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Identifying the effects of health insurance coverage on health care use when coverage is misreported and endogenous

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The examination of the causal impact of health insurance coverage on healthcare utilisation is a critical endeavour in both academic research and policy formulation. However, this endeavour faces challenges, notably the endogenous selection into coverage and prevalent misreporting of coverage status. This study pioneers an investigation into the effects of private health insurance (PHI) coverage on healthcare utilisation, considering the intricacies of misreporting and endogeneity. To address misreporting, we analyse linked survey and administrative data with a precise coverage indicator. For endogeneity, we employ four established methodologies, including an instrumental variable approach leveraging an age-based policy discontinuity to construct an instrument. Our findings unveil that individuals with PHI coverage tend to access healthcare services more frequently, particularly primary care visits and specialist consultations. Nonetheless, the magnitude and statistical significance of these effects exhibit variability across different healthcare services and methodological approaches. Additionally, we discern notable disparities in the magnitude of PHI estimates between survey-based and administrative PHI indicators, with varying discrepancies across services and methodologies. Notably, our preferred specification underscores that utilising a self-reported PHI indicator with a 10% misreporting rate would result in a substantial overestimation of PHI's impact on the two most commonly utilised healthcare services.

Keywords: Health Insurance; Measurement Error; Health Care Demand; Australia

JEL classifications: C18; C81; C83; H31; I12; I13; I18

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1. Introduction

The examination of health insurance coverage's impacts on healthcare utilisation has remained a focal point for researchers and policymakers alike (Manning *et al.* 1987; Taubman *et al.* 2014; Duckett *et al.* 2022). Studies globally frequently employ self-reported coverage measures to ascertain such impacts (Propper *et al.* 2001; Frean *et al.* 2017; Nguyen & Connelly 2017; Bonsang & Costa-Font 2022). Validation studies conducted in both the United States (Pascale *et al.* 2019; Lurie & Pearce 2021; Call *et al.* 2022) and Australia (Nguyen *et al.* 2023) have underscored significant reporting errors in self-reported health insurance coverage measures.

Furthermore, these validation studies have delineated a systematic correlation between health insurance reporting errors and various individual and household characteristics, implying that the measurement error in the potentially endogenous health insurance dependent variable does not adhere to the classical assumption (Bound *et al.* 2001; Hu & Schennach 2008; Meyer & Mittag 2017). Such findings challenge the underlying assumption of most methodologies aimed at correcting misreporting and suggest that applying Instrumental Variable (IV) methods to the binary endogenous health insurance variable may not yield consistent treatment estimates (Meyer *et al.* 2009; DiTraglia & García-Jimeno 2019; Nguimkeu *et al.* 2019).[1] However, the precise theoretical and empirical ramifications of this systematic survey error on estimates of health insurance treatment impacts remain elusive.

Providing empirical evidence to address this challenge is intricate due to data and identification constraints. Notably, there is a conspicuous dearth of suitable data encompassing both self-reported and true health insurance measures at the individual level (Lurie & Pearce 2021;

[1] Specifically, appropriate IV methods applied to a linear regression model may provide consistent estimates of the misreported endogenous health insurance variable. However, if the misreported health insurance coverage is measured as a binary variable, which is very common in the health insurance literature (Cameron & Trivedi 2013; Nguyen *et al.* 2023), the IV methodology cannot provide consistent estimates because the assumption of classical measurement error does not hold (for formal proofs, see Battistin *et al.* (2014), Nguimkeu *et al.* (2019), or Calvi *et al.* (2022)).

Meyer & Mittag 2021). Even when such datasets are available, identifying an appropriate method to mitigate the potential endogeneity of health insurance enrolment remains challenging. This endogeneity arises due to individual unobservable factors, such as risk preferences and health risks, which may simultaneously influence health insurance demand and healthcare utilisation (Cutler & Zeckhauser 2000).

This paper contributes to the literature by providing the first empirical evidence regarding the magnitude and direction of the bias resulting from failing to account for both endogeneity and misreporting in health insurance coverage. It surmounts the above-described critical research hurdles by utilising recently available linked survey and administrative individual data from Australia and employing various methodologies to address potential endogeneity issues in insurance enrolment. Specifically, to address the health insurance misreporting issue, we employ administrative health insurance coverage, which has been demonstrated to be largely error-free (Nguyen *et al.* 2023), as the true indicator. In addressing the potential endogeneity of insurance enrolment, we employ four alternative methodologies, most of which have been successfully applied in previous studies. These methodologies include (1) controlling for a comprehensive array of explanatory variables, (2) leveraging the functional form of endogenous explanatory and outcome variables, (3) utilising a previously employed instrument, and (4) deploying a novel and more credible instrument constructed by exploiting the discontinuity in an age-based policy.

The findings presented in this study bear significant implications for Australia, where previous investigations have predominantly relied on self-reported measures of private health insurance (PHI) coverage to examine its influence on healthcare utilisation (Cameron *et al.* 1988; Savage & Wright 2003; Cheng 2014; Doiron *et al.* 2014; Eldridge *et al.* 2017; Srivastava *et al.* 2017; Doiron & Kettlewell 2018; Kettlewell 2019; Baldwin *et al.* 2025; Nguyen & Mitrou 2025b). By harnessing newly accessible linked survey and administrative data, which provide a more

precise measure of PHI coverage, and employing empirically robust models, this paper aims to furnish more reliable evidence regarding the causal effects of PHI coverage on healthcare utilisation than previously attainable.

Furthermore, the utilisation of two instruments, each stemming from distinct PHI policies, facilitates the interpretation of PHI coverage estimates within an instrumental variable framework as the effects of the policies - via their impact on PHI enrolment - on healthcare use. When coupled with the incorporation of administrative healthcare utilisation measures, which capture actual health expenditures, particularly those subsidised by the Government, the implications for policy formulation become more substantive than those derived from existing evidence. This evidence assumes added significance against the backdrop of Australia's ongoing health insurance reforms (Department of Health (DOH), 2025), rendering it timely for informing policy decisions.

Moreover, the findings presented in this study hold relevance for other nations with healthcare systems analogous to that of Australia. Specifically, unlike the United States, which lacks a universal public health system, Australia operates a universal public health insurance program, known as Medicare.[2] Introduced in 1984, Medicare provides all Australians with publicly funded access to public hospitals, subsidized medical services offered by private practitioners, and subsidized prescription medications. PHI exists alongside Medicare, allowing policyholders to choose private care providers, access private hospitals, and benefit from faster treatment (Duckett & Nemet 2019).

Similar to Australia, numerous other high-income countries, including Canada, France, Germany, Japan, the Netherlands, New Zealand, Singapore, South Korea, Sweden, Switzerland, and the United Kingdom (WHO 2010), maintain a mixed healthcare system.

[2] For a comprehensive review of the history and objectives of the private health insurance system in Australia, refer to Duckett and Nemet (2019).

These systems ensure that citizens have access to essential healthcare services while offering the option to purchase additional private coverage for enhanced benefits. As in Australian studies, research utilizing data from these countries often relies on self-reported health insurance coverage measures, which are prone to error, to examine their determinants or impacts on healthcare utilization (Propper *et al.* 2001; Bonsang & Costa-Font 2022).

By presenting novel evidence on the extent of bias resulting from misreported and endogenous health insurance coverage, this study also significantly contributes to the extensive literature on measurement errors in survey data.[3] Within this literature, our study aligns closely with a growing body of research dedicated to addressing the issue of misreporting in the dependent endogenous variable (DiTraglia & García-Jimeno 2019; Calvi *et al.* 2022). In the absence of suitable data, previous studies have been compelled to employ methodologies relying on strong assumptions (Nguimkeu *et al.* (2019)[4] or that do not furnish precise estimates (Kreider 2010; Kreider *et al.* 2012; Tommasi & Zhang 2024).[5] By leveraging linked survey and administrative data and employing established econometric models without the need for additional assumptions, this study overcomes the limitations of current literature, providing precise estimates of the bias attributable to misreporting and endogeneity in health insurance coverage.

By using recently available linked survey and administrative datasets and employing a diverse array of methodologies to address the inherent endogeneity of health insurance coverage, this study offers two primary insights. Firstly, our analysis reveals that individuals with PHI coverage generally exhibit higher utilisation rates of healthcare services, particularly evident in primary care visits and specialist consultations. However, the extent and significance of these

[3] For excellent reviews of this literature, see, for instance, Bound *et al.* (2001), Meyer *et al.* (2015), DiTraglia and García-Jimeno (2019) or Schennach (2020).
[4] For example, in the absence of a definitive true indicator, the theoretical framework advanced by Nguimkeu *et al.* (2019) must assume unidirectional misreporting, typically exemplified by false negatives. However, empirical investigations have consistently revealed that misreporting tends to occur bidirectionally, encompassing both false negatives and false positives (Meyer *et al.* 2015; Nguyen *et al.* 2023).
[5] For instance, studies have utilised a bound regression approach, resulting in substantial ambiguity regarding the magnitude and direction of bias (Kreider 2010; Kreider *et al.* 2012).

effects demonstrate variability across different types of healthcare services and methodological approaches employed.

