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Is Hospital Treatment in Australia Inequitable? Evidence from the HILDA Survey

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Abstract

The pursuit of equity is a key objective of many health care systems, including Australia's Medicare. Using the Household, Income and Labour Dynamics in Australia (HILDA) survey, we measured the extent of inequity in the utilisation of hospital services. We used methodology developed by the ECuity project for measuring horizontal inequity indices. We examine income-related health care inequities in both inpatient and day patient access and utilisation, whilst controlling for morbidity, demographic and socio-economic variables. The probability of hospital inpatient admission appeared equitable, but the probability of a day patient visit demonstrated a pro-rich distribution. Even more pronounced were the findings on the quantity of visits. The positive horizontal inequality indices indicate a degree of inequity favouring the rich, especially for inpatient utilisation. The pro-rich distribution of the probability of a day patient visit was associated with whether individuals held private health insurance. These results suggest that in Australia, which has a universal and comprehensive health system, the rich and poor are not treated equally according to need. Further research should investigate whether the causes of inequities lie in the preferences of individuals or the preferences of health care providers.

1. Introduction

Many developed countries offer a health care system that is egalitarian in nature, providing fairly universal coverage for their population for a comprehensive package of health services at low or zero financial cost. Equity and efficiency are usually mutually exclusive health care objectives, therefore a trade-off may be required. Equity of access is regarded as a key element of health system performance by the Organisation for Economic Co-operation and Development (OECD, 2002). In Australia, one of the continuing tenets of Medicare is universal and equitable access to health care.

When referring to health, equity is defined as the absence of socially unjust or unfair health differences (Culyer and Wagstaff, 1993). However, equity can also be defined in terms of inequalities in the utilisation of health care services or in terms of opportunity of access. When measuring inequalities it is normal to distinguish between need and non-need variables and between horizontal and vertical equity.

There is considerable debate about whether equity should relate to health status, quantity of health care received or access to health care (Mooney, 1986; Wagstaff et al (2000). The most popular term used in the policy documents of a number of countries is 'equal access for equal need'. This can be defined in several ways, the most common being the 'opportunity of access'. Medicare's definition of universal access requires that all Australians should be able to use public hospitals free of charge. This therefore only refers to the absence of user charges in the hospital sector, and does not include the other 'costs' of accessing hospitals, such as the opportunity costs of time. Access can also be defined as utilisation, but this is somewhat different as it partly relies on the preferences of individuals in addition to the supply of health care services. Equality of utilisation for equal need is argued to be an unfavourable objective of the health care system as it implies that individuals should be coerced into using health care, regardless of their own preferences. In practice, the empirical literature has focussed on measuring income-related inequalities in health and also horizontal inequity in the utilisation of health care services (e.g. van Doorslaer and Koolman, 2004).

The aim of this paper is to examine horizontal inequity in the utilisation of hospital services in Australia. Previous research has focussed largely on general practitioner (GP) visits and has shown, across a number of OECD and other countries, that the distribution of GP visits is pro-poor or unrelated to income. Pro-poor distributions seem to be indicative of countries with no (or low) user charges. Pro-rich inequity for medical specialist utilisation is demonstrated in most of the countries examined. In spite of their lower need, better-off individuals are more likely to consult a specialist. The fact that every country exhibits some degree of pro-rich inequity, suggest a tendency for the better-off to use specialist care, irrespective of the health system. This suggests that it is the preferences of high income groups that are different to low income groups, rather than inequality necessarily being a function of the organisation and financing of the health care system, although this also plays a role.

The ubiquity of pro-rich medical specialist utilisation across Europe was greatest in the UK, Ireland, Portugal, Spain and Italy (van Doorslaer et al., 2004). In these countries, private health insurance (PHI) or private practice options are offered to purchase faster, preferential and convenient patient access (van Doorslaer et al, 2002). A number of studies suggest that underlying income-related differences in specialist utilisation are exacerbated by PHI (van Doorslaer et al, 2002; Lairson et al., 1995; Leeder, 2003; Mooney, 1997)

Previous research on hospital utilisation finds ambiguous results for inpatient treatment. To date, the estimation of health inequality indices in Australia have been limited to two studies. Lairson et al (2000) found inequality of GP/specialist and inpatient services favouring the better-off and inequality of outpatient's services favouring the worst-off. Van Doorslaer and Masseria (2004) demonstrated equitable GP visits and pro-poor inpatient treatment. Both studies were conducted prior to the private health insurance reforms in 1999/2000. A weakness of all studies examining hospital utilisation is that they consider overnight hospital stays only, and not the growing proportion of hospital activity that is now comprised of day case treatment and surgery.

The study adds to the literature in a number of ways. First, most of the literature has examined GP visits and specialist visits rather than hospital services. This is important as the utilisation of hospital services also says something about the effect of supply side factors on inequality, which should be a focus of policy. Who is admitted to hospital, and whether they receive day case or inpatient treatment, is more a function of the preferences of referring GPs, admitting hospital doctors, and the decisions of hospital managers about the provision of services, than of patients. The causes of inequality (and therefore policy implications) are therefore more likely to be within the health care system, rather than with 'legitimate' differences in the preferences of patients across income groups.

Second, day case treatment and surgery in hospitals represent higher quality of care and better health outcomes and is forming an increasing proportion of hospital activity in many countries. This has been ignored in previous research, yet it is important to see how this new technology is distributed amongst those using hospitals. A third way this paper adds to the literature is that it uses panel data to better identify the relationship between need and utilisation. Finally, the data contains more detailed information on income and wealth of individuals and households than has previously been used in studies of this type. This provides a more robust view of the extent of inequities.

We measure health inequities using concentration and health inequity indices. Two measures of hospital utilisation are examined; number of day case visits and occasions (or nights) treated as an inpatient, during a 12 months period. After a brief overview of the Australian health care system, the HILDA data used are described and the analytical framework outlined, including the probit model, two-stage zero truncated negative binomial model and computation of inequity indices. The penultimate section presents the results. A discussion of the results, limitations of the study and how this contributed to the literature is contained in the final section.

2. The Australian Health System

Under Medicare, all Australians have access to free medical treatment as a public patient in a public hospital. There are subsides for GP and specialist and diagnostic services through the Medicare Benefits Schedule (MBS), and subsidies for pharmaceuticals through the Pharmaceutical Benefits Scheme (PBS). The system receives 62% of its funding from federal and state governments, including a Medicare levy based on taxable income. A significant proportion of health spending, 32% in 2004/5, (larger than most OECD countries) is funded from non-government sources. Of this proportion, 60% of spending is from individuals reflecting co-payments and user charges, 20% is from private health insurance funds, and 20% is from other non-government sources (AIHW, 2004).

Private health insurance (PHI) plays a relatively large role in the health care system compared to many European countries. The initial success of Medicare, coupled with the real and perceived problems associated with PHI, resulted in the proportion of the population covered under PHI declining during the 1990s (Cormack, 2004). In an attempt to lessen the burden on public hospitals, the Australian Government introduced a number of important policy changes and subsidies in the late 1990s to encourage the purchase of PHI. A tax surcharge of 1% was introduced for those without a policy, followed by a 30 percent premium rebate and a limited type of age rating built into PHI premiums. The cumulative effect of these policies increased the proportion of Australians with PHI to 45 percent. The policy changes were undoubtedly effective at encouraging the uptake of PHI (Butler, 2002). A significant sum of public spending is used to fund the 30% rebate, which in 2004/5 amounted to \$2.9bn of additional government spending (AIHW, 2006). More importantly, these policy changes may have implications for the equity and efficiency of the health care sector.

The main beneficiaries of the new PHI policy changes were households from higher income and higher socio-economic standings, since this group were more likely to have purchased PHI without any incentive. It is estimated that 66 percent of singles and 82 percent of families would have purchased PHI without the new PHI policy changes, and consequently enjoy “deadweight benefits” (Dawkins et al, 2004). Furthermore, the new PHI policies appear to have done little to alleviate the burden on public hospitals (Lu and Savage, 2006). Consequently, the effectiveness, sustainability and equity of these new policies are questionable.

