaned unit record data from each of the linked data sources. Further descriptions of each type of data element are provided below.

Person-level metadata							Event data, derived from source specific datasets								
Personal characteristics				Y-axis order variables			Dataset ID		Hospital data			ED data	Medicare data		Death data
personid	age	sex	pph_num	order1	order2	order3	dataid	eventtype	hos_type	hos_start	hos_end	ed_date	consult_type	consult_date	dth_date
1	52	M	1	34	1966	34	Hospital	Preventable hospitalisation	PPH	08/04/10	10/04/10	-	-	-	-
1	52	M	1	34	1966	34	Hospital	Other hospitalisation	Other	11/04/10	11/04/10	-	-	-	-
1	52	M	1	34	1966	34	Hospital	Other hospitalisation	Other	30/05/10	01/06/10	-	-	-	-
2	45	F	2	4331	5141	4331	Hospital	Preventable hospitalisation	PPH	03/10/10	10/10/10	-	-	-	-
2	45	F	2	4331	5141	4331	Hospital	Preventable hospitalisation	PPH	13/10/10	17/10/10	-	-	-	-
3	84	F	0	-	-	10701	Hospital	Other hospitalisation	Other	18/01/10	30/01/10	-	-	-	-
3	84	F	0	-	-	10701	Hospital	Other hospitalisation	Other	16/02/10	18/02/10	-	-	-	-
…	…	…	…	…	…	…	…	…	…	…	…	…	-	-	-
266950	66	M	1	3130	123	3130	Hospital	Preventable hospitalisation	PPH	04/07/10	04/07/10	-	-	-	-
1	52	M	1	34	1966	34	ED	ED presentation	-	-	-	08/04/10	-	-	-
3	84	F	0	-	-	10701	ED	ED presentation	-	-	-	17/01/10	-	-	-
11	78	F	0	-	-	15888	ED	ED presentation	-	-	-	16/11/10	-	-	-
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
262132			0	-	-	11011	ED	ED presentation	-	-	-	22/08/10	-	-	-
1	52	M	1	34	1966	34	Medicare	GP consultation	-	-	-	-	GP	03/01/10	-
1	52	M	1	34	1966	34	Medicare	GP consultation	-	-	-	-	GP	02/04/10	-
1	52	M	1	34	1966	34	Medicare	Specialist consultation	-	-	-	-	Specialist	15/06/10	-
1	52	M	1	34	1966	34	Medicare	GP consultation	-	-	-	-	GP	09/09/10	-
1	52	M	1	34	1966	34	Medicare	Specialist consultation	-	-	-	-	Specialist	24/12/10	-
2	45	F	2	4331	5141	4331	Medicare	GP consultation	-	-	-	-	GP	01/10/10	-
2	45	F	2	4331	5141	4331	Medicare	GP consultation	-	-	-	-	GP	11/10/10	-
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
266950	66	M	1	3130	123	3130	Medicare	Specialist consultation	-	-	-	-	Specialist	19/11/10	-
11	78	F	0	-	-	.	Death	Death	-	-	-	-	-	-	31/05/10
52	88	M	3	6209	8120	6209	Death	Death	-	-	-	-	-	-	20/12/10
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
265381	49	F	0	-	-	14991	Death	Death	-	-	-	-	-	-	01/02/10

Person-level meta-data variables describe the person/study participant, and may include:

- A unique person ID, linking all records belonging to that person
- Personal characteristics of interest, such as age, sex, and in this case a variable identifying the number of preventable hospitalisations a person has had. These characteristics may be used to filter records or sort people along the y-axis, and any relevant personal characteristics can be included.
- Y-axis order variables. These determine the order of people to be presented on the y-axis, and will have been generated by the user at an earlier stage. As these are user generated, they can be as simple or complex as desired, which can be useful if more complex methods for ordering and grouping people are necessary.
- Note that this type of person-level meta-data is often be stored in a separate person-level 'index' file, with one record per person. In this case, this 'index' file was merged onto the appended unit-record dataset using a unique person ID.

'Dataset specific' variables are the unit-record data items that are to be plotted, and may include:

- A variable identifying the source of the data (e.g. hospitalisation, emergency department, etc.) or the type of health event (e.g. types of health events used for stratifying vertical panels of data).
- Date variables, identifying the dates of events to be plotted, such as start/end dates for interval events. These can be stored as raw date variables, but may also be easier to plot if they are centred on a meaningful date for analysis, such as the beginning of the plot, or the date of a sentinel event. These can be stored as different variables for each dataset (as in the example above), or stored in a common 'date' variable, which may be more efficient for very large data files.
- Any other variables which flag relevant characteristics of any of the health events. These can be used later to identify or separate specific types of health events if interested (e.g. using different colours to identify different types of preventable hospitalisations).
  Note that not all people will have a corresponding record in each dataset.

Supplementary File 3: Supplementary tables and figures

Supplementary Table 3.1:

Socio-demographic and health characteristics of study participants, as used in propensity matching participants admitted for a preventable hospitalisation in 2010 to non-admitted participants.

	Total study cohort		Participants admitted with preventable hospitalisation		Matched, non-admitted participants	
	n	% of N	n	% of N	n	% of N
Total people (N)	262,233	100.0%	8,715	100.0%	8,715	100.0%
Age at study entry						
45-54yrs	77,612	29.6%	992	11.4%	942	10.8%
55-64yrs	85,291	32.5%	1,864	21.4%	1,835	21.1%
65-74yrs	57,117	21.8%	2,415	27.7%	2,464	28.3%
75-84yrs	35,027	13.4%	2,624	30.1%	2,644	30.3%
85+yrs	7,185	2.7%	820	9.4%	830	9.5%
Sex						
Males	120,850	46.1%	4,503	51.7%	4,464	51.2%
Females	141,383	53.9%	4,212	48.3%	4,251	48.8%
Remoteness of residence (ARIA+)						
Major cities	103,023	39.3%	3,423	39.3%	3,447	39.6%
Inner regional	105,323	40.2%	3,464	39.7%	3,525	40.4%
Outer regional	46,164	17.6%	1,553	17.8%	1,484	17.0%
Remote / very remote	3,557	1.4%	131	1.5%	118	1.4%
Missing	4,166	1.6%	144	1.7%	141	1.6%
Highest level of education						
Did not complete high school	87,946	33.5%	3,759	43.1%	3,761	43.2%
High school or equivalent	109,083	41.6%	3,437	39.4%	3,436	39.4%
University or higher	60,943	23.2%	1,259	14.4%	1,268	14.5%
Missing/invalid	4,261	1.6%	260	3.0%	250	2.9%
Language at home						
English	237,254	90.5%	7,889	90.5%	7,844	90.0%
Other	24,977	9.5%	826	9.5%	871	10.0%
Marital status			525	6.0%	457	5.2%
Single	14,860	5.7%				
Married / partner	195,366	74.5%	5,632	64.6%	5,660	64.9%
Widowed or separated	50,430	19.2%	2,490	28.6%	2,533	29.1%
Missing	1,577	0.6%	68	0.8%	65	0.7%
Aboriginal or Torres Strait Islander						
Non Aboriginal	255,772	97.5%	8,345	95.8%	8,379	96.1%
Aboriginal	1,910	0.7%	107	1.2%	91	1.0%
Missing/invalid	4,551	1.7%	263	3.0%	245	2.8%
Employment status						
Not working	127,962	48.8%	6,535	75.0%	6,590	75.6%
Part time	50,127	19.1%	900	10.3%	891	10.2%
Full time	79,629	30.4%	1,131	13.0%	1,096	12.6%
Missing	4,515	1.7%	149	1.7%	138	1.6%
Annual household income						
<$10,000	14,367	5.5%	855	9.8%	837	9.6%
$10,000 - $29,999	61,433	23.4%	2,943	33.8%	2,999	34.4%
$30,000 - $49,999	39,903	15.2%	1,090	12.5%	1,160	13.3%
$50,000 - $69,999	27,649	10.5%	549	6.3%	549	6.3%
$70,000 or more	62,516	23.8%	913	10.5%	935	10.7%
Not specified	42,994	16.4%	1,583	18.2%	1,465	16.8%
Missing	13,371	5.1%	782	9.0%	770	8.8%
Private health insurance						

	Total study cohort		Participants admitted with preventable hospitalisation		Matched, non-admitted participants	
	n	% of N	n	% of N	n	% of N
Private w/ extras	129,357	49.3%	3,421	39.3%	3,442	39.5%
Private no extras	37,746	14.4%	1,128	12.9%	1,101	12.6%
DVA health care card	4,367	1.7%	405	4.6%	409	4.7%
Health care card	46,145	17.6%	2,522	28.9%	2,491	28.6%
None	44,618	17.0%	1,239	14.2%	1,272	14.6%
Number of people can depend on						
0 people	16,513	6.3%	552	6.3%	506	5.8%
1-4 people	100,682	38.4%	3,610	41.4%	3,578	41.1%
5-10 people	96,471	36.8%	2,900	33.3%	2,962	34.0%
11+ people	37,972	14.5%	1,104	12.7%	1,108	12.7%
Missing/invalid	10,595	4.0%	549	6.3%	561	6.4%
Health seeking behaviour score [a]						
0 behaviours	2,096	0.8%	92	1.1%	67	0.8%
1 behaviour	21,927	8.4%	952	10.9%	894	10.3%
2 behaviours	91,705	35.0%	3,583	41.1%	3,572	41.0%
3 behaviours	113,396	43.2%	3,276	37.6%	3,381	38.8%
4 behaviours	33,109	12.6%	812	9.3%	801	9.2%
Body mass index						
Underweight	20,419	7.8%	859	9.9%	767	8.8%
Healthy weight	89,551	34.1%	2,564	29.4%	2,619	30.1%
Overweight	95,583	36.4%	2,999	34.4%	3,131	35.9%
Obese	54,265	20.7%	2,175	25.0%	2,095	24.0%
Missing/invalid	2,415	0.9%	118	1.4%	103	1.2%
Self-reported health status						
Excellent	38,739	14.8%	431	4.9%	424	4.9%
Very good	94,388	36.0%	1,840	21.1%	1,851	21.2%
Good	85,598	32.6%	3,084	35.4%	3,105	35.6%
Fair	29,499	11.2%	2,274	26.1%	2,330	26.7%
Poor	4,947	1.9%	643	7.4%	558	6.4%
Missing	9,062	3.5%	443	5.1%	447	5.1%
Multi-morbid conditions [b]						
No conditions	108,236	41.3%	1,729	19.8%	1,699	19.5%
1 condition	91,957	35.1%	2,601	29.8%	2,634	30.2%
2 conditions	43,397	16.5%	2,413	27.7%	2,420	27.8%
3 or more conditions	18,643	7.1%	1,972	22.6%	1,962	22.5%
Functional limitation						
No limitation	78,969	30.1%	957	11.0%	934	10.7%
Minor limitation	39,496	15.1%	669	7.7%	642	7.4%
Mild limitation	43,892	16.7%	1,185	13.6%	1,217	14.0%
Moderate limitation	39,322	15.0%	1,661	19.1%	1,636	18.8%
Severe limitation	34,693	13.2%	3,173	36.4%	3,182	36.5%
Missing/unknown	25,861	9.9%	1,070	12.3%	1,104	12.7%
Psychological distress						
Low distress	199,578	76.1%	6,130	70.3%	6,071	69.7%
Moderate distress	37,927	14.5%	1,358	15.6%	1,416	16.2%
High distress	12,918	4.9%	535	6.1%	582	6.7%
Very high distress	5,160	2.0%	302	3.5%	281	3.2%
Missing	6,650	2.5%	390	4.5%	365	4.2%

[a] Of non-smoking status, safe level of alcohol consumption (<14 drinks per week), at least 2.5 hours of intensity-weighted physical activity per week, and meeting dietary guidelines for daily fruit (2 serves) and vegetable (5 serves) consumption.
[b] Of self-reported heart disease, high blood pressure, stroke, diabetes, blood clot, asthma, Parkinson's disease, and any cancer except skin cancer.