Secondly, this study emphasizes the crucial role of employing accurate measures of PHI coverage. We observe substantial discrepancies in the magnitude of PHI estimates derived from survey-based and administrative data sources. Notably, our preferred model suggests that utilising a self-reported PHI indicator with a 10% misreporting rate would lead to a significant overestimation of PHI's impact on the two most commonly used healthcare services. Overall, the comprehensive consideration of both endogeneity and misreporting in PHI coverage suggests that the positive relationships between PHI coverage and healthcare utilisation may be less pronounced than previously depicted.

The subsequent sections of this paper are structured as follows. Section 2 introduces the primary datasets utilised in this study and offers descriptive analyses regarding reporting error patterns and the relationship between PHI indicators and healthcare utilisation. In Section 3, we delineate the empirical models employed in our analysis, while Section 4 presents the key empirical findings. Further discussion on the empirical results is provided in Section 5, and Section 6 serves as the conclusion of the paper.

2. Data and descriptive analyses

2.1. Data

This study utilises data derived from the linked 2014-15 National Health Survey (NHS) and administrative Personal Income Tax (PIT), sourced from the Australian Bureau of Statistics (ABS)'s Person Level Integrated Data Asset (PLIDA), formerly known as the Multi-Agency Data Integration Project (MADIP). PLIDA amalgamates various datasets encompassing government payments, income and taxation, employment, health, education, and population demographics (including the Census) over time (ABS 2025). Data linkage was performed by the ABS via the Person Linkage Spine, a person-level identification key that broadly covers

Australia's resident population from 2006 onwards. The ABS conducts deterministic linkage of individual records using key identifiers such as first name, last name, address, birth date, and gender. The 2014-15 NHS, which has been probabilistically linked to the PLIDA asset (ABS 2020), is a nationally representative survey administered by the ABS during the 2014-15 financial year (i.e., between 1 July 2014 and 30 June 2015). This survey gathers information through face-to-face interviews with usual residents of private dwellings in Australia. Within each sampled private dwelling, the survey includes an adult and a child (if applicable). The 2014-15 NHS encompasses 19,257 individuals, among whom 14,560 are adults, residing in 14,723 private dwellings (ABS 2017).

2.2. Private health insurance measures

The administrative measure of PHI coverage utilised in this study is derived from PIT data obtained from the Australian Tax Office (ATO) and subsequently provided to the ABS. This dataset encompasses all individual income tax filers in Australia. Given that PIT data are recorded on a financial year basis, we align the 2014-15 NHS dataset with PIT data from the corresponding financial year of 2014-15. Specifically, our administrative PHI coverage indicator assigns a value of one to individuals who possessed an appropriate level[6] of private patient hospital cover, as documented in the PIT data at any point during the 2014-15 financial year, and a value of zero otherwise.

The PHI coverage status in the 2014-15 NHS is constructed from responses to a specific question directed at all selected individuals aged 18 years and over. Participants were asked, "Apart from Medicare, do you have private health insurance?" To ensure consistency with the administrative PHI coverage measure, which solely considers hospital cover, and following the

[6] The criteria for an appropriate level of cover stipulate a maximum excess of $750 for singles and $1,500 for couples or families (ATO 2024). It's important to note that "ancillary" cover, commonly referred to as "extras", which encompasses services like optical, dental, physiotherapy, or chiropractic treatment, does not constitute private patient hospital cover.

approach of Nguyen *et al.* (2023), individuals are classified as covered by PHI in the survey data if they (i) respond affirmatively to this question and (ii) indicate possession of either "hospital cover only" or "both hospital and ancillary cover". Conversely, individuals are designated as uninsured by PHI in the survey data for the purposes of this study if they (i) provide a negative response to the aforementioned question or (ii) respond affirmatively to the same question but specify possession of "ancillary cover only".

A validation study conducted by Nguyen *et al.* (2023), utilising the same datasets as ours, illustrates that the confluence of income tax filing practices, incentives related to PHI, and "high and good quality linkage rates" (ABS 2020), indicate that the administrative PHI coverage measure employed in this study is sufficiently devoid of errors. Therefore, we consider the administrative PHI coverage measure to be accurate, a practice consistent with prior research in the United States (Lurie & Pearce 2021; Celhay *et al.* 2024).

2.3. Health care use measures

In line with previous Australian studies, particularly those utilising survey data similar to ours,[7] we incorporate a comprehensive range of health care use variables available in the 2014-15 NHS. These variables encompass the number of General Practitioner (GP) or specialist visits, inpatient or outpatient treatments, Emergency Department (ED) or day clinic visits, and dental consultations. The time frame for these health care use indicators spans the last 12 months before the survey.

[7] Australian studies have extensively utilised the National Health Survey (NHS) to investigate the relationship between PHI coverage and health care use. These studies have often employed NHS data from earlier survey years compared to our study, ranging from 1977-78 (Cameron *et al.* 1988), 1989-90 (Savage & Wright 2003), 1994-95 and 2001-02 (Hopkins *et al.* 2013), 2004-05 (Eldridge *et al.* 2017), to 2011-12 (Kettlewell 2019). Each study has focused on different health care use outcomes, reflecting variations in research objectives and data availability. It's important to note that while some of our healthcare utilisation outcomes resemble those utilised in prior studies using the same NHS data, direct comparisons may be constrained by differences in questionnaires across NHS survey years and empirical methodologies. Furthermore, researchers have also utilised alternative Australian survey datasets, including the Household, Income and Labour Dynamics in Australia (HILDA) survey (Cheng 2014; Doiron & Kettlewell 2018; Baldwin *et al.* 2025; Nguyen & Mitrou 2025a, b) or The 45 and Up Study (Doiron *et al.* 2014). See Appendix Table A1 and Appendix Table A2 for variable descriptions and summary statistics of key variables in our study.

In addition to quantifying these health care use outcomes in counts, we dichotomize each variable to signify whether the individual utilised any such health care service during the respective period. This transformation serves three main purposes. Firstly, our health care use measures entail a mass zero issue and exhibit a noticeable left-skewness (see Appendix Table A2), mirroring typical distribution patterns observed elsewhere and suggesting concentration among a small subset of heavy users. This characteristic supports the adoption of these binary variables (Cameron & Trivedi 2013). Secondly, employing a binary variable approach aids in mitigating reporting errors inherent in these self-reported health care use measures (Bound *et al.* 2001; Meyer *et al.* 2015). Lastly, as will be elaborated further, the utilisation of health care use as a binary variable facilitates the application of an identification method that circumvents the necessity for an instrument to address potential endogeneity issues related to PHI coverage (Wooldridge 2010). For these reasons, we will present regression results for these binary outcomes first as our preferred specifications.

Appendix Table A3 outlines the correlation structure among the health care use measures utilised in this study, revealing that the pairwise correlations among all seven self-reported healthcare use measures are not particularly strong. The highest statistically significant correlation is 0.38, with not all correlations reaching the designated 1% significance level. These notably low pairwise correlations suggest that each measure captures distinct facets of healthcare utilization, allowing for individual examinations of the impact of PHI on each metric.

2.4. Sample

Out of the original sample in the 2014-15 NHS, 18,280 individuals (accounting for 95% of the original sample) have been successfully linked to the PLIDA. Among these linked individuals, 10,301 individuals filed their personal income tax returns during the 2014-15 financial year and are consequently observed in the 2014-15 PIT data. To ensure consistency, we exclude 232

individuals aged under 18 years during the 2014-15 financial year from this sample, as the question regarding PHI coverage was not applicable to them in the 2014-15 NHS. Additionally, we exclude 23 individuals who responded "don't know" to their PHI coverage status in the 2014-15 NHS data due to the small sample size of individuals with such responses, rendering separate analysis impractical. Similarly, we further drop 83 individuals who indicated "insured but type of cover not known" in response to the PHI cover type question for similar reasons. Following the elimination of observations with missing information on included variables, a final analytical sample comprising 9,762 adult individuals with valid information on PHI coverage and other important variables in both datasets is retained for analysis.

Appendix Table A4 delineates the factors associated with the likelihood of inclusion of a respondent in the final sample of the 2014-15 NHS. As anticipated, our sample primarily comprises tax filers, excluding low-income individuals who are exempt from personal income tax. Consequently, individuals included in our final sample tend to possess more favourable socio-economic backgrounds compared to the general population observed in the 2014-15 NHS. Notably, included individuals are more inclined to have higher educational qualifications, better health statuses, be in marital relationships, be employed, or possess higher income levels. Furthermore, our analysis reveals that individuals with PHI coverage (as documented in the survey data) exhibit a higher likelihood of inclusion in our sample, suggesting that the PHI coverage rate within our sample surpasses the average rate observed among all Australians. Given the over-representation of individuals with more favourable socio-economic backgrounds in our sample, caution is warranted when generalizing the results of this study to the entire population. However, these findings hold particular relevance, as individuals belonging to this demographic are typically the focal point of public policies aimed at augmenting publicly funded healthcare through increased PHI coverage (Duckett & Nemet 2019).