3. Data and variables

The research uses data from the Household, Income and Labour Dynamics in Australia (HILDA) survey (HILDA, 2007). The HILDA Survey is a nationally representative household-based panel study of the Australian population. The survey began in 2001, with each wave collected annually. The HILDA wave 4 (2005) dataset included 17209 individuals in 6987 households drawn from every state of Australia. Detailed information was collected from 12408 individuals via structured interviews. The remaining 4801 individuals are household members not interviewed because they are under 15 years old. Individual level data was used. Most data were extracted from wave four, as this is the only wave to include questions on hospital utilisation and PHI status. Lagged values of some potentially endogenous variables were taken from wave 3 (2004).

Hospital utilisation was defined in terms of inpatient treatment or day case visits. A dummy variable equalled 1 if the individual stayed in hospital (or received day case treatment) during the past 12 months and 0 otherwise. The quantity of health care received was measured as the number of occasions and number of nights stayed in hospital, and/or the number of day case visits.

Self assessed health status is the main health measure used. This was based on the question: *"In general, would you say your health is:"* The five point ordinal responses are *"Excellent, very good, good, fair and poor"*. These capture a combination of physical and psychological health aspects and are strong predictors of mortality and future changes in functioning among the elderly (e.g. Grant et al, 1995). Self-assessed health status is also a good predictor of future health care usage, a finding that is consistent across different socio-economic groups (van Doorslaer et al, 2000; Burstrom and Fredlund, 2001). Since health status is endogenous to health care utilisation because of reverse causality, health status in the previous wave of the survey (wave 3) was used to explain hospital utilisation in the current wave (wave 4).

Income was measured using household income, before taxes and deductions, of all household members from all sources. It includes income from employment and self-employment, from detailed questions on private non-labour income (from investments and property and private transfers to the household), pensions and other direct social transfers received. Total household income equals all net monetary income received by the household members during the preceding year of the HILDA wave 4. Again, this accounts for the potential endogeneity of income with hospital utilisation because of reverse causality. Household income is equivalised to take into account differences in size and composition of the households. The modified OECD equivalence scale is used to be consistent with previous studies (De Vos and Zaidi, 1997).

A number of other variables have been shown to affect health care utilisation are also included in the models. Education and marital status are assumed to affect the efficiency of health production and the propensity to seek care, whilst activity status and remoteness are more likely to affect the time price of health care use and the supply of health services. *Education* level was based on the individuals' highest qualification attainment; degree or higher, year 12 or certificate and year 11 or below. *Marital status* is separated into; married/living with someone, separated/divorced/widowed and unmarried not living with someone. *Activity status* was categorised according to: employed, unemployed and not in the labour force. *Remoteness* is classified into metropolitan and non-metropolitan regions. The age variable related to the age of the individual on 30 June 2004. For most of the analysis a continuous variable of age was used. For the remaining analysis age quintiles were generated giving; 15-34, 35-44, 45-64, 65-74 and 75 and over, age groups.

4. Econometric Framework

The quantity of hospital inpatient and day case visits are measured as count variables. Typically such data are concentrated on a few small values that are intrinsically non-negative and integer, and the distribution is substantially skewed. Also a sizeable fraction of the sample comprises non-users with zero use. The problem of a large number of zeros has motivated a variety of estimation strategies in the literature.

The Poisson distribution for the number of occurrences is usually too restrictive for health care utilisation, since the Poisson equidispersion property of equality of mean and variance is counter to the overdispersion displayed by most measures of health care use. Also the Poisson density predicts the probability of a zero count to be considerably less than is actually observed in the sample. To reduce these failures econometricians have used the negative binomial model. The negative binomial model allows for overdispersion as its conditional variance exceeds the conditional mean. However the negative binomial distribution may still under predict the number of zeros, especially when there is a substantial fraction of zeros and a long right tail. To overcome this complication we use a two-part (hurdle) model. Studies have shown that two-part models provide a better fit of health care utilisation data than Poisson / negative binomial models alone (Gerdtham, 1997; Pohlmeier and Ulrich, 1995). The first part is a binary outcome model that describes the determinants of use versus non-use. The second part models the distribution of use conditional on some use. By using the two-part model in conjunction with a negative binomial distribution for the positive counts, two sources of overdispersion can be allowed for, thus this model is flexible enough to handle either too few or too many zeros.

The two-part model used in this study to predict health care utilisation is based on a probit specification for the first part and a truncated negative binomial count model for the second (conditional) part. This model is based on the model proposed by Mullahy (1986) and subsequently used by Gerdtham (1997) and Wagstaff and Van Doorslaer (2000) to analyse equity in the utilisation of physician visits.

4.1 Estimation of access to hospital services

The probit model allows a mixture of categorical and continuous independent variables to predict one a dichotomous dependent variable. The following model was estimated:

1) $c_{it} = \sum_j \beta_j x_{ijt} + y_{it-1}\gamma + z_{it-1}\delta + \varepsilon_i$

Where c_{it} is a dichotomous dependent variable that takes the value of one if individual i was an inpatient (or day case patient) at least once during time t, and zero if they were not. y is the measure of equivalised household income at time $t-1$, x denotes the vectors of individual characteristics, such as age, education, gender and area of residence, they take the form of j dummy variables. Finally, z_{it-1} denotes the individual's health status z, at time $t-1$ and takes the form of a 1-year lagged categorical variable. The estimated coefficients of characteristics, income and health status are represented by β, γ and δ, respectively. The estimated coefficient γ is used to determine the direction of the inequity due to income group (i.e. positive or negative) and whether it is statistically significant.

4.2 Estimation of the utilisation of hospital services

4.2.1 Two-part model

The probit model estimates the probability of any positive health care utilisation in the HILDA wave 4 as:

2) $\Pr ob(y = 1|x) = \Lambda(x\beta)$

Where $\Lambda(.)$ is the cumulative density function of the probit distribution and β is the estimated parameter vector. For the second part a truncated negative binomial model was used with the truncation at zero. The expected value of positive utilisation with this model, conditional on utilisation being positive, is:

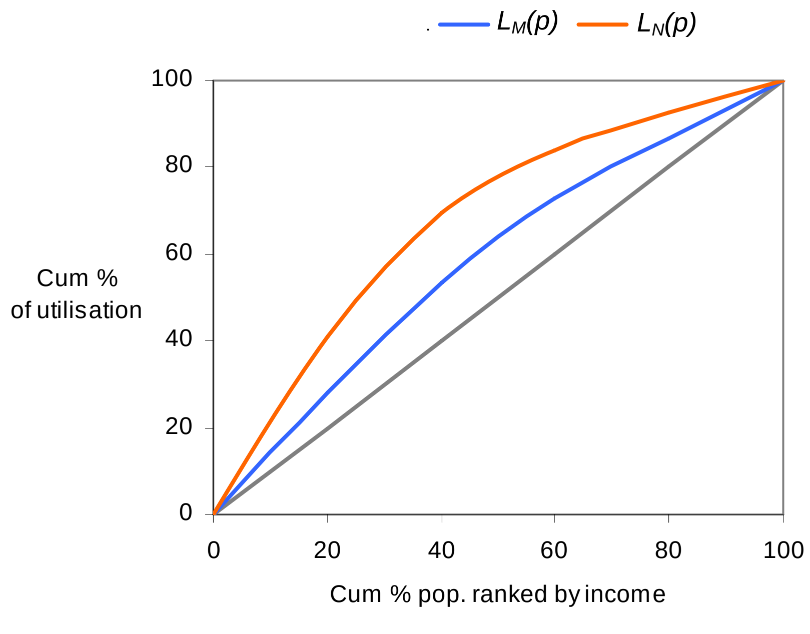
3) $E(y_i|y_i \geq 0, x) = \exp(x\beta)(\frac{1}{1-P_0})$

Where β is the estimated coefficient and P_0 is the probability of observing zero counts. $1/(1\text{-}P_0)$ is the adjustment factor to ensure that the probabilities of positive counts sum to one. The combined two-part model predictions of overall utilisation are obtained by multiplying the predictions from equation 2 and 3. Robust standard errors were calculated to allow for heteroskedasticity.

4.3 Measuring horizontal inequity

Empirically, horizontal equity can be measured by comparing the cumulative frequency curve of *observed* heath care utilisation across income, with the *expected* need adjusted distribution. Need is estimated from proxies such as health status indicators, age and sex. This approach is based on the use of concentration curves and draws heavily from the methodology proposed by Wagstaff and van Doorslaer (2000). The concentration curve of utilisation is defined as the cumulative proportion of utilisation as a function of the cumulative proportion of the population ranked by income. If health care utilisation were equal across socio-economic groups a uniform distribution would be expected (diagonal line, figure 1).