Supplementary Table 3.2:

Breakdown of preventable hospitalisations of 45 and Up Study participants in 2010 by type of condition

Category of preventable hospitalisation	Hospitalisations		
	Total admissions	Admitted patients	Average # admissions per patient
Preventable hospitalisation			
All preventable hospitalisations	11,645	8,715	1.3
Chronic conditions			
All chronic	7,351	5,228	1.4
Diabetes complications	1,911	1,429	1.3
Angina	1,703	1,364	1.2
COPD	1,576	986	1.6
Congestive cardiac failure	1,237	945	1.3
Iron deficiency anaemia	734	633	1.2
Asthma	190	159	1.2
Hypertension	164	154	1.1
Rheumatic heart disease	60	47	1.3
Nutritional deficiencies	6	4	1.5
Acute conditions			
All acute	4,103	3,614	1.1
Dehydration & gastroenteritis	1,118	1,061	1.1
Pyelonephritis	1,048	911	1.2
Cellulitis	873	739	1.2
Dental conditions	487	464	1.0
Convulsions & epilepsy	239	198	1.2
Ear, nose, throat infections	141	138	1.0
Perforated/bleeding ulcer	103	100	1.0
Gangrene	57	52	1.1
Pelvic inflammatory disease	19	17	1.1
Appendicitis	18	17	1.1
Vaccine-preventable conditions			
All vaccine-preventable	221	179	1.2
Influenza & pneumonia	198	160	1.2
Other vaccine-preventable	24	20	1.2

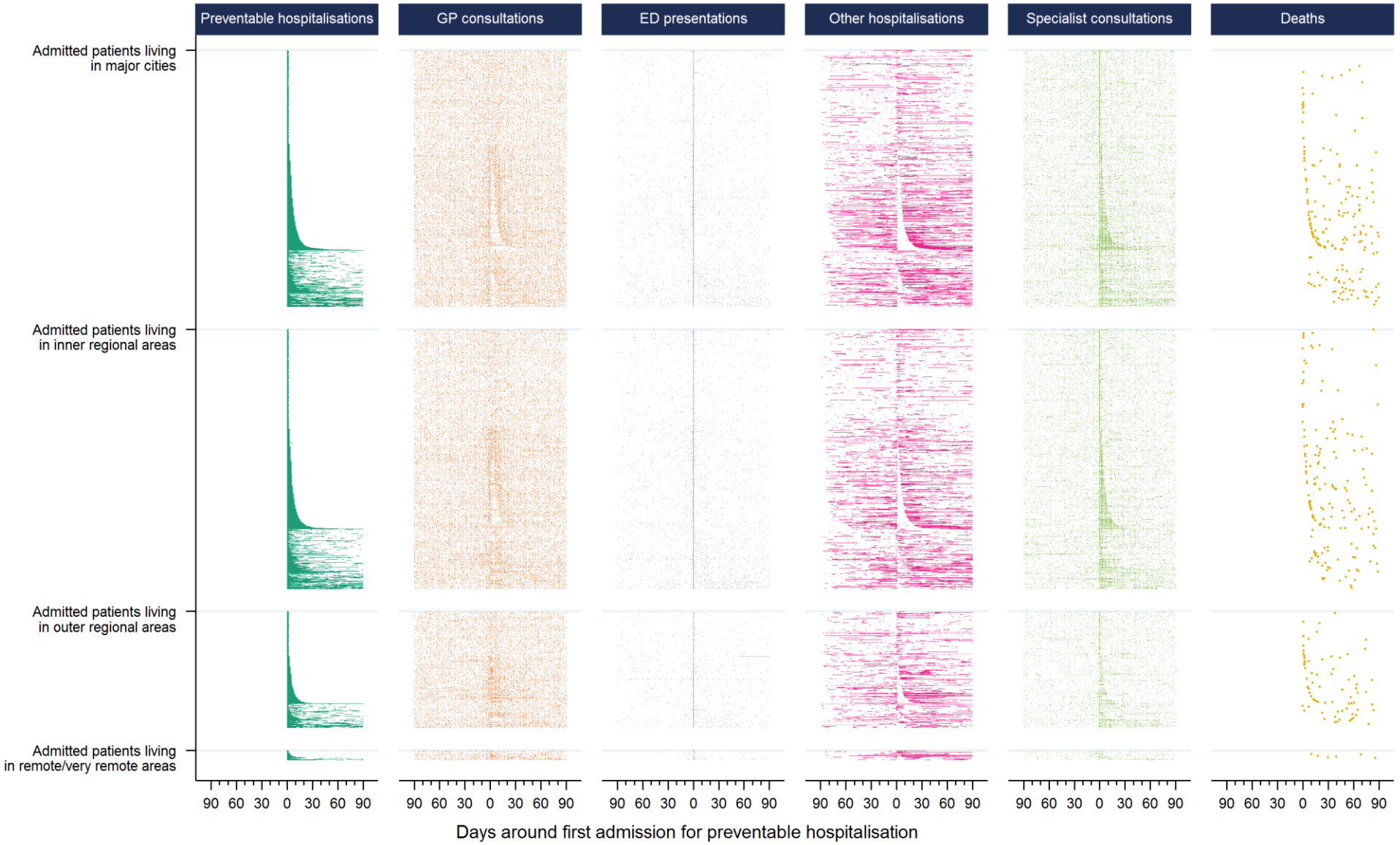
Supplementary Table 3.3:

Interaction between GP and specialist consultations in the period leading up to first preventable hospitalisation

Type of health event/health service use	Cumulative % of admitted patients with health event in period prior to day of first preventable hospitalisation			
	1 day	1 week	1 month	3 months
Prior to day of first admission				
GP consultation only	6.6%	23.9%	37.4%	30.7%
Specialist consultation only	2.5%	8.9%	10.5%	3.5%
Both GP and specialist consultation	0.1%	3.6%	27.4%	56.5%
Neither GP or specialist consultation	90.7%	63.6%	24.7%	9.2%

Supplementary Figure 3.1:

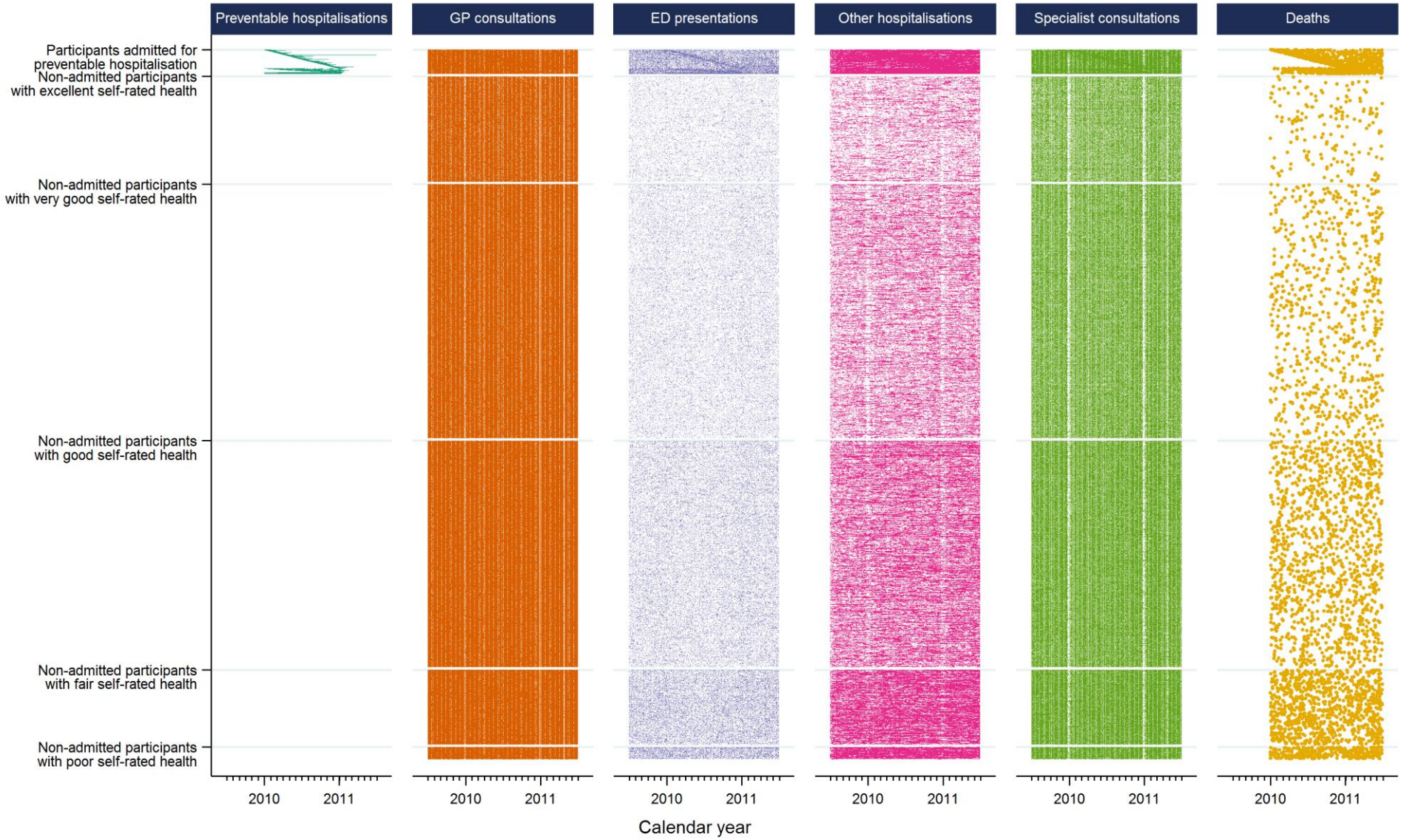
Patterns of health events and health service use in the 90 days leading up to and following first admission for a preventable hosptialisation, with patients sorted by the remoteness of hteir geographic area of residence, number of preventable hospitalisations in 2010 and length of hospital stay.



Visualising linked health data to explore health events around preventable hospitalisations in NSW Australia, Supplementary File 3

Supplementary Figure 3.2

Patterns of health events and health service use in the 8,715 study participants admitted for a preventable hospitalisation in 2010 (sorted by number of preventable hospitalisations, date of first admission), as well as health events and health service use in the remaining 258,235 study participants not admitted for a preventable hospitalisation (sorted by self-rated health).



Visualising linked health data to explore health events around preventable hospitalisations in NSW Australia, Supplementary File 3

OPEN

Sociodemographic and Health Characteristics, Rather Than Primary Care Supply, are Major Drivers of Geographic Variation in Preventable Hospitalizations in Australia

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Background: Geographic rates of preventable hospitalization are used internationally as an indicator of accessibility and quality of primary care. Much research has correlated the indicator with the supply of primary care services, yet multiple other factors may influence these admissions.

Objective: To quantify the relative contributions of the supply of general practitioners (GPs) and personal sociodemographic and health characteristics, to geographic variation in preventable hospitalization.

Methods: Self-reported questionnaire data for 267,091 participants in the 45 and Up Study, Australia, were linked with administrative hospital data to identify preventable hospitalizations. Multilevel Poisson models, with participants clustered in their geographic area of residence, were used to explore factors that explain geographic variation in hospitalization.

Results: GP supply, measured as full-time workload equivalents, was not a significant predictor of preventable hospitalization, and explained only a small amount (2.9%) of the geographic variation in hospitalization rates. Conversely, more than one-third (36.9%) of variation was driven by the sociodemographic composition, health, and behaviors of the population. These personal characteristics explained a greater amount of the variation for chronic conditions (37.5%) than acute (15.5%) or vaccine-preventable conditions (2.4%).

Conclusions: Personal sociodemographic and health characteristics, rather than GP supply, are major drivers of preventable hospitalization. Their contribution varies according to condition, and if used for performance comparison purposes, geographic rates of preventable hospitalization should be reported according to individual condition or potential pathways for intervention.