2.5. Descriptive statistics on reporting errors

Table 1, resembling a similar table outlined by Nguyen *et al.* (2023a),[8] provides unweighted (Panel A) and weighted (Panel B) sample sizes, along with additional statistics (Panel C), comparing PHI coverage according to survey and administrative records for the same individuals in our sample. Unweighted statistics from survey data indicate that during the 2014-15 financial year, 61% of individuals were covered by PHI, while administrative data suggest only 56% of individuals were covered. Notably, the reporting accuracy of PHI enrolment in survey data is high, with 90% of individuals displaying agreement between survey responses and administrative records. However, reporting errors are non-negligible, with 4.43% of individuals who self-identify as uninsured recorded as insured in the administrative data, denoted as "false negatives", following terminology from previous research (Meyer *et al.* 2015). Conversely, 17.37% of individuals who self-report as having PHI are not covered by PHI in the administrative data, hereafter referred to as "false positives". Weighted statistics, adjusted for survey sampling weights and reported in the last row of Table 1, exhibit a largely similar pattern in PHI coverage and reporting accuracy rates, suggesting that our findings are robust to whether we account for survey sampling weights.

2.6. Descriptive statistics of main variables by health insurance statuses

Table 2 provides summary statistics of the primary dependent and independent variables, categorized by PHI statuses as identified from survey and administrative data. A comparison of mean figures of key explanatory variables based on PHI statuses reveals two prominent patterns. Firstly, there exists a notable disparity in various characteristics between individuals with and without PHI coverage. Specifically, individuals with PHI coverage tend to exhibit older age and possess more favourable socio-economic backgrounds, characterized by factors such as being native-born Australians, having higher English proficiency, attaining higher

[8] The discrepancies in figures between the two studies stem from variations in sample restrictions.

qualifications, being in marital relationships, enjoying better health, having lower smoking prevalence, engaging in full-time employment, or belonging to higher-income households. Furthermore, this trend persists across both survey and administrative PHI indicators.

Summary statistics of key health care use outcomes variables presented near the end of Table 2 reveal two main patterns. First, comparing health care use by PHI statuses shows a mixed picture. On the one hand, individuals with PHI coverage use fewer GP or ED services. On the other hand, they use more of almost all other health care services, including specialist visits, inpatient treatments, and dental consultations. Second, these documented correlations between PHI coverage and health care uses persist across both survey and administrative PHI indicators. However, it should be noted that these simple comparisons do not account for other factors correlating with both PHI and health care use, as well as the potential endogeneity of PHI coverage. The next sections will address these issues.

3. Empirical models

We employ the following model to investigate the impact of PHI coverage on health care use outcome Y of individual i:

$$Y_i = \alpha_1 + \beta_1 PHI_i + X_i\gamma_1 + \mu_{1,i} \quad (1)$$

Here, PHI_i represents the PHI coverage status. X_i denotes a vector encompassing individual, household, and local attributes, and $\mu_{1,i}$ is an error term. The parameters to be estimated are α_1, β_1 and γ_1, with β_1 serving as our parameter of interest. While X_i comprises a comprehensive array of factors influencing an individual's health care demand, Model (1) fails to address unobservable characteristics such as the individual's risk preferences and health risks, which may covary with both PHI enrolment and health care utilisation, thus potentially biasing the estimate of PHI coverage (Cutler & Zeckhauser 2000).

To tackle the potential endogeneity of PHI coverage, we adopt four alternative methodologies. The first approach, termed the "rich control list" method, aims to minimize the influence of unobservable factors concurrently correlated with both PHI coverage and health care usage by incorporating an extensive range of variables in X_i. In line with prior Australian research (Doiron *et al.* 2014; Eldridge *et al.* 2017), we control for a comprehensive set of individual, household, and locational variables. Individual-level variables encompass age (including its square), gender, migration status, self-rated English proficiency, education, marital status, labour market status, health status indicators (e.g., poor health status, mental health distress, and disability status), and health behaviours (such as smoking status). As detailed earlier, the inclusion of health status and health behaviour variables aims to mitigate the influence of unobservable factors, such as health risks or risk preferences, which may be correlated with both PHI enrolment and healthcare utilisation. Household-level variables encompass the number of other adults, number of children, and taxable income (including its square to capture potential non-linear relationships).[9]

To address spatial disparities in factors affecting health care demand, we introduce a dummy variable indicating rural residency and a series of state/territory dummy variables. Additionally, we control for temporal variations in health care demand by incorporating survey month-year dummies, with July 2014 serving as the baseline group. The inclusion of survey timing also addresses the discrepancy in reference periods between the administrative and survey PHI

[9] We utilise household income as the means-test criterion for coupled individuals, in accordance with the majority of Australian PHI policies (Duckett & Nemet 2019). Specifically, household income is computed based on the taxable incomes of both the respondent and their spouse, sourced from PIT data. As part of the tax lodgement process for assessment purposes, all taxpayers with a spouse during the financial year are legally obligated to complete a spouse details section, which includes inquiries regarding the spouse's taxable income, among other particulars (ATO 2015). In instances where the spouse has no taxable income, such as when the spouse is unemployed or when the taxpayer is unmarried during the fiscal year, the spouse's taxable income is recorded as zero. For single individuals, household income pertains solely to their personal earnings. See Appendix Table A1 and Appendix Table A2 for variable descriptions and summary statistics.

coverage indicators (Jenkins & Rios-Avila 2023).[10] Similarly, to mitigate concerns regarding linkage errors potentially influencing our results, we further control for a variable measuring the linkage quality between NHS participants and PLIDA individuals (ABS 2020).

The second method to address the endogeneity of PHI coverage relies on the non-linear functional form of both the independent endogenous variable and health care utilisation variable. Pursuant to this method, we estimate an additional equation for PHI demand:

$$PHI_i = \alpha_2 + X_i\gamma_2 + \mu_{2,i} \quad (2)$$

Here, $\mu_{2,i}$ represents an error term, and α_2 and γ_2 are parameters to be estimated. The definition of X_i mirrors that in Equation (1), ensuring a consistent set of explanatory variables across both equations. This approach is solely applicable when both the endogenous explanatory variable and health care outcome are binary, with the system of the two equations (1) and (2) estimated using a suitable estimator respecting their binary nature (Wooldridge 2010). Consequently, we employ this method exclusively for binary health care outcomes and utilise a bivariate probit model, which accommodates the binary nature of both endogenous and outcome variables. Notably, early Australian studies have leveraged the non-linearity in the functional forms of both PHI and health care utilisation outcomes as a sole means of identification (Cameron *et al.* 1988; Savage & Wright 2003).

To further address the endogeneity issue of PHI coverage, we employ an instrumental variable (IV) approach, incorporating another additional equation for PHI demand:

$$PHI_i = \alpha_3 + Z_i\sigma + X_i\gamma_3 + \mu_{3,i} \quad (3)$$

[10] In particular, there exists a temporal misalignment between our administrative and survey PHI coverage measures, where the administrative records encompass coverage throughout the year while the survey inquiries pertain to present coverage status.

In Equation (3), Z_i denotes a set of instrument(s), $\mu_{3,i}$ is an error term, and α_3, σ and γ_3 are parameters to be estimated. X_i is defined as in Equation (1). In implementing this IV method, the primary challenges revolve around identifying a valid instrumental variable that is (i) sufficiently correlated with PHI uptake and (ii) uncorrelated with health care usage except through PHI enrolment.

First, we follow Eldridge *et al.* (2017) in exploiting the discontinuity in household income induced by the Medicare Levy Surcharge (MLS) policy[11] to construct an "MLS income threshold" instrument. This instrument assumes a value of one if household income for MLS purposes surpasses the threshold set for tier 1 during the 2014-15 financial year, and zero otherwise. The theoretical validity of this instrument stems from the notion that, conditional on controlling for the smooth income trend (i.e., income and its square), the exogenously determined MLS income threshold should directly influence individual PHI uptake, as demonstrated by Kettlewell and Zhang (2024b), albeit indirectly affecting health care demand via the PHI enrolment channel.

Leveraging our linked survey and administrative data, we purposely utilise administrative household income to construct this instrument, as it offers greater accuracy and reduced susceptibility to reporting errors compared to self-reported income in the 2014-15 NHS dataset (Meyer & Mittag 2021). This represents an enhancement over a similar instrument utilised in

[11] The MLS is a means-tested insurance mandate that imposes a tax penalty on high-income earners who do not purchase PHI. High-income earners are those whose income exceeds a specified threshold, which varies for individuals and couples and is adjusted for inflation and the number of dependent children. In the 2014-15 financial year, income levels above the threshold were categorised into three tiers, each with different MLS rates: 1% for tier 1, 1.25% for tier 2, and 1.5% for tier 3 (Duckett & Nemet 2019). A more effective approach might involve examining the discontinuity in the probability of obtaining private insurance as motivated by penalties across the three income levels. However, we choose not to pursue this in order to maintain comparability with the previous work by Eldridge *et al.* (2017), which employs only one income-based instrument. Additionally, in line with Eldridge *et al.* (2017), we refrain from restricting the sample to individuals with incomes near the income cutoff to ensure reasonable comparability. Such a restriction would necessitate a much larger sample size than is currently available.