Figure 1: Schematic concentration curve for actual and need adjusted hospital care



Health care utilisation is usually more concentrated amongst deprived groups, consequently such curves tend to lie above the diagonal, $L_M(P)$. The need-adjusted concentration curve $L_N(P)$ was calculated for the individual as predicted by a set of indicator variables. The extent of horizontal inequity was determined by comparing the observed and need-adjusted concentration curves. If $L_N(P)$ lies above $L_M(P)$, the lower income groups receive less care than expected on the basis of need and there is pro-rich horizontal inequity. Conversely, if $L_N(P)$ lies below $L_M(P)$, the lower income groups receive more medical care than expected on the basis of need and there is pro-poor horizontal inequity.

4.3.1 The indirect standardisation-based approach

To quantify inequity the regression approach needs to be extended to derive an index of inequity. Two indices have been proposed in the literature (Wagstaff et al., 2000; Wagstaff et al., 1991). We use the indirect standardisation approach, termed the Wagstaff-van Doorslaer index of horizontal inequity (HI_{VW}) (Wagstaff and van Doorslaer, 2000).

Let m_i denote the amount of medical care received by individual i in a given period. The concentration index, C_M, which corresponding to $L_M(P)$, indicates the degree of inequality in the distribution of medical care and can be measured as twice the area between $L_M(P)$ and the diagonal. This can be calculated as:

4) $HI_{WVP} = 1 - 2\int_0^1 L_m^{+}(p)\mathrm{d}p = C_m^{+}$

The degree of inequality of medical care needs to be compared to the degree of inequality in need. Using the indirect standardisation method, a predicted value of m_i* for each individual i is calculated based on the amount of medical care, on average, the individual would have received if they had been treated identically to others with the same need characteristics. The need for medical care is termed N and a concentration index of need C_N based on the concentration curve of need $L_N(P)$ can be calculation as:

5) $C_N = 1 - 2\int_0^1 L_N(R)\mathrm{dR},$

The degree of horizontal equity can be determined by comparing each income group's need-adjusted utilisation with its observed utilisation. If the $L_M(P)$ and $L_N(P)$ curves coincide, horizontal equity is observed; otherwise the horizontal inequity HI_{VW} is defined as twice the area between the concentration curves and can be computed as:

6) $HI_{WV} = 2\int_0^1 \left[L_N(p) - L_M(p)\right] \, \mathrm{d}p = C_M - C_N$

A positive value of HI_{VW} indicates horizontal inequity favouring the better-off. A negative value of HI_{VW} indicates horizontal inequity favouring the worst-off. A zero HI_{VW} indicates no horizontal inequity, i.e. the $L_N(P)$ and $L_M(P)$ curves are proportionately distributed across income levels. [a]

Indices are computed following the method suggested by Van Doorslaer *et al* (2000). Details of this can be found in the appendix.

5. Results

Table 1 provides a summary of personal and health characteristics of the sample population in wave 4. Chapman *et al* (2004) has demonstrated that women are over-represented and Sydney residents and immigrants from non-English speaking backgrounds are under-represented in HILDA. In spite of these differences the sample broadly reflects the Australian population.

For the regression analysis equivalised household income is ranked according to size. For ease of extrapolation, income quintiles were calculated. The mean income and standard deviation for each quintile are: The bottom 20% ($12312; 3364); 20 – 40% ($22117; 3122); 40 – 60% ($33569; 3370); 60 – 80% ($46584; 4613); and top 20% ($84296; 41718).

The self reported health questionnaire is completed by the participant and returned by mail. Consequently fewer observations are available because of non-respondents. Reported health variables were lagged from the HILDA wave 3 dataset. The majority of individuals (71.7% (7866/11125)) reported either good or very good health and 3.1% (340/11125) reported poor health. 13.2% (1638/12408) and 12.2% (1518/12408) received treatment in a hospital during the

[a] It is possible for the concentration curves to cross, with inequity favouring the poor on one side and inequity favouring the rich on the other side. If these inequities were counterbalanced the index value would also be zero.

past 12 months, either as inpatients or day case patients, respectively. 50.6% (6252/12355) had private health insurance.

Table 1: The HILDA survey population and health characteristics.

		Respondents	
		Number	Percent
Number of Individuals		12408	100.0
Age	(mean, range)	43.90 *	(15 – 93)*
Age quintiles	15 – 34	4219	34.0
	35 – 44	2514	20.3
	45 – 64	3762	30.3
	65 – 74	1087	8.8
	75 and over	826	6.7
Sex	Male	5872	47.3
	Female	6536	52.7
Remoteness	Metropolitan	10662	85.9
	Non-Metropolitan	1746	14.1
Birthplace	Australia	9680	78.0
	English-speaking country	1276	10.3
	Other country	1451	11.7
Labour Force Status	Employed	7764	62.6
	Unemployed	413	3.3
	Not in labour force	4231	34.1
Education	Degree or higher	2421	19.5
	Year 12 or certificate	5220	42.1
	Year 11 or below	4767	38.4
Personal Status	Married/Living with someone	7258	58.5
	Divorced/Separated/Widowed	2242	18.1
	Living alone	2908	23.4
Self Reported health **	Excellent	1318	11.9
	Very good	3997	35.9
	Good	3869	34.8
	Fair	1601	14.4
	Poor	340	3.1
Hospital utilisation	Inpatients stay	1638	13.2
	Number of occasions	1.543 *	(1.233) *
	Number of nights stayed	5.156 *	(9.873) *
	Day patients	1518	12.2
	Number of occasions	1.706 *	(5.397) *
Private Health Insurance		6251	50.6
Type of PHI cover ***	Hospital and extras	4628	37.5
	Hospital only	1127	9.1
	Extras only	428	3.5
	None	6108	49.4

Number of observations differs for each question depending upon the number of missing answers. The percent given relates to the observation excluding missing data.
* (Mean and standard deviation) excludes individuals who have not visited hospital
** Wave 3 lagged data
*** 68 individuals (0.55%) do not know the type of private health insurance they have.

5.1 Hospital utilisation

Tables 2 shows the number and percentage of individuals receiving at least one inpatient or day case visit, by income and health status. The last column in the table shows the distribution of visits by income only. In total 18.7% of the bottom income group received inpatient treatment compared to 11.4% of the highest income group.

Table 2: The percentage of individuals treated as inpatients and day case patients by income and self reported health status.

	Income quintiles	Excellent		very good		Good		fair		poor		Mean/Total	
		%	N	%	n	%	N	%	n	%	n	%	n
Inpatients	Bottom 20%	7.7	151	11.2	489	18.2	732	23.9	548	36.7	154	**18.7**	**2074**
	20 – 40%	11.0	217	7.1	743	10.2	756	24.0	367	40.1	79	**12.8**	**2162**
	40 - 60%	7.6	263	9.0	830	11.5	773	18.9	232	49.9	29	**11.5**	**2127**
	60 - 80%	9.9	282	8.8	870	10.8	755	17.7	219	34.7	40	**11.1**	**2166**
	Top 20%	8.4	353	9.7	922	11.1	693	19.1	156	56.7	31	**11.4**	**2155**
	Mean/Total	9.0	1266	9.0	3854	12.3	3709	21.7	1522	40.6	333	**13.0**	**10684**
	Q1/Q5	0.92		1.15		1.64		1.25		0.90		**1.64**	
Day case patients	Bottom 20%	9.1	151	11.4	489	11.5	731	19.6	548	24.2	154	**14.4**	**2073**
	20 - 40%	9.2	217	7.9	743	12.8	756	17.2	367	20.3	79	**11.8**	**2162**
	40 - 60%	7.7	263	10.0	830	10.3	773	18.1	232	31.0	29	**11.1**	**2129**
	60 - 80%	7.2	282	9.1	870	11.9	755	14.8	219	26.9	40	**10.8**	**2166**
	Top 20%	7.5	353	10.9	922	13.7	693	21.2	156	29.7	31	**12.4**	**2155**
	Mean/Total	8.0	1266	9.8	3854	12.0	3708	18.2	1522	24.7	333	**12.1**	**10683**
	Q1/Q5	1.21		1.04		0.84		0.92		0.81		**1.16**	

% = The percent of individuals treated as inpatient/day patients

n = Total number of individuals (inpatient/day patients + not inpatient/day patients)

HILDA weights applied to all data

This pro-poor relationship indicates that individuals from the lowest income quintile are 64% (18.7/11.4) more likely to receive inpatient treatment compared with the highest income group. This tendency for individuals from the lowest income group to have a higher propensity to consume health care is not unexpected and consistent with the literature. However, the origin of such variation may be merely a reflection of inferior health status. Poor reported health is more prevalent in the lowest income group (154 compared to 31 in the highest) and excellent health is more prevalent in the high income group (353 compared to 151 in the lowest). This finding is consistent with previous studies and might explain the pro-poor bias. After adjusting for health status much of the inequality in inpatient treatment can be attributed to prior health status. Pro-poor utilisation still exists when prior health was very good, or fair, but the degree of this inequality is less than when health status is unadjusted. Only when prior health was good is the same magnitude of inequality retained.

