Horizontal equity in the Australian healthcare system: Exploring the unknowns and updating the knowns

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Certificate of Authorship/Originality

I, Mohammad Habibullah Pulok, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy in Health Economics in the UTS Business School at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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List of Abbreviations

AATISH	Australian Aboriginal and Torres Strait Islander Health Survey
ABS	Australian Bureau of Statistics
AIHW	Australian Institute of Health and Welfare
BTOS	Broad type of services
BTOS	Broad type of services
CC	Concentration curve
CI	Concentration index
EI	Erreygers's index
FFS	Fee-for-service
GCI	Generalised concentration index
GDP	Gross domestic product
GP	General practitioner
HI	Horizontal Inequity
HILDA	Household, Income and Labour Dynamics in Australia
LTC	Long-term conditions
MBS	Medicare Benefit Schedule
NB	Negative binomial
NHS	National Health Survey
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary least square
OOP	Out-of-pocket
OR	Odds ratio
PBS	Pharmaceutical Benefits Scheme
PHI	Private health insurance
PHN	Primary health network
SAH	Self-assessed health
SDG	Sustainable development goal
SE	Standard error
SES	Socioeconomic status
UHC	Universal health coverage

UK	United Kingdom
USA	United States of America
WHO	World Health Organisation
WI	Wagstaff index

Abstract

Australia has a tax-funded universal health insurance system known as Medicare, which aims to ensure universal and equitable use of healthcare services. This thesis assesses the fairness of the Australian healthcare system in delivering healthcare services during the period of encouraging greater private healthcare financing. This thesis first measures the degree of horizontal inequity (unequal care for equal need) in eight indicators of healthcare use between 2011-12 and 2014-15. Secondly, it examines inequity in GP and specialist visit by making a distinction between the probability of visit and the conditional visit. Thirdly, this thesis investigates how co-payment is related to area-level socioeconomic inequality in Medicare-funded specialist care by using national administrative data. Finally, it measures and explains inequity in use of healthcare services within the non-remote Indigenous Australians.

The overall finding is that there was pro-rich inequity in use of out-of-hospital services while the utilisation of hospital-related services was almost equitable. There was a small degree of pro-rich inequity in the probability of GP visits, but significant pro-poor inequity in conditional visits to GP. On the contrary, there was considerable inequity in the probability of visiting a specialist favouring richer people. The distribution of conditional visits for this care was almost equitable, but it appears to be pro-rich when higher users were excluded from the analysis. Income, private health insurance, and education significantly accounted for pro-rich inequity while the contribution of concession card to inequity was pro-poor. The analysis of Medicare Benefit Schedule (MBS) data shows that inequality in specialist services was favourable to the individuals living in socioeconomically advantaged areas. Most importantly, this inequality was higher for visits with co-payment while there was almost no inequality in visits without co-payment. Finally, there was no evidence of inequity in the utilisation of GP services and inpatient admission within the Indigenous Australians. However, wealthier Indigenous Australians were higher users of specialist services than their poorer counterparts despite having similar levels of need. Pro-rich inequity in specialist services suggests the need for policy discussions to reform Medicare safety net arrangements so that poorer people have a chance to access larger benefits. Policy reforms should ensure that Medicare serves financially vulnerable and sicker people equitably.

Chapter 1: Introduction

1.1 Background

In general, Australians enjoy good health as marked by one of the highest life expectancies among the developed countries. For example, Australia was ranked sixth in the league table of life expectancy at birth among OECD countries in 2013 (OECD, 2015). In 2015, about 85% of Australian adults considered their health as ‘good’ or ‘better’ which placed Australia in fourth position among 34 OECD countries (AIHW, 2016a). The most recent global burden of disease study by Lim et al. (2016) placed Australia in the 10th position out of 188 countries for its overall performance in improving population health. Importantly, this high health performance is realised at a reasonable cost since Australia’s health expenditure as a percentage of gross domestic product (GDP) is close to the average of OECD countries (Duckett, 2018; OECD, 2016). The recent report by the Commonwealth Fund has ranked the Australian healthcare system as the second best among eleven developed countries (Schneider et al., 2017). This report has also recognised the healthcare system of Australia as the most efficient among these countries.

Overall progress is always desirable and welcomed, but the issue of achieving equity in health and healthcare is still an important concern for the Australian healthcare system. Like other developed countries, there is geographic and socioeconomic-related inequity in different indicators of health and healthcare in Australia (Thomas et al., 2015). For example, life expectancy is lower, while disease and injury rates are higher in rural and remote areas compared to the major cities (AIHW, 2016a). There is a wide gap in life expectancy between the Indigenous Australians and the rest of the Australian population. Indigenous people are more likely to experience disability and reduced quality of life due to ill health, and to die at younger ages than other Australians (AIHW 2013).

There exists inequality and inequity in use of and access to healthcare services. People living in rural and remote areas have less availability of healthcare services and less timely access to needed healthcare services compared to people from metropolitan areas (Turrell et al., 2008). In Australia, out-of-pocket costs (OOP) for using healthcare services is one the highest (20% of total health expenditure) among the OECD countries with similar economies, such as the United Kingdom (UK), the Netherlands, and New Zealand (OECD, 2015). This financial barrier excludes low income people from receiving needed healthcare services (Duckett et al., 2014). It is also worrying that OOP affects the most socioeconomically disadvantaged people who suffer from chronic conditions (Jan et al., 2012). It has been recently reported that Australia falls behind other developed countries in the equity domain of health system performance measurement (Schneider et al., 2017). Therefore, this PhD focuses on assessing the performance of the Australian healthcare system to achieve equity in healthcare service delivery.

1.2 Australian healthcare system

The health system of Australia shares many of features of other OECD health systems, however there are many dissimilarities which make the Australian system unique in the OECD. In Australia, healthcare expenditure accounted for more than 10% of the GDP in 2014-15 which is slightly above the OECD average (AIHW, 2016b). The system is characterised by a complex blend of funding mechanisms and service provision between the public and private sectors. Commonwealth and state/territory governments contribute around two-thirds of this expenditure while a significant proportion of health spending is financed from private sources (AIHW, 2016b). The contribution by individual Australians from their own pocket is about 20% of total expenditure (Duckett, 2018). About half of Australians purchase private health insurance (PHI), primarily used for private services in hospital.

Australia has a tax-funded universal health insurance system, commonly known as Medicare. Under Medicare, Australians are entitled to receive free treatment in public hospitals, subsidised out-of-hospital health services and prescription medicines at a discounted price (Duckett, 2004). Discounted payment on prescription medicines is available under the Pharmaceutical Benefit Scheme (PBS) of Medicare. In Australia, private medical professionals deliver primary care and specialist services in a fee-for-service environment where doctors can independently set their own fees (Johar et al., 2017). Patients usually get fixed rebates from Medicare for physician charges. Patients face an OOP cost for the service if the doctor’s fee is more than the rebate of the Medicare Benefits Schedule (MBS) set by the Australian Government. If the doctor accepts the Medicare rebate as the fee for the service provided, there is no gap payment for the patient. This practice is known as bulk-billing in Australia (Hua et al., 2017). The current system does not allow any insurance to cover the OOP cost for Medicare-funded out-of-hospital services (Wong & Hall 2018).

As private patients in public hospitals, Australians have the option to choose their doctors and avail themselves of extra services[1] (Cheng 2014; Stavrunova & Yerokhin 2014). In this case, Medicare covers 75% of the expenses of the inpatient services for the private patients in public hospitals and the rest could be covered by private health insurance and OOP. Medicare does not cover ancillary services such as dental care which are primarily financed by private sources of funding[2].

The goal of Medicare is to ensure affordable and equitable healthcare services to all Australians (Scotton & Deeble 1968). Medicare provided the same benefits for all Australians thus removing, or at least reducing the financial barriers to service use (Duckett, 2004). However, the achievement of Medicare as an equitable health delivery system is subject to question (Korda et al., 2009a; Leeder, 2003). There are some services (e.g. specialist care) where pro-rich inequity has always prevailed and this has not improved since the inception of Medicare in 1984 (Harris, 2012). The growing reliance on private sources of healthcare financing could be an indication of moving towards a less equitable healthcare system in Australia (Duckett et al., 2014; Hajizadeh et al., 2012).

1.3 Conceptual framework: Equity in healthcare as a performance indicator

Performance measurement of health systems is particularly important to evaluate how a health system meets the goal to improve the overall health of the population. There is an increasing pressure on health systems to improve their performance because of population ageing, growing prevalence of chronic diseases, progress of medical technologies, rising public expectations and rising expenditure in developed countries (Mcloughlin et al., 2001). Therefore, health system performance measurement has become a key policy issue in many OECD countries (Smith, 2002). In recent times, its importance has been also recognised among policymakers of many developing countries, which also strive to improve their health systems (Jacobs and El-Sadr, 2012; Kruk and Freedman, 2008).

[1] Private patients are those who declare to use their private health insurance in public hospitals, and it is not mandatory for private health insurance holders.
[2] The exception is teen dental service which is under Medicare coverage.

Generally speaking, health system performance measurement is a process to monitor, evaluate, and communicate the achievement of health system goals (Smith et al., 2009). Health system performance measurement offers a range of benefits to the key actors and stakeholders of the health system. For example, it enables patients to make informed choices about providers, and it helps providers to improve their service standards by comparing their performances against best practices. Performance measurement helps ensuring accountability and transparency in health system governance (Hurst and Jee-Hughes, 2001). Performance assessment provides an opportunity for policymakers to recognise existing problems and develop policies, plans or regulations to overcome those issues, and therefore to improve system performance (Smith et al., 2009).

Performance measurement can be undertaken at the international, national, regional, local or institutional level (Ibrahim, 2001). Many countries have developed and implemented their own national health performance frameworks. There are also two major international performance frameworks; the World Health Organisation (WHO) framework and the OECD framework. National frameworks are also developed to prioritise a country's own health system goals and objectives, while international frameworks focus on comparison of health systems' performance. These frameworks differ in terms of dimensions of performance, but the common goal is to improve the performance of the health system. However, indicators are needed to measure performance of the health system, and as a result, a wide range of indicators have been developed and reported to measure various dimensions of performance. This involves process indicators as well as outcome measures (Mant, 2001). Nevertheless, the central domains of health system performance frameworks are effectiveness, efficiency, and equity (Arah et al., 2003; Kruk and Freedman, 2008).

Improving the performance of health systems in terms of equity is well recognised in the policy agenda (Baum et al., 2009), and an equity-oriented health system can play a big role in achieving equity in health (Baum, 2016; Gwatkin et al., 2004). Therefore, equity is a key feature of a high performing health system. However, there is less consensus about establishing equity objectives of health systems even in the OECD countries (Hurst and Jee-Hughes, 2001). This is mainly because of the normative nature of equity as a health system goal. In this context, Wagstaff and van Doorslaer shared economists' perspectives as “while the question of what equity is all about is indeed a normative question, the questions of whether equity, defined in a specific sense, has been achieved, or has increased, or tends to be higher in one type of healthcare system than other, lie firmly within the realm of positive economics” (Wagstaff & van Doorslaer 2000a p.1805). This view has been echoed in an influential book by Evans et al. (2001a), as achieving equity requires *ethics to action*. Therefore, many performance frameworks now recognise quantifying of the level of inequity in health and healthcare as one of the main indicators of health system performance.

Despite varying degrees of ideological approach to measure equity among different countries, equity has been explicitly embodied in the policy documents of most OECD member states (Wagstaff and van Doorslaer, 2000a). Equity is now recognised as the fundamental principle of most OECD health systems and the Australian healthcare system is no exception. The Australian system has a three-tiered national health performance framework to report performance of health system at the national level. Tier three of this framework offers the conceptual basis for measuring health system performance against the stated goals. According to this framework, equity is one of the core elements across all three tiers against which performance should be evaluated. In the performance and accountability framework (PAF) of Australia, equity in access to and use of healthcare services is manifested as one of the key indicators to measure health system performance[3].

Equity in healthcare indicates the capacity of the health system to deliver comprehensive and high-quality services in an equitable way without the imposition of financial or other barriers. Equity objective is further distinguished between *horizontal equity*: equal treatment of equals, and *vertical equity*: appropriate unequal treatment of unequals. The OECD promotes horizontal equity in healthcare which requires *equal access* to healthcare services by everyone with *equal health need* regardless of the socioeconomic status (SES) (van Doorslaer et al., 2006). Horizontal equity in healthcare access has become a key indicator of the equity performance of healthcare systems in many OECD countries (Devaux and Looper, 2012). It compares how different health systems are performing in

[3] http://meteor.aihw.gov.au/content/index.phtml/itemId/554919

terms of equity in healthcare access. In general, horizontal equity in access to healthcare services in empirical studies is measured by the utilisation of healthcare services.

1.4 Research motivation and objectives

Horizontal equity or equal use of medical care services for equal need regardless of income or other socioeconomic characteristics is endorsed as the key policy objective in Australia like many other OECD countries. However, the complex funding arrangements and mixed provision of healthcare services makes it challenging to assess equity at a system level in Australia (Kelaher, Ferdinand & Taylor 2012). Existing literature in this area of research from Australia is coupled with several limitations. For example, previous studies have largely relied on National Health surveys and the findings are not regularly updated by applying recent methodological developments to measure and explain horizontal inequity. Identifying the factors contributing to inequity in healthcare use was only studied by van Doorslaer et al. (2008).

Australia is a geographically large and diverse country, but no existing study has examined of the regional or geographic variation in horizontal inequity of healthcare use. There are examples of studies from Canada which have examined provincial variation in horizontal inequity in healthcare use and these studies have provided important policy implications for a fairer healthcare system (Allin, 2008; Jiménez-Rubio et al., 2008). Regional variation of inequity was also studied in Finland to assess performance of health regions for equitable distribution of healthcare services (Lumme et al., 2008).

Understanding the extent of and reasons for horizontal inequity in the decisions to make an initial physician visit and subsequent visit could provide important insights for policy purposes (van Doorslaer et al., 2004a). However, horizontal inequity in this kind of decision-making process to visit medical professionals is yet to be studied in the Australian setting. This is mainly because of limited availability of data on healthcare utilisation. Also, there is no longitudinal study to provide a long run perspective of equity in healthcare use similar to those conducted in European countries by Bago d'Uva, Jones and van Doorslaer (2009). Additionally, there is no Australian literature which has examined inequity in use of healthcare services among the elderly population as in the UK, Europe, and the United States of America (US) by Allin, Masseria and Mossialos (2011, 2009). In Australia, inequity in use of healthcare services between the Indigenous and non-Indigenous population has been well studied, but there is no study to analyse horizontal inequity in healthcare utilisation within the Indigenous community in Australia.

Finally, and most importantly, the application of administrative data to study inequity in healthcare is limited in Australia. There is an increasing importance of using registry or administrative data for regular monitoring of equity of the health system in some countries like the UK and Finland. The Finnish National Institute for Health and Welfare is a notable example of a government agency which has been routinely reporting indictors of health equity using registered data for quite some time (Lumme et al., 2017). The importance of administrative data in developing equity indicators for healthcare services has also received increasing attention in Australia and Canada (Doiron et al., 2013; Olver, 2014). The limitations of the Australian literature discussed above thus suggest a need for a comprehensive assessment of inequity in healthcare utilisation. The specific aims of this thesis are to:

1) Present updated and extended empirical evidence on the extent of horizontal inequity in the utilisation of healthcare services.
2) Examine regional variation of horizontal inequity in healthcare use for performance measurement of states/territories in achieving equitable healthcare service delivery.
3) Investigate horizontal inequity in the two-stage decision process of physician visits.
4) Identify and explain the contributing factors of inequity in physician visits.
5) Demonstrate the importance and potential of using administrative data in the analysis of inequality and inequity in health services use.
6) Measure and explain horizontal inequity in healthcare use within the Indigenous Australian community.

Therefore, this thesis contributes to the current literature in this area of research by presenting a comprehensive evidence of how far the equity goal of Medicare is achieved in Australia. This thesis also aims to relate the current health policy context of Australia to the empirical results to highlight the implications of inequity in healthcare service delivery.

1.5 Thesis outline

The thesis consists of nine chapters. Chapters 2 to 4 reviews the concepts and theories, empirical method, and existing international and Australian literature. Chapters 5 to 9 present empirical analysis of inequity and inequality in healthcare use in Australia. Details of each chapter are given below:

Chapter 2 reviews fundamental and basic concepts in this area of research. Since equity in health is a widely debated concept, this chapter aims to understand a working definition of equity in relation to healthcare. This chapter further explains the difference between horizontal and vertical equity. The chapter also discusses the fundamental difference between access to and utilisation of healthcare services, and the implications for empirical research. The discussion in this chapter develops a conceptual foundation to advance the understanding of methodological approach taken in the latter chapters of this thesis.

Chapter 3 summarises the methodological developments, recent advances, and their implications to measure and explain horizontal inequity in healthcare use. This chapter first introduces the most widely used tool to measure inequalities in health and healthcare. The health economics approach of horizontal equity in healthcare use is then discussed in this chapter. It follows a discussion on the recent methodological debates and developments to examine inequity in healthcare use.

Chapter 4 reviews the empirical studies investigating inequity in healthcare use in Australia and other developed countries. The discussion in this chapter considers the existing studies which follow the methodological framework and recent developments outlined in Chapter 3. This chapter summarises the principal findings of international comparative empirical studies on horizontal equity in the delivery of healthcare from OECD countries. Australian empirical literature on the study and measurement of inequity in healthcare delivery is then reviewed in this chapter. This chapter also reviews the studies utilising administrative data to measure horizontal inequity in various contexts.

Chapter 5 addresses research goal one and two of this thesis. This chapter revisits and updates the existing empirical evidence on horizontal inequity in healthcare use in Australia. Data from the two recent National Health Surveys (NHS) of 2011-12 and 2014-15 are used in this chapter to measure the extent of horizontal inequity in eight indicators of healthcare service use. This chapter also examines the regional dimension of inequity by analysing state/territory-level variation of horizontal inequity in the utilisation of healthcare services.

Chapter 6 meets the third and fourth objectives of this thesis. This chapter extends the analysis of Chapter 5 to examine inequity in the decision-making process in out-of-hospital physician visits in Australia. The aim of this chapter is to provide an in-depth analysis of the current state of inequity in general practitioner (GP) and specialist visits in Australia. Inequity in the intensity of visit is measured by separating the decision to make an initial contact with the physician from the subsequent visit. The regression-based decomposition method is also applied to analyse how different determinants of doctor utilisation contribute to the observed horizontal inequity. The bootstrapped technique is used to give statistical inferences on the explanatory factors of inequity. In this way, this chapter addresses the limitations of Chapter 5 to offer a further assessment of inequity in medical professional visits and contributes to the existing literature from Australia.

Chapter 7 shows how national administrative data sources could be utilised to study inequality and inequity of the healthcare system of Australia. For this purpose, this chapter relies on unit record data from the Medicare Benefit Schedule (MBS) for the fiscal years of 2011-12 and 2014-15. This chapter particularly measures inequality in specialist services by area-level socioeconomic status. The contribution of this chapter is that it has studied inequality in specialist care by differentiating the services that incur out-of-pocket costs compared to those where there are zero costs to the patient.

Chapter 8 is specific to study horizontal inequity in healthcare utilisation within Indigenous Australians. Indigenous Australians should have higher access to healthcare services because of poorer health status compared to the general population (Mooney, 2003). Previous studies have documented that access to healthcare services by this group is low compared to other Australians (Kelaher et al., 2012). However, the 'closing the gap' initiative by the Australian Government has contributed to improvement of this situation in recent times. Despite this average improvement in access to healthcare services, inequity within the Indigenous Australians is still possible. Therefore, an examination of socioeconomic-related inequity in healthcare use within the Indigenous population would bear important implications for policy purposes. This chapter on the Indigenous Australians therefore measures and explains horizontal inequity in healthcare utilisation within the Indigenous community, drawing on data from the Australian Aboriginal and Torres Strait Islander Health Survey (AATSIHS), 2012-13.

Chapter 9 is the concluding chapter of this thesis. This chapter summarises the major findings from the empirical chapters and discusses some policy implications arising from the empirical analyses. This chapter also highlights the major contributions and limitations of this thesis. Finally, this chapter provides an agenda for a future avenue of research.

Chapter 2: Equity in healthcare: A conceptual review

2.1 Introduction

Equity is inherently a normative concept and it is challenging to find a single and agreed definition of equity. This is because of different philosophical standpoints on the definition of equity. Equity is concerned with ethics and human rights. It is a strongly value-laden idea founded in the doctrines of fairness and distributive justice (McCoy, 2003). There is an extensive literature in various disciplines such as economics, philosophy, psychology, and political science addressing the definition and understanding of the concept of equity. Therefore, there are also conflicting views which apply to health and healthcare. Competing theories of justice provide different notions of equity in health and healthcare. Measurement of equity entails a definition of equity, which implies normative judgements. The mammoth of existing literature on equity in health and healthcare indicates its critical importance in framing health policy. However, it carries different implications for different people in different contexts. Thus, the objective of this chapter is to review and discuss the fundamental concepts of equity in health and healthcare.

This chapter is organised as follows. The next section discusses why the definition of equity in health is widely debated and offers an overview of the common definitions of health equity. This is followed by a discussion on how the concept of equity in health is different from equality in health in section three. Section four presents the notion of equity in healthcare. The difference between horizontal and vertical equity in healthcare is explained in section five. The fundamental difference between access to and utilisation of healthcare services, and the implications for empirical research are provided in section six. The last section concludes to summarise the main discussions of this chapter.

2.2 Equity in health: The definition

Health equity is one of the most widely discussed issues in the public health and health policy domain of all countries with universal health coverage (UHC), or near to UHC seen as key to achieving it. Broadly speaking, equity is a normative concept which simply refers to fairness or social justice. According to the International Society for Equity in Health (ISEqH), health equity is “an ethical value, inherently normative, based on the principle of distributive justice and in line with the principles of human rights" (ISEqH, 2011). To date, equity in health has been a significantly researched topic in several disciplines ranging from economics to epidemiology. Nevertheless, it is not straightforward to define equity in health, "… because social justice and fairness can be interpreted differently by different people in different settings" (Braveman & Gruskin 2003, p.254). So, the notion of equity is widely debated and there is no universal definition of equity in health (Braveman, 2006).

Equity is like beauty, which is subject to the diverse interpretations and value judgment of the defining person (Le Grand, 1987a; Wagstaff et al., 1992). This disagreement on the definition of equity is perhaps because of different theoretical propositions of justice and fairness (Ataguba, 2012)[4]. As he noted, "different theories provide different ways of addressing the problem and there seems to be no consensus as to what a fair distribution might look like" (Ataguba 2012,p. 32). This chapter does not aim to counter this philosophical debate on the definition of equity as this domain of academic literature is already rich. An overview of the economics perspective on this discourse is nicely discussed in Ataguba (2012), Culyer (2001), Wagstaff and van Doorslaer (2000a), and Zamagni (1995). On the other hand, an application of a public health or health services research approach to relate major philosophical principles of equity to health and healthcare is also available in McGrail (2006) .

Equity in health has been defined in many ways. Braveman and her colleagues in a series of papers (Braveman 2014, 2012, 2006, 2003; Braveman et al. 2000; Braveman & Gruskin 2003), discussed the various dimensions of the different definitions of equity. Among these, the most influential, widely accepted and commonly cited definition of equity in health was given by Margaret Whitehead: "Equity in health implies that ideally everyone should have a fair opportunity to attain their full health potential and, more pragmatically, that none should be disadvantaged from achieving this potential, if it can be avoided" (Whitehead 1992, p. 433). Following this definition, Braveman and Gruskin (2003) provided a more operational definition of equity in health as "the absence of [significant, frequent or persistent] systematic disparities in health or in the major social

[4] These include the utilitarian, egalitarian, libertarian/entitlement, Rawls' maximin principle of justice and envy/no-envy principles.

determinants of health between groups with different levels of underlying social advantage/disadvantage" (Braveman & Gruskin 2003, p.254). It seems that this definition presents health equity as the absence of inequity.

The WHO has defined health equity as "the absence of avoidable or remediable differences among groups of people, whether those groups are defined socially, economically, demographically, or geographically" (WHO, 2011). In general, it can be summarised that equity in health does not necessarily indicate bringing everyone's health to the same level, but equity does require entitling everyone to obtain their full health potential.

2.3 Distinction between inequity and inequality

The terms 'equity (inequity)' and 'equality (inequality)' are often interchangeably used in health literature to denote fairness (unfairness). They are closely related but equity is not the same as equality (Culyer, 2007). Equity is about fairness, while equality is about similarity in a mathematical sense. Fairness indicates considering equals alike. So, equity requires equality, but it goes beyond equality. The distinction between inequality and inequity is not easy to uncover. As highlighted in Kawachi, Subramanian and Almeida-Filho (2002, p.648), "the crux of the distinction between equality and equity is that the identification of health inequities entails normative judgment premised upon (a) one's theories of justice; (b) one's theories of society; and (c) one's reasoning underlying the genesis of health inequalities".

Notwithstanding, it is important to understand this difference for practical (for example, measurement) and policy purposes. Whitehead defined health inequity as "differences in health that are not only unnecessary and avoidable but, in addition, are considered unfair and unjust" (Whitehead 1992, p.430). Variation in health status due to variation in biological or natural factors such as age or genetics is unavoidable; therefore, it is unfair to treat this variation in health as inequity. For example, younger adults are generally healthier than the elderly, and many women have obstetric problems that men do not suffer. Additionally, health differences due to individual free choice of a specific lifestyle (smoking or unhealthy food habits) are not unfair and unjust. On the other hand, health inequity can be defined as the variation in health due to unfair or unjust reasons. These differences are largely due to factors beyond the individual's control and are usually avoidable. For example, the prevalence of more premature deaths among children from low socioeconomic backgrounds compared to the rates in higher socioeconomic backgrounds is considered as inequity. The difference between inequality and inequity in health is nicely summarised by (Evans et al. 2001b, p.4) as “Inequalities in health describe the differences in health between groups independent of any assessment of fairness. Inequities refer to a subset of inequalities that are deemed unfair”. According to the WHO, “Health inequities entail a failure to avoid or overcome inequalities that infringe on fairness and human rights norms” (WHO, 2011). In this context, Braveman (2006) narrowed the definition of inequity in health as a “particular type of difference in health that can be shaped by policies”. In a nutshell, health inequities are policy amenable health differences across different population groups.

2.4 Equity in healthcare

Healthcare is one of the ways to improve and maintain health. Healthcare is markedly distinct from health where the former is the process and the latter is the outcome (Culyer, 2007). Equity in healthcare is one of the factors to promote equity in health (Culyer, 2001; Culyer & Wagstaff 1993). In terms of the definition, equity in healthcare follows as a similar proposition as equity in health. In a broader sense, equity in healthcare indicates the capacity of the health system to deliver comprehensive, high-quality services in an equitable way, without the imposition of financial or other barriers to receive care.

According to Whitehead, equity in healthcare is “equal access to available care for equal need, equal utilisation for equal need, and equal quality of care for all” (Whitehead 1992, p. 434). However, this definition does not include financing of healthcare payments which is an integral part of a health system (McGrail, 2007; van Doorslaer et al., 1993; Wagstaff et al., 1989). Therefore, equity in healthcare should encompass both access to healthcare and the financing of healthcare services. These are known as the twin principles of equity in healthcare, indicating fair allocation of resources and equitable access to healthcare services according to need. This approach should also ensure adherence to the ability to pay principle; payment for healthcare according to financial capability (assessing healthcare payment progressivity)[5]. This PhD emphasises the first principle, which is

[5] However, equity in healthcare financing should also consider the redistributive impact of healthcare payment on income or the fairness of health care payments (Wagstaff & van Doorslaer 2003, 2000a).

access to healthcare according to need, as healthcare financing is out of the scope of this thesis.

Like health inequity, inequity in healthcare is distinct from healthcare inequality. Inequality in healthcare measures differential access to healthcare without considering the need for healthcare. Equitable healthcare means healthcare need or capacity to benefit from healthcare services rather than the capability to pay should determine access to healthcare. The central point is that by examining differences in access to healthcare, one cannot immediately draw conclusions about equity. Inequity in healthcare indicates unfair or unjust inequality in healthcare. Some inequalities in healthcare access may be considered justified while others are not. For example, in high-income countries with universal health coverage, people from low socioeconomic backgrounds often make greater use of the healthcare services. However, this is largely due to their greater need. Obviously, such inequality in healthcare cannot be interpreted as inequity. This example suggests that the analysis of healthcare equity goes beyond analysis of inequality in healthcare. Therefore, equity in healthcare is achieved when need determines the allocation and use of healthcare services irrespective of other characteristics such as income, region, education, occupation etc.

2.5 Horizontal versus vertical equity in healthcare

Equity in health service provision indicates that access to or use of services follows the need for those services. According to Aristotelian principles of justice, equity is further distinguished between horizontal and vertical equity. Horizontal equity indicates considering individuals or groups equally who are equal in a relevant aspect. In vertical equity, individuals or groups are considered differently but proportionally, that is those who are different in a certain aspect. Culyer explained this difference as “horizontal equity is like treatment of like individuals and vertical equity is unlike treatment of unlike individuals, in proportion to the differences between them” (Culyer 2001, p.276). In healthcare, the horizontal equity principle requires everyone with a similar level of health need should have similar opportunity to access or use healthcare regardless of other characteristics (for example socioeconomic status, place of residence), while the vertical equity principle requires people with different levels of need should have different but appropriate opportunity to access healthcare (Culyer & Wagstaff 1993; Oliver & Mossialos 2004). The literature on equity in access to healthcare is primarily concerned with horizontal equity, whereas vertical equity is the central focus in equity of healthcare financing (Wagstaff & van Doorslaer, 2000a).

There is typically inequality in access to healthcare in relation to socioeconomic status and level of need. If access to healthcare by different groups in the population is in accordance with the differences in health need, the principle of equal access for equal need could be realised. To measure horizontal inequity in healthcare access, one seeks to establish whether there is differential access to healthcare by socioeconomic status (SES) after standardising for differences in the need for healthcare.

2.6 Access to healthcare: Utilisation or use as a measure of access

Apart from the social and economic determinants of health, timely and adequate access to healthcare is instrumental to optimise health. Equitable access to healthcare is one of the ways to reduce "potentially avoidable differences in health" (Braveman, 2006, p.180). Equity in access to healthcare is the central focus of the health system policy discussion, but the concept of access is often contested to define and operationalise (Gulliford et al., 2002; Oliver & Mossialos 2004). It is subject to diverse interpretations depending on the context (Goddard & Smith 2001). This makes the notion of access to health services complex and it has been subject to debate over the last four decades.

A range of definitions of access to healthcare is proposed in the literature of equity in healthcare. Access can be generalised as the interaction between individuals and the health system. A common definition of access is the availability of an appropriate opportunity to use health services. Mooney (1983) narrowly defined access as time spent and monetary expenses required to obtain healthcare. Although access is more often defined as a supply-side phenomenon, it is an array of both supply and demand-side aspects. Access to healthcare is indeed a multidimensional concept. Drawing from extensive literature on access, Evans, Hsu and Boerma (2013) identified three fundamental dimensions of access: availability, affordability and acceptability. These dimensions can influence the potential and actual access to the healthcare system. So, depending on the choice of focus, equity of access may be measured in terms of the availability, utilisation or outcomes of the services, including the quality (Gulliford et al., 2002) .

Many empirical studies claim to analyse equity in access to healthcare but result in employing utilisation of healthcare services as a measure of access (Goddard & Smith 2001). However, access to and use of healthcare services are not similar in terms of concept as well as measurement. Access to and the use or utilisation of healthcare services are often treated as similar. Despite a strong discourse about the notion of access, it is agreed in the literature that access is the same as use (Oliver & Mossialos 2004). Use of healthcare is often interpreted as a proof of access; access is the availability of opportunity to use healthcare services while use is the realisation of access. This whole issue has been widely debated in the literature in relation to equity and quality (Aday & Andersen 1981; Oliver & Mossialos 2004) as well as in relation to the measurement and operationalisation of the concept (Mooney et al. 1991, 1992; Culyer, van Doorslaer & Wagstaff 1992b, 1992a). Mooney et al. (1991, 1992) argued that empirical studies of equity in access to healthcare are misleading, as measurement of access is replaced by use or utilisation of healthcare services.

2.7 Conclusion

The importance of evaluating the performance of a health system in terms of equity has been in the spotlight for both policymakers and over the last two decades. This chapter has reviewed fundamental concepts of equity in health and healthcare which are important for the measurement of equity of health system. Although equity in health is an important goal, it is the outcome of many influences one of which is the contribution of healthcare. The health system should have the capacity to deliver comprehensive and high-quality services without financial or other barriers to use. This thesis will focus on equity in healthcare. The definition and measurement of access to healthcare is still subject to much debate in the literature. Most empirical applications avoid the difficulties in measuring access and take the pragmatic approach of measuring equality and equity in use of healthcare services. This approach as adopted in this thesis. Furthermore, there is a distinction between horizontal and vertical equity but this thesis, following the empirical work on this topic, focuses on horizontal equity. In sum, the thesis is focussed on measuring horizontal equity in the utilisation of healthcare services.

Chapter 3: Measuring inequity in healthcare: A review of methodological development

3.1 Introduction

Comprehensive assessment of the equity of any healthcare system requires examination and measurement of equity in: i) health; ii) healthcare delivery or use; and iii) healthcare financing. The empirical method for measuring and testing for inequity in health and healthcare is more or less analogous, while the analysis of inequity in healthcare financing and payment requires a broader welfare framework (van Doorslaer & van Ourti 2011)[6]. The contribution of non-economists in this field of literature is considerable, but health economists have contributed extensively in developing a methodological framework for empirical analysis (Wagstaff & van Doorslaer 2000a). The economic approach to dealing with equity in the health sector has advanced quantitative measurement tools, but this does not necessarily indicate economists' having the final say in the debate on equity in health and healthcare (Fleurbaey and Schokkaert, 2011).

This thesis is concerned with measuring horizontal inequity (HI) in healthcare service utilisation in the Australian healthcare system. The empirical analysis of HI in healthcare relies on testing the horizontal equity principle defined as "equal treatment for equal medical need, irrespective of other characteristics such as income, race, place of residence, etc."(van Doorslaer et al., 2000; Wagstaff et al., 1991b; Wagstaff and van Doorslaer, 2000b)[7].The HI approach has become the "workhorse" in health economics to study inequity in healthcare (Fleurbaey and Schokkaert, 2009). This method includes graphical presentation through the concentration curve (CC), the estimation of inequity indices through the concentration index (CI) and the explanation of inequity through

[6] Since equity in healthcare financing is beyond the scope of this thesis, this chapter presents an overview of the methodological developments for testing and measuring of inequity in the utilisation of healthcare services. A review of first generation literature on methods and empirics of equity in healthcare financing is discussed in Wagstaff and van Doorslaer (2000a). Ataguba (2012) reviewed recent methodological developments and empirical studies of equity in healthcare finance.

[7] Vertical equity principle is less discussed in literature without the exception in Sutton (2002) and Vallejo-Torres & Morris (2013).

decomposition analysis. In this approach, inequality in need-adjusted healthcare by socioeconomic status such as income is interpreted as HI, which could be pro-rich or pro-poor. The literature on horizontal inequity in healthcare has grown both in terms of theoretical and methodological developments and empirical applications in the last 30 years. Therefore, the aim of this chapter is to present an overview of the methodological developments and their implications in the assessment of horizontal equity in healthcare use.

The rest of the chapter is structured as follows. The next section sets out the background of this chapter by introducing the most widely used tool to measure health and healthcare inequity. Section three describes the economic approach to examining horizontal inequity in healthcare use builds on three steps: i) identification; ii) measurement; and iii) explanation. Methodological debates and developments to measure and explain HI in healthcare use in discussed in section four. The last section concludes the chapter by presenting a summary of the discussion.

3.2 Measurement of health and healthcare inequality

The method for measuring inequality in healthcare generally follows the measurement techniques of health inequality. Therefore, this section first presents how to measure inequality in health using a health economics approach[8]. The discussion in the previous chapter indicates the need to clearly differentiate inequity in health (unfair or illegitimate variation) from inequality in health (fair or legitimate variation) is comprehensively agreed in the literature. However, measuring inequality comes before measuring inequity as the former does not require any value judgment or normative position.

Wolfson and Rowe (2001) classified the literature of measuring health inequalities into two approaches: univariate and bivariate. The first one investigates total or overall inequality in health following the method of income inequality literature without considering other characteristics of individuals, while the second examines the variation in health across the distribution of another variable, specifically socioeconomic status, i.e. income (Wagstaff & Doorslaer 2004). Empirical studies (Le Grand 1987b, 1978;

[8] Mackenbach and Kunst (1997) presented an epidemiological overview of the available methods to quantify the magnitude of socioeconomic inequalities in health. A more recent review can be found in Regidor (2004a, 2004b).

Wagstaff & Doorslaer 2004) using the overall health inequality approach are limited while socioeconomic dimensions of health inequality are of great interest among the health economists (van Doorslaer & van Ourti 2011). However, the method to measure total health inequality works as the framework to measure socioeconomic-related inequality in health. The Gini health index and the concentration index are the two common measures of overall inequality and socioeconomic-related health inequality respectively in the literature. Therefore, the starting point is to present the measurement tools of total health inequality and socioeconomic health inequality.

3.2.1 The Gini health index and related health Lorenz curve

The analysis of total health inequality relies on measuring inequality by estimating the Gini index of health and presenting the associated health Lorenz curve. The contributions by economists to the empirical literature on the measurement of health inequalities are closely related to the development of rank-dependent measures in the income inequality literature (Bleichrodt &van Doorslaer 2006). The Lorenz curve and the Gini index were suggested by Le Grand (1989) for measuring total inequality in health.

The Gini index, developed by Gini in 1912, is the most widely used method of measuring inequality. It is derived from the Lorenz curve (Lorenz, 1905) which is a graphical representation of the distribution of specific variable within a population. Lorenz curve is a cumulative frequency curve that compares the distribution of a specific variable with the uniform distribution that stands for equality. In Figure 3.1, the health Lorenz curve, denoted by $L_h(p)$, is constructed by plotting the cumulative percentage of health in the vertical (y) axis against the cumulative percentage of the population ranked by health (moving from the sickest person to the healthiest person) in the horizontal (x) axis. The diagonal (45-degree) line stands for the line of perfect equality. Since the health variable is plotted on both axes, the health Lorenz curve cannot lie above the 45-degree line. This curve presents the distribution of health across the study population. In the case of no health inequality, the health Lorenz curve coincides with the line of equality. Otherwise, it lies below the diagonal. The larger the deviation of the Lorenz curve from the diagonal, the greater the extent of health inequality. In summary, the Lorenz curve is a univariate illustration of health inequality.

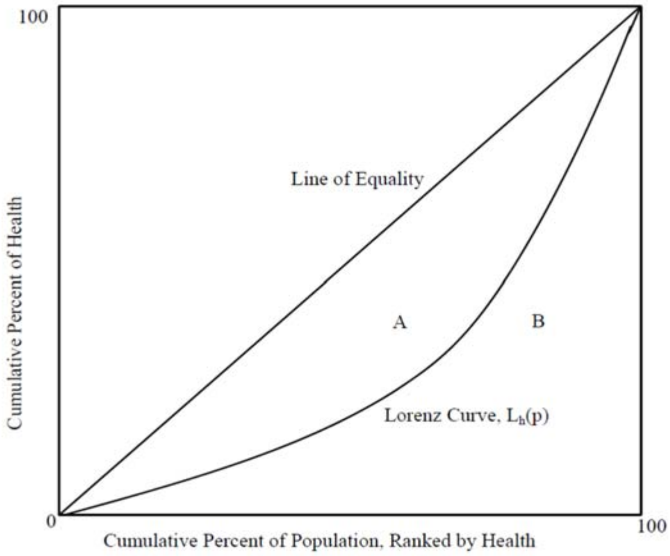

Figure 3.1: Example of health Lorenz curve

The health Gini index (G) is the summary measure of health inequality which quantifies health inequality derived from the health Lorenz curve. The health Gini coefficient is defined as the ratio of the area between the line of equality and the Lorenz curve to the total area of the triangle under the line of equality as presented in Figure 3.1. In other words, it is calculated as A/ (A + B). Since G is equivalent to twice the area between the health Lorenz curve and the 45-degree line, it could be alternatively calculated as one minus the area under the health Lorenz curve (the integration of area B). The formula to derive G can be expressed as below:

$$G = 1 - \int_0^1 L(P)dp \qquad (3.1)$$

The mathematical expression formulated in the following equation 3.2 can be used to estimate the health Gini index from micro or individual level data:

$$G = 1 - \frac{2}{n\mu}\sum_{i=1}^{n} h_i(1 - R_i^h) \qquad (3.2)$$

In the above equtation, n is the sample size within the population being analysed. The health indicator is h_i and the mean of the health variable is μ. $R_i^h = \frac{1}{n}$ denotes the fractional rank of the individual i in the health distribution. Individuals are ordered according to health ranging from i=1 (the sickest in the population) to i=n (the healthiest in the population). The health Gini coefficient ranges between 0 and 1 with a greater value representing a greater degree of total health inequality. A value of 0 indicates perfect health equality and 1 represents maximum health inequality (Wagstaff and Doorslaer, 2004). The health Gini inequality index measures relative inequality as it takes into account the entire distribution of the population. It allows health inequalities to be compared across time, different populations, countries or regions.

3.2.2 The concentration index and related concentration curve

The Gini index discussed above does not measure how health inequality is related to SES. For this reason, Wagstaff, van Doorslaer and Paci (1989) introduced the concentration index (CI) and its related concentration curve (CC) as the measurement of socioeconomic-related inequality in health and healthcare. The CI is computed in the same way as the Gini index, but it is a bivariate measure of the relationship between the distribution of health variable and an indicator of socioeconomic status (SES) such as income or education. In other words, health is used as both the dependant and ranking variable in the health Gini index, while SES is the ranking variable in the CI.

The CI is derived from a concentration curve in a similar fashion to the Gini coefficient from the Lorenz curve. However, the difference is that the ranking variable is a measure of socio-economic status in the CC instead of health as in the health Lorenz curve. Therefore, the CC is the extension of the Lorenz curve, which plots the cumulative share of health outcomes or healthcare use on the y-axis against the cumulative proportions of individuals in the population ranked from the lowest to the highest by income or other SES measure on the x-axis (Kakwani et al., 1997; Wagstaff et al., 1991a). Since the CC displays the bivariate relationship between a health indicator and an indicator of socioeconomic position such as income, it could lie above or below the line of equality. The CC of a healthcare variable beneath the line of equality indicates a pro-rich distribution of that health indicator and vice-versa. Therefore, income-related inequality in healthcare could be either pro-rich or pro-poor. The further the CC from the diagonal or 45-degree line, the greater the degree of inequality by income in the underlying health sector variable. Figure 3.2 is a graphical representation of the CCs of GP and specialist visits. Inequality in GP visits is biased toward poorer people as the CC is above the line of equality, while the opposite explanation applies to specialist visits.

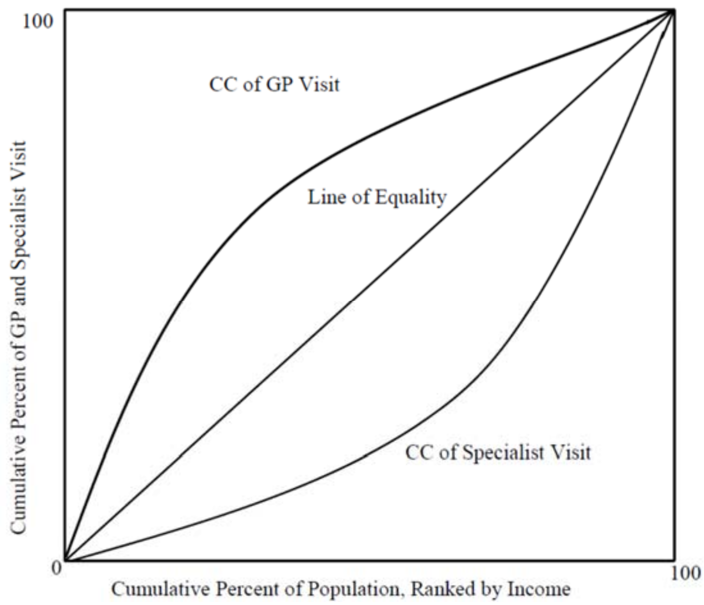

Figure 3.2: Example of the concentration curve of healthcare service use

The CC can be depicted using individual-level data in which data for the health variable and socioeconomic ranking is available for each individual as well as using grouped data in which, for each socioeconomic strata (e.g. income quintile), the average of the health variable is observed (O'Donnell et al., 2008). The CC allows us to compare inequality of a particular health sector variable across countries/regions or over time as well as to assess differences in inequality for different health indicators for the same country and time (O'Donnell et al., 2008). For example, the CC could be used to present whether specialist care is more unequally distributed than inpatient care. Again, the trend in inequality of GP visits over time for a specific country could be depicted using this graphical method.

The statistical difference between the CC and line of equality or the differences between two CCs could be examined following the method of dominance test. The statistical dominance could be performed using the multiple comparison approach (m.c.a.) and the intersection union principal (i.u.p.) of dominance testing as shown by O'Donnell et al. (2008). The first method signifies statistical dominance if there is even one significant difference between curves in one direction and none in the other direction and corrects for multiple comparisons. On the hand, the i.u.p. approach concludes dominance only if there are significant differences at all points. Curves are said to be crossed if one curve lies significantly above the other at one point and vice versa.

Although the CC is an attractive way to visualise inequality in the health variable related to income, it does not quantify the size of the inequality. In this case, the CI estimates how unequally the healthcare variable is distributed across the entire income distribution. The CI could be calculated as twice the area between the CC and the 45-degree line. There are various mathematical representations of the CI, but the following expression is the most common in the literature:

$$CI = 1 - 2\int_0^1 L_h(p)dp \qquad (3.3)$$

This index varies between −1 and +1 since it is a bivariate index of the relationship between healthcare use and the ranking variable as income in this case. A zero value indicates that the healthcare variable is equally distributed across the income distribution and the CC overlaps the line of equality (Wagstaff et al., 1991a). The higher the absolute value of the CI, the higher the level of inequality. When the CC is above the 45-degree line, the CI takes a negative value to indicate pro-poor distribution of the healthcare variable. A positive value of the CI indicates pro-rich distribution, and the CC is below the line of equality. The CI could also be defined using the following convenient formula, which is in fact the covariance between the healthcare variable and the fractional rank in the income distribution:

$$CI = \frac{2}{\mu}\text{cov}(h,r) \qquad (3.4)$$

In this expression, h is the healthcare indicator, r is the fractional rank and μ is the mean of health. When individual-level data is available, the above expression to estimate the CI can be formulated as below:

$$CI = 1 - \frac{2}{n\mu}\sum_{i=1}^{n} h_i(1 - R_i) \qquad (3.5)$$

In equation 3.5, μ is the average of health variable and n is the number of individuals (sample size). This is analogous to the estimation of the Gini index, but the ranking is now $R_i = \frac{1}{n}$ which stands for the fractional rank of the individual in the income distribution. Individuals are ranked from $i=1$ (the lowest in the income distribution) to $i=n$ (the highest in the income distribution).

Equation 3.5 shows that the estimation of the CI rests on the covariance between h_i and R_i. Therefore, the CI is a rank-dependent index of income-related inequality in healthcare because it is derived from the bivariate relationship between healthcare and ranking of the individual (not income itself, it is the order of the individual in the distribution by income). An estimate of the CI could be obtained by running a 'convenient regression' of the transformation of the healthcare variable on the fractional rank (Kakwani et al. 1997). This is expressed in equation 3.6 as follows:

$$2\sigma_R^2\left(\frac{h_i}{\mu}\right) = \alpha + \beta R_i + \varepsilon_i \qquad (3.6)$$

Where σ_R^2 is the variance of R_i. The ordinary least square (OLS) estimate β coefficient from the above regression gives the estimate of the CI. This way to estimate the CI is more convenient for statistical inferences. Standard errors of the CI could be derived using the delta method to test the statistical significance of the CI (Kakwani et al., 1997). O'Donnell et al. (2008) extended this approach to allow for sampling variability of the mean and to adjust for sample weights and cluster design of the survey. There is also application of bootstrapping techniques in the literature to derive standard errors around the CI.

By reviewing the properties of alternative measures of inequality in health or healthcare, Wagstaff, Paci and van Doorslaer (1991) proposed the CI as the best among the available measures of socioeconomic-related inequality. Their main argument in favour of the CI is that it takes into account the information from the entire socioeconomic distribution rather than the two extremes. The CI is also sensitive to changes in the distribution of the underlying socioeconomic ranking variable across the entire population. It has the additional advantage of graphical representation of socioeconomic inequality in health using the concentration curve. Wagstaff (2002) provided further extension of the CI to account for different levels of inequality aversion and the mean level of health. Finally, the index can be decomposed to explain the contribution of different factors to the observed inequality (Wagstaff et al., 2003).

3.3 Measuring and explaining horizontal inequity in healthcare use

The health economics literature clearly distinguishes between measuring inequality and inequity in healthcare use (Wagstaff & van Doorslaer 2000a). Inequality is a descriptive form of observed differences while inequity is the differences that are unfair or unjust. The discussion in the previous section focuses on methods to measure inequality in health or utilisation of healthcare services. The analysis of equity in healthcare is mainly concerned with the horizontal equity principle[9], defined as “equal treatment for equal medical need, irrespective of other characteristics such as income, race, place of residence, etc.” (van Doorslaer et al. 2000; Wagstaff et al. 1991b; Wagstaff & van Doorslaer 2000b). The CI of healthcare use measures the extent of inequality related to income, but it does not measure the degree of inequity. Measuring income-related inequality in healthcare use is not enough to assess the equity performance of the healthcare system (van Doorslaer & van Ourti 2011). This section discusses the methods measuring inequity in healthcare use. The section first outlines the regression method to identify the existence of horizontal inequity. The concentration index approach to quantify the degree of inequity is then discussed. Finally, the decomposition technique is presented to explain the contributing factors of horizontal inequity in healthcare use.

3.3.1 Identifying inequity: The regression approach

The regression method tests for inequity by examining the variation in healthcare use by socioeconomic status holding healthcare need and demographic factors constant. Wagstaff, van Doorslaer and Paci (1991) formalised this approach in the health economics literature. Let us assume that there are two socioeconomic groups, rich and poor, and their need for healthcare is measured in terms of two illness categories, sick and non-sick. Following Wagstaff and van Doorslaer (2000a), a model of healthcare utilisation could be estimated as:

$$y_i = \beta_0 + \beta_1 h_i + \beta_2 x_i + \beta_3 h_i x_i + \varepsilon_i \qquad (3.7)$$

Where y_i denotes healthcare use by the ith individual, h_i is a dummy variable of healthcare need (health status) taking a value of 1 if the individual is sick and 0 otherwise, and x_i stands for socioeconomic status with dichotomized values of 0= poor and 1= rich. In case of no inequity, healthcare use would only vary with health status h_i. Inequity be could identified by testing the null hypothesis of $H_0 : \beta_2 = 0$ and $\beta_3 = 0$. A rejection of this hypothesis indicates inequity in healthcare use which is unfair. This model could be extended by including other non-need variables interacting with SES (x_i) and it does not necessarily depend of the categorical measure of SES.

[9] Vertical equity principle is less discussed in literature with the exception of Vallejo-Torres and Morris (2013).

3.3.2 Measuring inequity: The concentration index approach

The method discussed in the previous section allows to identify inequity in healthcare use, but it does not quantify inequity into a single measure. Therefore, the next step in the analysis of the horizontal equity principle of "equal care for equal need" requires measuring the extent of inequity. The most critical issue in studying income-related inequity in healthcare is to adjust for differences in need for healthcare services among individuals with different income. The concentration index of unadjusted healthcare use helps us to measure the extent of inequality. Therefore, it is essential to standardise healthcare use according to an individual's health need to estimate the degree of horizontal inequity.

Using the inter-group comparison method, Le Grand (1978) made an early contribution to measuring horizontal inequity in healthcare. This approach makes a comparison between the extent of illness and the use of healthcare services across the socioeconomic groups. However, this method has the limitation of only focusing on "two extreme groups and does not consider their relative sizes" (Wagstaff, Van Doorslaer & Paci 1991, p. 171). To overcome this shortcoming, Wagstaff, van Doorslaer and Paci (1989) introduced the CC to extend Le Grand's strategy. They developed the Le Grand-type index of horizontal inequity as follows:

$$HI_{LG} = CI_{\exp} - CI_{ill}$$

Where CI_{exp} and CI_{ill} are the concentration indices for healthcare expenditures and illness respectively. A negative value of HI_{LG} indicates inequity in healthcare favouring the poor and vice-versa. However, this index still suffers from the problem of at least three biased assumptions[10] and could potentially identify pro-rich inequity in an equitable healthcare system where non-sick individuals also use health services (Wagstaff et al., 1991b).

Wagstaff, van Doorslaer and Paci (1991) addressed these limitations and suggested an alternative approach to measure the degree of inequity combining both Le Grand's and

[10] i) The proportionality assumption of only sick persons receiving healthcare.
ii) The assumption of chronic versus acute conditions which states that the individuals reporting sickness have equal need for healthcare.
iii) The confounding effects of demographic variables that may lead to different amounts of healthcare use across different SES groups.

regression methods. This technique estimates the horizontal inequity index, denoted as HI_{WVP}, using the direct-need standardisation method, which adjusts need for healthcare use in such a way that each socioeconomic group would have used healthcare if they had the same level of need as the entire population. The CC of actual healthcare use is denoted by $L_M(R)$ in the Figure 3.3 which plots the cumulative percentage of healthcare against the cumulative percentage of individuals, ranked by SES.

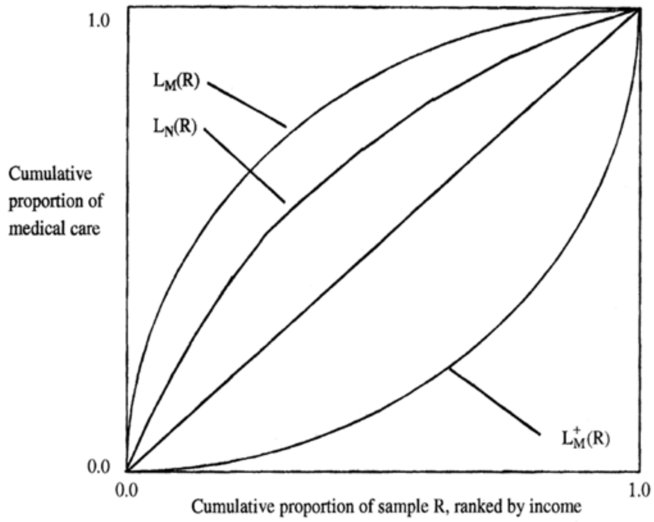

Figure 3.3: The concentration curves for medical care and need

Source: Wagstaff and van Doorslaer (2000b).

Its related concentration index C_M measures the degree of inequality in healthcare use which can be expressed as:

$$CI_M = 1 - 2\int_0^1 L_M(R)dR \qquad (3.8)$$

The CC for directly standardised healthcare use is depicted by $L^+_M(R)$. We can assess horizontal inequity by comparing the standardised concentration curve $L^+_M(R)$ with the line of equality. When $L^+_M(R)$ is below the 45-degree line, it indicates inequity favouring the rich and vice versa. There would be no inequity in the case of $L^+_M(p)$ overlapping or crossing the diagonal. The direct standardisation method of deriving the CI to quantify inequity in healthcare use can be expressed as:

$$HI_{WVP} = 1 - 2\int_0^1 L^+_M(R)dR = CI^+_M \qquad (3.9)$$

The interpretation of HI_{WVP} is analogous to the conventional CI with a range between -1 to +1.

The direct standardisation process is based on a grouped data approach and requires a complicated computational method for both estimation and statistical inference. Additionally, it does not consider within-group variation in the need for healthcare. In this regard, Wagstaff and van Doorslaer (2000b) proposed another convenient technique, known as 'indirect standardization', for assessing horizontal inequity. This approach is denoted as HI_{WV}. This method applies to both individual-level and grouped data. In this approach, the predicted value or need-expected value of healthcare use for everyone is generated by running a regression of healthcare use on need indicators of health. The need predicted CC is labelled as $L_N(R)$ in Figure 3.3. The CI of need expected healthcare use C_N, is defined as twice the area between $L_N(R)$ and the line of equality which is formulated below:

$$CI_N = 1 - 2\int_0^1 L_N(R)dR \tag{3.10}$$

The HI could be assessed by comparing the CC of actual healthcare use $L_M(R)$ and the CC of need for healthcare $L_N(R)$. There would be horizontal inequity if two CCs do not match together. If the need-expected CC is above (below) the CC of actual healthcare use, horizontal inequity favours the rich (poor). The alterative measure of horizontal inequity could be expressed as twice the area between $L_N(R)$ and $L_M(R)$. Expressed in another way, it is equal to the difference between CI_M and CI_N :

$$HI_{WV} = 2\int_0^1 [L_N(R) - L_M(R)]dR = CI_M - CI_N \tag{3.11}$$

Convenient regression by (Kakwani et al., 1997) is straightforwardly applied to estimate the horizontal inequity index, HI_{WV}. The formal steps to estimate HI_{WV} is described below:

1) Using a linear regression model, estimate the following healthcare use model:

$$y_i = \beta_0 + \beta_1 h_i + \beta_2 z_i + \varepsilon_i \tag{3.12}$$

Where y_i is the indictor of healthcare use by individual i at a given time, h_i is a vector need variables including age, gender and morbidity variables, and z_i is the vector of non-need indicators including socioeconomic status, health insurance, region etc. Inclusion of non-need variables in the above model allows to avoid potential omitted-variable bias (O'Donnell et al., 2008).