Eldridge *et al.* (2017), which solely relied on self-reported household income in their 2004-05 NHS data.

Additionally, we exploit the discontinuity in age introduced by the Lifetime Health Cover (LHC) policy[12] to construct another instrument. Specifically, we define an LHC age-based instrument, which equals one if an individual's age equals or exceeds 31 years at the study time and zero otherwise.[13] As noted earlier, we include age and its square in all regressions to assess any continuous or non-linear influence of age on health care or insurance demand. This instrument leverages the fact that individuals at different ages are subject to distinct exogenously determined LHC ages, making insurance more costly for those over 31 years old if they do not obtain a policy (Lee & Lemieux 2010). This instrument finds support in recent evidence by Kettlewell and Zhang (2024a), employing a Regression Discontinuity (RD) method to reveal that the introduction of a 2% premium loading increases uptake, albeit only at age 31. This age-based instrument is our preferred instrument because age is unlikely to be manipulated in our administrative data (Cattaneo & Titiunik 2022). Previous US studies have similarly employed an age-based instrument to address the health insurance endogeneity issue akin to ours (Anderson *et al.* 2014; Antwi *et al.* 2015; Yörük 2023).

[12] LHC imposes a penalty on individuals purchasing PHI for hospital cover after reaching the age of 30. The penalty is 2% above the hospital premium for each year over the age of 30 in which the individual did not have PHI hospital cover (Duckett & Nemet 2019).

[13] Eldridge *et al.* (2017) attempted to utilise this instrument; however, its estimate is statistically insignificant in their analysis. More recently, Baldwin *et al.* (2025) also employed this instrument in a cross-sectional regression framework using HILDA data to examine the effect of PHI coverage on health outcomes. While it is generally more appropriate to restrict the sample to individuals near the age cutoff to enhance comparability and improve the robustness of the analysis (Lee & Lemieux 2010; Cattaneo & Titiunik 2022), this approach, as shown in Baldwin *et al.* (2025), results in a weak instrument. We encounter a similar limitation with our linked survey-administrative data. Consequently, we refrain from adopting this more restrictive age-based sample and instead leave this more rigorous approach to future research utilising datasets with substantially larger sample sizes. Other Australian studies have explored alternative instruments, such as dental insurance premiums (Srivastava *et al.* 2017), whether an individual wears glasses (Hopkins *et al.* 2013; Kettlewell 2019), or partner's health and family aspirations (Doiron & Kettlewell 2018). Nevertheless, we opt not to incorporate these instruments in our study due to their limited relevance (e.g., the first two instruments are only pertinent for "ancillary" private insurance) or unavailability in our dataset.

We will utilise both instruments separately and in conjunction. This study marks the first instance in which two instruments are employed to address the potential endogeneity of PHI coverage, a notable advancement in the literature. The IV model with two instruments is favoured for two primary reasons. Firstly, given the presence of two instruments and one potentially endogenous variable, our model is over-identified, allowing for a Sargan test to formally evaluate the exogeneity of the two instruments, thereby providing additional empirical validation for our methodology. Secondly, by utilising both instruments, we expand the sub-population of interest, as each instrument captures a distinct source of PHI coverage selection. Consequently, each yields an estimate of the local average treatment effect (LATE) for a different subset of the population, specifically the compliers (Imbens & Angrist 1994).

As outlined earlier, when the health care use outcome is represented as a binary variable, we will utilise a Probit or bivariate probit model, respecting their binary nature. Conversely, when the health care use variable is quantified as a count, we will employ a Poisson model, acknowledging its count nature (Cameron & Trivedi 2013). Additionally, in both scenarios, we will employ a Probit model to estimate the PHI equation, considering the binary nature of the PHI indicator.

4. Empirical results

4.1. Main estimation results: Binary health care use outcomes

Table 3 displays estimates of PHI indicators derived from both survey data (odd columns) and administrative data (even columns) regarding seven binary health care use outcomes across five specifications. Panel A reports results from Probit regression models, controlling for a comprehensive list of explanatory variables. The findings indicate positive and statistically significant PHI estimates (at least at the 10% level) for most health care use outcomes, except outpatient treatment or ED visits. These significant estimates suggest that individuals with PHI coverage are more inclined to utilise these services, holding true for both PHI measures.

Contrasting the magnitude and statistical significance of estimates for PHI indicators obtained from survey and administrative data reveals notable differences in selected health care use outcomes. Specifically, as evident in the second-to-last row of Panel A, estimates for any specialist visit, any inpatient treatment, and any dental consultation are higher for the survey-based PHI indicator. Notably, the p-values, which are smaller than 0.05 as observed in the last row of Panel A resulting from a test for equality of PHI coverage coefficients in the two equations (i.e., survey and administrative PHI indicator equations), suggest that the two PHI estimates are statistically different at the 5% level. However, no statistically significant differences are observed in the PHI estimates for other health care use outcomes, as the p-values exceed 0.10.

Estimates of PHI indicators derived from bivariate probit regressions, which rely solely on the functional form of both dependent endogenous and outcome variables for identification, exhibit positive and statistically significant associations with selected health care use outcomes, including any GP visit, specialist visit, and dental consultation (Panel B). Notably, akin to the methodology adopted by Savage and Wright (2003), who similarly utilised this identification method, we observe a considerable increase in the magnitude of the estimates when transitioning from the rich control list method to this approach, by a factor of up to 4 (as evidenced in the estimates of the self-reported PHI indicator on any GP visit). This increase in magnitude of the PHI estimates is particularly evident for the three most frequently utilised health care services, namely any GP visit, specialist visit, and dental consultation.[14]

[14] Specifically, sample mean figures reported below the PHI estimates in Panel A of Table 3 highlight key insights into health care utilisation patterns. Among the seven health care use measures, the most commonly accessed service is GP visits, with 86% of individuals having at least one visit per year, followed by dental consultations (51%) and specialist visits (37%). Furthermore, the mean number of services underscores the prevalence of GP visits, with individuals averaging about 3.89 visits per year, followed by specialist visits (1.31) and dental consultations (1.04), as depicted in Table 4 – Panel A.

Furthermore, our results highlight statistically significant disparities in PHI estimates when utilising survey-based and administrative PHI indicators for any GP or specialist visit. Specifically, while estimates are positive for both any GP or specialist visit, they are greater in both magnitude and statistical significance for the survey PHI indicator compared to the administrative PHI indicator. Indeed, the reported p-values in the last row of Panel B suggest that these differences are statistically significant at the 10% level for any GP visit and the 1% level for any specialist visit, respectively.

PHI estimates from a bivariate probit estimator using the MLS income cutoff instrument, reported in Panel C, yield three main findings. Firstly, the first-stage F-statistic surpasses 68 in all regressions, robustly rejecting the null hypothesis of a weak instrument (Stock & Yogo 2005).[15] Secondly, estimates obtained from this estimator are largely similar to those estimated from the bivariate probit estimator using the functional form as the sole identification source. Thirdly, the estimate of the survey PHI indicator on any specialist visit is greater in terms of magnitude and statistical significance level than the estimate of the administrative PHI indicator, and this difference is statistically significant at the 1% level (Columns 3 and 4 - Panel C).

Similar trends are observed when employing the LHC age cutoff as an instrument (Panel D). Notably, the first-stage F-statistic exceeds 21 in all regressions, indicating the strength of this age-based instrument. Additionally, estimates obtained from this estimator closely resemble those derived from the bivariate probit estimator utilising the functional form as the sole identification source. Furthermore, the estimates of the survey PHI indicator on any GP visit or any specialist visit exhibit greater magnitude and statistical significance compared to the

[15] Full regression results for PHI equations are presented in Appendix Table A5. Appendix Table A6 reports full regression results for health care use equations.

estimates of the administrative PHI indicator. This difference is statistically significant at the 10% level and 1% level, respectively (Columns 1 to 4 – Panel D).

Consistent patterns emerge when utilising both the MLS income and LHC age cutoff instruments (Panel E). Specifically, the lowest first-stage F-statistic is 48, indicating the joint strength of these two instruments.[16] Moreover, the estimates of the survey PHI indicator on any GP visit or any specialist visit also demonstrate greater magnitude and statistical significance compared to those obtained using the administrative PHI indicator. This difference is statistically significant at the 10% level and 1% level, respectively (Columns 1 to 4 - Panel E).