The evidence for inequalities in day case visits is less compelling, since no obvious income trend was demonstrated. However the bottom income group are still more likely to receive day case treatment when compared to the other income quintiles. After adjusting for health status the degree of inequality in day patient treatment is negligible. For those in good, fair or poor health the top 20% are equally or more likely to be treated as day patients than those in the bottom 20%, (good Q1/Q5= 0.84; fair Q1/Q5= 0.92; poor Q1/Q5=0.81) with lower utilisation in the middle income groups.

5.2 Inpatient treatment - probit model

The probit model results for inpatient treatment are summarised in Table 3. The simplest model, model 1, compared income with treatment, without controlling for other factors. The income coefficient is significant and negative, indicating that as income increases the likelihood of inpatient treatment decreases. Model 2 controlled for health status with the reference category being excellent health. The estimated coefficients for reported health status are positive and significant for good, fair and poor health. This suggests that health status is associated with inpatient treatment and where health status is lower the likelihood of staying in hospital increases. Adding health dummies reduced the size of the income coefficient, which is still negative but no longer statistically significant.

Models 3 introduced age, gender, education, area of residence and employment status dummies to the regression. The 35-44 and 45-64 age groups are associated with a reduced likelihood of inpatient treatment when compared to the 15-35 age group. The 75 plus age groups are associated with an increased likelihood of inpatient treatment. Higher educated individuals are associated with a reduced probability of staying in hospital. Finally, unpaid workers/students and those retired are associated with an increased likelihood of inpatient treatment when compared to the employed. Overall, once health status is controlled for, inpatient utilisation seems equitably distributed as it does not depend on income.

Table 3: Probit model of the probability of being an inpatient

	Model 1		Model 2		Model 3		Model 4	
	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)
income	-0.0026***	(0.001)	-0.0010	(0.001)	0.0010	(0.001)	0.0007	(0.001)
health v.good $^{t-1}$			-0.0036	(0.056)	-0.0002	(0.058)	-0.0022	(0.058)
health good $^{t-1}$			0.1582**	(0.056)	0.1324*	(0.058)	0.1368*	(0.058)
health fair $^{t-1}$			0.5484***	(0.061)	0.4475***	(0.064)	0.4588***	(0.065)
health poor $^{t-1}$			1.0289***	(0.086)	0.8896***	(0.089)	0.9060***	(0.090)
age 35-44					-0.1474**	(0.047)	-0.1565**	(0.047)
age 45-64					-0.1417**	(0.043)	-0.1617***	(0.044)
age 65-74					0.0899	(0.070)	0.0635	(0.071)
age 75+					0.3235***	(0.079)	0.3071***	(0.080)
male					-0.0599	(0.033)	-0.0530	(0.033)
education_d2					0.0554	(0.045)	-0.0444	(0.045)
education_d3					-0.1201*	(0.047)	-0.1063*	(0.048)
remoteness					-0.0503	(0.045)	-0.0591	(0.045)
unemployed					0.0859	(0.097)	0.1074	(0.097)
unpaid/student					0.4001***	(0.044)	0.4132***	(0.044)
retired					0.2416***	(0.063)	0.2506***	(0.063)
private healthcare							0.0950**	(0.035)
constant	-1.0187***	(0.026)	-1.2790***	(0.055)	-1.2844***	(0.080)	-1.3227***	(0.082)
observations	10729		10729		10729		10729	
LR chi2	25.13		318.34		523.43		531.98	
Prob>chi2	0.000		0.000		0.000		0.000	
Pseudo R2	0.003		0.038		0.063		0.064	

level of significance * P = (0.05 – 0.01), ** P = (0.01 – 0.001), *** P < (0.001)

5.3 Day patient treatment - Probit model

The probit models for day case patients are summarised in Table 4. Model 1 shows that the income coefficient is not significant indicating no association between income and the probability of being a day patient. Model 2 controlled for health status with the reference category being excellent health. The estimated coefficients for reported health status are positive and significant for good, fair and poor health. This suggests that better health status is negatively associated with being a day patient and as health status deteriorates the likelihood of being a day patient increases. Adding health dummies increases the size of the income coefficient, which is now positive, but still insignificant.

Table 4: Probit model of day case patient against income

	Model 1		Model 2		Model 3		Model 4	
	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)
income	-0.0001	(0.000)	0.0008	(0.000)	0.0016**	(0.001)	0.0011*	(0.001)
health v.good $^{t-1}$			0.0996	(0.057)	0.0868	(0.058)	0.0783	(0.058)
health good $^{t-1}$			0.2320***	(0.057)	0.1939**	(0.058)	0.1945**	(0.058)
health fair $^{t-1}$			0.4815***	(0.063)	0.4013***	(0.066)	0.4140***	(0.066)
health poor $^{t-1}$			0.7043***	(0.091)	0.6076***	(0.094)	0.6307***	(0.094)
age 35-44					-0.0916	(0.047)	-0.1099*	(0.048)
age 45-64					0.0503	(0.042)	0.0192	(0.043)
age 65-74					0.3185***	(0.069)	0.2749***	(0.071)
age 75+					0.1098	(0.084)	0.0812	(0.084)
male					-0.1091**	(0.032)	-0.1000**	(0.033)
education_d2					-0.0378	(0.044)	-0.0136	(0.044)
education_d3					-0.1005*	(0.047)	-0.0701	(0.047)
remoteness					-0.0127	(0.045)	-0.0215	(0.046)
unemployed					0.1856*	(0.092)	0.2204*	(0.093)
unpaid/student					0.1536**	(0.046)	0.1752***	(0.046)
retired					0.0866	(0.063)	0.0995	(0.063)
private healthcare							0.1588***	(0.035)
constant	-1.1569***	(0.025)	-1.4184***	(0.056)	-1.3929***	(0.080)	-1.4020***	(0.083)
observations	10728		10728		10728		10728	
LR chi2	0.05		122.93		210.27		231.4	
Prob>chi2	0.8253		0.000		0.000		0.000	
Pseudo R2	0.000		0.015		0.027		0.029	

level of significance * P = (0.05 – 0.01), ** P = (0.01 – 0.001), *** P < (0.001)

Model 3 introduced age, gender, education, area of residence and employment dummies to the regression. With the reference category being the 15-34 age group, the 35-44 age groups are associated with a reduced likelihood of being a day patient. The 65-74 age group is significantly associated with being a day patient. Females, the unemployed and unpaid workers/students are significantly associated with an increased probability of being a day patient. Higher educated individuals are less likely to require day case treatment. Controlling for these variables increases the effect of income, which is now positive and statistically significant.

5.4 The role of private health insurance

Absence of PHI may influence an individual's decision to seek health care and act as a barrier to accessing health care. In the sample 50.6% (6251/12359) had PHI cover. Of those individuals receiving inpatient care 48.7% (795/1632) had PHI and 55.6% (842/1515) of those treated as day patients had PHI. Of those receiving inpatient care 45.6% (744/1632) were treated privately and those treated as day patients 55.6% (844/1518) were treated in a private hospital. Patients who stayed in hospital were more likely to be Medicare patients and patients receiving day case treatment were more likely to use the private health sector.

Private health insurance was added to the final models in Tables 3 and 4. PHI is positively associated with inpatient treatment. However, its introduction does not change the income effect. PHI is positively associated with the use of day patient care, and this association is statisitcially significant. The introduction of private health insurance reduces the effect of income, which is still positive and significant.