Key Words: preventable hospitalization, multilevel modelling, primary care

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Preventable hospitalizations (also known as hospitalizations for "ambulatory care sensitive conditions," "potentially avoidable hospitalizations," and "potentially preventable hospitalizations") are those considered to be preventable through timely access to quality primary and preventive care.[1–3] Rates of preventable hospitalization are reported internationally as an indicator of health

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The APHID Study investigator team comprises Louisa Jorm, Alastair Leyland, Fiona Blyth, Robert Elliot, Kirsty Douglas, Sally Redman, Michael Falster, Bich Tran, Sanja Lujic, Deborah Randall, Marjon van der Pol, Damilola Olajide, Danielle Butler, Neville Board, Douglas Lincoln, Kim Sutherland, Chris Shipway, and Nigel Lyons. This research was completed using data collected through the 45 and Up Study (http://www.saxinstitute.org.au). The 45 and Up Study is managed by the Sax Institute in collaboration with major partner Cancer Council NSW; and partners: the National Heart Foundation of Australia (NSW Division); NSW Ministry of Health; *beyondblue*; Ageing, Disability and Home Care, Department of Family and Community Services; and the Australian Red Cross Blood Service.

The authors declare no conflict of interest.

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system performance and, in Australia, are used to guide the allocation of health service resources.[4,5] Typically, this reporting involves comparing rates of preventable hospitalizations between geographic or health administrative areas,[5,6] with the underlying rationale that variation in admission rates is related to the accessibility or quality of primary care, based on measures such as the density of the general practitioner (GP) workforce,[7–9] perceived availability of health services,[10,11] the presence of community health centers,[12] or having a regular source of care.[13,14]

Health system performance indicators should reflect factors that can be influenced by, and are responsive to, health policy change.[15,16] Policy interventions to reduce preventable hospitalizations usually address health care systems, such as incentives to increase equity in the distribution of GPs.[17,18] However, multiple factors influence variation in preventable hospitalization, and interventions can also target clinical and self-management of conditions (such as chronic disease management and telemedicine programs) and primary prevention at population level (such as health promotion campaigns). Accordingly, the valid use and interpretation of preventable hospitalization as a measure of health system performance requires an understanding of the relative contributions of personal and health care factors,[15] particularly because more proximal interventions would be expected to drive change more quickly than those operating through primary prevention.

Most attempts to explore the multiple factors that drive preventable hospitalizations have used an ecological approach, analyzing area-based measures such as disease prevalence, average income, racial composition of the population, or area-level deprivation.[8,10,19–21] Interpretation of such analyses can be limited because they are subject to "ecological fallacy" by inferring risk factors for individuals based on population-level information, while it is not known which members of the population were actually hospitalized.[22,23] Few studies of preventable hospitalization have collected detailed sociodemographic or health data for individuals, and these have used these data only to construct aggregate area-level variables,[10,11] or else did not explore the role of personal characteristics in driving geographic variation in admission.[23–25]

Multilevel modelling, a statistical technique that structures data into hierarchies, such as individuals nested within their geographic area of residence, can estimate the relative contributions of factors at each of these levels to the total variation in an outcome.[26] Although multilevel modelling has increasingly been used to explore personal and contextual drivers of preventable hospitalizations, analyses to date have been limited by the use of administrative hospital[27–29] or US Medicare claims[7] data, which did not include detailed information about individual patients.

This study used multilevel modelling and detailed person-level data from a large-scale cohort study linked to routinely collected health data to investigate the relative contributions of the supply of GP services, relative to the contribution of personal sociodemographic, health and behavioral characteristics, to geographic variation in preventable hospitalizations.

METHODS

Study Population

This observational cohort study used data from the Assessing Preventable Hospitalisation InDicators (APHID) study, details of which have been published elsewhere.[30] Briefly, APHID includes participants from the Sax Institute's 45 and Up Study,[31] a prospective cohort of over 267,000 men and women aged over 45 in New South Wales (NSW), Australia. Study participants were recruited from 2006 to 2009 through Medicare Australia (Australia's national universal health insurer), and joined the study by completing a self-administered questionnaire, including information on demographic characteristics, indicators of socioeconomic status, self-reported health, number, and type of comorbidities and behavioral risk factors. Participants also provided consent for long-term follow-up, including linkage to administrative health data sets.

Self-reported survey data for 45 and Up Study participants were linked with hospital admissions data from the NSW Admitted Patient Data Collection, a census of all hospital separations (discharges, transfers, and deaths) from all NSW public and private sector hospitals and day-procedure centers, and mortality data from the NSW Registry of Births Death and Marriages mortality data file, which contains fact-of-death information on death registrations within Australia. Probabilistic data linkage was performed by the NSW Centre for Health Record Linkage (http://www.cherel.org.au/) using ChoiceMaker software. A manual clerical review on a sample of linkage records found a false-positive linkage rate of 0.3%.

Ethics approval for the 45 and Up Study was granted by the University of New South Wales Human Research Ethics Committee, and approval for the APHID study was granted by the NSW Population and Health Services Research, Aboriginal Health & Medical Research Council, and University of Western Sydney Research Ethics Committees.

Preventable Hospitalizations

Preventable hospitalizations were identified using the linked Admitted Patient Data Collection hospital admissions data and defined according to the preventable hospitalization indicator in the Australian 2012 National Healthcare Agreement.[32] This indicator is composed of admissions for 21 conditions, broadly categorized as "chronic," "acute," and "vaccine-preventable" (Supplementary Table 1, Supplemental Digital Content 1, http://links.lww.com/MLR/A897). To assess whether hospitalizations for these conditions differed from other hospitalizations, an additional category of "nonpreventable" hospitalizations was defined as all emergency hospitalizations not included in the preventable hospitalization indicator.

Personal-level Variables

Self-reported information from the 45 and Up Study baseline survey was used to identify characteristics of the study participants (Table 1). Sociodemographic characteristics included age, sex, Aboriginal or Torres Strait Islander status, annual household income, highest level of education,

TABLE 1. Person-level and Area-level Covariates Used in Models Predicting Rates of Preventable Hospitalization

Category	Variables	Included as Covariate in Model			
		1	2	3	4
Baseline demographics (person-level)	Age, sex	X	X	X	X
Health system factors (area-level)	Full-time workload equivalent general practitioners per 10,000 residents	—	X	X	X
Sociodemographic factors (person-level)	Aboriginal or Torres Strait Islander status, highest education qualification, language other than English spoken at home, marital status, employment status, annual household income, private health insurance, and number of people can depend on	—	—	X	X
Health and behavioral factors (person-level)	Number of healthy behaviors (of smoking, exercise, diet, and alcohol consumption), body mass index, self-rated health, number of comorbidities, functional limitation, and psychological distress	—	—	—	X

The "X" indicates which sets of variables have been included in the statistical models (reported in Table 3).

speaking a language other than English at home, marital status, health insurance status, and number of people outside their home they can depend on. Health and behavioral characteristics included body mass index (using self-reported height and weight), self-reported health status, level of functional limitation (using the Medical Outcomes Study physical functioning scale), level of psychological distress (using the K10 Scale), number of comorbidities (heart disease, high blood pressure, stroke, diabetes, blood clot, asthma, Parkinson's disease, and any cancer except skin cancer), and a positive health behavior score[33] calculated as the total number of the following reported behaviors: nonsmoking status, safe level of alcohol consumption (< 14 drinks/wk), at least 2.5 hours of intensity-weighted physical activity per week, and meeting daily dietary guidelines for fruit (2 serves) and vegetable (5 serves) consumption.

Geographic-level Variables

Geographic areas of residence were identified from the 45 and Up Study using Statistical Local Areas (SLAs), one of the smallest geographic units available in the Australian Standard Geographical Classification.[34] SLAs were defined using boundaries from the 2006 Australian Census. The 199 SLAs differ in size and population across the state due to variation in remoteness from urban centers (Supplementary Figure 1, Supplemental Digital Content 1, http://links.lww.com/MLR/A897), with mean population 33,883 (range, 357–138,322).[35]

The number of full-time workload equivalent (FWE) GPs within each SLA, measured the effective supply of primary care services.[18,36] It was estimated using aggregate state-level data from the Department of Health and Ageing[37] and aggregate SLA-level data from the 2011 Social Health Atlas of Australia.[38] FWE GPs were calculated as the number of Medicare claims for GP services for residents of each SLA, divided by the average number of claims per FWE GP in NSW. Population estimates were used to calculate the density of FWE GPs per 10,000 residents of each SLA, and divided into quintiles. A sensitivity analysis treated FWE GPs as population-weighted quintiles, and produced similar results (data not shown).

Statistical Methods

Multilevel Poisson models were used to analyze rates of preventable hospitalization, with individuals as the unit of analysis. Counts of the number of preventable hospitalizations for each individual were taken between the date of study entry and the end of follow-up through the linked hospital data (December 30, 2010), or death, whichever came first. The log of the follow-up time was used as an offset. Individuals were clustered in their geographic area of residence (SLA) using a random intercept parameter, which allowed the baseline risk of admission to vary between these geographic areas. Separate analyses were run for the 3 major categories of preventable admission, and where numbers allowed, the individual conditions.

Geographic variation in risk of preventable hospitalization was first quantified using multilevel models adjusted for age and sex (Model 1). The variance (σ^2) of the random intercept parameter for the SLAs was used to quantify the amount of variation in the risk of admission between geographic areas.[39]

Quintiles of the density of FWE GPs were added to the model as an area-level covariate (Model 2). Subsequent models (Table 1) sequentially added person-level confounders, starting with sociodemographic variables considered to be nonmodifiable and largely outside the scope of health policy action (Model 3), followed by health and behavioral characteristics considered potentially amenable to health interventions targeting populations or individuals (Model 4). Incidence rate ratios and 95% confidence intervals (CIs) were calculated for each of the variables by exponentiating the regression parameters. The amount of geographic variation in admission (from Model 1) which was explained by the variables in each subsequent model (Model n), was calculated as the proportional change in variance (PCV),[39] where $PCV = (\sigma^2_{(Model\ 1)} - \sigma^2_{(Model\ n)})/\sigma^2_{(Model\ 1)}$.

Missing values were treated as additional categories; incidence rate ratios for these "missing" categories are reported in Supplementary Figures 2–6, Supplemental Digital Content 1, http://links.lww.com/MLR/A897. A sensitivity analysis excluding (n = 90,678) persons with missing data on any variable found no notable changes in the patterns of individual-level predictors of admission or changes in

TABLE 2. Cohort Characteristics and Average Rate of Preventable Hospitalizations Per 100 Person-years of Follow-up

	Persons	Rate of Preventable Hospitalization*
Total cohort	262,755	4.2
Age (y)		
45–54	76,265	1.5
55–64	84,402	2.6
65–74	57,441	5.2
75–84	36,534	10.0
85+y	8113	14.4
Sex		
Males	121,813	4.9
Females	140,942	3.5
Aboriginal status		
Non-Aboriginal	256,181	4.1
Aboriginal	1910	9.1
Household income		
<$10,000	14,705	7.7
$10,000–$29,999	62,328	6.3
$30,000–$49,999	39,774	3.1
$50,000–$69,000	27,381	2.2
$70,000 or above	61,556	1.5
Healthy behaviors		
0 behaviors	2126	5.1
1 positive behaviors	22,194	5.8
2 positive behaviors	92,552	5.1
3 positive behaviors	112,939	3.4
4 positive behaviors	32,944	3.0
Self-rated health		
Excellent	38,153	1.2
Very good	93,583	2.0
Good	85,735	4.2
Fair	30,448	10.6
Poor	5564	23.3
No. comorbidities		
None	107,122	1.7
1 comorbidity	91,984	3.2
2 comorbidities	44,139	7.3
3+ comorbidities	19,510	15.2
Density of FWE GPs†		
Quintile 1 (2.64–6.90)	31,664	3.8
Quintile 2 (6.91–7.60)	42,961	4.1
Quintile 3 (7.63–8.64)	57,672	4.1
Quintile 4 (8.65–9.94)	76,508	4.2
Quintile 5 (9.95–13.3)	53,950	4.6

*Rate of hospitalizations per 100 person-years, from time of study entry to end of linked hospital data (December 31, 2010) or death, whichever came first. Participants were recruited from 2006 to 2009, with an average follow-up time of 2.8 years.