4.2. Main estimation results: Continuous health care use outcomes

Table 4 presents estimates of PHI indicators derived from both survey data (odd columns) and administrative data (even columns), focusing on seven continuous health care use outcomes across four specifications. Panel A reports results from Poisson regression models, which account for the count nature of these continuous outcomes and incorporate a comprehensive list of explanatory variables. The findings reveal positive and statistically significant PHI estimates (at the 1% level) for the number of specialist visits, number of inpatient treatments, number of day clinic visits, and number of dental consultations. These significant estimates suggest that individuals with PHI coverage are more inclined to utilise these services, a trend observed for both PHI measures.

Furthermore, a comparison of the magnitude of the statistically significant estimates for PHI indicators obtained from survey and administrative data unveils notable differences in three health care use outcomes: number of specialist visits, number of inpatient treatments, and

[16] We employ the biprobit command in STATA MP Version 18 to perform estimation via a bivariate probit model. It is noteworthy that biprobit employs a maximum-likelihood estimator, as elucidated by (Wooldridge 2010), for estimating this equation. It is crucial to acknowledge that while biprobit incorporates both instruments, it does not provide any statistical metric for assessing the exogeneity of the instruments. The next section provides evidence demonstrating that these two instruments are exogenous.

number of dental consultations. Specifically, estimates are higher for the survey-based PHI indicator, and this disparity is statistically significant at the 1% level.

Panel B in Table 4 presents PHI estimates derived from an IV Poisson regression model utilising the MLS income cutoff instrument.[17] The findings indicate that PHI coverage does not exert a significant effect on the demand for all the measured health care services, and this holds true for both PHI indicators. However, an exception arises in the form of negative and marginally statistically significant ($p > 0.05$) estimates concerning the number of inpatient treatments. This suggests that individuals with PHI coverage utilised 0.24 and 0.27 fewer inpatient treatments (per year) when PHI is derived from survey and administrative data, respectively.

Similar patterns are evident when utilising the LHC age cutoff as an instrument, as all PHI estimates are statistically insignificant (Panel C). Likewise, estimates of two PHI indicators from IV Poisson regression models using both the MLS income and LHC cutoff instruments are also statistically insignificant. Notably, p-values from the over-identification test reported at the bottom of Panel D suggest that both instruments are exogenous, as all p-values exceed 0.14. The statistically insignificant PHI estimates obtained from IV Poisson regressions imply that PHI coverage does not significantly influence the demand for all the measured health care services, and this holds true for both PHI indicators. Furthermore, these insignificant estimates also indicate that there is no meaningful difference in the PHI estimates using the two PHI indicators, as both estimates are statistically insignificant.

[17] In our analysis, we employ the ivpoisson command in STATA MP Version 18 to conduct estimation using an instrumental variable Poisson model. Notably, ivpoisson utilises a Generalized Method of Moments (GMM) estimator, as described by Wooldridge (2010), for estimating this equation. It is important to note that while ivpoisson incorporates the instrument(s), it does not furnish any test statistic for evaluating the strength of the instrument(s). To enhance the interpretability of the estimation results obtained from this model, we present PHI estimates in terms of marginal effects (ME). However, it is essential to acknowledge that there is no formal test available for assessing the equality of the two PHI estimates (in marginal effects) following the ivpoisson procedure.

5. Discussion

The regression findings derived from a comprehensive control list approach indicate a tendency for individuals with PHI coverage to utilise a greater volume of healthcare services. This observation holds true across most healthcare utilisation metrics and for both PHI indicators, as illustrated in Panel A of Tables 3 and 4. It is pertinent to acknowledge that direct comparisons of estimates may be limited by variations in datasets, healthcare utilisation metrics, or empirical methodologies employed across this study and prior Australian investigations. Nonetheless, this finding aligns with the conclusions drawn in a study by Doiron *et al.* (2014), which utilised a similar empirical framework to address PHI coverage endogeneity, revealing increased utilisation of elective surgeries among individuals with PHI coverage.

Furthermore, our analysis reveals statistically significant disparities in the magnitude of PHI estimates between survey-based and administrative PHI indicators. Specifically, instances where statistically significant differences are observed tend to show higher estimates for the self-reported PHI indicator. In terms of magnitude, the disparities in the estimates of survey and administrative PHI indicators are moderate, ranging from 0.97% of the respective mean of the dependent variable in the sample (as evidenced in the case of any specialist visit) to 6.73% of the corresponding sample mean (pertaining to the number of dental consultations).[18]

Employing the non-linear functional form of both endogenous independent and outcome variables as the sole identification source, we continue to observe statistically significant and positive PHI estimates on selected health care use outcomes such as any GP visit, specialist visit, or dental consultation (Table 3 - Panel B). This finding aligns with evidence presented in

[18] These figures are calculated by dividing the difference between the self-reported PHI estimate and the administrative PHI estimate by the respective mean of the dependent variable and then multiplying by 100. PHI estimates and sample means of all dependent variables are reported in Tables 3 and 4. For example, for any specialist visit, 0.97% is approximately equal to (0.36 / 37.01) * 100.

two early Australian studies that utilised the same identification approach, demonstrating that individuals with PHI coverage tend to utilise more health care services (Cameron *et al.* 1988; Savage & Wright 2003). Moreover, our results indicate that using a self-reported PHI indicator would lead to an overestimation of the PHI treatment impacts on any GP visit by 4.15 percentage points (pp) and any specialist visit by 7.14 pp, respectively. The magnitude of this bias is substantial, representing 4.80% of the sample mean for any GP visit and 19.28% for any specialist visit.

Utilising an instrumental variable method to address the endogeneity of PHI coverage, we identify statistically significant and positive PHI estimates pertaining to three binary health care outcomes: any GP visit, specialist visit, or dental consultation. These findings persist across both PHI indicators and the two instruments employed. These outcomes align with findings from prior Australian studies that employed instrumental variable methods, demonstrating a higher likelihood of hospital admission as a private patient for individuals with PHI coverage (Cheng 2014; Eldridge *et al.* 2017; Doiron & Kettlewell 2018), as well as increased utilisation of dental services among those with ancillary PHI coverage (Hopkins *et al.* 2013; Srivastava *et al.* 2017; Kettlewell 2019).[19]

Moreover, our findings suggest a notable overestimation of the impact of PHI on two binary health outcomes, namely any GP visit and specialist visit, when utilising a self-reported PHI indicator. Specifically, the preferred instrumental variable estimates using both instruments reveal that employing a self-reported PHI indicator results in an overestimation of the PHI treatment effects on any GP visit by 2.94 pp and any specialist visit by 5.41 pp, respectively.

[19] It should be noted that prior studies have primarily concentrated on ancillary PHI coverage (Hopkins *et al.* 2013; Srivastava *et al.* 2017; Kettlewell 2019), whereas our study focuses specifically on private hospital cover. Interestingly, our data reveal a high likelihood of individuals with private hospital cover also possessing ancillary PHI coverage. To elaborate, among the sample comprising all insured individuals in the 2014-15 NHS dataset, approximately 80% reported having "both hospital and ancillary cover", 11% reported "hospital cover only", 8% reported "ancillary cover only", and 1% reported being "insured but the type of cover not known".

This bias is significant, representing 3.40% of the sample mean for any GP visit and 14.62% for any specialist visit.

In summary, the results derived from the preferred IV model employing two instruments reveal that individuals with PHI tend to utilise selected health care services more frequently, as indicated by their higher likelihood of having any GP visit, specialist visit, or dental consultation. Although this pattern is not consistently observed across all health care use measures or when health care measures are assessed in counts, the statistically significant and positive PHI estimates related to these three binary self-reported health care measures carry three notable implications.

Firstly, among all health care use measures analysed in this study, these particular health care services exhibit the highest frequency of utilisation among individuals in our sample, as evidenced by their largest reported sample means. Secondly, it's important to note that these healthcare outcomes are commonly utilised in Australian literature and are typically assessed in binary form within both Australian and international contexts (Cameron & Trivedi 2013; Nguyen *et al.* 2023). Thirdly, the observed patterns, coupled with another key finding from our preferred regressions indicating an overestimation of the true positive impacts of PHI coverage when using the self-reported PHI indicator for two of these three health care use measures, suggest the following inference: Employing the true PHI indicator would likely yield less pronounced positive relationships between PHI coverage and health care utilisation than those currently described in existing literature.

6. Conclusion

This study investigates the impact of PHI coverage on healthcare utilisation using linked survey and administrative data in Australia. Employing various empirical methodologies to address endogeneity and misreporting issues, our findings reveal nuanced insights into the relationship between PHI coverage and healthcare utilisation. Firstly, we observe that individuals with PHI

coverage generally utilise more healthcare services, particularly for primary care visits and specialist consultations. However, the magnitude and significance of these effects vary across different healthcare services and methodological approaches.

Secondly, our inquiry underscores the critical necessity of employing precise measures to assess PHI coverage accurately. We have identified substantial disparities in the magnitude of PHI estimates between survey-based and administrative indicators. However, the extent and significance of these differences fluctuate across various healthcare service categories and methodological frameworks. Noteworthy among our findings is the indication from our preferred specification that the utilisation of a self-reported PHI indicator with a 10% misreporting rate would lead to a significant overestimation of PHI's impact on the two most frequently utilised healthcare services. Collectively, our comprehensive examination of both endogeneity and misreporting in PHI coverage implies that the positive associations between PHI coverage and healthcare utilisation may be less pronounced than those depicted in existing literature.