The following analysis splits the sample into those with and without PHI. After controlling for health status, age, gender, education, area of residence and employment, individuals with PHI show a positive association between income and inpatient treatment (Table 5). The same association is demonstrated between income and day case treatment. Both findings are statistically significant, which indicates pro-rich inequity within the group with PHI. Individuals without PHI exhibit a negative association between income and the likelihood of inpatient or day patient treatment. However, these findings are not significant.

The analysis of the role of PHI only refers to the association between PHI and utilisation. It is difficult to conclude anything about causality since there may be unobserved factors that influence the uptake of PHI that are also correlated with hospital utilisation, and hospital utilisation may also lead individuals to purchase PHI (Fiebig et al, 2006). Furthermore, the specification of a full behavioural model of hospital utilisation, in order to properly investigate the causes of inequity, requires more data on supply side variables, such as hospital and doctor characteristics. This would also improve the goodness of fit of the models.

Table 5: Probit regression of inpatients and day patients by private health insurance status, adjusting for health, sex, education and remoteness.

	Inpatients						Day Patients					
	Complete sample$^{\Psi}$		With PHI		Without PHI		Complete sample$^{\Psi}$		With PHI		Without PHI	
	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)
income	0.0011	(0.001)	0.0012*	(0.001)	-0.0020	(0.001)	0.0016*	(0.001)	0.0014*	(0.001)	-0.0002	(0.001)
health v.good $^{t-1}$	0.0005	(0.058)	0.0548	(0.078)	-0.0675	(0.087)	0.0827	(0.058)	0.0928	(0.075)	0.0513	(0.092)
health good $^{t-1}$	0.1356*	(0.058)	0.1770*	(0.079)	0.0921	(0.086)	0.1922*	(0.058)	0.1729*	(0.077)	0.2180*	(0.090)
health fair $^{t-1}$	0.4488***	(0.065)	0.4759***	(0.092)	0.4068***	(0.092)	0.3972***	(0.066)	0.4593***	(0.091)	0.3933***	(0.099)
health poor $^{t-1}$	0.8914***	(0.089)	1.3299***	(0.144)	0.6483***	(0.120)	0.6037***	(0.094)	0.5502***	(0.152)	0.6592***	(0.126)
age 35-44	-0.1473**	(0.047)	-0.1315*	(0.067)	-0.1856**	(0.068)	-0.0951	(0.048)	-0.1113	(0.066)	-0.1102	(0.069)
age 45-64	-0.1435**	(0.043)	-0.1608**	(0.060)	-0.1758**	(0.065)	0.0491	(0.042)	0.0245	(0.058)	0.0092	(0.065)
age 65-74	0.0894	(0.070)	0.0625	(0.097)	0.0540	(0.106)	0.3173***	(0.070)	0.3385***	(0.093)	0.1956	(0.111)
age 75+	0.3248***	(0.079)	0.2855*	(0.115)	0.2954**	(0.114)	0.1098	(0.084)	0.0515	(0.119)	0.1143	(0.122)
male	-0.0582	(0.033)	-0.0586	(0.046)	-0.0423	(0.048)	-0.1085**	(0.033)	-0.1428**	(0.044)	-0.0515	(0.049)
education_d2	-0.0564	(0.045)	-0.0476	(0.056)	-0.0423	(0.080)	-0.0342	(0.044)	-0.0527	(0.054)	0.0752	(0.083)
education_d3	-0.1235**	(0.048)	-0.0805	(0.061)	-0.1398*	(0.081)	-0.0992	(0.047)	-0.0736	(0.060)	-0.0152	(0.085)
remoteness	-0.0516	(0.045)	-0.0454	(0.069)	-0.0640	(0.060)	-0.0088	(0.046)	0.0343	(0.069)	-0.0636	(0.061)
unemployed	0.0924	(0.097)	0.2431	(0.174)	0.0446	(0.120)	0.1912	(0.093)	0.0964	(0.179)	0.2467*	(0.111)
unpaid/student	0.4029***	(0.044)	0.3431***	(0.065)	0.4605***	(0.063)	0.1577*	(0.046)	0.1360*	(0.067)	0.1920**	(0.065)
retired	0.2427***	(0.063)	0.1990*	(0.084)	0.3001**	(0.098)	0.0881	(0.063)	0.1248	(0.081)	0.0546	(0.102)
constant	-1.2850***	(0.079)	-1.3067***	(0.112)	-1.1819***	(0.129)	-1.3967***	(0.082)	-1.3375***	(0.111)	-1.3626***	(0.134)
observations	10696		5571		5125		10695		5571		5124	
LR chi2	524.45		250.74		306.51		210.56		122.64		108.00	
Prob>chi2	0.000		0.000		0.000		0.000		0.000		0.000	
Pseudo R2	0.063		0.059		0.076		0.026		0.028		0.030	

level of significance * P = (0.05 – 0.01), ** P = (0.01 – 0.001), *** P < 0.001, $^{\Psi}$ 33 individuals did not indicate their private health insurance status

5.5 Health care utilisation adjusted for health status and income

Our focus has been whether an individual received hospital treatment during the previous 12 month period. No account was made for the quantity of health care received. Table 6 shows the quantity of health care consumed by individuals conditional on receiving hospital treatment. Three measures of hospital utilisation are described: 1) the mean number of discrete occasions stayed in hospital as an inpatient, 2) the mean number of nights stayed during the most recent inpatient stay and 3) the mean number of day case visits.

Table 6: Mean number of occasions and nights stayed in hospital, and number of times treated as a day patient, by income and self reported health status.

		Self report health status							
	Income quintiles	Excellent or very good		good		fair or poor		**Mean/total**	
		mean	(n)	mean	(n)	mean	(n)	**mean**	**(n)**
Occasions treated as inpatient	Bottom 20%	1.199	(67)	1.493	(131)	1.934	(189)	**1.658**	**(387)**
	20 - 40%	1.471	(82)	1.667	(82)	1.758	(121)	**1.653**	**(285)**
	40 - 60%	1.204	(104)	1.245	(92)	1.815	(57)	**1.375**	**(253)**
	60 - 80%	1.262	(100)	1.422	(77)	1.707	(52)	**1.419**	**(229)**
	Top 20%	1.194	(121)	1.555	(72)	1.546	(46)	**1.382**	**(239)**
	Mean/Total	1.259	(474)	1.471	(454)	1.804	(465)	**1.515**	**(1393)**
	Q1/Q5	1.004		0.960		1.251		**1.200**	
Nights stayed in hospital	Bottom 20%	4.833	(67)	5.312	(131)	7.598	(190)	**6.348**	**(388)**
	20 - 40%	4.215	(82)	4.570	(83)	7.933	(121)	**5.970**	**(286)**
	40 - 60%	3.573	(104)	3.956	(91)	5.368	(56)	**4.165**	**(251)**
	60 - 80%	5.443	(100)	3.710	(77)	9.569	(52)	**5.778**	**(229)**
	Top 20%	3.000	(119)	3.818	(72)	5.409	(46)	**3.760**	**(237)**
	Mean/Total	4.140	(472)	4.371	(454)	7.396	(465)	**5.330**	**(1391)**
	Q1/Q5	1.611		1.391		1.405		**1.688**	
Occasions treated as a day patient	Bottom 20%	1.202	(71)	1.444	(85)	3.995	(148)	**2.631**	**(304)**
	20 - 40%	1.170	(87)	1.315	(101)	2.331	(78)	**1.595**	**(266)**
	40 - 60%	1.208	(107)	1.209	(83)	3.275	(46)	**1.682**	**(236)**
	60 - 80%	1.284	(100)	1.492	(95)	1.369	(42)	**1.382**	**(237)**
	Top 20%	2.026	(128)	1.359	(95)	1.867	(42)	**1.757**	**(265)**
	Mean/Total	1.434	(493)	1.366	(459)	2.931	(359)	**1.836**	**(1308)**
	Q1/Q5	0.593		1.063		2.140		**1.497**	

(HILDA weights applied to all data)

When only considering the relationship between income and utilisation (last column), all measures of utilisation exhibit a propensity for higher utilisation amongst the lower income groups. However, the top 20% of the income distribution have a higher number of day patient visits than those in the middle income groups. The results show that individuals from the lowest income group are likely to spend 69% (6.348/3.760) more nights in hospital than their high earning counterparts, although the 60-80% income quintile showed high utilisation. They are also likely to stay in hospital on 20% (1.658/1.382) more occasions and be day patients on 50% (2.631/1.757) more occasions.

