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ARTICLE

Understanding household healthcare expenditure can promote health policy reform

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Abstract
Studies of health care expenditure often exclude explanatory variables measuring wealth, despite the intuitive importance and policy relevance. We use the Household, Income and Labour Dynamics in Australia Survey to assess impacts of income and wealth on health expenditure. We investigate four different dependent variables related to health expenditure and use three main methodological approaches. These approaches include a first difference model and introduction of a lagged dependent variable into a cross-sectional context. The key findings include that wealth tends to be more important than income in identifying variation in health expenditure. This applies for health variables which are not directly linked to means testing, such as spending on health practitioners and for being unable to afford required medical treatment. In contrast, the paper includes no evidence of different impacts of income and wealth on spending on medicines, prescriptions or pharmaceuticals. The results motivate two novel policy innovations. One is the introduction of an asset test for determining rebate eligibility for private health insurance. The second is greater focus on asset testing, rather than income tests, for a wide range of general welfare payments that can be used for health expenditure. Australia's world-leading use of means testing can provide a test case for many countries.

Keywords: Financial assets; health expenditure; health policy; income; means testing; private health insurance; wealth

JEL: D14; I12; I13; I14; I18

1. Introduction

Health care expenditures vary significantly across different geographies and over time. Understanding the major determinants of health care expenditures is crucial to explain the optimal level of health care spending in countries and in the design of policies. There are different factors explaining variations in per-capita health care spending across countries such as institutional and socio-demographic factors (Gerdtham *et al*., 1992), the age profile of the population (Grossman, 1972; Leu, 1986; Culyer, 1988; Hitiris and Posnett, 1992; Di Matteo and Di Matteo, 1998; Baltagi and Moscone, 2010), the role of government funded health care (Leu, 1986; Culyer, 1988; Hitiris and Posnett, 1992), the role of real prices (Grossman, 1972; Gerdtham *et al*., 1992; Murthy and Ukpolo, 1994; Okunade *et al*., 2004; Hartwig, 2008), technological progress (Newhouse, 1992; Weil, 1995; Baker and Wheeler, 2000; Gerdtham and Lothgren, 2000; Di Matteo, 2003) and the R&D spending for health care (Okunade and Murthy, 2002). However, studies on impacts of other key variables such as wealth are scarce (Kendall *et al*., 2019; Pinilla and López-Valcárcel, 2020).

On the other hand, income has been defined as a key determinant explaining variety in the level of health care expenditure. Therefore, literature has often focused on the income elasticity of health care and its health policy implications for the financing of health care. The studies investigating the effect of income on health care expenditures have employed several methodologies including simple bivariate regressions on cross-sections, multivariate regressions on cross-sections, time-series techniques and error-correction models and these studies have used international, national and regional level datasets (Di Matteo, 2003). These studies differ significantly in terms of their results due to heterogeneity in methodologies. Getzen (2000) state that the value of income elasticity can differ based on the level of analysis.

Therefore; our study aims to shed light on these issues by (1) defining particular health care expenditures in the analysis that include spending on health practitioners, private health insurance and medicines, prescriptions or pharmaceuticals; (2) performing one country analysis with multiple controls; (3) implementing three different methodologies that accounts for trade-offs between identification and alignment with the research question; (4) focusing on the distinct influences of wealth and income to stimulate means-testing policy enhancements; and (5) analysing impacts of components of wealth rather than just aggregate measures.

In this paper, we investigate the determinants of health care expenditures in Australia, where per-capita health expenditure has increased in recent years. Australia spent \$185 billion on health care in 2017–2018, that is \$7485 per person. In 2018–2019, total health spending was \$195.7 billion, equating to \$7772 per person and this was \$111 (1.5%) more per person than in 2017–2018 in real terms. Health spending constituted 10% of overall economic activity.

2. Literature review

2.1 International studies

There is a substantial literature that addresses the determinants of health care expenditures and, particularly, the income elasticity of health care expenditures. Existing studies have often used international datasets, with a range of results for the elasticity. Gerdtham *et al.* (1992) explore the effect of GDP and several socio-demographic factors on aggregate health care spending for a single cross section of OECD countries and they state that health care has income elasticity larger than one. Similarly, Newhouse (1977) and Leu (1986) provide empirical evidence that health care has elasticity above one. Among these studies, Newhouse (1977) investigates the effect of GDP per capita on per capita health care expenditures covering both private and government spending for 13 countries. Leu (1986) investigates the income elasticity of health care expenditure using cross-section data for 19 OECD countries in 1974 and states that income elasticity values are greater than one.

Panel studies also investigate income impacts on health expenditures. Dregen and Reimers (2005) explore the relationship between health care expenditures and GDP for 21 OECD countries between 1975 and 2001 and they use panel cointegration techniques. Their analysis accounts for life expectancy, infant mortality and the share of the elderly in addition to income as a determinant of health care expenditure. They conclude that the income elasticity is not different from unity. Baltagi and Moscone (2010) examine the long-run relationship between income and total health care expenditure. They use panel data for 20 OECD countries between 1971 and 2004 and employ a heterogenous panel model with cross sectionally correlated errors to explore the non-stationarity and cointegration properties between health care spending and income and thus to measure income elasticity of health care, showing health care as a necessity good.

2.2 National or regional analysis

Di Matteo (2003) suggests that income elasticity varies by level of analysis with international income elasticities being generally larger than national or regional studies. This study uses

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multiple datasets that include United States state level data for personal health expenditure between 1980 and 1997 and Canadian province level data for government health expenditure between 1965 and 2000, and implements non-parametric techniques, namely locally weighted scatterplot smoothing approach, where there is a room for variations in the income elasticity of health expenditure as income changes. Di Matteo (2003) finds that income elasticities are higher at low-income levels and lower at higher income levels. In addition, Di Matteo and Di Matteo (1998) explore the relationship between government health care expenditure and income in Canada using a pooled approach between 1965 and 1991 and find that income elasticity is smaller than one. Also, Murthy and Ukpolo (1994) use a time series dataset and employ a cointegration approach to examine the United States between 1960 and 1987 and find that the income elasticity of aggregate health care expenditure is not significantly different from one.

2.3 Household level analysis

Household-level analysis usually indicates lower income elasticities. Newhouse (1992) states that income elasticities of demand for medical care within the United States have tended to be in the range of 0.2–0.4 using cross-sectional observations across households. Getzen (2000) reports that income elasticities of health care expenditure at an individual level are often close to zero while income elasticities at a national level generally exceed one.