This research provides valuable insights for studies utilising datasets similar to ours to investigate the relationship between health insurance and health care utilisation. However, it is important to acknowledge certain limitations, which highlight avenues for further inquiry. Firstly, the generalizability of our findings to other datasets from Australia or to healthcare systems in different countries remains uncertain and warrants further investigation. Secondly, the potential influence of unobservable time-invariant individual factors on reporting error patterns and their subsequent effects on the estimation of health insurance treatment effects remains unclear. To address these gaps, additional research utilising datasets from diverse contexts, data with more comprehensive information on health care utilisation, or longitudinal data is necessary.

Declarations

Funding Declaration

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Ethics approval

The study was approved by the University of Western Australia Human Research Ethics Committee (Reference: 2023/ET000389).

Conflict of interests

The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

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Table 1: Surveyed and administrative records of private health insurance coverage status

Administrative PHI coverage status	Survey PHI coverage status					
	No		Yes		Total	
	Number of observations	Row percentage (%)	Number of observations	Row percentage (%)	Number of observations	Row percentage (%)
Panel A: Unweighted						
No	3,548	82.63	746	17.37	4,294	100.00
Yes	242	4.43	5,226	95.57	5,468	100.00
Total	3,790	38.82	5,972	61.18	9,762	100.00
Panel B: Weighted						
No	4,495,692	81.22	1,039,664	18.78	5,535,357	100.00
Yes	299,279	4.59	6,227,353	95.41	6,526,631	100.00
Total	4,794,971	39.75	7,267,017	60.25	12,061,988	100.00
Panel C: Additional statistics						
	Unweighted	Weighted				
PHI coverage rate (%)						
Survey data	61.18	60.25				
Administrative data	56.01	54.11				
False negative rate (%)	4.43	4.59				
False positive rate (%)	17.37	18.78				
Any false rate (%)	10.12	11.10				

Notes: Sample of matched individuals aged 18 years or over, with no missing information on all included variables. “Weighted” figures are adjusted for NHS sampling weight. “False negatives” indicate cases where individuals have PHI in administrative data but have no PHI in survey data. “False positives” indicate cases where individuals have no PHI in administrative data but have PHI in survey data. “Any false” indicates either “False negatives” or “False positives”.

Table 2: Summary statistics by PHI coverage statuses

	Survey PHI coverage			Administrative PHI coverage		
	Yes	No	Difference (Yes - No)	Yes	No	Difference (Yes - No)
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Age	47.41	42.47	4.94***	48.45	41.74	6.71***
Male	0.48	0.49	-0.02*	0.47	0.50	-0.03***
Born in Australia	0.73	0.69	0.04***	0.74	0.68	0.06***
Poor English proficiency	1.04	1.09	-0.04***	1.03	1.10	-0.07***
Year 12 or lower	0.26	0.38	-0.12***	0.26	0.37	-0.11***
Diploma/Certificate	0.32	0.39	-0.07***	0.33	0.38	-0.05***
Bachelor or higher	0.41	0.23	0.19***	0.41	0.24	0.17***
Never married	0.25	0.36	-0.11***	0.23	0.38	-0.15***
Widowed	0.04	0.03	0.01***	0.04	0.03	0.01***
Divorced	0.10	0.13	-0.03***	0.10	0.12	-0.02***
Separated	0.04	0.06	-0.03***	0.04	0.06	-0.02***
Married	0.58	0.42	0.16***	0.60	0.42	0.18***
Poor health	0.09	0.13	-0.04***	0.09	0.12	-0.03***
Mental distress	0.07	0.13	-0.06***	0.07	0.12	-0.05***
Disable	0.32	0.31	0.01	0.33	0.31	0.02***
Smoker	0.10	0.24	-0.14***	0.09	0.23	-0.14***

Notes: Figures are sample mean. Tests are performed on the significance of the difference between the sample mean for “Yes” and “No” sub-group. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 2: Summary statistics by PHI coverage statuses (continued)

	Survey PHI coverage			Administrative PHI coverage		
	Yes	No	Difference (Yes - No)	Yes	No	Difference (Yes - No)
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Full-time employed	0.58	0.55	0.03***	0.58	0.56	0.02*
Part-time employed	0.23	0.28	-0.05***	0.24	0.28	-0.04***
Unemployed	0.01	0.04	-0.03***	0.01	0.04	-0.03***
Not in the labour force	0.17	0.12	0.05***	0.17	0.12	0.05***
Number of adults in household	1.95	1.91	0.05***	1.94	1.94	0.00
Number of children in household	0.64	0.74	-0.09***	0.65	0.72	-0.08***
Household annual income ($100,000)	1.27	0.68	0.59***	1.32	0.69	0.62***
LHC age threshold	0.87	0.76	0.11***	0.90	0.74	0.16***
MLS income threshold	0.27	0.05	0.22***	0.29	0.05	0.23***
Linkage quality	50.56	50.12	0.44***	50.70	49.99	0.7***
Number of GP visits	3.76	4.09	-0.33***	3.74	4.08	-0.34***
Number of specialist visits	1.47	1.06	0.41***	1.48	1.08	0.4***
Number of inpatient treatments	0.18	0.15	0.03***	0.18	0.15	0.03**
Number of outpatient treatments	0.23	0.25	-0.02	0.23	0.25	-0.03
Number of ED visits	0.15	0.20	-0.05***	0.15	0.20	-0.05***
Number of day clinic visits	0.14	0.12	0.02	0.14	0.12	0.03
Number of dental consultations	1.24	0.72	0.52***	1.26	0.77	0.49***
Observations	5,972	3,790		5,468	4,294	

Notes: Figures are sample mean. Tests are performed on the significance of the difference between the sample mean for “Yes” and “No” sub-group. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 3: Estimates of survey and administrative PHI coverage indicators on binary health care use outcomes

Health care use outcome:	Any GP visit		Any specialist visit		Any inpatient treatment		Any outpatient treatment		Any ED visit		Any day clinic visit		Any dental consultation	
PHI coverage from:	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel A: Probit regression model, treating PHI coverage as exogenous														
PHI estimate (ME, pp)	3.68***	3.82***	8.43***	8.07***	2.89***	2.51***	-1.01*	-0.95	-0.42	-0.53	1.08*	1.10*	19.86***	18.39***
	(0.75)	(0.76)	(1.04)	(1.04)	(0.75)	(0.74)	(0.61)	(0.61)	(0.71)	(0.71)	(0.56)	(0.56)	(1.04)	(1.06)
Sample mean	86.41		37.01		12.05		7.93		11.22		6.40		50.55	
Difference (Survey - Admin)	-0.14		0.36		0.38		-0.06		0.11		-0.02		1.47	
Equality test (p value)	0.32		0.04		0.00		0.51		0.37		0.82		0.00	
Panel B: Bivariate probit regression model, without exclusion restriction														
PHI estimate (ME, pp)	14.22***	10.07*	15.45**	8.31	-3.16	-0.84	-3.49	-3.15	-5.77	-2.90	-0.61	3.51	22.38***	22.31***
	(5.39)	(5.28)	(6.38)	(6.31)	(4.95)	(5.44)	(4.32)	(4.18)	(5.55)	(6.56)	(4.12)	(6.83)	(7.84)	(7.68)
Difference (Survey - Admin)	4.15		7.14		-2.32		-0.34		-2.87		-4.12		0.07	
Equality test (p value)	0.10		0.00		0.29		0.79		0.38		0.69		0.95	
Panel C: Bivariate probit regression model, with exclusion restriction – MLS income cutoff as instrument														
PHI estimate (ME, pp)	11.03**	8.32*	16.03***	10.20*	-7.59	-6.18	-2.54	-3.47	-8.25*	-6.23	-0.66	2.22	24.29***	24.34***
	(4.89)	(4.75)	(5.59)	(5.73)	(4.69)	(4.93)	(3.93)	(4.01)	(4.95)	(5.30)	(3.92)	(4.80)	(6.84)	(6.72)
F statistic	77.95	68.41	80.58	69.29	85.13	72.21	80.07	69.50	81.87	70.35	80.02	68.79	79.76	70.03
Difference (Survey - Admin)	2.71		5.83		-1.41		0.93		-2.02		-2.88		-0.05	
Equality test (p value)	0.15		0.00		0.42		0.25		0.33		0.48		0.98	
Panel D: Bivariate probit regression model, with exclusion restriction – LHC age cutoff as instrument														
PHI estimate (ME, pp)	13.31***	8.90*	15.07**	8.75	-3.39	-1.02	-4.93	-4.46	-5.26	-1.68	-2.05	-0.79	20.43***	18.59***
	(5.14)	(4.86)	(6.13)	(5.92)	(4.69)	(4.82)	(4.18)	(3.94)	(5.28)	(5.78)	(3.96)	(4.65)	(7.52)	(7.21)
F statistic	21.28	36.95	21.63	37.36	22.02	37.49	22.67	38.42	21.57	37.23	22.32	37.64	21.66	37.23
Difference (Survey - Admin)	4.41		6.32		-2.37		-0.47		-3.58		-1.26		1.84	
Equality test (p value)	0.06		0.00		0.19		0.72		0.23		0.69		0.43	
Panel E: Bivariate probit regression model, with exclusion restriction – MLS income and LHC age cutoffs as instruments														
PHI estimate (ME, pp)	10.53**	7.59*	15.63***	10.22*	-7.35	-5.45	-3.78	-4.66	-7.67	-4.93	-1.94	-0.70	22.62***	21.10***
	(4.69)	(4.42)	(5.44)	(5.45)	(4.49)	(4.50)	(3.87)	(3.84)	(4.78)	(4.90)	(3.89)	(4.32)	(6.67)	(6.47)
F statistic	48.67	51.51	50.02	52.09	52.52	53.53	50.23	52.76	50.60	52.34	50.15	52.09	49.59	52.15
Difference (Survey - Admin)	2.94		5.41		-1.9		0.88		-2.74		-1.24		1.52	
Equality test (p value)	0.09		0.00		0.23		0.27		0.18		0.62		0.42	