2) Need predicted, or x-expected values of healthcare use could be generated using the following formula:

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 h_i + \hat{\beta}_2 \overline{z}_i \qquad (3.13)$$

Equation 3.13 predicts how much healthcare individuals would have received if the health system would realise actual need. The influence of the non-need indicators is neutralised by setting them equal to their average. Note that if β_1 in equation 3.13 is not significantly different from zero or large enough, the horizontal inequity analysis would not be able to identify inequity. In other words, there must be variation in healthcare use with respect to need.

3) Indirectly standardised values of healthcare utilisation could be obtained by subtracting need-predicted healthcare use from actual healthcare use and adding sample mean of healthcare use. This is equivalent to the following expression:

$$y_i^{IS} = y_i - \hat{y}_i + \overline{y}_i \qquad (3.14)$$

4) The horizontal inequity index HI_{WV} can be computed in a similar fashion to the concentration index. The idea is to first calculate the CI of actual healthcare use and need predicted use and obtain HI_{WV} as the difference between them. It could be alternatively estimated as the CI of indirectly need-standardised healthcare use to quantify horizontal inequity. The followings are the steps to estimate HI_{WV}:

i) The concentration index of actual healthcare use could be estimated using the following convenient regression:

$$CI_M = 2\sigma_R^2(\frac{y_i}{\mu}) = \alpha + \delta_1 R_i + \varepsilon_i$$

ii) The concentration index of need predicated healthcare use is similarly computed as:

$$CI_N = 2\sigma_R^2(\frac{\hat{y}_i}{\mu}) = \alpha + \delta_2 R_i + \varepsilon_i$$

iii) Finally, the estimate of the horizontal inequity index could be obtained as:

$$CI_{IS} = HI_{WV} = 2\sigma_R^2(\frac{y_i^{IS}}{\mu}) = \alpha + \delta_3 R_i + \varepsilon_i$$

Or

$$HI_{WV} = \hat{\delta}_3 = \hat{\delta}_1 - \hat{\delta}_2$$

The value of HI_{WV} also ranges between -1 to +1. A positive value indicates a pro-rich distribution of healthcare utilisation even though richer people have equal need for healthcare as poorer people. The higher the absolute value of HI_{WV}, the greater the extent of horizontal inequity in healthcare use. The horizontal inequity index is thus a summary measure of inequity in healthcare utilisation which is estimated as the concentration index of need-standardised healthcare use. In other words, it measures inequality in healthcare use by income or other socioeconomic status indicator and this inequality is considered as unjust or unfair.

3.3.3 Explaining horizontal inequity: The decomposition approach

The final part of this approach is to explain the contribution of several factors to inequity in healthcare utilisation though the decomposition analysis. The decomposition approach uses regression analysis to partition or decompose the concentration index into the correlates or explanatory variables of generating inequity. Borrowing from the labour economics and the income inequality literature[11], Wagstaff, van Doorslaer and Watanabe (2003) introduced this method to explain socioeconomic-related inequality in health. Later on, van Doorslaer, Koolman and Jones (2004) extended and applied this approach to partition the contribution of different factors to inequity of healthcare use.

The CI can be separated into the contribution of each individual factor, in which each contribution is the product of the elasticity of the healthcare variable of interest with respect to that factor and the extent of unequal distribution of that factor across the socioeconomic distribution such as income (van Doorslaer et al., 2004b). For example, for private health insurance to be a contributing factor of inequity in healthcare, it must be significantly associated with healthcare use (non-zero elasticity) as well as to be unequally distributed by income (non-zero CI). Therefore, the decomposition analysis is different from the conventional regression method in the sense that it allows explaining

[11] See Fortin et al.(2011), Heshmati (2004), Oaxaca (1973), and Oaxaca and Ransom (1999) for further discussion.

inequity rather than the variation in the dependant variable. The decomposition analysis makes measurement and explanation of horizontal inequity more flexible as it estimates HI_{WV} as the difference between the unstandardized CI and the contribution of need variables to inequality in healthcare use. Following van Doorslaer, Koolman and Jones (2004), an extended specification[12] of equation 3.12 can be written as:

$$y_i = \beta_0 + \beta_1 h_i + \beta_2 x_i + \beta_3 z_i + \varepsilon_i \qquad (3.15)$$

In equation 3.5, h_i is the measure of health status-related variable, x_i is the indicator of socioeconomic status such as income, and z_i includes other policy relevant variables. The estimate of unadjusted concentration index or CI_M can be now expressed as:

$$CI_M = \underbrace{(\frac{\beta_1 \bar{h}}{\mu})CI_h}_{A} + \underbrace{(\frac{\beta_2 \bar{x}}{\mu})CI_x}_{B} + \underbrace{(\frac{\beta_3 \bar{z}}{\mu})CI_z}_{C} + \underbrace{\frac{GC_\varepsilon}{\mu}}_{D} \qquad (3.16)$$

The first three terms in the above equation consist of the deterministic part (i.e. explained components) of the CI of healthcare use, and the last term is the residual part (i.e. unexplained component). In the above equation, $\frac{\beta_1 \bar{h}}{\mu}$ is the elasticity healthcare use with respect to need for healthcare, and the same interpretation is applicable for part B and C. The computation of the CI with respect to income for each part, except the last part in the above expression, is the same as discussed in section 3.3.2. As it is assumed that the mean of the error term in a linear regression is zero, the mean of this term is not included to compute the CI of the residual component. The product of the elasticity of each covariate and its concentration index provides the contribution of that covariate to the inequality. The contribution can be positive or negative but a zero value of either elasticity or the CI of a particular variable makes the contribution zero. The estimate of HI index, HI_{WV} could be also obtained as the difference between CI_M and the need contributions, designated by part A as shown below:

$$HI_{WV} = CI_M - (\frac{\beta_1 \bar{h}}{\mu})CI_h \qquad (3.17)$$

The decomposition analysis is a useful technique in health equity studies as it not only partitions the contributions of different explanatory variables but also measures the strength of these variables to the inequity contribution. The decomposition approach is

[12] The assumption is that healthcare utilisation (with a continuous dependent variable) model is a linear additive regression function of the independent variables.

thus a powerful tool to disentangle the contribution of different factors contributing to inequity in healthcare. The strength of the decomposition is that graphical presentation of this approach makes it attractive for the policymakers (O'Donnell et al., 2008).

3.4 Debates and developments

The discussion in the previous section provides the fundamental aspects of measuring horizontal equity in healthcare within the scope of health economics literature. Empirical studies applying this method to examine the violation of horizontal equity principle in healthcare have increased considerably since early 2000 in both developed and developing countries. This approach is also employed for both cross-country comparisons and over-time trend analysis of the extent of inequity in healthcare use. The increase in empirical applications of this technique has resulted due to the growing interest in equity in healthcare among the policymakers, multilateral organisations like the WHO, the World Bank, the OECD etc., as well as the availability of powerful computer software and household data sets on health (Erreygers 2009a, 2009b; Erreygers & Van Ourti, 2011; Kjellsson & Gerdtham 2013; Wagstaff 2011a, 2011b, 2005). However, this methodology is not beyond limitations and criticisms, and it is always under theoretical scrutiny. This includes measurement issues in healthcare use, the selection of socioeconomic indicators, need adjustment for healthcare, long-run feature of inequity, application of administrative data etc. Therefore, the aim of this section is to present an overview of the recent developments and debate on measuring equity in healthcare. The discussion is limited to methodological aspects and their implications in empirical applications.

3.4.1 Measurement scale and bounds of healthcare variables

Measurement scale and bounds of the healthcare indicators have been in the centre of theoretical debate in recent literature on methodological developments (Wagstaff, 2005). When healthcare use is a continuous and unbounded non-negative variable (ratio scale), the CI is an ideal measure of inequity. A good example of such ratio scale variables is healthcare expenditure which takes the value between 0 and ∞. However, the typical nature of healthcare use is often no-ratio scale such as non-negative integer counts or binary indicators. This leads to non-linear specification of the healthcare utilisation model. This non-linearity brings complexity in both need-standardisation as well as in the decomposition method.

Wagstaff (2005) first raised the mean dependence problem of using a dichotomous healthcare indicator to derive the CI. According to Wagstaff (2005), the bounds of the CI for binary variables do not range between -1 and +1 because of the variability in the distribution of the mean of binary variables which determine the minimum and maximum possible values of the CI. In fact, the CI ranges between μ-1 and 1-μ which makes the interpretation of the CI complex. It also complicates the comparison of the CIs across population groups with different mean levels of healthcare use. The proposed solution by Wagstaff (2005) is to normalise the CI by dividing its value by 1 minus the mean of the variable of interest which can be formulated as:

$$CI_W = \frac{CI}{1-\mu} \tag{3.18}$$

However, this solution by Wagstaff (2005) has been contested in recent time as discussed in Erreygers (2009c), Erreygers & Van Ourti (2011), and Wagstaff (2011b, 2011a, 2009). In this regard, Erreygers (2009c) provided an alternative correction to the CI which is applicable for not only the dichotomous healthcare indicator but also for other bounded health sector variables[13]. The Erreygers's corrected index can be expressed as[14]:

$$CI_E = 4\mu CI \tag{3.19}$$

It is apparent that both indices are interrelated. Therefore, the relationship between Wagstaff normalisation and Erreygers's correction of the CI can be established as:

$$CI_E = 4\mu(1-\mu)CI_W \tag{3.20}$$

The key difference between these two propositions is that the first one is a relative measure of inequality while second one is an absolute measure of inequity. There was a heated debate between these two strands around 2010 to establish their superiority but Kjellsson & Gerdtham (2013) reconciled this contest by arguing that the choice between two solutions depends on the researchers' perspective about inequality of binary healthcare variable.

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[13] Erreygers (2009a) and Erreygers and Van Ourti (2011) can be consulted for further technical explanation of the normalisation process.

[14] An alternative formulation to this can be written as: $CCI_E = \frac{4\bar{h}}{h^{\max} - h^{\min}} CI$

Nonlinear specification of healthcare regression models is problematic in need-standardisation because the predicted probability may not be limited to the (0,1) range for dichotomous indicators and or beyond zero for the counts. It leads to inaccurate neutralization of the non-need variables in equation (3.13) by setting them equal to their means or any particular vector of constants(van Doorslaer et al., 2004b). The variance of need-standardised use, in a nonlinear setting, would depend on the value taken by all the explanatory variables and it affects the estimate of the HI. One possible solution is to exclude non-need factors from indirect standardisation process, but it induces omitted variable bias in the estimation (Gravelle, 2003). Another potential approach is to generate an approximation to the need standardized healthcare variable calculated as the gap between the actual and the need-predicted healthcare variable plus the mean of the prediction (O'Donnell et al., 2008).

3.4.2 Evaluation of the decomposition approach

This approach was primarily developed for a continuous outcome of health variable with a linear additive function of the explanatory variables. The non-linear nature of healthcare indicators generates a specification problem in the decomposition analysis. As discussed earlier, van Doorslaer, Koolman and Jones (2004) demonstrated that the concentration index for need-standardised use is equivalent to the gap between the concentration index of actual healthcare use and the contributions of the need variables. In a linear setting, both indirect standardisation and decomposition approaches provide an identical estimate of horizontal inequity, but this may not hold in a non-linear setting. However, it is still possible to apply this method using non-linear models of healthcare use by imposing a linear approximation to non-linear models (van Doorslaer et al., 2004b). They have suggested testing the robustness of the estimate of HI_{WV} from this solution by comparing with the estimate of HI_{WV} from two-step standardisation procedure. A microsimulation method has been proposed by Huber (2008) to address the issue of non-linearity in the decomposition approach. This was later applied by Abu-Zaineh et al. (2011) to study inequity in healthcare service delivery in the Occupied Territory of Palestine.

The decomposition technique has become exceedingly popular and extensively applied in explaining horizontal inequity in healthcare use in various contexts. However, several criticisms have been raised in recent literature (Erreygers & Kessels 2013; Heckley et al. 2016; van Ourti et al. 2009). For example, Kessels and Erreygers (2013) criticised the traditional approach of decomposition as unidimensional because it considers the extent of variation in health indicators only rather than the covariance between health indicators and socioeconomic rank. To address this problem, an application of the structural equation modelling approach to derive a class of bi-dimensional decomposition techniques has been suggested, which takes into account covariance between health indicator and rank (Kessels & Erreygers, 2016).

The decomposition approach is often criticised for its failure to provide causal interpretation of the determining factors of inequity in healthcare. However, this criticism of the decomposition approach is exaggerated because this method does not claim to provide any causal interpretation of the contributing factors. The conventional decomposition is indeed "a simple descriptive accounting exercise" (Heckley et al., 2016). Most empirical studies using the standard approach failed to meet four basic identifying assumptions of the traditional decomposition approach (Heckley et al., 2016)[15]. In this regard, a more flexible decomposition method based on re-entered influence function regression is proposed by Heckley, Gerdtham and Kjellsson (2016). This new method relies on fewer identifying assumptions to provide casual interpretation of the causes of inequity.

3.4.3 Measuring socioeconomic status

The need-standardised concentration index quantifies inequity in healthcare use by examining the bivariate relationship between healthcare use and socioeconomic status. The selection of SES plays a central role in estimation of the CI as it is used to rank individuals from lowest to highest in the SES distribution. Although education and occupation-related inequity have been studied to some context, economic welfare is the main indicator of SES in the majority of the studies (Bago D'Uva et al., 2011; Lindelow, 2006; van Doorslaer & O'Donnell, 2011). The measurement of welfare has received less attention and has been debated less in the literature compared to measurement issues of health indicators (O'Donnell et al., 2008). This section discusses how the choice of

[15] The four assumptions are:
i. The determinants of health do not determine rank (rank ignorability).
ii. The determinants of health do not determine the weighting function (weighting function ignorability).
iii. Health can be modelled as a function linear in variables X and an error term.
iv. Exogeneity: The errors from the health regression have zero conditional mean.

welfare, as well as the measurement of welfare, could have implications regarding the conclusion of inequity.

Income is the most common indicator of SES used in empirical studies of inequity in healthcare. Most studies have used equivalised household income to allow for comparison across different populations (Rodrigues et al., 2018; Walsh et al., 2012). In the absence of information about income, consumption data and the wealth index are employed as the SES measure (Lindelow, 2006; Wagstaff & Watanabe, 2003). These two indicators have been primarily used as the ranking variable in studies from developing countries (O'Donnell et al., 2008). Area-based SES measures are also used in a few recent studies (Meadows et al., 2015; Siegel et al., 2015).

The choice of welfare indicator measure depends on the correlation between rank differences and health indicator, and it has implications for measuring inequity (Lindelow, 2006). In fact, Allin, Masseria and Mossialos (2009) emphasised the need for attention in selecting the SES indicator, as differences in the ranking of individuals can lead to different conclusions about inequity. In the case of studying both the employed and retired elderly population, for example, the choice of SES measure (income vs. wealth) may influence the findings about inequity in healthcare (Rodrigues et al., 2018).

Despite the debate about the selection of socioeconomic measures, there is agreement in favour of using continuous variables over categorical variables of SES. Using a continuous measure of SES to rank the individuals generally provides a more accurate estimate of the CI (Chen & Roy, 2009a). The argument is that the greater uniqueness in the fractional ranking variable enables the estimate of the CI more precisely. Clarke & Van Ourti (2010) proposed an instrumental variable (IV) approach and overall correction approach to estimate unbiased CI when income data is grouped or categorical. Their innovation is particularly useful when inequity would be measured using categorical SES measures such as educational status or occupational class.

3.4.4 Longitudinal perspective

The existing studies on horizontal inequity in healthcare use following the method of the concentration index and the decomposition approach largely rely on cross-sectional data. This is a 'snap shot' examination of inequity in the utilisation of healthcare. A longitudinal perspective has been absent in this area of research due to the lack of theoretical contribution and unavailability of panel data (Bago d'Uva, Jones & van Doorslaer, 2009). They argued for "a longer view of healthcare utilisation that smooths short-term fluctuations in healthcare use" (Bago d'Uva, Jones & van Doorslaer, 2009, p.1). The authors have introduced a long-run perspective in the analysis of inequity in healthcare by applying the panel data methods. They accounted for unobserved time-invariant heterogeneity in need standardisation employing the latent class hurdle model of healthcare use.

A longitudinal viewpoint of horizontal inequity enabled Bago d'Uva, Jones and van Doorslaer (2009) to find that long-run estimates of the CI are higher than the average of short-run estimates of the CI. Their proposed 'conservative' approach to estimate the CI provided higher long-run indices compared to a 'conventional' approach. Analysis based on panel data thus allows powerful examination of the trends and dynamics of inequity in healthcare over time. This approach is particularly useful when dealing with the endogeneity problem due to reverse causality, omitted variable bias or measurement error in the healthcare utilisation model.

3.4.5 Application of administrative data

The method discussed above has been developed and designed for analysis of healthcare inequity based on survey data. Until recently, methodological debates and developments have focused on refining the technique to get a more precise estimate of horizontal inequity and to better explain the sources of inequity in healthcare use. Empirical analyses based on survey data provide valuable insights for policymakers to enable them to make informed decisions to address inequity in healthcare utilisation. However, majority of the surveys only focus on collecting information about the use of general healthcare services such as GP visits or specialist visits which are regularly used by a large segment of the population. Information about preventive care such as immunisation or cancer screening is also collected in limited cases. The problem of recall bias and subjective measurement of healthcare use and health status is another limitation of using survey data in empirical studies. Additionally, surveys may not be representative of the population due to sample selection problems. Finally, surveys are expensive, complex, and time-consuming to administer which limit the possibility of routine monitoring of equity in healthcare.

In this context, administrative or registered data provides a ‘new frontier’ of research in this area to overcome the above-mentioned limitations of surveys (Cookson et al., 2012). Administrative data is a better source of reliable information on healthcare use with relatively less measurement error. Administrative data usually consists of information on a wide range of healthcare service indicators and covers the whole population. Therefore, it has the potential to address subjectivity and recall bias to measure healthcare use. Finally, data is readily available in most cases allowing a better opportunity for regular reporting of equity indicators. It would be helpful for policymakers to design evidence-based and timely interventions to address the problem of inequity in healthcare.

Some studies have used administrative data to test for and quantify horizontal inequity in healthcare use (Cunningham et al., 2011; McGrail, 2008; Orueta et al., 2013) However, most of these studies have directly applied this technique without further methodological development. Some of these studies have contributed to need standardisation of healthcare using diagnosis-related information (McGrail, 2008). Lumme, Leyland and Keskimäki (2008) have developed a modified concentration index using the multilevel regression modelling technique to examine regional variation in the HI of healthcare use in Finland. This development has later been applied by Lumme, Manderbacka and Keskimäki (2017) to examine the trend in the HI in access to coronary revascularisations among the Finnish population.

The main limitation of using administrative data in the analysis of inequity in healthcare services is that individual level indicators of SES are not available in most databases. Another important caveat is that measuring need for healthcare services is restricted without data linkage across several sources. When data linkage is not possible, measurement of need could be less comprehensive. Administrative data could also be problematic as it has information only about the individuals who are in contact with the health system. In other words, most of the analysis based on this kind of data excludes non-users which could lead to selection problem and may not be representative of the entire population. It needs individual-level linking of clinical records or claims data with the census and other administrative records to overcome these problems. However, legislative binding to protect privacy of patients’ information, in many cases, does not allow data linkage across various sources of data.

3.5 Conclusion

This chapter has presented a discussion of the method for measuring horizontal inequity in healthcare utilisation. It is apparent that this method follows the technique used to estimate socioeconomic-related inequality in health. The widely-applied concentration index provides the estimate of horizontal inequity when healthcare utilisation is equalised for everyone according to need. This approach also allows disentangling the components of the HI through the decomposition method. The strengths and limitations of this method are presented in the chapter will be useful in the empirical applications in the subsequent chapters of this thesis. This chapter has also summarised the recent methodological debates in the literature which have contributed to improve the measurement properties of this approach. The horizontal inequity approach to measure inequity and the decomposition technique to explain the overserved inequity in healthcare use have been applied in many empirical studies from both developed and developing countries. This methodology, in fact, has become the "workhorse" for studying horizontal inequity in healthcare use (Fleurbaey and Schokkaert, 2009). Therefore, this method has been adopted for the empirical analysis in this thesis.

Chapter 4: Inequity in healthcare use: An empirical review

4.1 Introduction

There exists a large body of empirical literature assessing health system performance from the perspective of equity. In the late 1990s the European Commission funded the ECuity project that significantly contributed to the advancement of both methodological and empirical research on inequality and inequity in health, healthcare access, and healthcare financing in Europe (van Doorslaer & Jones, 2004). It has been further strengthened by the OECD Health project, the World Bank, and the WHO in the new millennium. According to O'Donnell et al. (2008), this development has been driven by both demand (e.g. increased interest among policymakers, international organisations) and supply (e.g. availability of data, computer power) side factors. In the case of healthcare use, to what extent the horizontal equity principle— "equal treatment for equal need"—has been achieved, is a fundamental policy concern in most of the OECD countries. As a result, the empirical literature on quantifying and explaining horizontal inequity in use of healthcare has grown rapidly over the last decades[16].

The objective of this chapter is to review the empirical studies of equity in healthcare use. The discussion primarily focuses on the literature which follows the methodological framework outlined in the previous chapter[17]. It should be mentioned that the review in this chapter is limited to the literature from OECD countries. In what follows, section two summarises the findings from major international comparative empirical studies of horizontal inequity in the utilisation of healthcare services. A discussion of the Australian literature is presented in section three. An overview of the studies that have used administrative data to study inequity in various contexts is provided in section four. The last section concludes the chapter with a summary of the main points of these discussions.

[16] The number of articles with equity in the abstract published in *Medline* indexed journals has increased by 260% between 1980 and 2005 (4.3 articles per 10,000 articles in 2005 compared to 1.2 in 1980) as in O'Donnell, et al. (2008).

[17] A positive horizontal inequity (HI) index denotes pro-rich inequity (the distribution of use in favour of the better off) in health use and vice-versa.

4.2 Empirical evidence from the OECD countries

International comparative studies of horizontal equity in the use of or delivery of healthcare services have become an integral part of the OECD policy documents. Several studies have resulted from the ECuity project and the OECD Health project. International comparative studies of equity analysis in healthcare are important sources of evidence for policymakers. Cross-country analysis of horizontal inequity in healthcare use provides better understanding of the sources of inequity (Wagstaff & van Doorslaer 2000b). In general, it could be useful to understand the role of policy reforms on equity at system level in different countries. Therefore, the focus of this section is to review the empirical evidence of horizontal inequity in healthcare use from the OECD member states. This review is not exhaustive, but it aims to cover the most important findings from selected OECD countries[18].

Wagstaff, van Doorslaer and Paci (1989) conducted one of the first international comparative studies of horizontal equity in the delivery of healthcare. They estimated Le Grand-type horizontal inequity index (HI_{LG}) for the aggregated imputed expenditures on general practitioner (GP) consultations, outpatient hospital visits and inpatient days using data from Italy, the Netherlands and Britain. They found inequity favouring the poor in the Netherlands but there was pro-rich bias in the distribution of healthcare use in Britain and Italy. The methodological approach in Wagstaff, van Doorslaer and Paci (1989) considered only sick people accessing healthcare service and it did not take into account between-group demographic differences.

Wagstaff, van Doorslaer and Paci (1991) developed an alternative approach to measure horizontal inequity to overcome the limitations of Le Grand-type analysis. This method quantifies horizontal inequity (HI_{WVP}) in healthcare use based on the direct standardisation method to adjust need for healthcare. The estimates (HI_{WVP}) from this study revealed pro-poor inequity in the distribution of healthcare expenditures in both Italy and the Netherlands. In a subsequent eight-country comparative study (seven European countries and the US), van Doorslaer et al. (1992) found the distribution of

[18] A systematic review of equity in the use of curative services from developed countries has been conducted by Hanratty, Zhang and Whitehead (2007). However, a distinction between different methods of equity analysis is not clear in their study.

healthcare expenditure to be biased towards rich when the need for healthcare was adjusted using several indicators rather than one single indicator. Need-standardisation based on chronic illness, however, resulted in negative HI_{WVP} (pro-poor) for Denmark, France, Ireland, Italy, the Netherlands, the UK, and Switzerland. However, the findings of this study are difficult to compare because all the proxies of healthcare need were not available for each country.

van Doorslaer et al. (2000) updated and extended their earlier cross-country comparative analysis using a newly-developed indirect standardisation method to estimate inequity indices (HI_{wv}) for physician contacts (GP and specialist visits) and hospital services. In this study, 10 European countries and the US were included but the data were sourced from different time points, for example 1987 for the US, to 1996 for Finland. In general, there was almost no inequity in the distribution of *total medical care expenditure* in eight countries out of 11 (a positive but insignificant HI_{WV} for Switzerland and the US, and a negatively significant HI_{WV} only in the case of Belgium). On the other hand, they have found significant pro-rich inequity in *all physician contacts* for at least five countries: Finland, East Germany, the Netherlands, Sweden, and the US. Separate analysis for GP and specialist services in a subgroup of six countries (Belgium, Denmark, Finland, Ireland, the Netherlands, and the UK) has shown almost no inequity in *GP contacts* in all countries except for Belgium and Ireland (significant and negative HI_{WV}).

In this study, horizontal inequity in *outpatient specialist consultations* was strongly pro-rich in Denmark, Finland, and the Netherlands and it was either neutral or moderately pro-poor in the other three countries. On the other hand, inequity in inpatient care was pro-poor, though HI_{WV} indices were insignificant in most cases. Findings of this study indicate that inequity in doctor visits could be pro-rich, particularly for specialist consultations, in any type of healthcare system. For example, it existed in Denmark with complete coverage as well as in the US with incomplete coverage. Additionally, GP gatekeeping role (the Netherlands vs Belgium) or co-payment (Belgium vs Denmark) was not systematically related to the pattern of inequity in medical specialist utilisation.

In a further update and extension[19], van Doorslaer, Koolman and Puffer (2002) found the distribution of GP visits, after adjusting for need, significantly pro-poor in Belgium, Ireland, Luxemburg, and Spain while it was almost evenly distributed in the other countries[20]. On the contrary, there was pro-rich inequity in specialist services in every country except in Luxemburg. The HI_{WV} indices for this type of care were particularly high in Ireland (0.1496) and Portugal (0.1904). Sensitivity analysis revealed that the contribution of unequal distribution of private insurance in Ireland was larger while regional disparity played a greater part in Italy, Greece, and Spain to drive this pro-rich inequity. Finally, the extent of inequity in the use of total physician visits was pro-rich only in Greece (0.0273), Austria (0.0403), Portugal (0.0635) and the US (0.0550). Again, regional differences in physician visit in Southern European countries and low insurance coverage in the US might be responsible for this finding. This study was more comparative and meaningful as it employed more harmonised and contemporary household survey data to measure horizontal inequity in healthcare utilisation.

Data from the European Community Household Panel (ECHP) from 12 countries were used by van Doorslaer, Koolman and Jones (2004) to estimate horizontal inequity indices by distinguishing between the probability of a visit and conditional number of visits for GP and specialist visit. They also applied decomposition analysis to explain the sources of horizontal inequity in healthcare use. The findings of their study show that the HI_{WV} indices for the probability of a GP visit were positive and significant for Belgium, the UK, and the Netherlands. In contrast, they were either negative or insignificant for conditional number of visits and total numbers in most countries.

The findings of this study supplied the evidence that the HI_{WV} index for the probability of a specialist visit was significantly biased in favour of higher income people in all countries except Denmark. The distribution of conditional number of specialist visits was significantly pro-poor only in Luxembourg while it was pro-rich or insignificant otherwise. There was also significant pro-rich bias for the total number of specialist visits

[19] This includes 14 countries. Data came from European Community Household Panel (ECHP) from 12 European countries, National Population Health Survey (NPHS, Canada), and Medical Expenditure Panel Survey (MEPS, the US) in 1996.

[20] Separate GP and specialist analysis were not feasible in the case of the US due to the aggregated nature of doctor utilisation data

in all countries except Belgium and Luxembourg. Overall, the pattern of horizontal inequity in this analysis was like the earlier study. Low education, retirement status, and absence from the labour force were found to be the main factors contributing to pro-poor GP use, while inequality in income and education contributed most significantly to pro-rich inequity in specialist services (van Doorslaer, Koolman & Jones 2004). This might be due to private provision of specialist services (for example in Portugal and Italy) and the expansion of supplemental private health insurance among the higher income group in Ireland, Spain, and the UK.

In another extension and update, van Doorslaer and Masseria (2004) studied inequity in medical care in 21 OECD countries using data from around the year 2000[21]. They updated the previous analysis of van Doorslaer, Koolman and Puffer (2002) and extended country coverage as well as including dental care services for the first time in an international comparative study[22]. The conclusion is almost similar as earlier studies: fair or pro-poor use of GP care and pro-rich use of specialist care. For example, there was significant horizontal inequity favouring the rich both for the probability and the total number of all physician visits in about half of the countries. The extent of inequity was the highest in the US, followed by Mexico, Finland, Portugal, and Sweden. There was fair or pro-poor distribution of GP services in all countries except for Finland. Inequity in hospital inpatient care was pro-rich in Portugal and Mexico while it was fair or pro-poor otherwise. Pro-rich inequity in specialist and dentists visit existed in all OECD countries. Decomposition results were almost similar to that found in van Doorslaer, Koolman and Jones (2004).

A long run perspective was brought into the literature for the first time by Masseria, Koolman and van Doorslaer (2004) in a pooled analysis of five ECHP waves (1994-98). Their analysis revealed significant pro-rich inequity in the probability of inpatient hospital admission in seven of the 12 European countries. This was particularly high again in Southern Europe (Portugal, Greece, and Italy). However, the distribution of inpatient probability for people without specialist visits was fairer in all countries except Greece

[21] Seventeen European countries include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. The US, Canada, Australia, and Mexico are the four non-European OECD countries.

[22] This study is later published as van Doorslaer et al. (2006).

and Germany. This suggested that pro-rich inequity in inpatient care was strongly related to the pro-rich inequity in specialist care which was strongly evident in all countries. This might be the case because of the referral system in most European countries.

Bago d'Uva, Jones and van Doorslaer (2009) applied panel data technique to bring a longitudinal perspective in the analysis of horizontal equity of healthcare utilisation. They used eight waves of the ECHP (1994-2001) survey to estimate both short-run and long-run HI indices for the number of GP and specialist visits in 10 European countries. They found inequity in primary care to be pro-poor in all countries except Finland, Austria and Portugal, and pro-rich inequity in specialist care in all countries. This longitudinal method also led to reliable evidence of higher level of horizontal inequity (more pro-rich and less pro-poor) in physician care in most countries. They termed this new scenario as the income mobility contribution to inequity of healthcare use. Overall, their findings thus, with better precision, reinforced the conclusion about horizontal inequity from the earlier cross-sectional studies.

Devaux and Looper (2012) conducted the most recent and the largest OECD project on horizontal inequity in healthcare using data from around 2008-09. This study updated the results of (van Doorslaer & Masseria, 2004) for 13 countries, included six more OECD countries (Czech Republic, Estonia, New Zealand, Poland, Slovak Republic, and Slovenia) that were previously not included in the analysis . Furthermore, the analysis was extended to include indicators of preventive care use (breast and cervical cancer screening for females). They found that for the probability of doctor visit, the HI_{WV} index was significantly positive but smaller in size for 13 countries[23]. Although inequity indices were insignificant for the total number of doctor's visits in most countries, there was significantly pro-rich inequity in Poland, the United States, Spain, and Finland for this indictor.

This study found no significant inequity for the probability of GP consultations in nine countries (Czech Republic, Spain, Switzerland, Ireland, Austria, Belgium, United Kingdom, Hungary, and Slovenia) while small but significant pro-rich inequity was found in seven countries (Estonia, Canada, Finland, Poland, New Zealand, the Slovak Republic,

[23] It was the highest for the United States followed by Estonia, Finland, and Poland.

and France). It was only pro-poor in Denmark. On the other hand, significant pro-poor inequity appeared for the frequency of GP visits in six countries (Denmark, Belgium, Austria, France, New Zealand, and Canada) and it was almost fair distribution in the other nine countries. There was pro-rich inequity in both the probability and the number of specialist visits in almost all countries[24]. Pro-rich inequality was the greatest in dental visits in all countries with the US on top of the list[25]. It should be noted that correction of HI_{WV} indices using the methods of Wagstaff (2005a) and Erreygers (2009a) using the same data resulted in larger values for all indicators in Devaux (2015).

Horizontal equity in healthcare among elderly people was also examined in cross-country settings. Availability of survey data on the elderly population such as the Survey on Healthy Ageing and Retirement in Europe (SHARE) has provided new opportunity to examine cross-country inequity among elderly people in late 2000s. It has been found that horizontal inequity in the probability of physician visit among elderly people in Europe and the US also follows a similar pattern observed among the general population (Allin et al., 2009). The degree of inequity among elderly people is particularly high with regard to the use of dental care services (Allin et al., 2009; Listl, 2011). Lack of public dental coverage in many European countries may be one of the reasons of this inequity among elderly people (Palència et al., 2014).

Inequity in preventative care services was also found in international comparative studies. For example, inequality in cervical cancer screening favouring the well-off was evident in all OECD member states (Devaux, 2015; McKinnon et al., 2011). It was pro-rich for breast cancer screening in about half of all OECD countries (Devaux, 2015). Inequity favouring the well-off group has been also found in the utilisation of preventative care services among elderly Europeans (Carrieri & Wuebker 2013; Jusot et al. 2012).

Education-related inequity in different healthcare services utilisation has also been identified in Europe, which is similar to the findings of income-related inequity (Or et al. 2008; Stirbu et al. 2011; Tchicaya & Lorentz 2014). For example, it was pro-educated for specialist and dentist services as well as for hospitalisations but there was almost no

[24] France and Spain were the two countries with the most inequitable specialist visits favouring the rich.
[25] Healthcare need was not adjusted for dental visit and preventive care services.

inequity in GP visit (Terraneo, 2015). For adults 50 years and older in 12 European countries, Terraneo (2015) surprisingly found this inequity to be greater in Scandinavian and Southern European welfare regimes, contrary to Bismarckian welfare regimes. Education-related inequity in specialist care favouring the better-educated among elderly Europeans became even greater when taking into account self-rated health bias in need adjustment of healthcare (Bago D'Uva et al., 2011). Most importantly, correcting for measurement error in this study also resulted in more pro-educated distribution in inequity for GP visits.

The pattern of inequity in healthcare use in the OECD countries discussed above cannot be tied to a specific health system. It exists in tax-funded health systems as well as in social insurance-based health systems. Several factors might lead to this phenomenon. For example, out-of-pocket payments and private provision of services were found to be related with pro-rich inequity in healthcare service use in almost every developed country (Devaux & Looper 2012; Gelormino et al. 2011). It was also associated with a lower share of government health expenditure in GDP (Or et al., 2008). Additionally, up-front payment at the point of service delivery and reimbursement later might be one of the reasons of pro-rich inequity as it generates barriers for low-income people. Absence of a nationwide programme might lead to higher pro-rich inequity in preventative care even though it is free of cost in most of the OECD countries (Palencia et al., 2010).

4.3 Empirical evidence from Australia

The horizontal equity principle in the utilisation of healthcare services is inherently embodied in Medicare in Australia. However, there are limited empirical studies to examine horizontal equity in Australia (Hajizadeh et al., 2014). It also appears from the above discussion that Australia has been included in very few international comparative studies. This section reviews the existing Australian literature which has studied inequity in healthcare use following the methods discussed in Chapter 3.

Using 1989-90 National Health Survey (NHS) data, Lairson, Hindson and Hauquitz (1995) first examined inequity in healthcare delivery and financing in Australia. They employed the direct standardisation approach to estimate the HI_{WVP} index for the imputed expenditures of three types of care (physician consultations, outpatient and inpatient care services). Self-assessed health, serious chronic illness and serious illness were the separate indicators to adjust need for healthcare in their study and their findings are sensitive to these measures of need-standardisation. According to their analysis, inequity in outpatient services was in favour of the worst-off across all indicators of need adjustment. Inequity was pro-rich for physician (both GP and specialist) visits and in use of inpatient services and the total of the three types of care. On the other hand, using serious or chronic illness to adjust healthcare need resulted in substantial pro-poor inequity in inpatient care while other types of care and GP and specialist visits were fairly equitable. The overall conclusion of this study is that the Australian system performed less well than many European countries in terms of equity in healthcare delivery at that time.

van Doorslaer et al. (2008) have used data from 2001 NHS to estimate and explain horizontal inequity in the Australian healthcare system. Their analysis highlighted that equity in healthcare use in Australia follows a similar pattern to most OECD countries where the distribution of GP visits is pro-poor and specialist visits is pro-rich. Their results also suggest that the distribution of probability of admission as a public patient is substantially pro-poor[26]. Decomposition analysis from this study reveals that insurance and employment status were the two most important sources of income-related inequity in the use of different healthcare services. For example, private health insurance had a significant and positive contribution in pro-rich inequity of specialist visit and hospital admission, but employment plays the opposite role to reduce pro-rich inequity in these services. Holding a concession card, on the other hand, was the key contributing factor of pro-poor inequity in the probability distribution of GP and all physician visits. Their conclusion is that Medicare has fairly contributed to achieve equity healthcare utilisation in 2001 but there was a sign of substitution of private hospital services for public hospital services and specialist services for GP services.

Hospital care, including day procedures constitutes an integral component of the health system in developed countries like Australia (Goodall & Scott 2008). They studied inequity in hospital care use (inpatient and day cases) using data from wave four (2005) of the Household Income and Labour Dynamics in Australia (HILDA) panel survey.

[26] This is opposite in the case of admission as a private patient.

Using self-assessed health as a measure of need for healthcare, they followed the indirect standardisation method to estimate HI_{WV} indices for the number of inpatient nights and occasions as well as for the number of day cases. This study found that day visits were equitable (positive but insignificant HI_{WV} index) but inequity in inpatient hospital services were pro-rich. According to their observation, inequity in inpatient hospital care had been increasing overtime despite a universal and comprehensive healthcare system in Australia. However, this conclusion is based on analyses from different data sets and methodological approaches.

Employing data from six time points of NHS, FitzGerald et al. (2011) conducted a trend analysis of inequity in use of dental care services over 1977-2005. Their empirical findings revealed that pro-rich inequity was more pronounced among the youngest (15-19 years) and oldest (60 or years) for the entire period. The general conclusion of this study is that the distribution of dental care use was in favour of the better-off during this period and this pro-rich inequity increased significantly after 1995. One plausible explanation of this trend may be the expansion of private health insurance among the higher income groups. However, this study has not adjusted for need for dental care due to limited and inconsistent information in the NHSs.

Hajizadeh, Connelly and Butler (2012) studied the impact of two major policy changes: the introduction of Medicare in 1984, and the implementation of private health insurance (PHI) policy reforms[27] between 1997 and 2000, on horizontal equity of utilisation of healthcare services using five rounds of NHS between 1983 and 2005. This study employed the direct standardisation method to estimate HI_{WVP} indices for six types of healthcare services: hospital admissions, GP visits, specialist visits, dentist visits, any physician visits and ambulatory care visits. Analysis from this study suggests that the inequity in GP and any physician visits, as well as hospital services, was pro-poor while it was pro-rich for specialist, dentist, and ambulatory care visits over this period. Their estimates suggest that the HI_{WVP} index was the highest for dental services followed by specialist consultations during this period. They concluded that pro-poor horizontal inequity in GP visits and hospital admissions became larger after the introduction of

[27] These are the Private Health Insurance Incentives Scheme (PHIIS) (including the Medicare Levy Surcharge (MLS) and subsidies (30% rebates) for PHI in 1997–99) and the Lifetime Cover scheme for PHI (July 1, 2000).

Medicare in Australia. However, different policies to encourage private health insurance uptake in the late 1990s may have a pro-rich effect on the utilisation of healthcare services since 2005.

4.4 Empirical evidence: Application of administrative data

Although administrative or registered data has been utilised to examine inequity in healthcare for a long time in public health literature, the application of the concentration index approach employing register data is relatively new in this area of research. In a review of 26 papers, Hanratty, Zhang and Whitehead (2007) found that 90% of the articles used survey data. The major limitation of using the method of Wagstaff and van Doorslaer in an administrative data setting is restricted availability of SES measures and indicators of healthcare need. This problem primarily arises due to legislative obligations to link across different data sources to keep privacy of data. However, there is evidence of a growing effort to apply the technique discussed in Chapter Three to identify and measure horizontal inequity in the utilisation of healthcare services in routine data setting. This section briefly reviews these examples.

There is a potential for better understanding of the equity picture of the health system using administrative data. More indicators of healthcare service use are available in these data sources compared to surveys. Surveys are restricted to collect information on general indicator of healthcare uses. Another advantage of using administrative data is the routine monitoring of equity in access to healthcare by a national reporting agency. Time series analysis is useful in this kind of analysis. However, this potential has been barely realised with the exception of some countries like Finland, which has made a substantial progress to utilise administrative data for routinely monitoring equity in health and healthcare. Finnish registered data provides a good opportunity to exploit the methodology of Wagstaff and van Doorslaer to measure horizontal inequity in healthcare use.

In Finland, one of the earlier studies was conducted by Hetemaa et al. (2003) to examine inequity in use of coronary revascularisations among the Finnish population. They found evidence of an increasing trend in coronary procedures but socioeconomic inequity favouring the well-off and better-educated persisted from 1988-95. In a concurrent study by Keskimäki (2003) investigated the impact of economic recession on socioeconomic equity in hospital care utilisation between 1988 and 1996. Overall, the distribution of hospital care use was biased towards the socioeconomically less well-off group but there was an indication of moving towards pro-rich inequity, especially for surgical care.

Lumme, Leyland and Keskimäki (2008) studied regional variations of equity in the use of coronary revascularisations (coronary artery bypass grafting: CABG, and percutaneous transluminal coronary angioplasty: PTCA). Among the Finnish population aged 45-84, pro-rich inequity in use of coronary procedures was higher for men compared to women but there was little evidence between area differences in horizontal inequity. In general, a similar gender gradient was found in a 12-year trend analysis for inequity in different elective surgical treatments (Manderbacka et al., 2009). However, there existed a persistent pro-rich inequity for lumber disc operations and hysterectomy among women over this period. A further study from 1985 to 2010 by Manderbacka, Arffman and Keskimäki (2014) found overall inequity in the use of different hospital specialist services gradually increased to favour higher income groups around 2010.

In Canada, McGrail (2008) used linked health data from the province of British Columbia to assess the feasibility of employing administrative data to measure the changes in horizontal equity in healthcare between 1992 and 2002. Findings of this study indicate a pro-poor bias in the distribution of conditional use of GPs and acute inpatient care, but pro-rich bias in specialist uses and day care surgeries. It was also observed that the probability distribution of using a day care procedure became more pro-rich in 2002. Data from similar sources was employed by Cunningham et al. (2011) who provided evidence of pro-rich inequity in specialist services and prescription drugs among the end-of-life cohort[28]. HI indices were generally larger compared to that of the general population estimated in McGrail (2008). It was also found that the extent of inequity was greater among elderly males.

In Spain and Israel, two studies utilised administrative data to study horizontal inequity. Orueta et al. (2013), using data for over 2 million people, found all types (including specialist and prescription drugs) of healthcare provision to be pro-poor in the Basque Country, Spain. This was particularly higher among women. In Israel, healthcare equity analysis of linked administrative and survey data showed pro-poor inequity in all services except for secondary physician care (Shmueli, 2014).

[28] The final year of life among people aged 65 or greater.

In Australia, Meadows et al. (2015) examined the effectiveness of the 'Better Access to Mental Healthcare' initiative to obtain equitable provision of mental health services for adults over 2007-08 to 2010-11. National Medicare data on several items of mental healthcare services aggregated at postcode level were used for analysis in this study. The findings highlighted that long consultation items favoured the patients from advantaged regions, but the distribution of short consultation items was either pro-poor or fair. However, the main drawback of this study is that it has not adjusted for need for mental health services which might underestimate the extent of inequity. Their overall conclusion was that the Better Access initiative is not following the egalitarian of principle of Medicare.

Inequity in healthcare among Australian children has been recently studied by Dalziel et al. (2018) who linked Medicare data on healthcare utilisation with the Longitudinal Study of Australian Children. They found that inequity in overall Medicare spending among children aged 0-11 years was pro-rich. Their study has shown that Medicare expenditure for GP services was equitable, but inequity in specialist and diagnostics and imaging spending was favourable to children from high-income families. However, the extent of pro-rich inequity in the early years of life decreased in the adolescence period.

4.5 Conclusion

Despite being a relatively new field of research, there has been an upsurge in empirical studies on horizontal inequity in recent years. The first wave of empirical literature (1989-99) was mainly concerned with identifying and quantifying horizontal inequity in healthcare use. In this wave, healthcare utilisation was measured by imputed expenditures for physician visits. Horizontal equity estimates relied on the direct standardisation procedure to equalise need for healthcare. It is to be noted that separate use of self-assessed health (SAH) and the subjective morbidity indicator in need-standardisation often resulted in mixed findings.

In addition to measuring the extent of inequity, the second wave of literature (2000-09) focused on explaining the sources of horizontal inequity. This segment of literature also started to distinguish between different type of services such as GP and specialist visits and inpatient care. Moreover, the probability of any visit and the conditional number of visits were also employed as the indicators of healthcare service utilisation. Longitudinal perspective, advanced econometric modelling of healthcare function and the combination of multiple indicators in need adjustment were also the major innovations in second-generation literature. A growing recognition of using of administrative data in the literature was observed in this period.

The current wave (2010-to date) has expanded the indicators to preventive services along with increasing importance on dental care services. Inequity in healthcare utilisation among the elderly population has also started to be explored, and education-related inequity is studied to some extent. Application of administrative data has also become more prominent. Availability of administrative data, data linkage across different sources and progress health information technology have made this development promising. It has extended equity analysis to specific measurements of healthcare service from only broad types of services. Finally, a wide range of theoretical developments has been applied in different settings.

In general, empirical review in this chapter suggests that universal health coverage in many OECD countries does not realise the goal of equitable delivery of healthcare services according to need. Although the distribution of GP use and inpatient services was found to favour lower socioeconomic people in many instances, the use of specialist medical services were always in favour of higher income people. Pro-rich inequity in preventive care services is also present in these countries. This feature of inequity was not an attribute of a specific healthcare system. It existed in tax financed health systems as well as in social insurance health systems and occurred irrespective of the supplementary or complementary role of private health insurance. Inequity preventative care inequity could also happen in any physician payment and referral system. Recent evidence suggests an increasing trend in pro-rich inequity in specialist and dental care services and less pro-poor bias in the distribution of GP services. On this note, Bago D'Uva et al. (2011) emphasised that pro-poor or fair distribution of primary care services might be overestimated, and pro-rich inequity in specialist care may be underestimated due to methodological limitations and homogeneous assumption in need for healthcare across population groups.

In conclusion, the review of empirical studies in this chapter emphasises a need for updating and extending the current empirical evidence on horizontal inequity of healthcare utilisation in Australia using the latest available data. A revisit of the existing empirical evidence following new methodological developments outlined in the last chapter is important in several aspects. For example, it would be useful to compare the performance of Australian healthcare system with other OECD health systems to achieve horizontal equity in healthcare service delivery in the era of increasing healthcare expenditure and pressure in the public system. This would also enable us understanding the long run implications of health policies for equity in healthcare (Hajizadeh et al., 2012). The application of population-based administrative data to examine inequity would provide new knowledge for regular monitoring of equity. The review of existing studies has also identified lack of empirical evidence on horizontal inequity in healthcare utilisation within the indigenous community in Australia and other similar countries. Therefore, an empirical study focusing on inequity of healthcare use within the Indigenous Australians would contribute to fill this gap in the literature.

Chapter 5: Horizontal inequity of healthcare: Updated and extended evidence from Australia

Abstract

The aim of this chapter is to present updated and extended empirical evidence on horizontal inequity (HI) of healthcare use in Australia in the era of greater reliance of private healthcare financing. This chapter has measured the level of income-related HI in overall use, out-of-hospital visits, and hospital-related care in 2011-12 and 2014-15. It has also analysed regional variations in HI by quantifying state/territory level inequity. The findings suggest a small but pro-rich inequity in the probability of GP visit for the first time in Australia. The distribution of specialist and dentist visits has remained in favour of richer people as found in earlier studies from Australia and other OECD countries. On the other hand, hospital-related care was almost equitably utilised compared to the pro-poor pattern found in the earlier studies. The findings also reveal that overall utilisation measured by any visit or hospital admission was pro-rich, but the extent was small. There was limited evidence of regional variation in inequity of specialist and dentist visits. Despite the universal health insurance system in Australia, there was inequity in use of needed healthcare services. This is relevant to other countries as governments move to higher out-of-pocket payments to reduce public expenditure.

Keywords: Inequity; regional variation; out-of-pocket cost; specialist visit; GP visit.

5.1 Introduction

In Australia, Medicare aims to ensure affordable and equitable delivery of healthcare services according to health need by removing financial barriers (Scotton & Deeble 1968). Every citizen and permanent resident of Australia is entitled to receive needed healthcare services regardless of their income, education, residence, occupation etc. In other words, horizontal equity (equal care for equal need irrespective of socioeconomic status of the individuals) is one of the cornerstones of Medicare. The empirical review in the Chapter 3 highlights that horizontal inequity (HI) in healthcare use in Australia follows a similar pattern found in most of OECD countries. That is the distribution of primary care use is favourable to the poor (pro-poor), but specialist use is pro-rich (van Doorslaer et al., 2008). In addition, the distribution of healthcare services provided in hospital settings is largely pro-poor or equitable (van Doorslaer et al., 2008). Inequity in dental care is typically biased towards wealthier people (Fitzgerald et al., 2011; Hajizadeh et al., 2012). There also remain challenges to ensure equity in use of specialist, psychological and dental care services (Harris, 2012). Furthermore, recent empirical evidence reveals an increasing pro-rich effect on the inequity of healthcare service utilisation (Hajizadeh et al., 2012).

The goal of this chapter is to assess whether the horizontal equity principle of Medicare is being realised in an era of encouraging greater private healthcare financing in Australia. The first aim is to update the evidence on the extent of income-related HI in healthcare service utilisation in Australia. Studies examining HI in healthcare use in Australia are limited compared to other OECD countries (Hajizadeh et al., 2014). Additionally, Australia is not included in some recent international comparative reports on healthcare inequity by the OECD (Devaux & Looper 2012). In recent times, there has been an increasing reliance on private sources of healthcare financing as evidenced by rising OOP expenditure and increasing private health insurance premiums (Duckett, 2018; OECD, 2015). This could also have indirect implications for inequity in use of healthcare services. In this context, this chapter revisits and updates the empirical evidence on HI of healthcare use presented by (Hajizadeh et al., 2012; van Doorslaer et al., 2008) using data from the two most recent National Health Survey (NHS) of 2011-12 and 2014-15.

This second aim of this chapter is to extend the earlier studies on HI of healthcare use from Australia by examining the regional dimension of the HI. Despite having a large landmass, diverse geography and remoteness structure, the analysis of regional variation in inequity of healthcare utilisation is currently absent in the Australian literature[29]. This aspect might be overlooked because of the federal funding mechanism through Medicare to deliver healthcare services in Australia. However, there are differences across the Australian states for the provision of healthcare services. For example, the State Governments in Tasmania and Queensland cover ambulance cost, while this is not covered in other states and territories. State governments have role of "system managers" to run the public hospitals, given their responsibility in planning, regulation, funding, and governance of public hospitals. According to the Medicare Statistics of the Department of Health, bulk-billing rate for most of the Medicare-funded services is substantially lower in the Australian Capital Territory (ACT) compared to other states (Department of Health, 2017a). There are also variations in fee charged by the medical professional and in OOP cost for using out-of-hospital services across the regions (Callander et al., 2017; Freed and Allen, 2017; Hillis et al., 2017). In the context of such regional variations, this chapter aims to study the spatial dimension of inequity in healthcare service use by analysing the state-level variation of HI.

The rest of this chapter is organised as follows. Section two discusses the empirical methods employed in this chapter. This follows a discussion on data source and variable description in section three. Section four describes the empirical results of this study. Section six discusses the main findings of this chapter in the light of relevant literature. The concluding section concludes the chapter.

5.2 Empirical strategy

There is typically inequality in the utilisation of healthcare services in relation to socioeconomic status and level of need. Consequently, if the use of healthcare by different groups in the population is in accordance with differences in health need, the principle of equal use for equal need could be realised (O'Donnell et al., 2008). To measure income-related horizontal inequity in healthcare use, one seeks to establish whether there is differential utilisation of healthcare by income after standardising for differences in the need for healthcare in relation to income.

[29] This chapter defines six Australian states and two territories as 'region.' The term 'state' is used in this study to refer to these states and territories.

The method for measuring horizontal inequity of healthcare use in this chapter follows the well-established method proposed by Wagstaff, van Doorslaer and Paci (1991), and later advanced by Wagstaff and van Doorslaer (2000). The starting point in this approach is to visualise and measure the degree of inequality in actual healthcare use by the concentration curve (CC) and the concentration index (CI). The CC presents inequality in the utilisation of healthcare service across the entire distribution of a ranking variable such as income (O'Donnell et al., 2008). This curve plots the cumulative proportion of utilisation on the y-axis against the cumulative share of individuals ranked (from the lowest to the highest) by income on the x-axis. In case of no income-related inequality in healthcare use, the CC overlaps with the 45-degree line or line of equality. The CC above (below) the line of equality indicates greater use of healthcare services among poorer (richer). The further the CC lies from the line of equality or the diagonal, the greater is the degree of inequality.

Although the CC is a nice graphical tool to depict inequality in healthcare use by income or other measures of SES, it does not quantify inequality. To overcome this limitation, income-related inequality can be quantified by estimating the CI. The CI is defined as twice the area between the concentration curve and the line of equality (Wagstaff, van Doorslaer & Paci 1991). The following 'convenient regression' approach is most commonly used when individual-level data on healthcare use and income is available:

$$2\sigma_r^2\left(\frac{y_i}{\mu}\right) = \alpha + \delta r_i + \varepsilon_i \qquad (5.1)$$

In equation 5.1, y_i is healthcare utilisation variable, r_i is the fractional ranking of individuals by income, μ is the mean of healthcare use, ε_i is the error term , and σ_r^2 is the variance of fractional rank. In the above regression framework, the OLS estimate of δ gives the value of the CI. The CI is a rank-dependent measure of relative inequality in healthcare use which ranges between -1 and 1. When the CI is zero, healthcare utilisation is equally distributed across the income distribution(Wagstaff et al., 1991b). A negative CI indicates higher utilisation among the poor (pro-poor) while a positive value indicates greater utilisation among the rich (pro-rich).

The CI is an index to measure income-related relative inequality of a non-negative ratio scale healthcare use variable. The details of the properties of the CI is available in

O'Donnell (2008). The standard CI is a relative measure of inequality and invariant to equi-proportionate changes in the healthcare use variable. According to Wagstaff et al. (1991), the CI-respecting the absolute invariance can be obtained through a multiplication of the standard CI by the mean of healthcare use. This CI is referred as the generalised concentration index or GCI. Multiplication by the mean gives this parameter an important role in the assessment of absolute inequality. When two distributions display the same level of relative inequality, the one with the higher mean will correspond to greater absolute inequality (O'Donnell et al., 2016).

When the healthcare indicator is binary, the lower and the upper bounds of the CI depend on the mean values of the outcome variable (Wagstaff, 2005). This is potentially problematic for comparing inequality between the two groups of population with different averages of healthcare use (Erreygers, 2009a, 2009b). This suggests that the extent of inequality as measured by the CI could be affected considerably if the mean of the variable of interest changes across time and populations. Wagstaff (2005) proposed the following normalisation to address this problem:

$$WI = \frac{CI}{1-\mu} \tag{5.2}$$

Erreygers (2009) proposed an alternative correction to Wagstaff's normalisation which is not only applicable to binary variables but also to other bounded indicators of healthcare use. Erreygers's corrected version of the CI or the EI for binary healthcare outcome can be expressed in various forms as shown below:

$$EI = 4\mu CI = 4GCI = 4\mu(1-\mu)WI \tag{5.3}$$

The EI is an absolute measure of inequality in healthcare that satisfies both the properties of mirror and absolute invariance (Kjellsson & Gerdtham 2013). On the other hand, the WI respects the mirror condition but not absolute invariance. This chapter does not consider the superiority of any of the indices over others as the selection of an index is a normative exercise (O'Donnell et al., 2016).