Table 6 also shows the mean health care utilisation by income and subdivided into health status. To minimise errors and spurious findings resulting from small numbers, excellent health and very good health have been collapsed into one column. For the same reason, fair health and poor health have also been collapsed into one column.

Much of the inequality in the number of separate occasions stayed in hospital can be attributed to prior health status, especially when prior health was good or better. Pro-poor utilisation still exists when prior health was poor, albeit to a lesser extent than when health status is unadjusted. The mean number of nights stayed in hospital increases when prior health status is poor. However, in all health categories, number of nights stayed in hospital is consistently higher in lower income groups.

For day case visits pro-poor utilisation still exists when prior health was poor and the degree of this inequality is more than when health status is unadjusted. When health status is very good or excellent, pro-rich inequality is evident, with the highest income group likely to have 69% more visits (2.026/1.202) than their low income counterparts.

5.6 Number of occasions treated as a inpatient – negative binomial regression analysis

The regression model results for number of occasions receiving inpatient treatment are summarised in Table 7. Model 1 shows that the income coefficient is significant and negative, indicating that as income increases the number of occasions receiving inpatient treatment decreases. Model 2 controlled for health status with the reference category being excellent health. The estimated coefficients for reported health status are positive and significant for good, fair and poor health. This suggests that health status is associated with inpatient treatment and as health status deteriorates the occasions receiving inpatient treatment increases. Adding health dummies reduced the magnitude of the income coefficient, which is still negative but no longer statistically significant.

Table 7: Negative binomial regression model of the number of occasions treated as an inpatient

	Model 1		Model 2		Model 3		Model 4	
	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)
income	-0.0026**	(0.001)	-0.0013	(0.001)	-0.0004	(0.001)	-0.0002	(0.001)
health v.good $^{t-1}$			0.0496	(0.097)	0.0523	(0.098)	0.0539	(0.099)
health good $^{t-1}$			0.2203*	(0.093)	0.2240*	(0.096)	0.2229	(0.097)
health fair $^{t-1}$			0.3318**	(0.095)	0.3146**	(0.100)	0.3104	(0.101)
health poor $^{t-1}$			0.5830***	(0.104)	0.5686***	(0.109)	0.5669	(0.110)
age 35-44					-0.0196	(0.072)	-0.0176	(0.072)
age 45-64					-0.0041	(0.064)	0.0022	(0.065)
age 65-74					0.0438	(0.092)	0.0528	(0.093)
age 75+					-0.0370	(0.099)	-0.0316	(0.100)
male					0.0167	(0.046)	0.0132	(0.046)
education_d2					0.0559	(0.067)	0.0504	(0.067)
education_d3					0.1035	(0.068)	0.0975	(0.068)
remoteness					-0.1573**	(0.057)	-0.1517**	(0.058)
unemployed					0.4703***	(0.122)	0.4653*	(0.122)
unpaid/student					0.0904	(0.059)	0.0830	(0.060)
retired					0.0255	(0.083)	0.0204	(0.083)
private healthcare							-0.0442	(0.048)
constant	0.5126***	(0.035)	0.2325***	(0.092)	0.2180	(0.121)	0.2351	(0.122)
observations	1402		1402		1402		1402	
LR chi2	11.97		69.93		97.14		97.55	
Prob>chi2	0.001		0.001		0.000		0.000	
Pseudo R2	0.003		0.018		0.024		0.027	

level of significance * P = (0.05 – 0.01), ** P = (0.01 – 0.001), *** P < (0.001)

Models 3 introduced age, gender, education, area of residence dummies and employment status to the regression. The effect of income remains insignificant. The coefficient for area of residence is negative and significant suggesting that individuals from rural areas are likely to receive inpatient treatment on more occasions. Being unemployed is associated with receiving inpatient treatment on more occasions. Private health insurance was added to the final model. PHI is negatively associated with the number of occasions receiving inpatient treatment. However, its introduction does not change the income effect.

5.7 Length of inpatient treatment – negative binomial regression analysis

The regression model results for number of nights receiving inpatient treatment are summarised in Table 8. Model 1 shows that the income coefficient is significant and negative, indicating that as income increases the number of nights stayed in hospital decreases. Model 2 controlled for health status with the reference category being excellent health. The effect of income remains statistically significant. The estimated coefficients for reported health status are positive and significant for fair and poor health. This suggests that health status is associated with inpatient treatment and as health status deteriorates the length of hospital stay increases.

Table 8: Negative binomial regression model of the number of nights treated as an inpatient

	Model 1		Model 2		Model 3		Model 4	
	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)
income	-0.0049***	(0.001)	-0.0032***	(0.001)	-0.0013	(0.001)	-0.0013	(0.001)
health v.good $^{t-1}$			0.0051	(0.109)	-0.0080	(0.108)	-0.0102	(0.109)
health good $^{t-1}$			0.0483	(0.106)	-0.0047	(0.108)	-0.0108	(0.108)
health fair $^{t-1}$			0.4675***	(0.110)	0.3088**	(0.112)	0.3026**	(0.112)
health poor $^{t-1}$			0.6562***	(0.128)	0.5296***	(0.129)	0.5230***	(0.129)
age 35-44					-0.1055	(0.086)	-0.1077	(0.086)
age 45-64					0.0393	(0.078)	0.0391	(0.078)
age 65-74					0.1948	(0.114)	0.1925	(0.115)
age 75+					0.5385***	(0.123)	0.5380***	(0.123)
male					0.0546	(0.056)	0.0554	(0.056)
education_d2					-0.1746*	(0.077)	-0.1721*	(0.077)
education_d3					-0.3414***	(0.079)	-0.3381***	(0.079)
remoteness					0.0810	(0.075)	0.0814	(0.075)
unemployed					-0.0128	(0.180)	-0.0141	(0.180)
unpaid/student					0.3459***	(0.071)	0.3475***	(0.071)
retired					0.2172*	(0.104)	0.2169*	(0.104)
private healthcare							0.0078	(0.059)
constant	1.7794***	(0.042)	1.4978***	(0.104)	1.3287***	(0.140)	1.3302***	(0.141)
observations	1400		1400		1400		1400	
LR chi2	28.79		110.39		215.69		214.15	
Prob>chi2	0.000		0.000		0.000		0.000	
Pseudo R2	0.004		0.015		0.029		0.028	

level of significance * P = (0.05 – 0.01), ** P = (0.01 – 0.001), *** P < (0.001)

Models 3 introduced age, gender, education, area of residence dummies and employment to the regression. The 75+ age group are more likely to stay longer in hospital. Education is negatively associated with length of hospital stay. Being an unpaid worker/student is associated with length of hospital stay. Income is not associated with number of nights once other factors have been controlled for. Private health insurance was added to the final model. PHI was not associated with length of hospital visit.

5.8 Number of occasions treated as a day patient – regression analysis

The regression model results for number of occasions receiving day patient treatment are summarised in Table 9. Model 1 compared income with treatment. The income coefficient is negative and significant, indicating an income effect on the number of occasions receiving day patient treatment. Model 2 controlled for health status. Only when health status was fair or poor did the association between health and treatment become significant.