†Full-time workload equivalent (FWE) generalist practitioners (GPs) per 10,000 residents in each Statistical Local Area.

area-level variation between models (data not shown). All models used a second-order penalized quasi-likelihood estimation procedure, and all analyses were performed in SAS 9.3 and MLwiN 2.25.

RESULTS

Of the N = 267,091 45 and Up Study participants, 1.6% (n = 4336) were excluded because their age or geographic area of residence was unknown, they resided outside of NSW, or had incompatible dates for records in the linked data (eg, death before study entry), leaving n = 262,755 for analysis (Table 2) over an average of 2.8 years of follow-up between 2006 and 2010. At the area-level, the rate of FWE GPs ranged from 2.6 to 13.3 per 10,000 residents (Supplementary Figure 1, Supplemental Digital Content 1, http://links.lww.com/MLR/A897).

Of the study participants, n = 20,009 (7.6%) participants had a preventable hospitalization, with n = 14,525 having 1, n = 3425 having 2, and n = 2059 having 3 or more admissions, giving a total of 30,553 hospitalizations. More participants had preventable hospitalizations for chronic conditions than for acute or vaccine-preventable conditions (Table 3), and the mean number of admissions per admitted person was greater for the chronic than for the acute or vaccine-preventable conditions (mean of 1.6, 1.2, and 1.1 admissions/y, respectively).

There was significant variation between areas in the age-adjusted and sex-adjusted rate of preventable hospitalization ($\sigma^2 = 0.103$, $P < 0.001$). The amount of variation differed across major categories of conditions (Table 3), and was greater for admissions for vaccine-preventable ($\sigma^2 = 0.328$, $P = 0.003$), than for chronic ($\sigma^2 = 0.144$, $P < 0.001$) or acute ($\sigma^2 = 0.058$, $P < 0.001$) conditions, although vaccine-preventable conditions had a larger standard error due to the low number of events.

The inclusion of area-level FWE GPs in the model (Table 3) explained little of the area-level variation in preventable hospitalization (PCV = 2.9%), and the rate of preventable hospitalization was not significantly related to area-level quintiles of FWE GPs in either an age-sex adjusted model, or models further adjusted for personal sociodemographic or health characteristics (Fig. 1). Similarly, no clear trend was evident across major categories of preventable hospitalization (Fig. 1) and most individual conditions (Supplementary Figure 7, Supplemental Digital Content 1, http://links.lww.com/MLR/A897). There was an inverse association between quintiles of FWE GPs and the rate of hospitalizations for vaccine-preventable conditions (primarily influenza and pneumonia), and a higher rate of hospitalization in the upper quintiles for dental conditions, although CIs for these estimates were wide.

The addition of person-level sociodemographic characteristics to the model (Table 3) explained an additional 23.3% of area-level variation in preventable hospitalizations (PCV = 26.2%), whereas a further 13.6% was explained by the addition of person-level health and behavioral characteristics (PCV = 39.8%). Combined, these person-level characteristics explained 36.9% of the area-level variation in preventable hospitalizations, with this proportion being greater for admissions for chronic (37.5%) than for acute (15.5%) or vaccine-preventable (2.4%) conditions. Among individual causes, person-level characteristics explained the greatest area-level variation for chronic obstructive pulmonary disease (COPD) (44.8%), diabetes (25.6%), congestive cardiac failure (24.7%), and angina (22.2%), the 4 most common chronic causes of preventable admissions. However, small numbers of admissions for the less common causes limited the extent to which cause-specific comparisons could be drawn.

TABLE 3. Area-level Variance, σ^2, Across 199 Statistical Local Areas in Rate of Preventable Hospitalizations, and the Proportional Change in Area-level Variance (PCV)* Between an Age and Sex-adjusted Multilevel Poisson Model (Model 1) With Additional Models Sequentially Adjusted for General Practitioner Workforce Supply (Model 2), Sociodemographic Factors (Model 3), and Health and Behavioral Factors (Model 4)

				Area Level Variance σ^2, and SE of σ^2, in Adjusted Rate of Admission							
	Hospitalizations			Model 1	Model 2		Model 3		Model 4		
Category of Preventable Hospitalization	Total Admissions	Admitted Patients	Average # Admissions Per Patient	σ^2 (SE of σ^2)	σ^2 (SE of σ^2)	PCV (%)	σ^2 (SE of σ^2)	PCV (%)	σ^2 (SE of σ^2)	PCV (%)
Preventable hospitalization										
All preventable hospitalizations	30,553	20,009	1.5	0.103 (0.012)	0.100 (0.011)	2.9	0.076 (0.009)	26.2	0.062 (0.007)	39.8
Chronic conditions										
All chronic	20,022	12,297	1.6	0.144 (0.017)	0.139 (0.016)	3.5	0.105 (0.013)	27.1	0.085 (0.011)	41.0
Diabetes complications	7090	4291	1.7	0.227 (0.029)	0.219 (0.028)	3.5	0.179 (0.024)	21.1	0.161 (0.022)	29.1
Angina	4162	3375	1.2	0.126 (0.020)	0.125 (0.020)	0.8	0.107 (0.018)	15.1	0.097 (0.017)	23.0
COPD	3944	2109	1.9	0.299 (0.040)	0.273 (0.037)	8.7	0.176 (0.026)	41.1	0.139 (0.022)	53.5
Congestive cardiac failure	2893	2067	1.4	0.154 (0.026)	0.146 (0.025)	5.2	0.128 (0.022)	16.9	0.108 (0.020)	29.9
Iron deficiency anemia	1829	1445	1.3	0.252 (0.043)	0.246 (0.043)	2.4	0.237 (0.042)	6.0	0.239 (0.042)	5.2
Asthma	536	410	1.3	0.475 (0.101)	0.403 (0.091)	15.2	0.376 (0.088)	20.8	0.361 (0.085)	24.0
Hypertension	421	387	1.1	0.692 (0.139)	0.657 (0.135)	5.1	0.604 (0.128)	12.7	0.588 (0.125)	15.0
Rheumatic heart disease	99	89	1.1	—	—	—	—	—	—	—
Nutritional deficiencies	6	6	1.0	—	—	—	—	—	—	—
Acute conditions										
All acute	10,066	8591	1.2	0.058 (0.009)	0.057 (0.009)	1.7	0.052 (0.008)	10.3	0.048 (0.008)	17.2
Dehydration and gastroenteritis	2999	2794	1.1	0.119 (0.021)	0.117 (0.021)	1.7	0.110 (0.020)	7.6	0.105 (0.019)	11.8
Pyelonephritis	2328	2015	1.2	0.117 (0.023)	0.109 (0.022)	6.8	0.107 (0.021)	8.5	0.102 (0.021)	12.8
Cellulitis	1957	1612	1.2	0.138 (0.027)	0.132 (0.027)	4.3	0.138 (0.028)	0.0	0.150 (0.029)	−8.7
Dental conditions	1299	1210	1.1	0.335 (0.060)	0.302 (0.056)	9.9	0.278 (0.053)	17.0	0.274 (0.052)	18.2
Convulsions and epilepsy	563	429	1.3	0.212 (0.061)	0.202 (0.060)	4.7	0.170 (0.055)	19.8	0.171 (0.055)	19.3
Ear, nose, throat infections	390	380	1.0	0.395 (0.102)	0.357 (0.097)	9.6	0.339 (0.095)	14.2	0.328 (0.093)	17.0
Perforated/bleeding ulcer	242	232	1.0	—	—	—	—	—	—	—
Appendicitis	129	103	1.3	—	—	—	—	—	—	—
Pelvic inflammatory disease	90	86	1.0	—	—	—	—	—	—	—
Gangrene	72	72	1.0	—	—	—	—	—	—	—
Vaccine-preventable conditions										
All vaccine-preventable	570	508	1.1	0.328 (0.078)	0.296 (0.074)	9.8	0.292 (0.073)	11.0	0.288 (0.072)	12.2
Influenza and pneumonia	514	462	1.1	0.358 (0.086)	0.311 (0.080)	13.1	0.307 (0.079)	14.2	0.306 (0.079)	14.5
Other vaccine-preventable	57	47	1.2	—	—	—	—	—	—	—
"Nonpreventable" emergency										
All "nonpreventable"	75,421	45,282	1.7	0.095 (0.010)	0.093 (0.010)	2.1	0.073 (0.008)	23.2	0.068 (0.007)	28.4

*Proportional change in area-level variance σ^2 between Model 1 and subsequent models (Model n) calculated as $PCV = (\sigma^2_{(Model\ 1)} - \sigma^2_{(Model\ n)})/\sigma^2_{(Model\ 1)}$.
COPD indicates chronic obstructive pulmonary disease.

Most person-level variables in the fully adjusted model were found to be significant predictors of preventable hospitalization (Fig. 2). Overall, admission rates were highest for participants who were older, had poorer self-reported health, greater functional limitation, greater number of comorbidities, or were Aboriginal or Torres Strait Islander. Admission rates were lower for females, participants who were employed, had higher levels of income, or reported greater numbers of positive health behaviors. Predictors of admission differed slightly between the major categories of preventable hospitalization, with the higher rate of admissions associated with older age and poorer health being most pronounced for chronic conditions, and a slightly different pattern of association for acute admissions among females and participants who speak a language other than English at home.

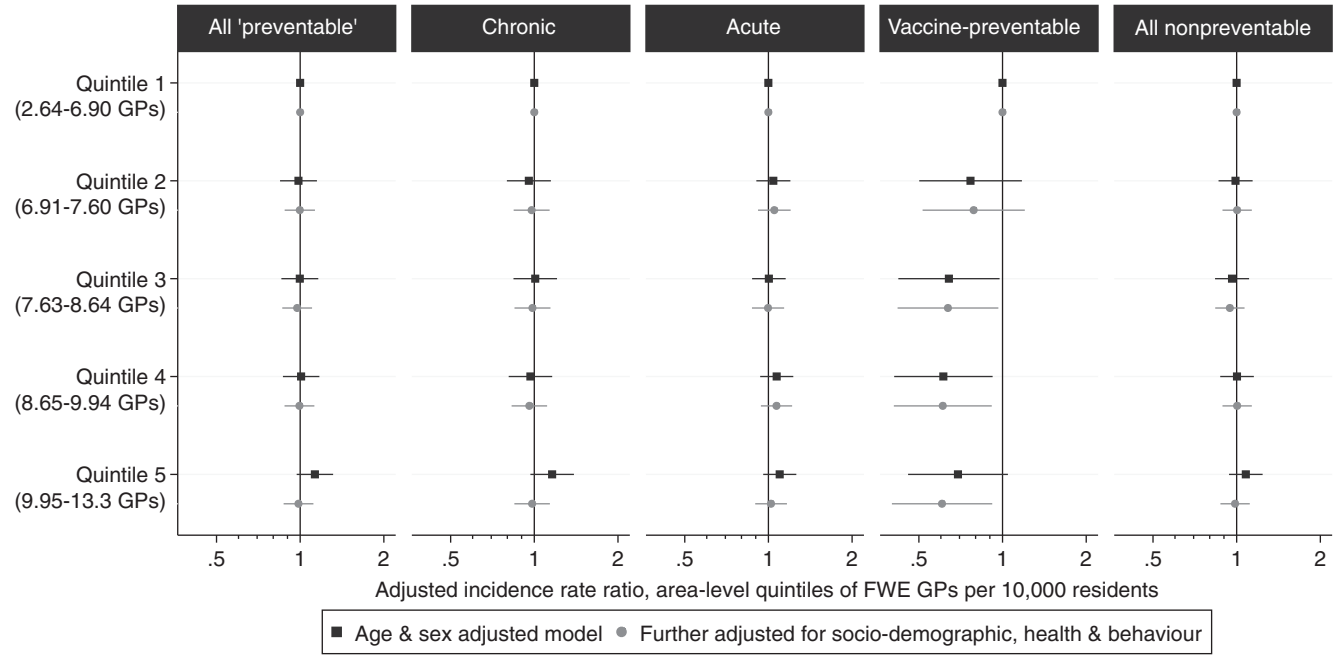

FIGURE 1. Association between quintiles of the density of full-time workload equivalent (FWE) general practitioners (GPs) per capita within Statistical Local Areas, with the rate of preventable and "nonpreventable" hospitalizations, from multilevel Poisson models adjusted for age and sex, and further adjusted for personal sociodemographic, health, and behavioral characteristics.