Only limited empirical analysis has assessed determinants of pharmaceutical expenditures using household-level data (Sanwald and Theurl, 2017). One of these limited number of studies is from the European context where income is found to have insignificant influences on pharmaceutical expenditure using the Austrian household budget survey (Sanwald and Theurl, 2017). This motivates us to consider assets as well, and partly informs our expectation that assets may have a more important influence on some health expenditures relative to income influences. Also from Europe, Costa-Font *et al.* (2007) found a low income elasticity of demand for pharmaceuticals in Catalonia. This study also found mixed results for a smoking coefficient, suggesting that the influence of smoking on health expenditure may depend on which expenditure variable is considered.

Bernard *et al.* (2009) use a nationally representative United States household survey from Medical Expenditure Panel Survey Household Component for the years 2002 and 2003, and they examine the correlation between wealth and private insurance purchase. They employ a multivariate analysis to control for income and socio-demographic variables such as age and self-reported physical health. They structure two measures of wealth; financial assets and net worth. The wealth model predicts the demand for insurance based on wealth in addition to other controls. The dependent variable is whether the family has private health insurance. The wealth model includes indicators for wealth quartiles and income quartiles. They find that privately insured families had higher levels of financial assets and wealth than the uninsured families in 2002 and 2003. Accordingly, results suggest that assets and total wealth are important determinants of demand for insurance in the United States.

3. Health funding and means testing in Australia

Health policy in Australia relies on a mix of public and private funding. Public funding is used to cover fees for some general practitioner (GP) health services which are financed by the federal government. Some doctors in Australia have used 'bulk billing' where they send a bulk bill to the Australian government via the Medicare system, meaning that there are no user charges in these cases. However, other doctors providing the same service may charge a fee to patients which exceeds the Medicare rebate, meaning that user charges apply in these cases (Australian Government, 2022). Means testing is not relevant for these publicly provided health services.

Private health insurance is a private strand of the Australian health system. This is not used for GP services. Instead, private health insurance can partly cover payments for other non-GP services such as dental, physiotherapy, chiropractic and in-patient hospital visits. Hospital services are also provided through a mix of public and private institutions. Public funding covers inpatient services at public hospitals. An annual rebate which can be around 30% of private health insurance premiums is available for families or individuals depending on income for the respective financial year. Asset thresholds are not used. Private health insurance is voluntary in Australia, although an extra tax is applied for households without adequate private health insurance and who have income above a threshold (Australian Taxation Office, 2023).

Subsidised medication is available in Australia through the Pharmaceutical Benefits Scheme (PBS). All Australian residents who hold a current Medicare card are eligible for discounted medicines under the PBS, meaning that non-residents are not eligible unless their home country has a reciprocal agreement. Out-of-pocket payments generally apply for all medicines. For medicines covered by the PBS, there has been a discounted maximum price for general payments and an even more discounted maximum price for concession card holders. Private health insurance does not cover medicines expenditure for items covered by the PBS but can cover some other medications in a quite limited range of circumstances (HCF, 2018). While general eligibility for this scheme is not subject to means testing, the amounts of co-payments required by individuals may indirectly be subject to means testing. For instance, to be eligible for the concessional co-payment of $6.80 instead of the larger co-payment of $42.50, individuals must qualify through one of several avenues, such as having a Pensioner Concession Card or a Commonwealth Seniors Health Card. Both cards are means-tested, and pensioners need to pass both an asset and an income test.

General welfare policies are relevant in the context of health policies. This was evident in relation to the PBS description above and it is also evident when considering that welfare payments are a source of income that can be used for health payments which are not covered by government funding or insurance benefits. The Australian welfare system uses both income and asset tests for determining eligibility. Households or individuals must pass both tests (and other criteria according to the specific benefit) to receive the full welfare benefit.

4. Data

This paper uses Australian household data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. Data are available at either the individual or household level. This paper primarily uses the household level because key variables are at the household level, health policies consider families/households, and because economic resources are shared across households. Some individual-level variables for people responding on behalf of their household are used as controls. Variables are described in detail in Table 1.

HILDA provides an annual panel of socioeconomic variables. However, key wealth variables are only available every four years, with the two most recent years being 2014 and 2018. There were approximately 9500 responding households in the 2018 wave, although the results in this paper have slightly smaller samples due to unavailability of some variables such as prior-year variables or probability weights. 41 households are also dropped when ‘person 1’ has an age below 15 years.

This paper considers both temporal and cross-sectional contexts. The temporal context can reduce concerns over unobserved time-invariant heterogeneity. After establishing significant relationships in this context, the paper switches to a cross-sectional context, given the nature of the research question and data. This includes the context for health policies which includes some inherently cross-sectional aspects. For example, eligibility for a rebate for private health insurance in Australia depends on income for the previous year. Income above a threshold in other preceding years is not relevant. Also, wealth variation is far more pronounced cross-sectionally compared to temporally. The correlation between wealth in 2014 and in 2018 is 0.8, indicating that if a household is wealthy in one period, they are also likely to be wealthy in subsequent

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Table 1. Variable descriptions

Variable	Description
Dependent	
Expenditure on health practitioners	Total household annual expenditure on fees paid to health practitioners in Australian dollars, where health practitioners are defined broadly beyond just GPs. For example, health practitioners also include specialists. For a small number of values, imputation is used by the survey provider (Melbourne Institute, Applied Economic & Social Research; The University of Melbourne) for missing data using a longitudinal imputation approach or a nearest neighbour approach for households without sufficient data across waves. Values are imputed for less than 15% of households. The survey provider recommends using the imputed data rather than introducing sample selection bias by dropping households. This is a household-level variable where one person can answer on behalf of the household. The survey administrator averages amounts across individual responses if there is more than one response per household. We use the data provided in the survey without adjustment for inflation. This is appropriate for our context as we seek to explain health-care expenditure without a breakdown into real and inflationary components. Inflation in Australia was also low during our study period.
Private health insurance spending	Household annual expenditure - private health insurance; dollars; imputed. Expenditure on private health insurance refers to the insurance premium.
Expenditure on MPP	Household annual expenditure - medicines, prescriptions, pharmaceuticals (MPP) and alternative medicines in Australian dollars; out-of-pocket expenditure.
Can't afford medical treatment	Unable to afford to get medical treatment when needed: a binary variable = 1 if this material deprivation = Yes. This covers medical treatment in general, rather than any single aspect of medical treatment such as medicines.
Wealth	
Net wealth	Net worth for the household. This equals financial assets plus non-financial assets less household debt, in Australian dollars. Values are imputed by the survey provider in cases where data are missing, such as for net worth and its components such as financial assets, non-financial assets and debt (i.e. liabilities).
Financial assets	Household financial assets; dollars; imputed; weighted top-code. Top-coding means that average values for households above a threshold are used instead of the actual value. The substituted value is the average for the households subject to top-coding, so the sample mean is unchanged. All financial assets are included such as equity, bank accounts and superannuation (private pensions).
Non-financial assets	Household non-financial assets; dollars; imputed; weighted top-code. Residential housing is the primary contributor.
Household debt	This is the sum of debt for property, business operations, total credit card debt, student-loan debt and other debt, including overdue household bills. Debt for residential property is a major component of household debt in Australia and makes up around 85% of the debt variable.
Financial asset quartiles	4 quantiles of financial assets; the 25% of households with the lowest financial assets are in quartile 1. This is the reference category.
Non-financial asset quartiles	4 quantiles of non-financial assets: quartile 1 is the lowest
Debt above median	2 quantiles of household debt: quantile 1 is the lowest. Quartiles are not feasible as more than 25% of households have zero debt.
Decile 1 of net wealth	A binary variable = 1 if net worth is in the bottom decile.
Income	
Household income	Gross annual (financial year) regular household income; dollars; imputed; weighted top-code