The approach discussed above measures the degree of inequality in healthcare use by income, but the focus of this chapter is to measure the extent of inequity in healthcare use. The horizontal equity principle is commonly defined as "equal treatment for equal medical need, irrespective of other characteristics such as income, race, place of residence, etc." (O'Donnell et al., 2008). In other words, income-related HI in healthcare refers to the unequal utilisation of healthcare services by income given the same level of need among the individuals. In this approach, inequality in need-standardised utilisation of healthcare services by income is interpreted as horizontal inequity (HI). Need-standardisation of healthcare use can be accomplished using a direct or indirect approach (as previously discussed in Chapter Three). This chapter follows the indirect method which can be described in three steps.

The first step is to estimate a regression model of healthcare use (y for individual i) as a function of both need and non-need variables. The purpose of including non-need variables in predicting need for healthcare is to avoid omitted variable bias in modelling healthcare use (Gravelle, 2003; O'Donnell et al., 2008; van Doorslaer et al., 2004a). This is because non-need variables such as income, education, etc. may be correlated with need variables. Since the outcome of healthcare utilisation variable in this chapter is a non-linear function of the explanatory variables, the following model is estimated using logistic regression technique:

$$y_i = G(\alpha + \sum_j \beta_j X_{ji} + \sum_k \gamma_k Z_{ki}) + \varepsilon_i \qquad (5.4)$$

In equation 5.4, X_j and Z_k are the vectors of need and non-need variables, α, β, and γ are the parameter vectors to be estimated, and ε_i is the error term. In the second step, the need-predicted or need-expected distribution of healthcare is obtained as follows:

$$\hat{y}_i = G(\hat{\alpha} + \sum_j \hat{\beta}_j X_{ji} + \sum_k \hat{\gamma}_k \bar{Z}_{ki}\ ) \qquad (5.5)$$

The effects of non-need variables are neutralised by setting them equal to their means in equation 5.5 to generate need-predicted utilisation of healthcare services[30]. Need-predicated utilisation specifies the amount of healthcare an individual would have used if he or she had been treated, on average, as others with the same need level (O'Donnell et al., 2008; van Doorslaer et al., 2004b). In other words, this would be the ideal level of

[30] This could be problematic in the case of non-linear models as the variance of the need-predicted utilisation will rely on the the values to which the z variables are set. This could induce bias in estimating inequity in healthcare use. Linear probability model (LPM) is suggested to avoid this problem, but the results remain almost identical to those obtained using logistic models in this study.

treatment provided by the healthcare system to everyone. In the third and final step, need-standardised use $\hat{y}_i{}^{IS}$ can be calculated as follows:

$$y_i^{IS} = y_i - \hat{y}_i + \bar{\hat{y}} \tag{5.6}$$

It should be noted that the mean of the predicted value ($\bar{\hat{y}}$) is added to indirectly standardised values to ensure that the mean of the actual use equals the mean of the need-standardised use.

Income-related HI can now be measured by estimating the CI of the need-standardised use as presented in equation 5.1, or as the difference between the CI of actual and need-predicted healthcare utilisation with respect to income[31]. This chapter follows the former approach. Like the CI, the HI index takes the value between -1 and +1 with a zero indicating no inequity in healthcare use. A negative (positive) and significant HI estimate indicates inequity is pro-poor (pro-rich) or healthcare use is more concentrated among the poor (rich) given the same level of health need among the individuals of the income distribution. The higher the absolute value of the HI index, the greater the degree of inequity.

Since healthcare utilisation is measured by a set of binary variables in this chapter, the HI indices are corrected applying both the Wagstaff and Erreygers approaches. However, the discussion of the results is primarily centred on Erreygers's corrected horizontal inequity index (hereafter the EHI) as this index satisfies all the four properties of a rank dependent inequity measure (Kjellsson & Gerdtham 2013). Moreover, Erreygers approach is preferable as the chapter aims to compare inequity over time and across the regions (Erreygers and Van Ourti, 2011). Statistical inference on the significance of point estimates of the indices is obtained using the convenient regression method as explained by (O'Donnell et al., 2008).

Several statistical issues are considered in the empirical analysis. The variance inflation factor (VIF) is used to test for the multicollinearity among the variables. This test is used because multicollinearity among the independent variables can lead to higher standard errors of the point estimates. In other words, if affects the efficiency or precision of the

[31] This may not give identical estimates because of errors in the linear approximation of non-linear healthcare use models in the need-standardisation process.

coefficients by increasing the variance. Sample weights provided in the NHSs are applied in descriptive, regression, inequality, and inequity analysis to account for survey design of the NHSs. This allows the estimates to be representative of the Australian population. Finally, robust standard errors are obtained by applying the robust command in Stata (data analysis and statistical software) to precisely estimate the standard errors (SE) of the coefficients.

This chapter has conducted several sensitivity analyses by changing the ranking variable in estimating inequality and inequity indices. Chen and Roy (2009) suggested that continuous income variable offers higher variation ranking which leads to more accurate estimation of the concertation index. Hence, this study exploits the availability of the continuous household income measure to test the robustness of the indices obtained from categorical income ranking. Individual-level income is also used in ranking to check the sensitivity of the indices as suggested by Frick and Ziebarth (2013). Lastly, following Siegel, Mielck and Maier (2015), individuals are ranked from the lowest to the highest by using area-level socioeconomic measures to test the whether the findings are robust to different SES measure .

5.3 Data and variable

5.3.1 Data source and access

The analysis of this chapter uses data from the two most recent NHSs of Australia. These surveys were undertaken by the Australian Bureau of Statistics (ABS) in 2011-12 and 2014-15. These two NHSs are the sixth and seventh in a series of continuous population-based surveys to collect data on a wide range of health-related topics, and to allow the monitoring of trends in health over time in Australia. The NHS represents approximately 97% of the Australian population (ABS, 2017a). These cross-sectional surveys were conducted using a stratified multistage sampling technique that covers Australian residents living in private dwellings in all six states and two territories of Australia. However, individuals residing in very remote areas of Australia and discrete Aboriginal and Torres Strait Islander communities were excluded from these surveys. Details about sampling procedure, data items and other information on the NHS are available from the ABS website[32].

The data of both surveys can be accessed in three ways. The basic confidential unit record files (CURFs) are available in CD-ROM to be used in the researcher's own analysis environment. The expanded CURF can be retrieved through the Remote Access Data Laboratory (RADL) environment and the onsite DataLab facility at designated ABS onsite facilities. The basic and expanded CURFs hold almost identical information but some data items are grouped in the basic version[33]. It is to be noted that the RADL environment restricts the use of some advanced commands in Stata and other analytic software which precludes complex analysis of these surveys. As a result, the analysis was performed using data from basic CURF in CD-ROM and expanded CURF accessed through the ABS onsite facility in Sydney, Australia.

5.3.2 Analytic sample

The response rates of the surveys were respectively 84.8% and 82.0% in 2011-12 and 2014-15 (ABS, 2017a, 2013a). Person-level data is available for 20,426 and 19,257 individuals in the respective surveys. This chapter focuses on the adult sample aged 18 years or older. Individuals with missing information are also excluded from the analysis. Therefore, the final samples consist of 15,475 and 14,560 adult respondents in 2011-12 and 2014-15 respectively.

5.3.3 Measure of healthcare utilisation

The outcome variable of this study is the probability of using a healthcare service. This is a dichotomous variable which is measured in the NHSs as, "In the last 12 months, have you consulted any medical professionals or visited/admitted to hospital?". Eight commonly used healthcare services are used as the dependent variables in this study. These outcomes are grouped into three classes: (i) overall healthcare use; (ii) out of hospital care; and (iii) hospital-related care. Overall utilisation is measured as at least any visit to a health professional or hospital admission/visit in the previous 12 months preceding the survey. Out of hospital care is measured by three outcomes: the consultation with a general practitioner (GP), specialist, and dentist. Admission to

[32] http://www.abs.gov.au/ausstats/abs@.nsf/mf/4364.0.55.001 (Accessed on 1 March 2017).
[33] For instance, the data on household equivalised income is available only in deciles in basic CURF, but it is reported in continuous form in the expanded version.

hospital for at least one night (inpatient admission), visit to an outpatient clinic, visit to a day clinic and emergency department visit are classified as hospital services.

5.3.4 Independent variables

Table 5.1 describes all the variables included in this study. Age, gender, and health status are the need variables as these variables causes legitimate (or fair) variation in healthcare service use (van de Poel et al., 2012; van Doorslaer & van Ourti, 2011). Non-need indicators are the variables which influence healthcare use but are considered illegitimate or unfair (Fleurbaey & Schokkaert 2011a; O'Donnell et al. 2008; Sözmen & Ünal 2016). In this chapter, the indicator of need variable consists of a vector of seven age dummies: gender, self-assessed health (SAH) status, mental health score, number of longer-term conditions, disability status and diabetes. While both the number of long-term conditions and having diabetes depend on having been diagnosed by a doctor and hence having visited a doctor, this is unlikely to be a major problem of endogeneity in this study. First, most Australians have at least one doctor visit in a year, and that proportion rises for two years; second, there are several other indicators included in the measure of need.

Equivalised weekly household income recorded in deciles is the main non-need variable in this study[34]. This is also used as the measure of the socioeconomic status of the individuals. This variable is used to derive the fractional ranking of individuals which ranks individuals from poorest to richest[35]. Other non-need determinants of healthcare use include country of birth, private health insurance status, concession card holding, employment, education, language spoken at home, residing in a remote area, state/territory and the area-level index of relative socio-economic disadvantage[36].

The relative economic and social conditions of a neighbourhood are measured by the socioeconomic indexes for area, commonly known as SEIFA in Australia (Johar et al., 2013). The SEIFA is a composite index of how an area is economically and socially developed compared to other areas (ABS, 2011). There are four types of SEIFA constructed by the ABS using 2011 Australian census data. However, the *Index of Relative Socio-Economic Disadvantage (IRSD)* is reported in the NHSs. IRSD is a

[34] ABS applied 'modified OECD' equivalence scale to calculate equivalised total weekly household income.
[35] Alternative ranking variables used in robustness analysis are equivalised household income in continuous form, gross weekly individual income in deciles and continuous form and SEIFA deciles.
[36] Private health insurance (PHI) in Australia is used as supplementary health cover for hospital and ancillary services. This information was collected for persons aged 18 years and over in the NHSs at the time of the survey.

summary index of relative socioeconomic disadvantage. This index ranks areas on a continuum from most disadvantaged to least disadvantaged (Biddle, 2009). The areas of respondents in the survey were coded into 10 deciles; the lower decile of this index indicates a high share of relatively disadvantaged individuals in an area.

Table 5.1: Description of independent variables

	Variable	Measurement scale	Description
Need variables	Age	Categorical	Seven age groups are recoded as 18-24, 25-34, 35-54, 55-64, 65-74 and 75 years or above.
	Gender	Binary	Gender is recoded into a dummy variable (1=female and 0=male).
	Self-assessed health (SAH)	Categorical	Self-reported measure of health classified as excellent (reference), very good, good, fair and poor.
	Mental health score	Continuous	A mental distress indicator measured by Kessler psychological distress scale (K10) ranges from 10 to 50. Higher score indicates greater mental distress.
	Long-term conditions	Count	The number of current long-term conditions reported by the respondents.
	Disability status	Categorical	Coded into four groups as no disability (reference), some disability, moderate disability and severe disability.
	Diabetes		Whether the individual has diagnosed diabetes (reference =No).
Non-need variables	Country of birth	Binary	1= if born in Australia and 0= foreign born (reference)
	Language at home	Binary	The main language spoken at home codes as 1= English and 0= other (reference)
	Health insurance	Binary	1= Yes and 0=No (reference)
	Concession card	Binary	1= Yes and 0=No (reference)
	Education	Categorical	The level of highest educational attainment is recoded as 8 years or less=0 (reference), 9-11 years of education=1 and 12 years or more=2
	Labour force status	Categorical	Out-of-labour force=0 (reference), employee=1, self-employee=2 and unemployed=3.
	Area of residence	Categorical	Remoteness area categories according to ASGS 2011 coded as residence of other area=0 (reference), residence of major city=1 and residence of inner region=2.
	Region	Categorical	Eight Australian states and territories in which New South Wales (NSW)=0 is the reference region.
	Income	Categorical	Deciles of equivalised weekly household income in which decile 1 is the reference group. Higher decile represents higher income.
	Area SES (SEIFA)	Categorical	Index of relative socio-economic disadvantage (SEIFA) in deciles. SEIFA=1 is the reference category. The higher SEIFA deciles indicate the individual is in a lower socio-economic disadvantage area.

5.4 Results

5.4.1 Descriptive statistics

Table A5.1 in Appendix 5 presents the weighted summary statistics of the independent variables used in the regression analysis. About 5% of respondents reported poor health in both surveys while about 80% of the respondents considered their health to be at least good during the time of the surveys. The mean of mental health score slightly increased from 14.62 in 2011-12 to 14.96 in 2014-15. Table A5.1 shows that about 70% of the population were born in Australia and most people speak English at home. The proportions of people with private health insurance and concession card were about 57% and 32% respectively. More than half of the population had 12 or more years of education. The proportion of people out of the labour force was about 29%.

Table 5.2 shows the summary statistics of eight types of healthcare utilisation (visits /admission) in the preceding 12 months of 2011-12 and 2014-15 in Australia. Overall, there was no notable change in healthcare utilisation between 2011-12 and 2014-15. For example, the proportion of any visit was about 92% and 93 % in the respective years. The probability of GP visit was also higher than other indicators of healthcare use.

Table 5.2: Summary statistics of healthcare utilisation in Australia

	2011-12	2014-15
Any visit	0.92	0.93
GP visit	0.86	0.87
Specialist visit	0.36	0.38
Dentist visit	0.47	0.46
Inpatient admission	0.14	0.13
Outpatient visit	0.09	0.08
Emergency visit	0.12	0.12
Emergency visit	0.07	0.06

Tables A5.2 and A5.3 in Appendix 5 report the distribution healthcare use by demographic, health status and socioeconomic background. The utilisation rate of all types of services was higher among females compared to males. For example, the share of GP and specialist visits was about 92% and 42% for females, while it was 82% and 35% for males in 2014-15. In general, the elderly and young adults used more services compared to the middle-aged cohort. Healthcare utilisation of all types of care other than dental services was always higher among the people who reported their health status as fair or poor.

Tables A5.2 and A5.3 show that healthcare utilisation typically varied between people with and without private health insurance as well as concession card. For example, 42% of individuals with health insurance reported a visit to a specialist which was about 33% for the people without in 2014-15. The proportion of specialist visit was about 17% higher for concession card holders in both surveys. In general, persons out of the labour force and less educated utilised more healthcare services. However, unemployed, and less educated people had the lowest proportion of dentist visits. Overall, there was no significant variation in healthcare use by state/territory in Australia. People living in major cities used more specialist and dental care services in 2012-13 but this variation had almost disappeared in 2014-15 for the probability of specialist visit. Table A5.2 reveals that there were variations in healthcare use by area-level socioeconomic disadvantage (SEIFA deciles) for specialist and dental visits. For instance, the probability of receiving care from a dental professional in 2011-12 was about 20% lower among the lowest SEIFA decile compared to the highest SEIFA decile.

5.4.2 Determinants of healthcare use

The results from the logistic regression analyses are discussed in this section to examine the association of need and non-need variables with eight selected indicators of healthcare utilisation. Estimated odd ratio (OR) and the respective statistical significance are provided for any visit and visit to three medical professionals in Table 5.3, and for hospital-related services in Table 5.4. Overall, the regression results for need variables are as expected, i.e. higher need was associated with higher utilisation of healthcare services[37]. Females had significantly higher probability of visiting medical professionals as well as inpatient admission and outpatient visit, but there was no difference in emergency department and day clinic visits by gender. In general, utilisation of healthcare services is found to be positively associated with age except for inpatient admission and day clinic visits.

[37] It is common in the literature to use a vector of interactions between age and gender in the regression analysis for need-standardisation(O'Donnell et al., 2008). This study has also used 14 age-gender dummies to generate need predicated values of healthcare utilisation but the results obtained remains largely identical. Therefore, regression models include age and gender as the separate covariates.

The probability of using more healthcare services in the last year preceding the survey was higher among the individuals reporting poor or fair health. For example, the likelihood a specialist visit was about three times (OR: 3.18) in 2014-15 among the people who reported their health as poor compared to their counterparts with excellent health. However, this was not the case for dentist visit. Table 5.3 shows that the likelihood of dentist visit was significantly lower among the respondents with lower categories of self-assessed health. People with more long-term conditions had a higher probability of all types of healthcare utilisation. Results show that individuals with moderate to severe disability and diabetes were more likely to visit GPs and specialists as well as to receive care from a hospital or day clinic.

Table 5.3 shows that private health insurance (PHI) is significantly and positively associated with any visit and visit to GP, specialist, and dentist. For example, individuals with PHI were about 1.6 and 2.5 times more likely to visit a specialist and a dentist respectively in 2011-12. On the other hand, health insurance is found to be negatively associated with outpatient visit (Table 5.4). It is also found that the positive association of PHI with inpatient admission was rather weak. Having a concession card was a significant and positive predictor of any use and GP visit. However, no significant association is found between the probability of specialist visit and any hospital-related care. In general, individuals with 12 or more years of education were more likely to visit a specialist and dentist. Among the hospital-related services, the probability of visiting a day clinic was higher among better-educated people but only in 2011-12. The results suggest no significant association between employment and medical professional visits (Table 5.3).

The regression results reported in Table 5.3 reveal that the residents of inner regions and other areas of Australia had a lower probability of GP, specialist, and dental service utilisation. However, this association became insignificant for specialist and dentist visits in 2014-15. In general, area of residence was not a significant determinant of inpatient admission and other hospital visits (Table 5.4). Out of all healthcare use indicators, the probability of outpatient visit was significantly higher in all other states compared to New South Wales (NSW). The likelihood of a specialist visit was significantly lower among

Table 5.3: Logistic regression models for any visit and GP, specialist, and dentist visit

	Any visit		GP visit		Specialist visit		Dentist visit	
	2011-12	2014-15	2011-12	2014-15	2011-12	2014-15	2011-12	2014-15
	OR	OR	OR	OR	OR	OR	OR	OR
Female	2.112***	2.405***	2.004***	2.201***	1.274***	1.235***	1.350***	1.237***
Age (Ref: 18-24 year)								
Age 25-34 year	1.065	0.907	0.976	1.134	1.006	1.218	0.847	1.141
Age 35-44 year	1.048	0.664*	1.091	0.724**	1.048	1.219	1.070	1.336**
Age 45-54 year	0.965	0.586**	1.101	0.726*	1.104	1.167	1.273**	1.332**
Age 55-64 year	0.994	1.141	1.552**	1.329	1.523***	1.702***	1.420***	1.857***
Age 65-74 year	1.811	1.336	1.691*	1.713**	1.962***	2.196***	1.368**	1.548***
Age 75+ year	3.992***	3.420***	3.536***	3.570***	2.289***	2.615***	1.042	1.348*
SAH (Ref: Excellent)								
Very good	1.143	1.481***	1.283***	1.474***	1.084	1.290***	0.906	0.824***
Good	1.177	1.391**	1.270**	1.464***	1.316***	1.385***	0.802***	0.704***
Fair	1.204	1.552	1.422**	1.505*	1.986***	1.917***	0.770**	0.691***
Poor	1.109	2.604*	1.180	3.970***	2.488***	3.184***	0.803	0.524***
K10 score	1.015	1.014	1.015*	1.033***	1.014***	1.021***	1.011**	0.999
No. of long-term conditions	1.367***	1.310***	1.266***	1.304***	1.141***	1.149***	1.056***	1.060***
Disability (Ref: No)								
Some disability	1.658***	1.222	1.327**	1.110	1.439***	1.126	1.122	0.925
Moderate disability	1.421*	1.976***	1.322*	1.323*	1.839***	1.571***	1.132	1.011
Severe disability	2.806	1.374	2.216**	1.864	2.607***	2.139***	0.981	1.011
Diabetes	2.345***	3.571***	2.280***	2.187***	1.380***	1.534***	1.078	1.086
Australian-born	1.081	1.200	1.165	1.224**	1.172**	1.113	1.013	0.978
English at home	1.268	1.387*	1.188	1.219	1.100	1.345***	1.128	1.192*
Health insurance	1.689***	1.806***	1.228**	1.387***	1.645***	1.563***	2.479***	2.357***
Concession card	1.774***	1.874***	1.625***	1.823***	1.094	1.100	1.110	1.338***
Education (Ref: Year 8 or less)								
Year 9-11	0.973	1.355	0.900	1.192	1.152	1.489***	1.180*	1.024
Year 12 or more	1.066	1.833**	0.848	1.317	1.378***	1.669***	1.604***	1.366**
Employment (Ref: Out of labour force)								
Employee	1.115	1.217	1.208	1.260*	0.977	0.978	0.991	0.999
Self-employee	1.048	1.107	0.893	0.957	0.915	1.202*	1.238*	1.067
Unemployed	1.256	0.913	1.010	1.087	0.892	1.183	0.810	0.966
Residence (Ref: Major City)								
Inner region	0.930	0.613***	0.834*	0.622***	0.836**	0.903	0.842**	0.895
Other or remote	0.748*	0.600***	0.707***	0.728**	0.801**	0.941	0.810**	0.936
State (Ref: NSW)								
VIC	1.372**	0.911	1.238*	1.006	1.127	0.998	0.947	1.031
QLD	1.306*	0.944	1.221*	0.851	1.029	0.797***	1.018	1.210**
SA	0.988	1.053	1.075	0.942	1.057	0.988	1.135	1.196**
WA	1.018	0.772	0.911	0.678***	0.934	0.816**	0.930	0.906
TAS	1.099	1.133	1.127	0.953	1.014	0.845	0.929	1.000
NT	1.195	0.956	1.358*	0.736	1.012	0.722**	0.830	0.842
ACT	1.018	0.857	0.944	0.725**	0.795**	0.673***	0.972	1.006
Household Income (Ref: Decile 1)								
Decile 2	1.098	1.590*	1.529*	1.676**	0.922	0.808*	0.915	0.992
Decile 3	1.183	1.604*	1.530**	1.444*	1.217	0.846	0.921	1.041
Decile 4	1.230	1.343	1.429*	1.295	0.993	1.036	1.107	1.201
Decile 5	1.384	1.798***	1.472**	1.543**	1.221	0.878	1.130	1.169
Decile 6	1.570*	1.996***	1.749***	1.742***	1.320**	0.938	1.147	1.290**
Decile 7	1.621**	2.070***	1.775***	1.654***	1.392**	1.039	1.206	1.402**
Decile 8	2.070***	1.972***	1.809***	1.519**	1.412**	0.970	1.428***	1.292*
Decile 9	1.913***	2.068***	1.741***	1.624**	1.384**	1.182	1.334**	1.620***
Decile 10	2.090***	2.458***	1.903***	1.621**	1.511***	1.232	1.789***	1.716***
Area socioeconomic status (Ref: SEIFA 1)								
SEIFA 2	1.073	0.784	0.976	0.877	1.070	1.147	1.127	1.062
SEIFA 3	1.164	0.829	0.993	0.891	1.258*	1.215	1.071	0.957
SEIFA 4	1.291	1.083	0.931	0.932	1.091	1.545***	1.143	0.928
SEIFA 5	1.619**	1.096	1.095	1.093	1.186	1.448***	1.247*	1.035
SEIFA 6	1.399	1.136	1.206	1.328	1.185	1.482***	1.402***	1.061
SEIFA 7	1.040	0.827	0.881	1.012	1.133	1.351**	1.266**	1.139
SEIFA 8	1.042	1.319	1.068	1.071	1.363**	1.741***	1.315**	1.386**
SEIFA 9	1.358	0.996	1.086	0.977	1.284*	1.551***	1.230*	1.274*
SEIFA 10	1.726**	1.124	1.431*	1.030	1.567***	1.870***	1.459***	1.503***

Notes: OR is odd ratio and significance level *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5.4: Logistic regression models for utilisation of hospital-related care

	Inpatient admission		Outpatient visit		Emergency visit		Day clinic visit	
	2011-12	2014-15	2011-12	2014-15	2011-12	2014-15	2011-12	2014-15
	OR	OR	OR	OR	OR	OR	OR	OR
Female	1.196**	1.309***	0.884	1.289***	0.953	0.991	1.022	1.155
Age (Ref: 18-24 year)								
Age 25-34 year	1.730***	1.348*	1.066	1.467*	0.846	1.003	1.033	0.813
Age 35-44 year	0.984	0.939	1.077	1.250	0.807	0.628***	0.869	0.702
Age 45-54 year	1.021	0.764	0.966	1.241	0.561***	0.464***	0.938	0.917
Age 55-64 year	1.134	0.949	0.880	1.525*	0.408***	0.494***	1.115	0.803
Age 65-74 year	0.912	1.080	0.900	1.594*	0.435***	0.599**	1.180	0.921
Age 75+ year	1.167	1.354	0.859	1.797**	0.469***	0.700	1.346	0.691
SAH (Ref: Excellent)								
Very good	1.075	1.026	1.029	1.367**	1.145	1.182	1.197	1.429**
Good	1.496***	1.418***	1.418**	1.555***	1.466***	1.604***	1.533***	1.570**
Fair	1.756***	1.933***	1.804***	2.246***	1.964***	1.708***	1.805***	1.794***
Poor	2.242***	3.235***	2.410***	3.353***	1.876***	2.902***	1.885**	1.713**
K10 score	1.014**	1.007	1.009	1.006	1.027***	1.016**	1.022***	0.990
No. of long-term conditions	1.081***	1.045***	1.118***	1.063***	1.113***	1.074***	1.066***	1.119***
Disability (Ref: No)								
Some disability	1.123	1.319**	1.359**	1.492***	1.290**	1.775***	1.250	1.459***
Moderate disability	1.126	1.470***	1.637***	1.484***	1.060	1.479***	1.082	1.912***
Severe disability	1.678***	1.809***	1.871***	1.804***	1.682***	2.515***	1.532**	1.550**
Diabetes	1.321***	1.215*	1.352***	1.121	1.349***	1.078	1.186	1.186
Australian-born	1.297***	1.149	1.175	0.974	1.212**	1.171	1.279**	1.096
English at home	1.352**	1.074	1.182	1.365*	1.352*	1.287	1.733**	1.117
Health insurance	1.168*	1.250**	0.783**	0.819**	0.834**	0.888	1.130	1.094
Concession card	1.046	1.115	0.971	1.198	1.236*	0.911	1.198	0.885
Education (Ref: Year 8 or less)								
Year 9-11	1.058	1.175	1.232	1.183	1.017	0.922	1.540**	1.381*
Year 12 or more	0.971	1.113	1.198	1.198	0.985	0.861	1.485**	1.365
Employment (Ref: Out of labour force)								
Employee	0.746***	0.803*	0.677***	0.960	0.999	1.375**	1.087	0.806
Self-employee	0.656***	0.981	0.786	1.050	0.872	1.325*	0.858	0.999
Unemployed	0.721	0.804	0.430***	1.122	1.451	0.997	1.427	1.108
Residence (Ref: Major City)								
Inner region	1.117	1.050	0.960	0.922	0.987	1.463***	1.126	0.947
Other or remote	0.942	0.970	1.162	1.137	1.035	1.264*	1.107	1.043
State (Ref: NSW)								
VIC	1.103	0.878	1.657***	1.436***	1.309**	0.974	1.321**	1.027
QLD	1.129	0.955	1.918***	2.041***	1.254**	0.981	1.245	1.216
SA	1.242**	1.199	1.823***	1.885***	1.043	0.871	1.144	1.272
WA	1.251**	0.898	1.787***	1.613***	1.152	1.133	0.991	1.107
TAS	0.926	0.928	1.629***	1.486**	1.196	0.801	0.702*	0.950
NT	1.272	1.099	1.900***	1.869***	1.284	1.054	1.390	1.126
ACT	1.187	0.875	1.472**	1.744***	1.257	1.163	1.055	1.164
Household Income (Ref: Decile 1)								
Decile 2	0.980	0.935	0.947	0.948	0.982	1.042	1.214	0.988
Decile 3	1.071	0.898	0.793	1.071	0.888	1.079	1.082	1.378
Decile 4	0.935	1.120	0.959	1.176	1.079	1.203	1.226	1.300
Decile 5	1.046	1.253	0.866	1.203	1.292	1.223	1.072	1.382
Decile 6	1.027	0.969	1.044	0.920	1.211	0.816	1.396	1.145
Decile 7	0.965	1.121	1.040	0.857	1.319	1.142	1.207	0.901
Decile 8	1.070	0.882	0.997	1.094	1.136	0.929	1.133	1.446
Decile 9	0.949	1.014	0.986	1.015	1.271	1.414*	1.199	1.136
Decile 10	1.004	1.134	1.228	1.257	1.188	1.241	1.153	1.376
Area socioeconomic status (Ref: SEIFA 1)								
SEIFA 2	1.200	0.979	1.102	1.218	1.307*	0.849	1.442*	1.201
SEIFA 3	1.236	0.849	1.062	0.843	1.268	0.729*	1.295	1.156
SEIFA 4	0.972	0.970	0.980	1.451**	1.300	0.932	1.107	1.459
SEIFA 5	0.981	1.038	1.194	1.429*	1.240	0.732*	1.243	1.746**
SEIFA 6	0.920	0.983	0.957	1.240	1.046	0.820	1.319	1.568*
SEIFA 7	0.986	0.997	0.873	1.326	0.993	0.706*	1.551**	1.702**
SEIFA 8	1.071	1.283	1.319	1.225	1.233	0.716*	1.441*	1.538*
SEIFA 9	1.164	0.967	0.977	1.053	1.070	0.728	1.362	1.824**
SEIFA 10	1.292	1.002	0.823	0.999	1.132	0.681*	1.467*	1.298

Notes: OR is odd ratio and significance level *** $p<0.01$, ** $p<0.05$, * $p<0.1$

the people in the Australian Capital Territory (ACT) compared to those in NSW. Household income was significantly associated with the probability of GP, specialist and dentist visits in 2011-12, but this relationship almost became statistically insignificant in 2014-15 for specialist visits. On the other hand, living in a socioeconomically advantaged area (higher the SEIFA deciles) significantly raised the likelihood of visiting a specialist in 2014-15 compared to 2011-12. No significant association between GP visit and SEIFA is revealed from the regression analysis. Table 5.4 shows that income was not associated with any of the hospital-related services, while only the probability of day clinic visits was positively related with SEIFA.

5.4.3 Horizontal inequity in healthcare use

Table 5.5 reports the estimates of inequality and horizontal inequity indices (with 95% confidence intervals) of all eight indicators of healthcare use measured by Erreygers's method. The CCs for actual, need-predicted, and need-standardised utilisation as well as four versions of the inequality and inequity indices are presented in figures A5.1 to A5.8 in Appendix A5. All the EIs are negative and statistically significant in both years except for any visit and dentist visit. The EI for any visit is positive but insignificant, while it is significant and positive for dentist visit (Table 5.5). These results indicate that both poor and rich had equal probability of visiting a doctor or receiving care from a hospital, but inequality in the likelihood of a dentist visit was pro-rich in the study period. On the contrary, inequality was pro-poor for all other six indicators of healthcare use. In other words, the distribution of these services was more concentrated among the poorer. There was no statistically significant change in pro-poor inequality between 2011-12 and 2014-15 in Australia.

The estimate of EI do not inform anything about inequity in healthcare use because it does not consider the variation in need for healthcare services among the study population. Therefore, the estimates of the EHI which are obtained after adjusting need (rich and poor have similar need) represent inequity in the utilisation of healthcare services. The EHIs of any visit and out-of-hospital services (GP, specialist, and dentist) are positive and significantly different from zero suggesting a pro-rich horizontal inequity

Table 5.5: Erreygers's inequality and horizontal inequity indices of healthcare use

	Inequality (EI)				Inequity (EHI)			
	2011-12		2014-15		2011-12		2014-15	
Any visit	0.003	[-0.010,0.017]	0.006	[-0.008,0.019]	0.013***	[0.009,0.018]	0.014***	[0.009,0.018]
GP visit	-0.028***	[-0.046, -0.010]	-0.038***	[-0.056, -0.020]	0.012***	[0.006,0.018]	0.008***	[0.003,0.014]
Specialist visit	-0.059***	[-0.084, -0.035]	-0.068***	[-0.095, -0.042]	0.041***	[0.033,0.048]	0.039***	[0.031,0.047]
Dentist visit	0.174***	[0.149,0.199]	0.159***	[0.133,0.186]	0.069***	[0.061,0.077]	0.065***	[0.056,0.074]
Inpatient admission	-0.061***	[-0.078, -0.044]	-0.068***	[-0.086, -0.049]	-0.003	[-0.008,0.003]	-0.004	[-0.010,0.002]
Outpatient visit	-0.059***	[-0.073, -0.044]	-0.059***	[-0.073, -0.044]	-0.005**	[-0.009, -0.000]	-0.003	[-0.008,0.001]
Emergency visit	-0.039***	[-0.055, -0.024]	-0.035***	[-0.053, -0.017]	0.001	[-0.005,0.006]	0.004	[-0.002,0.010]
Day clinic visit	-0.023***	[-0.036, -0.010]	-0.020***	[-0.034, -0.007]	0.003	[-0.002,0.007]	0.005**	[0.000,0.009]

Notes: 95% confidence intervals in brackets and significance level * $p<0.10$, ** $p<0.05$, *** $p<0.01$

in use of these services. This finding suggests that people with higher income utilised more medical professional services even though they had similar level of need as lower income people. Table 5.5 also indicates that pro-rich inequity was the highest for the probability of visit to a dentist (EHI: 0.61 in 2014-15) followed by a specialist visit (EHI: 0.039 in 2014-15). The value of positive EHIs is found to be smaller for the probability of GP visit. The results reveal that pro-rich inequity in medical professional visit did not change significantly between the two surveys. However, the extent of pro-rich inequity was comparatively less in the use of GP, specialist, and dental services in 2014-15 as shown by lower values of the EHIs.

Results from Table 5.5 reveal that the EHIs are mostly statistically insignificant for hospital-related care suggesting a fair distribution of these services. The only exception was in the case of day clinic visit indicator for which the EHI is positive and significant at the 5% level in 2014-15. However, the magnitude of the index is small suggesting a pro-rich but less extent of inequity in this type of care. It should be noted that the HI indices obtained through different versions of the CI reported in Appendix A5.1 provide similar results about inequity healthcare use.

5.4.4 Regional variation in horizontal inequity of healthcare use

The variation in income-related horizontal inequity among the eight regions of Australia is presented in Figures 5.1 to 5.8. There is some evidence of variation in HI of any visit as shown in Figure 5.1. For example, the EHIs were statistically significant and pro-rich in New South Wales (NSW), South Australia (SA) and Victoria (VIC), while the EHIs in other regions were insignificant in 2011-12. Figure 1 also reveals that inequity became favourable to richer people in Queensland (QLD) in addition to pro-rich inequity in the above three states in 2014-15. This finding suggests that rich people utilised more healthcare services despite the same level of need as poor people in some regions of Australia. For GP visit, inequity was pro-rich in SA and VIC in 2011-12 while it was only positive and significant in NSW in 2014-15, suggesting almost no variation across the states and territories as well as over time within the regions (Figure 5.2).

Figure 5.3 depicts statistically significant pro-rich inequity in specialist visit across all regions of Australia. There is also some variation across the states over time. For example, pro-rich inequity appears to have increased in the ACT and SA while it decreased in Western Australia (WA) in 2014-15. For the probability of dentist visit, a variation is also observed across the regions in both periods, but this variation became less in 2014-15. It is found that the pro-rich inequity in dental visits decreased in the Northern Territory (NT), NSW and WA but appeared to have increased in SA in 2014-15.

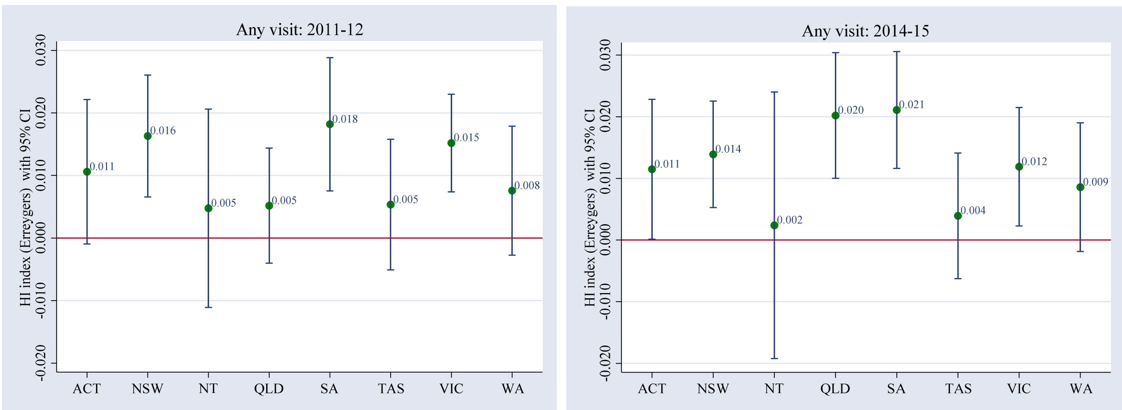


Figure 5.1: Regional variation of horizontal inequity in any visit

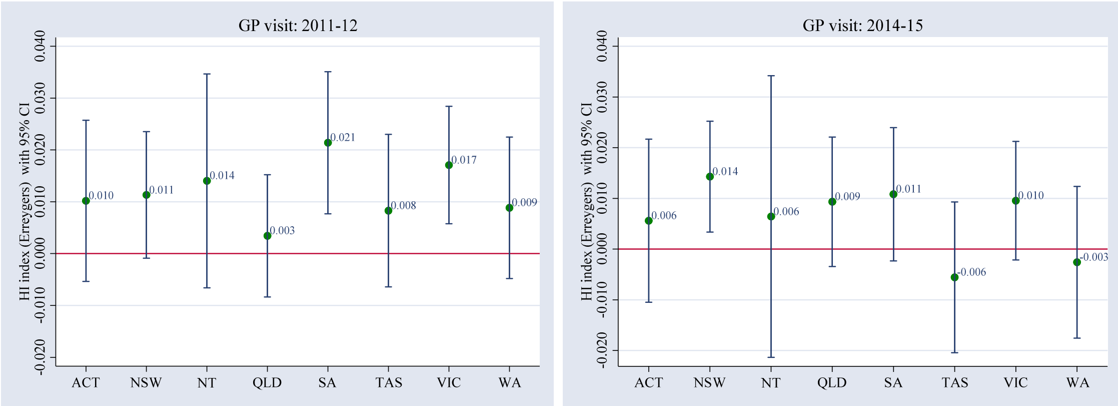


Figure 5.2: Regional variation of horizontal inequity in GP visit

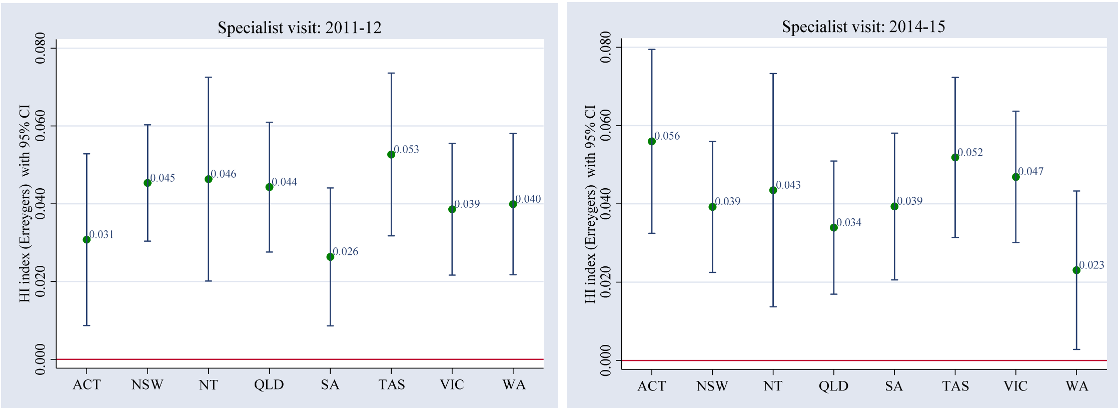


Figure 5.3: Regional variation of horizontal inequity in specialist visit

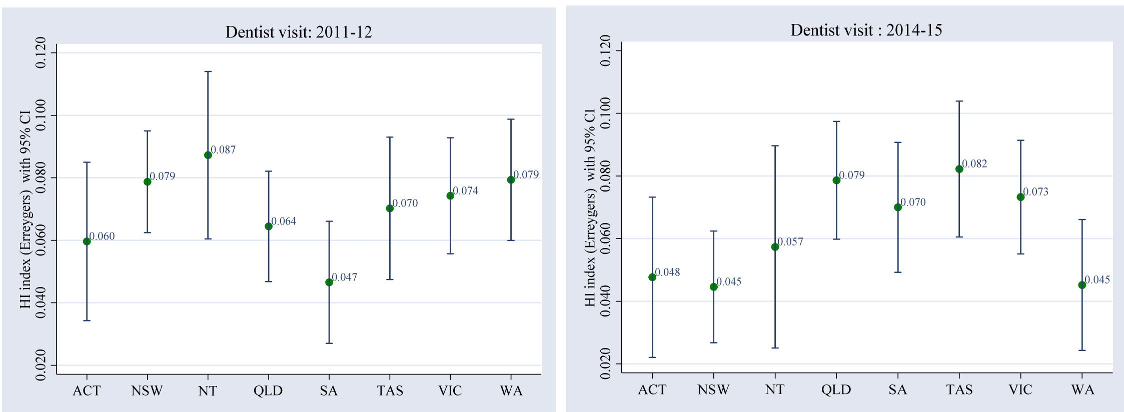


Figure 5.4: Regional variation of horizontal inequity in dentist visit

In general, there was almost no significant variation across the states in inequity in hospital-related services (Figure 5.5 to 5.8) except for day clinic visit in 2014-15. This is because of almost equitable distribution of these services among the states of Australia. As shown in Figure 5.5, EHI indices for inpatient admissions are found to be insignificant in all states except for SA in 2011-12, which was negative and statistically significant.

For outpatient visits, a similar pattern is observed but statically significant pro-poor distribution is found in SA in both surveys. In the case of day clinic visit, it is found that pro-rich inequity (EHI: 0.023) was significantly higher in the ACT compared to other states in 2014-15. In the same year, inequity has become more favourable to richer people in other states but all of them were virtually insignificant except in SA.

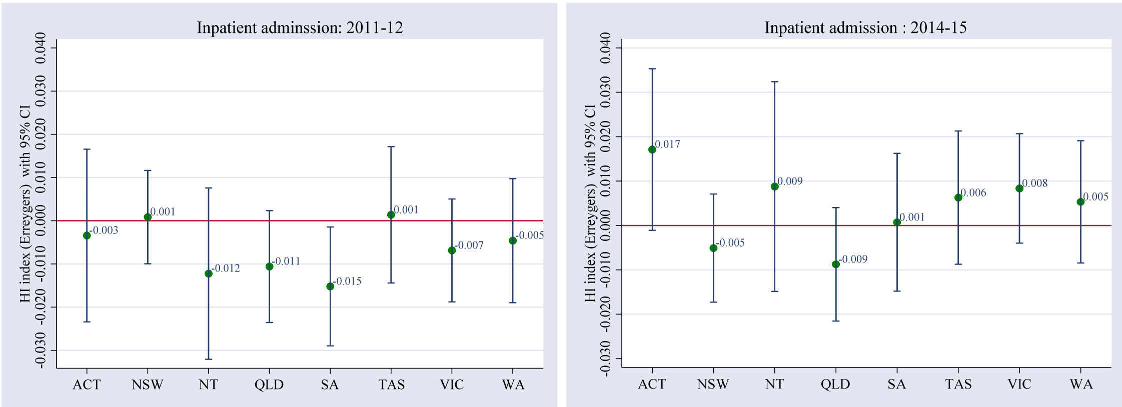


Figure 5.5: Regional variation of horizontal inequity in inpatient admission

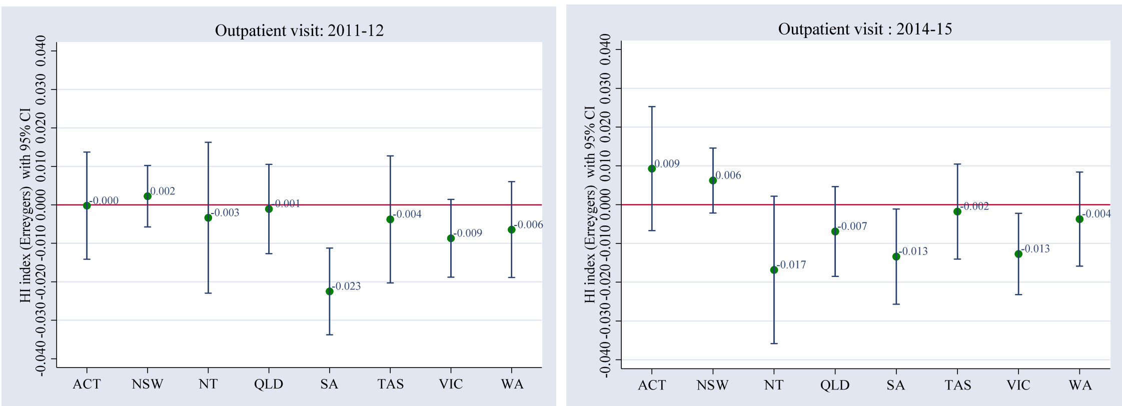


Figure 5.6: Regional variation of horizontal inequity in outpatient visit

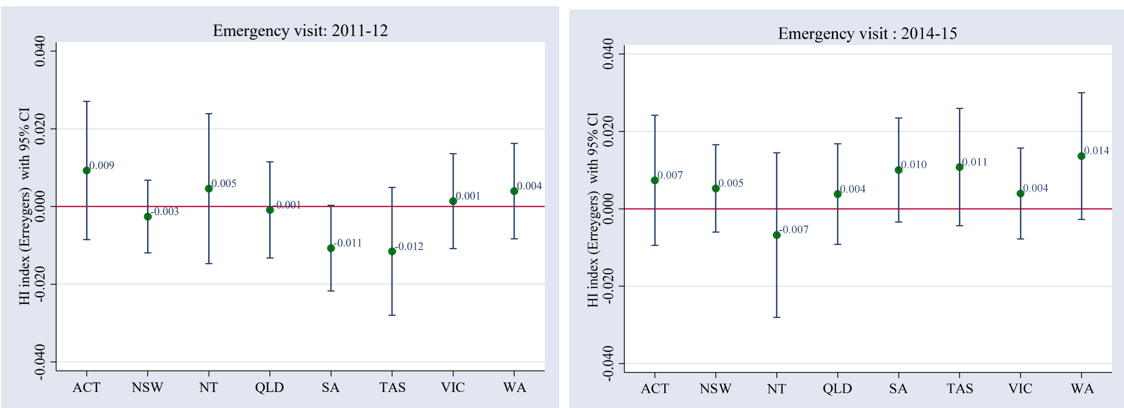


Figure 5.7: Regional variation of horizontal inequity in emergency visit

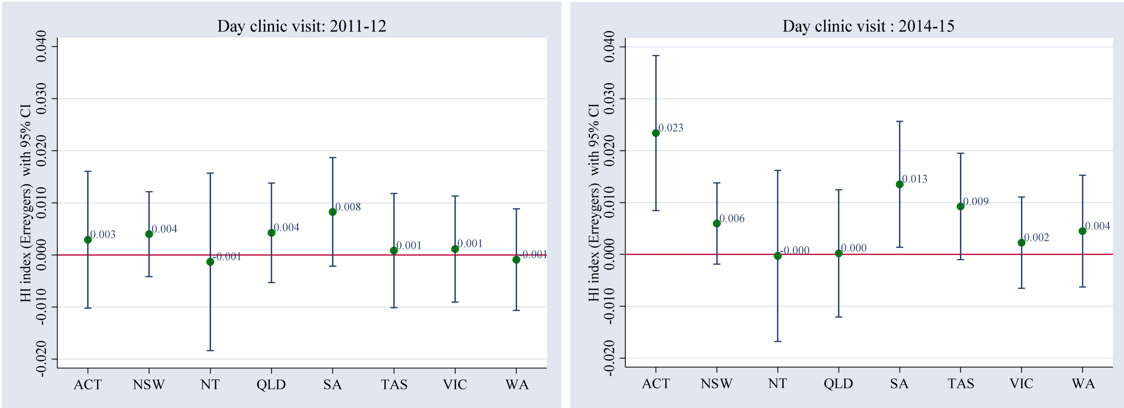


Figure 5.8: Regional variation of horizontal inequity in day clinic visit

5.4.5 Robustness results

Table 5.6 presents the results of the robustness of the inequity indices which is performed using different measures of ranking variables to rank the individuals. Equivalised household income in continuous form, individual income in deciles and continuous form and the SEIFA deciles are used alternative ranking variables in this analysis. Overall, no significant change is found in the inequity estimates when continuous household income is used instead of deciles as the ranking variable. This suggests that the extent of horizontal inequity remains similar regardless of using a continuous or categorical measure of household income. However, the size of the indices appears to be smaller when individual income is used as the ranking indicator. For example, the EHI is 0.023 for specialist visit when individual income is used for ranking compared to the EHI 0.038 of employing household income in 2014-15. Another noticeable change is that inequity in specialist visit has increased in 2014-15 when SEIFA is a ranking indicator.

In general, robustness results in Table 5.6 show that the overall conclusion about horizontal inequity in healthcare use is not sensitive to use of continuous or categorical measures of income. The results of robustness analysis for inequality indices are presented in Table A5.4 in Appendix 5. The important change found is that the inequality indices for any use, specialist and dentist visit are statistically significant and positive when the SEIFA is used as the ranking indicator. Otherwise, there has been no qualitative differences in results and the conclusion about robustness of the inequality remains similar.

Table 5.6: Robustness of inequity estimates (EHI) using different ranking variables

	2011-12				2014-15			
	Household income	Individual income		SEIFA	Household income	Individual income		SEIFA
	Continuous	Continuous	Deciles	Deciles	Continuous	Continuous	Deciles	Deciles
Any	0.013***	0.010***	0.010***	0.011***	0.014***	0.008***	0.008***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
GP	0.012***	0.011***	0.011***	0.011***	0.008***	0.003	0.003	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Specialist	0.039***	0.027***	0.027***	0.036***	0.038***	0.023***	0.022***	0.043***
	(0.00)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Dentist	0.069***	0.048***	0.046***	0.061***	0.065***	0.0484***	0.047***	0.062***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Inpatient	-0.003	-0.001	-0.001	0.001	-0.004	-0.006*	-0.005*	0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Outpatient	-0.005**	-0.004*	-0.004*	-0.004*	-0.003	-0.003	-0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Emergency	-0.001	0.001	0.001	-0.004	0.003	0.004	0.003	-0.008***
	(0.002)	(0.009)	(0.009)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Day clinic	0.002	0.0034	0.004*	0.004*	0.005**	0.003	0.003	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Notes: Robust standard errors in parentheses and significance level *** p<0.01, ** p<0.05, * p<0.10

5.5 Discussion

Equity in healthcare is a fundamental policy objective of Medicare in Australia. In other words, Australians should have equal access to healthcare services for equal need regardless of their socioeconomic background, race, residence etc. Therefore, the goal of Medicare is to achieve horizontal equity in the utilisation of healthcare services. This chapter has updated and extended the previous empirical evidence on HI in healthcare utilisation of the earlier studies (Hajizadeh et al., 2012; van Doorslaer et al., 2008). This study has quantified the extent of income-related horizontal inequity (HI) in overall use, out-of-hospital services, and hospital-related care in 2011-12 and 2014-15. The analysis in this chapter also extends the existing literature by examining the variation of inequity in healthcare use across the states and territories of Australia.

This chapter finds that overall healthcare utilisation measured by any visit was pro-rich, but the extent of inequity was not large in 2011-12 and 2014-15. This is contrasting to the conclusion drawn in earlier Australian studies which demonstrated either pro-poor or equitable distribution of any doctor visit (Hajizadeh et al., 2012; van Doorslaer et al., 2008). Additionally, a very recent study found that the distribution of Medicare spending for GP services among Australian children is fairly equitable as indicated by a positive (0.005) but insignificant inequity index (Dalziel et al., 2018a). However, the result from this study is not directly comparable to earlier studies due to differences in recall period, study population, and estimation approach.

The findings of this study also highlight that there was pro-rich inequity in out-of-hospital services while hospital-related services were largely equitable in Australia. In general, pro-rich inequity became less pro-rich in 2014-15 but this change was not statistically significant. The study further finds limited evidence of spatial variation in inequities but within-state variation over time is observed for some services. The results are summarised in Table 5.7.

Table 5.7: Summary of inequality and inequity in healthcare use

Outcome variable		2011-12 Inequality	2011-12 Inequity	2014-15 Inequality	2014-15 Inequity	State variation
Overall care	Any visit	equal	pro-rich	equal	pro-rich	No
Physician visit	GP visit	pro-poor	pro-rich	pro-poor	pro-rich	No
	Specialist visit	pro-poor	pro-rich	pro-poor	pro-rich	Limited
	Dentist visit	pro-rich	pro-rich	pro-rich	pro-rich	Limited
Hospital care	Inpatient admission	pro-poor	equitable	pro-poor	equitable	No
	Outpatient visit	pro-poor	pro-poor	pro-poor	equitable	No
	Emergency visit	pro-poor	equitable	pro-poor	equitable	No
	Day clinic visit	pro-poor	equitable	pro-poor	pro-rich	Limited

One of the key findings of this chapter is that there is pro-rich inequity in the probability of GP visit despite a small value of the HI index. This finding is important as significant pro-poor inequity in GP utilisation has been previously found in Australia (Hajizadeh et al., 2012; van Doorslaer et al., 2008). This different finding could arise due to differences in the recall period. The recall period in this study is the past 12 months while it was two weeks in the earlier studies. It could be argued that 12 months is a long recall period for GP visits. There could be some recall bias due to income; if the better off recall more accurately, while the poorer people are more likely to forget some GP visits. However, the probability of any GP visit as the outcome could be less prone to this problem as the 12-month longer recall period was found to be minimising the bias in estimating healthcare utilisation (Dalziel et al., 2018b). It is also suggested that the earlier pro-poor inequity in GP visit has become less pro-poor in the period of implementing private health insurance policies in the late 1990s and early 2000s (Hajizadeh et al., 2012).

A small but pro-rich inequity in the probability of GP visit found in this chapter is important in the current health policy context in Australia where a high and rising bulk-billing rate for GP visit is often referred as an indicator of affordability and equity in primary care. However, recent data has shown that about 33% of the patients do not use bulk-billed GP services. This implies that a sizable number of patients pay up-front for primary care services. Furthermore, about 5% of the Australians needed to visit a GP delayed or skipped visiting a GP due to financial barrier (ABS, 2017b). Some studies have also suggested that OOP costs for GP visit have in fact, increased for individuals without concession cards following the policy of the 'Strengthening Medicare reforms'(Wong et al., 2017). This could be a plausible explanation of the emergence of pro-rich inequity in GP service, but other factors might be at play.

The results of this chapter support findings from earlier studies suggesting a pro-rich inequity in specialist and dental care in Australia as seen in other OECD countries. Pro-rich inequity in specialist care also follows conclusion of the recent study by Dalziel et al. (2018), albeit their analysis is restricted to Australian children aged 0-11 years. It was found that area-level socioeconomic status is an important predictors of specialist services especially in 2014-15 which partially offset household income gradient in this service. This could be due to the fact the supply of specialist is mainly concentrated in better SES area of Australia. As expected, the extent of pro-rich inequity was the greatest in dentist visits given that Medicare does not cover dental care services in Australia and people heavily rely on OOP payments and private health insurance to finance dental care. This conclusion follows the previous work of FitzGerald et al. (2011) which suggested a significant increase in inequality in dental care visits between 1995 and 2005, a period of greater promotion for private health insurance uptake. The plausible reason is that the richer people can afford to buy private health insurance and pay for dental care from their own pocket.

The results from the analysis of hospital-related care reveal that pro-poor inequity in inpatient admission from the previous studies (Hajizadeh et al., 2012; van Doorslaer et al., 2008) is found to be equitable in this study. van Doorslaer et al. (2008) reported pro-poor inequity in inpaitenet admission as a public patient but pro-rich inequity when admitted as private paitent in the public hospitals. Although data in this study does not allow such analysis, it could be the case that pro-rich inequity in private admissions have become more extensive. This could make overall pro-poor inequity in inpatinent admssion equitable, which was found by Goodall & Scott (2008) using data from HILDA surevy. Pro-rich inequity in the probability of day clinic in 2014-15 found in this chapter also follows the conclusion of Goodall & Scott (2008)

Finally, this study finds limited evidence of state-level variation in inequity of healthcare use compared to higher provincial variation in inequity in access to healthcare as shown in two Canadian studies (Allin, 2008; Jiménez-Rubio et al., 2008). Insignificant variation in hospital-related care across Australia suggests that people from lower income groups could be using these services more compared to their higher income counterparts.