Study participants had 75,421 "nonpreventable" emergency hospitalizations during the corresponding period. There was a significant area-level variation in the rates of "nonpreventable" hospitalization ($\sigma^2 = 0.095$, $P < 0.001$), of which 2.1% was explained by the inclusion of FWE GPs in the model, and a further 26.3% by the sociodemographic, health, and behavioral characteristics of the population (Table 3). As for preventable hospitalizations, there was no significant association between the rates of "nonpreventable" hospitalization and the area-level quintile of FWE GPs (Fig. 1).

DISCUSSION

This study was the first to use detailed person-level data to assess how both the supply of GP services and the composition of the population influences geographic variation in preventable hospitalizations—a key consideration in the valid use of preventable hospitalizations as a health system performance indicator. We found that supply of GP services explained only a small amount (2.9%) of the geographic variation in rates of preventable hospitalization, and that these rates did not vary significantly according to quintiles of GP supply, but that more than one-third (36.9%) of geographic variation in preventable hospitalizations was driven by personal sociodemographic and health characteristics.

The lack of a significant association between the supply of GP services and preventable hospitalizations was unexpected, because much of the literature has demonstrated inverse associations.[7–9,40] However, results have been inconsistent,[19–21,28] and much of the research has used practitioner headcount measures or self-rated access to care rather than more objective measures of effective supply. Most of the existing research was performed in the United States with few studies in Australia.[11] Australia has a higher number of annual physician visits per capita (6.5) than the United States (3.9), United Kingdom (5.0), and Canada (5.5), with a "safety net" scheme to improve access to health care services for low-income groups, and targeted interventions to reduce health disparities for more vulnerable populations.[41] It may be that current strategies to improve access to GPs have been effective, with fewer barriers to accessing care than in countries such as the United States, and the use of primary care services in Australia may be more reflective of the underlying health need of the population. Although previous ecological-level research in Australia found an inverse association between full-time equivalent GPs and preventable hospitalizations,[11] this association disappeared after adjusting for sociodemographic and health characteristics of areas.

This study instead indicated that preventable hospitalizations may be more representative of gradients in health than in health care.[20] Prior research has found that up to half the variation in preventable hospitalization between areas was attributed to factors other than accessibility of primary care, such as sociodemographic, health, or hospital service factors,[11,15] although interpretation of these findings was limited by the use of aggregate area-level measures of risk exposure, or a small sample size for geographic areas. Many studies have adjusted for sociodemographic or health characteristics, and such adjustment is recommended for the standard reporting of the indicator.[42] This study shows that care should be taken to unpack, not just adjust for, the

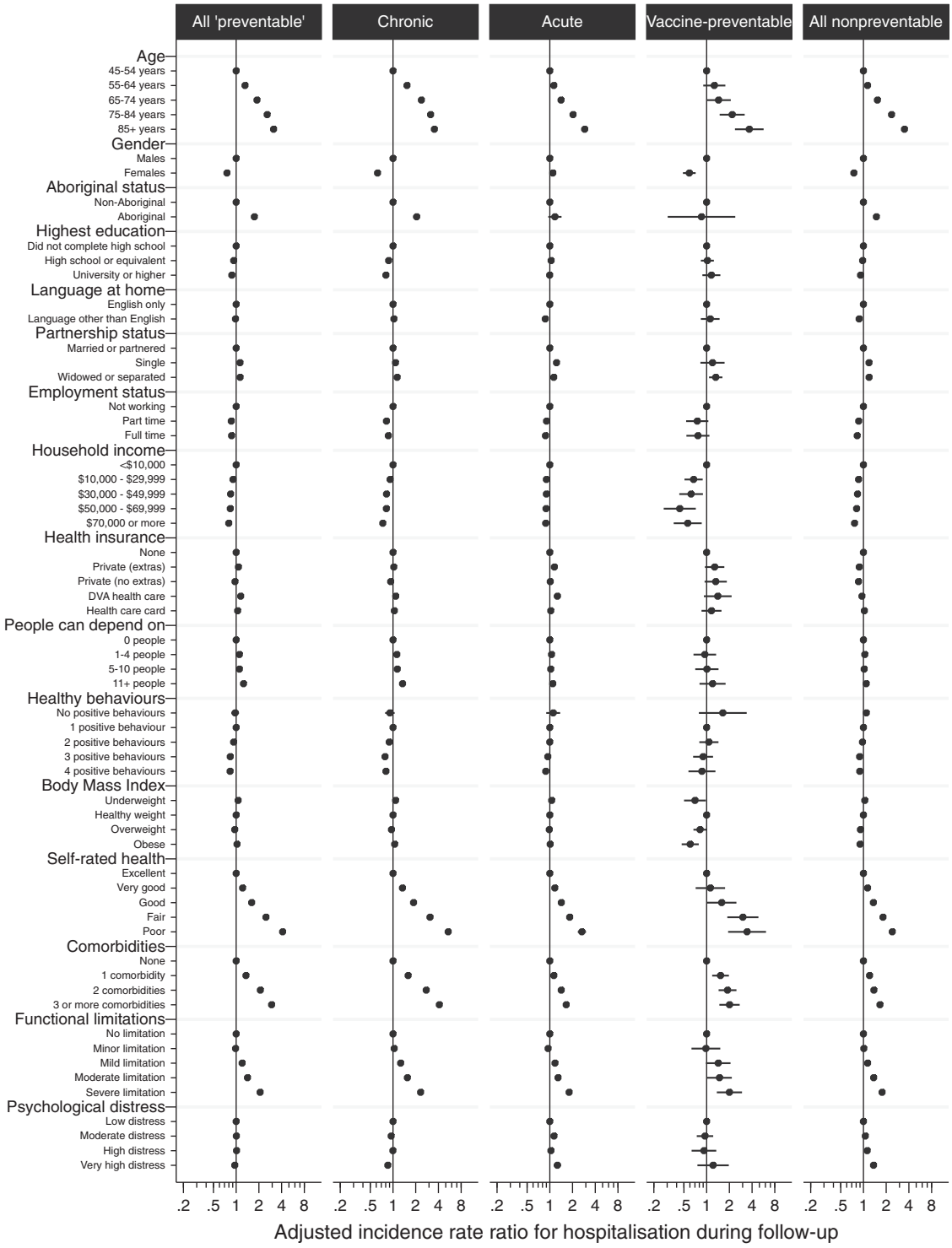

FIGURE 2. Incidence rate ratios for person-level predictors of preventable hospitalization, in multilevel Poisson models simultaneously adjusted for all person-level variables and area-level quintiles of full-time workload equivalent general practitioners.

contribution of these factors, as good performance measures should be both attributable and responsive to policy change,[16] and such adjustment may actually mask the most important drivers of admission.

Few prior studies have detailed person-level data with which to investigate person-level predictors of hospitalization,[23,24] with much of the evidence coming from aggregate ecological analyses or analyses on specific

conditions.[2,42,43] Our findings with regard to the demographic characteristics of the population are consistent with the literature, with higher rates of preventable hospitalization among men, older persons, and Aboriginal or Torres Strait Islander people.[23,43,44] Similarly, the inverse associations between markers of socioeconomic status—such as income, education, and employment—are consistent with strong associations reported in the literature, as are the higher rates among participants with poorer self-rated health, greater number of comorbidities, and higher levels of functional limitation.[2,23,43,45] Fewer studies have investigated the role of social support, health behaviors, and mental health, and the findings have been less consistent.[33,43,45]

Although it is well understood that chronic, acute, and vaccine-preventable conditions in the indicator relate to primary care in different ways,[2] only some reporting systems stratify their results accordingly.[3,6] It is argued there may be insufficient events to analyze conditions separately,[42] and that the use of condition-specific indicators can lead to "tunnel vision" with a concentration of performance efforts around those conditions being monitored.[27] This study found the contribution of various factors to geographic variation in preventable hospitalization varied markedly according to condition, and vaccine-preventable conditions alone appeared to have an inverse association with GP supply. Conversely, the high-volume chronic conditions—diabetes complications, COPD, congestive cardiac failure, and angina—were most strongly driven by the sociodemographic and health characteristics of the population. Our finding that area-level supply of primary care services and person-level sociodemographic factors made similar contributions to geographic variation in "preventable" and "nonpreventable" hospitalizations casts further doubt on the value of the aggregate indicator. Where possible we suggest that it is desirable to separate the indicator according to conditions that present different pathways for intervention.

Our findings do not downplay the potential role of primary care, and the broader health system, in reducing rates of unnecessary hospitalization for chronic conditions. However, they point to the need for further work to identify effective interventions and appropriate performance measures for these. Although social determinants of health may be targeted through long-term primary prevention, the responsiveness of these strategies may be low and influenced by factors outside of the health system. Admissions for chronic conditions may be more amenable to disease management and strategies to improve the quality of care, because multimorbid patients require complex case management, patient adherence to guidelines is often poor,[42] and medication-related hospitalizations for people with chronic disease are common.[46] Quality of care may also be improved by focussing on the primary care system more broadly, not just GP care, such as support of pharmacist and physician assistants for check-ups, diagnoses, and repeat prescriptions.[18]

The core strengths of this study include the availability of detailed person-level information with linked hospital admissions data, and the use of multilevel modelling to examine how population composition influences geographic variation in admission. Reliable area-level data that is representative of the population, such as disease prevalence, can be difficult to obtain,[47] and while a number of studies have had either detailed person-level data,[23,24] or used multilevel modelling to incorporate individual factors into small-area analyses of preventable admission,[7,27,28] this is the first study to our knowledge to incorporate both. This study is also one of the few to present results stratified by both major categories and individual conditions[6,11,15,20,42] that are included in the indicator. This is especially useful because a number of versions of the indicator have been used over time and in different jurisdictions,[6,48] hindering direct comparisons between these different aggregate indicators.

A limitation of this study is that participants in the 45 and Up Study are older and potentially healthier than the general population,[31] and given the low participation rate (18%) there may be concerns about generalizability. However, persons aged 45 years and above have the highest rate of preventable admissions per capita, and contribute two-thirds of preventable hospitalizations in Australia.[6] As it is a healthier cohort, participants may be more likely to access primary care services. However, internal relative risk estimates from the 45 and Up Study have found to be comparable with those from population health surveys,[49] and the large sample size provides substantial heterogeneity to allow for valid within-cohort comparisons.[50] Another potential limitation of the study was its reliance on the FWE GP measure as a sole measure of GP supply. However, the use of FWE GPs accounted for multiple worksites and differing caseloads of GPs in regional and rural areas, and is theoretically preferable to headcounts as a measure of realized access to primary care services.[18] The study was also unable to account for all potential drivers of admission, such as variations in hospital characteristics, which would require assigning potential pools of patients to their likely hospital(s) of admission.[51] Residual overdispersion in the model may have also resulted in less accurate variance estimates and CIs.