(*Continued*)

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Table 1. (*Continued.*)

Variable	Description
Income quartiles	4 quantiles of household income: quartile 1 is the lowest
Decile 1 of income	A binary variable = 1 if income is in the bottom decile.
Controls	
Hospitalisation	A binary variable = 1 if 'during the last 12 months, have you ever been a patient in a hospital overnight?' = Yes. This variable is from the 2017 survey as it was not available in 2018. It is based on 'person 1' of the household. The 0 values include those not responding.
Smoking	Binary variables for smoking cigarettes/tobacco products based on a categorical variable with these categories: no valid response, 'I have never smoked', 'I no longer smoke', 'I smoke daily', 'I smoke at least weekly (but not daily)', 'I smoke less often than weekly'. This variable is based on the response of 'person 1' of the household.
Self-assessed health change	Binary variables based on a categorical variable for health compared to one year ago with these categories: no valid response, 'much better than a year ago', 'somewhat better', 'about the same as one year ago', 'somewhat worse than one year ago', 'much worse'. This variable is based on 'person 1'.
Change in the number of people	The change in the number of people in the household.
Age	Age last birthday at June 30 2018: person 1
Elderly (#)	The number of people who are aged 65 or above in each household.
Domestic birth	A binary variable = 1 if 'Country of birth' = Australia. The 0 values include those not responding. This is based on 'person 1'.
State/territory of residence	State of residence: binary variables for 8 states/territories (one omitted as a reference category)

Notes: Variables are generally used as at 2018 in the Results section, unless otherwise specified.

years. In contrast, the standard deviation of wealth across a population, at a point in time, is very large. For example, the standard deviation for household net wealth in this paper's sample is A$1.4 million, which is larger than the mean of A$0.9 million.

Other descriptive statistics are also provided in Table 2. The age variable is defined with respect to 'person 1', where 'person 1' is defined by the survey. The average age of person 1 is 50, the average age of person 2 is 43, and the average age of subsequent people tends to be 17 and below. Statistics are also shown in Table 2 for the change in the health-related expenditure variables from 2014 to 2018. This includes the change in private health insurance without any log transformation. This reveals that expenditure was $148 higher in 2018 compared to 2014, which equates to an increase of 12%.

Table 2 also indicates that quantile variables are used, such as quartiles. This is useful in the context of means testing of health policies, where families/households are eligible for support when they have economic resources below a threshold, at a point in time. This approach is also useful to reduce concerns over measurement error. For example, there may be concerns over the accuracy of wealth variables, as described in Table 1. For instance, non-financial assets primarily include housing assets (for homeowners), which requires estimates to be made by survey respondents. When using quartiles, these measurement issues are likely to have negligible impacts, since very few households would change from one quartile to another on account of measurement issues. Appendix Table A.1 shows ranges for each economic quartile, along with the mean of each quartile. For example, the range of financial asset quartile 1 is 0 to $36,948 with a mean of $11,830.

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Table 2. Descriptive statistics, 2018 unless otherwise specified

Variable	Mean	Standard deviation
Dependent		
Spending on health practitioners	901.61	2032.11
Spending on private health insurance	1409.39	1799.92
Spending on MPP	431.17	676.49
Can't afford medical treatment	0.01	0.10
Change: health spending (2014–18)	−32.98	2542.75
Change: insurance spending (14–18)	147.92	1441.83
Change: MPP spending (2014–18)	−8.39	1033.54
Wealth		
Net wealth	875,784.50	1,350,264
Financial assets	372,290.50	724,589.10
Non-financial assets	690,201.70	1,031,713
Household debt	185,641.00	383,096.30
Financial asset quartile	2.50	1.12
Non-financial asset quartile	2.49	1.12
Debt relative to median	1.50	0.50
Decile 1 for net wealth	0.10	0.30
Income		
Household income	107,959.50	98,671.95
Income quartile	2.50	1.12
Decile 1 for income	0.10	0.30
Controls		
Hospitalisation (2017)	0.14	0.35
Smoking	n/a	n/a
Health change (2018 vs 2017)	n/a	n/a
Change in number of people (17–18)	−0.05	0.71
Age	49.75	18.37
Elderly (#)	0.37	0.67
Domestic birth	0.78	0.41
State/territory of residence	n/a	n/a

Notes: There are 9508 observations (households) for each variable, except there are 9370 observations for the change in the number of people (in each household) and 9227 for the expenditure change variables. The mean for the non-financial asset quartile is less than 2.50 as $20,000 is reported for 114 households for non-financial assets, which is the upper threshold for quartile 1, meaning that quartile 1 has just over 114 more households than quartile 2.

A key pattern is evident in the data, prior to more comprehensive regression analysis. Figure 1 gives an example of asset variables being more effective in identifying diversity in health outcomes. The bottom quartile based on financial assets is more likely to have the adverse health experience of being unable to afford medical treatment, compared to the bottom income quartile. Non-financial assets give an intermediate case in-between income and financial assets. For above-median households (quartile 3 and 4), there are lower proportions for assets compared to income,

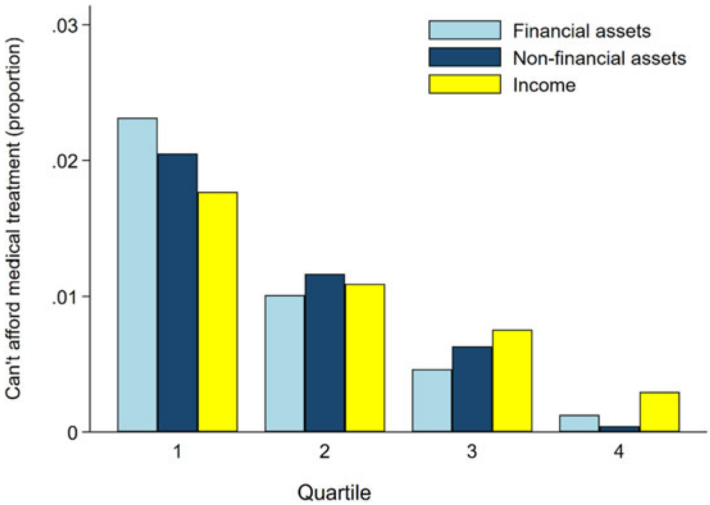

Figure 1. Proportion of households unable to afford medical treatment, split into quartiles according to either financial assets, non-financial assets or income. Data: HILDA (2021).

confirming the greater variability which is identified by the asset variables. This pattern is repeated for the other health dependent variables in this paper: spending on health practitioners, private health insurance and medicines, prescriptions or pharmaceuticals.