Table 9: Negative binomial regression model of the number of occasions treated as a day patient

	Model 1		Model 2		Model 3		Model 4	
	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)
income	-0.0024**	(0.001)	-0.0005	(0.001)	0.0006	(0.001)	0.0009	(0.001)
health v.good $^{t-1}$			0.1238	(0.120)	0.1011	(0.121)	0.1063	(0.121)
health good $^{t-1}$			0.0929	(0.118)	0.0619	(0.120)	0.0603	(0.120)
health fair $^{t-1}$			0.7947***	(0.120)	0.6927***	(0.125)	0.6884***	(0.126)
health poor $^{t-1}$			0.5615***	(0.150)	0.4221**	(0.155)	0.4070**	(0.156)
age 35-44					-0.0081	(0.092)	-0.0033	(0.092)
age 45-64					-0.0087	(0.078)	-0.0018	(0.078)
age 65-74					-0.0813	(0.117)	-0.0647	(0.118)
age 75+					-0.3063*	(0.142)	-0.2974*	(0.142)
male					0.0986	(0.058)	0.0893	(0.059)
education_d2					0.0806	(0.081)	0.0671	(0.082)
education_d3					0.1004	(0.086)	0.0818	(0.087)
remoteness					0.1806	(0.083)	0.1819	(0.083)
unemployed					0.5322***	(0.149)	0.5259***	(0.149)
unpaid/student					0.3218***	(0.079)	0.3078***	(0.080)
retired					0.3003**	(0.107)	0.2949**	(0.107)
private healthcare							-0.0829	(0.063)
constant	0.6177***	(0.044)	0.2267*	(0.114)	-0.1671	(0.157)	-0.1170	(0.161)
observations	1314		1314		1314		1314	
LR chi2	7.84		129.01		165.42		166.99	
Prob>chi2	0.0051		0.0000		0.0000		0.0000	
Pseudo R2	0.002		0.029		0.037		0.037	

level of significance * P = (0.05 – 0.01), ** P = (0.01 – 0.001), *** P < (0.001)

Models 3 & 4 indicate that the over 75s consume less day care visits. Being unemployed, unpaid/student or retired are positively associated with day patient treatment. The effect of income on the number of day patient visits is not significant once other factors have been controlled for.

5.9 Horizontal inequality indices

The estimated C_M, C_N and HI_{WV} indices are presented in Table 10 for the number of occasions stayed in hospital, number of nights stayed in hospital and number of day case visits. The negative concentration indices for all hospital utilisation measures confirm that individuals from lower income groups use hospital services more often than high income groups. However, this unequal distribution is reversed when the distribution is controlled for health status, age, gender, education, area of residence and employment. The significant, positive HI_{WV} indices indicate horizontal inequality favouring the rich. This phenomenon is present in both measures of inpatient utilisation. The day patient HI_{WV} index is positive but not significant.

Table 10: $\mathbf{HI_{WV}}$ indices for inpatient stay and day case visits

	Concentration indices				HI_{wv} indices	
	(unstandardised)		(standardised)			
	coef.	(se)	coef.	(se)	coef.	(se)
Inpatient						
number of occasions	-0.0543	(0.012)	-0.2532	(0.018)	0.1997***	(0.019)
number of nights	-0.0165	(0.004)	-0.2491	(0.019)	0.1474***	(0.028)
Day case patient						
number of occasions	-0.0780	(0.048)	-0.1363	(0.02)	0.0595	(0.061)

level of significance * P = (0.05 – 0.01), ** P = (0.01 – 0.001), *** P < 0.001
Unstandardised CI = C_M, Standardised CI = C_N

Previous Australian studies demonstrated access to inpatients services favoured the worst-off, but the number of nights treated was equitable and inequity of inpatient services favouring the better-off and inequality of outpatient's services favouring the worst-off (van Doorslaer et al., 2002; Lairson et al, 1995). Furthermore, by comparing the results presented here using 2004 data, with the two previous Australian studies, the degree of inequality in inpatient utilisation appears to be increasing (HI_{WV} 2004 = 0.199; 2000 = -0.049; 1989/90 = 0.050). The degree of inequalities in day care utilisation appears to have become equitable rather than pro-poor (HI_{WV} 2004 = 0.059; 1989/90 = -0.103). However, these studies have used different data and so are not directly comparable.

6. Conclusions

This paper provides the most recent evidence regarding inequality and inequity in the utilisation of hospital services in Australia. It is also the first study to use the HILDA survey for this purpose and the first to differentiate between day and inpatient treatment. Our measures of both household income and health status are lagged to reduce any reverse causality. Individuals from the lowest income group are twice as likely to receive inpatient treatment compared with the highest income group. For inpatient treatment, there is no evidence of income-related inequities in access. However, horizontal inequality indices examining the number of inpatient episodes and length of stay shows inpatient treatment was inequitable, favouring the higher income groups. The reverse is the case for day patient treatment. There is evidence of inequities in access favouring the rich once we adjust for health care need. However, the quantity of day case treatments appears to be equitable.

Previous studies demonstrated that Mexico and Portugal have pro-rich inequity for inpatient treatment, whilst pro-poor inequity was demonstrated in countries with diverse health services such as, Switzerland, Canada, and the United States(Van Doorslaer and Masseria, 2004; Van Doorslaer et al., 2002). In most European countries inpatient treatment was equitable. Previous Australian studies demonstrated access to inpatients services favoured the worst-off, but the number of nights treated was equitable (Van Doorslaer et al., 2002) and Lairson *et al* (1995) found inequity of inpatient services favouring the better-off and inequity of outpatient's services favouring the worst-off. Furthermore, by comparing the results presented here using 2004 data, with previous Australian studies, the degree of inequity in inpatient utilisation appears to be increasing (HI_{WV} 2004 = 0.199; 2000 = -0.049; 1989/90 = 0.050)[17 20]. The degree of inequalities in day care utilisation appears to have become equitable rather than pro-poor (HI_{WV} 2004 = 0.059; 1989/90 = -0.103). However, these studies have used different data and so are not directly comparable.

The reasons for these inequities are also partly investigated, although further research is required. Inpatient treatment is more likely to occur in public hospitals whilst day case patients predominantly used the private sector. The pro-rich inequity in access for day patients is partly accounted for by those with PHI. Individuals with PHI demonstrate a positive association between income and access, suggesting that PHI increases the probability of receiving day case treatment. Supplementary PHI may provide faster access to treatment within a private hospital. Conversely, absence of PHI may provide a barrier to using health care, especially when co-payments are applicable. In terms of the inequities in the utilisation of inpatient treatment, there was no evidence that PHI played a role.

There are a number of caveats to this study. The analysis of the role of PHI only refers to the association between PHI and utilisation. It is difficult to conclude anything about causality since there may be unobserved factors that influence the uptake of PHI that are also correlated with hospital utilisation, and hospital utilisation may also lead individuals to purchase PHI (Burstrom and Fredlund, 2001). Furthermore, the specification of a full behavioural model of hospital utilisation, in order to properly investigate the causes of inequity, requires more data on supply side variables, such as hospital and doctor characteristics. This would also improve the goodness of fit of the models.

We only used hospital utilisation data. Obviously, individuals have other treatment options. Lower income groups may receive more treatment within primary care, or are more likely to use emergency departments. Previous studies have shown equitable utilisation of GP services (Van Doorslaer et al., 2002; Van Doorslaer et al., 2000), although these did not include Australia. Individuals from lower income groups may delay seeking hospital treatment and consequently rely more upon emergency services. Ideally determining equity within an entire health system requires investigation of GP and emergency services, plus complimentary and alternative medicine use.

A key unresolved issue in studies such as this is examination of the causes of pro-rich inequity. Only by further investigating these causes can policies be devised to reduce inequity, if so desired. The causes may therefore include differences in the preferences of higher income patients and in the preferences of health care providers. Good health is an important element of a persons functioning, but if people have the opportunity to achieve this functioning and yet choose not do to so, we cannot infer automatically that all inequalities in health care are inequitable. It is possible that for any level of need, higher income 'better educated' individuals are more inclined to seek treatment. Therefore the policy aim may be to achieve equity of access and accept whatever consumption of health care prevails. However, there is growing agreement that inequalities in health outcomes between rich and poor are unjust and unfair[46], because they correspond to differing constraints and opportunities, rather than a propensity to make different choices (Alleyne et al, 2000; Le Grand, 1987; Wagstaff, 2001).

Once a patient has visited a health care provider, the existence of the agency relationship and asymmetry of information suggest that patients' progress through the system is more heavily influenced by the preferences of providers and the organisation and financing of the system. This may also be a source of inequity if patients of different socio-economic background and education levels receive different types of treatment, and this has been shown to be the case. For example, although more men than women suffer from coronary heart disease, there is no evidence to suggest that women are less likely to benefit from treatment. However, gender and age inequalities in the provision of revascularisation have been demonstrated in the UK (Shaw et al, 2004; Petticrew et al, 1993). Gender and socio-economic inequalities in the access to cardiac procedures have been found in Sweden (Haglund et al., 2004). Rates of cardiac catheterisation after acute myocardial infarction have been shown to increase with socio-economic status in Canada (Pilote et al., 2003). Finally, in the United States, high-income individuals are 22% more likely to undergo catheterisation, 74% more likely to undergo PTCA, and 48% more likely to undergo CABG, than low-income individuals, even after adjusting for other risk factors (Philbin et al., 2000).