This chapter has some limitations like other studies in this area of research. The probability of visit/admission is a crude measure of healthcare service utilisation. In addition, it is not possible to differentiate between high users and low users of healthcare services, and the extent of inequity could be different between the probability of use and intensity of use. Recall bias and measurement errors by self-reporting is a standard caveat of this study just the same as any other studies relying on information from health surveys (Clarke et al., 2008; Kjellsson et al., 2014). Distinction could not be made between public and private hospital admissions due the limited information in the data.

Another limitation is that need-standardisation of healthcare using the same set of health need variables for all indicators might have induced bias in quantifying the extent of horizontal inequity. For example, need for specialist and GP services could be different. This is especially challenging in estimating inequity of dental care (Grignon et al. 2010; Nguyen & Häkkinen 2004). For example, health status was to be inversely related to dentist visit which might have resulted in underestimation of the degree of horizontal inequity. This sort of downward bias in the estimation of HI in dentist care is also reported in a Canadian study (Zhong, 2010). This chapter is not able to consider inequity in quality of healthcare which is a typical limitation of this kind of research using survey data (O'Donnell et al., 2008; van Doorslaer et al., 2004a). Finally, the area-level socioeconomic relative disadvantage is based on information from the 2011 census in both surveys which might have changed between the health surveys, therefore, it may not fully capture the neighbourhood gradient in horizontal inequity of healthcare utilisation. Some of these limitations are addressed in next two chapters of this thesis.

Despite the limitations mentioned above, the strength of this chapter is that it has used a consistent measure of healthcare use (12 months' recall period) for both periods which was not the case in the earlier Australian studies. This study has also controlled for area-level SES in need-standardisation of healthcare use which was not considered in the previous studies. The findings of this chapter are also robust to use of categorical or continuous measures of income as the ranking variable used to derive the inequity indices. This robustness analysis supports virtually no empirical bias for data with more than 10 income categories(Clarke and Van Ourti, 2010).

5.6 Conclusion

This chapter has contributed to the literature by presenting recent empirical evidence on whether the horizontal equity principle of Medicare is achieved in an era of encouraging private sources of healthcare funding. Despite the universal health insurance system, there is inequity in some sectors of healthcare services, and it varies across the states and territories of Australia. It could be the result of higher OOP costs to access specialist services and the lack of private health insurance among poorer people for privately-provided dental care services. On the contrary, the equitable distribution of hospital services might be related to free provision of needed services in the public hospitals. The Australian healthcare system is characterised by a complex blend of funding mechanisms and service provision between the public and private sectors. The complex funding arrangements and mixed responsibility for providing healthcare services might make the Australian system challenging to deliver equitable healthcare services. This is relevant to other countries as governments move to higher OOP payments with the aim of reducing public expenditure.

Chapter 6: Horizontal inequity in doctor visits in Australia

Abstract

This chapter has examined horizontal inequity (HI) in doctor visits in Australia which has an unregulated fee market for the private provision of medical care services in the out of hospital setting. For this purpose, HI in general practitioner (GP) and specialist visits is analysed for three measures of visit; the probability of a visit, intensity of visit and the conditional visit. This study has applied bootstrapped decomposition method to explain the contributing factors of this inequity. The results show modest evidence of pro-rich inequity in the probability of GP visit but, significant pro-poor distribution appears in conditional GP visits. This is due to the large and significant contribution of holding a concession card in the pro-poor direction of inequity. Pro-rich inequity is found in the probability of visiting a specialist while the distribution of conditional specialist visits is almost equitable. Richer and better educated individuals are more likely to visit a specialist than the poorer and less educated people. Inequality in income and education has explained a larger part of the pro-rich inequity. Unequal distribution of private health insurance coverage also is associated with the pro-rich inequity in specialist visit. Area-level socioeconomic status has also partly explained the pro-rich distribution of specialist visit. Findings of this study reveal that exclusion of higher users in the estimation of inequity has a pro-rich effect and this consequence is more pronounced for specialist visits. The conclusion is that rich and poor are not getting equal doctor services in Australia despite having a universal health insurance system since 1984.

Keywords: Horizontal inequity; decomposition analysis; specialist; private health insurance.

6.1 Introduction

The egalitarian healthcare systems of many countries in the OECD aim to ensure universal coverage of a comprehensive package of healthcare services for free or at a negligible cost. Public provision of healthcare services in these countries generally includes consultations with physicians, cancer screening services, diagnostic examinations, and hospital care (Devaux, 2015). Effort on fairer provision of healthcare services is made under the arrangement of a tax-financed national health system (the UK), social insurance system (Germany, the Netherlands), and tax-financed universal insurance system (Australia).

Despite differences in opinion on the definition of equity in healthcare, there is a broad consensus that the contributions for healthcare payment should follow ability to pay, and healthcare services should be distributed according to need (Culyer & Wagstaff 1993; Fleurbaey & Schokkaert 2011b; Wagstaff & van Doorslaer 2000a). The performance of the health systems in terms of equity matters, and equity in access to healthcare is a principal indicator of performance measurement of the OECD member states (Kelley & Hurst 2006). To be more specific, the horizontal equity principle in healthcare defined as 'equal care for equal need' is the stated policy goal of publicly-funded universal health systems in many European countries, Canada, and Australia. However, there remains unequal utilisation of various types of healthcare services by socioeconomic status (SES) despite universal coverage in these countries (Hajizadeh, 2017; Hanratty et al., 2007; Korda et al., 2009a; Stirbu et al., 2011).

The health economics literature on equity in healthcare typically relies on the horizontal inequity (HI) approach; that is inequality in utilisation after adjusting for healthcare need by income or other measures of SES (Wagstaff et al. 1991b; Wagstaff & van Doorslaer 2000b). Horizontal inequity (hereafter inequity) in certain types of healthcare service delivery is well documented in many OECD countries (Allin et al., 2011; Devaux, 2015; Grignon et al., 2010; Jiménez-Rubio et al., 2008; Lu et al., 2007; San Sebastián et al., 2017; van Doorslaer et al., 2004b). More specifically, income-related inequity in physician services or doctor utilisation such as general practitioner (GP) visit and medical specialist visit, has received substantial interest among the policymakers in these countries.

Broadly speaking, inequity in specialist services is found to be pro-rich in many developed countries and this has remained almost similar in the last three decades (Devaux & Looper 2012). This implies that better-off individuals are more likely to visit specialists given their same level of need as worse-off individuals, and they also tend to visit specialist doctors more often than the poor (Allin & Hurley, 2009; van Doorslaer et al., 2006, 2004). In general, higher pro-rich inequity in specialist visit exists in the countries with private health insurance and significant out-of-pocket payments (Devaux, 2015; van Doorslaer et al., 2006). In contrast, the pattern of inequity in primary care services is mixed over time in the OECD. Earlier studies demonstrated that the utilisation of GP services was either equitable or pro-poor, and frequency of visits to GP was comparatively higher among lower income people (van Doorslaer et al., 2006). However, pro-rich inequity has been found in the probability of GP visit in nine out of 16 developed countries in recent studies (Devaux, 2015). This is generally higher in countries (e.g. New Zealand) where a co-payment is required for consulting a GP. The conclusion on horizontal inequity from cross-sectional studies is found to be generally robust in longitudinal studies (Allin et al., 2011; Bago d'Uva et al., 2009).

The international evidence on inequity of doctor visits is also relevant in the context of the Australian healthcare system which aspires to achieve equity in access to and use of healthcare services. Although, the Australian healthcare system performs relatively well in terms of efficiency, it falls behind other developed health systems in its aim to achieve equity (Schneider et al., 2017).There is evidence of inequity in physician services in Australia. For example , inequity in physician visits (both GP and specialist) typically favoured higher income groups during the earlier period of Medicare (Lairson et al., 1995). van Doorslaer et al. (2008) found pro-poor bias in the distribution of need-adjusted GP visit while visit to specialists were pro-rich in 2001. They explained that inequality in private health insurance status of the patients by income could be a factor behind this differential mix of physician utilisation by rich and poor. The most recent study concluded that pro-poor inequity in GP utilisation has become less pro-poor while pro-rich specialist utilisation has remained similar after 2000 in Australia (Hajizadeh et al., 2012). The empirical results in the previous chapter has shown that inequity in the likelihood of GP visit has become slightly pro-rich in recent times. Furthermore, inequity in the probability of specialist visit has continued to be favourable to the richest.

Therefore, the aim of this chapter is to further explore the issue of income-related horizontal inequity in GP and specialist visits in Australia[38]. This chapter builds on the findings of the Chapter 5 but extends the empirical analysis in several ways. First, the chapter explicitly considers the two-stage decision-making of physician visit by exploiting the 12 months recall period in the National Health Survey, 2014-15. It examines inequity in the probability of visit and the conditional (positive) number of visits by employing a two-part model (Cameron and Trivedi, 2013). This is particularly important as first visit is usually decided by the patient while the second visit is a joint decision of doctor and patient (Bago d'Uva et al., 2009; van Doorslaer et al., 2004b). This allows an examination of total inequity, as well as the first and second part of inequity. In brief, this is done by studying inequity in the intensity of visits and conditional visit. Secondly, this chapter investigates the role of neighbourhood SES in the inequity of doctor utilisation for the first time in the Australian setting. Finally, employing the bootstrapped procedure, this chapter tests for the statistical significance of the contributing factors of inequity in physician visit.

This chapter is structured in six sections. The next section presents a brief overview of how the market for physician services work in Australia and its relevance for inequity in visit to medical doctors. Section three discusses methods for measuring and explaining inequity. This follows a description of the data and variables used in this study. Section five presents the results and interprets the findings from empirical analysis. Section six concludes the chapter with a summary of the key findings of this chapter and presents a future avenue of research.

6.2 Physician service provision, OOP cost and equity in Australia

The healthcare system in Australia shares many similar features of other OECD health systems, but the unique feature is it has an unregulated fee market for privately provided physician services. Out-of-hospital services are predominantly provided by private physicians under a fee-for-service (FFS) system. GPs are generally responsible for providing necessary services at the community level and patients enjoy freedom to select

[38] It should be noted that this chapter does not analyse inequity in dental care. This is because of unavailability of need indicators for dental service use in the NHS of 2014-15, and the fact that most dental care services are not funded by Medicare.

their own GPs (Wong & Hall 2018). No compulsory enrolment is required with GPs, but they act as the gate-keeper of the system (Wong et al., 2017). That is, a referral from GP is generally needed to access other parts of the healthcare system.

Australia has an unregulated fee market for privately provided physician services where doctors can charge any fees to any patient (Johar, 2012; Johar et al., 2017). Patients can claim reimbursement for doctor charges from Medicare according to the Medicare Benefits Schedule (MBS) rebate set by the Federal Government. This rebate can be thought of as a floor price for medical care in the out of hospital setting. When the provider bills Medicare directly and the cost is equal to the rebate of the MBS, patients do not pay any up-front fees at the point of service. This practice is famously known as bulk-billing in Australia. Bulk-billing in primary care is largely higher compared to secondary care. For example, more than 85% of GP attendances were bulk-billed while this rate is about 30% for specialist consultations in 2016-17 (Department of Health, 2017a).

Patients incur out-of-pocket (OOP) cost as the difference between the fee set by the physician and the Medicare fixed rebate. OOP costs could also arise when the patient pays for a prescription drug (Carpenter et al., 2015). Patients are not allowed to use private health insurance to cover co-payments of any out-of-hospital services funded by Medicare under the current Australian law (Duckett, 2004; Wong and Hall, 2018). There are several mechanisms to limit OOP faced by the Australians. For example, GPs are provided extra incentives to bulk-bill patients from low income households and pensioners with a medical concession card (Wong & Hall 2018). Additionally, there are 'Medicare Safety Net' arrangements to contain all OOP cost related to medical expenditure when an individual or family reaches a certain annual threshold (van Gool et al., 2009; Wong et al., 2017). Despite these initiatives, OOP expenditure in Australia is one of the highest among OECD member countries and it has been rising continuously in recent times (Wong et al., 2017). This high OOP might have implications for inequity in physician visit (Kiil & Houlberg 2014). For example, about 7% of the patients in need of specialist care delayed or skipped the appointment to visit a specialist because of cost (ABS, 2017b).

6.3 Empirical method

6.3.1 Measuring and explaining inequity

This chapter follows the widely-applied horizontal inequity (HI) approach of Wagstaff, van Doorslaer & Paci (1991) which was later advanced by Wagstaff and van Doorslaer (2000) and van Doorslaer et al. (2004). This method estimate the extent of inequity through the HI index and explains the underlying mechanisms of inequity in healthcare use by the decomposition method (García-Gómez et al., 2015; van de Poel et al., 2012). The concentration index (CI) is central to this methodology which is one of the most frequently employed indicators to measure socioeconomic-related inequality and inequity in healthcare use (O'Donnell et al., 2008). The following formula calculate the CI:

$$CI = \frac{2}{\mu}\operatorname{cov}(y_i, R_i) \tag{6.1}$$

In this expression, y_i is the healthcare use variable, R_i is the relative or fractional rank of the individuals in the income distribution and μ is the mean of healthcare use. Equation 6.1 specifies that the CI is a covariance between the measure of health service use and the fractional ranking, divided by the mean of healthcare use. This formula is multiplied by 2 to make sure that the CI ranges between −1 and +1. There would be no inequality in healthcare utilisation by income when the CI is zero or statistically insignificant. A positive CI indicates higher use of healthcare services among richer people (pro-rich) and vice versa.

The CI does not estimate inequity as it does not account for need differences among the individuals. For this purpose, the regression-based decomposition method is employed to adjust health need to measure the HI and to explain income-related inequity in healthcare utilisation (van de Poel et al., 2012; van Doorslaer et al., 2004b). By assuming the healthcare variable is a linear and additively separable function of need (x) and non-need (z) variables, a model for healthcare utilisation can be written as:

$$y_i = \alpha + \sum_k \beta_k x_{ki} + \sum_j \beta_j z_{ji} + \varepsilon_i \tag{6.2}$$

Equation 6.2 allows us to test for the existence of the HI by examining the sign and statistical significance of coefficients of the non-need variables which are not supposed to affect healthcare utilisation. It then follows the estimation of the HI if income and other non-need variables are found to be significantly associated with health service use. According to Wagstaff, van Doorslaer and Watanabe (2003), the unadjusted CI be can be obtained as the additive sum of the product of the CI of each covariate and elasticity of healthcare use with respect to that covariate. Thus, the decomposition of the CI of unadjusted healthcare use variable can be formulated as:

$$CI = \sum_k CI_x (\frac{\beta_x}{\overline{y}} \overline{x}_k) + \sum_j CI_z (\frac{\beta_z}{\overline{y}} \overline{z}_j) + \frac{GC_\varepsilon}{\overline{y}} \qquad (6.3)$$

In equation 6.3, $\overline{x}_k, \overline{z}_j$ and $\overline{y}$ are the means of need, non-need, and dependent variables, respectively. CI_x and CI_z stand for the CIs of need and non-need variables with respect to income. Finally, GC_ε is the generalised concentration index of the error term which measures the unexplained component of income-related inequality in healthcare use. Expression 6.3 implies that the unadjusted CI is the weighted sum of the CIs of the determinants for healthcare use in relation to income, where the weights are the responsiveness of healthcare use with respect to each explanatory variable. Two conditions need to be satisfied for a variable to explain inequality in healthcare use: (1) an association with use; and (2) an unequal distribution across the income distribution as captured by its own CI (Bonfrer et al., 2014).

The first part of equation 6.3 is the contribution to inequality in healthcare use due to the differences in need (age, gender, morbidity, and self-reported health) among the population. The need component in the decomposition equation is considered justifiable or legitimate inequality (O'Donnell et al., 2008). The second part of the equation 6.3 refers to the unjustifiable or avoidable part of inequality contributed by the non-need factors (income, private health insurance, education etc.) of healthcare service use. Therefore, the horizontal inequity (HI) index can be obtained by deducting the contributions of need factors from the CI as in equation 6.4:

$$HI = CI - \sum_k CI_x (\frac{\beta_x}{\overline{y}} \overline{x}_k) \qquad (6.4)$$

Equation 6.4 states that any income-related inequality in healthcare utilisation after accounting for need factors can be interpreted as the HI. The value of the HI ranges between -1 and +1. This means that the HI could be either pro-rich or pro-poor. A positive HI indicates pro-rich inequity which could be interpreted as richer individuals utilising more healthcare services than poorer despite the level of need being similar across all individuals in the income distribution (Wagstaff & van Doorslaer 2000b). On the other hand, a negative HI indicates inequity favouring poorer individuals or pro-poor. A zero or insignificant HI refers to no inequity in healthcare service utilisation.

This chapter applies the bootstrapped technique to obtain standard errors (SEs) of the HI index and estimates of the contributions to inequality in the decomposition analysis as outlined by Doorslaer, Koolman and Jones (2004). This is done by drawing a random sub-sample of the size equal to the original sample with replacement, and then deriving the estimates for the entire decomposition procedure with 500 replications (Sortsø et al., 2017). This procedure allows us to make inference about the statistical significance of the factors explaining the HI.

6.3.2 Econometric issues

The regression analysis has significance importance in the above discussed empirical strategy. Health service utilisation variables are intrinsically non-linear (such as binary and non-negative counts) in nature (Cameron and Trivedi, 2013; Jones, 2000). Non-linear estimation of the regression models in the decomposition approach to calculate horizontal inequity induces approximation error (O'Donnell et al., 2008). When non-linear regression techniques (e.g. probit or negative binominal models) are applied, the HI index obtained by the above decomposition technique is not identical to the HI from indirectly standardisation discussed in Chapter 3. This is because of the reliance on the approximation in obtaining the marginal effects (van Doorslaer et al., 2004a). Therefore, this chapter applies the ordinary least square (OLS) method in the decomposition to obtain the coefficients of need and non-need variables in estimating the HI index and explaining factors of the HI.

Although the decomposition analysis makes use of linear models in this chapter, it also presents the regression results from both linear and non-linear models. Linear probability model (LPM) and probit model are used for the binary indicators. For the total number of visits, both OLS and count models are estimated. In this case, negative binomial (NB) models are preferred over Poisson models as over-dispersion tests suggest that NB models are appropriate. Modelling of conditional visit requires estimation of a two-part or so-called hurdle model (Jiménez-Martín et al., 2002; Pohlmeier et al., 1995; van Ourti, 2004). The first part analyses the decision to visit at least once (i.e. use vs no use) and the second part analyses the subsequent visits conditional on being a user (Jones et al., 2007). This is implemented by estimating a probit regression to model the likelihood of visiting a doctor which is followed by a truncated negative binomial model at zero to estimate the frequency of visits conditioned on at least one visit. The results of non-linear models are presented using average marginal effect (AME)[39].

6.4 Description of data and variables

6.4.1 Data source and sample

The data for empirical analysis of this chapter originates from the latest Australian National Health Survey (NHS) conducted in 2014-15. The NHS is a nationally representative cross-sectional survey conducted by the Australian Bureau of Statistics (ABS) every three years. The 2014-15 survey is the seventh in the NHS series with a response rate of about 82.0% (ABS, 2017a). The survey is administered on the individual occupants living in private dwellings, selected at random using a multistage sample design technique. This survey covers approximately 97% of the population living across urban, rural and remote areas of six states and two territories of Australia (ABS, 2017a). However, it does not include people living in very remote areas of Australia, discrete Indigenous communities, and people from non-private residences. The sample size of this survey is around 19,000 individuals from about 14,700 private residences across Australia (ABS, 2017a).

The data of this survey are self-reported and collected by face-to-face interviews using a structured questionnaire. A wide range of information about demographic, socioeconomic, health status, long-term health conditions, health service use, health risk factors etc. was collected in this survey. The analysis of this chapter focuses on adult individuals; therefore, the sample size is restricted to observations for age 18 years and over. After excluding the persons with missing information, the final sample consisted of 14,560 adult respondents for the statistical analysis. Further information about the sampling procedure and data items of this survey is available elsewhere (ABS, 2017a).

[39] AME for a given covariate is calculated as the partial effect of that covariate for every observation in the sample and averaging the estimate over all observations.

6.4.2 Dependant variables

Physician or doctor visit is the indicator of healthcare service use in this chapter. A distinction is made between visits to GPs and specialists to measure doctor consultation. During the survey, participants were asked two distinct question about how many times they had consulted a GP and a specialist in the 12 months preceding the survey. Using this information, three different measures of visit are created as the outcome variables of this study. The first is the probability of a visit recoded as a dichotomous variable which takes the value of one if the respondents had a visit to either GP or specialist in the last year or zero otherwise. Secondly, the intensity of visits is the total number of visits which includes no visit as well as positive visits. Finally, the conditional or subsequent number of visits is analysed based on at least one visit.

6.4.3 Explanatory variables

The selection of explanatory variables in this study follows the previous literature from Australia and other OECD countries (Allin & Hurley 2009; Devaux, 2015; Hajizadeh et al. 2012; van Doorslaer et al. 2008). The regression models of physician visit include the following need-related variables: gender, age, self-assessed health (SAH), mental health condition, number of long-term conditions, disability status, morbidity status, diabetes, and hypertension. Age of the respondents are grouped into seven bands: 18-24 years, 25-34 years, 35-44 years, 45-54 years, 55-64 years, 65-74 years, and 75 years or above. SAH is measured on five scales as poor, fair, good, very good and excellent. The Kessler Psychological Distress Scale (Kessler-10 or K10) measures the mental health and well-being of the respondents. The K10 is a continuous variable ranging from 10 to 50 with a higher score indicating a greater level of psychological distress (Kessler et al., 2002). The number of long-term conditions describes the chronic conditions suffered by the respondents. Disability status measures daily activity limitations because of health-related reasons and is classified into four categories of no, some, moderate and severe. Respondents were asked to report on comorbidity which includes diabetes, kidney disease and cardiovascular disease (CVD). This variable is grouped as no morbidity, one morbidity, and multi-morbidity.

Equivalised weekly income of the household in deciles is the indicator of income in this chapter[40]. Missing information on income accounted for about 20% of the sample respondents, which are therefore excluded from the analysis. To estimate the CIs, income is used to rank the individuals from the poorest to the richest in the income distribution. A continuous measure of income provides better ranking of the individuals which leads to more accurate estimation of the CI (Chen & Roy 2009). Categorical income data may result in an underestimation of the CI (Clarke & van Ourti 2010). However, analysis from the earlier chapter shows that the indices differ little comparing two measures of income. This is also supported by the earlier findings from Canada and Ireland (Allin, 2008; Allin & Hurley 2009; Grignon et al. 2010; Walsh et al. 2012).

Among other non-need variables, Australian born is a dummy variable which takes a value 1 if the individual was born in Australia. English at home is a dichotomous variable which takes a value of 1 if the main language spoken at home is English or zero otherwise. Educational attainment of the survey participants is classified into three levels as 8 years or less of schooling, 9-11 years of schooling and 12 or more years of schooling. Employee, self-employed, unemployed, and out of the labour force are the four categories of employment status of individuals. A person's region of residence is coded as inner region=2, major city= 1, and other area=0. This is based on the Accessibility Remoteness Index of Australia (ARIA) which classifies areas according to their distance from the nearest service centre (M R McGrail & Humphreys 2009).

Private health insurance (PHI) in Australia is used as supplementary health cover for hospital and ancillary services, and this information was collected for persons aged 18 years and over in the NHS at the time of the survey. A government health concession card provides certain healthcare benefits such as discounts on the price of healthcare services and medicines to pensioners, seniors and families belonging to the low-income group in Australia[41]. The holder of this card is also eligible for a higher refund on their out-of-pocket cost for out-of-hospital services (van Gool et al., 2009).

[40] ABS has adjusted income of household by household size and composition following the OECD-modified scale. This scale applies a weight equal to 1 to the main household individual, 0.5 to the following adult in the household and 0.3 to children.

[41] https://www.humanservices.gov.au/individuals/subjects/concession-and-health-care-cards#a1

Finally, regression models in this chapter include area-level socioeconomic status as another major explanatory variable. In Australia, the relative economic and social conditions of a neighbourhood is measured by the socioeconomic indexes for area or commonly known SEIFA (ABS, 2011; Biddle, 2009). SEIFA is a composite index used to measure how an area is economically and socially developed compared to other areas. This variable is extensively used in many studies examining the association between socio-economic disadvantage and different social outcomes in Australia (Johar et al., 2014). There are four types of SEIFA constructed by the ABS using 2011 Australian census data, but the NHSs contain the *Index of Relative Socio-Economic Disadvantage* (IRSD) which summarises variables that indicate relative disadvantage of an area. This index ranks areas on a continuum from most disadvantaged to least disadvantaged. The areas of respondents in the survey are coded into 10 deciles, with the lower decile of this index indicating a high share of relatively disadvantaged individuals in an area.

6.5 Results

6.5.1 Summary statistics

Table A6.1 of Appendix 6 presents descriptive statistics of the independent variables included in the analysis. The result is presented using proportion (mean for the continuous variable) and standard deviations (SD). About 55% of the individuals reported their health as excellent or very good compared to only about 5% reporting poor health. The proportion of people without disability and any morbidity was about 0.63 and 0.74 respectively in the 2014-15 survey. The average K10 score is about 15 (SD: 5.9) and the average number of long-term conditions is about 3.6 (SD: 3.2) in this sample population. More than 11 % of the respondents had diabetes at the time of survey.

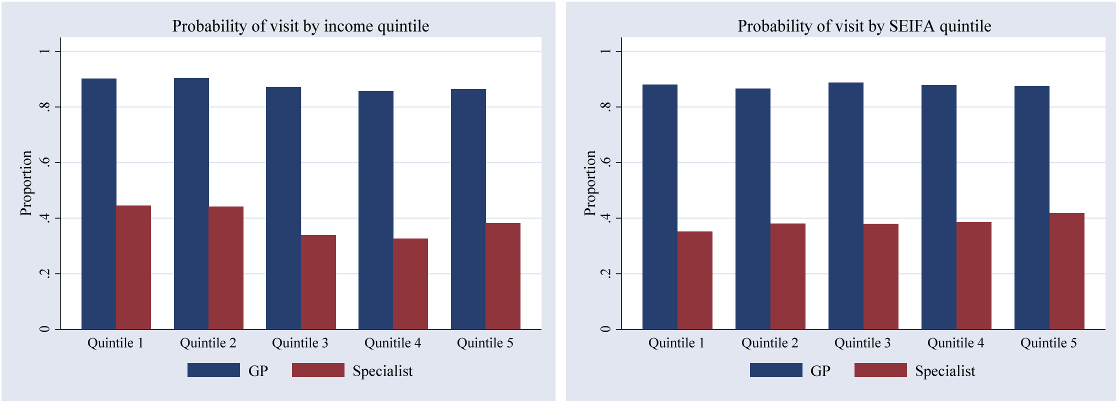
Table A6.1 reports that about 69% of the sample individuals are Australian-born and most of them (87%) speak English at home. The proportion of people with more than 12 years of education is about 0.57. About 54% of the respondents declared themselves as employees at the time when the survey. More than half (57%) of Australians had some form of private health insurance, and about 32% were concession card holders in 2014-15. According to Table A6.1, about 90% of the respondents live in major cities and inners regions of Australia. Finally, the sample population is almost evenly distributed among the household income and SEIFA deciles.

Table 6.1 reports that about 88% and 38% of the population reported to have at least one GP and one specialist visit respectively in the year preceding the survey. The mean of total and conditional number of GP visits was about 4.01 and 4.58. The average number of total specialist visits in Australia was about 1.25 (95% CI: 1.207-1.297). On average, individuals visited a GP 4.6 times and a medical specialist 3.2 times conditional on at least one visit (Table 6.1).

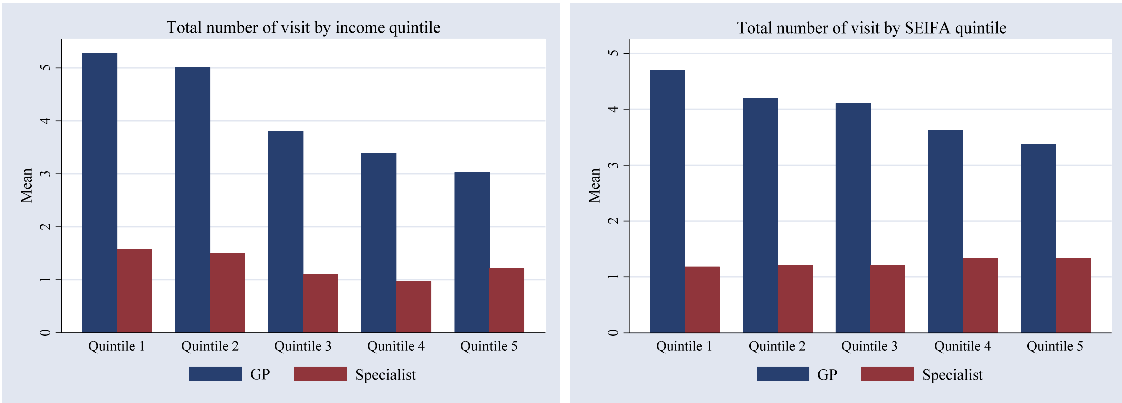
Table 6.1: Summary statistics of GP and specialist visit

	GP		Specialist	
	Proportion /Mean	95% CI	Proportion /Mean	95% CI
Probability of visit	0.877	[0.871 ,0.883]	0.383	[0.374,0.392]
Total number of visits	4.015	[3.949 ,4.081]	1.252	[1.207,1.297]
Conditional number of visits	4.575	[4.507 ,4.643]	3.270	[3.182,3.359]

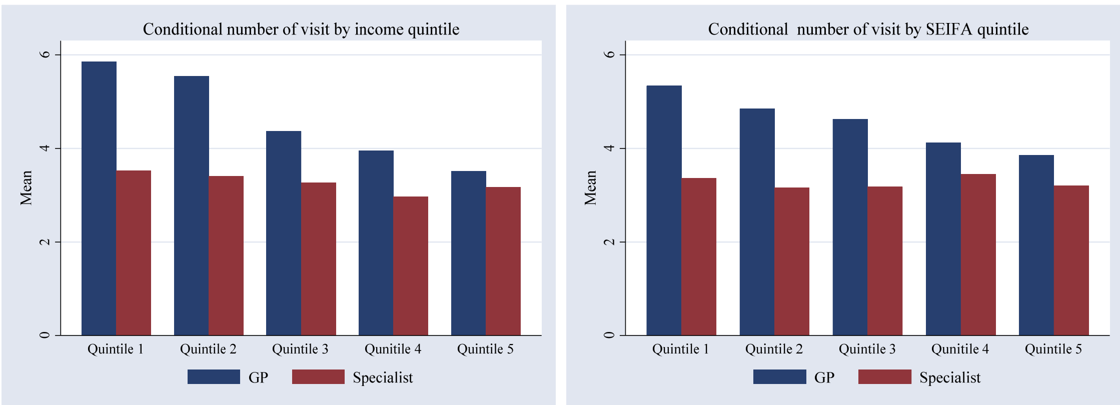
Figure 6.1 illustrates quintile distributions of three types of GP and specialist visits by income and SEIFA. The proportion of both GP and specialist visit appears to be higher among the individuals of the first two income quintiles compared to the other three income quintiles (Panel a). However, the proportion of specialist visit is higher among the highest quintile (38%) compared to the third and fourth quintiles (33%). Panel (a) also shows that the probability of both types of visit was almost similar among SEIFA quintiles. Panels (b) and (c) in Figure 1 present that the quintile distributions both total and conditional number of GP visits are more concentrated among the lower income groups. In other words, there was a negative gradient by income and SEIFA quintile for number of GP visits. On the other hand, the distribution of these two types of visit to medical specialists follows a similar pattern of probability of visit.



Panel a: Distribution of probability of visit



Panel b: Distribution of total number of visits



Panel c: Distribution of conditional number of visits

Figure 6.1: Distribution of visit to GP and specialist by income and SEIFA quintiles

6.5.2 Regression results

Tables 6.2 and 6.3 present regression results for three outcomes of GP and specialist visits, respectively. Ordinary least squares (OLS) and probit regressions are estimated to model the probability of visit. OLS and negative binomial (NB2) models are fitted for total and conditional number of visits[42]. Although there is almost no significant qualitative difference in the coefficients between linear and non-linear models, results are presented from both models for the sake of completeness. Average marginal effect (AME) is used to interpret the results of probit and negative binomial models.

Tables 6.2 and 6.3 show that females had a higher probability of visit, and the frequency and conditional number of visits was also higher among females compared to male. The likelihood of visiting both GPs and specialists increased with age, however, age was negatively associated with conditional numbers of both visits and this relationship is more pronounced for specialist visit. For the total number of visits, the negative association with age is more significant for GPs (Table 6.2). As expected, individuals with poorer self-assessed health (SAH) have higher likelihood of doctor visits as well as a greater number of total and conditional visits. For example, an individual reporting poor health is predicted to have two more GP visits (Model 4 in Table 6.3) and one more specialist visit (Model 4 in Table 6.4) compared to people reporting excellent health. Tables 6.2 and 6.3 also report that other measures of need variables have a significant and positive association with all three types of GP and specialist services utilisation.

Regarding the non-need variables, Australian-born individuals have a significantly higher probability and intensity of physician visit except for conditional specialist visit. According to Table 6.3, speaking English at home is a significant and positive predictor of all types of specialist visit. However, the conditional number of GP visit is lower among the individuals speaking English at home (Table 6.2). A positive and significant association is found between education and specialist visit but not for GP visit. Table 6.3 shows that employed people visit specialists less frequently compared to the individuals who are not in the labour force. It appears from regression results that residents of inner

[42] The likelihood ratio test of the over-dispersion parameter or alpha is always significant which favours use of NB2 model over Poisson model.

regions and other areas in Australia have lower likelihood of both types of physician visits as well as their frequency of total and conditional visits.

Table 6.2 shows that private health insurance significantly increases the likelihood of seeking care from GPs, but it has no significant association with the total and conditional number of GP visits in 2014-15. In case of specialists, private health insurance strongly and positively matters for the probability of visit and total number of visits (Table 6.3). However, it does not have any significant relation to the conditional number of visits albeit a positive association. Holding a concession card is a strong predictor of all three types of GP services (Table 6.2), it has no statistically significant relation with any measure of specialist visit (Table 6.3).

Regression results in Table 6.2 show that income is significantly and positively related only to the probability of GP visit but not to the other two types of GP visits. On the other hand, area-level socioeconomic status (SEIFA) is found to be significantly related (negative) with both total and conditional number of GP visits. Table 6.3 reveals that the observed association between specialist visit and SEIFA is stronger compared to the association with household income. For example, individuals belonging to SEIFA 4^{th} to 10^{th} deciles have a higher probability of and total number of specialist visits. On the contrary, people belonging to only 9^{th} and 10^{th} income deciles had positive and significant association with these visits. This suggests that people living in better SES areas use more specialist services compared to people from poorer SES areas. People from the top two income deciles have a significantly higher probability of and total number of specialist visit compared to people belonging to the rest of the income deciles. However, this association is not observed the in case of conditional number of visits

Table 6.2: Regression models for GP visit

	Probability of visit				Total number of visits				Conditional number of visits			
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	OLS		Probit		OLS		NB2		OLS		NB2	
	Coef.	SE	AME	SE	Coef.	SE	AME	SE	Coef.	SE	AME	SE
Need variables												
Female	0.068***	(0.006)	0.060***	(0.006)	0.699***	(0.057)	0.852***	(0.063)	0.536***	(0.060)	0.673***	(0.069)
Age (Ref: 18-24 year)												
Age 25-34 year	0.014	(0.016)	0.008	(0.012)	0.057	(0.131)	0.051	(0.158)	0.020	(0.142)	-0.025	(0.177)
Age 35-44 year	-0.007	(0.016)	-0.012	(0.011)	-0.178	(0.129)	-0.241	(0.157)	-0.171	(0.141)	-0.284	(0.175)
Age 45-54 year	-0.002	(0.016)	-0.021*	(0.012)	-0.485***	(0.133)	-0.509***	(0.160)	-0.498***	(0.145)	-0.641***	(0.178)
Age 55-64 year	0.043***	(0.016)	0.019	(0.013)	-0.418***	(0.137)	-0.376**	(0.160)	-0.600***	(0.148)	-0.718***	(0.179)
Age 65-74 year	0.045***	(0.017)	0.029*	(0.017)	-0.353**	(0.162)	-0.224	(0.177)	-0.537***	(0.173)	-0.524***	(0.196)
Age 75+ year	0.055***	(0.017)	0.080***	(0.022)	0.187	(0.188)	0.172	(0.188)	-0.054	(0.196)	-0.134	(0.206)
SAH (Ref: Excellent)												
Very good	0.039***	(0.010)	0.025***	(0.007)	0.356***	(0.067)	0.660***	(0.101)	0.306***	(0.072)	0.662***	(0.122)
Good	0.041***	(0.010)	0.023***	(0.008)	0.932***	(0.081)	1.327***	(0.107)	0.946***	(0.086)	1.488***	(0.126)
Fair	0.058***	(0.011)	0.049***	(0.014)	1.619***	(0.128)	1.810***	(0.128)	1.588***	(0.131)	1.949***	(0.145)
Poor	0.046***	(0.013)	0.077***	(0.027)	2.505***	(0.189)	2.078***	(0.150)	2.461***	(0.188)	2.240***	(0.164)
Disability (Ref: No)												
Some disability	0.026***	(0.008)	0.007	(0.009)	0.306***	(0.083)	0.559***	(0.091)	0.296***	(0.085)	0.575***	(0.102)
Moderate disability	0.022***	(0.007)	0.016	(0.011)	1.056***	(0.100)	1.043***	(0.089)	1.058***	(0.101)	1.136***	(0.097)
Severe disability	0.010	(0.010)	0.048*	(0.026)	1.641***	(0.189)	1.245***	(0.135)	1.632***	(0.187)	1.373***	(0.141)
Morbidity (Ref: Zero)												
One morbidity	0.064***	(0.006)	0.081***	(0.010)	0.652***	(0.080)	0.738***	(0.074)	0.459***	(0.081)	0.575***	(0.083)
Multi-morbidity	0.025**	(0.010)	0.085**	(0.034)	0.859***	(0.179)	0.608***	(0.138)	0.734***	(0.179)	0.575***	(0.149)
K10 score	0.002***	(0.001)	0.002***	(0.001)	0.051***	(0.007)	0.045***	(0.006)	0.047***	(0.007)	0.041***	(0.006)
No. of long-term conditions	0.008***	(0.001)	0.019***	(0.002)	0.206***	(0.013)	0.161***	(0.011)	0.176***	(0.013)	0.143***	(0.012)
Diabetes	0.031***	(0.008)	0.035**	(0.014)	0.241**	(0.106)	0.313***	(0.093)	0.152	(0.106)	0.216**	(0.102)
Non-need variables												
Australian-born	0.024***	(0.007)	0.023***	(0.007)	0.182***	(0.069)	0.242***	(0.077)	0.129*	(0.073)	0.177**	(0.086)
English at home	0.035***	(0.013)	0.018*	(0.010)	-0.170	(0.109)	-0.106	(0.124)	-0.324***	(0.118)	-0.328**	(0.134)
Health insurance	0.036***	(0.007)	0.033***	(0.006)	0.100	(0.064)	0.123*	(0.070)	-0.019	(0.068)	-0.032	(0.077)
Concession card	0.054***	(0.009)	0.051***	(0.010)	0.690***	(0.102)	0.731***	(0.104)	0.523***	(0.107)	0.576***	(0.114)
Education (Ref: Year 8 or less)												
Year 9-11	-0.004	(0.009)	0.007	(0.016)	-0.178	(0.140)	-0.109	(0.111)	-0.157	(0.142)	-0.082	(0.119)
Year 12 or more	0.007	(0.010)	0.013	(0.016)	-0.283*	(0.146)	-0.211*	(0.122)	-0.315**	(0.149)	-0.262**	(0.131)

Employment (Ref: Out of LFS)												
Employee	0.022**	(0.009)	0.021**	(0.009)	0.016	(0.094)	0.041	(0.100)	-0.079	(0.098)	-0.073	(0.111)
Self-employee	-0.020	(0.013)	-0.011	(0.011)	-0.230**	(0.115)	-0.335**	(0.135)	-0.225*	(0.122)	-0.311**	(0.152)
Unemployed	-0.012	(0.020)	-0.010	(0.017)	-0.194	(0.193)	-0.156	(0.191)	-0.181	(0.206)	-0.121	(0.201)
Residence (Ref: Major City)												
Inner region	-0.036***	(0.008)	-0.036***	(0.008)	-0.359***	(0.078)	-0.386***	(0.082)	-0.266***	(0.082)	-0.288***	(0.089)
Other or remote	-0.031***	(0.009)	-0.030***	(0.008)	-0.394***	(0.081)	-0.423***	(0.089)	-0.328***	(0.086)	-0.354***	(0.098)
Household Income (Ref: Decile 1)												
Decile 2	0.025**	(0.011)	0.031**	(0.016)	0.088	(0.149)	-0.035	(0.128)	-0.026	(0.154)	-0.153	(0.136)
Decile 3	0.028**	(0.012)	0.031**	(0.015)	0.163	(0.152)	0.115	(0.134)	0.052	(0.157)	0.004	(0.142)
Decile 4	0.017	(0.013)	0.016	(0.014)	-0.004	(0.145)	-0.018	(0.141)	-0.069	(0.153)	-0.089	(0.151)
Decile 5	0.029**	(0.014)	0.031**	(0.014)	0.004	(0.144)	-0.033	(0.147)	-0.118	(0.152)	-0.177	(0.160)
Decile 6	0.032**	(0.015)	0.031**	(0.014)	0.140	(0.148)	0.140	(0.155)	0.019	(0.156)	-0.002	(0.167)
Decile 7	0.045***	(0.015)	0.041***	(0.014)	0.349**	(0.149)	0.358**	(0.158)	0.202	(0.158)	0.201	(0.174)
Decile 8	0.029*	(0.016)	0.024*	(0.014)	0.083	(0.149)	0.045	(0.166)	-0.029	(0.158)	-0.100	(0.184)
Decile 9	0.039**	(0.016)	0.030**	(0.014)	0.079	(0.148)	0.057	(0.165)	-0.079	(0.156)	-0.164	(0.184)
Decile 10	0.028*	(0.016)	0.021	(0.014)	-0.010	(0.150)	-0.098	(0.170)	-0.128	(0.159)	-0.301	(0.192)
Area socioeconomic status (Ref: SEIFA 1)												
SEIFA 2	-0.005	(0.012)	-0.000	(0.014)	-0.273**	(0.139)	-0.232*	(0.130)	-0.308**	(0.145)	-0.255*	(0.138)
SEIFA 3	-0.010	(0.013)	-0.007	(0.014)	-0.174	(0.140)	-0.143	(0.131)	-0.151	(0.145)	-0.114	(0.138)
SEIFA 4	-0.005	(0.013)	0.001	(0.013)	-0.291**	(0.137)	-0.278**	(0.135)	-0.312**	(0.143)	-0.292**	(0.146)
SEIFA 5	-0.003	(0.013)	0.004	(0.013)	-0.092	(0.134)	-0.078	(0.130)	-0.119	(0.141)	-0.073	(0.140)
SEIFA 6	0.008	(0.013)	0.014	(0.014)	-0.133	(0.136)	-0.125	(0.136)	-0.205	(0.142)	-0.188	(0.147)
SEIFA 7	-0.002	(0.013)	0.002	(0.014)	-0.351**	(0.136)	-0.331**	(0.138)	-0.404***	(0.143)	-0.386**	(0.151)
SEIFA 8	-0.002	(0.014)	0.002	(0.014)	-0.336**	(0.140)	-0.342**	(0.146)	-0.380***	(0.147)	-0.406**	(0.160)
SEIFA 9	0.008	(0.014)	0.011	(0.014)	-0.353**	(0.138)	-0.299**	(0.144)	-0.430***	(0.144)	-0.415***	(0.159)
SEIFA 10	0.003	(0.014)	0.008	(0.014)	-0.392***	(0.138)	-0.366**	(0.148)	-0.473***	(0.145)	-0.471***	(0.165)
Alpha (Test of equidispersion)								0.286(p=0.000)				0.248(p=0.000)
Observations	11,423		11,423		11,423		11,423		10,088		10,088	
R-squared	0.094				0.345				0.316			

Notes: Robust standard errors in parentheses, AME= Average marginal effect and significance level *** p<0.01, ** p<0.05, * p<0.10, NB2=Negative binomial model version 2

Table 6.3: Regression models for specialist visit

	Probability of visit				Total number of visits				Conditional number of visits			
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	OLS		Probit		OLS		NB2		OLS		NB2	
	Coef.	SE	AME	SE	Coef.	SE	AME	SE	Coef.	SE	AME	SE
Need variables												
Female	0.038***	(0.009)	0.040***	(0.009)	0.271***	(0.044)	0.341***	(0.053)	0.351***	(0.088)	0.329***	(0.089)
Age (Ref: 18-24 year)												
Age 25-34 year	0.043**	(0.018)	0.048**	(0.020)	0.246**	(0.109)	0.320**	(0.147)	0.198	(0.313)	0.156	(0.241)
Age 35-44 year	0.045**	(0.018)	0.053***	(0.020)	0.073	(0.105)	0.126	(0.145)	-0.399	(0.303)	-0.394*	(0.239)
Age 45-54 year	0.024	(0.019)	0.032	(0.021)	-0.238**	(0.107)	-0.207	(0.148)	-1.088***	(0.300)	-1.106***	(0.250)
Age 55-64 year	0.078***	(0.020)	0.082***	(0.021)	-0.175	(0.111)	-0.068	(0.146)	-1.205***	(0.300)	-1.179***	(0.247)
Age 65-74 year	0.129***	(0.023)	0.129***	(0.024)	-0.033	(0.131)	0.068	(0.159)	-1.217***	(0.322)	-1.162***	(0.266)
Age 75+ year	0.176***	(0.026)	0.176***	(0.027)	-0.101	(0.145)	0.127	(0.170)	-1.512***	(0.336)	-1.408***	(0.287)
SAH (Ref: Excellent)												
Very good	0.041***	(0.012)	0.043***	(0.012)	0.059	(0.052)	0.147*	(0.086)	-0.138	(0.133)	-0.099	(0.154)
Good	0.057***	(0.013)	0.057***	(0.013)	0.204***	(0.061)	0.330***	(0.088)	0.197	(0.143)	0.272*	(0.155)
Fair	0.114***	(0.018)	0.111***	(0.018)	0.570***	(0.097)	0.650***	(0.104)	0.582***	(0.176)	0.618***	(0.175)
Poor	0.193***	(0.025)	0.194***	(0.025)	1.277***	(0.174)	1.011***	(0.125)	1.102***	(0.239)	0.995***	(0.203)
Disability (Ref: No)												
Some disability	0.060***	(0.013)	0.055***	(0.012)	0.253***	(0.064)	0.415***	(0.074)	0.315***	(0.121)	0.358***	(0.129)
Moderate disability	0.134***	(0.014)	0.120***	(0.013)	0.702***	(0.079)	0.774***	(0.072)	0.630***	(0.124)	0.699***	(0.121)
Severe disability	0.164***	(0.023)	0.151***	(0.023)	1.220***	(0.166)	0.963***	(0.112)	1.091***	(0.214)	1.035***	(0.168)
Morbidity (Ref: Zero)												
One morbidity	0.064***	(0.012)	0.057***	(0.011)	0.029	(0.062)	0.139**	(0.063)	-0.260**	(0.105)	-0.246**	(0.108)
Multi-morbidity	0.104***	(0.025)	0.105***	(0.025)	0.328**	(0.157)	0.175	(0.113)	-0.066	(0.214)	-0.097	(0.181)
K10 score	0.003***	(0.001)	0.003***	(0.001)	0.025***	(0.006)	0.024***	(0.005)	0.028***	(0.009)	0.019***	(0.007)
No. of long-term conditions	0.021***	(0.002)	0.021***	(0.002)	0.109***	(0.012)	0.098***	(0.010)	0.065***	(0.018)	0.058***	(0.015)
Diabetes	0.049***	(0.016)	0.045***	(0.015)	0.330***	(0.094)	0.346***	(0.081)	0.347**	(0.146)	0.349***	(0.128)
Non-need variables												
Australian-born	0.025**	(0.011)	0.026**	(0.011)	0.150***	(0.054)	0.171***	(0.064)	0.160	(0.107)	0.156	(0.109)
English at home	0.054***	(0.015)	0.060***	(0.017)	0.340***	(0.069)	0.622***	(0.104)	0.595***	(0.162)	0.669***	(0.182)
Health insurance	0.096***	(0.010)	0.097***	(0.010)	0.347***	(0.049)	0.445***	(0.062)	0.150	(0.104)	0.093	(0.102)
Concession card	0.013	(0.014)	0.013	(0.015)	0.070	(0.082)	0.071	(0.086)	0.080	(0.160)	0.007	(0.138)
Education (Ref: Year 8 or less)												
Year 9-11	0.080***	(0.018)	0.074***	(0.018)	0.432***	(0.090)	0.357***	(0.095)	0.412***	(0.156)	0.334**	(0.157)
Year 12 or more	0.120***	(0.019)	0.115***	(0.019)	0.635***	(0.096)	0.575***	(0.103)	0.566***	(0.170)	0.464***	(0.169)

Employment (Ref: Out of LFS)												
Employee	-0.017	(0.014)	-0.017	(0.014)	-0.186**	(0.078)	-0.255***	(0.082)	-0.393***	(0.146)	-0.331***	(0.128)
Self-employee	0.016	(0.018)	0.017	(0.017)	-0.084	(0.091)	-0.137	(0.104)	-0.367**	(0.172)	-0.369**	(0.176)
Unemployed	0.034	(0.027)	0.034	(0.027)	0.180	(0.168)	0.129	(0.153)	0.116	(0.319)	-0.008	(0.227)
Residence (Ref: Major City)												
Inner region	-0.026**	(0.012)	-0.025**	(0.012)	-0.140**	(0.061)	-0.182***	(0.069)	-0.199*	(0.117)	-0.275**	(0.112)
Other or remote	-0.030**	(0.012)	-0.030**	(0.012)	-0.244***	(0.059)	-0.293***	(0.078)	-0.450***	(0.126)	-0.459***	(0.135)
Household Income (Ref: Decile 1)												
Decile 2	-0.020	(0.020)	-0.020	(0.020)	-0.048	(0.111)	-0.058	(0.108)	-0.013	(0.197)	-0.026	(0.173)
Decile 3	-0.004	(0.020)	-0.005	(0.020)	-0.031	(0.107)	0.037	(0.111)	-0.006	(0.193)	0.078	(0.178)
Decile 4	0.023	(0.020)	0.021	(0.020)	0.166	(0.106)	0.150	(0.115)	0.237	(0.197)	0.248	(0.182)
Decile 5	0.014	(0.020)	0.012	(0.021)	0.095	(0.106)	0.088	(0.124)	0.120	(0.205)	0.116	(0.194)
Decile 6	0.005	(0.021)	0.006	(0.021)	0.205*	(0.114)	0.193	(0.130)	0.492**	(0.224)	0.397*	(0.206)
Decile 7	0.017	(0.021)	0.020	(0.022)	0.181	(0.111)	0.192	(0.134)	0.330	(0.227)	0.275	(0.222)
Decile 8	0.014	(0.022)	0.016	(0.022)	-0.018	(0.110)	-0.008	(0.138)	-0.183	(0.221)	-0.240	(0.230)
Decile 9	0.048**	(0.022)	0.049**	(0.022)	0.218*	(0.115)	0.301**	(0.136)	0.232	(0.225)	0.267	(0.221)
Decile 10	0.054**	(0.023)	0.055**	(0.022)	0.251**	(0.117)	0.333**	(0.135)	0.289	(0.226)	0.284	(0.226)
Area socioeconomic status (Ref: SEIFA 1)												
SEIFA 2	0.002	(0.019)	0.004	(0.019)	0.057	(0.100)	0.117	(0.114)	0.103	(0.208)	0.105	(0.182)
SEIFA 3	0.028	(0.019)	0.031	(0.020)	0.039	(0.098)	0.103	(0.115)	-0.162	(0.200)	-0.139	(0.183)
SEIFA 4	0.069***	(0.019)	0.070***	(0.019)	0.245**	(0.099)	0.292***	(0.112)	0.036	(0.202)	0.013	(0.186)
SEIFA 5	0.053***	(0.018)	0.056***	(0.019)	0.165*	(0.096)	0.253**	(0.114)	-0.055	(0.197)	-0.023	(0.183)
SEIFA 6	0.042**	(0.019)	0.044**	(0.020)	0.081	(0.098)	0.104	(0.115)	-0.183	(0.207)	-0.154	(0.196)
SEIFA 7	0.053***	(0.019)	0.055***	(0.020)	0.255**	(0.104)	0.378***	(0.121)	0.186	(0.213)	0.196	(0.193)
SEIFA 8	0.055***	(0.020)	0.058***	(0.021)	0.254**	(0.108)	0.449***	(0.125)	0.151	(0.221)	0.240	(0.203)
SEIFA 9	0.042**	(0.020)	0.045**	(0.021)	0.111	(0.103)	0.231*	(0.123)	-0.007	(0.213)	0.030	(0.207)
SEIFA 10	0.080***	(0.021)	0.081***	(0.021)	0.262**	(0.106)	0.383***	(0.124)	0.005	(0.213)	0.013	(0.204)
Alpha (Test of equidispersion)							2.352(p=0.000)				1.254(p=0.000)	
Observations	11,423		11,423		11,423		11,423		4,515		4,515	
R-squared	0.166				0.152				0.117			

Notes: Robust standard errors in parentheses, AME= Average marginal effect and significance level *** p<0.01, ** p<0.05, * p<0.10, NB2=Negative binomial model version 2

It should be noted that the number of doctor visits was censored at 12 or more visits in NHS, 2014-15. Figure 6.2 which depicts the normal density plot of both the number of GP and specialist visits. The right censoring of outcome variables indicates that the information about independent variables in the regression analysis is observed for individuals who reported visits more than 12, but the actual number of visits is unknown for these respondents. This kind of censoring could have implications for the regression analysis as well as in the estimation of the HI indices. Therefore, sensitivity analysis is conducted by excluding the censored observations.

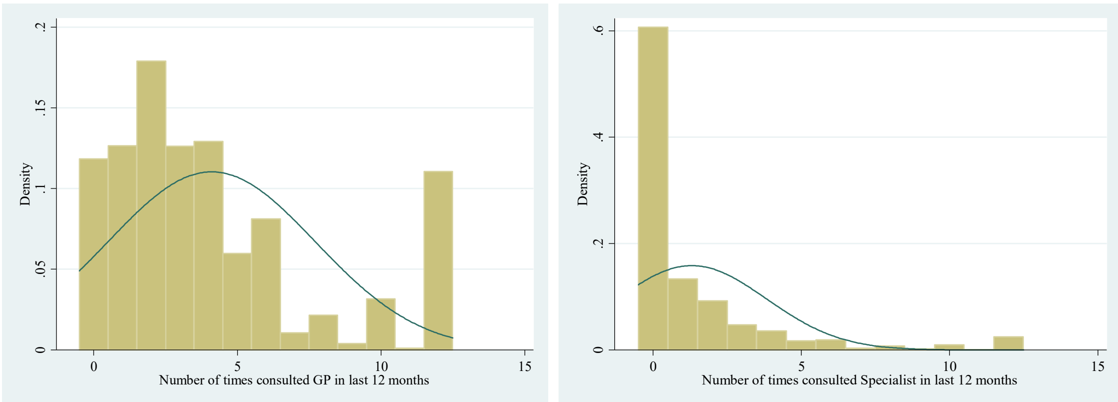


Figure 6.2: Distribution of GP and specialist visits in last 12 months

Tables A6.2 and A6.3 in Appendix 6 present the corresponding regression results for GP and specialist visits. The focus of the analysis is on non-need variables. It is found that the association with income is similar as before, but the size of the coefficients has increased in the probability models. The association between income deciles and total as well as conditional number of visits has now become significant and more pronounced for total visits for both types of services. The strength and direction of relationship with other non-need variables has remained similar.

6.5.3 Concentration and horizontal indices

The estimates of the CI and the HI index for three measures of visit to GPs and specialists are reported in Table 6.4[43]. The CIs for the probability of a visit, the total number and the conditional of visit are negative and highly significant. This suggests that the probability of visit as well as frequency of visits to GPs is higher among lower income Australians compared to those with higher income. In other words, inequality in GP utilisation is pro-poor in Australia. Income-related HI index for the probability of visit to GP is statistically significant and positive. This indicates a pro-rich inequity in the likelihood of GP contact, but the extent of this inequity is not substantial (around 0.006). On the other hand, the HI indices for total and subsequent visit for GP services are mostly negative and significant except for total visit indicator without the individuals censored at 12 or more visits. However, HI indices becomes less negative because of the exclusion of these respondents. In sum, a small pro-rich inequity exists in the decision to contact a GP, but inequity intensity of visit and conditional visit is pro-poor in Australia.