This study has confirmed that personal characteristics are major drivers of preventable hospitalization, and importantly, the contribution of these factors varies according to condition. In the Australian setting at least, variations in GP supply explain little of the geographic variation in rates of preventable hospitalization. Our findings suggest the need for caution in the international adoption of health system performance indicators that have largely been developed and tested within the US health care system. International comparative work using similar individual-level data and multilevel modelling methods will potentially shed light on how the use and interpretation of this performance indicator may vary across countries and according to health system characteristics.

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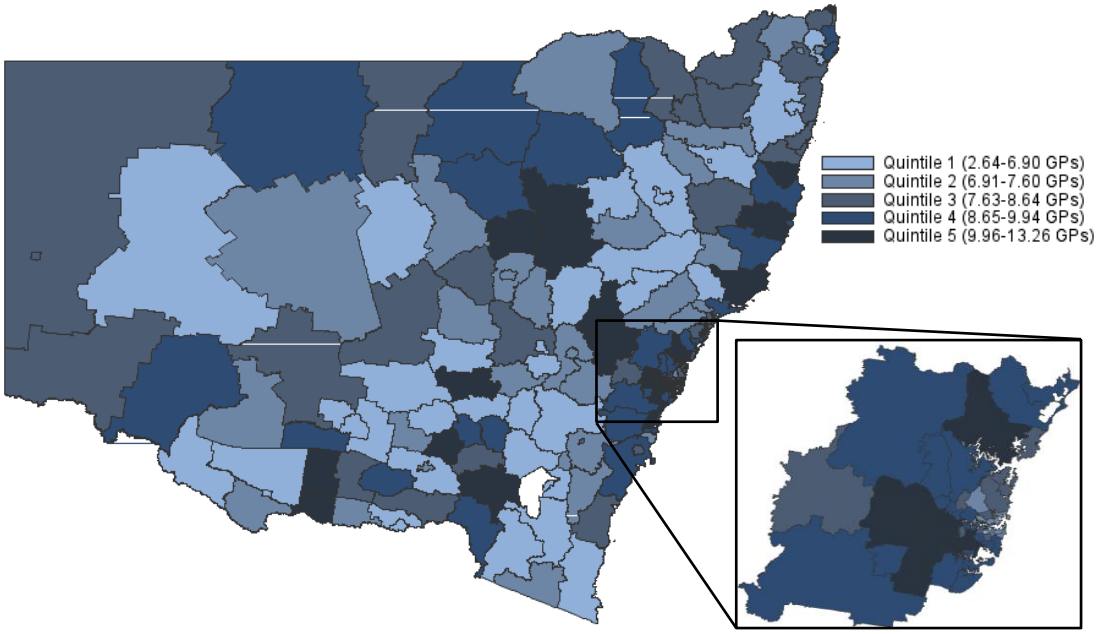
Supplementary Table 1: Conditions included in the Australian 2012 National Healthcare Agreement preventable hospitalisation indicator

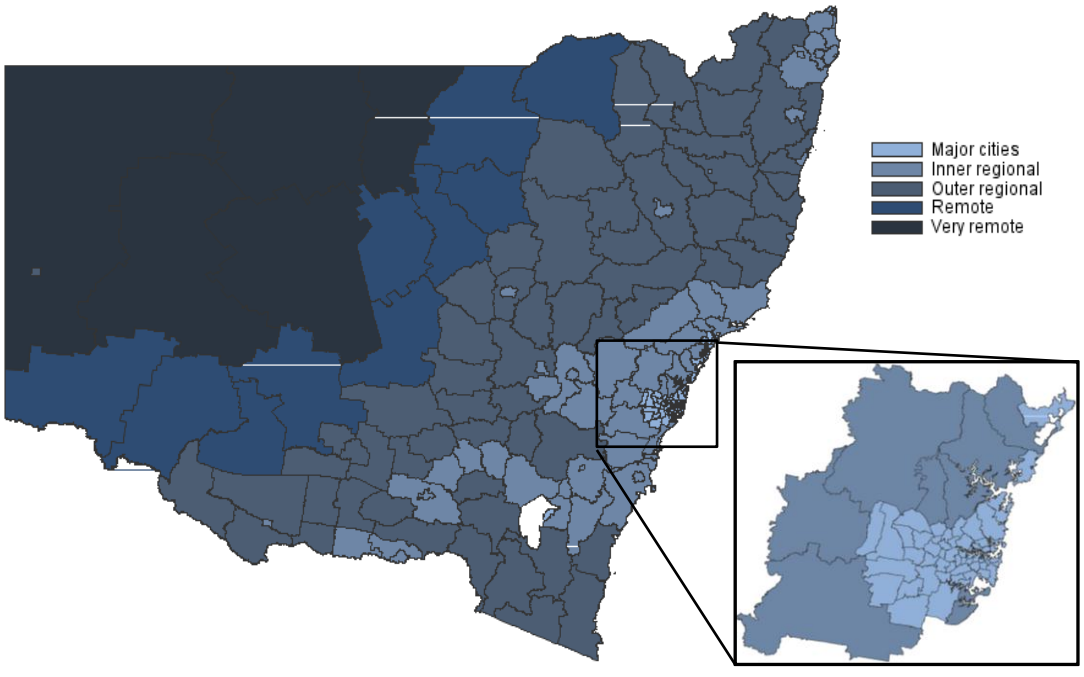
Category	ICD-10-AM diagnosis and procedure codes
Chronic	
Angina	I20, I24.0, I24.8, I24.9 as principal diagnosis only, exclude cases with procedure codes not in blocks [1820] to [2016]
Asthma	J45, J46 as principal diagnosis only
Chronic obstructive pulmonary disease (COPD)	J20, J41, J42, J43, J44, J47 as principal diagnosis only, J20 only with additional diagnoses of J41, J42, J43,J44, J47
Congestive cardiac failure	I50, I11.0, J81 as principal diagnosis only, exclude cases with the following procedure codes: 33172-00, 35304-00, 35305-00, 35310-02, 35310-00, 38281-11, 38281-07, 38278-01, 38278-00, 38281-02, 38281-01, 38281-00, 38256-00, 38278-03, 38284-00, 38284-02, 38521-09, 38270-01, 38456-19, 38456-15, 38456-12, 38456-11, 38456-10, 38456-07, 38456-01, 38470-00, 38475-00, 38480-02, 38480-01, 38480-00, 38488-06, 38488-04, 38489-04, 38488-02, 38489-03, 38487-00, 38489-02, 38488-00, 38489-00, 38490-00, 38493-00, 38497-04, 38497-03, 38497-02, 38497-01, 38497-00, 38500-00, 38503-00, 38505-00, 38521-04, 38606-00, 38612-00, 38615-00, 38653-00, 38700-02, 38700-00, 38739-00, 38742-02, 38742-00, 38745-00, 38751-02, 38751-00, 38757-02, 38757-01, 38757-00, 90204-00, 90205-00, 90219-00, 90224-00, 90214-00, 90214-02.
Diabetes complications	E10–E14.9 as principal diagnoses, and E10–E14.9 as additional diagnoses where the principal diagnosis was: hypersmolarity (E87.0), acidosis (E87.2), transient ischaemic attack (G45), nerve disorders and neuropathies (G50–G64), cataracts and lens disorders (H25–H28), retinal disorders (H30–H36), glaucoma (H40–H42), myocardial infarction (I21–I22), other coronary heart diseases (I20, I23–I25), heart failure (I50), stroke and sequelae (I60–I64, I69.0–I69.4), peripheral vascular disease (I70–I74), gingivitis and periodontal disease (K05), kidney diseases including end-stage renal disease (N00–N29), and renal dialysis (Z49)
Hypertension	I10, I11.9 as principal diagnosis only, exclude cases with procedure codes according to the list of procedures excluded from the Congestive cardiac failure category above.
Iron deficiency anaemia	D50.1, D50.8, D50.9 as principal diagnosis only.
Nutritional deficiencies	E40, E41, E42, E43, E55.0, E64.3 as principal diagnosis only.
Rheumatic heart disease	I00 to I09 as principal diagnosis only. (Note: includes acute rheumatic fever)
Acute	
Appendicitis with generalised peritonitis	K35.0 in any diagnosis field
Cellulitis	L03, L04, L08, L88, L98.0, L98.3 as principal diagnosis only, exclude cases with any procedure except those in blocks 1820 to 2016 or if procedure is 30216-02, 30676-00, 30223-02, 30064-00, 34527-01, 34527-00, 90661-00 and this is the only listed procedure
Convulsions and epilepsy	G40, G41, O15, R56 as principal diagnosis only
Dehydration and gastroenteritis	A09.9, E86, K52.2, K52.8, K52.9 as principal diagnosis only.
Dental conditions	K02, K03, K04, K05, K06, K08, K09.8, K09.9, K12, K13 as principal diagnosis only.
Ear, nose and throat infections	H66, H67, J02, J03, J06, J31.2 as principal diagnosis only.
Gangrene	R02 in any diagnosis field
Pelvic inflammatory disease	N70, N73, N74 as principal diagnosis only.
Perforated/bleeding ulcer	K25.0, K25.1, K25.2, K25.4, K25.5, K25.6, K26.0, K26.1, K26.2, K26.4, K26.5, K26.6, K27.0, K27.1, K27.2, K27.4, K27.5, K27.6, K28.0, K28.1, K28.2, K28.4, K28.5, K28.6 as principal diagnosis only.
Pyelonephritis	N10, N11, N12, N13.6, N39.0 as principal diagnosis only.
Vaccine-preventable	
Influenza and pneumonia	J10, J11, J13, J14, J15.3, J15.4, J15.7, J15.9, J16.8, J18.1, J18.8 in any diagnosis field, excludes cases with additional diagnosis of D57 (sickle-cell disorders) and people under 2 months
Other vaccine-preventable conditions	A35, A36, A37, A80, B05, B06, B16.1, B16.9, B18.0, B18.1, B26, G00.0, M01.4 in any diagnosis field

Supplementary Figure 1: Distribution of: (a) density of full time workload equivalent (FWE) general practitioners (GPs) per 10,000 residents across Statistical Local Areas (SLAs) in NSW. (b) Remoteness categories across SLAs in NSW, using remoteness categories from the Accessibility/Remoteness Index of Australia (ARIA+).