The reasons for these differences include the preferences GPs to refer and the preferences of the hospital doctors or private specialists to admit and treat a patient. Income may not only influence the patients' decisions to seek treatment, but stimulate provider incentives. For example, higher income patients are financially more attractive to health care providers because they generate higher fees. The policy implications of this suggests it is not just about health care services being in the right place, but also about the preferences of health care providers and the incentives they face. If factors other than clinical need determine a patient's path through the system and the amount of resources they use, then this is an important source of inequity that needs to be addressed.

Appendix 1 - Computing and testing of inequity indices

Indices are computed following the method suggested by Van Doorslaer *et al* (2000). If m (m^*) is the sample mean of m_i (m_i^*), then the concentration indices corresponding to actual medical use, C_M, can be computed using:

$$7)\quad C_M = \frac{2}{N \cdot m} \sum_{i=1}^{N} m_i R_i - 1$$

Where N is the sample size and R_i is the relative rank of the ith person. C_N can be calculated in the same way by replacing m_i and m with m_i^* and m^*, respectively.

The concentration indices, C_M and C_N can also be computed using the regression suggested by Kakwani *et al* (1997). For example C_M can be computed using:

$$8)\quad 2\sigma_R^2 \left[m_i / m \right] = \gamma_1 + \delta_1 R_i + u_i$$

Where σ_R^2 denotes the variance of the relative rank. The OLS estimator of δ_1 is equal to:

$$9)\quad \widehat{\delta}_1 = \frac{2}{N \cdot m} \sum_{i=1}^{N} \left(m_i - m \right) \left(R_i - \frac{1}{2} \right)$$

Which means $\widehat{\delta}_1$ is equal to C_M in equation 7.

The inequity indices are calculated from the dataset, therefore in order to test for statistical significance of these indices, standard errors need to be computed. Application of OLS to equation 8 automatically provides standard errors for C_M and C_N. However C_M and C_N are not independently distributed, consequently obtaining standard errors for HI_{VW} requires further elaboration using the following regression:

$$10)\quad 2\sigma_R^2 \left[\frac{m_i}{m} - \frac{m_i^*}{m^*} \right] = \gamma_2 + \delta_2 R_i + u_i$$

The OLS estimate of δ_2 is equal to HI_{VW} and from the regression, standard errors of HI_{VW} are obtained. To allow for heteroskedasticity robust standard errors for equation 10 using White's and Huber's corrections are generated in Stata version 9.

Appendix 2.

Table A2. Negative binomial regression of hospital services by private health insurance status, adjusting for health, sex, education and remoteness.

	Inpatients (number of occasions)						Inpatients (number of nights)						Day patients (number of occasions)					
	Complete sample$^{\Psi}$		With PHI		Without PHI		Complete sample$^{\Psi}$		With PHI		Without PHI		Complete sample$^{\Psi}$		With PHI		Without PHI	
	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)	coef.	(se)
income	-0.0004	(0.001)	0.0002	(0.001)	-0.0016	(0.002)	-0.0013	(0.001)	-0.0010	(0.001)	-0.0027	(0.003)	0.0006	(0.001)	0.0017	(0.001)	-0.0025	(0.003)
health v.good $^{t-1}$	0.0523	(0.099)	0.1359	(0.138)	-0.0458	(0.144)	-0.0095	(0.109)	0.0592	(0.143)	-0.0978	(0.170)	0.1021	(0.121)	0.1691	(0.143)	0.0986	(0.210)
health good $^{t-1}$	0.2231*	(0.096)	0.2538	(0.138)	0.1958	(0.136)	-0.0105	(0.108)	0.0639	(0.144)	-0.0860	(0.164)	0.0625	(0.120)	0.1010	(0.145)	0.1279	(0.202)
health fair $^{t-1}$	0.3151**	(0.101)	0.3784*	(0.146)	0.2412	(0.141)	0.3020**	(0.112)	0.3674*	(0.156)	0.2618	(0.167)	0.6961***	(0.125)	0.6118***	(0.151)	0.6897**	(0.211)
health poor $^{t-1}$	0.5680***	(0.110)	0.6052***	(0.160)	0.5199**	(0.153)	0.5233***	(0.130)	0.7413***	(0.180)	0.3553	(0.190)	0.4237**	(0.155)	0.2135	(0.230)	0.4373	(0.238)
age 35-44	-0.0214	(0.072)	-0.0785	(0.103)	0.0282	(0.102)	-0.1070	(0.086)	-0.0642	(0.113)	-0.1525	(0.132)	-0.0102	(0.092)	0.1120	(0.112)	-0.2281	(0.151)
age 45-64	-0.0056	(0.064)	-0.0519	(0.092)	0.0372	(0.092)	0.0406	(0.077)	0.0314	(0.105)	0.0631	(0.118)	-0.0115	(0.078)	-0.1529	(0.100)	0.2222	(0.123)
age 65-74	0.0422	(0.064)	-0.1355	(0.139)	0.2031	(0.127)	0.1943	(0.114)	0.1151	(0.155)	0.2518	(0.172)	-0.0837	(0.117)	-0.2885*	(0.144)	0.3028	(0.201)
age 75+	-0.0389	(0.099)	-0.0380	(0.150)	-0.0292	(0.135)	0.5382***	(0.123)	0.0842	(0.172)	0.8998***	(0.180)	-0.3094*	(0.142)	-0.1954	(0.187)	-0.2090	(0.223)
male	0.0162	(0.046)	0.0074	(0.066)	0.0171	(0.064)	0.0549	(0.056)	0.0116	(0.075)	0.0646	(0.084)	0.0980	(0.059)	0.0631	(0.074)	0.1597	(0.095)
education_d2	0.0565	(0.067)	0.0812	(0.083)	0.0117	(0.117)	-0.1733*	(0.077)	-0.1770	(0.091)	-0.1160	(0.144)	0.0805	(0.081)	0.0798	(0.089)	0.0762	(0.174)
education_d3	0.1051	(0.068)	0.0882	(0.088)	0.0898	(0.116)	-0.3395***	(0.078)	-0.2866**	(0.098)	-0.3205*	(0.141)	0.1021	(0.086)	-0.1494	(0.101)	0.2981	(0.176)
remoteness	-0.1563**	(0.057)	-0.2181*	(0.092)	-0.0940	(0.075)	0.0824	(0.074)	0.1353	(0.112)	0.0248	(0.102)	0.1810*	(0.083)	-0.0443	(0.114)	0.4095**	(0.120)
unemployed	0.4679***	(0.122)	0.4158*	(0.198)	0.4704**	(0.161)	-0.0150	(0.180)	-0.0723	(0.276)	-0.0295	(0.243)	0.5290***	(0.149)	1.2516***	(0.220)	-0.0339	(0.209)
unpaid/student	0.0891	(0.059)	0.0547	(0.087)	0.0733	(0.088)	0.3466***	(0.071)	0.399***	(0.095)	0.2632*	(0.112)	0.3191***	(0.079)	0.3425**	(0.102)	0.1747	(0.132)
retired	0.0244	(0.083)	0.1348	(0.118)	-0.0898	(0.121)	0.2167*	(0.104)	0.4192**	(0.134)	-0.0558	(0.164)	0.2985**	(0.107)	0.3521**	(0.124)	0.0908	(0.194)
constant	0.2194	(0.121)	0.2088	(0.168)	0.2925	(0.196)	1.3325***	(0.140)	1.1980***	(0.181)	1.4813***	(0.251)	-0.1653	(0.157)	0.0551	(0.191)	-0.3756	(0.286)
observations	1398		715		683		1396		712		684		1311		748		563	
LR chi2	96.71		42.78		55.50		214.13		110.83		118.29		165.23		105.01		117.49	
Prob>chi2	0.000		0.000		0.000		0.000		0.000		0.000		0.1494		0.000		0.000	
Pseudo R2	0.024		0.022		0.027		0.028		0.030		0.031		0.037		0.042		0.057	

level of significance * P = (0.05 – 0.01), ** P = (0.01 – 0.001), *** P < 0.001,

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