The three main health-related expenditures are somewhat distinct, as evident with correlations of only 0.3 between each pair. These expenditures are reported annually based on the recollection of one or more people in the household. This type of recollection reporting has been widely used and can provide valid information when expenditure questions are broken down into many specific aspects, as they are in the HILDA survey (Browning *et al*., 2003; Sun, 2010). The use of annual reporting for private health insurance is especially appropriate, as some households pay their premium annually, while multiplying monthly payments by 12 is simple for other households. Measurement error can also be anticipated, as will be the case in nearly all data sources, although the reputation and the experience of the data provider will mitigate this issue.

Another data issue is that some variables have both zero/negative values and skewed distributions. Net wealth is a key example, as the difference between assets and debt can be negative. For health expenditure, some households have zero spending in a given year for some spending types. In this context, standard log transformations would lead to many households being dropped due to logs of zero or negative values being undefined. One approach to retain these households is the inverse hyperbolic sine (IHS) transformation, which is given in equation (1):

$$\text{IHS transformation of } z\text{:}\ln[z + (z^2 + 1)^{0.5}] \tag{1}$$

Our use of the IHS transformation allows for a log transformation, even though there are zero annual expenditures for some health categories. As expected, there are a relatively high number of households with zero expenditure on private health insurance, given that this insurance is voluntary, with 43% of households having zero expenditure. For the other main categories, 26% of households had zero annual expenditure on health practitioners and 12% had zero expenditure on medicines, prescriptions or pharmaceuticals.

5. Method

The paper uses three types of models. A first differences model is included initially (where each variable is a first difference). Then, a cross-sectional model with variables in levels is used. Third, a lagged variable is introduced to the cross-sectional model to give an intermediate outcome where levels are used for the explanatory variables, but their effect is interpreted on the change (i.e. difference) in the dependent variable. This three-model approach accounts for trade-offs between identification and alignment with the research question.

Health expenditure (E) can initially be stated as a function of wealth (W), income (I) and control (X) variables in equation (2). Households are identified by the i subscript and time is denoted by t. Equation (2) also shows a term which is constant with respect to time (α_i) to capture time-invariant heterogeneity that is not accounted for by the measured variables, and an error term (ε_{it}).

$$E_{it} = \alpha_i + \beta W_{it} + \gamma I_{it} + \zeta X_{it} + \varepsilon_{it} \text{ for } t = 1 \text{ and } 2. \tag{2}$$

The first model used in the paper is given in equation (3). This is obtained by taking the first difference of each variable in equation (2).

$$\Delta E_i = \beta \Delta W_i + \gamma \Delta I_i + \zeta \Delta X_i + \Delta \varepsilon_i \tag{3}$$

The time-invariant unobserved heterogeneity (α_i) is removed by taking the first difference. Controls (X) from the cross-sectional model are generally not included in the Results section as there is often no variation across time in some variables (e.g. country of birth) or very little variation (e.g. state of residence).

The second model in the paper focuses on cross-sectional variation. A single value of t is investigated, meaning that the t subscript can be dropped from equation (2) to give the model in levels in equation (4).

$$E_i = \alpha + \beta W_i + \gamma I_i + \zeta X_i + \varepsilon_i \tag{4}$$

Adding a lagged dependent variable to the model in levels helps to control for some otherwise unobserved heterogeneity. Intuitively, health spending in a lagged period should be a good indicator of health spending in the current period. This intuition is based on the persistence of some health outcomes, as well as persistence in many forms of human tendencies and behaviour.

Adding the lagged dependent variable effectively implies that all other explanatory variables can be interpreted as being associated with the change in the dependent variable, rather than the level. This is evident when viewing equation (5) which adds the lagged explanatory variable to equation (4), before subtracting the same term ($E_{i,lag}$) from both sides of equation (6), which maintains the equality of both sides in equation (5). Note that subtracting $E_{i,lag}$ on both sides of equation (6) has no impact on the coefficients for W, I and X.

$$E_i = \alpha + \sigma E_{i,lag} + \tau W_i + \upsilon I_i + \varphi X_i + \varepsilon_i \tag{5}$$

$$E_i - E_{i,lag} = \alpha + (\sigma - 1) E_{i,lag} + \tau W_i + \upsilon I_i + \varphi X_i + \varepsilon_i \tag{6}$$

6. Results

Table 3 shows the first differences model for the impact of wealth and income variables on expenditure for health practitioners. In column (1), the change in net wealth is positively associated with the change in spending on health practitioners, with statistical significance at the 1% level. In contrast, the change in income is not a significant explanatory variable.

The wealth variable is split into its components for the other columns of Table 3. There are positive and significant coefficients for both asset components (financial and non-financial). Each of the variables uses the change from 2014–2018, as these are the two most

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Table 3. First differences model, explaining spending on health practitioners

	(1)	(2)	(3)
Income	0.051	0.033	0.043*
	(0.037)	(0.037)	(0.024)
Net wealth	0.039***		
	(0.010)		
Financial assets		0.099***	0.101***
		(0.028)	(0.019)
Non-financial assets		0.077***	0.072***
		(0.028)	(0.013)
Debt		−0.005	0.011
		(0.012)	(0.007)
Probability weights	Yes	Yes	No
Observations	9054	9054	9054
R^2	0.035	0.038	0.047

Notes: ***, **, * show statistical significance at the 1, 5 and 10% levels respectively. The change in the number of people is also an explanatory variable. Other controls in Table 2 are not included as there is little or no variation. These controls are useful in the cross-sectional model in levels.

recent dates for the wealth variables. First differences of variables transformed by the IHS transformation are used, since some households have zero values for variables such as debt. Column (3) does not use probability weights and produces coefficients with similar magnitudes to column (2) which does use probability weights. The remaining tables do not use probability weights, as Table 3 shows that this raises standard errors, lowers the *R*-squared, and it also restricts the sample size as probability weights are unavailable for a small number of households.

Table 4 switches to the models in levels, after having established significant coefficients for wealth variables in the first-differences model in Table 3. Column (1) of Table 4 shows positive and significant coefficients for both income and components of wealth when explaining the level of expenditure on health practitioners (with the IHS transformation). These positive and significant coefficients are for quartile variables, relative to the reference category of quartile 1 in each case. The point estimates of these coefficients increase from quartile 2 to 4, as expected. This indicates that being in a successively higher quartile, which shows higher levels of economic resources, is associated with greater spending on health practitioners.