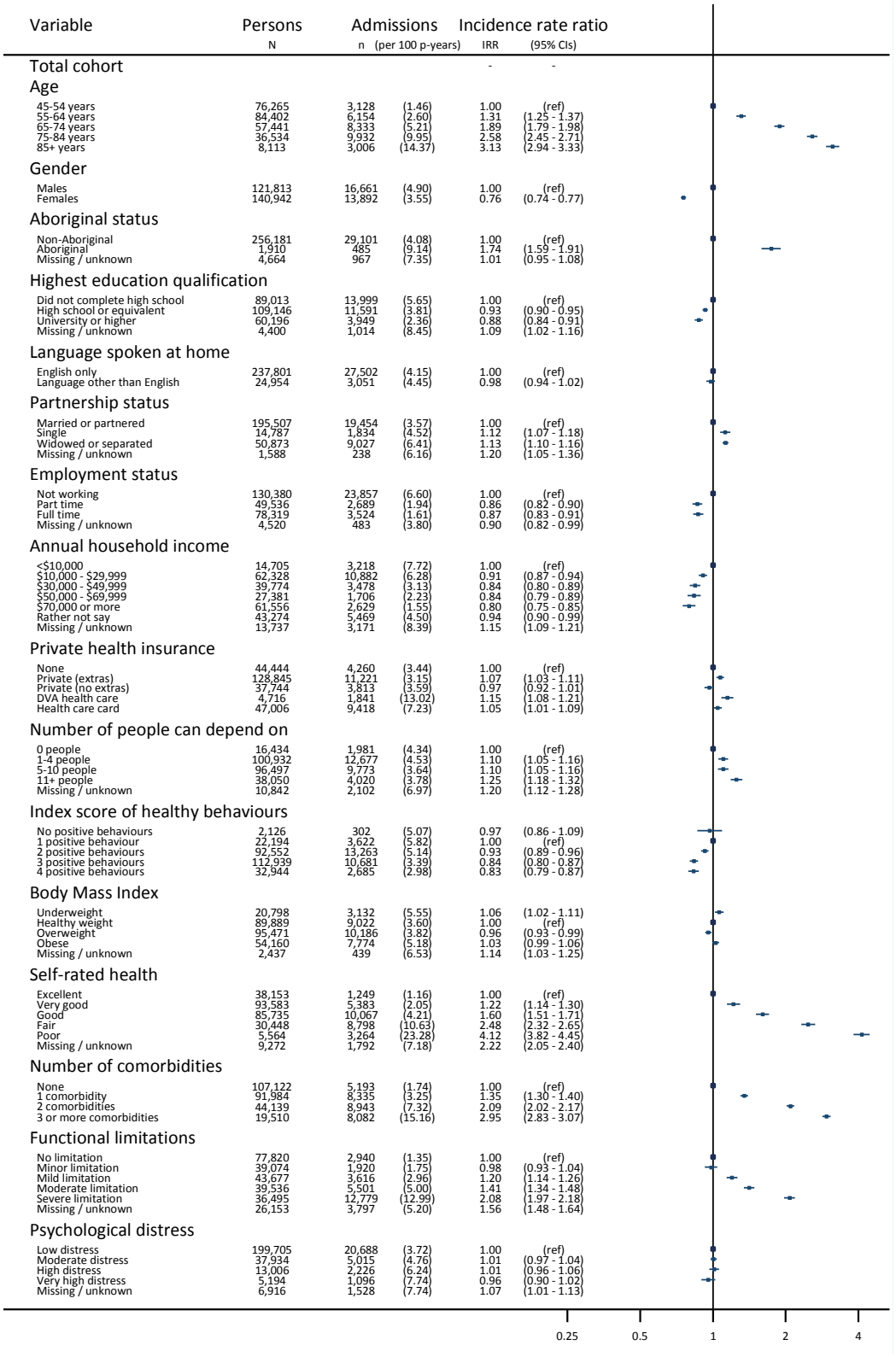
(a) Quintiles of the density of full time workload equivalent GPs per 10,000 residents



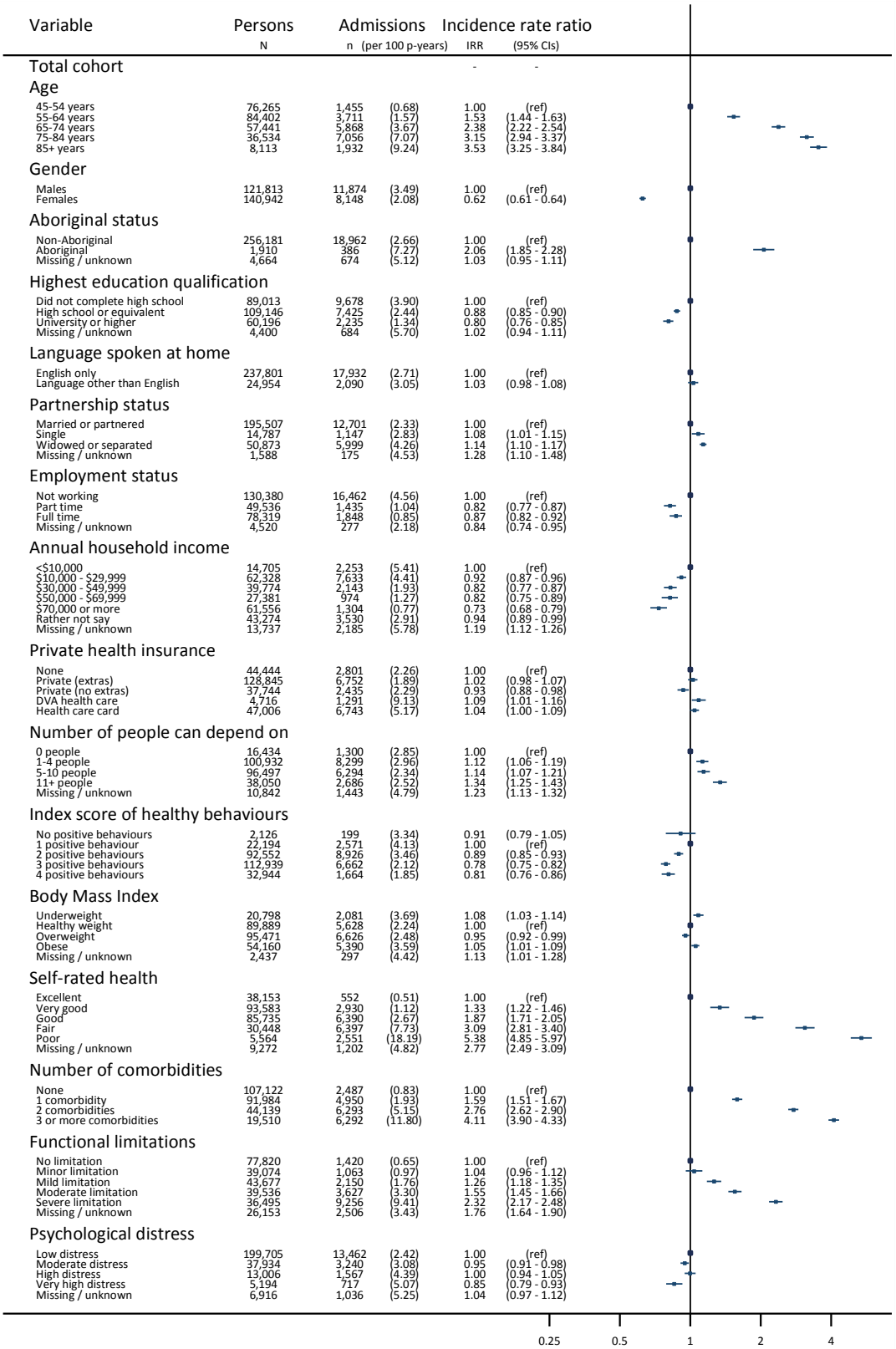
(b) Remoteness of area (ARIA+)



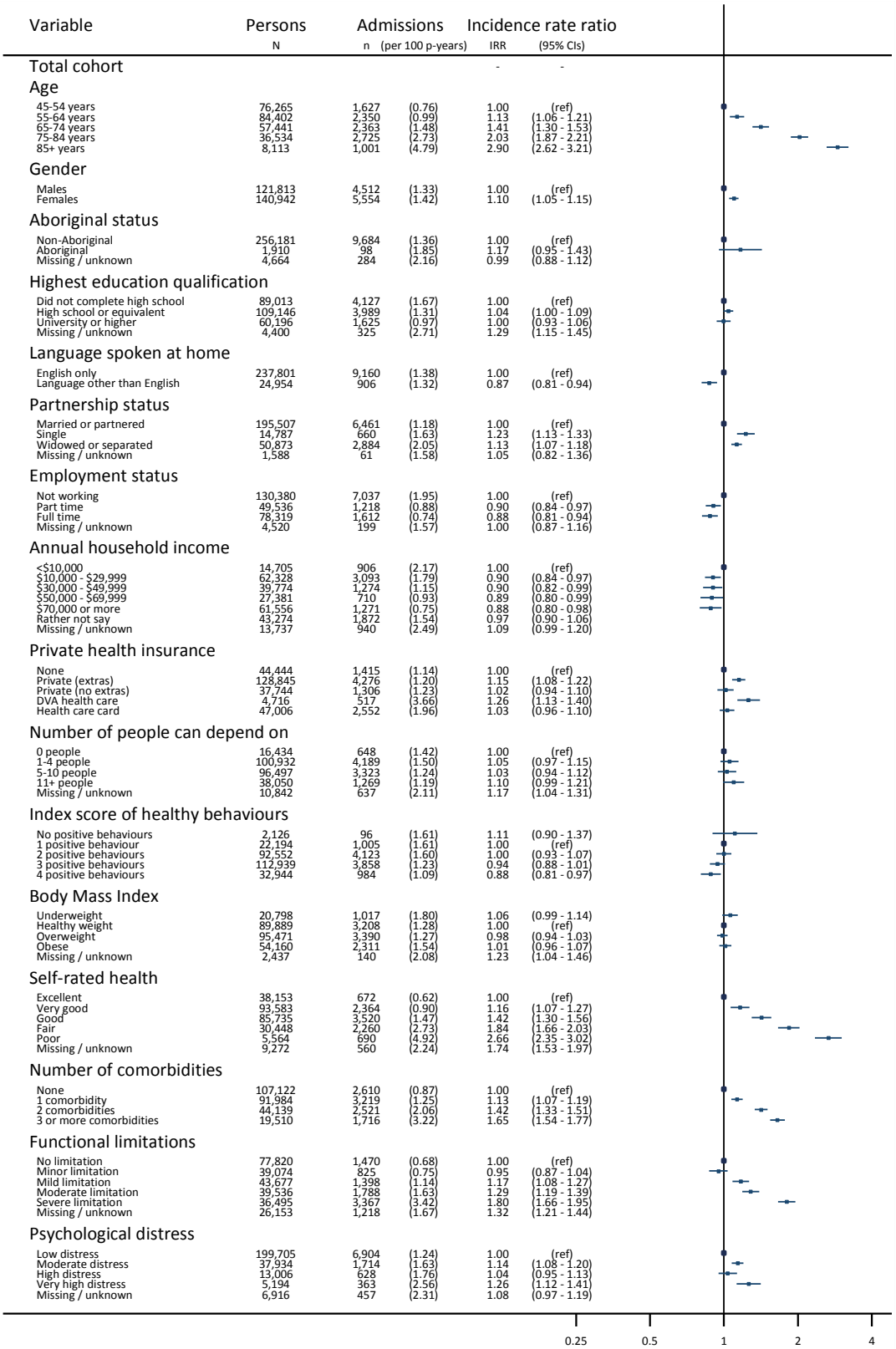
Supplementary Figure 2: Number of admissions and incidence rate ratios (IRRs) for person-level predictors of any preventable hospitalisation, in multilevel Poisson models simultaneously adjusted for all person-level variables and area-level quintiles of full time workload equivalent GPs