Notes: Sample size for all regressions: 9,762. Results (estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. PHI estimates are reported in Marginal Effects (ME). All regressions control for a list of individual, household and locality variables as described in the text. "Equality test" indicates p value from a test for equality of PHI coverage coefficients in two equations. "F statistic" from a Wald-type test for a null hypothesis that the estimate(s) of instrument(s) from the coverage equation is (are) zero. Robust standard errors are in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 4: Estimates of survey and administrative PHI coverage indicators on continuous health care use outcomes

Health care use outcome:	Number of GP visits		Number of specialist visits		Number of inpatient treatments		Number of outpatient treatments		Number of ED visits		Number of day clinic visits		Number of dental consultations	
PHI coverage from:	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel A: Poisson regression model, treating PHI coverage as exogenous														
PHI estimate (ME)	0.03	-0.08*	0.43***	0.38***	0.05***	0.04***	0.01	-0.01	-0.01	-0.01	0.03***	0.03***	0.49***	0.42***
	(0.04)	(0.05)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)
Sample mean	3.89		1.31		0.17		0.24		0.17		0.13		1.04	
Difference (Survey - Admin)	0.11		0.05		0.01		0.02		0.00		0.00		0.07	
Equality test (p value)	0.00		0.00		0.00		0.00		0.01		0.39		0.00	
Panel B: Instrumental variable Poisson regression model with MLS income cutoff as instrument														
PHI estimate (ME)	-0.95	-0.95	0.66	0.64	-0.24**	-0.27*	-0.32	-0.35	-0.14	-0.16	0.02	0.02	0.18	0.18
	(0.88)	(0.88)	(0.84)	(0.80)	(0.11)	(0.14)	(0.30)	(0.33)	(0.20)	(0.22)	(0.15)	(0.16)	(0.35)	(0.34)
Difference (Survey - Admin)	0.00		0.02		0.03		0.03		0.02		0.00		0.00	
Panel C: Instrumental variable Poisson regression model with LHC age cutoff as instrument														
PHI estimate (ME)	-1.13	-0.90	0.20	0.15	0.15	0.11	0.00	0.00	-0.03	-0.02	-0.63	-0.31	-0.50	-0.38
	(2.29)	(1.85)	(1.43)	(1.05)	(0.28)	(0.19)	(0.81)	(0.55)	(0.34)	(0.27)	(1,683.15)	(1.06)	(0.87)	(0.65)
Difference (Survey - Admin)	-0.23		0.05		0.04		0.00		-0.01		-0.32		-0.12	
Panel D: Instrumental variable Poisson regression model with MLS income and LHC age cutoffs as instruments														
PHI estimate (ME)	-0.97	-0.94	0.54	0.46	-0.19*	-0.18	-0.29	-0.29	-0.12	-0.10	-0.00	-0.01	0.09	0.06
	(0.81)	(0.79)	(0.66)	(0.56)	(0.11)	(0.12)	(0.29)	(0.31)	(0.19)	(0.19)	(0.14)	(0.14)	(0.31)	(0.29)
Difference (Survey - Admin)	-0.03		0.08		-0.01		0.00		-0.02		0.01		0.03	
Over-identification test (p value)	0.94	0.98	0.79	0.72	0.22	0.15	0.76	0.66	0.77	0.70	0.46	0.46	0.43	0.41

Notes: Sample size for all regressions: 9,762. PHI estimates are reported in Marginal Effects (ME). All regressions control for a list of individual, household and locality variables as described in the text. "Equality test" indicates p value from a test for equality of PHI coverage coefficients in two equations. "Over-identification test" reports p value from a Sargan test for exogeneity of the instruments. Robust standard errors are in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Online Appendix

For refereeing purposes and to be published online

Appendix Table A1: Variable description and summary statistics of key explanatory variables

Variable	Description	Mean	SD	Min	Max
Age	Age at the survey time (years)	45.49	15.06	18.25	89.17
Male	Dummy variable: = 1 if male and = 0 if otherwise	0.48	0.50	0.00	1.00
Born in Australia	Dummy variable: = 1 if born in Australia and = 0 if otherwise	0.71	0.45	0.00	1.00
Poor English proficiency	Self-rated proficiency in spoken English: = 1 if "very well", 2 "well", 3 "not well", and 4 "not at all"	1.06	0.28	1.00	3.00
Year 12 or lower	Dummy variable: = 1 if completed qualification is Year 12 or lower and = 0 if otherwise	0.31	0.46	0.00	1.00
Diploma/Certificate	Dummy variable: = 1 if completed qualification is diploma or certificate and = 0 if otherwise	0.35	0.48	0.00	1.00
Bachelor or higher	Dummy variable: = 1 if completed qualification is bachelor or higher and = 0 if otherwise	0.34	0.47	0.00	1.00
Never married	Dummy variable: = 1 if registered marital status is never married and = 0 if otherwise	0.29	0.45	0.00	1.00
Widowed	Dummy variable: = 1 if registered marital status is widowed and = 0 if otherwise	0.03	0.18	0.00	1.00
Divorced	Dummy variable: = 1 if registered marital status is divorced and = 0 if otherwise	0.11	0.31	0.00	1.00
Separated	Dummy variable: = 1 if registered marital status is separated and = 0 if otherwise	0.05	0.21	0.00	1.00
Married	Dummy variable: = 1 if registered marital status is married and = 0 if otherwise	0.52	0.50	0.00	1.00
Poor health	Dummy variable: = 1 if self-assessed health is rated as "fair" or "poor" and = 0 if otherwise	0.10	0.30	0.00	1.00
Mental distress	Dummy variable: = 1 if Kessler 10 score is categorised as high or very high distress and = 0 if otherwise	0.09	0.29	0.00	1.00
Disable	Dummy variable: = 1 if currently has a disability and = 0 if otherwise	0.32	0.47	0.00	1.00
Smoker	Dummy variable: = 1 if currently smokes cigarette and = 0 if otherwise	0.15	0.36	0.00	1.00
Full-time employed	Dummy variable: = 1 if current employment status is full-time employed and = 0 if otherwise	0.57	0.49	0.00	1.00
Part-time employed	Dummy variable: = 1 if current employment status is part-time employed and = 0 if otherwise	0.25	0.44	0.00	1.00
Unemployed	Dummy variable: = 1 if current employment status is unemployed and = 0 if otherwise	0.02	0.15	0.00	1.00
Not in the labour force	Dummy variable: = 1 if current employment status is not in the labour force and = 0 if otherwise	0.15	0.36	0.00	1.00
Number of adults in household	Number of individuals aged 18 or older in household	1.94	0.78	1.00	5.00
Number of children in household	Number of children aged 0-17 years in household	0.68	1.03	0.00	5.00
Household annual income ($100,000)	Own and spouse's income for MLS purposes ($100,000 per financial year) – from PIT data	1.04	1.09	0.00	9.47
LHC age cutoff	Dummy variable: = 1 if age >= 31 years old at the start of 2014-15 financial year and = 0 if otherwise	0.83	0.38	0.00	1.00
MLS income threshold	Dummy variable: = 1 if household income for MLS purposes > the base MLS tier and = 0 if otherwise	0.18	0.39	0.00	1.00
Linkage quality	Quality metric for links: a higher value indicates a higher quality link	50.39	6.21	29.52	58.58

Notes: Sample of 9,762 individuals aged 18 or older, without missing information all important variables. Minimum and maximum values are calculated among a group of at least 10 observations for confidentiality purposes.