In extra results available through the Stata code, we find positive and significant coefficients for the log of income and asset variables in explaining the log health expenditure. These regressions allow for elasticities to be calculated on the smaller sample of households who have positive values for logged variables including the log of health-related expenditures. We find an income elasticity of expenditure on health practitioners of 0.2 using our household-level analysis, consistent with health care being a necessity. The corresponding wealth elasticity is also equal to 0.2, as are most other elasticities with respect to the other types of health-related expenditure on private health insurance and medicines. Low income elasticities are also found in other household-level studies, such as by Sanwald and Theurl (2017).

A key outcome in Table 4 is that financial asset coefficients are larger in magnitude compared to the corresponding income coefficients. For quartile 2, the financial asset coefficient is 1.015, compared to 0.343 for income. These coefficients are statistically different to each other at the 1% level, as are the other sets of corresponding coefficients. This is also true in column (2)

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Table 4. Results explaining annual expenditure for health practitioners (IHS)

	(1)	(2)
Reference: quartile 1		
Income quartile 2	0.343***	0.121
	(0.097)	(0.082)
Income quartile 3	0.732***	0.400***
	(0.110)	(0.095)
Income quartile 4	1.137***	0.590***
	(0.118)	(0.102)
Reference: quartile 1		
Financial assets quartile 2	1.015***	0.571***
	(0.104)	(0.089)
Financial assets quartile 3	1.660***	0.872***
	(0.111)	(0.097)
Financial assets quartile 4	1.975***	1.020***
	(0.118)	(0.102)
Reference: quartile 1		
Non-financial assets quartile 2	0.408***	0.276***
	(0.103)	(0.088)
Non-financial assets quartile 3	0.882***	0.485***
	(0.111)	(0.095)
Non-financial assets quartile 4	1.234***	0.656***
	(0.118)	(0.103)
Reference: below median		
Debt: above median	0.175**	0.073
	(0.078)	(0.067)
Hospitalisation	0.052	−0.089
	(0.087)	(0.074)
Reference: smoke every day		
Smoke: never	1.311***	0.727***
	(0.102)	(0.091)
Smoke: no longer	1.077***	0.620***
	(0.109)	(0.096)
Smoke: weekly	0.867***	0.587***
	(0.252)	(0.222)
Smoke: less than weekly	0.979***	0.592**
	(0.312)	(0.282)
Reference: health unchanged		
Health much better	−0.022	0.014

(*Continued*)

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Table 4. (*Continued.*)

	(1)	(2)
	(0.162)	(0.142)
Health better	0.254***	0.126
	(0.096)	(0.083)
Health worse	0.379***	0.256***
	(0.087)	(0.074)
Health much worse	0.500**	0.435*
	(0.253)	(0.223)
Age	0.016***	0.009***
	(0.003)	(0.002)
Elderly (#)	0.162***	0.076
	(0.060)	(0.052)
Country of birth	0.166**	0.049
	(0.075)	(0.064)
Lagged dependent		0.494***
		(0.011)
Observations	9370	9370
R^2	0.251	0.441

Notes: ***, **, * show statistical significance at the 1, 5 and 10% levels respectively. The smoking and health-change variables also have a level for 'no valid response'. The mean variance inflation factor is 1.9 for column (2). Further explanatory variables for the change in the number of people and the state of residence are available through the Stata code.

when controlling for the lagged dependent variable, although statistical significance for the difference for quartile 4 coefficients has a p-value of 0.012. These results imply that health spending is impacted more by being in the lowest quartile for financial assets rather than income. The differences between the coefficients are evident in Figure 2, which shows that the 95% confidence intervals do not overlap when comparing corresponding financial asset and income quartiles. There is again more variation in relation to financial asset quartiles when using 2014 asset data, relative to income quartiles from 2014. The same pattern exists when using terciles or quintiles, with results available through the Stata code.

The value of using the lagged dependent variable is evident in Table 4. The coefficients for income and components of wealth are always lower in column (2) compared to column (1). This is reasonable, since the lagged dependent variable in column (2) controls for some otherwise unobserved heterogeneity, leaving less variation to be explained by the other coefficients.

Demographic and health variables also have impacts on health spending, as shown in Table 4. One of the controls is a variable for the number of elderly individuals in the household, here defined as people aged 65 and over. The variable for the number of elderly individuals in the household is positive and significant in column (1), which is consistent with the idea that elderly individuals would require higher health care spending, all else equal. Relative to the reference category for households with a respondent who smokes every day, every other type of household (e.g. never smoked) has higher health spending. While there is limited evidence in prior studies on the impact of smoking on some specific types of health care expenditure, there is some evidence of smokers spending less on general-practitioner services. For example, Costa-Font *et al.* (2007) found a negative effect of smoking on GP visits in Catalonia. This gives a similar outcome

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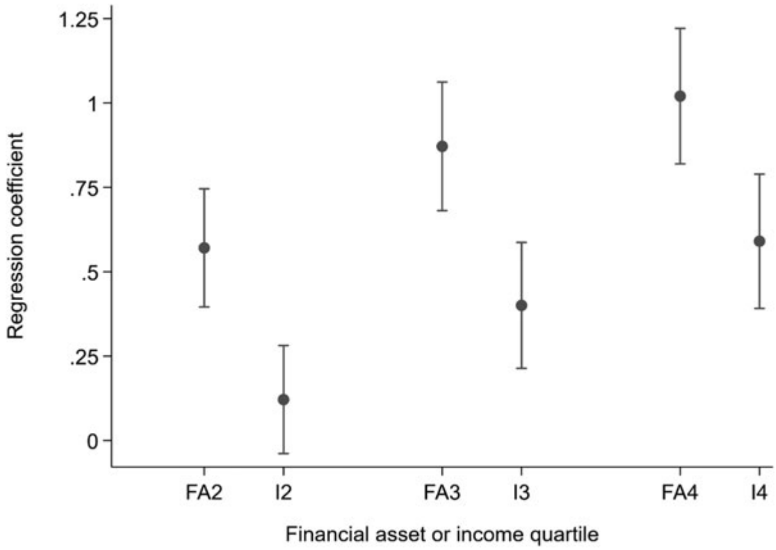

Figure 2. Financial asset (FA) and income (I) coefficients for quartiles compared to the reference groups for quartile one, with 95% confidence intervals, from column (2) of Table 4 which explains spending on health practitioners. Sources: author calculation; HILDA (2021).

to our result of lower spending on health practitioners for households with a respondent who smokes every day.