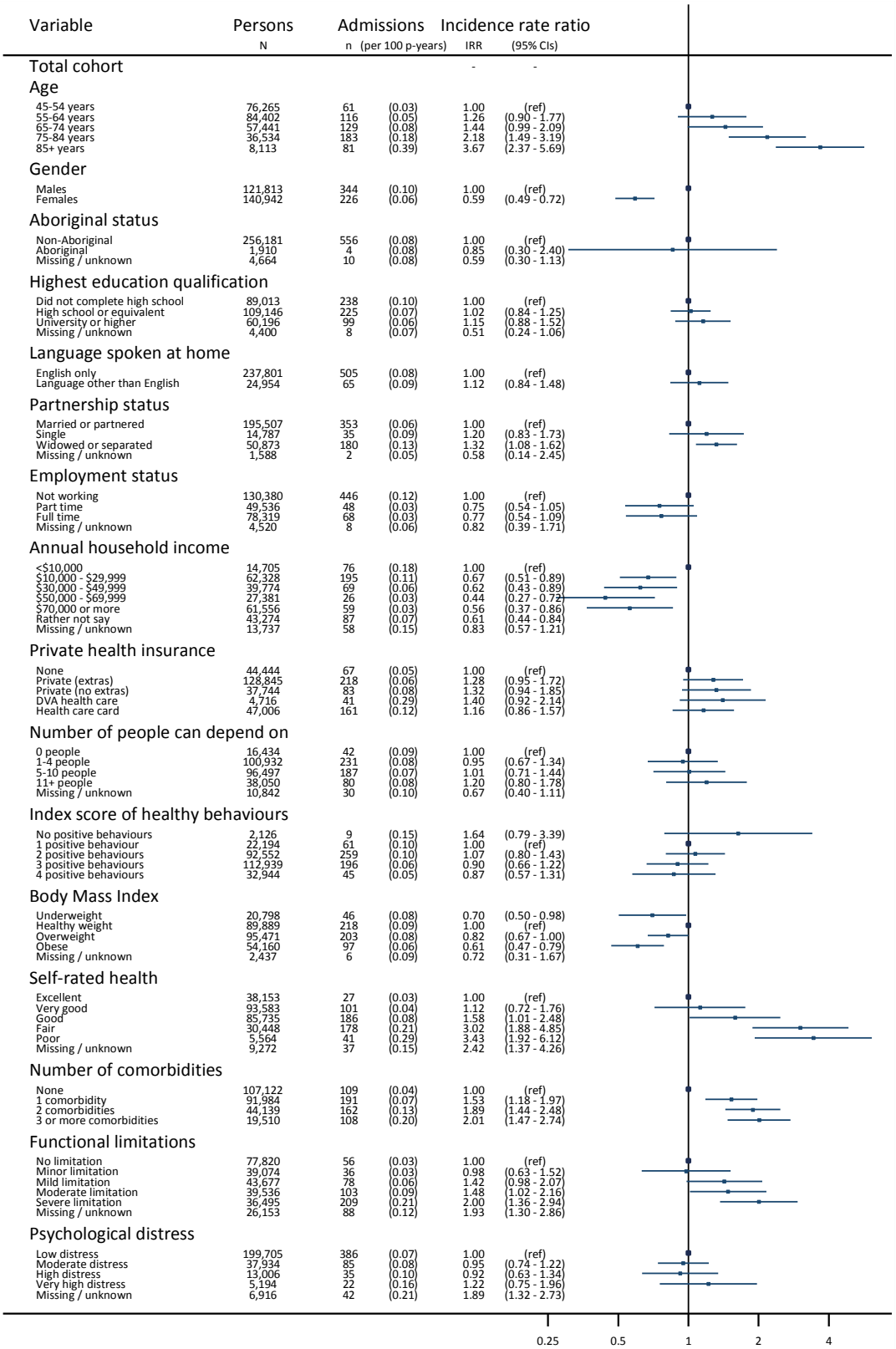
Supplementary Figure 3: Number of admissions and incidence rate ratios (IRRs) for person-level predictors of chronic preventable hospitalisations, in multilevel Poisson models simultaneously adjusted for all person-level variables and area-level quintiles of full time workload equivalent GPs



Supplementary Figure 4: Number of admissions and incidence rate ratios (IRRs) for person-level predictors of acute preventable hospitalisations, in multilevel Poisson models simultaneously adjusted for all person-level variables and area-level quintiles of full time workload equivalent GPs

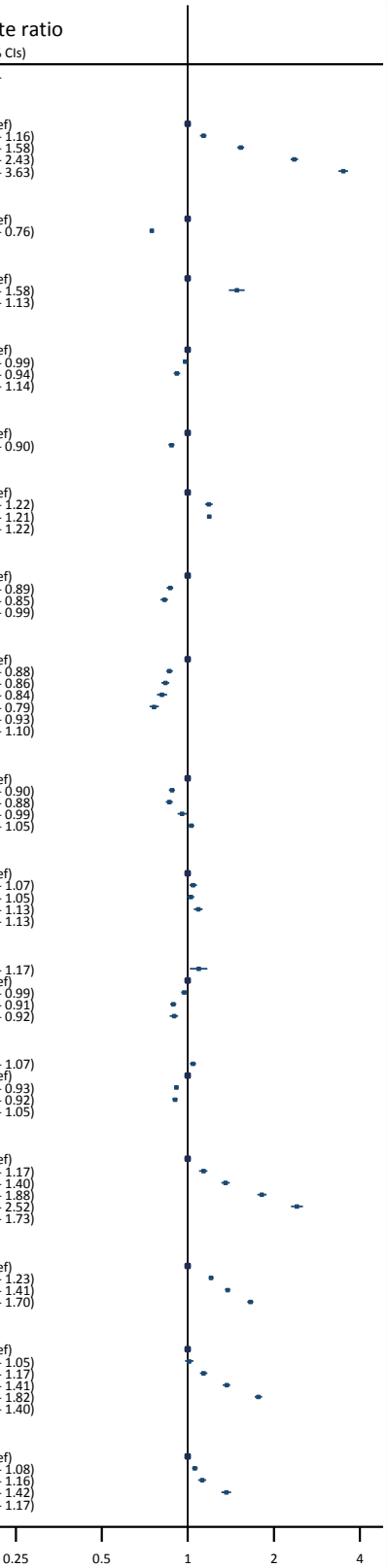


Supplementary Figure 5: Number of admissions and incidence rate ratios (IRRs) for person-level predictors of vaccine-preventable hospitalisations, in multilevel Poisson models simultaneously adjusted for all person-level variables and area-level quintiles of full time workload equivalent GPs



Supplementary Figure 6: Number of admissions and incidence rate ratios (IRRs) for person-level predictors of 'non-preventable' emergency hospitalisation, in multilevel Poisson models simultaneously adjusted for all person-level variables and area-level quintiles of full time workload equivalent GPs

Variable	Persons N	Admissions n	(per 100 p-years)	Incidence rate ratio IRR	(95% CIs)
Total cohort				-	-
Age					
45-54 years	76,265	10,323	(4.82)	1.00	(ref)
55-64 years	84,402	15,655	(6.63)	1.13	(1.10 - 1.16)
65-74 years	57,441	18,225	(11.40)	1.53	(1.49 - 1.58)
75-84 years	36,534	22,805	(22.85)	2.36	(2.29 - 2.43)
85+ years	8,113	8,413	(40.23)	3.50	(3.37 - 3.63)
Gender					
Males	121,813	40,362	(11.86)	1.00	(ref)
Females	140,942	35,059	(8.97)	0.75	(0.74 - 0.76)
Aboriginal status					
Non-Aboriginal	256,181	71,940	(10.10)	1.00	(ref)
Aboriginal	1,910	994	(18.73)	1.48	(1.39 - 1.58)
Missing / unknown	4,664	2,487	(18.91)	1.09	(1.04 - 1.13)
Highest education qualification					
Did not complete high school	89,013	32,867	(13.26)	1.00	(ref)
High school or equivalent	109,146	29,546	(9.72)	0.98	(0.96 - 0.99)
University or higher	60,196	10,585	(6.33)	0.92	(0.89 - 0.94)
Missing / unknown	4,400	2,423	(20.18)	1.10	(1.05 - 1.14)
Language spoken at home					
English only	237,801	68,236	(10.30)	1.00	(ref)
Language other than English	24,954	7,185	(10.47)	0.88	(0.86 - 0.90)
Partnership status					
Married or partnered	195,507	47,202	(8.65)	1.00	(ref)
Single	14,787	4,894	(12.06)	1.19	(1.15 - 1.22)
Widowed or separated	50,873	22,789	(16.18)	1.19	(1.17 - 1.21)
Missing / unknown	1,588	536	(13.88)	1.12	(1.03 - 1.22)
Employment status					
Not working	130,380	55,945	(15.49)	1.00	(ref)
Part time	49,536	7,770	(5.61)	0.87	(0.84 - 0.89)
Full time	78,319	10,362	(4.74)	0.83	(0.80 - 0.85)
Missing / unknown	4,520	1,344	(10.58)	0.94	(0.89 - 0.99)
Annual household income					
<$10,000	14,705	7,869	(18.88)	1.00	(ref)
$10,000 - $29,999	62,328	25,454	(14.69)	0.86	(0.84 - 0.88)
$30,000 - $49,999	39,774	9,064	(8.15)	0.84	(0.81 - 0.86)
$50,000 - $69,999	27,381	4,657	(6.08)	0.81	(0.78 - 0.84)
$70,000 or more	61,556	7,485	(4.43)	0.76	(0.73 - 0.79)
Rather not say	43,274	13,347	(10.99)	0.91	(0.88 - 0.93)
Missing / unknown	13,737	7,545	(19.96)	1.06	(1.03 - 1.10)
Private health insurance					
None	44,444	12,191	(9.85)	1.00	(ref)
Private (extras)	128,845	26,623	(7.47)	0.88	(0.86 - 0.90)
Private (no extras)	37,744	9,463	(8.92)	0.86	(0.84 - 0.88)
DVA health care	4,716	3,980	(28.16)	0.96	(0.92 - 0.99)
Health care card	47,006	23,164	(17.77)	1.03	(1.00 - 1.05)
Number of people can depend on					
0 people	16,434	5,211	(11.42)	1.00	(ref)
1-4 people	100,932	31,560	(11.27)	1.04	(1.01 - 1.07)
5-10 people	96,497	24,262	(9.03)	1.02	(0.99 - 1.05)
11+ people	38,050	9,404	(8.84)	1.09	(1.05 - 1.13)
Missing / unknown	10,842	4,984	(16.53)	1.09	(1.04 - 1.13)
Index score of healthy behaviours					
No positive behaviours	2,126	844	(14.16)	1.09	(1.02 - 1.17)
1 positive behaviour	22,194	8,432	(13.55)	1.00	(ref)
2 positive behaviours	92,552	31,769	(12.32)	0.97	(0.95 - 0.99)
3 positive behaviours	112,939	27,408	(8.71)	0.89	(0.87 - 0.91)
4 positive behaviours	32,944	6,968	(7.73)	0.89	(0.86 - 0.92)
Body Mass Index					
Underweight	20,798	7,977	(14.13)	1.04	(1.02 - 1.07)
Healthy weight	89,889	25,131	(10.02)	1.00	(ref)
Overweight	95,471	25,356	(9.50)	0.91	(0.90 - 0.93)
Obese	54,160	16,061	(10.70)	0.90	(0.88 - 0.92)
Missing / unknown	2,437	896	(13.32)	0.98	(0.92 - 1.05)
Self-rated health					
Excellent	38,153	4,621	(4.29)	1.00	(ref)
Very good	93,583	16,822	(6.41)	1.13	(1.10 - 1.17)
Good	85,735	26,065	(10.91)	1.35	(1.31 - 1.40)
Fair	30,448	18,233	(22.02)	1.81	(1.75 - 1.88)
Poor	5,564	5,333	(38.03)	2.41	(2.30 - 2.52)
Missing / unknown	9,272	4,347	(17.42)	1.65	(1.58 - 1.73)
Number of comorbidities					
None	107,122	18,293	(6.12)	1.00	(ref)
1 comorbidity	91,984	24,985	(9.74)	1.21	(1.18 - 1.23)
2 comorbidities	44,139	18,669	(15.28)	1.38	(1.35 - 1.41)
3 or more comorbidities	19,510	13,474	(25.27)	1.66	(1.61 - 1.70)
Functional limitations					
No limitation	77,820	9,927	(4.56)	1.00	(ref)
Minor limitation	39,074	6,084	(5.54)	1.01	(0.98 - 1.05)
Mild limitation	43,677	9,803	(8.02)	1.14	(1.10 - 1.17)
Moderate limitation	39,536	14,099	(12.82)	1.37	(1.33 - 1.41)
Severe limitation	36,495	25,819	(26.25)	1.76	(1.71 - 1.82)
Missing / unknown	26,153	9,689	(13.27)	1.36	(1.31 - 1.40)
Psychological distress					
Low distress	199,705	51,695	(9.29)	1.00	(ref)
Moderate distress	37,934	11,719	(11.13)	1.06	(1.04 - 1.08)
High distress	13,006	5,081	(14.25)	1.12	(1.09 - 1.16)
Very high distress	5,194	3,019	(21.33)	1.36	(1.31 - 1.42)
Missing / unknown	6,916	3,907	(19.79)	1.13	(1.09 - 1.17)



Supplementary Figure 7: Association between density of full time workload equivalent (FWE) general practitioners (GPs) per capita within Statistical Local Areas, with the rate of preventable and 'non-preventable' hospitalisations, from multilevel Poisson models adjusted for age and sex, and further adjusted for personal socio-demographic, health and behavioural characteristics.