In the case of specialist visits, the CIs are significantly negative for three types of visit but excluding higher uses makes the indices statistically insignificant. The negative values of the CI imply that poorer individuals use more specialist service than richer people given that need for such care was more concentrated among the poor. However, once the distribution of need for specialist visit is equalised between rich and poor, there appears pro-rich inequity in all three types of specialist visit except for conditional visit for the entire sample. It is also notable that this pro-rich inequity in probability and total number of visits becomes even higher when the individuals with censored visits are excluded. In that case, pro-rich inequity in conditional specialist visit is also pro-rich. The plausible explanation is that there might be equitable or pro-poor distribution of specialist visits among higher users.

[43] This chapter also has applied Wagstaff's correction and Erreygers's normalisation in the case of probability of physician visit (binary indicator of visit to GP and specialist). As the results remain qualitatively similar, this chapter does not report these findings.

Table 6.4: Inequality and inequity in GP and specialist visit

Type of visit	GP				Specialist			
	Inequality		Inequity		Inequality		Inequity	
	CI	SE	HI	SE	CI	SE	HI	SE
Probability of visit	-0.015***	(0.002)	0.006***	(0.002)	-0.045***	(0.007)	0.074***	(0.006)
Probability of visit[1]	-0.010***	(0.002)	0.007***	(0.002)	-0.013	(0.008)	0.087***	(0.007)
Total number of visits	-0.130***	(0.005)	-0.031***	(0.004)	-0.073***	(0.010)	0.076***	(0.010)
Total number of visits [1]	-0.068***	(0.004)	-0.004	(0.004)	-0.011	(0.011)	0.105***	(0.011)
Conditional number of visits	-0.116***	(0.004)	-0.034***	(0.004)	-0.027***	(0.008)	0.011	(0.007)
Conditional number of visits [1]	-0.058***	(0.004)	-0.010***	(0.004)	0.002	(0.008)	0.021***	(0.008)

Notes: [1] Excluding the observations for which visit censored at 12 or more.
Bootstrapped standard errors in parentheses and significance level *** p<0.01, ** p<0.05, * p<0.1

6.5.4 Decomposition analysis

Tables 6.5 and 6.6 present the decomposition results to explain income-related inequality and inequity in GP and specialist visit[44]. Statistical inference about the contributing factors in the decomposition analysis is obtained using the bootstrapped technique as discussed in section 6.2 of this chapter. Income-related inequality in physician visits due to need-related determinants of healthcare services is legitimate or fair inequality. On the contrary, income related-inequality caused by non-need variables is unfair or illegitimate. The latter is the focus of this chapter because the contributions of the non-need determinants of physician visit together constitute horizontal inequity. Figures 6.3 and 6.4 summarise the contributions of non-need factors which are interpreted as the components of horizontal inequity in physician consultations.

The concentration indices of health measures are mostly negative indicating need was mainly concentred among the poor. For example, the CI of poor SAH is -0.464 and highly significant. As expected, Tables 6.5 and 6.6 reveal that the contributions of most of the need variables are negative and statistically significant for all types of GP and specialist visits. This finding suggests that inequality in physician consultation would be pro-poor in cases where visits were solely dependent on heath need. The number of long-term conditions constitute the largest contribution to inequality in physician visit. For example, number of long-term conditions accounted for about 60% of inequality in the probability of specialist visit (Table 6.6). About 32% of inequality in the likelihood of GP visit is explained by this variable. Four categories of SAH jointly explain about 41% and 15 %

[44] Contribution does not refer to causal interpretation in the decomposition exercise.

of income-related inequality in probability of both type of physician visit. Although the amount of contributions differs, the findings for need variables are almost similar for intensity and conditional number of visits.

Since pro-rich inequity in the probability of a GP visit is small and the other two types of GP visit exhibit pro-poor inequity, the contributions of non-need variables are expected to be insignificant (Table 6.5). Private health insurance, concession card and income are the major non-need components of HI in probability of GP visit. The direction of contribution of these variables is also mixed. For example, Figure 6.3 reveals that private health insurance and income variables would make inequity in the probability of GP visit pro-rich, while concession card plays the opposite role. The explanation is that holding a concession card is prevalent among the poorest and has a strong positive association with GP visits. The SEIFA contribution to inequity in total and conditional GP visits is towards pro-poor direction.

Table 6.5: Decomposition results for GP visits

		Probability of visit		Total number of visits		Conditional number of visits	
	CI	Contribution to CI	%	Contribution to CI	%	Contribution to CI	%
Need variables							
Female	-0.055***	-0.002***	0.154	-0.005***	0.038	-0.003***	0.028
Age (Ref: 18-24 year)							
Age 25-34 year	0.189***	0.0010	-0.036	0.000	-0.004	0.000	-0.001
Age 35-44 year	0.141***	0.0000	0.015	-0.001	0.009	-0.001	0.009
Age 45-54 year	0.136***	0.0000	0.003	-0.003***	0.021	-0.003***	0.023
Age 55-64 year	-0.005	0.0000	0.003	0.000	-0.001	0.000	0.000
Age 65-74 year	-0.306***	-0.002***	0.143	0.003**	-0.027	0.005***	-0.042
Age 75+ year	-0.461***	-0.003***	0.183	-0.002	0.015	0.001	-0.005
SAH (Ref: Excellent)							
Very good	0.106***	0.002***	-0.116	0.003***	-0.025	0.003***	-0.023
Good	-0.046***	-0.001***	0.042	-0.003***	0.023	-0.003***	0.022
Fair	-0.270***	-0.002***	0.139	-0.012***	0.093	-0.011***	0.096
Poor	-0.464***	-0.001***	0.088	-0.015***	0.113	-0.014***	0.120
Disability (Ref: No)							
Some disability	0.046***	0.000**	-0.014	0.001**	-0.004	0.000**	-0.004
Moderate disability	-0.298***	-0.001***	0.102	-0.015***	0.118	-0.015***	0.125
Severe disability	-0.392***	0.0000	0.014	-0.008***	0.058	-0.007***	0.061
Morbidity (Ref: Zero)							
One morbidity	-0.144***	-0.003***	0.179	-0.006***	0.044	-0.004***	0.032
Multi-morbidity	-0.354***	-0.001**	0.036	-0.004***	0.030	-0.003***	0.028
K10 score	-0.044***	-0.002***	0.112	-0.008***	0.062	-0.007***	0.060
No. of long-term conditions	-0.126***	-0.005***	0.321	-0.025***	0.191	-0.020***	0.173
Diabetes	-0.169***	-0.001***	0.054	-0.001**	0.010	-0.001*	0.007
Non-need variables							
Australian-born	0.013***	0.000**	-0.017	0.000*	-0.003	0.000	-0.003
English at home	0.016***	0.001**	-0.038	-0.001	0.004	-0.001***	0.008
Health insurance	0.191***	0.004***	-0.307	0.003	-0.020	0.000	0.004
Concession card	-0.495***	-0.011***	0.744	-0.030***	0.227	-0.021***	0.177
Education (Ref: Year 8 or less)							
Year 9-11	-0.167***	0.0000	-0.018	0.003	-0.022	0.002	-0.019
Year 12 or more	0.192***	0.0010	-0.052	-0.007*	0.054	-0.007**	0.060
Employment (Ref: Out of LFS)							
Employee	0.284***	0.004**	-0.254	0.001	-0.004	-0.003	0.022
Self-employee	0.121***	-0.000*	0.019	-0.001**	0.005	-0.001**	0.005
Unemployed	-0.524***	0.0000	-0.015	0.001	-0.006	0.001	-0.005
Residence (Ref: Major City)							
Inner region	-0.147***	0.001***	-0.079	0.002***	-0.019	0.002***	-0.014
Other or remote	-0.055***	0.000***	-0.021	0.001***	-0.006	0.001***	-0.006

Household Income (Ref: Decile 1)									
Decile 2	-0.707***	-0.002**	0.138		-0.002	0.012		0.000	-0.004
Decile 3	-0.512***	-0.001**	0.103		-0.002	0.014		-0.001	0.005
Decile 4	-0.322***	-0.0010	0.042		0.000	0.000		0.000	-0.004
Decile 5	-0.129***	-0.000*	0.028		0.000	0.000		0.000	-0.002
Decile 6	0.065***	0.000**	-0.016		0.000	-0.002		0.000	0.000
Decile 7	0.266***	0.001***	-0.095		0.002**	-0.018		0.001	-0.011
Decile 8	0.473***	0.002**	-0.111		0.001	-0.008		0.000	0.003
Decile 9	0.683***	0.003**	-0.218		0.001	-0.011		-0.001	0.011
Decile 10	0.895***	0.003*	-0.204		0.000	0.002		-0.003	0.022
Area socioeconomic status (Ref: SEIFA 1)									
SEIFA 2	-0.261***	0.0000	-0.010		0.002**	-0.014		0.002**	-0.015
SEIFA 3	-0.181***	0.0000	-0.015		0.001	-0.006		0.001	-0.005
SEIFA 4	-0.084***	0.0000	-0.004		0.001**	-0.005		0.001*	-0.005
SEIFA 5	-0.010	0.0000	0.000		0.000	0.000		0.000	-0.001
SEIFA 6	0.034**	0.0000	-0.002		0.000	0.001		0.000	0.002
SEIFA 7	0.112***	0.0000	0.001		-0.001**	0.007		-0.001**	0.008
SEIFA 8	0.170***	0.0000	0.002		-0.001**	0.010		-0.001**	0.012
SEIFA 9	0.234***	0.0000	-0.014		-0.002***	0.014		-0.002***	0.017
SEIFA 10	0.370***	0.0000	-0.009		-0.004***	0.027		-0.004***	0.032
Residual		0.000	0.000	0.000		0.000	0.000		0.000

Note: Significance level *** p<0.01, ** p<0.05, * p<0.1

Table 6.6: Decomposition results for specialist visits

		Probability of visit		Total number of visits		Conditional number of visits	
	CI	Contribution to CI	%	Contribution to CI	%	Contribution to CI	%
Need variables							
Female	-0.055***	-0.003***	0.062	-0.006***	0.083	-0.002***	0.074
Age (Ref: 18-24 year)							
Age 25-34 year	0.189***	0.004**	-0.079	0.006**	-0.085	0.002	-0.079
Age 35-44 year	0.141***	0.003***	-0.071	0.002	-0.021	-0.004	0.139
Age 45-54 year	0.136***	0.001	-0.032	-0.004**	0.059	-0.007***	0.249
Age 55-64 year	-0.001	0.000	0.004	0.000	-0.002	-0.003	0.096
Age 65-74 year	-0.306***	-0.013***	0.293	0.001	-0.014	0.015***	-0.569
Age 75+ year	-0.461***	-0.019***	0.418	0.003	-0.045	0.025***	-0.912
SAH (Ref: Excellent)							
Very good	0.106***	0.004***	-0.087	0.002	-0.024	-0.002	0.083
Good	-0.046***	-0.002***	0.042	-0.002***	0.028	0.000	0.013
Fair	-0.270***	-0.009***	0.197	-0.014***	0.185	-0.007***	0.257
Poor	-0.464***	-0.012***	0.261	-0.024***	0.324	-0.014***	0.504
Disability (Ref: No)							
Some disability	0.046***	0.001***	-0.023	0.001***	-0.018	0.002**	-0.061
Moderate disability	-0.298***	-0.020***	0.449	-0.032***	0.442	-0.014***	0.532
Severe disability	-0.392***	-0.008***	0.172	-0.018***	0.241	-0.010***	0.360
Morbidity (Ref: Zero)							
One morbidity	-0.144***	-0.006***	0.129	-0.001	0.011	0.003**	-0.109
Multi-morbidity	-0.354***	-0.005***	0.108	-0.005**	0.064	0.001	-0.022
K10 score	-0.044***	-0.005***	0.116	-0.013***	0.172	-0.007***	0.270
No. of long-term conditions	-0.126***	-0.027***	0.595	-0.042***	0.571	-0.013***	0.475
Diabetes	-0.169***	-0.003***	0.060	-0.006***	0.077	-0.003**	0.124
Non-need variables							
Australian-born	0.013***	0.001**	-0.013	0.001**	-0.014	0.001	-0.028
English at home	0.016***	0.002***	-0.043	0.004***	-0.050	0.002***	-0.088
Health insurance	0.191***	0.026***	-0.583	0.029***	-0.395	0.005	-0.184
Concession card	-0.495***	-0.006	0.127	-0.010	0.130	-0.005	0.172
Education (Ref: Year 8 or less)							
Year 9-11	-0.167***	-0.013***	0.296	-0.022***	0.300	-0.009**	0.331
Year 12 or more	0.192***	0.031***	-0.683	0.049***	-0.676	0.019***	-0.702
Employment (Ref: Out of LFS)							
Employee	0.284***	-0.006	0.138	-0.021**	0.288	-0.018***	0.672
Self-employee	0.121***	0.000	-0.011	-0.001	0.011	-0.002**	0.076
Unemployed	-0.524***	-0.001	0.030	-0.002	0.030	0.000	0.017
Residence (Ref: Major City)							
Inner region	-0.147***	0.002**	-0.041	0.003**	-0.042	0.002*	-0.057
Other or remote	-0.055***	0.001**	-0.015	0.002***	-0.022	0.001***	-0.055

Household Income (Ref: Decile 1)									
Decile 2	-0.707***	0.004	-0.079		0.003	-0.036		0.000	-0.013
Decile 3	-0.512***	0.000	-0.011		0.001	-0.015		0.000	-0.003
Decile 4	-0.322***	-0.002	0.040		-0.004*	0.054		-0.002	0.062
Decile 5	-0.129***	0.000	0.010		-0.001	0.012		0.000	0.003
Decile 6	0.065***	0.000	-0.002		0.001**	-0.014		0.002**	-0.070
Decile 7	0.266***	0.001	-0.027		0.004*	-0.052		0.003	-0.104
Decile 8	0.473***	0.002	-0.038		-0.001	0.009		-0.002	0.090
Decile 9	0.683***	0.009**	-0.193		0.012**	-0.166		0.005	-0.181
Decile 10	0.895***	0.013**	-0.282		0.018**	-0.247		0.008	-0.310
Area socioeconomic status (Ref: SEIFA 1)									
SEIFA 2	-0.261***	0.000	0.003		-0.001	0.016		-0.001	0.029
SEIFA 3	-0.181***	-0.001	0.028		-0.001	0.007		0.001	-0.035
SEIFA 4	-0.084***	-0.002***	0.035		-0.002**	0.023		0.000	0.003
SEIFA 5	-0.001	0.000	0.003		0.000	0.002		0.000	-0.004
SEIFA 6	0.034**	0.000	-0.008		0.000	-0.003		0.000	0.007
SEIFA 7	0.112***	0.001**	-0.033		0.002*	-0.030		0.001	-0.021
SEIFA 8	0.170***	0.002***	-0.049		0.003**	-0.043		0.001	-0.029
SEIFA 9	0.234***	0.002*	-0.051		0.002	-0.025		0.000	0.002
SEIFA 10	0.370***	0.008***	-0.167		0.008**	-0.103		0.000	-0.002
Residual		0.000	0.000	0.000		0.000	0.000		0.000

Note: Significance level *** p<0.01, ** p<0.05, * p<0.1

Table 6.6 reports that pro-rich inequity in the probability and total number of specialist visits is primarily a result of a significant contribution of income and private health insurance. The income contribution to the HI in these two types of specialist visit mainly stems from the significant contribution of the two highest household income deciles. About 59% of the pro-rich inequity in the probability of specialist visit is explained by private health insurance. In other words, the interaction between significant inequality in private health insurance by income favouring rich (CI value: 0.191) and its significant positive relationship with the likelihood of specialist visit contributed to pro-rich HI. The pro-rich inequity is also augmented by the partial role of all other non-need factors except for concession card and employment status (Figure 6.4). For example, the deciles of area-level SES or SEIFA together account for 24% and 15% of pro-rich inequity in the probability of and total specialist visit.

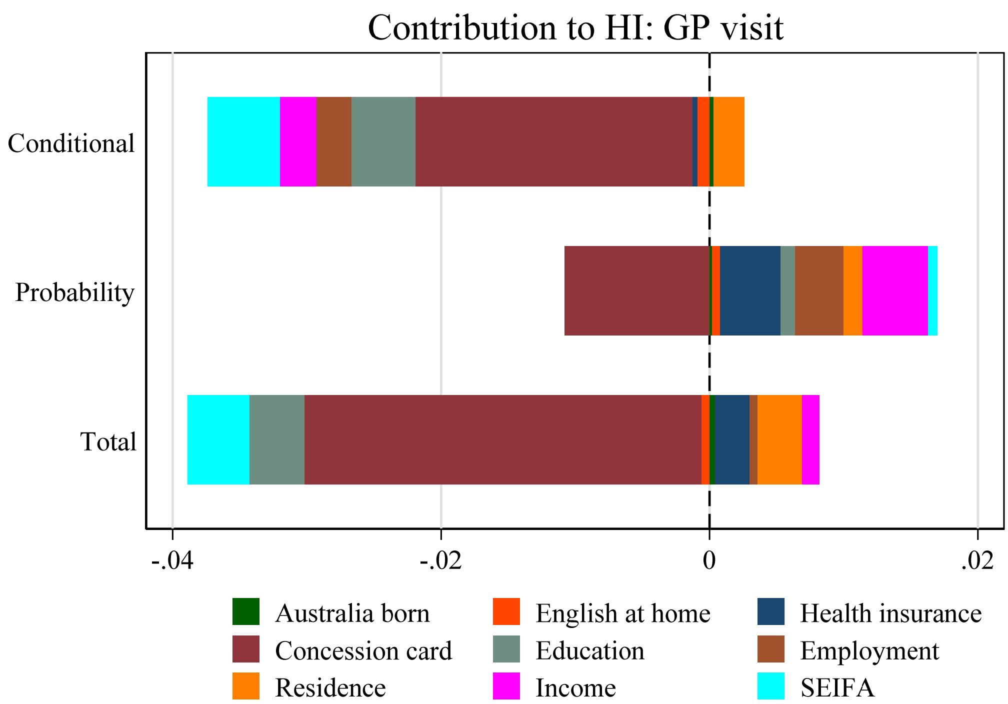


Figure 6.3: Components of horizontal inequity in GP visits

It appears from Table 6.6 that speaking English at home and the area of residence contribute significantly and positively to pro-rich inequity in all types of specialist consultations, but the magnitudes of their contribution are trivial. Concession card is not a significant contributor of inequity in any type of specialist visit as it is not associated with specialist visit. However, the pro-poor contribution of employment is statistically significant for total and conditional visits to a specialist but not for the probability of specialist visit. For example, employment status contributes to reducing pro-rich inequity in total and conditional specialist visit by about 29% and 67% respectively.

Appendix 6 presents the results from the decomposition for restricted sample (dropping observations with visits censored at 12 or more). This is performed for specialist visit as censoring only affects the inequity in this service. Table A6.4 shows that decomposition results for the restricted sample follow an almost similar pattern to that found in the full sample. Figure A6.1 depicts the summary of inequity components. One notable exception is that the contribution of private health insurance is now insignificant because conditional specialist visit is no longer significantly associated with it (Table A6.4), and private health insurance now has much less contribution. Finally, it is worth mentioning that the residual contribution in every model is zero confirming the robustness of regression specifications in this chapter.

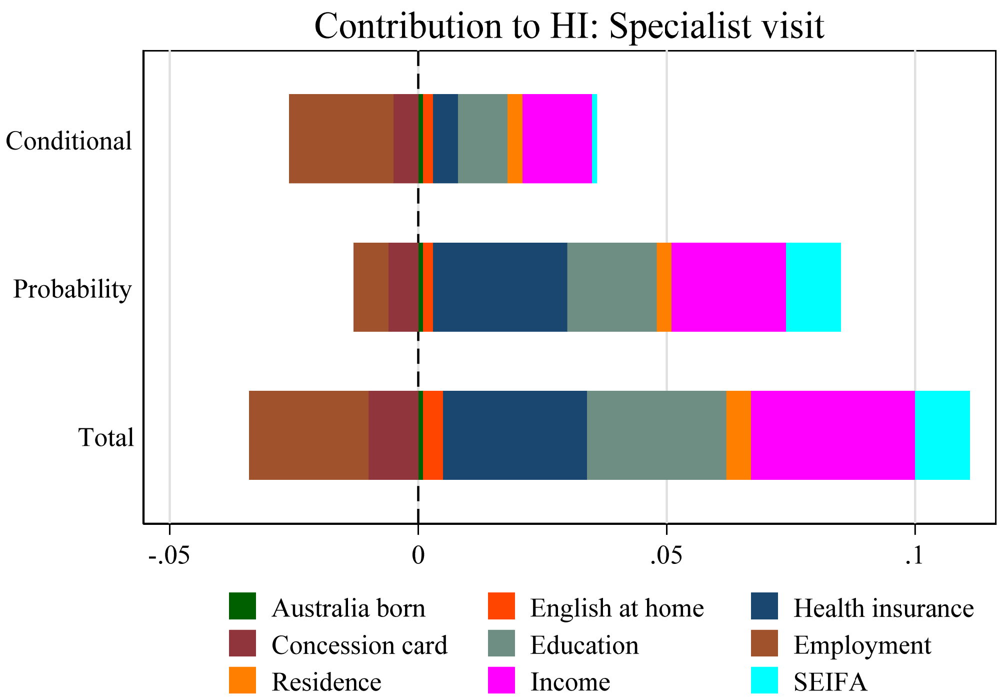


Figure 6.4: Components of horizontal inequity in specialist visits

6.6 Conclusion

This study contributes to the large empirical literature on inequity in healthcare utilisation by examining inequity in the two-stage decision process of physician visits in Australia where medical professionals offer services in an unregulated fee market. To this end, this chapter measures income-related horizontal inequity (HI) in GP and specialist visits by making a distinction between the probability of visit and conditional visits. The bootstrapped decomposition technique is also applied to explain the driving factors of the HI. The analysis shows a small but pro-rich HI in the probability of a GP visit while there is a significant pro-poor distribution in conditional visits to GP. This is because of the significant contribution of holding a concession card in the pro-poor direction. The findings show that inequity in the probability of specialist visit is significantly pro-rich, but the distribution of conditional number of visits for specialist is almost equitable. The decomposition analysis reveals that income, private health insurance, and education are the largest and significant contributors of pro-rich inequity.

The analysis reveals that inequity in the probability of a GP visit is small, but statistically significant. This finding is contradictory to the findings of previous studies from Australia (Hajizadeh et al., 2012; van Doorslaer et al., 2008). This could be a surprising result given the existing evidence, but pro-poor inequity in GP visit has become less pro-poor in early 2000 (Hajizadeh et al., 2012). Moreover, this is consistent with the conclusion of studies from other OECD countries where there exists a small but pro-rich inequity in the probability of GP visits (Allin 2008; Allin & Hurley 2009; Devaux, 2015; Paraje & Vásquez 2012). Despite a record level of bulk-billing in Australia, a considerable number of patients pay up-front to use primary care. For example, the OOP cost for a GP visit has increased for individuals without concession cards following the policy of the 'Strengthening Medicare reforms'(Wong et al., 2017). Therefore, OOP cost could be a plausible reason for inequity in first contact with a GP in Australia. This is also shown in other OECD countries where patients face a substantial co-payment to use primary care services (Devaux, 2015).

The results show a pro-poor inequity in the intensity and conditional number of GP visits. This finding is in line with the conclusions of studies from other OECD countries (Allin and Hurley, 2009; van Doorslaer et al., 2004a). This implies that poorer individuals use GP services more intensively despite the same level of need as richer individuals. A plausible explanation is that poorer people may substitute for specialist services by intensively using GP services. Nevertheless, the substitution of GP services for specialist services raises the question about the quality of primary care provided to people with low-income and living in socioeconomically disadvantage areas. Inequity in the quality of GP services could prevail in Australia despite higher GP utilisation rate among poorer individuals; longer GP consultations have been found to favour better-off people in Australia (Furler et al., 2002).

Pro-rich inequity in the probability of specialist and total visits found in this chapter is consistent with both Australian and international evidences (Allin & Hurley 2009; Hajizadeh et al. 2014; Sözmen & Ünal 2016; van Doorslaer et al. 2008, 2004). It was recently found that Medicare spending for specialist services is also significantly biased towards children from wealthier families in Australia (Dalziel et al., 2018a). The implication is that poorer people are in greater need of specialist services, but it is more favourably distributed to the richest. However, the findings of this study demonstrate almost no inequity in the subsequent number of visits to specialist which follows the international evidence. For example, van Doorslaer et al. (2004) found that once a contact with a specialist is made, the pro-rich inequity in subsequent visits was relatively small in most of the European countries. This implies that inequity is not physician-induced, rather it depends on patients making the initial visit which is influenced by socioeconomic status. This chapter also finds that exclusion of higher users in the estimation of inequity has a pro-rich effect and this consequence is more pronounced for specialist visits. For example, no inequity in conditional specialist visits becomes significant and pro-rich.

The decomposition analysis of this chapter offers several important insights to understand the contributing factors of inequity in physician visit. This exercise reveals that private health insurance, along with income, is the largest driver of pro-rich inequity in specialist visits as evident in earlier studies from Australia, Canada and Ireland (Allin & Hurley 2009; van Doorslaer et al. 2008; Walsh et al. 2012). This is due to a greater concentration of private health insurance among richer and well-off individuals and its stronger association with specialist service utilisation (Korda et al., 2012). However, private health insurance does not cover the OOP payments for specialist services subsidised by Medicare in Australia. The effect of private health insurance could be indirectly related to this inequity as private health insurance holders are more able to pay for specialist fees.

This study has found that holding a concession card has a substantial negative contribution to pro-rich HI in the probability of GP visits as well as the pro-poor distribution of total and conditional number of GP visits. The possible explanation is that GPs usually bulk-bill concession card holders which leads to zero OOP expense for GP visit (Johar, 2012; van Doorslaer et al., 2008). Therefore, it has a significant and large role in making inequity in GP visit less pro-rich which was also argued by Korda et al. (2009). However, this explanation is not plausible for specialist visits as holding a concession card is not associated with the utilisation of specialist care (Johar et al., 2017; Korda et al., 2009a). This study has further found that area-level SES has a positive contribution towards pro-rich inequity in both the probability of and total visit to specialists as richer people living in better neighbourhoods have higher utilisation of specialist care. The contribution of education towards pro-rich inequity is due to the fact that specialist services were more utilised by better educated people who are also high income earners (van Doorslaer et al., 2008, 2004b).

The finding of this chapter is subject to some limitations. The decomposition analysis examines the contributing factors of inequity, but it does not imply causal interpretation of the results. The recently proposed general method of decomposition by Heckley et al. (2016) has the potential to address this shortcoming but relies on strong identification assumptions and requires richer data. It could be argued that this is of less interest in the income-related inequity in GP visits as 87% of respondents visited a GP in the last year. This chapter acknowledges that this could undermine the importance of analysing inequity by separating the probability of GP visit and conditional GP visit. However, this analysis sheds some light on the possible substitution of specialist services by GP services among poorer people.

Another limitation is that the chapter could not examine inequity in specialist visits conditioning on a GP visit. It could be the case that people from lower income groups have faced longer waiting periods for the first visit to a specialist. This could result in pro-rich inequity in the probability of specialist visits. However, this is methodologically challenging as the data sets are for one-year period, and the potential waiting times for specialist appointments could cross from one year into the next. Finally, understanding the implications of financial barriers such as the role of co-payments for the observed pro-rich inequity would be useful for policy purposes. However, no information about the cost of using healthcare services is available in the NHS of 2014-15 which precludes such analysis. This issue is partly addressed in the next chapter using administrative data for specialist utilisation.

Chapter 7: Inequality in specialist care: Evidence from Australian Medicare data

In Australia, people from the lower socioeconomic backgrounds utilise less specialist services compared to their better-off counterparts. The goal of this chapter is to examine socioeconomic inequality in Medicare-funded specialist care in Australia and to understand how this inequality varies by the indicator of co-payment. Using data of about 6.3 and 6.8 million individuals from Medicare Australia in fiscal year of 2011-12 and 2014-15, three outcomes of specialist care are analysed: all visits, bulk-billed visits (without co-payment), and non-bulk-billed visit (with co-payment). Count data models and the concentration index are used to identify and quantify the extent of inequality by area-level socioeconomic status. Results show inequality in Medicare-funded specialist use by area-level socioeconomic status, and patients from remote and very remote areas of Australia had lower utilisation of specialist services. Most importantly, this inequality was higher in the specialist visits associated with out of pocket cost while there was almost no inequality in bulk-billed services. The exist limited spatial variation in the overserved socioeconomic gradient in specialist services by states/territories of Australia. The conclusion is that persistent out-of-pocket cost to access specialist care might partly undermine the equity principle of Medicare in Australia.

Keywords: Medicare; bulk-billing; inequality; specialist visit; remoteness; concentration index.

7.1 Introduction

In many OECD countries, there is socioeconomic inequality in specialist care which is typically in favour of people from better socioeconomic backgrounds (Allin et al. 2011; Allin & Hurley 2009; Grignon et al. 2010; Morris et al. 2005; Sözmen & Ünal 2016; Terraneo 2015; van Doorslaer et al. 2004). This socioeconomic gradient in specialist care is also evident in Australia (Korda et al., 2009a, 2009b). Consistent with the conclusion from earlier studies by Hajizadeh et al. (2012) and van Doorslaer et al. (2008), the findings from chapters five and six have affirmed that income-related distribution in specialist visits (after need adjustment) continues to favour people from higher income groups in Australia. Moreover, the results from Chapters Five and Six have also highlighted the existence of inequality in specialist use (before need adjustment) by area-level SES.

Most of the earlier studies examining the socioeconomic dimension of inequality in specialist services relied on self-reported information from the surveys. The main problem of using survey data is the measurement error of healthcare use due to recall bias. Surveys are often restricted to collecting information of general indicators, and suffer from under-representation of the extremely deprived and privileged groups (Bilheimer & Klein 2010; Cookson et al. 2012). In this context, administrative data allows us to overcome these limitations. In fact, use of administrative data to investigate various dimensions of inequality and inequity in healthcare use has become a 'new frontier' of research (Cookson et al., 2015, 2012). The main advantage of administrative data on healthcare use is that it has objective information about everyone using health system services and routine availability of the data. A number of Finnish studies have shown that administrative data offers a comparatively inexpensive, easy and quick way to monitor inequity and inequality in healthcare (Lumme et al., 2017; Manderbacka et al., 2014, 2009; McCallum et al., 2013).

In Australia, healthcare data from various administrative sources (e.g. Medicare claims records, admitted patient care data) are available and could be utilised for research purposes. There is indeed a growing importance for using routinely collected administrative datasets in healthcare research in the Australian setting (Ellis et al., 2013; Johar et al., 2017; Tew et al., 2017). However, the complexity and fragmentation in the service delivery and financial mechanisms of the Australian healthcare system make it challenging for the better utilisation of these data sources. That is why empirical studies on inequality in healthcare services using administrative data are infrequent in Australia. A few recent studies used administrative data to study socioeconomic inequality in healthcare use (Hua et al., 2017; Knott J. et al., 2012; Meadows et al., 2015). However, these studies are limited by using aggregated data at large geographic levels and confined to specific population groups or services. For example, Hua et al. (2017) examined the distribution of OOP costs for healthcare services using linked survey and Medicare data but the study population is restricted to a small sample of elderly people. In addition, Meadows et al. (2015) studied inequality in the utilisation of mental healthcare services funded by Medicare, but the outcome variables of this study were aggregated at postcode level. To the best of our knowledge, there is no study using individual level data for the entire Australian population in the analysis of inequality in specialist care.

The aim of this chapter is to demonstrate the potential of measuring and reporting indicators of socioeconomic inequality in healthcare service delivery using Australian Medicare data. More specifically, this study measures the extent of inequality in the utilisation of Medicare-funded specialist services by area-level SES. Measurement of inequality in specialist care using unit record Medicare data is a unique opportunity to test the validity of the evidence about inequality and inequity found in the earlier empirical studies based on survey data from Australia.

The unregulated fee-for-service system for the provision of specialist services in Australia is an interesting context for studying inequality in specialist care. In this setting, medical specialists have the discretion to charge any fee to any patient, and the patient receives a fixed reimbursement from Medicare which is generally 85% of the scheduled fee set by the Government (Cheng et al., 2012; Johar et al., 2017). If the doctor accepts the Medicare rebate as the cost of the service provided, there is no out-of-pocket (OOP) cost or co-payment for the patients. This is commonly known as bulk-billing in Australia (Wong & Hall 2018). However, many patients usually pay a substantial amount as OOP costs to visit a specialist (Carpenter et al., 2015; Johar et al., 2017). For example, about 70% of specialist consultations were not bulk-billed in 2016-17 (Department of Health, 2017a). It is also reported that the per capita OOP cost for out-of-hospital services increased by about 75% between 2003 and 2012 (Hua et al., 2017). High and rising fees of specialist services and stagnant Medicare rebates could be one of the drivers behind this surge in OOP cost (Johar et al., 2017; McRae and van Gool, 2017). Therefore, high OOP costs could act as a potential barrier to the use of specialist services and have implications for socioeconomic inequality in specialist care in the Australian context.

The contribution of this chapter is to measure socioeconomic inequality in specialist care by differentiating specialist visits between the non-bulk-billed (with OOP cost) and bulk-billed (no OOP cost) claims. This analysis, thus, allows us to understand the role of co-payments in inequality in the utilisation of specialist care. This chapter also compares the level of inequality in specialist services between 2011-12 and 2014-14. This study further explores regional variation in the degree of inequality by comparing inequality across the states and territories of Australia. However, this chapter acknowledges that the analysis is limited to the individuals who have used at least one Medicare funded specialist service in a fiscal year. This could potentially lead to selection problems and the interpretations of the findings are confined to the users. In other words, the findings of this chapter should be interpreted as inequality in the conditional use of Medicare funded specialist services. Moreover, this chapter is concerned with the analysis of socioeconomic inequality in specialist care rather than horizontal inequity as Medicare data does not have any information to adjust for need for specialist services.

In what follows, section two discusses the data and methodology used in the statistical analysis of this chapter. Section three presents the results of the empirical analysis. The main findings are discussed in section four. The section also discusses the policy implications. Section five concludes the chapter by discussing some potential areas for future research.

7.2 Materials and Method

Data source:

This chapter uses data from Medicare Australia which maintains an administrative database to keep record of services rendered by medical professionals under the Medicare arrangement. The data for health service utilisation is extracted from the Medicare Benefit

Schedule (MBS) database[45]. This population-based claims data is the most reliable source of information about healthcare utilisation in Australia (Parkinson et al., 2011). The MBS data has detailed information about Medicare-funded healthcare services for all the Australian citizens and permanent residents who have used any of these services in their lifetime. This includes data on services provided under fee-for-service arrangements for which a payment is claimed from the Department of Human Services. There are no data in the case of no benefit claimed, in cases where payment is from another source other than Medicare. It should be noted that MBS data do not include services provided free of charge to public patients in hospitals, to Department of Veterans' Affairs beneficiaries, to some patients under compensation arrangements and through other publicly-funded programmes. Access to de-identified individual-level MBS data has been provided by the Australian Institute of Health and Welfare (AIHW) through its internal server.

Study population:

The unit of analysis in this study is the individual patient who has used at least one specialist service in a financial year[46]. Age, gender, enrolment postcode, and information related to service use of the patients are extracted from the MBS data. Services are counted according to the date of service provided rather than the date of process of reimbursement claimed. Demographic information such as age and enrolment postcode of the individual could change in a reference period leading to over counting of the patients. Therefore, age and enrolment postcode are obtained from the last date of the service provision. Finally, individuals with a post box address are discarded from the analysis. The final study population consists of 6,343,176 and 6,799,265 individuals in 2011-12 and 2014-15 respectively[47].

Outcome variables:

The outcome of interest in this study is the number of specialist services provided to the patients on a fee-for-service basis and covered by Medicare subsidy. However, specialist services provided within hospitals were excluded from the analysis since funding could

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[45] The other one is Pharmaceutical Benefits Scheme (PBS) which keeps record of prescription drug reimbursements.

[46] Financial year runs from 1 July to 30 June and it is the standard unit of time measurement in most government reports in Australia.

[47] Data from National Health Survey of Australia are also available for these two periods which allows comparison of the results with findings from previous chapters.

be a combination of Medicare subsidy and private health insurance. This also avoids the problem of double counting. This study follows the broad type of services (BTOS) classification of Medicare services to extract information about specialist visits. The Department of Health (DoH), Australia has developed BTOS to categorise various statistics of Medicare (Department of Health, 2017b). Specialist attendance or visit is labelled as 'BTOS-0200' and is the combination of various services provided by different specialists. A full list of the item numbers that constitute specialist attendances is given in Appendix 7. Specialist service is further categorised into bulk-billed and non-bulk-billed services using the bulk-billing identifier in the MBS data. As discussed earlier, bulk-billed services do not incur any OOP costs to patients.

Explanatory variables:

This chapter aims to measure socioeconomic-related inequality in specialist services. However, the MBS does not have any information related to individual socioeconomic characteristics such as income, education, etc. Therefore, this study relies on the SES of the areas where the patients lived in the respective years of the study. The index of relative socioeconomic advantage and disadvantage (IRSAD) is used as the proxy for area-level SES. The IRSAD is one of four indicators in the Socio-Economic Index for Area (SEIFA). The SEIFA is developed by the Australian Bureau of Statistics (ABS) to measure the social and economic status of areas in Australia (ABS, 2011). This is a composite index constructed through principal component analysis using information of several socioeconomic indicators such as income, education, employment etc. from the Australian Census of 2011 (ABS, 2013b)[48]. This is an ordinal measure to rank the areas from the lowest to the highest. A higher IRSAD score means an area is socioeconomically least disadvantaged.

This chapter also uses remoteness as an explanatory variable which has been found to affect healthcare utilisation in Australia (Strobel et al., 2017). This is measured by the Accessibility Remoteness Index of Australia (ARIA) which classifies areas according to their distance from the nearest service centres (McGrail & Humphreys 2009). The ABS has used ARIA score as an ordinal measure of Remoteness to classify the entire Australia into five categories: major cities, inner regional, outer regional, remote, and very remote.

[48] The SEIFA from the Census of 2016 is not available at the time of analysis. Therefore, the IRSAD of 2011 is used for both periods.

Patient's area of residence is mapped using the ABS postal area concordance file and assigned to the IRSAD deciles, ARIA category, and state/territory of residence. Age (six categories) and gender are patient-level independent variables included in this analysis.

Statistical methods:

In this study, the number of specialist visits per patient is inherently a non-negative discrete integer or count variable. So, the count data method is employed to investigate the relationship between dependent and independent variables. The Poisson regression could be used to model healthcare utilisation. However, this model relies on the strong equi-dispersion assumption (Jones & O'Donnell 2002). In other words, estimates are efficient if the conditional mean equals the conditional variance of the outcome variable. This is a very restrictive assumption which is unlikely to hold in many instances (Jones et al., 2007). The alternative method is to use the negative binomial two or NB2 model which relaxes this assumption. This chapter applies negative binomial version two or NB2 model which assumes that variance is a quadratic function of the mean (Jones, 2007). The NB2 models are tested against the Poisson model using the likelihood ratio test of the over-dispersion parameter (alpha) of the Poisson distribution (Srivastava & McGuire 2016).

This chapter employs the concentration index (CI) as the summary measure of socioeconomic inequality in specialist care. This is one of the most widely used indicators to measure inequality in health and healthcare in health economics literature (van Doorslaer & van Ourti 2011). The CI quantifies how unequally a healthcare utilisation indicator is distributed by an indicator of socioeconomic status and it ranges between −1 and +1 (O'Donnell et al., 2008). The larger the absolute value, the greater the extent of inequality. A positive and significant value of the concentration index would suggest that inequality in specialist visit is pro-rich. In other words, the distribution of specialist visits favours individuals living in higher socioeconomic areas. The CI is a relative measure of inequality in healthcare use. In this study, the generalised version of CI or GCI is also estimated as the CI times the mean of specialist use to report absolute inequality indicators (O'Donnell et al., 2016).

The deciles of IRSAD were used in regression analysis while the continuous score ranked the patients from the lowest to the highest according to their area of residence. We also estimated robust standard errors clustered at postcode level to account for unequal variance and correlated observations. SAS Enterprise Guide (SAS Institute Inc., Cary, NC) version 7.1 is used to process the MBS data, and the statistical analysis is performed in Stata (Stata Corp., College Station, TX) version 14.2.

7.3 Results

Table 7.1 reports the mean and standard deviation (SD) the three measures of specialist care: overall, bulk-billed, and non-bulk-billed specialist visits according to age, gender, remoteness, state/territory and IRSAD deciles. In general, there was no notable change in the distribution of specialist visits between 2011-12 and 2014-15. The average number of specialist visits was about 3.0 in both years and it was higher among older Australians. There was almost no difference in average visits between male and female. The statistics in Table 7.1 reveal that the average number of specialist visits was the highest in major cities of Australia across all three categories of specialist attendances. For example, the mean of total visit was 3.12 in major cities while it was about 1.98 in very remote areas in 2014-15. For the bulk-billed category, the ratio between major cities and very remote areas was about 1.45 in 2014-15.

The results suggest some variations in the average number of visits across the states and territories of Australia. This was the highest in New South Wales (NSW) while it was the lowest in Northern Territory (NT). On average, the number of specialist visits was higher among the people belonging to higher IRSAD deciles. In addition, the variation in all visits and non-bulk-billed visits across the IRSAD deciles was higher than average of bulk-billed visits. As an example, the rate ratio between the highest and the lowest decile for non-bulk-billed specialist visits in 2011-12 was about 1.25 while it was about 0.92 for bulk-billed services. Figure A 7.1 in Appendix 7 depicts the distribution of three types of specialist visit by SEIFA quintiles.

Table 7.1: Summary statistics of the number of specialist visits by independent variables

	All				Non-bulk-billed				Bulk-billed			
	2011-12		2014-15		2011-12		2014-15		2011-12		2014-15	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall	2.99	3.41	3.01	3.35	2.49	2.87	2.47	2.73	2.47	2.78	2.45	2.72
Age groups												
Age: 0-4	2.25	1.91	2.18	1.86	2.07	1.53	1.98	1.48	1.91	1.90	1.87	1.80
Age: 5-14	2.09	1.94	2.07	1.89	1.78	1.45	1.77	1.40	2.06	2.05	1.99	1.98
Age: 15-24	2.28	2.75	2.33	2.74	2.06	2.53	2.07	2.51	2.02	2.35	2.02	2.26
Age: 25-34	2.47	3.34	2.46	3.16	2.20	3.15	2.16	2.96	2.13	2.63	2.08	2.44
Age: 35-44	2.66	3.63	2.64	3.43	2.29	3.34	2.25	3.13	2.33	2.96	2.25	2.70
Age: 45-54	2.84	3.66	2.80	3.45	2.37	3.20	2.30	2.92	2.50	3.11	2.43	2.95
Age: 55-64	3.13	3.57	3.12	3.48	2.57	2.97	2.50	2.79	2.59	3.02	2.57	2.96
Age: 65-74	3.64	3.52	3.64	3.52	2.88	2.70	2.83	2.64	2.72	2.81	2.71	2.82
Age: 75+	4.01	3.60	4.10	3.69	3.10	2.73	3.11	2.72	2.82	2.69	2.86	2.81
Gender												
Female	3.02	3.54	3.05	3.46	2.54	3.06	2.51	2.89	2.44	2.78	2.43	2.72
Male	2.94	3.24	2.97	3.21	2.43	2.62	2.41	2.52	2.50	2.77	2.48	2.71
Remoteness												
Major city	3.11	3.66	3.12	3.56	2.58	3.12	2.55	2.95	2.59	2.96	2.54	2.86
Inner	2.79	2.83	2.86	2.91	2.33	2.23	2.34	2.20	2.27	2.42	2.30	2.47
Outer	2.51	2.38	2.60	2.56	2.10	1.81	2.12	1.89	2.10	2.10	2.18	2.24
Remote	2.14	1.91	2.22	2.04	1.89	1.57	1.88	1.58	1.82	1.60	1.92	1.77
Very remote	1.91	1.66	1.98	1.80	1.79	1.41	1.80	1.48	1.68	1.40	1.75	1.58
State and Territory												
ACT	2.60	2.79	2.63	2.79	2.27	2.38	2.25	2.32	2.16	2.34	2.14	2.30
NSW	3.14	3.55	3.17	3.51	2.47	2.83	2.46	2.73	2.66	2.95	2.64	2.88
NT	2.05	1.93	2.07	1.90	1.82	1.42	1.80	1.39	1.86	1.77	1.88	1.72
QLD	2.79	3.19	2.85	3.26	2.50	2.78	2.49	2.72	2.20	2.68	2.27	2.79
SA	3.02	3.33	2.99	3.22	2.44	2.74	2.40	2.62	2.49	2.67	2.41	2.52
TAS	2.81	3.02	2.77	2.82	2.44	2.55	2.35	2.23	2.30	2.55	2.21	2.39
VIC	3.07	3.65	3.10	3.51	2.59	3.27	2.57	3.02	2.48	2.76	2.46	2.66
WA	2.58	2.58	2.56	2.51	2.34	2.23	2.29	2.13	1.96	2.09	1.92	1.98

IRSAD												
Decile 1	2.95	3.00	2.98	3.04	2.27	2.15	2.25	2.07	2.59	2.68	2.61	2.72
Decile 2	2.81	2.91	2.86	2.95	2.30	2.22	2.28	2.21	2.46	2.61	2.44	2.62
Decile 3	2.91	2.99	2.97	3.07	2.31	2.20	2.32	2.20	2.40	2.57	2.43	2.63
Decile 4	2.82	3.00	2.87	3.02	2.36	2.45	2.37	2.41	2.43	2.63	2.43	2.60
Decile 5	2.99	3.22	3.02	3.24	2.41	2.47	2.40	2.46	2.41	2.65	2.43	2.65
Decile 6	2.95	3.27	2.98	3.28	2.49	2.76	2.46	2.70	2.51	2.85	2.50	2.81
Decile 7	3.00	3.50	3.02	3.44	2.58	3.14	2.56	3.03	2.47	2.84	2.44	2.78
Decile 8	3.09	3.79	3.09	3.63	2.63	3.31	2.59	3.01	2.48	2.91	2.43	2.77
Decile 9	3.14	3.99	3.11	3.75	2.72	3.63	2.66	3.32	2.51	2.98	2.42	2.82
Decile 10	3.21	4.15	3.20	3.90	2.82	3.74	2.77	3.47	2.45	3.01	2.38	2.78

Tables 7.2 to 7.4 present the regression results from the count data models in the form of incidence rate ratios (IRR). There is almost no significant difference in the results obtained from both Poisson and NB2 models across types of visits. However, the over-dispersion parameter, *alpha* is highly significant in all models suggesting strong evidence in favour of NB2 models. Therefore, IRR from the NB2 models are interpreted to discuss the results. As expected, age was significantly and positively associated with all three types of specialist visit. For example, the IRRs of people aged 75 years or older were 1.89, 1.59 and 1.54 for total, non-bulk-billed and bulk-billed visit respectively in 2014-15. The likelihood of visits was higher for females, but males had marginally more bulk-billing visit in both periods.

Results in Tables 7.2-7.4 suggest that area of residence was a significant determinant of all types of specialist visit in Australia. In general, this was lower for the people living in all other areas of Australia compared to the Australians in major cities. In 2014-15, for example the frequency of all visit and non-bulk-billed visits was about 28% and 22% less among people from very remote areas compared to people from major cities (Table 7.2 and 7.3). It is found that specialist visits were higher in all states and territories compared to the Australian Capital Territory (ACT). However, the rate of bulk-billed visit was about 9% and 12% was lower in Western Australia (WA) compared to ACT in the respective years (Table 7.4).

The regression results in Tables 7.2-7.4 document that the area-level socioeconomic gradient in the utilisation of specialist services was more pronounced for non-bulk-billed and bulk-billed visits compared to all visits. For example, there was no statistically significant difference between the people in IRSAD Deciles 3 to 6 and people in Decile 1 for all specialist visit (Table 7.2). The most important result is that the association between area-SES and specialist visits was not similar when a distinction is made between the types of visits. The relationship between non-bulk-billed visits and IRSAD was positive while this association was negative for bulk-billed visits. For example, Table 7.3 shows that patients from the highest IRSAD Decile had 22% more non-bulk-billed visits compared to the people from the lowest decile in 2014-15. On the other hand, bulk-billed visits were about 13% lower among the patients in Decile 10 in the same year (Table 7.4).

Therefore, area-based SES gradient was favourable to the patients from lower SES areas for bulk-billed specialist visits.

Table 7.2: Count Data regression of specialist visit (All)

	2011-12				2014-15			
	Poisson		NB2		Poisson		NB2	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE
Age (Ref: 0-4 year)								
5-14	0.941***	(0.004)	0.941***	(0.004)	0.959***	(0.004)	0.959***	(0.004)
15-24	1.018***	(0.005)	1.015***	(0.005)	1.072***	(0.005)	1.070***	(0.004)
25-34	1.090***	(0.005)	1.087***	(0.005)	1.122***	(0.004)	1.119***	(0.004)
35-44	1.174***	(0.006)	1.170***	(0.006)	1.204***	(0.005)	1.200***	(0.005)
45-54	1.264***	(0.007)	1.259***	(0.007)	1.287***	(0.006)	1.283***	(0.006)
55-64	1.404***	(0.008)	1.399***	(0.008)	1.442***	(0.007)	1.438***	(0.007)
65-74	1.642***	(0.010)	1.636***	(0.010)	1.690***	(0.009)	1.684***	(0.008)
75+	1.799***	(0.011)	1.790***	(0.011)	1.894***	(0.010)	1.887***	(0.010)
Gender (Ref: Female)	0.972***	(0.001)	0.968***	(0.001)	0.972***	(0.001)	0.968***	(0.001)
Remoteness (Ref: Major city)								
Inner	0.891***	(0.005)	0.894***	(0.005)	0.909***	(0.005)	0.911***	(0.005)
Outer	0.817***	(0.007)	0.820***	(0.007)	0.845***	(0.007)	0.847***	(0.007)
Remote	0.738***	(0.006)	0.741***	(0.006)	0.769***	(0.007)	0.771***	(0.007)
Very remote	0.687***	(0.013)	0.689***	(0.013)	0.714***	(0.014)	0.717***	(0.013)
State (Ref: ACT)								
NSW	1.273***	(0.008)	1.263***	(0.008)	1.252***	(0.007)	1.243***	(0.007)
NT	1.091***	(0.020)	1.086***	(0.019)	1.037***	(0.013)	1.033**	(0.014)
QLD	1.176***	(0.008)	1.175***	(0.008)	1.164***	(0.008)	1.164***	(0.008)
SA	1.227***	(0.009)	1.224***	(0.009)	1.181***	(0.009)	1.179***	(0.008)
TAS	1.276***	(0.019)	1.275***	(0.019)	1.195***	(0.017)	1.194***	(0.017)
VIC	1.242***	(0.009)	1.238***	(0.009)	1.224***	(0.008)	1.221***	(0.008)
WA	1.047***	(0.008)	1.046***	(0.007)	1.017**	(0.007)	1.016**	(0.007)
IRSAD (Ref: Decile 1)								
Decile 2	0.978**	(0.010)	0.978**	(0.010)	0.973***	(0.010)	0.973***	(0.009)
Decile 3	0.992	(0.011)	0.992	(0.011)	0.993	(0.011)	0.993	(0.011)

Decile 4	0.995	(0.011)	0.996	(0.011)	0.994	(0.009)	0.995	(0.009)
Decile 5	1.002	(0.011)	1.002	(0.011)	1.001	(0.010)	1.001	(0.010)
Decile 6	1.016	(0.010)	1.015	(0.010)	1.015*	(0.009)	1.014	(0.009)
Decile 7	1.022**	(0.010)	1.022**	(0.010)	1.016*	(0.009)	1.016*	(0.009)
Decile 8	1.041***	(0.011)	1.040***	(0.010)	1.031***	(0.009)	1.031***	(0.009)
Decile 9	1.073***	(0.012)	1.072***	(0.011)	1.056***	(0.010)	1.054***	(0.010)
Decile 10	1.062***	(0.012)	1.062***	(0.012)	1.049***	(0.010)	1.048***	(0.010)
Constant	1.898***	(0.020)	1.914***	(0.020)	1.875***	(0.018)	1.890***	(0.018)
Alpha (p-value)			0.355***	(0.003)			0.353***	(0.002)

Notes: Robust standard error (clustered at postcode level) in parentheses
Significance level: *** p<0.01, ** p<0.05, * p<0.1
NB2: Negative binomial version two

Table 7.3: Count Data regression of specialist visit (Non-bulk-billed)

	2011-12				2014-15			
	Poisson		NB2		Poisson		NB2	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE
Age (Ref: 0-4 year)								
5-14	0.870***	(0.005)	0.871***	(0.005)	0.897***	(0.004)	0.898***	(0.004)
15-24	0.997	(0.006)	0.995	(0.006)	1.046***	(0.005)	1.044***	(0.005)
25-34	1.057***	(0.006)	1.055***	(0.006)	1.085***	(0.005)	1.084***	(0.005)
35-44	1.102***	(0.006)	1.100***	(0.006)	1.127***	(0.006)	1.126***	(0.006)
45-54	1.149***	(0.007)	1.147***	(0.007)	1.159***	(0.005)	1.157***	(0.005)
55-64	1.259***	(0.007)	1.258***	(0.007)	1.277***	(0.006)	1.276***	(0.006)
65-74	1.423***	(0.008)	1.422***	(0.008)	1.454***	(0.007)	1.453***	(0.007)
75+	1.529***	(0.010)	1.527***	(0.009)	1.595***	(0.009)	1.593***	(0.009)
Gender (Ref: Female)	0.957***	(0.001)	0.955***	(0.001)	0.959***	(0.001)	0.957***	(0.001)
Remoteness (Ref: Major city)								
Inner	0.921***	(0.005)	0.921***	(0.005)	0.932***	(0.005)	0.931***	(0.005)
Outer	0.846***	(0.005)	0.846***	(0.005)	0.861***	(0.006)	0.860***	(0.006)
Remote	0.789***	(0.009)	0.789***	(0.009)	0.798***	(0.009)	0.798***	(0.009)
Very remote	0.760***	(0.013)	0.762***	(0.013)	0.780***	(0.016)	0.782***	(0.015)
State (Ref: ACT)								
NSW	1.195***	(0.009)	1.192***	(0.009)	1.188***	(0.009)	1.185***	(0.009)
NT	1.077***	(0.016)	1.075***	(0.016)	1.049***	(0.016)	1.050***	(0.016)
QLD	1.245***	(0.009)	1.243***	(0.009)	1.232***	(0.010)	1.231***	(0.010)
SA	1.200***	(0.010)	1.198***	(0.010)	1.175***	(0.010)	1.174***	(0.010)
TAS	1.318***	(0.029)	1.318***	(0.029)	1.254***	(0.025)	1.254***	(0.025)
VIC	1.254***	(0.010)	1.250***	(0.010)	1.243***	(0.011)	1.241***	(0.010)
WA	1.125***	(0.009)	1.125***	(0.009)	1.104***	(0.009)	1.104***	(0.009)
IRSAD (Ref: Decile 1)								
Decile 2	1.023***	(0.008)	1.022***	(0.008)	1.027***	(0.008)	1.026***	(0.008)
Decile 3	1.035***	(0.009)	1.034***	(0.009)	1.042***	(0.009)	1.042***	(0.009)
Decile 4	1.056***	(0.010)	1.055***	(0.010)	1.068***	(0.011)	1.067***	(0.011)

Decile 5	1.056***	(0.008)	1.055***	(0.008)	1.064***	(0.009)	1.063***	(0.008)
Decile 6	1.086***	(0.009)	1.085***	(0.009)	1.094***	(0.010)	1.092***	(0.010)
Decile 7	1.122***	(0.010)	1.121***	(0.010)	1.130***	(0.010)	1.128***	(0.010)
Decile 8	1.152***	(0.011)	1.150***	(0.011)	1.152***	(0.011)	1.150***	(0.010)
Decile 9	1.204***	(0.012)	1.201***	(0.011)	1.196***	(0.011)	1.192***	(0.011)
Decile 10	1.235***	(0.014)	1.231***	(0.014)	1.229***	(0.014)	1.224***	(0.013)
Constant	1.619***	(0.018)	1.628***	(0.018)	1.562***	(0.017)	1.570***	(0.017)
Alpha (p-value)			0.262***	(0.004)			0.251***	(0.004)

Notes: Robust standard error (clustered at postcode level) in parentheses
Significance level: *** p<0.01, ** p<0.05, * p<0.1
NB2: Negative binomial version two

Table 7.4: Count data regression of specialist visit (Bulk-billed)

	2011-12				**2014-15**			
	Poisson		NB2		Poisson		NB2	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE
Age (Ref: 0-4 year)								
5-14	1.085***	(0.005)	1.085***	(0.005)	1.075***	(0.005)	1.075***	(0.005)
15-24	1.067***	(0.006)	1.066***	(0.006)	1.099***	(0.006)	1.098***	(0.006)
25-34	1.112***	(0.007)	1.111***	(0.007)	1.122***	(0.006)	1.122***	(0.006)
35-44	1.219***	(0.008)	1.217***	(0.008)	1.212***	(0.007)	1.211***	(0.007)
45-54	1.315***	(0.009)	1.312***	(0.009)	1.314***	(0.007)	1.312***	(0.007)
55-64	1.359***	(0.009)	1.356***	(0.009)	1.386***	(0.008)	1.384***	(0.008)
65-74	1.428***	(0.011)	1.423***	(0.010)	1.464***	(0.010)	1.460***	(0.009)
75+	1.475***	(0.012)	1.469***	(0.012)	1.541***	(0.011)	1.536***	(0.011)
Gender (Ref: Female)	1.023***	(0.002)	1.022***	(0.002)	1.018***	(0.002)	1.017***	(0.002)
Remoteness (Ref: Major city)								
Inner	0.867***	(0.008)	0.871***	(0.008)	0.887***	(0.007)	0.891***	(0.007)
Outer	0.818***	(0.010)	0.822***	(0.010)	0.856***	(0.010)	0.859***	(0.009)
Remote	0.739***	(0.008)	0.742***	(0.008)	0.790***	(0.010)	0.793***	(0.010)
Very remote	0.691***	(0.020)	0.693***	(0.019)	0.722***	(0.019)	0.724***	(0.019)
State (Ref: ACT)								
NSW	1.207***	(0.010)	1.204***	(0.010)	1.183***	(0.011)	1.180***	(0.011)
NT	1.089***	(0.025)	1.085***	(0.024)	1.031	(0.024)	1.027	(0.024)
QLD	1.053***	(0.011)	1.055***	(0.011)	1.061***	(0.011)	1.062***	(0.011)
SA	1.129***	(0.011)	1.130***	(0.011)	1.072***	(0.011)	1.074***	(0.011)
TAS	1.174***	(0.018)	1.174***	(0.018)	1.075***	(0.014)	1.076***	(0.013)
VIC	1.137***	(0.011)	1.138***	(0.010)	1.113***	(0.011)	1.115***	(0.010)
WA	0.911***	(0.010)	0.911***	(0.010)	0.880***	(0.010)	0.880***	(0.010)
IRSAD (Ref: Decile 1)								
Decile 2	0.979	(0.015)	0.978	(0.015)	0.959***	(0.013)	0.959***	(0.013)
Decile 3	0.943***	(0.015)	0.945***	(0.015)	0.936***	(0.014)	0.938***	(0.014)
Decile 4	0.968**	(0.015)	0.971*	(0.015)	0.955***	(0.014)	0.956***	(0.013)
Decile 5	0.948***	(0.015)	0.950***	(0.015)	0.938***	(0.013)	0.939***	(0.012)
Decile 6	0.950***	(0.015)	0.952***	(0.014)	0.938***	(0.013)	0.940***	(0.013)
Decile 7	0.958***	(0.015)	0.961***	(0.014)	0.936***	(0.012)	0.938***	(0.012)
Decile 8	0.938***	(0.012)	0.940***	(0.012)	0.912***	(0.010)	0.914***	(0.010)

Decile 9	0.942***	(0.013)	0.944***	(0.012)	0.907***	(0.010)	0.909***	(0.010)
Decile 10	0.896***	(0.012)	0.900***	(0.012)	0.866***	(0.010)	0.870***	(0.010)
Constant	1.827***	(0.025)	1.826***	(0.025)	1.841***	(0.024)	1.840***	(0.024)
Alpha (p-value)			0.320***	(0.003)			0.312***	(0.003)

Notes: Robust standard error (clustered at postcode level) in parentheses
Significance level: *** p<0.01, ** p<0.05, * p<0.1
NB2: Negative binomial version two

Table 7.5 reports the estimates of the concentration index which quantifies area-level SES inequality in specialist visits in Australia. Statistically significant and positive estimates of all visits and non-bulk-billed visits suggest inequality was in favour of the patients living in higher SES-areas. In other words, inequality was pro-rich for these services. For all visits, the concentration index declined from 0.021 in 2011-12 to 0.016 in 2014-15. The degree of pro-rich inequality was higher for non-bulk-billed services as shown by the larger values of the indices. However, the extent of inequality decreased in 2014-15 as shown by the reduction in the positive value of the concentration indices. On the other hand, inequality in bulk-billed specialist attendances was pro-poor as the concentration indices were negative in both periods. The concentration index of this indicator was more negative in 2014-15 suggesting inequality to become favourable for the people from more disadvantaged areas. The findings stay similar when absolute inequality is measured using the generalised concentration indices which are reported in Table A7.1 in Appendix 7.