The robustness of these results is evident in numerous ways. The results follow a similar theme when using a dependent variable of expenditure without a log transformation. That is, assets appear to be more important than income in explaining expenditure on health practitioners. More specifically, the quartile coefficients for financial assets are positive and significant at the 1% level. Being in quartile 2 for financial assets is associated with around $176 in additional annual expenditure, relative to being in quartile 1. The corresponding income quartile coefficient is insignificant when explaining expenditure. We note that means testing has not been directly applicable for spending on health practitioners, so prior means testing should not explain these results.

Results are similar when using more detailed locational controls for 13 regions instead of states/territories; this is useful because health-service access may differ across geographical regions. Results are similar when the age of 'person 2' is used instead of the age of 'person 1' for the smaller sample of households who have at least two people. Results for economic variables are similar when including the lag of medicines expenditure using the IHS transformation. This captures the connection between prior medicines use and the need for future visits to health practitioners. The link between different health-related expenditures can also be considered by summing these expenditures to assess economic impacts on the aggregate health expenditure. Corresponding analysis with this aggregate variable again shows that financial asset quartiles have larger coefficients, compared to the income coefficients. In a further robustness test, we include a categorical variable for self-reported health status. However, this variable has insignificant coefficients and does not have major impacts on the other coefficients.

Table 5 explains spending on private health insurance (with the IHS transformation). There are similar patterns, including that being in a higher quartile for income or assets is associated with higher health spending. The financial asset and income coefficients are again statistically different to each other at the 1% level for column (1). Figure 3 shows that the confidence intervals for the income and financial asset coefficients do not overlap. However, when including the

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Table 5. Results explaining annual expenditure on private health insurance (IHS)

	(1)	(2)
Reference: quartile 1		
Income quartile 2	0.288***	0.090
	(0.108)	(0.068)
Income quartile 3	0.814***	0.309***
	(0.128)	(0.082)
Income quartile 4	1.801***	0.599***
	(0.142)	(0.092)
Reference: quartile 1		
Financial assets quartile 2	0.904***	0.260***
	(0.115)	(0.076)
Financial assets quartile 3	2.159***	0.594***
	(0.132)	(0.082)
Financial assets quartile 4	2.964***	0.731***
	(0.144)	(0.090)
Reference: quartile 1		
Non-financial assets quartile 2	0.083	0.031
	(0.116)	(0.072)
Non-financial assets quartile 3	1.135***	0.263***
	(0.133)	(0.081)
Non-financial assets quartile 4	1.650***	0.316***
	(0.145)	(0.089)
Reference: below median		
Debt: above median	0.150	0.020
	(0.091)	(0.058)
Lagged dependent		0.775***
		(0.008)
Observations	9370	9370
R^2	0.330	0.746

Notes: ***, **, * show statistical significance at the 1, 5 and 10% levels respectively. Coefficients for further explanatory variables for smoking, health change, hospitalisation in the previous year, age, the number of elderly individuals, country of birth, the change in the number of people and the state of residence are available through the Stata code.

lagged dependent variable in column (2), only the quartile 3 coefficients (0.593 vs 0.309) are statistically different to each other, and this is only at the 5% level. While the results in Table 5 again suggest that financial assets are better than income at identifying variation in health spending, the evidence for spending on private health insurance is not as strong as for spending on health practitioners.

The economic and other control variables explain a large proportion of the variation in Table 5 for spending on private health insurance. This is particularly evident with an R-squared value of 0.75 in column (2). It is reasonable that economic resources are more useful in explaining variation in private health insurance expenditure compared to other health spending, as insurance

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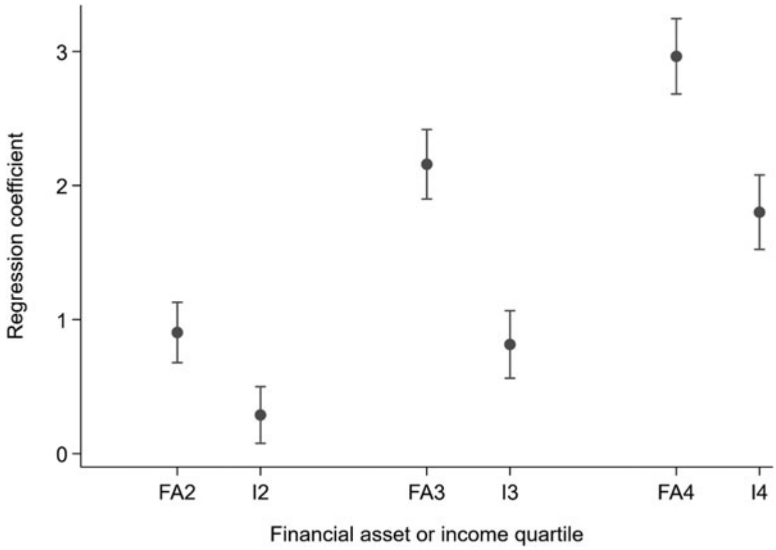

Figure 3. Financial asset and income coefficients for quartiles compared to the reference groups for quartile one, with 95% confidence intervals, from column (1) of Table 5 which explains spending on private health insurance. Sources: author calculation; HILDA (2021).

has the weakest link with actual health outcomes of the spending variables in this paper. Private health insurance involves upfront payments to help reduce future payments for health conditions which often do not even exist at the time of insurance-premium payment. In contrast, spending on health practitioners would generally relate to specific health conditions, even if some spending relates to general diagnostic discussions. The following results for medicines/prescriptions/pharmaceuticals (MPP) are tied closely to actual health issues. Control variable coefficients are not shown to save space but can be seen through the Appendix.

Table 6 investigates spending on medicines, prescriptions and pharmaceuticals (IHS transformation). Similar patterns are observed, such that having more economic resources (income or assets) is associated with greater health spending. A key difference from results in the other tables is that income coefficients are sometimes higher than corresponding coefficients for financial assets in Table 6. This is also shown in Figure 4, where the confidence intervals overlap for the corresponding income and financial-asset coefficients.

The available Stata code can be used to show results which are robust to using a dependent variable two years later (in 2020 rather than 2018). This helps to lessen concerns over reverse causation, as health expenditure in 2020 does not cause changes in wealth or income in 2018. One of the drawbacks of 2020 data is a lower sample size, as some households have left the sample after the most recently available wealth data in 2018. The lagged dependent variables also reduce concerns on reverse causation, as the explanatory variables then give an impact on the change in the dependent variable (not the level). An instrumental variable approach where 2014 net wealth is an instrument for 2018 net wealth is a further robustness test in the Stata code which shows similar results.

Table 7 has results for a logit model for a binary dependent variable which equals one when households report being unable to afford required medical treatment. Since this important form of deprivation is restricted to around 1% of Australian households, the explanatory variables are also modified to focus more on the bottom of the distributions for income and wealth. There is a positive and significant coefficient for being in the bottom decile for net wealth in explaining the deprivation in Table 7. The magnitude for the wealth coefficient shows that being in the bottom

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Table 6. Annual expenditure on medicines, prescriptions, pharmaceuticals (IHS)

	(1)	(2)
Reference: quartile 1		
Income quartile 2	0.261***	0.158***
	(0.072)	(0.061)
Income quartile 3	0.620***	0.402***
	(0.082)	(0.071)
Income quartile 4	0.811***	0.475***
	(0.089)	(0.076)
Reference: quartile 1		
Financial assets quartile 2	0.288***	0.207***
	(0.073)	(0.064)
Financial assets quartile 3	0.471***	0.274***
	(0.078)	(0.067)
Financial assets quartile 4	0.591***	0.334***
	(0.083)	(0.072)
Reference: quartile 1		
Non-financial assets quartile 2	0.118	0.064
	(0.073)	(0.063)
Non-financial assets quartile 3	0.231***	0.138**
	(0.077)	(0.066)
Non-financial assets quartile 4	0.263***	0.136*
	(0.085)	(0.073)
Reference: below median		
Debt: above median	0.195***	0.106**
	(0.058)	(0.051)
Lagged dependent		0.483***
		(0.012)
Observations	9370	9370
R^2	0.163	0.372

Notes: ***, **, * show statistical significance at the 1, 5 and 10% levels respectively. Coefficients for further explanatory variables for smoking, health change, hospitalisation in the previous year, age, the number of elderly individuals, country of birth, the change in the number of people and the state of residence are available through the Stata code.

decile for wealth makes it more likely by over one percentage point that a household will report being unable to afford medical treatment. This is a large impact when considering that the mean value for this variable is 1%. In contrast, the coefficient for being in the bottom income decile is not significant.

Additional robustness tests for all dependent variables, as included in available Stata code, use the ratio of income to wealth, instead of separate explanatory variables for income and wealth. There are negative and significant coefficients for this ratio in explaining each of the health-expenditure dependent variables. That is, higher ratios of income to wealth are associated with lower health care expenditure. This implies that wealth is more important than income since

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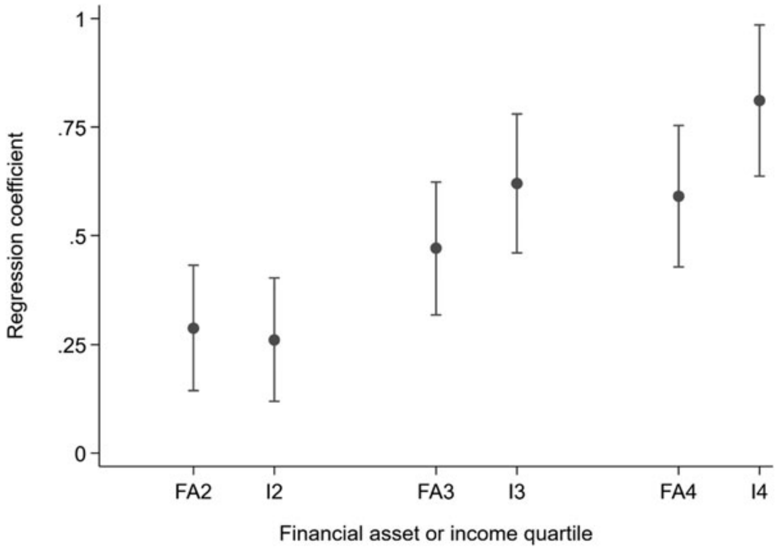

Figure 4. Financial asset and income coefficients for quartiles compared to the reference groups for quartile one, with 95% confidence intervals, from column (1) of Table 6 which explains spending on medicines, prescriptions and pharmaceuticals. Data: HILDA (2021).

Table 7. Marginal effects on deprivation – unable to afford medical treatment

	Marginal effect	Standard error
Reference: decile 2–10		
Income decile 1	0.004	0.003
Reference: decile 2–10		
Net wealth decile 1	0.011***	0.003

Notes: ***, **, * show statistical significance at the 1, 5 and 10% levels respectively. There are 9300 observations since one state/territory had zero of 70 households reporting being unable to afford medical treatment. The pseudo R-squared for the logit model (binary dependent variable) is 0.083. Coefficients for further explanatory variables are available through the Stata code.

the wealth influence from the denominator is outweighing the income influence from the numerator. This supports our main analysis where wealth coefficients are often statistically different to income coefficients. It is consistent with our focus on comparing wealth and income impacts to inform health policy reform. It contrasts with current health policy approaches focusing on income. We note that contexts where income tests exist, but assets tests do not, could affect the relative magnitude of asset and income coefficients. However, this issue relates to the private health insurance variable rather than our other three health variables. The policy implication that more focus on assets is warranted remains regardless of whether income means testing is impacting on income coefficients in the regressions explaining private health insurance spending.

7. Conclusion

This study finds that wealth is more influential than income in explaining a range of health expenditure variables. Households in the bottom quartile for financial assets have significantly lower spending on health practitioners, private health insurance and medicines. While this pattern is also evident for income, the financial asset impacts are more pronounced than for income for a range of outcomes related to health expenditure. The greater variation in

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expenditure between asset quartiles, rather than income quartiles, reveals that targeting support for low asset levels will help those households who are the most constrained.

The paper contributes through extensive analysis of four different dependent variables related to health expenditure, presenting broad understanding across different health contexts. This is useful to allow for generalised findings that are not subject to idiosyncratic features of particular variables, such as different subsidisation across services. The three different methodological approaches and numerous robustness tests enable confidence in the findings. The models can be considered in conjunction. For example, the model in levels shows an association between low asset levels and low health care expenditure. This motivates attention by policymakers. In addition, when explaining the change in health care expenditure, which is also positively related to assets, there is even greater motivation for policy changes. Our results show that low assets are linked to both low levels of health-related spending and to lower changes in this spending.

The paper also seeks to contribute to the sparse literature on wealth impacts (Kendall *et al.*, 2019; Pinilla and López-Valcárcel, 2020). The few papers on wealth impacts have tended to concentrate on health outcomes or one type of health expenditure rather than extensive understanding across multiple health expenditure contexts. Our study also contrasts with the more common assessments of income impacts. The results are crucial in directly supporting two novel policy suggestions, as described below.

Two novel policy suggestions include introducing an asset test when determining private health insurance rebate eligibility and escalating the focus on asset testing for general welfare payments. The introduction of an asset test for private health insurance is justified by financial assets tending to have a larger influence on private health insurance spending compared to income. For the second policy suggestion, while general welfare payments currently include an asset test in Australia, eligibility is more often determined by an income test based on the details of the thresholds (Chomik and Piggott, 2016). Since assets are more influential in identifying which households are more likely to experience deprivation related to being unable to afford medical expenses, there is scope for greater assistance for households with low levels of assets.