Table 7.5: Relative inequality in specialist visit (standard concentration index)

	2011-12			2014-15		
	Estimate	SE	95% CI	Estimate	SE	95% CI
All	0.021***	[0.000]	(0.020, 0.021)	0.016***	[0.000]	(0.016 ,0.017)
Non-bulk-billed	0.042***	[0.000]	(0.041, 0.043)	0.038***	[0.000]	(0.038, 0.039)
Bulk-billed	-0.002***	[0.000]	(-0.002, -0.001)	-0.009***	[0.000]	(-0.010, -0.009)

Notes: Robust standard error (clustered at postcode level) in brackets
95% confidence interval in parentheses
Significance level: *** p<0.01, ** p<0.05, * p<0.1

Figures 7.1-7.3 present the regional variation of inequality in three indicators of specialist visits. In general, there were some variations in inequality across the states and territories, and these variations remained almost similar in both periods. The variation was greater for inequality in non-bulk-billed visit. It appears from Figures 7.1 and 7.3 that the pro-rich inequality in all visit and bulk-billed visit was the highest in the NT. However, visits that were not bulk-billed appeared to be more equally distributed in the NT compared to other states/territories of Australia (Figure 7.2). The degree of inequality was lower in the ACT compared to the rest of Australia. The highest level of inequality was found in Victoria (VIC) in non-bulk-billed visit in both periods. Figures A7.2 - A7.4 in Appendix

7 depict absolute inequality indices, but the pattern of variation inequality does not change.

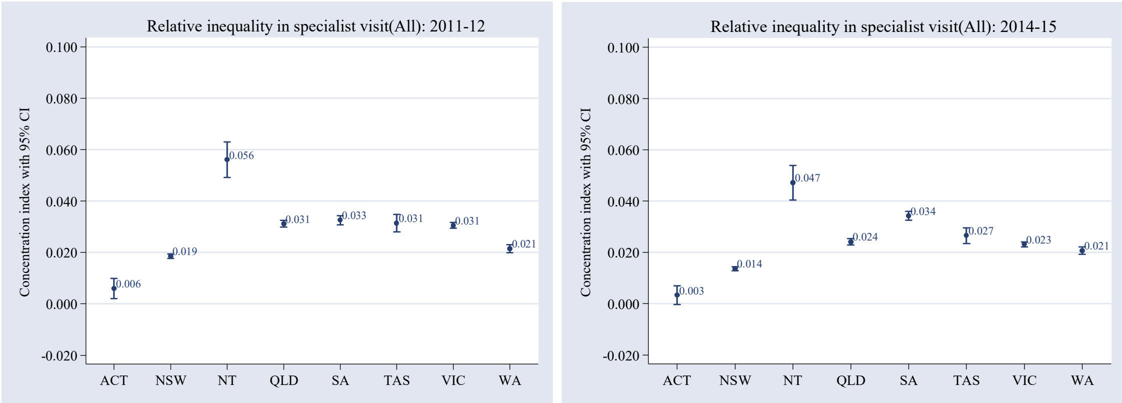


Figure 7.1: State and territory variation of inequality in all specialist visit

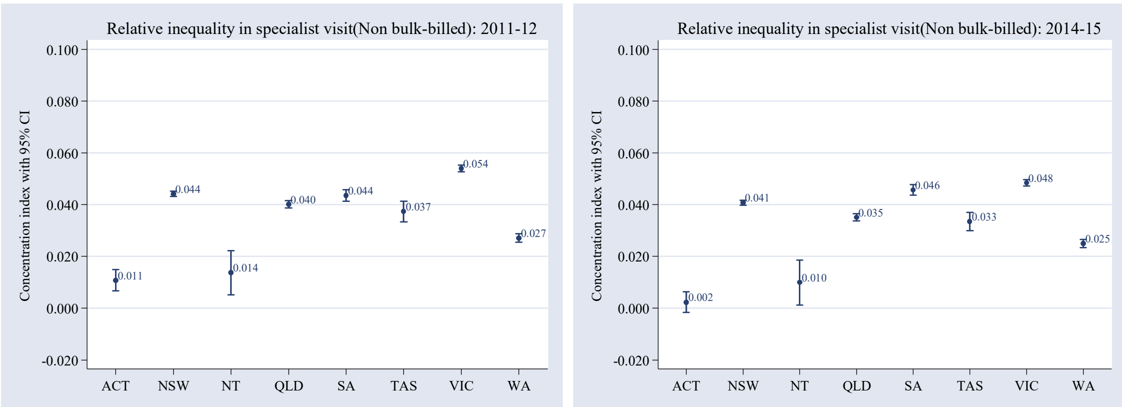


Figure 7.2: State and territory variation of inequality in non-bulk-billed specialist visit

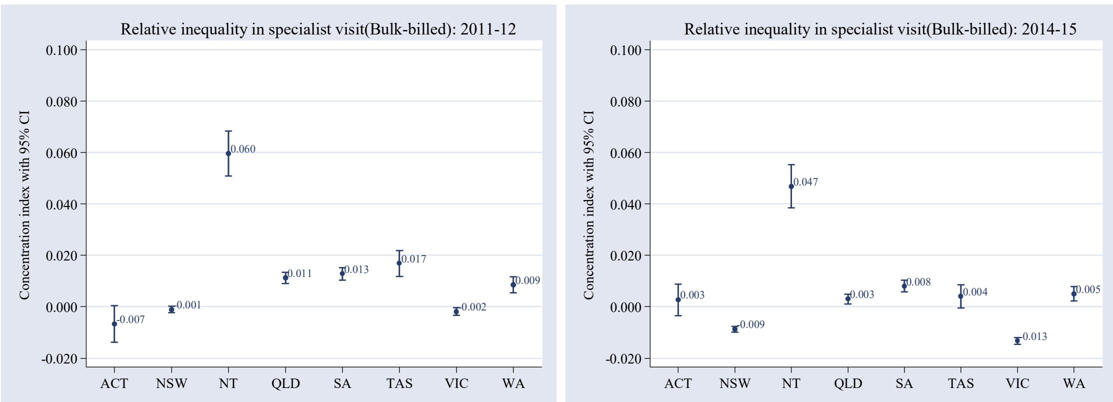


Figure 7.3: State and territory variation of inequality in bulk-billed specialist visit

7.4 Discussion

This chapter estimates area-level socioeconomic inequality in Medicare funded specialist care in Australia and examines how this inequality differs depending on patients' co-payment to visit a specialist. The analysis of this chapter has demonstrated that national Medicare data could be effectively used to report inequality indicators of healthcare use. The general finding is that there was inequality in Medicare-funded specialist services by area-level SES in Australia. People living in lower socioeconomic areas typically used fewer specialist services compared to those living in more affluent areas. However, the extent of inequality appeared to decline in 2014-15 compared to that in 2011-12. The most important finding of this chapter is that pro-rich socioeconomic inequality was the highest for specialist visits associated with OOP costs while there was almost equitable distribution in the visits incurring no OOP costs. The study results also reveal some evidence of spatial variation in inequality of specialist services across the states and territories of Australia. Another important finding is that patients residing in remote and very remote areas of Australia had significantly lower utilisation of specialist services.

In general, pro-rich inequality in specialist care by neighbourhood-level SES found in this study is consistent with the Australian and international evidence. In Australia, substantial income-related inequality in bariatric surgery among the obese population was found and the level inequality was even greater when measured by area-level SES (Korda et al., 2012). Area-level SES inequality was also pro-rich for Medicare-subsidised consultant psychiatry services between 2007 and 2011 (Meadows et al., 2015). In Canada, the distribution of specialist visits was found to be favourable to individuals from higher income areas in the province of British Columbia (McGrail, 2008). In France, specialist care utilisation was positively associated with the higher density of better educated areas (Chaix et al., 2005). The findings from this chapter also suggest that there was almost no area-level SES inequality in specialist visits if doctors opted to offer bulk-billing to the patients. However, the distribution of specialist services incurring OOP cost favours patients from socioeconomically advantaged areas. Therefore, financial barriers may, at least, be partly responsible for inequality in specialist care as argued by other Australian studies (Carpenter et al., 2015; Johar et al., 2017). The argument is that patients facing OOP cost either delay or skip specialist appointments and this financial barrier hits the people from socioeconomic disadvantage areas harder (Freed & Allen, 2017). Inequality in specialist care due to remoteness is similar to findings on primary care services found in other Australian studies (Day et al., 2005; Turrell et al., 2008).

The findings of study bear some important policy implications to address inequality in specialist services in Australia. Previous research has revealed that specialists price-discriminate, offering lower fees to lower income households (Johar et al., 2017). Yet, despite these discounts (and resulting lower OOP cost), they are insufficient to remove barriers to access for patients living in low socioeconomic areas. Furthermore, when patients face no OOP cost for specialist services, inequality virtually disappears as shown in this study. Well-designed incentives mechanisms to encourage specialists to offer more bulk-billed services, particularly for low income residents, may have an impact on the degree of inequality in healthcare services in Australia. Such incentives may need to be higher in rural and remote areas where there are lower bulk-billing rates than in metropolitan areas. However, the maldistribution of specialists needs to be considered before such a policy initiative is implemented. This kind of incentive has already been implemented in 2005 for general practice consultations which had a noticeable impact on bulk-billing rates (Wong et al., 2017). Similar financial incentives could be designed for specialist consultations, although more research is required on the level of the incentives that would maximise behaviour change among specialists and minimise unintended consequences on Government expenditure and other (e.g. higher income) patients.

The analysis of this chapter has a few limitations worth mentioning. The analysis is restricted to the users of Medicare-funded specialist services. It was not possible to study inequality in specialist care among the patients with other funding sources. However, Medicare is the universal health insurance system in Australia which covers all the necessary specialist services and the proportion services covered by other sources is relatively small. This chapter's findings are consistent with the previous studies and chapter 5 of this thesis that use self-reported measure of specialist utilisation. Even MBS data under-represents specialist use, it is unlikely to introduce bias in inequality estimates based on area-level SES.

Another limitation is that individuals were ranked from the lowest to the highest based on the SES of the areas where they lived. This has perhaps resulted in the common problem of ‘ecological fallacy’ similar to other studies which combine individual-level data to area-level socioeconomic characteristics (Cookson et al., 2012; McGrail, 2008). There could be heterogeneity among the individuals living within an area. It might not be the case that all richer and better-educated people reside in more socioeconomically advantaged areas (Cookson et al., 2012). However, analysis from chapters 5 and 6 suggests that area-level SES is an important factor of specialist service utilisation after controlling for individual level SES.

An important limitation is that this study has not adjusted for need for specialist services, which restricts us in drawing any conclusion about inequity. However, earlier studies reported that inequality favouring the better-off socioeconomic groups becomes even higher after need adjustment (van Doorslaer et al., 2004b). Finally, quality of care could not be considered in the inequality analysis because no information was available in the data.

7.5 Conclusion

Despite several limitations, the chapter has shown that Medicare data has the potential to be used for reporting indicators of inequality in health service use in Australia. The empirical analysis in this study is the first of its kind to present evidence on area-level socioeconomic inequality in specialist care by distinguishing between bulk-billed and non-bulk-billed services. This study has provided evidence of neighbourhood-level socioeconomic inequality in specialist care which is the highest for services incurring OOP payments. This conclusion does not confirm the equitable healthcare service delivery objective of Medicare in Australia. Further studies are needed for effective policy design to address this socioeconomic gradient in specialist services.

Future studies could be undertaken for better measurement and monitoring of socioeconomic inequality in health service use by addressing the limitations of this study. Medicare data would become a richer source of information if it could be linked to data on personal characteristics. For example, ecological fallacy problems could be mitigated by linking individual-level Medicare data to tax file data. Individual healthcare identifiers already exist for the Australian population and are used to support the development of the electronic health record. In the future, these might be available to support more in-depth analysis of inequality and inequity of the Australian healthcare system. This would also enable a better understanding of geographic variation at the lower level e.g. primary health networks (PHN) in Australia. Further studies could be undertaken to examine inequality in different types of specialist services as well as other healthcare use indicators.

One area for future research is to investigate how MBS data could be used to measure healthcare need. Healthcare needs based on claims data have clear endogeneity issues. However, it may be plausible to derive estimates of healthcare needs based on particular types of claims. For example, use of specific patterns of chemotherapy or radiation oncology claims may identify patients with cancer. The identification of health needs based on claims data would require careful clinical expertise and validity checking. Linking MBS data to hospital records would be another avenue to measure need for healthcare services based on the Charlson index, or diagnoses-based morbidity indices. This would allow future research to go beyond inequality analysis to study horizontal inequity in healthcare use. Finally, studies using linked hospital records and Medicare data would be an opportunity to analyse substitution of services due to inequality in one area of the healthcare sector.

Chapter 8: Inequity in healthcare use within Indigenous Australians

Abstract

This chapter measures and explains the extent of income-related horizontal inequity in healthcare utilisation among the non-remote Indigenous Australians using data from the Australian Aboriginal and Torres Strait Islander Health Survey, 2012-13. The concentration curve and the concentration index are used to measure income-related inequity in healthcare utilisation. Regression-based decomposition approach is also applied to explain the contributions of the determinants of healthcare use to inequity. The regression results show no evidence income-related inequity in the utilisation of GP services and inpatient admission. However, wealthier Indigenous Australians were the higher users of specialist care than their poorer counterparts despite having the similar need. Income inequality, unequal distribution of private health insurance and inequality in education were the key drivers of pro-rich inequity in specialist visits. Despite universal health insurance in Australia, patients face a significant co-payment to use specialist services and this could be one of reasons for pro-rich inequity among the Indigenous people to visit a medical specialist. There is need for further research to understand the link between co-payment and inequity in healthcare use in Australia and other developed countries with vulnerable population groups.

Keywords: Inequity; Indigenous people; specialist use; concentration index; Australia

8.1 Introduction

The Indigenous population is one of the most vulnerable communities in the world. Despite marked improvement in population health in developed countries during the last two decades, the major health indicators clearly reveal a consistent inequity in health outcomes between the indigenous and general populations (Cooke et al., 2007). In general, their burden of disease is higher, but utilisation of healthcare services is lower compared to the general population (Anderson et al., 2006; Gao et al., 2008). This disadvantaged population group has more need for healthcare services but, they do not always receive needed care (Balsa et al., 2011; Cissé et al., 2007; Lu et al., 2007). Inequity in healthcare use may contribute to worsening inequalities in health (Looper & Lafortune 2009).

In Australia, the health of indigenous people is also significantly worse than that of the mainstream population. The gap in life expectancy at birth between the Indigenous Australians[49] and the rest of the Australian population is wider than that in other developed countries such as Canada, New Zealand and the United States (Hill et al., 2007). Australia also falls behind these countries in its effort to narrow this well-documented life expectancy gap (Otim et al., 2014). Like other indigenous populations in the world, they experience significant social exclusion, discrimination, poverty, and unemployment (Zhao et al., 2016).

Since health of the Indigenous community in Australia is markedly worse than the general population, they should have higher access to and use of healthcare services because of poorer health status compared to the general population (Gubhaju et al., 2013). However, it is well documented in Australia that Indigenous people living in both remote and non-remote areas experience lower access to health services given their need for healthcare services (Kelaher et al., 2012). Low utilisation of preventive care services, less access to Medicare-funded specialist services, higher waiting time for surgeries, and poor access to eye care services are few examples.

[49] Australian Indigenous population refers to Aboriginal and Torres Strait Islander people and constitutes 3% of the total Australian population according to estimates of the Australian Bureau of Statistics (ABS, 2012).

Despite higher hospitalisation rates among Indigenous people, their rate of specific surgical procedures was lower during any stay in hospital (Cunningham, 2002). For example, Indigenous people in the Australian state of Queensland were found to be provided with less cancer care than non-Indigenous people regardless of the SES background (Moore et al., 2014). Medicare benefit expenditure is lower for the Indigenous Australians while it is higher for hospital expenditure (Alford, 2015; Angell et al., 2017).

Recent data shows some evidence of progress in healthcare utilisation among this vulnerable group due to several initiatives by the Australian Government with the aim of closing the life expectancy gap by 2031 (AIHW, 2016a). This could possibly narrow the disparity in access to and use of some healthcare services between Indigenous and non-Indigenous Australians. For example, the rate of Medicare-funded general practitioner (GP) services are now higher among Indigenous Australians compared to non-Indigenous Australians (AHMAC, 2017).

Despite average improvement in access to healthcare services due to various government interventions, there is a possibility of inequality and inequity in use of healthcare services within the Indigenous population. Based on findings from the Northern Territory, Zhao et al.(2013) suggested exploring socioeconomic inequities in health and healthcare within the Indigenous population. There is also a need to understand heterogeneity in healthcare use within Indigenous Australians (Whelan & Wright, 2013). Inequity in healthcare use within the Indigenous population may have potential implications for understanding why the gap in healthcare service use between the Indigenous and non-Indigenous populations persists in Australia (Marrone, 2012). It is important to know whether all members of the indigenous population are similarly disadvantaged in their access to and use of healthcare or if some are substantially more disadvantaged than other. This is also important from a policy perspective as understanding the extent and causes of inequity in healthcare service utilisation will allow the development of informed policy decisions.

Inequity in use of healthcare services between the Indigenous and non-Indigenous population is well studied in Australia and other similar countries. However, previous research has largely overlooked the potential of inequity in use of healthcare services *within* the Indigenous population. Therefore, socioeconomic inequity in healthcare use within the Indigenous population warrants a detailed empirical examination. There are previous studies on horizontal inequity among the general population but no study yet to examine horizontal inequity in healthcare services use within this group in Australia. Therefore, this chapter aims to fill this gap in the literature by measuring the extent of income-related horizontal inequity in healthcare use among the Indigenous Australians. This chapter also aims to examine the role of different socioeconomic factors in explaining the degree and direction of horizontal inequity.

The rest of this chapter is outlined as follows. The next section introduces the methodology and estimation strategy of this chapter. A description of data and variables used in the empirical analysis is presented in section three. Section four describes the results of this study. This is followed by a discussion of the major findings in section five. The last section concludes the chapter.

8.2 Methodology

The statistical analysis of this study begins with presenting descriptive statistics of all explanatory and dependent variables. This is followed by a multivariate regression analysis to examine the relationship between healthcare utilisation and income after controlling for health-related variables and other socioeconomic variables. Since the measure of healthcare use is binary in this study, logistic regression specification is used to model the healthcare utilisation. A statistically significant coefficient of income indicates the existence of inequity in health service use by income after accounting for other observable characteristics.

Regression analysis tests the presence of income-related inequality in use of healthcare, but it does not allow us to quantify the magnitude of inequality (Wagstaff & van Doorslaer 2000a).Therefore, this chapter applied the well-established methodology of the concentration curve (CC) and the related concentration index (CI) to present and measure the extent of income-related inequality and inequity in healthcare use (Kakwani et al., 1997; O'Donnell et al., 2008; Wagstaff et al., 1991b, 1991a).The analysis is further extended to unpack the contributing factors of income-related inequality and inequity using the regression-based decomposition approach (van Doorslaer et al., 2004b; Wagstaff et al., 2003).

Inequality in healthcare use can be presented by the concentration curve (CC) which plots the cumulative proportion of healthcare use in the vertical axis against the cumulative share of population in the horizontal axis ranked from the lowest to the highest by income. Healthcare utilisation is equally distributed if the CC coincides with the 45-degree line or line of equality. A CC above the line of equality indicates the presence of inequality favouring the poor and vice-versa. The CC does not provide an estimate of inequality in use of healthcare services, rather it is a visual presentation of inequality. Therefore, the extent of inequality can be quantified by estimating the concentration index (CI) which is twice the area between the concentration curve and the line of equality (O'Donnell et al., 2008). This index can be calculated using the following formula which shows the covariance between the fractional rank of income and healthcare utilisation[50]:

$$CI = \frac{\mu}{2}\operatorname{cov}(y_i, R_i) \qquad (8.1)$$

In the above equation, y_i and R_i stand for healthcare use and the fractional income rank of each individual respectively; μ is the mean of healthcare use among the study population. The value of the CI falls within the range of -1 to +1. A positive value indicates pro-rich inequality and a negative indicates pro-poor inequality. When the index is zero or statically insignificant, there is no income-related inequality in the utilisation of healthcare services. However, the measurement of inequality using the CI is problematic when a healthcare use is a binary indicator. In this case, the value of the index is influenced by the mean of healthcare use and may not lie between +1 and -1(Wagstaff, 2005). This problem could be addressed by applying either Wagstaff's correction or Erreygers's normalisation (Erreygers, 2009a; Wagstaff, 2005). This study follows the Erreygers's index (EI) which can be written as:

$$EI = \frac{4\mu}{(b_y - a_y)} CI(y) \;=\; 4 * \mu * CI(y) \qquad (8.2)$$

[50] In practice, a convenient (weighted least squares) regression of (transformed) y on the relative rank of individual in the income distribution is used to construct the confidence interval of the CI for statistical inference. See (Kakwani et al., 1997) for details.

In equation 8.2, b_y and a_y are the upper and lower bounds of the healthcare use variable. The justification to employ Erreygers's version of the CI is that this is the only rank-dependent index of inequality that satisfies together the properties of mirror (inequality in use 'mirrors' inequality in non-use) and quasi-absoluteness (the EI is not sensitive to any feasible equal addition to the use variable) (Erreygers & Van Ourti 2011)[51].

In universal healthcare systems, poorer people generally use more healthcare services because of higher need for healthcare due to their poor health status. The above approach measures income-related inequality in healthcare utilisation but does not tell us anything about inequity in use. Strictly speaking, the variation in need for healthcare services is not considered in the technique discussed in the previous section. Therefore, income-related inequity is estimated using the horizontal inequity (HI) index.

The HI can be best described as the unequal use of healthcare services by income given the same level of need among the population (O'Donnell et al. 2008; Wagstaff et al. 1991b; Wagstaff & van Doorslaer 2000b). In other words, the HI refers to avoidable or unfair inequality in healthcare utilisation. The methodology requires adjusting need for healthcare services so that poor and rich have the same level of need. In this study, the indirect standardisation method is used to estimate need adjusted healthcare use following O'Donnell et al. (2008). Therefore, the steps for measuring income-related horizontal inequity in healthcare use in the concentration index approach are discussed below:

In the first step, a regression model for healthcare utilisation including both need and non -need variables is run to estimate the coefficients:

$$y_i = \alpha + \beta income_i + \sum_k \lambda_k Z_{k,i} + \sum_p \delta_p X_{p,i} + \varepsilon_i \quad (8.3)$$

In this equation, Z_k and X_p are the vectors of non-need and need variables; α, β, λ and δ are the parameter vectors; and ε_i is the error term. Since healthcare variable is binary in the study, logistic models are used to estimate the coefficients[52]. In the second step, need-

[51] Wagstaff's index is also estimated and presented but it does not change the conclusion of the study. In addition, a generalised concentration index is also measured multiplying the standard concentration index by the mean of healthcare use. Again, the conclusion remains similar.

[52] Many studies have used the linear probability model (LPM) but predicted probabilities are found to be outside the range 0-1 in this paper. There are examples of using non-linear models for need-standardisation, for example logistic regression models, as in (Rodrigues et al., 2018).

predicted value for healthcare utilisation for everyone is generated using the following equation:

$$\hat{y}_i^X = \hat{\alpha} + \hat{\beta} income^m + \sum_k \hat{\lambda}_k Z_k^m + \sum_p \hat{\delta}_p X_{p,i} \qquad (8.4)$$

In equation 8.4, $\hat{y}_i^X$ is the need expected utilisation for each person which is only influenced by need-related variables. This is obtained by setting the values of income and other non-need variables equal to their sample average (denoted by ^{m}) and setting the value of all need variables at the actual value for each person. Equation 8.4 refers to the ideal level of healthcare services an individual would have received given his or her health need (van Doorslaer et al., 2004b). In the next step, need-standardised utilisation for all individuals is calculated using the formula below:

$$\hat{y}_i^{IS} = y_i - \hat{y}_i^X + \hat{y}^m \qquad (8.5)$$

Finally, the degree of income-related horizontal inequity is quantified by estimating the concentration index of need-standardised utilisation obtained in equation 8.5. The HI index, like the CI, lies between -1 and +1. A positive HI indicates pro-rich inequity and vice-versa. A pro-rich (pro-poor) inequity suggests that healthcare utilisation is concentrated among richer (poorer) individuals after accounting for need differences (van Doorslaer et al. 2004; Wagstaff & van Doorslaer 2000b). An insignificant or zero HI suggests no income-related inequity in use of healthcare services. It should be noted that Erreygers's normalisation is also applied in the estimation of the HI as before to avoid the limitations of standard CI for bounded variable of healthcare use. HI is a measure of income-related inequity in healthcare use. Income and other non-need related variables, such as education and employment could be a source of this inequity. So, this study applies the regression-based decomposition method to explain how these factors contribute to inequity in healthcare use (van Doorslaer et al., 2004b; Wagstaff et al., 2003). Since healthcare variable is binary in this analysis, Erreygers's version of decomposition is applied following van de Poel et al. (2012)[53]. Using the model of healthcare utilisation in equation 8.3, this method involves decomposing the unadjusted EI as follows:

$$EI = 4\left[\beta * income^m * CI_{income} + \sum_k \lambda_k * Z_k^m * CI_{Z_k} + \sum_p \delta_p * X_p^m * CI_{X_p} + GCI_{\varepsilon}\right] \qquad (8.6)$$

[53] Recent empirical applications of Erreygers's decomposition in explaining horizontal inequity in health care use can be found in Dorjdagva et al. 2017 and García-Gómez et al. 2015.

The marginal effects (β, λ and δ) in equation 8.6 are the average of the marginal effects after estimating a logistic regression model which follows the procedure of (van Doorslaer et al., 2004b; Walsh et al., 2012) in a non-linear decomposition[54]. Equation 8.6 shows that the EI can be decomposed into four parts which enables us to unpack the contribution of different determinants to total income-related inequality in healthcare use. The first part is the direct contribution of income, the second part is the contribution of other non-need variables and the third part is the contribution of need variables. The final part is the generalised CI of the residual term which represents unexplained income-related inequality of the unobserved factors. The main interest of the decomposition in this analysis is the first two sources of the EI which constitute the contribution to horizontal inequity in healthcare use[55]. In this approach, a factor explains inequity through the interaction of its marginal effect on healthcare use and own unequal distribution by income[56]. Decomposition is a powerful mechanism to underpin the causes of inequity in healthcare utilisation. For example, a pro-rich inequity in use of healthcare could be explained by inequality in private health insurance and its strong association with healthcare use rather than income itself.

8.3 Data and variables

Data source and study sample

Empirical analysis of this study draws data from the Australian Aboriginal and Torres Strait Islander Health Survey (AATSIHS) 2012-13[57]. The survey was administered by the Australian Bureau of Statistics (ABS) in both remote and non-remote areas of Australia. The AATSIHS is a nationally representative survey of Aboriginal and Torres Strait

[54] The marginal effects of the explanatory variables are firstly obtained using the respective actual values for everyone in the sample. These are then averaged across individuals. These are calculated in Stata 15.1 using the margin command. These marginal effects are different from the marginal effects estimated at the sample mean of the independent variables.

[55] Alternatively, Erreygers's HI can be computed by subtracting the sum of need contribution from the EI in equation 8.6 as shown by García-Gómez et al. (2015). However, it would not be equal to the HI obtained from the indirect standardisation approach due to non-linear specification of the regression model.

[56] There would be no contribution of an explanatory variable to inequality and inequity in healthcare utilisation in two cases. The first case is that the variable itself has no significant association with healthcare use, and in the second case there is equal distribution of the variable itself by income.

[57] The unit record data has been accessed using the secured DataLab environment of Australian Bureau of Statistics based in Sydney, Australia. Each session was limited to 3.5 hours per day which precluded advanced statistical analysis such as bootstrapping of confidence interval of decomposition estimates.

Islander people in Australia with a sample of 13,000 persons (ABS, 2013c). The selection of sample follows a multistage stratified sampling technique. This survey has a similar structure to Australian national health surveys, in which data has been collected on a wide range of information on general health, long-term health conditions, health risk factors, use of health care, and socioeconomic status.

This study restricts the sample to non-remote Indigenous people since information for some variables (e.g. private health insurance) are only available for the non-remote sample. Moreover, there are special arrangements for providing services to very remote areas of Australia and some of these services have funding provisions other than Medicare. The analytic sample is further restricted to individuals aged 18 years and over, since information about mental health conditions is only available for adults. Finally, about 13% of the sample with missing data on income are also excluded from the analysis. Therefore, the final sample of this study consists of 2,823 adult Indigenous individuals living in non-remote areas of Australia.

Variable description

Health service use is captured by four binary outcomes of whether the respondent visited a doctor or health professional in the last two weeks of the survey, and whether an individual was admitted to hospital in the last 12 months prior to the survey. These are: individuals' consultation with any doctor (any visit), visit to a general practitioner (GP visit), consultation with a medical specialist (specialist visit) in the last two weeks, and at least one-night stay in hospital as an inpatient (inpatient admission) in the last year.

The need for healthcare is measured by self-assessed health (SAH), age, gender, mental health condition, disability status and diabetes. SAH is in five categories ranging from excellent to poor. The Kessler Psychological Distress Scale (Kessler-5 or K5) is used in the AATSIHS to capture the mental health and well-being of the respondents (Kessler et al., 2002). The K5 is a continuous variable ranging from 5 to 25 with a higher score indicating a greater level of psychological distress. This has been discussed in detail elsewhere (Cunningham & Paradies 2012; Yiengprugsawan et al., 2014). Disability status measures daily activity limitations because of health-related reasons and is recoded into three categories of no, some/moderate and severe.

Equivalised household income in deciles is the main variable of interest in this study[58]. Income is used to rank individuals from the poorest to the richest in inequality and inequity analysis. Other non-need variables include employment status, education, holding a concession card and private health insurance status.

8.4 Results

Summary statistics

Table 8.1 presents descriptive statistics of the socioeconomic and demographic characteristics of the Indigenous population living in non-remote areas of Australia in 2012-13. About 36% of the study population reported to be in good health, while only 9% reported to be in excellent health. Table 8.1 shows that about 50% of the sample had some sort of disability (some/moderate to severe). The prevalence of diabetes was about 22% among the Indigenous population living in the non-remote areas of Australia.

More than a quarter (26%) of the respondents belonged to the lowest income decile while only 3% were in the highest income decile (Table 8.1). The proportion of the study population with any form of private health insurance was about 22% in 2012-13. On the other hand, about 60% of the sample had a concession card. Figure 8.1 presents the income quintile and self-assessed health (SAH) distribution of private health insurance and concession card status. Both income and SAH gradient are observed in these two variables. For example, about 70 % of the people in the highest income quintile had private insurance which was only about 6 % in the lowest income quintile. However, more than 90% of the people from the poorest quintile had a concession card. Figure 8.1 also shows that people reporting better health had a higher rate of private health insurance while concession card holders reported worse health. Finally, about 26% of the respondents had an education level equivalent to Year 12 or beyond, and 45% reported being employed in the survey period.

[58] The 'modified OECD' equivalence scale is applied by ABS to calculate equivalised total weekly income of the household in the AATSIHS.

Table 8.1: Descriptive statistics of the independent variables

	Mean	Std. Err.	95% CI
Female	0.59	0.01	(0.57 0.61)
Age: 18-24	0.17	0.01	(0.16 0.19)
Age: 25-34	0.22	0.01	(0.20 0.24)
Age: 35-44	0.23	0.01	(0.21 0.24)
Age: 45-54	0.18	0.01	(0.17 0.20)
Age: 55-65	0.11	0.01	(0.10 0.12)
Age 65 and above	0.09	0.01	(0.08 0.10)
SAH: Excellent	0.09	0.01	(0.08 0.10)
SAH: Very good	0.25	0.01	(0.23 0.26)
SAH: Good	0.36	0.01	(0.35 0.38)
SAH: Fair	0.20	0.01	(0.19 0.22)
SAH: Poor	0.10	0.01	(0.09 0.11)
Kessler 5 score	10.19	0.09	(10.02 10.36
Disability: No	0.50	0.01	(0.48 0.52)
Disability: Moderate	0.41	0.01	(0.39 0.43)
Disability: Severe	0.09	0.01	(0.08 0.10)
Diabetes	0.22	0.01	(0.20 0.23)
Household Income: Decile 1	0.26	0.01	(0.24 0.28)
Decile 2	0.14	0.01	(0.13 0.15)
Decile 3	0.13	0.01	(0.12 0.15)
Decile 4	0.12	0.01	(0.11 0.14)
Decile 5	0.09	0.01	(0.08 0.10)
Decile 6	0.07	0.01	(0.06 0.08)
Decile 7	0.06	0.01	(0.05 0.07)
Decile 8	0.06	0.00	(0.05 0.07)
Decile 9	0.04	0.00	(0.03 0.05)
Decile 10	0.03	0.00	(0.02 0.03)
Private health insurance	0.21	0.01	(0.19 0.22)
Concession card	0.61	0.01	(0.59 0.63)
Education: Year 12 or above	0.26	0.01	(0.24 0.28)
Education: Year 9-11	0.59	0.01	(0.57 0.61)
Education: Year 8 or below	0.14	0.01	(0.13 0.16)
Education: Never attended	0.01	0.00	(0.00 0.01
Employment: Employed	0.45	0.01	(0.43 0.47)
Employment: Unemployed	0.11	0.01	(0.09 0.12)
Employment: Out of labour force	0.44	0.01	(0.43 0.46)

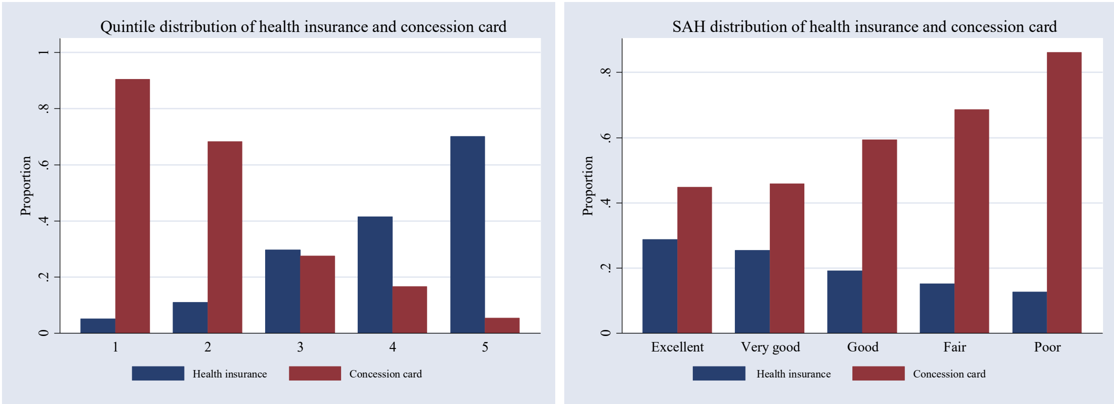


Figure 8.1: Health insurance and concession card by income quintile and SAH

Table 8.2 reports healthcare services utilisation rate among Indigenous population of non-remote Australia. In general, about 43% of the respondents either visited any health professional or received health services from an institutional healthcare facility (e.g. hospital treatment or ambulatory care service) in the two weeks preceding the survey. The proportion of people visiting a GP and a specialist in the two weeks before the survey was about 25% and 7% respectively. About 23% reported being admitted to a hospital for at least one night in the year prior to the survey.

In general, use of health services was higher among women except for specialist visit. The probability of receiving any visit, GP visits and specialist visits is found to be higher among the older Indigenous population, but there was almost no variation in inpatient admission by age groups. As expected, people reporting fair or poor health used more healthcare services compared to people in excellent or good health. For example, the proportion of specialist visit was more than four times higher among people reporting poor health (17%) compared to people with excellent health (4%). Similar results are found for the other three health-need variables: disability status, mental health condition and diabetes (Table 8.2). For example, GP visit was higher among diabetes patients (35%) compared to people having no diabetes (22%).

Overall, a socioeconomic gradient is observed in visit to specialists in 2012-13 among Indigenous Australians. Table 8.2 reveals income gradient in specialist utilisation which is the probability of visit was higher among upper income deciles. For example, about 7 % of individuals belonging to the poorest household (decile 1) consulted a medical specialist which was about 14% for their richest (decile 10) counterparts.

Table 8.2: Health service utilisation (proportion) by the independent variables

	Any visit	GP visit	Specialist visit	Inpatient admission[1]
Overall	0.43	0.25	0.07	0.23
Need variables				
Male	0.35	0.20	0.06	0.18
Female	0.50	0.30	0.07	0.27
Age: 18-24	0.34	0.20	0.06	0.20
Age: 25-34	0.40	0.23	0.05	0.24
Age: 35-44	0.44	0.23	0.06	0.23
Age: 45-54	0.46	0.26	0.09	0.22
Age: 55-65	0.50	0.35	0.09	0.26
Age 65 and above	0.56	0.36	0.10	0.21
SAH: Excellent	0.38	0.19	0.04	0.20
SAH: Very good	0.32	0.16	0.05	0.18
SAH: Good	0.40	0.23	0.06	0.20
SAH: Fair	0.53	0.34	0.08	0.29
SAH: Poor	0.66	0.45	0.17	0.38
Disability: No	0.33	0.18	0.04	0.17
Disability: Moderate	0.48	0.29	0.08	0.28
Disability: Severe	0.74	0.47	0.25	0.36
* Mental health: Low/moderate	0.38	0.21	0.05	0.19
* Mental health: High	0.51	0.33	0.10	0.31
Diabetes (No)	0.39	0.22	0.06	0.21
Diabetes (Yes)	0.57	0.35	0.10	0.31
Non-need variables				
Household Income:				
Decile 1	0.42	0.26	0.07	0.27
Decile 2	0.41	0.26	0.04	0.23
Decile 3	0.48	0.30	0.10	0.22
Decile 4	0.40	0.22	0.06	0.20
Decile 5	0.48	0.30	0.04	0.18
Decile 6	0.43	0.20	0.08	0.25
Decile 7	0.32	0.19	0.06	0.15
Decile 8	0.41	0.22	0.09	0.26
Decile 9	0.43	0.16	0.06	0.26
Decile 10	0.41	0.20	0.14	0.20
Private health insurance (No)	0.40	0.24	0.06	0.23
Private health insurance (Yes)	0.51	0.26	0.11	0.21
Concession card (No)	0.37	0.20	0.06	0.17
Concession card (Yes)	0.47	0.29	0.08	0.27
Education: Year 12 or above	0.45	0.24	0.09	0.21
Education: Year 9-11	0.41	0.24	0.06	0.23
Education: Year 8 or below	0.46	0.30	0.07	0.24
Education: Never attended	0.36	0.25	0.02	0.43
Employment: Employed	0.38	0.20	0.05	0.18
Employment: Unemployed	0.37	0.21	0.06	0.19
Employment: Out of labour force	0.50	0.32	0.09	0.30

[1] In the last 12 months

* For reporting descriptive statistics

Again, specialist utilisation was almost twofold higher among private health insurance holders (11% versus 6%) compared to people with no private health insurance. Moreover, highly-educated Indigenous Australians were more likely to see a specialist compared to the less educated ones. On the other hand, the proportion of specialist visit was higher among the respondents who were out of the labour force at the time of the survey.

Regression results

Table 8.3 presents the results from the multivariate logistic regression analysis to examine the association between the utilisation of healthcare services and need and socioeconomic variables. The regression results are reported as the odds ratio (OR) with 95% confidence intervals. The regression results indicate that females had a higher probability of utilising healthcare services except for specialist services. For example, the odds of visiting a GP was 1.47 (95% CI: 1.21, 1.77) times higher for females. There was a statistically significant and positive relationship between age and any visit. In other words, older Indigenous Australians were more likely to use healthcare services. For GP visits, individuals aged 65 and above were likely to have 1.84 higher probability compared to young adults (18-24 years). The OR of SAH indicates that people reporting poor health visited any health professional, GP and specialist more compared to people with better health. For instance, the OR was 2.29 (95% CI: 1.05, 4.98) for poor health in the case of specialist visit. Table 8.3 reveals no significant association between SAH and inpatient admission. It is found that Kessler 5 score, disability status and having diabetics, significantly increased the likelihood of using all four types of healthcare services.

Table 8.3 reports that almost all non-need indicators, except private health insurance, were not significantly related to use of GP service. It appears from the results that household income was significantly associated only with any visit and specialist visit. For example, the probability of going to a medical specialist was about three (OR 2.96) times higher for the respondents from the households of highest income decile compared to their lowest counterparts. Although the likelihood of an inpatient admission was higher among the individuals from the highest deciles (8, 9, and 10), the relationship was not statistically significant. Private health insurance is found to be a significant predictor of any healthcare visit, GP visit and specialist visit. For example, the OR of private health insurance in Table 8.3 suggests that likelihood of visiting a specialist was more than two times higher for private health insurance holders compared to people with no private health insurance. Concession card only appears to be associated with any visit. It is observed that less educated Indigenous Australians had significantly lower likelihood of visiting a specialist. However, education was not significantly correlated with GP visit and inpatient admission. Although being out of the labour force increased the probability of using three types of healthcare services studied in this study, it was only a significantly correlated with inpatient admission.

Table 8.3: Logistic regression results of the probability four types of healthcare use

	Any visit		GP visit		Specialist visit		Inpatient admission[1]	
	Odds ratio	95% CI	Odds ratio	95% CI	Odds ratio	95% CI	Odds ratio	95% CI
Female	1.62***	(1.37 - 1.92)	1.47***	(1.21 - 1.77)	0.85	(0.61 - 1.17)	1.33***	(1.10 - 1.63)
Age: 18-24	Reference		Reference		Reference		Reference	
Age: 25-34	1.44***	(1.10 - 1.88)	1.26	(0.93 - 1.71)	0.97	(0.57 - 1.67)	1.31*	(0.98 - 1.75)
Age: 35-44	1.17	(0.89 - 1.54)	1.03	(0.75 - 1.41)	0.81	(0.46 - 1.41)	0.84	(0.62 - 1.14)
Age: 45-54	1.42**	(1.04 - 1.92)	1.34*	(0.96 - 1.87)	0.96	(0.55 - 1.71)	0.75*	(0.54 - 1.06)
Age: 55-65	1.37*	(0.96 - 1.94)	1.23	(0.84 - 1.79)	0.84	(0.44 - 1.59)	0.78	(0.53 - 1.15)
Age 65 and above	2.02***	(1.34 - 3.04)	1.84***	(1.20 - 2.82)	0.91	(0.41 - 2.00)	0.65*	(0.41 - 1.03)
SAH: Excellent	Reference		Reference		Reference		Reference	
SAH: Very good	0.97	(0.71 - 1.32)	1.22	(0.83 - 1.79)	0.79	(0.39 - 1.61)	1.00	(0.70 - 1.43)
SAH: Good	1.08	(0.80 - 1.46)	1.29	(0.89 - 1.87)	1.13	(0.59 - 2.16)	0.85	(0.60 - 1.21)
SAH: Fair	1.19	(0.85 - 1.67)	1.64**	(1.10 - 2.46)	1.32	(0.65 - 2.66)	1.06	(0.72 - 1.57)
SAH: Poor	1.72**	(1.13 - 2.63)	1.92***	(1.21 - 3.05)	2.29**	(1.05 - 4.98)	1.37	(0.87 - 2.16)
Kessler 5 score	1.06***	(1.04 - 1.08)	1.05***	(1.02 - 1.07)	1.04**	(1.00 - 1.08)	1.02*	(1.00 - 1.04)
Disability: No	Reference		Reference		Reference		Reference	
Disability: Moderate	1.72***	(1.43 - 2.08)	1.56***	(1.26 - 1.92)	2.08***	(1.38 - 3.15)	1.75***	(1.40 - 2.18)
Disability: Severe	3.66***	(2.57 - 5.21)	2.84***	(2.03 - 3.97)	4.84***	(2.80 - 8.36)	2.20***	(1.55 - 3.13)
Diabetes (Yes)	1.58***	(1.28 - 1.95)	1.48***	(1.20 - 1.84)	1.49**	(1.03 - 2.14)	1.32**	(1.05 - 1.66)
Household Income: Decile 1	Reference		Reference		Reference		Reference	
Decile 2	1.18	(0.90 - 1.55)	0.99	(0.74 - 1.32)	1.14	(0.68 - 1.93)	0.70**	(0.51 - 0.94)
Decile 3	1.26	(0.95 - 1.67)	1.09	(0.81 - 1.47)	1.13	(0.65 - 1.96)	0.84	(0.62 - 1.14)
Decile 4	1.23	(0.91 - 1.68)	0.93	(0.67 - 1.30)	1.47	(0.82 - 2.64)	0.72*	(0.51 - 1.02)
Decile 5	1.59**	(1.11 - 2.26)	1.24	(0.84 - 1.83)	1.04	(0.46 - 2.35)	0.88	(0.57 - 1.35)
Decile 6	1.62**	(1.10 - 2.39)	1.01	(0.66 - 1.55)	2.64***	(1.29 - 5.39)	1.16	(0.74 - 1.83)
Decile 7	1.17	(0.77 - 1.78)	0.95	(0.60 - 1.52)	2.11*	(0.95 - 4.66)	0.94	(0.56 - 1.56)
Decile 8	1.16	(0.75 - 1.80)	0.82	(0.49 - 1.36)	1.68	(0.74 - 3.82)	1.42	(0.87 - 2.31)
Decile 9	1.82**	(1.12 - 2.97)	1.04	(0.60 - 1.80)	2.70**	(1.13 - 6.48)	1.57	(0.89 - 2.77)
Decile 10	1.47	(0.82 - 2.65)	1.20	(0.64 - 2.26)	2.96**	(1.13 - 7.77)	1.44	(0.74 - 2.80)
Private health insurance	1.69***	(1.34 - 2.14)	1.38**	(1.07 - 1.78)	2.14***	(1.38 - 3.31)	1.03	(0.78 - 1.36)
Concession card	1.33**	(1.03 - 1.70)	1.12	(0.85 - 1.46)	1.25	(0.74 - 2.12)	1.13	(0.84 - 1.51)
Education: Year 12 or above	Reference		Reference		Reference		Reference	
Education: Year 9-11	0.85	(0.69 - 1.04)	0.88	(0.70 - 1.10)	0.68**	(0.46 - 1.00)	0.91	(0.72 - 1.14)
Education: Year 8 or below	0.72**	(0.52 - 0.98)	0.81	(0.58 - 1.13)	0.52**	(0.29 - 0.94)	0.73*	(0.51 - 1.05)
Education: Never attended	0.57	(0.21 - 1.52)	0.88	(0.33 - 2.30)	0.27	(0.03 - 2.41)	1.74	(0.67 - 4.50)
Employment: Employed	Reference		Reference		Reference		Reference	
Employment: Unemployed	0.88	(0.64 - 1.22)	0.95	(0.66 - 1.38)	1.33	(0.70 - 2.53)	0.97	(0.65 - 1.43)
Employment: Out of labour force	0.99	(0.77 - 1.27)	1.12	(0.85 - 1.47)	1.23	(0.74 - 2.03)	1.57***	(1.18 - 2.08)
Constant	0.11***	(0.06 - 0.18)	0.07***	(0.04 - 0.12)	0.02***	(0.01 - 0.04)	0.14***	(0.08 - 0.24)
Observations	2,748		2,747		2,748		2,748	
Pseudo R-squared	0.0993		0.0815		0.107		0.0556	
Log pseudo likelihood	-1705		-1492		-619.1		-1421	

Notes: [1] Inpatient hospital admission in last year
Robust standard errors are used to construct 95% CI in parentheses
Significance level *** p<0.01, ** p<0.05, * p<0.1

Inequality and inequity in specialist visit

This section discussed the results of income-related inequality and inequity in specialist visit since specialist visit is found to be significantly associated with non-need variables[59]. Figure 8.2 shows the quintile and decile distributions of actual, need-predicted and need-standardised visit to a specialist. The distribution of actual specialist visit was pro-rich as it was more concentrated among people of higher income quintiles and deciles. Need-predicted distribution reflects the case when specialist visit would follow the need of the individuals. In other words, poorer should use more specialist services given their higher level of need. It appears from Figure 8.2 that income gradient in specialist use becomes even stronger after adjusting for health need. Quintile and decile distributions are useful to examine income gradient in healthcare utilisation, but a more refined picture can be presented by the CC. Because the CC considers the entire distribution of the individuals rather than just income groups.

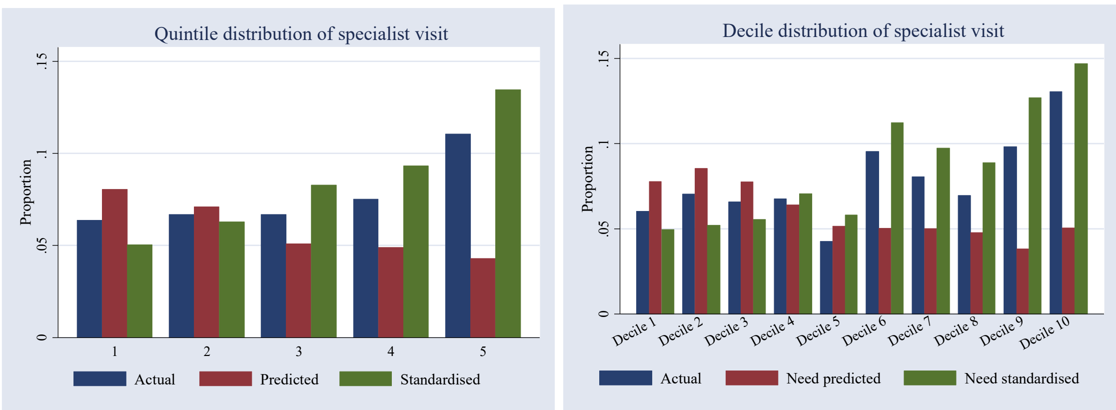


Figure 8.2: Distribution of specialist visit by quintiles and deciles of income

The CC of unadjusted utilisation shows the degree of inequality while the CC of need-standardised utilisation shows the degree of inequity. Figure 8.3 depicts that the CC of actual visit is below the line of equality in the lower and upper part of the distribution, but it is tangent to the line of equality in the middle of the distribution. The CC of need-predicted visit is well above the 45-degree line suggesting a pro-poor distribution of need-predicted use of specialist service. However, a pro-rich distribution of need-standardised specialist visit is observed, as the CC of need-standardised specialist visit is well below the line of equality. For example, the poorest 40% of Indigenous Australians utilised only

[59] Inequality estimates of other three indicators are presented in Table A8.1 of Appendix 8.

about 22% of specialist services, given the same level of need for this service as the richest.

The CI (inequality) and HI (inequity) indices are plotted with 95% confidence interval in Figure 8.4. The estimates of income-related inequality indices are positive but none of them are statistically significant at 5% level as shown in Panel (a) of Figure 8.4. Insignificant inequality indices thus suggest that there was no income-related inequality in specialist visit within Indigenous Australians. However, all the HI indices presented in Panel (b) of Figure 8.4 are positive as well as statistically significant. For example, the value of Erreygers's HI is 0.016 and significant at 1% level. This suggests that specialist visit was more concentrated among richer individuals although their level of need was similar to poorer people. Strictly speaking, inequity in medical specialist utilisation was pro-rich. This finding thus confirms that income-related HI in the probability of specialist utilisation favoured wealthier Indigenous Australians.

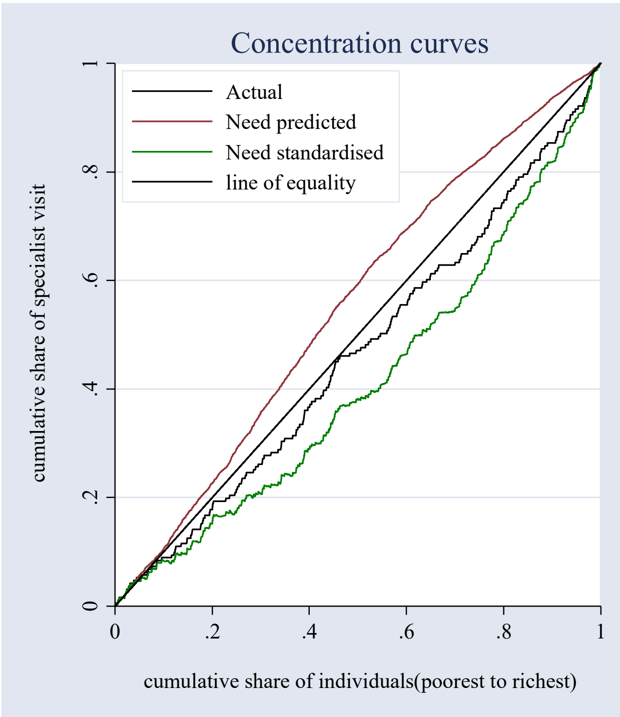
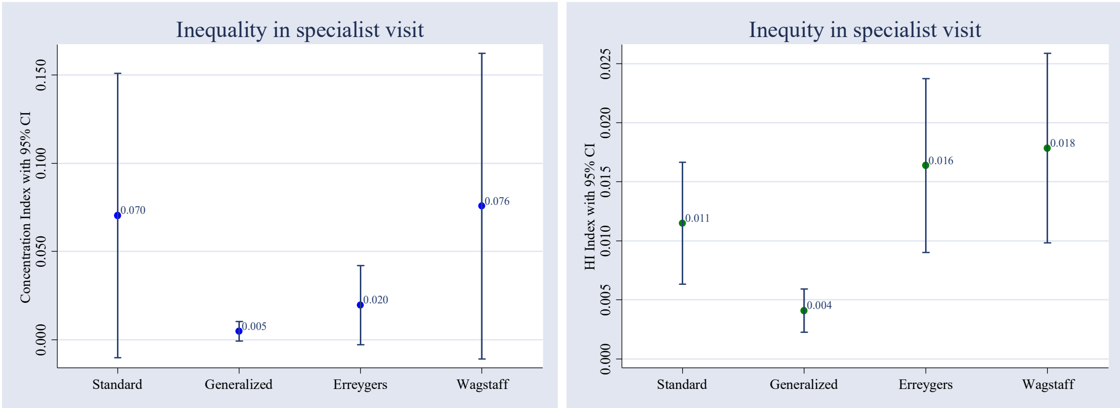


Figure 8.3: Concentration curves of specialist visit



Panel (a) Panel (b)

Figure 8.4: Income-related inequality and horizontal inequity in specialist visit

Decomposition results:

The results from the decomposition analysis of income-related inequality are presented in detail in Table 8.4 and summarised in Figure 8.6. Income-related inequality in specialist visit is decomposed into four components: (a) the contribution of income; (b) the contribution of the need variables; (c) the contribution of other non-need variables; and (d) a residual contribution. The contribution of a variable is measured as the product of the marginal effect of specialist visit and the CI of that variable[60]. Figure 8.6 reveals that the aggregate contribution of need-related variables is negative because need is more concentrated among poorer individuals and increases the probability of visiting medical specialists. The role of need in income-related inequality is legitimate or fair as it would make inequality less pro-rich. In other words, need as the sole determinant of utilisation would make inequality pro-poor.

The contributions of non-need indicators are of more interest as they are considered as an illegitimate or unfair source of inequality in healthcare use. The non-need contributions together constitute horizontal inequity. It is evident from Table 8.4 and Figure 8.6 that income was the largest contributor towards pro-rich inequity in specialist visit, and the contribution was positive. This indicates that inequality in income and its positive association with specialist visits was responsible to make the HI more pro-rich. This was further aggravated by the influence of other non-need variables. For example, private

[60] Due to time-limited access to ABS DataLab, bootstrapping the entire decomposition procedure was not possible to estimate standard errors for the contributions.

health insurance and education positively contributed to pro-rich inequity in specialist use. The interpretation is that educated people belonged to higher income groups and PHI was also concentrated among richer people. Figure 8.6 however, shows that the contribution of concession card and employment status was negative. It should be noted from Table 8.4 that employment and concession card did not have a significant relationship with specialist use as shown by the marginal effects of these variables.

Table 8.4: Erreygers's decomposition for the probability specialist visit

	Marginal effect	Concentration index	Absolute contribution	% contribution
Inequality component: need contribution				
Female	-0.010	-0.055	0.001	0.065
Age: 18-24				
Age: 25-34	-0.002	-0.019	0.000	0.001
Age: 35-44	-0.013	0.088	-0.001	-0.051
Age: 45-54	-0.002	0.082	0.000	-0.007
Age: 55-65	-0.010	-0.047	0.000	0.011
Age 65 and above	-0.006	-0.148	0.000	0.015
SAH: Excellent				
SAH: Very good	-0.014	0.133	-0.002	-0.092
SAH: Good	0.007	0.010	0.000	0.005
SAH: Fair	0.017	-0.124	-0.002	-0.084
SAH: Poor	0.050**	-0.255	-0.005	-0.251
Kessler 5 score	0.002**	-0.059	-0.006	-0.293
Disability: No				
Disability: Moderate	0.044***	-0.053	-0.004	-0.196
Disability: Severe	0.095***	-0.191	-0.007	-0.336
Diabetes	0.024**	-0.096	-0.002	-0.100
Inequity component: non-need contribution				
Household Income: Decile 1				
Decile 2	0.008	-0.341	-0.002	-0.078
Decile 3	0.007	-0.069	0.000	-0.014
Decile 4	0.023	0.187	0.002	0.110
Decile 5	0.003	0.396	0.000	0.018
Decile 6	0.058***	0.554	0.009	0.477
Decile 7	0.045*	0.690	0.008	0.399
Decile 8	0.031	0.811	0.006	0.297
Decile 9	0.060**	0.909	0.009	0.452
Decile 10	0.065**	0.975	0.006	0.326
Private health insurance	0.046***	0.464	0.017	0.887
Concession card	0.014	-0.291	-0.010	-0.491
Education: Year 12 or above				
Education: Year 9-11	-0.024**	-0.039	0.002	0.111
Education: Year 8 or below	-0.039**	-0.264	0.006	0.299
Education: Never attended	-0.078	-0.374	0.001	0.046
Employment: Employed				
Employment: Unemployed	0.017	-0.336	-0.002	-0.123
Employment: Out of labour force	0.012	-0.330	-0.007	-0.370
Unexplained inequality: residual		0.001	0.003	-0.031

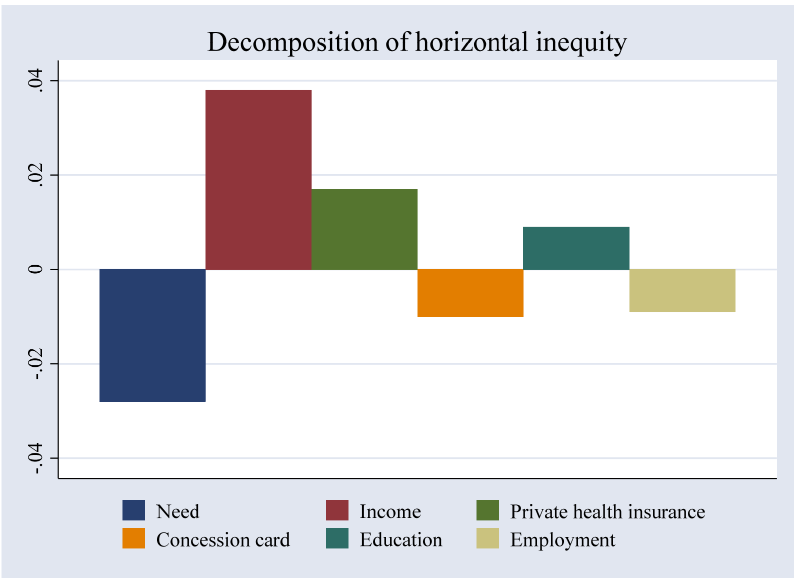


Figure 8.5: Summary of the decomposition results for specialist visits

8.5 Discussion

This study has used unique survey data to examine whether there is horizontal inequity in healthcare use among the Indigenous population living in non-remote areas of Australia. In other words, this paper addresses the question of whether better-off Indigenous people use greater healthcare services despite having similar need as worse-off. The findings reveal that socioeconomic status was not strongly associated with healthcare utilisation except for the probability of specialist visits. This result follows the conclusion of Whelan and Wright (2013) who also found that education and income were not the significant predictors of health service use by the Indigenous Australians. The analysis from this study provides evidence of no income-related inequality and inequity in the utilisation of GP services and inpatient hospital services within this community.

This study finds that income-related inequality in specialist visit was pro-rich but insignificant. However, there was a pro-rich horizontal inequity in specialist visit among this community. Therefore, the study results highlight that for the similar level of need, wealthier Indigenous Australians were higher users of specialist services compared to their poorer counterparts. This evidence is generally in line with the pro-poor or equitable use of GP and inpatient care services among the general population of Australia (Hajizadeh et al., 2012; van Doorslaer et al., 2008). These findings also follow similar evidence in most developed European countries and Canada (Allin, 2008; Devaux, 2015; Jiménez-Rubio et al., 2008; van Doorslaer et al., 2004b).

In Australia, out-of-hospital services (both primary and specialist care) are mostly rendered by private providers on a fee-for-service basis. However, about 85% of GP visits do not incur any out-of-pocket costs (Department of Health, 2017a). Access to inpatient hospital services in a public hospital as a public patient is also free. Therefore, the fact there is almost no financial burden to use these services could be the reason behind almost no inequity. On the other hand, utilisation of specialist services could incur substantial costs from the patients' pocket in the Australian setting (Freed & Allen 2017). For instance, co-payment was required for about 34% of Indigenous people to visit a medical specialist in non-remote areas in 2012-13 (AHMAC, 2017). Therefore, horizontal inequity in specialist services favouring richer Indigenous individuals might be the result of this financial barrier. However, understanding the link between excessive OOP and pro-rich bias in the distribution of specialist services is beyond the scope of this study and it thus requires further investigation.

The decomposition analysis of this study highlights that private insurance status plays a significant role, after equivalised household income, in increasing the extent of pro-rich HI in specialist visit within the Indigenous community of Australia. This result is largely consistent with the general findings for specialist visit in Australia, for cancer screening in Ireland and for both GP and specialist care in Ontario, Canada (Allin & Hurley 2009; van Doorslaer et al. 2008; Walsh et al. 2012). Another plausible explanation is that low income Indigenous individuals have greater cultural barriers to access specialist services. However, examining the validity of this explanation is also beyond the scope of this study.

This study is subject to several limitations. The first caveat is that results found in this paper only examine the association between income and healthcare use. Any conclusion about causality cannot be drawn from the findings because of the cross-sectional study design of this paper. The availability of longitudinal data would perhaps resolve this limitation and a life-course perspective would further strengthen the conclusion from this kind of study. Another usual limitation is the subject measurement of healthcare use and health status in this study. This limitation is mostly inevitable without linked survey and administrative data.

Previous studies demonstrated lack of or weak relationship between health status and typical measure of income for Australian Indigenous people (Cunningham 2010; Cunningham & Paradies 2012). This type of weak relationship is also found for the utilisation of healthcare services (Whelan & Wright 2013). It was observed by Taylor et al. (2004) that measurement error in income may undermine the identification of a systematic association between income and healthcare use among the indigenous Australians. Therefore, traditional definitions of income for the Indigenous population could possibly mask this relationship, and further research could explore the possibility of using different measures of socioeconomic status. Finally, the study has applied a conventional measure of horizontal inequity which might not be appropriate for analysing inequity for a vulnerable population group such as the Indigenous community.

8.6 Conclusion

There is no doubt that the health status of Indigenous Australians is far worse than other Australians. This study presents the very first analysis of horizontal inequity in health service use among the Indigenous Australians. Overall, this study has not found any evidence of inequity in the likelihood of inpatient admission and GP service utilisation. On the other hand, this study has found pro-rich inequity in specialist services that is inequity was favourable to better-off Indigenous people despite their same level of need as the poor.

Chapter 9: Conclusion

9.1 Introduction

Equity, efficiency, and effectiveness are the three vital features of a well performing health system. Equity is one of the most important dimensions of health system performance assessment; it goes beyond equality as it is concerned with fairness and justice in the health system. Therefore, achieving equity is a central policy goal of many healthcare systems of OECD countries including Australia.

Medicare is the universal health insurance system of Australia, Under Medicare Australians are entitled to get free treatment in public hospitals as public patients. Private medical professionals render primary and specialist care in an unregulated fee market where there is no cap on the charges. However, patients get a fixed subsidy from Medicare to the payment for out-of-hospital services charges. There is no gap payment for the patients when the service fee equals Medicare subsidy. About 85% of the GP services does not incur any OOP cost but the patient faces a significant amount of OOP cost for specialist services. About half of the Australians buy private health insurance which is used to cover the gap payment for treatment in a public hospital as a private patient[61]. The cost of other services such as dental care is privately financed through the combination of private health insurance and personal payment. Patients cannot use private insurance to cover co-payment for the out-of-hospital services under Medicare coverage.

Australians are proud of Medicare and they rely on it. In 1984, Medicare was established with objective of providing universal and equitable access to healthcare services. Medicare's objective access and utilisation of needed healthcare services should not be determined by the financial ability of individuals. However, it has been recently argued that efficiency triumphs over the equity goal of Medicare in the face of increasing healthcare expenditure. There is also more emphasis on the privatisation of healthcare provision and financing. Therefore, a performance assessment of the system through an equity lens could answer some critical questions about the fairness of Medicare. Horizontal equity defined as 'equal use of healthcare services for equal need regardless

[61] Medicare covers 75 % of treatment cost in public hospitals if the patients decide to be admitted as private patient.

of socioeconomic status' is adopted as a yardstick in this thesis to comprehensively examine inequity in healthcare service utilisation. This thesis has developed through four empirical chapters to achieve this general goal.

The next section of this concluding chapter summarises the key findings of this thesis. Section three discusses some important policy implications following the empirical findings in chapter 5 to 8. The contributions of this thesis to the current literature is highlighted in section four. Section five discusses the limitations of this thesis. This follows a general discussion on potential areas and scope for future research in section six. Finally, a general conclusion is drawn in the last section.

9.2 Thesis summary and major findings

This thesis has developed in two distinct ways. The first part (chapter 2 to 3) reviews the theoretical, methodological, and empirical literature in this area of research. The second part (chapter 5 to 8) of the thesis consists of four empirical studies to present updated as well as new evidence on inequity in the utilisation healthcare services in Australia.

Chapter 2 of this thesis has reviewed the fundamental concepts surrounding equity in health and healthcare. The chapter has emphasised that understanding of these concepts is of utmost important for empirical analysis of equity in the health sector. One of the most important lessons of this chapter is that there is complexity in defining and measuring equity in healthcare. Definition and measurement hinge on diverse philosophical, ideological, and theoretical standpoints. Utilisation of healthcare services as a measure of access is also subject to debate. Despite these theoretical debates, empirical evidence on inequity in healthcare system is important for policymakers to make decisions about achieving equity.

Chapter 3 has presented an overview of the method to examine, quantify and explain horizontal inequity in healthcare utilisation. This chapter has also discussed the methodological debates and developments towards better measurement of inequity in healthcare use which was particularly relevant for the empirical analysis in this thesis. The chapter has argued this method is currently the best among the available methods to achieve the empirical objectives of this thesis.

Chapter 4 has presented a summary of international and Australian evidence on the extent of horizontal inequity in healthcare services utilisation. The discussion in this chapter has highlighted that extended empirical investigations are necessary to present new evidence on equity performance of the Australian healthcare system. This includes understating of regional variation, application of administrative data and examination of within-group inequity among Indigenous Australians.

Chapter 5 has revisited and updated earlier empirical evidence on horizontal inequity of healthcare use in Australia, drawing on data from two most recent Australian National Health Surveys of 2011-12 and 2014-15. This chapter has measured the level of income-related horizontal inequity (HI) in overall use, medical professional use and use in hospital-related services. It has also analysed the regional variations in the HI of healthcare utilisation by quantifying state/territory-level inequity. Although the extent of HI was small, inequity in the probability of GP visits is found to be pro-rich in the study period. This result is observed for the first time, as previous studies from Australia always found significant pro-poor HI in GP service utilisation. Inequity in the probability of specialist and dentist visits has remained in favour of richer people as shown in earlier empirical studies from Australia as well as other OECD countries. The chapter has found that the utilisation of hospital-related care was almost equitable. The findings also reveal that overall utilisation measured by any visit or hospital admission was pro-rich, but the extent was small. It could be argued that pro-rich inequity in specialist and dental visits has contributed to this finding. There was limited evidence of state/territory variation in inequity which is mainly observed for specialist and dentist visits. Finally, this chapter has found no significant change in the extent of income-related HI between 2011-12 and 2014-15.

Chapter 6 has further examined horizontal inequity in doctor utilisation in Australia following the conclusion of Chapter 5. Inequity in GP and medical specialist services utilisation has been analysed for three measures of utilisation: the probability of visit, the intensity of visits and conditional number of visits using data from the NHS of 2014-15. In particular, inequity has been measured by making a distinction between the probability of visit and conditional visits to, understand whether the observed inequity is patient-initiated or physician-driven. This chapter has also applied the bootstrapped decomposition technique to explain the driving factors of income-related HI. The results show little evidence of pro-rich inequity in the probability of a GP visit, but significant pro-poor distribution in conditional visits to GP. This is because of the significant contribution of concession card in the pro-poor direction as shown by the decomposition exercise. On the contrary, considerable inequity is found in the probability of visiting a specialist favouring richer people after equalising health need between poor and rich. The distribution of conditional visit for specialist was almost equitable but it appeared to be pro-rich when higher users are excluded from the study population. The decomposition analysis reveals that richer and better educated individuals appear to be more likely to visit a specialist than poorer and less- educated people, and inequality in income and education can explain a large part of that pro-rich inequity. Unequal distribution of private health insurance coverage, which is mostly held by richer people, also explained the pro-rich inequity in specialist visit. Area socioeconomic status has also partly explained the pro-rich distribution of specialist visit.

Chapter 7 has used Medicare data to examine area-level inequality in specialist care in Australia. For addressing the problem of subjective measurement of specialist care utilisation in the survey data, this chapter has exploited more objective measures from Medicare data for the entire Australian population. However, this chapter has not adjusted the need for specialist services as no information was available in the data. Therefore, this chapter measures inequality rather than inequity. Moreover, area-level SES is used as the ranking variable in the measurement of inequality instead of individual SES due to data limitations. The key feature of this study is that it has investigated inequality in specialist care by differentiating specialist attendances between non-bulk-billed and bulk-billed items. The general conclusion is that inequality in specialist services was biased to those individuals living in socioeconomically more advantaged areas. Most importantly, this inequality was higher in specialist visits associated with out-of-pocket costs, while there was almost no inequality in bulk-billed services. The study results also indicate variation in inequality of specialist services among the Australian states/territories.

Chapter 8 of this thesis has examined whether the extent and the pattern of income-related horizontal inequity in use of health services within Indigenous Australians follows similar conclusions found in the earlier chapters. Largely speaking, this chapter finds that socioeconomic status was not strongly associated with healthcare utilisation except for specialist services. There was evidence of no income-related inequality and inequity in the utilisation of GP services and inpatient admission within the Indigenous community. However, this study highlights that richer Indigenous Australians were higher users of specialist services than their poorer counterparts despite having similar needs for specialist care. In other words, horizontal inequity was pro-rich in the probability of a specialist visit as found for the general population. Again, income inequality and unequal distribution of private health insurance as well education were the key drivers of pro-rich inequity in specialist visit.

9.3 Policy implications

This section discusses the important policy implications of the conclusions drawn in the empirical chapters of this thesis. The empirical evidence presented in this thesis suggests that the performance of the Australian healthcare system in providing healthcare services is comparable to most health systems of OECD countries. However, income-related horizontal inequity in some areas of the healthcare sector deserves policy attention. For example, a small but pro-rich inequity in the probability of GP contact found in this thesis implies that high and increasing bulk-billing rates for GP services often considered as an indicator of equitable access to primary care services could be misleading. It is true that the bulk-billing rate for GP services has been continuously rising in recent years in Australia(Department of Health, 2017a). However, the limitation of quoting GP bulk-billing rates as an equity indicator of GP services rests on the way it is reported to the public- it is calculated at service level but not at patient level. Very high and frequent GP users could account for the major share of bulk-billing GP services leaving other people to face co-payment to access primary care (Ackermann, 2016). The analysis in Chapter 6 also indicates that inequity becomes less pro-poor once higher users of healthcare services are excluded from the analysis. These points together suggest that other indicators of equity such as the horizontal inequity index could be considered for reporting and monitoring equity in primary care in Australia.

Pro-rich inequity in specialist services indicates a need for initiating policy discussion for potential reform in Medicare safety net arrangements. In Australia, patients face significant out-of-pocket cost (OOP) to access specialist care services, and OOP cost could act as one of the major barriers to access these services for low income people (Johar et al., 2017). Previous studies have suggested that distribution of OOP in Australia is pro-rich indicating affluent people share a greater proportion of financial cost than poorer and socioeconomically disadvantaged people (Hua et al., 2017). However, we should bear in mind that poorer households spend a larger share of their income to cover the medical care cost (Duckett et al., 2014).

Since richer people use more specialist services, it is reasonable to assume that they could reach the Medicate safety net threshold and be eligible to receive higher rebates on OOP cost more easily than the poor. Although the equity impact of higher fees could not be fully captured in this thesis, the findings of Chapter 7 show an almost equitable distribution of bulk-billed specialist visits. Therefore, designing incentives for specialists to charge reasonable fees could have a positive impact on equity in the specialist sector. Any policy change leading to higher fees for specialist services could be inequity-promoting. Policy reform must ensure that financially vulnerable people are not left behind in Medicare.

Inequality in private health insurance by income is an important policy concern in Australia. Since private health insurance cannot be used for gap payment of out-of-hospital services subsidised by Medicare, it is critical from a policy point of view to understand the reason for higher utilisation of specialist services among private health insurance subscribers. Therefore, this thesis argues that policies encouraging higher private funding of healthcare services would undermine the equity principle of Medicare.

Dental care is a classic example of a privately provided and funded healthcare service in which there is always a large extent of inequity in favour of richer people. Although dental problems may not be life threating, they could have an impact on overall quality of life (Benyamini et al., 2004). Expensive treatment costs and lack of public funding deter poorer households from accessing dental care. More reliance on co-payment and OOP cost would be detrimental for achieving equity in healthcare. Evidence from European countries shows that inequity in dental care utilisation is generally lower in countries with some level of public funding of dental care compared to countries with no public financing (Palència et al., 2014). Therefore, expansion of Medicare to cover medically necessary dental care for socioeconomically disadvantaged households could be considered in policy discussions.

The most important policy perspective of this thesis is that equity should be taken seriously in the policy discussion. This thesis has shown that inequity in primary care and hospital-related care is no longer pro-poor in Australia which contrasts with the favourability to the lower-income people groups until 2005. Although it was not the objective of empirical analyses of this thesis to determine what polices have driven this change in the equity scenario, this clearly indicates a requirement for policymakers to become aware of the equity impact of policy reforms. Overall, the principles of universal and publicly-funded health care systems should be sustained and protected, not weakened.

Finally, this thesis suggests the need for developing robust indicators of equity in healthcare and reporting routinely to generate policy discussions among researchers and policy makers towards improving the fairness of Medicare. Development of an equity dashboard by National Health Services (NHS) in the UK is an excellent example for other countries including Australia which have well-structured administrative data sources of healthcare access (Cookson et al., 2018). Empirical application of Medicare data in chapter seven of this thesis has shown an example to regularly report equity indicators of healthcare use in Australia.

9.4 Thesis contributions

This thesis has primarily threefold contributions to make to the Australian literature studying equity in healthcare. Firstly, income-related horizontal inequity in doctor visits is examined by considering three measures of GP and specialist utilisation. In this way, total inequity is measured by separating the probability of any visit and visits conditional on a first visit. This is important from an Australian perspective where OOP cost may hinder the initial contact with the health system. The examination of (regional) variation in inequality and inequity across the states and territories of Australia is another important contribution to the literature. It has enabled us to know how regions performs to achieve equity in healthcare utilisation. Another contribution is that this thesis has applied bootstrapped technique to obtain statistical inferences about the contributing factors to explain the sources of horizontal inequity. The extended review on the measurement issues arising from recent debates in the literature will be useful for methodological developments in future studies of socioeconomic-related of horizontal inequity in healthcare.

Secondly, this thesis for the first time, has examined horizontal inequity in the utilisation of healthcare services within the Indigenous community of Australia. This specific study has highlighted that conventional measures of socioeconomic status of the Indigenous community may be a challenge to study inequity in healthcare utilisation. The analysis from this chapter suggests that there is critical need for developing a theoretical and methodological framework to understand inequity within vulnerable and marginalised populations.

Last but not the least, this thesis has documented that national Medicare data could be utilised for monitoring inequality in healthcare with an application of the concentration index approach. However, there is always room for improvement to develop methods for reporting and monitoring equity using administrative data. Use of Medicare data allows us to examine inequality in specialist services by making a distinction between services bulk-billed and non-bulk-billed which is usually not possible using survey data. In this way, this thesis has contributed to the current discussion of how 'big data' for example Medicare data, could be better utilised for research and policy purposes.

9.5 Thesis limitations

This thesis acknowledges several limitations. The first limitation is that measuring and explaining horizontal inequity is important for performance analysis and policy perspectives, but it gives us only a partial understanding of the extent of income-related inequity. A full picture on inequity might be revealed by integrating the vertical inequity dimension because of heterogeneity in the need for healthcare services between rich and poor (Vallejo-Torres et al., 2014). Secondly, the empirical method of this thesis relies on equalising need for medical care across the income distribution. The way it standardises need for healthcare is debated in the literature (Bago D'Uva et al., 2011; van de Poel et al., 2012). This is mainly because of need for healthcare is an elusive concept. Need measured by self-reported health indicators is a subjective assessment and it varies across population subgroups (Baron-Epel et al., 2005; Simon et al., 2000).

Thirdly, this thesis suffers from the problem of measurement error in self-reported data for income, healthcare use and health status which is a general limitation of this type of research. Indicators of healthcare use in this thesis are the general measures which might mask inequity in more specific healthcare services, for example inequity in cancer treatment, elective surgeries etc. Another limitation of this thesis is that the role of supply side factors in modelling healthcare utilisation, as well as in the decomposition analysis could not be captured due to unavailability of information in the NHS and Medicare datasets. The restricted analysis on non-remote Indigenous people in Chapter 8 might result in a partial picture of horizontal inequity within this community. Finally, lack of causal interpretation of the decomposition results might not be entirely conclusive for policy implications of this thesis.

9.6 Avenues for future research

This thesis has identified several future research areas following the empirical studies and findings. First, a life-course approach to measure and explain inequity in healthcare use would provide further insights about inequity in the Australian healthcare system. Empirical analyses of this thesis as well as earlier studies on income-related inequity in healthcare, rely on cross-sectional data. These studies present only a snap shot of inequity and ignore how inequity evolves over time. The *Household, Income and Labour Dynamics in Australia* (HILDA) is a potential source of panel data for dynamic analysis of income-related inequity in the Australian setting. The possible problem of endogeneity could be also addressed using the HILDA survey. Additionally, longitudinal analysis of socioeconomic-related horizontal inequity could help to better understand the impact of policy reforms on equity of healthcare use. Heterogeneity in the relationship between need and income could also be taken into account in panel data analysis.

There is need for rigorous inquiry into the socioeconomic-related inequity in dental care to lead to better policy suggestions from an Australian perspective. The problem of need-standardisation in the analysis of dental care could be potentially tackled in further research using data from ongoing National Study of Adult Oral Health, 2017-18. This would be useful and important in analysing how potential policy for the extension of public dental coverage, or in designing subsidy mechanisms for reduction in inequity of dental care.

Understanding inequity in healthcare use among various sub-populations as well as in other important aspects of healthcare utilisation, is an important avenue for future research. For example, inequity in the use of preventive care such as cancer screening is well studied in other OECD countries, but less evidence is available from Australia. Therefore, further studies could consider examining the pattern and extent of socioeconomic-related inequality in different types of cancer screening in Australia. Examination of inequity among the elderly population for critical healthcare services such as long-term care is another potential avenue for research These types of studies could be conducted using the 45 and Up Study which is linked with various administrative health records in the state of New South Wales. Future research could also consider studying inequity in unmet need for healthcare services which is largely overlooked in the literature (Allin et al., 2010). Another potential area of research would be to consider using Pharmaceutical Benefit Schedule data from Medicare to examine inequity in prescription drug access which has also received less attention in the current Australian literature.

The most important area of future research is to undertake methodological research for better utilisation of linked administrative data at the national level for reporting equity indicators. Linked hospital data with Medicare data would be extremely valuable for routine reporting of equity indicators of various measures of healthcare access and use. Furthermore, linking administrative health data with taxation file data could potentially solve ecological fallacy problems. This would also enable analysis of spatial variation in inequity of healthcare use at a more local level such as primary health networks. Future research should seriously consider this possible area of investigation. Adapting multilevel modelling analysis using administrative data is an opportunity to examine regional variations in equity of healthcare (Lumme et al., 2008). Finally, further studies could be undertaken to develop methodological tools, and to then apply them to examine the impact of policy interventions on inequity of healthcare utilisation.

Appendix: 5

Table A5.1: Summary statistics of the independent variables

	2011-12		2014-15	
	Mean	**Std. Err.**	**Mean**	**Std. Err.**
Female	0.50	0.00	0.51	0.01
Age: 18-24	0.10	0.00	0.09	0.00
Age: 25-34	0.19	0.00	0.20	0.00
Age: 35-44	0.19	0.00	0.19	0.00
Age: 45-54	0.18	0.00	0.18	0.00
Age: 55-64	0.15	0.00	0.15	0.00
Age: 65-75	0.10	0.00	0.11	0.00
Age 75+	0.08	0.00	0.08	0.00
SAH: Excellent	0.20	0.00	0.19	0.00
SAH: Very good	0.35	0.00	0.36	0.00
SAH: Good	0.30	0.00	0.30	0.00
SAH: Fair	0.11	0.00	0.11	0.00
SAH: Poor	0.04	0.00	0.05	0.00
Kessler 10 score	14.62	0.05	14.96	0.06
No. of long-term conditions	3.35	0.03	3.67	0.03
No disability	0.64	0.00	0.63	0.01
Some disability	0.14	0.00	0.15	0.00
Moderate disability	0.18	0.00	0.18	0.00
Severe disability	0.04	0.00	0.05	0.00
Diabetes	0.11	0.00	0.12	0.00
Australia born	0.70	0.00	0.69	0.00
English at home	0.89	0.00	0.88	0.00
Private health insurance	0.57	0.00	0.57	0.01
Concession card	0.31	0.00	0.32	0.00
Education: 8 years or less	0.08	0.00	0.07	0.00
Education: Year 9-11	0.40	0.00	0.37	0.01
Education: Year 12 or more	0.53	0.00	0.56	0.01
Employee	0.59	0.00	0.54	0.01
Self-employed	0.08	0.00	0.11	0.00
Unemployed	0.03	0.00	0.03	0.00
Out of labour force	0.31	0.00	0.31	0.00
Major cities	0.70	0.00	0.70	0.00
Inner regional	0.19	0.00	0.19	0.00
Other	0.11	0.00	0.11	0.00
NSW	0.34	0.00	0.34	0.00
VIC	0.23	0.00	0.23	0.00
QLD	0.20	0.00	0.20	0.00
SA	0.08	0.00	0.08	0.00
WA	0.10	0.00	0.11	0.00
TAS	0.03	0.00	0.03	0.00
NT	0.01	0.00	0.01	0.00
ACT	0.02	0.00	0.02	0.00
Household Income: Decile 1	0.08	0.00	0.09	0.00
Decile 2	0.08	0.00	0.08	0.00
Decile 3	0.09	0.00	0.09	0.00
Decile 4	0.09	0.00	0.10	0.00
Decile 5	0.11	0.00	0.10	0.00
Decile 6	0.10	0.00	0.10	0.00
Decile 7	0.12	0.00	0.11	0.00
Decile 8	0.11	0.00	0.11	0.00
Decile 9	0.11	0.00	0.11	0.00
Decile 10	0.10	0.00	0.11	0.00
Area SES: SEIFA 1	0.10	0.00	0.09	0.00
SEIFA 2	0.09	0.00	0.11	0.00
SEIFA 3	0.10	0.00	0.10	0.00
SEIFA 4	0.11	0.00	0.11	0.00
SEIFA 5	0.10	0.00	0.11	0.00
SEIFA 6	0.10	0.00	0.10	0.00
SEIFA 7	0.10	0.00	0.10	0.00
SEIFA 8	0.10	0.00	0.09	0.00
SEIFA 9	0.10	0.00	0.09	0.00
SEIFA 10	0.09	0.00	0.10	0.00
No. of observations	15,475		14,560	

Table A5.2: Summary statistics of any visit and out of hospital services by independent variables

	Any visit		GP visit		Specialist visit		Dentist visit	
	2011-12	2014-15	2011-12	2014-15	2011-12	2014-15	2011-12	2014-15
Male	0.89	0.90	0.81	0.82	0.32	0.35	0.42	0.43
Female	0.95	0.96	0.91	0.92	0.39	0.42	0.51	0.49
Age: 18-24	0.88	0.90	0.78	0.82	0.22	0.26	0.43	0.42
Age: 25-34	0.89	0.91	0.80	0.84	0.25	0.28	0.40	0.39
Age: 35-44	0.91	0.90	0.84	0.82	0.29	0.32	0.46	0.46
Age: 45-54	0.92	0.91	0.86	0.84	0.34	0.35	0.51	0.47
Age: 55-64	0.95	0.96	0.91	0.92	0.45	0.48	0.55	0.54
Age: 65-75	0.98	0.97	0.94	0.95	0.55	0.56	0.49	0.50
Age 75+	0.99	0.99	0.98	0.98	0.60	0.62	0.42	0.43
SAH: Excellent	0.89	0.89	0.78	0.80	0.25	0.27	0.50	0.53
SAH: Very good	0.92	0.92	0.85	0.86	0.30	0.33	0.49	0.48
SAH: Good	0.93	0.93	0.87	0.89	0.37	0.39	0.45	0.42
SAH: Fair	0.96	0.96	0.93	0.93	0.56	0.57	0.43	0.42
SAH: Poor	0.98	0.99	0.96	0.98	0.71	0.77	0.45	0.36
No disability	0.90	0.90	0.83	0.83	0.29	0.29	0.46	0.46
Some disability	0.95	0.95	0.91	0.91	0.42	0.42	0.49	0.49
Moderate	0.98	0.98	0.95	0.95	0.60	0.60	0.45	0.45
Severe	0.99	0.99	0.98	0.98	0.75	0.75	0.43	0.43
Australian born	0.93	0.93	0.88	0.88	0.40	0.40	0.47	0.47
Foreign born	0.91	0.91	0.85	0.85	0.35	0.35	0.44	0.44
English at home: Yes	0.93	0.93	0.88	0.88	0.40	0.40	0.47	0.47
English at home: No	0.88	0.88	0.81	0.81	0.29	0.29	0.36	0.36
Health insurance: Yes	0.94	0.95	0.87	0.89	0.40	0.42	0.58	0.57
Health insurance: No	0.90	0.90	0.84	0.85	0.30	0.33	0.31	0.31
Concession card: Yes	0.96	0.96	0.92	0.94	0.47	0.50	0.42	0.43
Concession card: No	0.91	0.91	0.83	0.84	0.31	0.33	0.49	0.47
Education: 8 years or less	0.96	0.96	0.94	0.95	0.49	0.49	0.38	0.37
Education: Year 9-11	0.92	0.92	0.87	0.88	0.37	0.42	0.42	0.42
Education: Year 12 or more	0.92	0.93	0.84	0.86	0.33	0.35	0.52	0.50
Employee	0.91	0.92	0.84	0.85	0.30	0.31	0.48	0.47
Self-employed	0.90	0.90	0.81	0.80	0.31	0.38	0.47	0.50
Unemployed	0.90	0.88	0.80	0.83	0.26	0.36	0.38	0.35
Out of labour force	0.96	0.96	0.92	0.93	0.48	0.50	0.45	0.45
NSW	0.93	0.93	0.86	0.87	0.36	0.39	0.48	0.45
VIC	0.92	0.92	0.86	0.87	0.36	0.40	0.45	0.46
QLD	0.93	0.93	0.86	0.86	0.35	0.36	0.47	0.46
SA	0.91	0.94	0.86	0.89	0.37	0.40	0.48	0.48
WA	0.92	0.92	0.84	0.84	0.35	0.35	0.48	0.47
TAS	0.92	0.94	0.86	0.88	0.35	0.38	0.40	0.41
NT	0.90	0.90	0.83	0.81	0.30	0.32	0.40	0.42
ACT	0.93	0.94	0.86	0.87	0.35	0.37	0.55	0.53
Major cities	0.92	0.93	0.86	0.87	0.36	0.38	0.49	0.48
Inner regional	0.93	0.92	0.86	0.85	0.35	0.38	0.43	0.40

Other	0.92	0.91	0.84	0.87	0.32	0.38	0.41	0.40
Decile 1	0.92	0.90	0.84	0.85	0.37	0.41	0.38	0.37
Decile 2	0.96	0.97	0.94	0.95	0.46	0.48	0.38	0.38
Decile 3	0.94	0.95	0.91	0.92	0.44	0.46	0.37	0.39
Decile 4	0.92	0.92	0.87	0.88	0.35	0.43	0.41	0.44
Decile 5	0.91	0.92	0.85	0.87	0.34	0.34	0.43	0.40
Decile 6	0.92	0.92	0.86	0.86	0.31	0.34	0.43	0.45
Decile 7	0.92	0.93	0.85	0.86	0.33	0.33	0.47	0.48
Decile 8	0.93	0.93	0.85	0.86	0.32	0.33	0.51	0.47
Decile 9	0.93	0.93	0.85	0.87	0.33	0.36	0.53	0.55
Decile 10	0.94	0.95	0.86	0.86	0.37	0.40	0.64	0.60
SEIFA 1	0.91	0.92	0.86	0.88	0.33	0.36	0.33	0.34
SEIFA 2	0.91	0.92	0.86	0.88	0.34	0.36	0.40	0.38
SEIFA 3	0.91	0.90	0.85	0.86	0.35	0.37	0.39	0.40
SEIFA 4	0.92	0.93	0.85	0.86	0.34	0.39	0.42	0.40
SEIFA 5	0.93	0.93	0.86	0.87	0.36	0.39	0.45	0.41
SEIFA 6	0.92	0.92	0.86	0.87	0.33	0.37	0.48	0.43
SEIFA 7	0.91	0.92	0.83	0.87	0.33	0.37	0.48	0.49
SEIFA 8	0.92	0.93	0.86	0.86	0.40	0.39	0.53	0.54
SEIFA 9	0.94	0.95	0.86	0.88	0.37	0.40	0.54	0.57
SEIFA 10	0.95	0.95	0.88	0.87	0.41	0.44	0.63	0.62

Table A5.3: Summary statistics of hospital -related care by independent variables

	Inpatient admission		Outpatient visit		Emergency visit		Day clinic visit	
	2011-12	2014-15	2011-12	2014-15	2011-12	2014-15	2011-12	2014-15
Male	0.12	0.12	0.09	0.07	0.11	0.12	0.07	0.06
Female	0.15	0.15	0.09	0.10	0.12	0.12	0.07	0.07
Age: 18-24	0.10	0.10	0.06	0.04	0.14	0.14	0.06	0.05
Age: 25-34	0.14	0.12	0.06	0.06	0.12	0.13	0.06	0.04
Age: 35-44	0.10	0.10	0.07	0.07	0.12	0.10	0.05	0.05
Age: 45-54	0.12	0.10	0.09	0.08	0.10	0.09	0.07	0.07
Age: 55-64	0.15	0.14	0.10	0.11	0.09	0.11	0.09	0.08
Age: 65-75	0.17	0.19	0.13	0.13	0.12	0.13	0.10	0.10
Age: 75+	0.23	0.25	0.15	0.15	0.15	0.17	0.11	0.09
Male	0.12	0.12	0.09	0.07	0.11	0.12	0.07	0.06
Female	0.15	0.15	0.09	0.10	0.12	0.12	0.07	0.07
SAH: Excellent	0.09	0.08	0.05	0.04	0.07	0.07	0.05	0.03
SAH: Very good	0.10	0.10	0.05	0.06	0.09	0.09	0.06	0.06
SAH: Good	0.15	0.13	0.09	0.08	0.13	0.13	0.08	0.07
SAH: Fair	0.22	0.22	0.16	0.16	0.20	0.18	0.11	0.10
SAH: Poor	0.35	0.39	0.30	0.28	0.28	0.32	0.16	0.13
No disability	0.09	0.09	0.05	0.05	0.08	0.08	0.04	0.04
Some disability	0.13	0.13	0.10	0.10	0.14	0.14	0.08	0.08
Moderate	0.23	0.23	0.16	0.16	0.18	0.18	0.12	0.12
Severe	0.32	0.32	0.25	0.25	0.30	0.30	0.13	0.13
Australian born	0.14	0.14	0.09	0.09	0.13	0.13	0.07	0.07
Foreign born	0.12	0.12	0.08	0.08	0.09	0.09	0.05	0.05
English at home: Yes	0.14	0.14	0.09	0.09	0.12	0.12	0.07	0.07
English at home: No	0.10	0.10	0.05	0.05	0.08	0.08	0.04	0.04
Health insurance: Yes	0.13	0.13	0.07	0.07	0.10	0.10	0.07	0.07
Health insurance: No	0.14	0.13	0.11	0.10	0.14	0.14	0.07	0.06
Concession card: Yes	0.19	0.20	0.14	0.14	0.16	0.16	0.09	0.09
Concession card: No	0.11	0.10	0.06	0.06	0.10	0.10	0.06	0.05
Education: 8 years or less	0.21	0.21	0.14	0.16	0.15	0.18	0.08	0.08
Education: Year 9-11	0.15	0.15	0.10	0.10	0.13	0.13	0.08	0.08
Education: Year 12 or	0.11	0.11	0.07	0.07	0.10	0.10	0.06	0.06
Employee	0.11	0.09	0.06	0.06	0.10	0.11	0.06	0.05
Self-employed	0.10	0.12	0.07	0.07	0.10	0.11	0.06	0.06
Unemployed	0.12	0.12	0.06	0.10	0.18	0.12	0.09	0.07
Out of labour force	0.20	0.20	0.14	0.13	0.14	0.14	0.09	0.09
NSW	0.13	0.13	0.06	0.06	0.10	0.11	0.06	0.06
VIC	0.13	0.13	0.09	0.08	0.12	0.12	0.07	0.07
QLD	0.14	0.14	0.10	0.12	0.13	0.12	0.08	0.07
SA	0.15	0.15	0.11	0.11	0.11	0.11	0.07	0.07
WA	0.15	0.12	0.09	0.08	0.11	0.12	0.07	0.06
TAS	0.14	0.16	0.11	0.10	0.13	0.15	0.05	0.07
NT	0.14	0.13	0.12	0.11	0.12	0.15	0.08	0.06
ACT	0.14	0.12	0.08	0.08	0.12	0.12	0.07	0.07

Major cities	0.13	0.13	0.08	0.08	0.11	0.10	0.07	0.06
Inner regional	0.16	0.14	0.09	0.09	0.13	0.16	0.08	0.07
Other	0.13	0.15	0.11	0.12	0.13	0.15	0.08	0.07
Decile 1	0.17	0.16	0.13	0.11	0.14	0.12	0.08	0.07
Decile 2	0.20	0.20	0.15	0.14	0.15	0.16	0.10	0.09
Decile 3	0.18	0.18	0.11	0.13	0.12	0.16	0.08	0.10
Decile 4	0.15	0.17	0.11	0.11	0.13	0.14	0.08	0.08
Decile 5	0.14	0.15	0.08	0.09	0.13	0.13	0.06	0.08
Decile 6	0.12	0.11	0.08	0.06	0.11	0.09	0.07	0.06
Decile 7	0.11	0.11	0.07	0.05	0.11	0.11	0.06	0.04
Decile 8	0.12	0.09	0.06	0.07	0.10	0.09	0.06	0.07
Decile 9	0.11	0.10	0.06	0.06	0.10	0.12	0.06	0.05
Decile 10	0.11	0.11	0.07	0.06	0.09	0.10	0.06	0.06
SEIFA 1	0.14	0.15	0.10	0.09	0.13	0.15	0.07	0.05
SEIFA 2	0.17	0.15	0.10	0.11	0.15	0.14	0.08	0.06
SEIFA 3	0.14	0.13	0.10	0.09	0.13	0.12	0.07	0.06
SEIFA 4	0.14	0.13	0.09	0.10	0.13	0.14	0.07	0.06
SEIFA 5	0.13	0.15	0.10	0.10	0.12	0.13	0.07	0.07
SEIFA 6	0.12	0.13	0.08	0.09	0.11	0.12	0.07	0.07
SEIFA 7	0.12	0.13	0.07	0.08	0.10	0.10	0.07	0.07
SEIFA 8	0.14	0.12	0.10	0.07	0.12	0.08	0.08	0.06
SEIFA 9	0.13	0.11	0.07	0.07	0.09	0.11	0.07	0.07
SEIFA 10	0.13	0.12	0.06	0.05	0.10	0.09	0.08	0.06

Table A5.4: Robustness of inequality estimates (EI) using different ranking variables

	2011-12				2014-15			
	Household income	Individual income		SEIFA	Household income	Individual income		SEIFA
	Continuous	Continuous	Deciles	Deciles	Continuous	Continuous	Deciles	Deciles
Any	0.0043	-0.0172**	-0.0187**	0.0240***	0.0049	-0.0198**	-0.0183**	0.0212***
	(0.0071)	(0.0075)	(0.0074)	(0.0076)	(0.0071)	(0.0077)	(0.0078)	(0.0074)
GP	-0.0271***	-0.0509***	-0.0499***	0.0157	-0.0380***	-0.0638***	-0.0615***	-0.0003
	(0.0094)	(0.0100)	(0.0099)	(0.0097)	(0.0094)	(0.0100)	(0.0100)	(0.0094)
Specialist	-0.0608***	-0.0983***	-0.0963***	0.0516***	-0.0693***	-0.0934***	-0.0930***	0.0476***
	(0.0127)	(0.0133)	(0.0131)	(0.0128)	(0.0136)	(0.0137)	(0.0136)	(0.0136)
Dentist	0.1767***	0.1026***	0.0965***	0.1781***	0.1599***	0.1060***	0.1038***	0.1801***
	(0.0128)	(0.0138)	(0.0137)	(0.0132)	(0.0136)	(0.0141)	(0.0140)	(0.0137)
Inpatient	-0.0605***	-0.0571***	-0.0572***	-0.0222**	-0.0692***	-0.0738***	-0.0718***	-0.0253***
	(0.0088)	(0.0092)	(0.0091)	(0.0089)	(0.0094)	(0.0095)	(0.0094)	(0.0095)
Outpatient	-0.0589***	-0.0575***	-0.0558***	-0.0315***	-0.0585***	-0.0509***	-0.0504***	-0.0263***
	(0.0073)	(0.0076)	(0.0075)	(0.0070)	(0.0075)	(0.0074)	(0.0073)	(0.0071)
Emergency	-0.0235***	-0.0232***	-0.0216***	-0.0000	-0.0198***	-0.0233***	-0.0231***	0.0051
	(0.0066)	(0.0067)	(0.0067)	(0.0065)	(0.0070)	(0.0070)	(0.0070)	(0.0066)
Day clinic	-0.0409***	-0.0422***	-0.0409***	-0.0344***	-0.0368***	-0.0312***	-0.0324***	-0.0555***
	(0.0082)	(0.0087)	(0.0087)	(0.0083)	(0.0091)	(0.0089)	(0.0089)	(0.0092)

Notes: Robust standard errors in parentheses and significance level *** p<0.01, ** p<0.05, * p<0.1

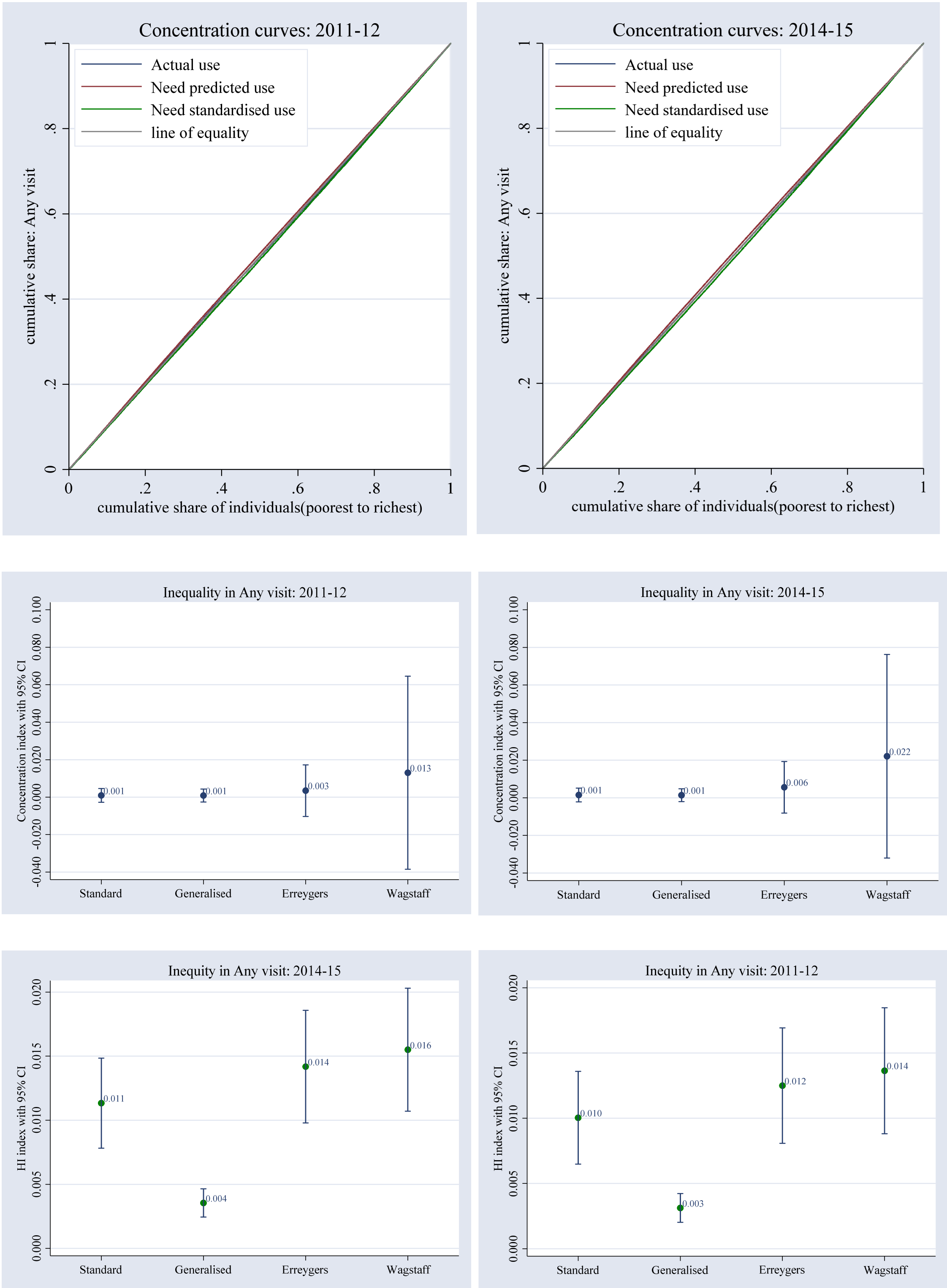


Figure A5.1: The concentration curves and inequality and inequity estimate for any visit

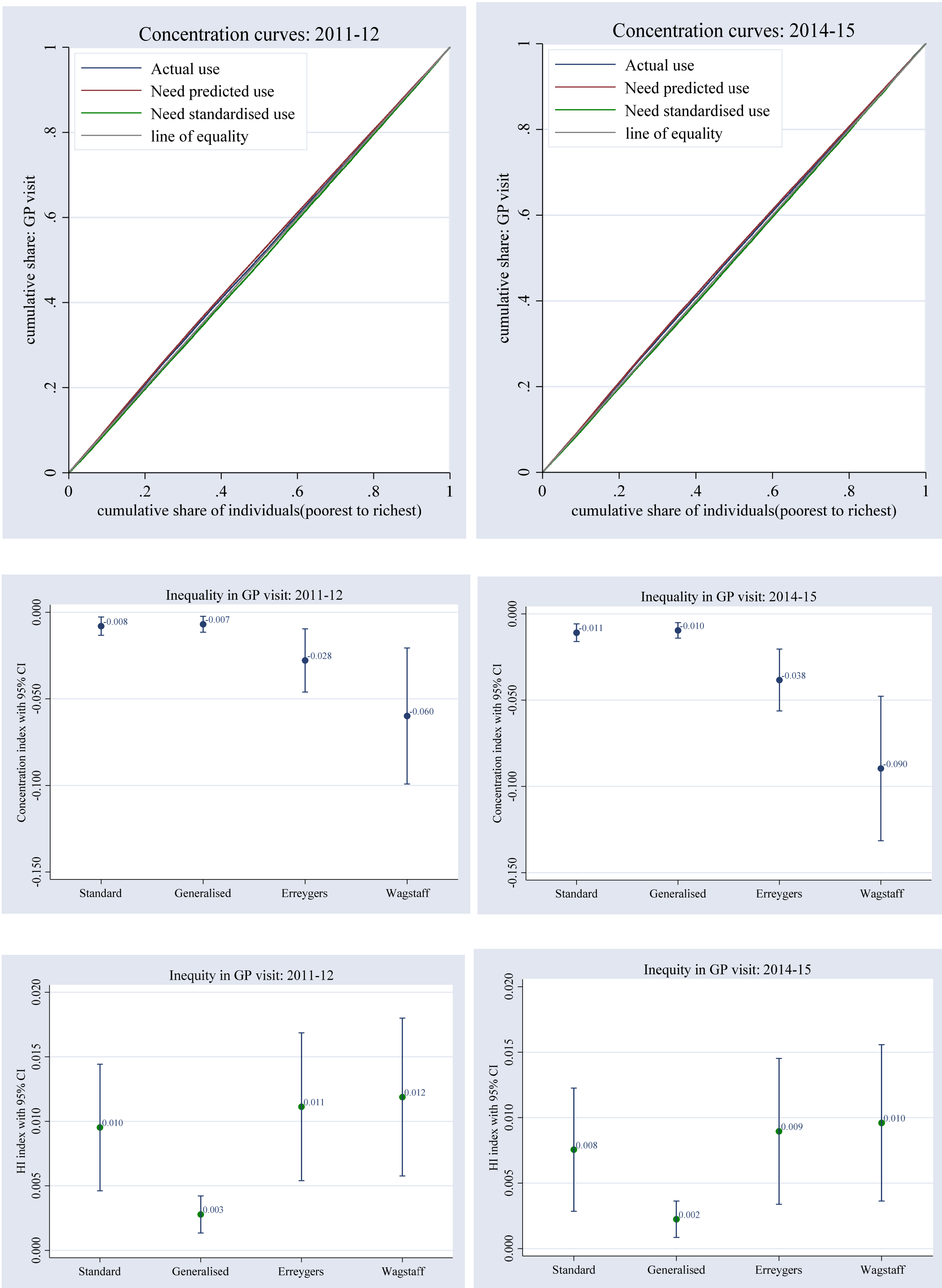


Figure A5.2: The concentration curves and inequality and inequity estimate for GP visit