Future research can further progress to assess impacts of policy changes and use more extensive and detailed data, if available. If the two novel policy suggestions above are implemented in the future, the impact of these policy changes on health spending can be assessed. In addition, the availability of wealth variables in every year, rather than every four years, could allow for more extensive analysis. More detailed categories of health spending could also allow for analysis of impacts on different areas of general health spending. Data on national spending on free health services that are funded through bulk billing could also allow for more detailed comparisons of health care utilisation. Differences across states and territories are substantial, motivating future studies to investigate the reasons for these differences. While speculatory, future research may consider possible reasons for differences such as different policies for different health-related expenditures, different regularity of payment and differences in which type of people are more likely to spend on various health expenditures.

Data. The Stata code is available on request. The data are available for approved users via the Melbourne Institute: Applied Economic and Social Research; https://melbourneinstitute.unimelb.edu.au/hilda

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Competing interest. The authors have no conflict of interests to declare.

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Appendix

Table A1. Ranges and mean for each economic quartile, 2018

	Lower value	Mean	Upper value
Financial assets			
Quartile 1	0	11,830	36,948
Quartile 2	36,962	81,444	139,833
Quartile 3	139,854	244,172	396,000
Quartile 4	396,567	1,151,716	5,579,734
Non-financial assets			
Quartile 1	0	6425	20,000
Quartile 2	20,044	221,631	438,000
Quartile 3	438,300	636,259	880,000
Quartile 4	882,000	1,903,436	10,400,000
Income			
Quartile 1	−40,162	26,370	43,303
Quartile 2	43,400	63,670	85,583
Quartile 3	85,602	112,487	145,000
Quartile 4	145,050	229,656	1,365,448

Note: 18 households reported negative income, which could occur for reasons such as negative investment income.

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Table A2. Results for annual expenditure on private health insurance (IHS), controls shown

	(1)	(2)
Reference: quartile 1		
Income quartile 2	0.288***	0.090
	(0.108)	(0.068)
Income quartile 3	0.814***	0.309***
	(0.128)	(0.082)
Income quartile 4	1.801***	0.599***
	(0.142)	(0.092)
Reference: quartile 1		
Financial assets quartile 2	0.904***	0.260***
	(0.115)	(0.076)
Financial assets quartile 3	2.159***	0.594***
	(0.132)	(0.082)
Financial assets quartile 4	2.964***	0.731***
	(0.144)	(0.090)
Reference: quartile 1		
Non-financial assets quartile 2	0.083	0.031
	(0.116)	(0.072)
Non-financial assets quartile 3	1.135***	0.263***
	(0.133)	(0.081)
Non-financial assets quartile 4	1.650***	0.316***
	(0.145)	(0.089)
Reference: below median		
Debt: above median	0.150	0.020
	(0.091)	(0.058)
Hospitalisation	0.300***	0.106*
	(0.099)	(0.059)
Reference: smoke every day		
Smoke: never	1.471***	0.270***
	(0.109)	(0.068)
Smoke: no longer	1.016***	0.214***
	(0.118)	(0.069)
Smoke: weekly	0.051	−0.355**
	(0.284)	(0.178)
Smoke: less than weekly	0.915***	−0.158
	(0.318)	(0.241)
Reference: health unchanged		
Health much better	−0.002	−0.096
	(0.182)	(0.122)

(*Continued*)

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Table A2. (*Continued.*)

	(1)	(2)
Health better	0.096	0.020
	(0.111)	(0.063)
Health worse	−0.047	−0.011
	(0.106)	(0.060)
Health much worse	−0.110	0.098
	(0.299)	(0.175)
Age	0.017***	0.006***
	(0.003)	(0.002)
Elderly (#)	0.354***	0.090**
	(0.076)	(0.043)
Country of birth	0.177**	0.067
	(0.089)	(0.055)
Lagged dependent		0.775***
		(0.008)
Observations	9370	9370
R^2	0.330	0.746

Notes: ***, **, * show statistical significance at the 1, 5 and 10% levels respectively. The smoking and health-change variables also have a level for 'no valid response'. Further explanatory variables for the change in the number of people and the state of residence are available through the Stata code.

Table A3. Annual expenditure on medicines, prescriptions, pharmaceuticals (IHS), controls

	(1)	(2)
Reference: quartile 1		
Income quartile 2	0.261***	0.158***
	(0.072)	(0.061)
Income quartile 3	0.620***	0.402***
	(0.082)	(0.071)
Income quartile 4	0.811***	0.475***
	(0.089)	(0.076)
Reference: quartile 1		
Financial assets quartile 2	0.288***	0.207***
	(0.073)	(0.064)
Financial assets quartile 3	0.471***	0.274***
	(0.078)	(0.067)
Financial assets quartile 4	0.591***	0.334***
	(0.083)	(0.072)

(*Continued*)

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Table A3. (*Continued.*)

	(1)	(2)
Reference: quartile 1		
Non-financial assets quartile 2	0.118	0.064
	(0.073)	(0.063)
Non-financial assets quartile 3	0.231***	0.138**
	(0.077)	(0.066)
Non-financial assets quartile 4	0.263***	0.136*
	(0.085)	(0.073)
Reference: below median		
Debt: above median	0.195***	0.106**
	(0.058)	(0.051)
Hospitalisation	0.356***	0.201***
	(0.061)	(0.052)
Reference: smoke every day		
Smoke: never	0.487***	0.208***
	(0.079)	(0.068)
Smoke: no longer	0.545***	0.298***
	(0.083)	(0.070)
Smoke: weekly	0.290	0.064
	(0.203)	(0.173)
Smoke: less than weekly	0.346	0.094
	(0.242)	(0.205)
Reference: health unchanged		
Health much better	−0.108	−0.033
	(0.123)	(0.104)
Health better	0.243***	0.154**
	(0.074)	(0.063)
Health worse	0.452***	0.315***
	(0.059)	(0.050)
Health much worse	0.502***	0.446***
	(0.165)	(0.154)
Age	0.032***	0.017***
	(0.002)	(0.002)
Elderly (#)	0.096**	0.037
	(0.043)	(0.039)
Country of birth	−0.001	0.015
	(0.052)	(0.045)

(*Continued*)

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Table A3. (*Continued.*)

	(1)	(2)
Lagged dependent		0.483***
		(0.012)
Observations	9370	9370
R^2	0.163	0.372

Notes: ***, **, * show statistical significance at the 1, 5 and 10% levels respectively. The smoking and health-change variables also have a level for 'no valid response'. Further explanatory variables for the change in the number of people and the state of residence are available through the Stata code.

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