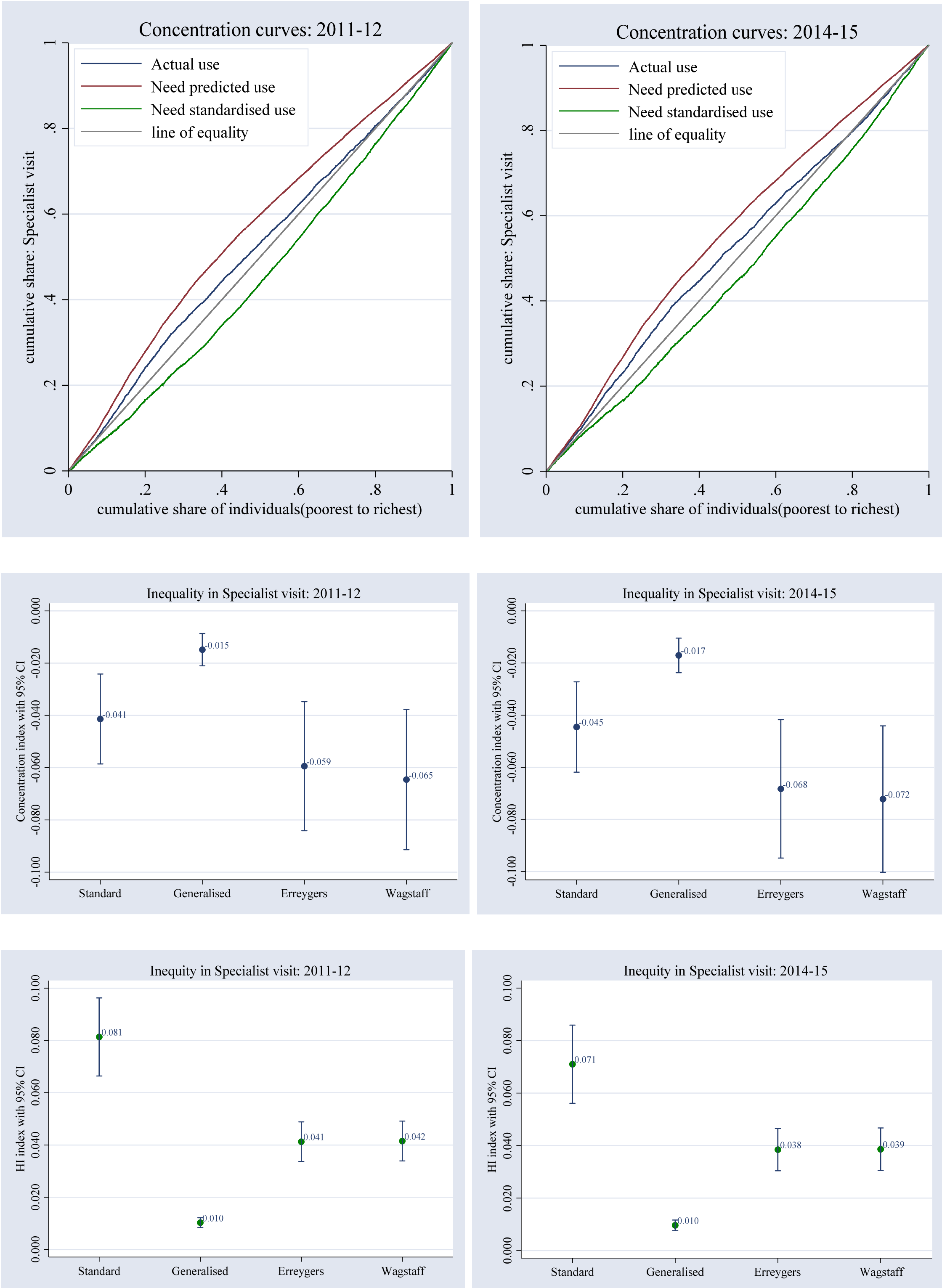


Figure A5.3: The concentration curves and inequality and inequity estimate for specialist visit

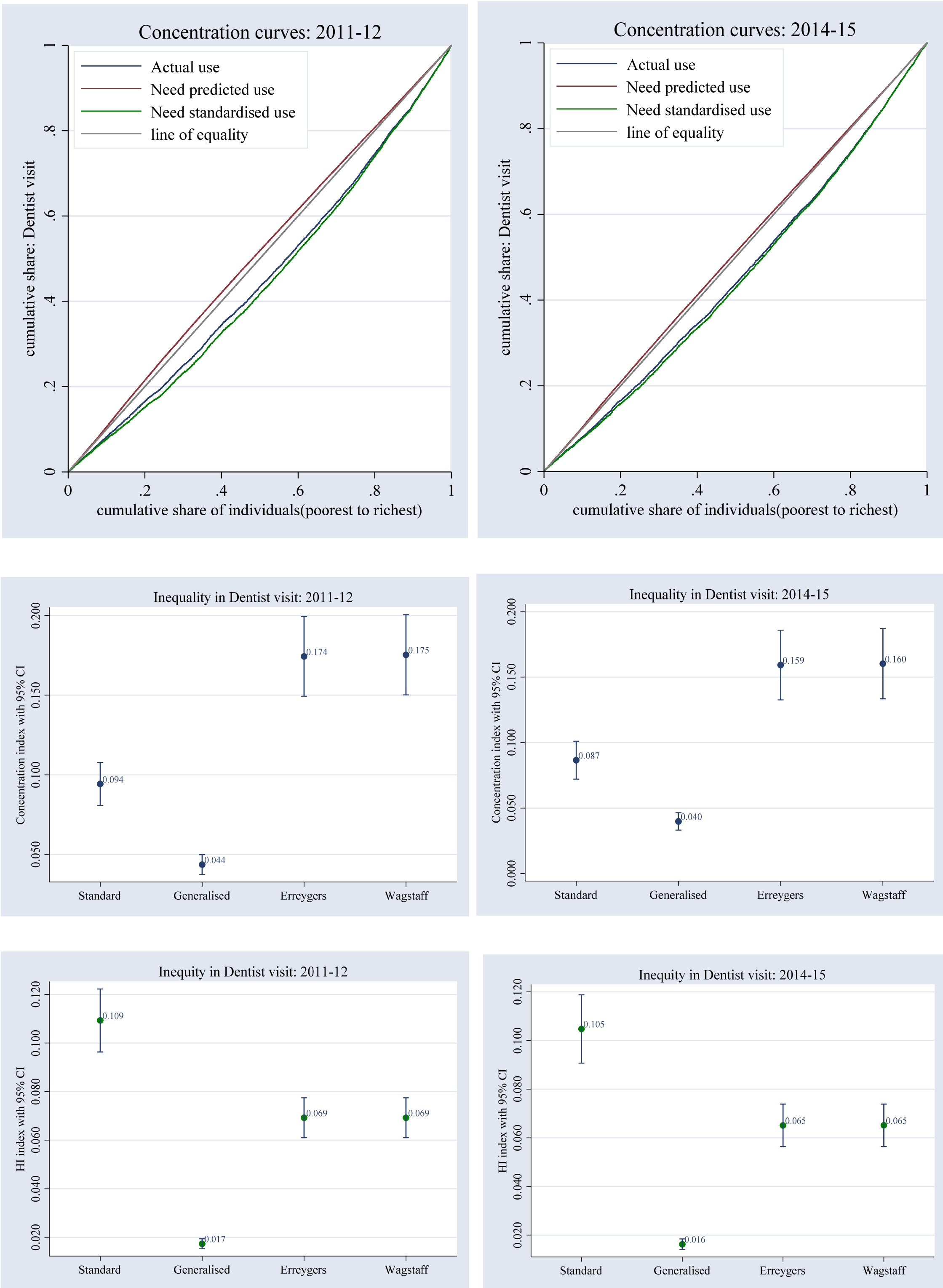


Figure A5.4: The concentration curves and inequality and inequity estimate for dentist visit

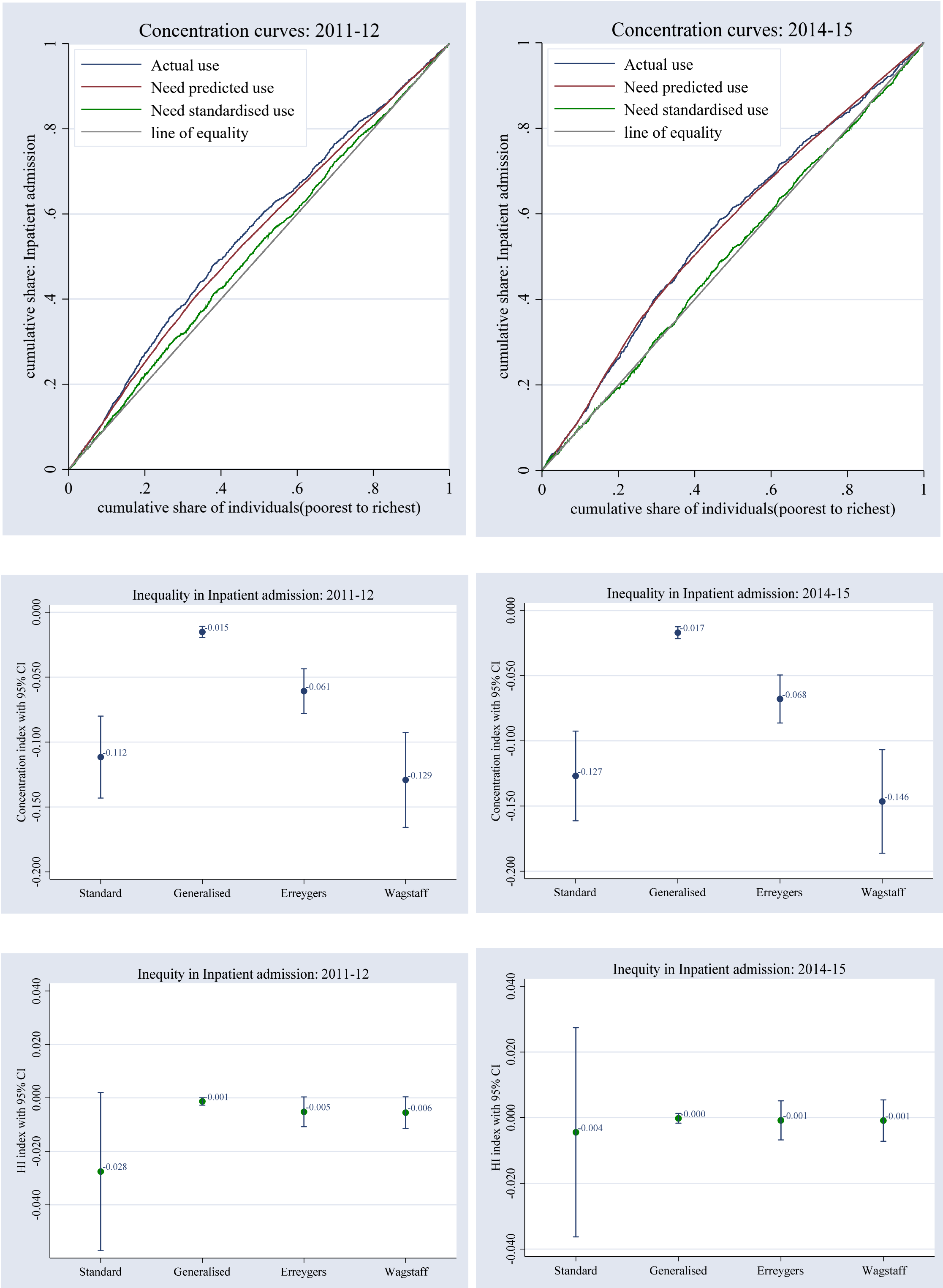


Figure A5.5: The concentration curves and inequality and inequity estimate for inpatient admission

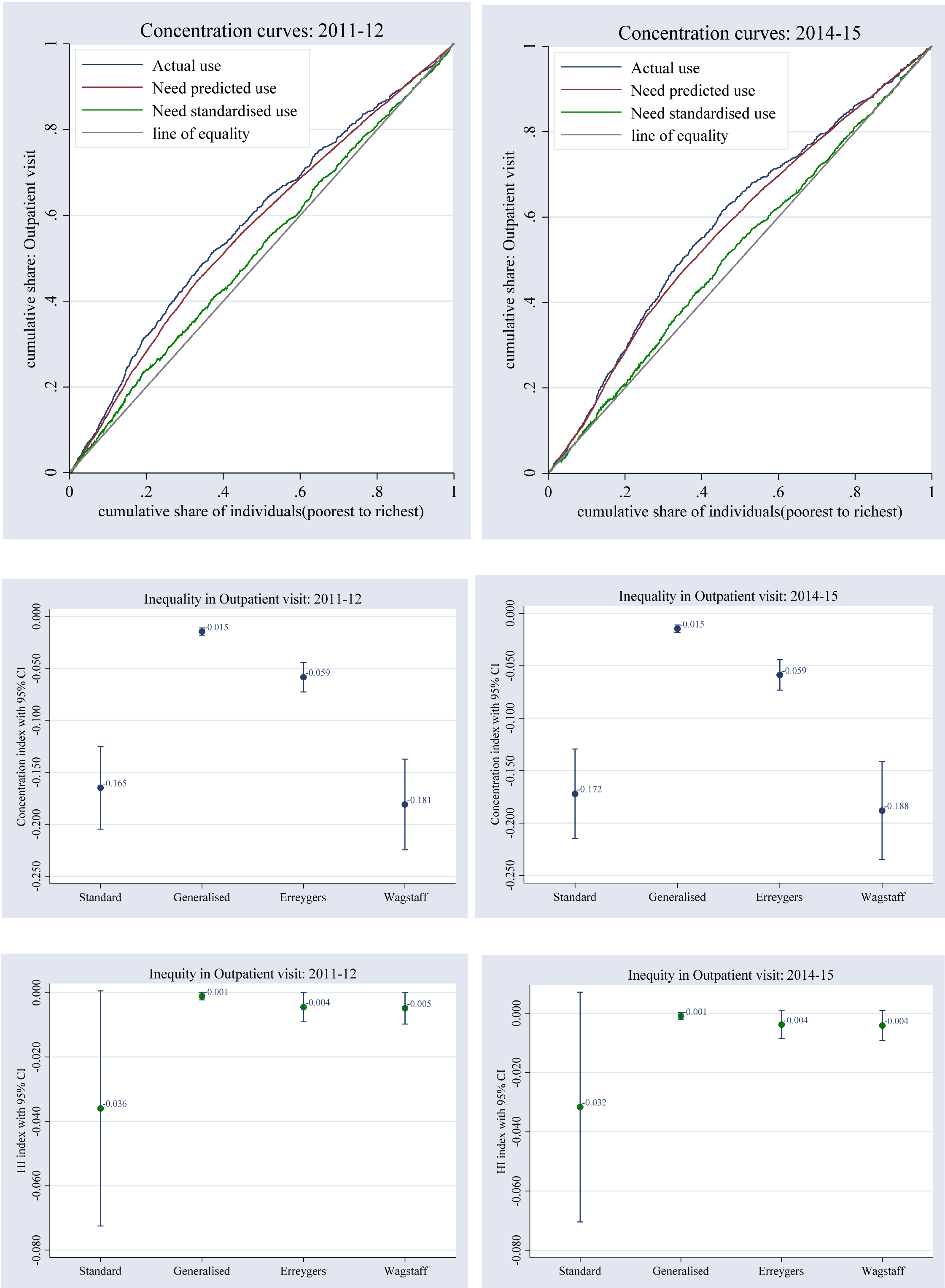


Figure A5.6: The concentration curves and inequality and inequity estimate for outpatient visit

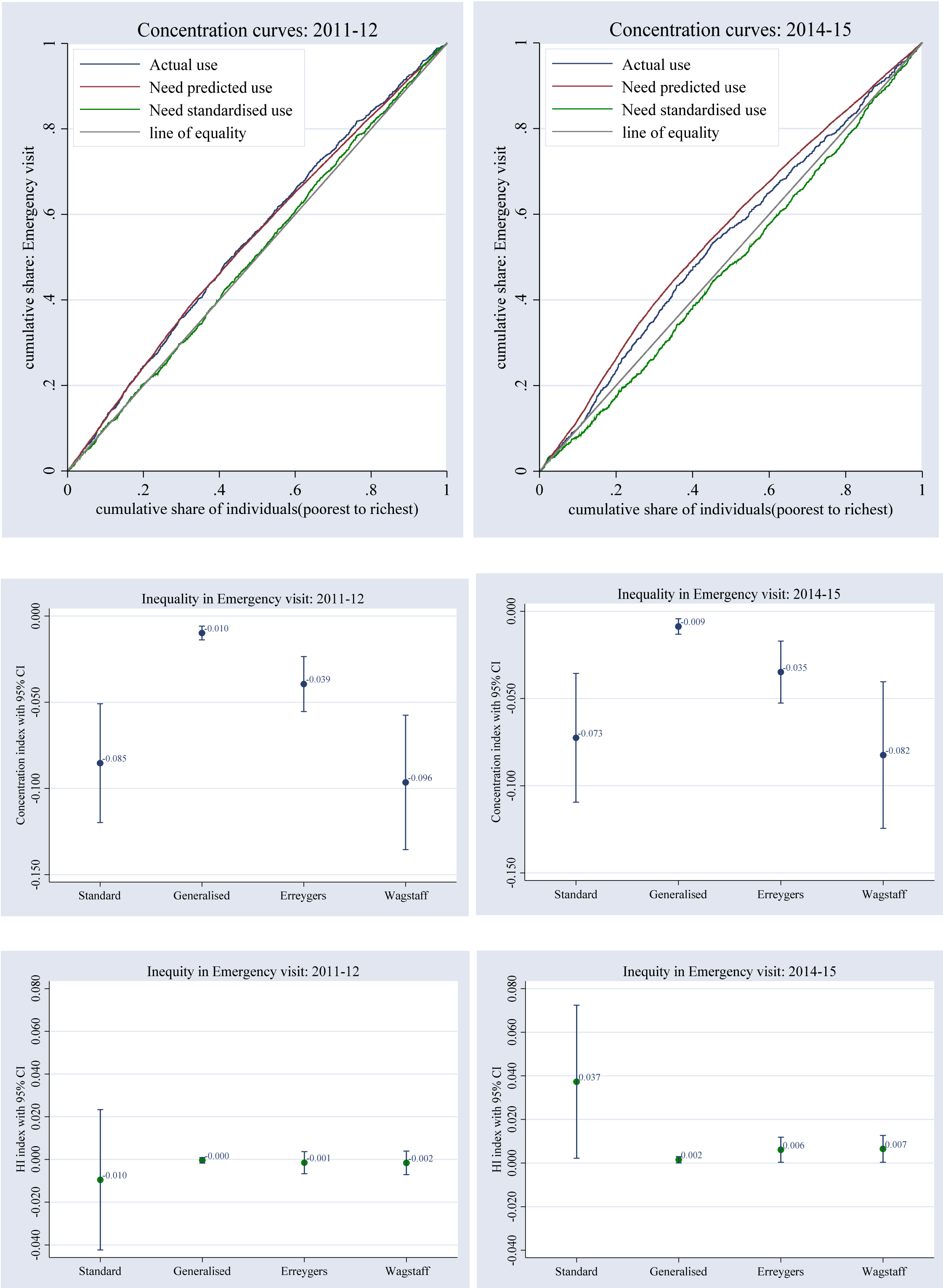


Figure A5.6: The concentration curves and inequality and inequity estimate for emergency visit

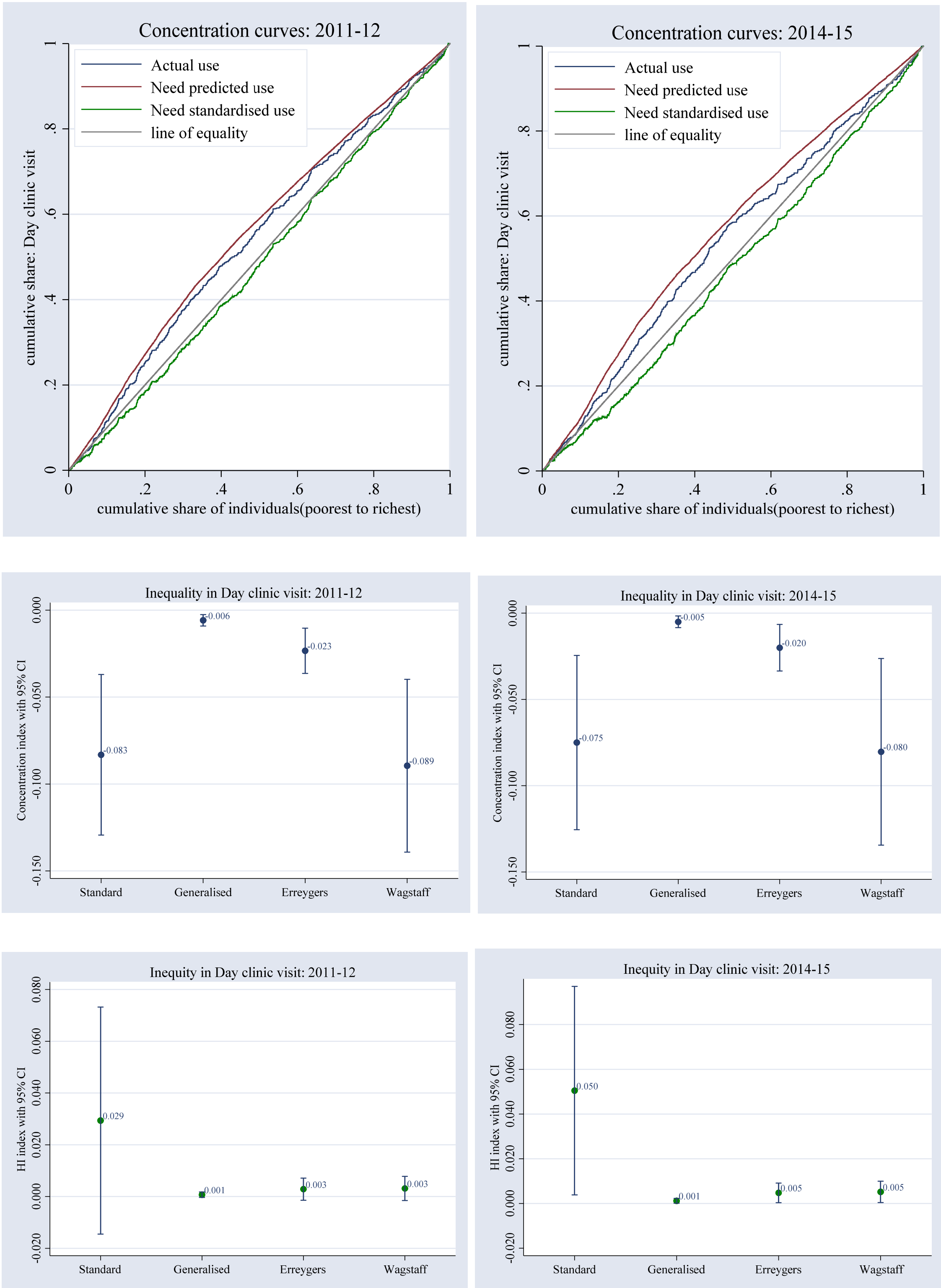


Figure A5.8: The concentration curves and inequality and inequity estimate for day clinic visit

Appendix: 6

Table A6.1: Summary statistics of the independent variables (N= 11,423)

Need variables	Mean	SD
Female	0.508	0.500
Age (Ref: 18-24 year)	0.122	0.327
Age 25-34 year	0.191	0.393
Age 35-44 year	0.179	0.383
Age 45-54 year	0.172	0.378
Age 55-64 year	0.150	0.358
Age 65-74 year	0.109	0.312
Age 75+ year	0.076	0.265
SAH (Ref: Excellent)	0.191	0.393
Very good	0.362	0.481
Good	0.294	0.456
Fair	0.107	0.309
Poor	0.046	0.209
Disability (Ref: No)	0.633	0.482
Some disability	0.143	0.350
Moderate disability	0.178	0.382
Severe disability	0.046	0.209
Comorbidity (Ref: Zero)	0.738	0.439
One morbidity	0.215	0.411
Multi morbidity	0.047	0.211
K10 score	14.925	5.949
No. of long-term conditions	3.600	3.277
Diabetes	0.117	0.322
Non-need variables		
Australia born	0.682	0.466
English at home	0.872	0.334
Health insurance	0.567	0.495
Concession card	0.316	0. 464
Education (Ref: Year 8 or less)	0.066	0.249
Year 9-11	0.360	0.480
Year 12 or more	0.574	0.495
Employee	0.537	0.499
Self-employee	0.117	0.322
Unemployed	0.035	0.184
Employment (Ref: Out of labour force)	0.310	0.463
Health insurance	0.573	0.495
Concession card	0.316	0.465
Major City (Ref)	0.719	0.449
Inner Region	0.179	0.383
Other remote	0.102	0.303
Household Income (Decile 1)	0.089	0.284
Decile 2	0.078	0.269
Decile 3	0.087	0.282
Decile 4	0.098	0.298
Decile 5	0.099	0.299
Decile 6	0.104	0.305
Decile 7	0.110	0.312
Decile 8	0.109	0.311
Decile 9	0.113	0.317
Decile 10	0.112	0.316
Area socioeconomic status (SEIFA 1)	0.088	0.283
SEIFA 2	0.106	0.307
SEIFA 3	0.094	0.291
SEIFA 4	0.103	0.304
SEIFA 5	0.106	0.307
SEIFA 6	0.097	0.295
SEIFA 7	0.101	0.301
SEIFA 8	0.104	0.305
SEIFA 9	0.093	0.291
SEIFA 10	0.109	0.312

Table A6.2: Regression models for GP visit (excluding the censored observations at 12 or more)

	Probability of visit				Total number of visits				Conditional number of visits			
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	OLS		Probit		OLS		NB2		OLS		NB2	
	Coef.	SE	AME	SE	Coef.	SE	AME	SE	Coef.	SE	AME	SE
Need variables												
Female	0.072***	(0.007)	0.066***	(0.007)	0.571***	(0.045)	0.627***	(0.047)	0.408***	(0.046)	0.480***	(0.052)
Age (Ref: 18-24 year)												
Age 25-34 year	0.013	(0.017)	0.007	(0.013)	-0.047	(0.109)	-0.034	(0.119)	-0.099	(0.116)	-0.108	(0.132)
Age 35-44 year	-0.012	(0.017)	-0.016	(0.013)	-0.308***	(0.107)	-0.330***	(0.118)	-0.322***	(0.114)	-0.386***	(0.131)
Age 45-54 year	-0.006	(0.017)	-0.023	(0.014)	-0.481***	(0.110)	-0.473***	(0.120)	-0.516***	(0.116)	-0.595***	(0.133)
Age 55-64 year	0.046***	(0.017)	0.025*	(0.015)	-0.255**	(0.114)	-0.205*	(0.122)	-0.439***	(0.120)	-0.478***	(0.135)
Age 65-74 year	0.045**	(0.019)	0.035*	(0.019)	-0.181	(0.129)	-0.130	(0.133)	-0.356***	(0.135)	-0.368**	(0.147)
Age 75+ year	0.056***	(0.019)	0.090***	(0.025)	0.222	(0.147)	0.159	(0.141)	-0.005	(0.152)	-0.075	(0.155)
SAH (Ref: Excellent)												
Very good	0.037***	(0.010)	0.028***	(0.008)	0.363***	(0.054)	0.486***	(0.070)	0.320***	(0.057)	0.498***	(0.084)
Good	0.036***	(0.011)	0.023**	(0.009)	0.661***	(0.064)	0.794***	(0.075)	0.663***	(0.066)	0.893***	(0.087)
Fair	0.053***	(0.013)	0.049***	(0.016)	0.930***	(0.099)	0.982***	(0.095)	0.886***	(0.100)	1.051***	(0.106)
Poor	0.045**	(0.017)	0.062*	(0.032)	1.228***	(0.171)	1.102***	(0.134)	1.195***	(0.166)	1.191***	(0.142)
Disability (Ref: No)												
Some disability	0.019**	(0.009)	0.007	(0.010)	0.214***	(0.065)	0.296***	(0.064)	0.202***	(0.065)	0.299***	(0.072)
Moderate disability	0.013	(0.009)	0.012	(0.012)	0.505***	(0.078)	0.468***	(0.068)	0.509***	(0.077)	0.523***	(0.074)
Sever disability	-0.005	(0.014)	0.026	(0.030)	0.578***	(0.161)	0.406***	(0.117)	0.597***	(0.160)	0.502***	(0.126)
Morbidity (Ref: Zero)												
One morbidity	0.068***	(0.007)	0.091***	(0.012)	0.525***	(0.061)	0.532***	(0.055)	0.338***	(0.060)	0.395***	(0.062)
Multi morbidity	0.029**	(0.012)	0.095**	(0.040)	0.730***	(0.145)	0.519***	(0.111)	0.616***	(0.143)	0.501***	(0.122)
K10 score	0.002***	(0.001)	0.002**	(0.001)	0.030***	(0.005)	0.029***	(0.005)	0.026***	(0.005)	0.025***	(0.005)
No. of long-term conditions	0.012***	(0.001)	0.020***	(0.002)	0.145***	(0.012)	0.121***	(0.010)	0.112***	(0.011)	0.101***	(0.010)
Diabetes	0.035***	(0.009)	0.039**	(0.016)	0.232***	(0.084)	0.261***	(0.073)	0.140*	(0.082)	0.177**	(0.080)
Non-need variables												
Australia born	0.026***	(0.008)	0.026***	(0.008)	0.192***	(0.054)	0.212***	(0.057)	0.142**	(0.055)	0.169***	(0.065)
English at home	0.036**	(0.014)	0.021*	(0.012)	-0.189**	(0.090)	-0.165*	(0.097)	-0.349***	(0.095)	-0.379***	(0.105)
Health insurance	0.042***	(0.008)	0.038***	(0.007)	0.103**	(0.050)	0.129**	(0.052)	-0.015	(0.052)	-0.008	(0.058)
Concession card	0.057***	(0.011)	0.056***	(0.011)	0.458***	(0.079)	0.457***	(0.078)	0.304***	(0.080)	0.324***	(0.086)
Education (Ref: Year 8 or less)												
Year 9-11	-0.003	(0.012)	0.011	(0.018)	0.058	(0.109)	0.034	(0.091)	0.082	(0.109)	0.080	(0.099)
Year 12 or more	0.008	(0.013)	0.018	(0.019)	-0.050	(0.114)	-0.068	(0.099)	-0.080	(0.114)	-0.100	(0.107)
Employment (Ref: Out of labour force)												
Employee	0.026**	(0.010)	0.025**	(0.011)	0.105	(0.074)	0.110	(0.074)	0.025	(0.075)	0.029	(0.083)
Self-employee	-0.017	(0.014)	-0.010	(0.013)	-0.131	(0.088)	-0.190*	(0.098)	-0.116	(0.091)	-0.167	(0.111)
Unemployed	-0.012	(0.023)	-0.009	(0.019)	0.090	(0.160)	0.122	(0.158)	0.142	(0.168)	0.190	(0.167)

Residence (Ref: Major City)												
Inner region	-0.041***	(0.009)	-0.041***	(0.009)	-0.337***	(0.060)	-0.336***	(0.062)	-0.246***	(0.062)	-0.260***	(0.068)
Other or remote	-0.034***	(0.010)	-0.033***	(0.009)	-0.348***	(0.063)	-0.341***	(0.067)	-0.282***	(0.064)	-0.296***	(0.075)
Household Income (Ref: Decile 1)												
Decile 2	0.038***	(0.014)	0.038**	(0.018)	0.134	(0.113)	0.120	(0.103)	0.020	(0.116)	0.006	(0.111)
Decile 3	0.039***	(0.015)	0.040**	(0.017)	0.262**	(0.116)	0.247**	(0.107)	0.151	(0.118)	0.146	(0.114)
Decile 4	0.027*	(0.016)	0.022	(0.016)	0.140	(0.110)	0.150	(0.108)	0.074	(0.112)	0.082	(0.116)
Decile 5	0.043***	(0.016)	0.042***	(0.015)	0.278**	(0.113)	0.294**	(0.115)	0.163	(0.117)	0.184	(0.125)
Decile 6	0.041**	(0.017)	0.037**	(0.016)	0.329***	(0.116)	0.349***	(0.119)	0.229*	(0.119)	0.257**	(0.129)
Decile 7	0.058***	(0.017)	0.051***	(0.016)	0.511***	(0.117)	0.539***	(0.121)	0.378***	(0.121)	0.426***	(0.132)
Decile 8	0.040**	(0.018)	0.033**	(0.016)	0.244**	(0.116)	0.246**	(0.124)	0.136	(0.120)	0.130	(0.137)
Decile 9	0.049***	(0.017)	0.038**	(0.016)	0.351***	(0.118)	0.375***	(0.124)	0.225*	(0.121)	0.250*	(0.138)
Decile 10	0.038**	(0.018)	0.028*	(0.016)	0.224*	(0.119)	0.220*	(0.128)	0.129	(0.122)	0.098	(0.143)
Area socioeconomic status (Ref: SEIFA 1)												
SEIFA 2	-0.004	(0.015)	0.000	(0.015)	-0.103	(0.108)	-0.096	(0.104)	-0.122	(0.111)	-0.113	(0.112)
SEIFA 3	-0.010	(0.015)	-0.006	(0.016)	-0.001	(0.110)	-0.003	(0.105)	0.030	(0.112)	0.035	(0.112)
SEIFA 4	-0.004	(0.015)	0.001	(0.015)	-0.166	(0.105)	-0.185*	(0.106)	-0.185*	(0.108)	-0.213*	(0.115)
SEIFA 5	-0.002	(0.015)	0.005	(0.015)	0.113	(0.106)	0.073	(0.102)	0.117	(0.109)	0.103	(0.110)
SEIFA 6	0.012	(0.015)	0.017	(0.016)	0.039	(0.106)	0.018	(0.105)	-0.015	(0.109)	-0.026	(0.114)
SEIFA 7	-0.000	(0.016)	0.003	(0.016)	-0.097	(0.109)	-0.099	(0.109)	-0.123	(0.111)	-0.127	(0.119)
SEIFA 8	-0.003	(0.016)	0.001	(0.016)	-0.158	(0.110)	-0.186*	(0.112)	-0.183	(0.113)	-0.226*	(0.124)
SEIFA 9	0.009	(0.016)	0.013	(0.016)	-0.051	(0.110)	-0.048	(0.110)	-0.096	(0.112)	-0.106	(0.121)
SEIFA 10	0.003	(0.016)	0.010	(0.016)	-0.113	(0.110)	-0.122	(0.113)	-0.158	(0.113)	-0.175	(0.125)
Alpha (Test of equidispersion)							0.155(p=0.000)				0.097(p=0.000)	
Observations	9,995		9,995		9,995		9,995		8,664		8,664	
R-squared	0.091				0.217				0.175			

Notes: Robust standard errors in parentheses, AME= Average marginal effect and significance level *** p<0.01, ** p<0.05, * p<0.10, NB2=Negative binomial model version 2

Table A6.3: Regression models for specialist visit (excluding the censored observations at 12 or more)

	Probability of visit				Total number of visits				Conditional number of visits			
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	OLS		Probit		OLS		NB2		OLS		NB2	
	Coef.	SE	AME	SE	Coef.	SE	AME	SE	Coef.	SE	AME	SE
Need variables												
Female	0.028***	(0.009)	0.031***	(0.009)	0.129***	(0.033)	0.174***	(0.037)	0.173**	(0.068)	0.173**	(0.071)
Age (Ref: 18-24 year)												
Age 25-34 year	0.042**	(0.018)	0.050**	(0.022)	0.188***	(0.073)	0.291***	(0.107)	0.264	(0.237)	0.247	(0.210)
Age 35-44 year	0.048***	(0.018)	0.059***	(0.022)	0.090	(0.070)	0.181*	(0.104)	-0.162	(0.226)	-0.148	(0.209)
Age 45-54 year	0.037*	(0.020)	0.050**	(0.022)	-0.032	(0.071)	0.064	(0.106)	-0.468**	(0.223)	-0.513**	(0.213)
Age 55-64 year	0.102***	(0.021)	0.111***	(0.023)	0.087	(0.075)	0.216**	(0.106)	-0.533**	(0.224)	-0.565***	(0.212)
Age 65-74 year	0.150***	(0.025)	0.154***	(0.026)	0.204**	(0.092)	0.301***	(0.116)	-0.525**	(0.243)	-0.551**	(0.232)
Age 75+ year	0.212***	(0.029)	0.211***	(0.029)	0.365***	(0.107)	0.420***	(0.123)	-0.493*	(0.256)	-0.528**	(0.246)
SAH (Ref: Excellent)												
Very good	0.043***	(0.012)	0.046***	(0.012)	0.074*	(0.040)	0.112**	(0.056)	-0.095	(0.103)	-0.082	(0.115)
Good	0.046***	(0.013)	0.049***	(0.014)	0.145***	(0.046)	0.206***	(0.060)	0.125	(0.110)	0.155	(0.118)
Fair	0.084***	(0.020)	0.086***	(0.019)	0.279***	(0.075)	0.310***	(0.075)	0.217	(0.140)	0.236*	(0.141)
Poor	0.182***	(0.034)	0.179***	(0.032)	0.681***	(0.148)	0.550***	(0.099)	0.435**	(0.206)	0.428**	(0.181)
Disability (Ref: No)												
Some disability	0.045***	(0.014)	0.044***	(0.013)	0.119**	(0.047)	0.180***	(0.050)	0.089	(0.088)	0.134	(0.098)
Moderate disability	0.096***	(0.016)	0.087***	(0.014)	0.379***	(0.060)	0.376***	(0.052)	0.343***	(0.098)	0.388***	(0.098)
Sever disability	0.130***	(0.031)	0.118***	(0.029)	0.722***	(0.150)	0.480***	(0.089)	0.652***	(0.202)	0.640***	(0.160)
Morbidity (Ref: Zero)												
One morbidity	0.063***	(0.013)	0.056***	(0.012)	0.080*	(0.047)	0.109**	(0.043)	-0.129	(0.081)	-0.133	(0.088)
Multi morbidity	0.109***	(0.031)	0.100***	(0.028)	0.467***	(0.128)	0.249***	(0.083)	0.270	(0.175)	0.226	(0.156)
K10 score	0.002**	(0.001)	0.002**	(0.001)	0.008*	(0.004)	0.013***	(0.004)	0.008	(0.008)	0.008	(0.007)
No. of long-term conditions	0.023***	(0.002)	0.022***	(0.002)	0.079***	(0.009)	0.070***	(0.008)	0.043***	(0.015)	0.038***	(0.014)
Diabetes	0.046***	(0.018)	0.043***	(0.016)	0.143**	(0.069)	0.149***	(0.055)	0.081	(0.114)	0.092	(0.108)
Non-need variables												
Australia born	0.024**	(0.011)	0.023**	(0.011)	0.100**	(0.041)	0.086*	(0.044)	0.095	(0.082)	0.092	(0.087)
English at home	0.050***	(0.016)	0.059***	(0.018)	0.169***	(0.054)	0.326***	(0.078)	0.206	(0.139)	0.254	(0.156)
Health insurance	0.092***	(0.010)	0.094***	(0.010)	0.230***	(0.035)	0.318***	(0.044)	0.023	(0.079)	0.052	(0.083)
Concession card	0.013	(0.015)	0.014	(0.016)	0.062	(0.060)	0.088	(0.065)	0.077	(0.125)	0.098	(0.122)
Education (Ref: Year 8 or less)												
Year 9-11	0.082***	(0.021)	0.074***	(0.021)	0.188**	(0.077)	0.116	(0.077)	-0.048	(0.144)	-0.074	(0.143)
Year12 or more	0.127***	(0.022)	0.119***	(0.022)	0.343***	(0.080)	0.297***	(0.083)	0.050	(0.152)	0.036	(0.152)
Employment (Ref: Out of labour force)												
Employee	-0.017	(0.015)	-0.017	(0.015)	-0.120**	(0.058)	-0.176***	(0.060)	-0.278**	(0.117)	-0.294***	(0.113)
Self-employee	0.016	(0.019)	0.017	(0.018)	-0.005	(0.070)	-0.034	(0.075)	-0.141	(0.140)	-0.141	(0.145)
Unemployed	0.040	(0.029)	0.041	(0.029)	0.109	(0.110)	0.114	(0.120)	0.015	(0.234)	-0.013	(0.216)
Residence (Ref: Major City)												
Inner region	-0.027**	(0.012)	-0.026**	(0.012)	-0.133***	(0.044)	-0.115**	(0.050)	-0.194**	(0.090)	-0.231**	(0.095)
Other or remote	-0.029**	(0.013)	-0.028**	(0.013)	-0.167***	(0.044)	-0.163***	(0.055)	-0.304***	(0.096)	-0.344***	(0.111)

Household Income (Ref: Decile 1)												
Decile 2	-0.005	(0.022)	-0.002	(0.022)	0.019	(0.080)	0.031	(0.087)	0.077	(0.157)	0.056	(0.165)
Decile 3	0.006	(0.022)	0.007	(0.022)	0.065	(0.077)	0.081	(0.087)	0.130	(0.150)	0.145	(0.161)
Decile 4	0.027	(0.021)	0.025	(0.022)	0.165**	(0.076)	0.157*	(0.089)	0.293*	(0.154)	0.314*	(0.164)
Decile 5	0.028	(0.022)	0.027	(0.023)	0.195**	(0.077)	0.230**	(0.094)	0.382**	(0.161)	0.418**	(0.174)
Decile 6	0.003	(0.022)	0.004	(0.023)	0.088	(0.076)	0.089	(0.096)	0.226	(0.159)	0.226	(0.179)
Decile 7	0.033	(0.023)	0.035	(0.023)	0.267***	(0.082)	0.296***	(0.099)	0.578***	(0.179)	0.562***	(0.186)
Decile 8	0.028	(0.023)	0.031	(0.024)	0.133*	(0.081)	0.176*	(0.102)	0.193	(0.173)	0.191	(0.197)
Decile 9	0.062***	(0.024)	0.063***	(0.024)	0.306***	(0.083)	0.338***	(0.098)	0.463***	(0.170)	0.490***	(0.185)
Decile 10	0.066***	(0.024)	0.067***	(0.024)	0.316***	(0.086)	0.339***	(0.099)	0.474***	(0.175)	0.487***	(0.189)
Area socioeconomic status (Ref: SEIFA 1)												
SEIFA 2	0.024	(0.020)	0.030	(0.022)	0.119*	(0.071)	0.171*	(0.094)	0.201	(0.172)	0.169	(0.178)
SEIFA 3	0.049**	(0.020)	0.054**	(0.022)	0.122*	(0.071)	0.188**	(0.092)	0.027	(0.165)	-0.004	(0.176)
SEIFA 4	0.083***	(0.020)	0.087***	(0.021)	0.241***	(0.070)	0.289***	(0.089)	0.113	(0.164)	0.046	(0.173)
SEIFA 5	0.063***	(0.020)	0.068***	(0.021)	0.203***	(0.070)	0.213**	(0.089)	0.133	(0.165)	0.066	(0.172)
SEIFA 6	0.068***	(0.021)	0.074***	(0.022)	0.163**	(0.069)	0.193**	(0.090)	-0.022	(0.165)	-0.047	(0.180)
SEIFA 7	0.064***	(0.021)	0.069***	(0.022)	0.203***	(0.072)	0.269***	(0.091)	0.157	(0.165)	0.110	(0.174)
SEIFA 8	0.066***	(0.022)	0.072***	(0.022)	0.242***	(0.078)	0.329***	(0.094)	0.233	(0.175)	0.200	(0.180)
SEIFA 9	0.063***	(0.022)	0.068***	(0.022)	0.209***	(0.076)	0.268***	(0.093)	0.205	(0.172)	0.147	(0.182)
SEIFA 10	0.094***	(0.022)	0.097***	(0.022)	0.293***	(0.077)	0.334***	(0.092)	0.177	(0.170)	0.104	(0.178)
Alpha (Test of equidispersion)							2.115(p=0.000)				0.698(p=0.000)	
Observations	9,995		9,995		9,995		9,995		3,443		3,443	
R-squared	0.135				0.107				0.060			

Notes: Robust standard errors in parentheses, AME= Average marginal effect and significance level *** p<0.01, ** p<0.05, * p<0.10, NB2=Negative binomial model version 2

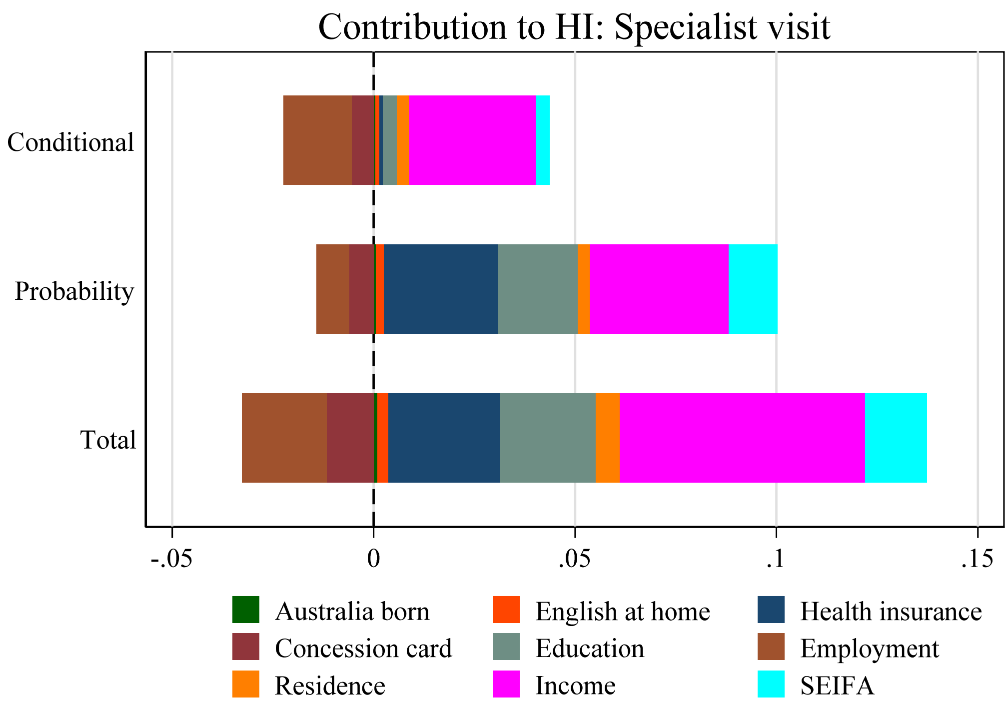
Table A6.4: The decomposition analysis for specialist visit (excluding the censored observations at 12 or more)

		Probability of visit		Total number of visits		Conditional number of visits	
	CI	Contribution	%	Contribution	%	Contribution	%
Non-need variables							
Female	-0.054***	-0.002***	0.180	-0.004***	0.381	-0.001**	-0.586
Age (Ref: 18-24 year)							
Age 25-34 year	0.167***	0.004**	-0.291	0.007**	-0.597	0.004	1.710
Age 35-44 year	0.123***	0.004**	-0.272	0.003	-0.236	-0.002	-0.938
Age 45-54 year	0.138***	0.003**	-0.205	-0.001	0.081	-0.004*	-2.054
Age 55-64 year	0.005	0.000	-0.019	0.000	-0.008	-0.002	-1.108
Age 65-74 year	-0.321***	-0.018***	1.363	-0.009**	0.858	0.009**	4.368
Age 75+ year	-0.491***	-0.024***	1.837	-0.016***	1.468	0.011*	5.154
SAH (Ref: Excellent)							
Very good	0.075***	0.004***	-0.281	0.002*	-0.224	-0.002	-0.767
Good	-0.063***	-0.002***	0.187	-0.003***	0.273	-0.001	-0.395
Fair	-0.259***	-0.006***	0.459	-0.008***	0.709	-0.003	-1.381
Poor	-0.452***	-0.007***	0.508	-0.010***	0.881	-0.004**	-1.803
Disability (Ref: No)							
Some disability	0.018	0.000	-0.028	0.000	-0.034	0.000	0.163
Moderate disability	-0.289***	-0.013***	1.032	-0.021***	1.882	-0.009***	-4.091
Sever disability	-0.387***	-0.004***	0.324	-0.009***	0.835	-0.005***	-2.251
Morbidity (Ref: Zero)							
One morbidity	-0.134***	-0.006***	0.431	-0.003*	0.257	0.002	0.930
Multi morbidity	-0.338***	-0.004***	0.327	-0.007***	0.647	-0.002	-1.125
K10 score	-0.030***	-0.003**	0.213	-0.004*	0.378	-0.002	-0.797
No. of long-term conditions	-0.095***	-0.022***	1.733	-0.030***	2.739	-0.008**	-3.764
Diabetes	-0.142***	-0.002**	0.168	-0.003*	0.242	-0.001	-0.374
Non-need variables							
Australia born	0.012***	0.001*	-0.044	0.001*	-0.087	0.001	0.241
English at home	0.016***	0.002**	-0.158	0.003***	-0.246	0.001	0.435
Health insurance	0.179***	0.028***	-2.179	0.028***	-2.523	0.001	0.430
Concession card	-0.526***	-0.006	0.471	-0.012	1.067	-0.006	-2.628
Education (Ref: Year 8 or less)							
Year 9-11	-0.174***	-0.016***	1.233	-0.014**	1.313	0.001	0.675
Year12 or more	0.176***	0.036***	-2.768	0.038***	-3.475	0.002	1.014
Employment (Ref: Out of labour force)							
Employee	0.249***	-0.007	0.529	-0.019**	1.721	-0.016***	-7.524
Self-employee	0.098***	0.000	-0.039	0.000	0.005	-0.001	-0.498
Unemployed	-0.554***	-0.002	0.143	-0.002	0.179	0.000	-0.036
Residence (Ref: Major City)							
Inner region	-0.162***	0.002***	-0.187	0.005***	-0.425	0.002*	1.068
Other or remote	-0.047***	0.001*	-0.048	0.001***	-0.128	0.001	0.362

Household Income (Ref: Decile 1)							
Decile 2	-0.739***	0.001	-0.065	-0.001	0.127	-0.002	-1.068
Decile 3	-0.572***	-0.001	0.066	-0.003	0.315	-0.003	-1.235
Decile 4	-0.396***	-0.003	0.226	-0.007***	0.639	-0.004**	-1.837
Decile 5	-0.202***	-0.002	0.129	-0.004**	0.409	-0.002**	-0.960
Decile 6	-0.002	0.000	0.000	0.000	0.002	0.000	0.121
Decile 7	0.208***	0.002	-0.165	0.007***	-0.625	0.005***	2.249
Decile 8	0.428***	0.004	-0.302	0.007*	-0.664	0.003	1.467
Decile 9	0.656***	0.014***	-1.052	0.027***	-2.416	0.014***	6.477
Decile 10	0.886***	0.020***	-1.512	0.037***	-3.328	0.020***	9.725
Area socioeconomic status (Ref: SEIFA 1)							
SEIFA 2	-0.270***	-0.002	0.143	-0.004*	0.330	-0.002	-0.918
SEIFA 3	-0.177***	-0.002**	0.190	-0.002*	0.218	0.000	-0.094
SEIFA 4	-0.099***	-0.003***	0.197	-0.003***	0.265	0.000	-0.230
SEIFA 5	-0.023	0.000	0.035	-0.001	0.052	-0.001	-0.267
SEIFA 6	0.027*	0.001	-0.042	0.001	-0.046	0.000	-0.007
SEIFA 7	0.101***	0.002***	-0.148	0.002***	-0.216	0.001	0.238
SEIFA 8	0.159***	0.003***	-0.227	0.004***	-0.388	0.001	0.684
SEIFA 9	0.208***	0.004***	-0.289	0.005***	-0.448	0.002	0.814
SEIFA 10	0.352***	0.010***	-0.802	0.013***	-1.158	0.003	1.412
Residual		0.000	0.000	0.000	0.000	0.000	0.000

Note Significance level *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure A6.1. Components of horizontal inequity in specialist visits (excluding the censored observations at 12 or more)



Appendix: 7

Mapping of Medicare items to specialist Broad Type of Service (BTOS)

Specialist Attendances (BTOS-0200)

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, 825-830, 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, 6018-6019, 6023-6026, 6028-6029, 6031-6032, 6034-6035, 6037-6038, 6042, 6051-6052, 6057-6060, 6062-6065, 6067-6068, 6071-6075, 6080-6081, 10801-10816, 17603-17690.

Source: Medicare Australia Statistics, Department of Human Services, Australian Government

http://medicarestatistics.humanservices.gov.au/statistics/do.jsp?_PROGRAM=/statistics/std_btos_map&start_dt=0&end_dt=0 (Accessed on 1 December 2017)

Figure A7.1: SEIFA quintile distribution of specialist services in 2011-12 and 2014-15

Table A7.1: Absolute inequality in specialist visit (Generalised concentration index or GCI)

	2011-12			2014-15		
	GCI	SE	95% CI	GCI	SE	95% CI
All	0.062***	[0.001]	(0.060, 0.064)	0.0481***	[0.001]	(0.047, 0.050)
Non-bulk-billed	0.104***	[0.001]	(0.103, 0.106)	0.0941***	[0.001]	(0.093, 0.096)
Bulk-billed	-0.004***	[0.001]	(-0.006, -0.002)	-0.0231***	[0.001]	(-0.025, -0.021)

Notes: Robust standard errors (clustered at postcode level) in brackets and 95% confidence intervals in parentheses

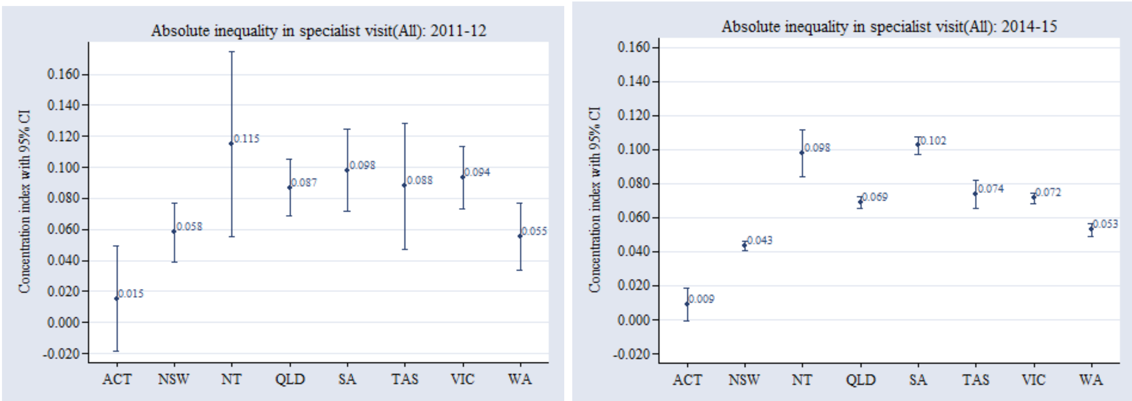


Figure A7.2: State and territory variation of inequality in all specialist visit

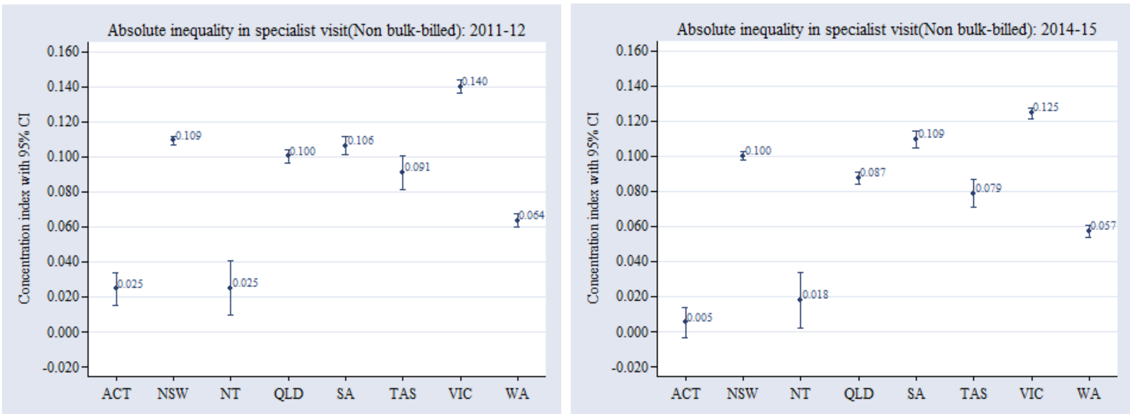


Figure A7.3: State and territory variation of inequality in non-bulk-billed specialist visit

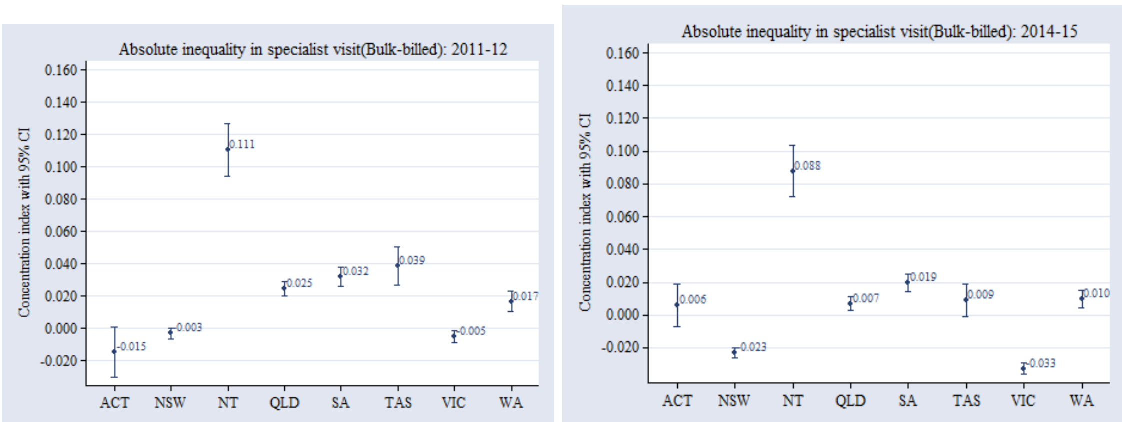


Figure A7.4: State and territory variation of inequality in bulk-billed specialist visit

Appendix: 8

Table A8.1: Inequality in healthcare use (Erregyers's index)

	EI	SE	95% CI
Any visit	-0.017	(0.022)	-0.060, 0.025
GP visit	-0.072***	(0.019)	-0.110, -0.035
Specialist visit	0.020*	(0.011)	-0.003, 0.042
Inpatient admission	-0.062***	(0.019)	-0.099, -0.025

Notes: Robust standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

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