Appendix Table A2: Variable description and summary statistics for main health care use variables

Variable	Description	Mean	SD	Min	Max	Number of observations with zero values
Number of GP visits	Number of times consulted GP in last 12 months	3.89	6.06	0.00	50.00	1,327
Number of specialist visits	Number of times consulted specialist in last 12 months	1.31	3.38	0.00	30.00	6,149
Number of inpatient treatments	Number of times admitted to hospital as inpatient in last 12 months	0.17	0.54	0.00	4.00	8,585
Number of outpatient treatments	Number of times visited outpatient clinic hospital in last 12 months	0.24	1.55	0.00	14.00	8,978
Number of emergency department visits	Number of times visited emergency/casualty department in last 12 months	0.17	0.67	0.00	5.00	8,666
Number of day clinic visits	Number of times visited a day clinic in last 12 months	0.13	0.90	0.00	10.00	9,134
Number of dental consultations	Number of consultations with dentist/dental professional in last 12 months	1.04	1.65	0.00	12.00	4,826

Notes: Sample of 9,762 individuals. Minimum and maximum values are calculated among a group of at least 10 observations for confidentiality purposes.

Appendix Table A3: Correlation structure among main health care use variables

	Number of GP visits	Number of specialist visits	Number of inpatient treatments	Number of outpatient treatments	Number of ED visits	Number of day clinic visits	Number of dental consultations
Number of GP visits	1.00						
Number of specialist visits	0.27	1.00					
Number of inpatient treatments	0.24	0.32	1.00				
Number of outpatient treatments	0.12	0.19	0.21	1.00			
Number of ED visits	0.20	0.15	0.38	0.12	1.00		
Number of day clinic visits	0.10	0.22	0.18	0.11	0.08	1.00	
Number of dental consultations	0.07	0.09	0.05				1.00

Notes: Sample of 9,762 individuals. Only correlation which is statistically significant at 1% level is listed.

Appendix Table A4: Factors influencing match probability between 2014-15 NHS and PIT

Variable	Estimates (ME)
Age	0.18
	(0.11)
Age squared	-0.00***
	(0.00)
Male	1.42**
	(0.65)
Born in Australia	0.56
	(0.73)
Poor English proficiency	-4.23***
	(0.82)
Diploma/Certificate [(a)]	3.51***
	(0.69)
Bachelor or higher [(a)]	5.30***
	(0.86)
Widowed [(b)]	0.53
	(1.35)
Divorced [(b)]	1.77
	(1.12)
Separated [(b)]	3.02**
	(1.49)
Married [(b)]	5.06***
	(0.96)
Poor health	-4.77***
	(0.82)
Mental distress	1.00
	(0.89)
Disable	-2.51***
	(0.66)
Inpatient treatment	0.05
	(0.85)
Outpatient treatment	-0.66
	(0.97)
Smoker	-3.55***
	(0.80)
Part-time employed [(c)]	-6.42***
	(1.01)
Unemployed [(c)]	-22.38***
	(1.53)
Not in the labour force [(c)]	-33.38***
	(0.84)
Had private hospital	9.15***
	(0.67)
Number of adults in household	-1.45***
	(0.56)
Number of children in household	-0.02
	(0.36)
Annual household income (survey) ($100,000)	4.98***
	(1.30)
Annual household income squared (survey)	-0.36**
	(0.17)
Rural areas	2.37**
	(1.07)
Linkage quality	0.11*
	(0.05)
Observations	11,151
Sample mean	72.05

Notes: Results (in marginal effects (ME), multiplied by 100) from a Probit regression model regression. [(a)], [(b)], and [(c)] denotes "Year 12 or under", "Single", and "Full-time employed" as the base group, respectively. Other control variables include state dummies and survey month-year dummies. Robust standard errors are in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Appendix Table A5: Determinants of PHI enrolment

Instrument:	MLS income cutoff instrument		LHC age cutoff instrument		Two instruments	
PHI indicator from:	Survey	Admin	Survey	Admin	Survey	Admin
	(1)	(2)	(3)	(4)	(5)	(6)
MLS income cutoff instrument	50.57***	45.48***			29.66***	39.85***
	(5.73)	(5.50)			(6.66)	(6.72)
LHC age cutoff instrument			30.52***	40.73***	50.17***	44.95***
			(12.81)	(13.68)	(5.73)	(5.51)
Age	-3.40***	-2.18***	-0.80	1.22**	-3.30***	-2.09**
	(0.83)	(0.83)	(0.61)	(0.61)	(0.83)	(0.83)
Age squared	0.04***	0.04***	0.02***	0.01	0.04***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Male	-5.79*	-8.40***	-6.73**	-9.26***	-6.81**	-9.36***
	(3.00)	(3.01)	(3.01)	(3.02)	(3.02)	(3.03)
Born in Australia	30.70***	35.50***	29.91***	34.49***	30.37***	35.07***
	(3.41)	(3.42)	(3.43)	(3.42)	(3.43)	(3.43)
Poor English proficiency	-14.95***	-40.53***	-15.92***	-41.20***	-15.88***	-41.51***
	(5.25)	(5.74)	(5.24)	(5.72)	(5.25)	(5.75)
Diploma/Certificate [(a)]	7.04**	8.26**	7.27**	8.52**	7.06**	8.24**
	(3.39)	(3.43)	(3.39)	(3.43)	(3.40)	(3.44)
Bachelor or higher [(a)]	42.75***	39.47***	41.87***	38.66***	41.60***	38.25***
	(3.74)	(3.75)	(3.76)	(3.76)	(3.76)	(3.76)
Widowed [(b)]	-14.84	-8.59	-10.64	-3.51	-13.23	-6.95
	(9.34)	(9.31)	(9.37)	(9.32)	(9.41)	(9.36)
Divorced [(b)]	-12.64**	-10.35*	-13.82**	-11.21**	-13.71**	-11.05**
	(5.37)	(5.38)	(5.41)	(5.41)	(5.41)	(5.41)
Separated [(b)]	-16.79**	-13.35*	-16.93**	-13.12*	-17.27**	-13.50*
	(7.13)	(7.21)	(7.18)	(7.25)	(7.18)	(7.25)
Married [(b)]	0.57	5.39	8.29**	13.19***	7.58*	12.17***
	(4.11)	(4.12)	(4.19)	(4.20)	(4.20)	(4.21)
Poor health	-12.06**	-11.61**	-11.57**	-10.94**	-11.81**	-11.29**
	(4.78)	(4.83)	(4.78)	(4.83)	(4.79)	(4.84)
Mental distress	-13.26***	-12.45**	-13.05***	-12.27**	-12.96***	-12.18**
	(4.94)	(5.03)	(4.94)	(5.02)	(4.95)	(5.03)
Disable	4.16	5.66*	4.16	5.57*	4.18	5.62*
	(3.24)	(3.25)	(3.25)	(3.25)	(3.25)	(3.26)
Smoker	-43.28***	-44.79***	-42.40***	-43.79***	-42.80***	-44.29***
	(3.95)	(4.04)	(3.95)	(4.04)	(3.96)	(4.05)

Notes: Results (multiplied by 100) in each column are from a separate instrumental variable bivariate probit regression, with instrument(s) listed on the top row. [(a)], [(b)], [(c)], and [(d)] denotes "Year 12 or under", "Single", "Full-time employed", and "New South Wales" as the base group, respectively. Other control variables include state dummies and survey month-year dummies. "F statistic" from a Wald-type test for a null hypothesis that the estimate(s) of instrument(s) from the coverage equation is (are) zero. Robust standard errors are in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Appendix Table A5: Determinants of PHI enrolment (continued)

Instrument:	MLS income cutoff instrument		LHC age cutoff instrument		Two instruments	
PHI indicator from:	Survey	Admin	Survey	Admin	Survey	Admin
	(1)	(2)	(3)	(4)	(5)	(6)
Part-time employed [c]	-4.48	-2.84	-4.71	-3.05	-4.80	-3.09
	(3.59)	(3.63)	(3.60)	(3.63)	(3.60)	(3.63)
Unemployed [c]	-23.67**	-29.19***	-27.20***	-32.78***	-26.59***	-31.95***
	(9.62)	(10.13)	(9.63)	(10.13)	(9.63)	(10.14)
Not in the labour force [c]	16.93***	12.96**	16.22***	12.58**	15.61***	11.77**
	(5.07)	(5.09)	(5.07)	(5.09)	(5.07)	(5.09)
Number of adults in household	6.21***	4.26**	6.37***	4.01**	7.33***	5.36***
	(1.99)	(2.03)	(1.99)	(2.02)	(2.00)	(2.04)
Number of children in household	-10.08***	-10.09***	-7.64***	-6.95***	-9.51***	-9.46***
	(1.63)	(1.65)	(1.58)	(1.59)	(1.63)	(1.65)
Household income for MLS purposes (100,000$)	70.57***	71.72***	52.81***	55.20***	52.45***	54.83***
	(2.99)	(2.89)	(3.63)	(3.54)	(3.63)	(3.55)
Household income for MLS purposes (100,000$) squared	-2.11***	-2.16***	-1.61***	-1.69***	-1.60***	-1.68***
	(0.15)	(0.14)	(0.16)	(0.16)	(0.16)	(0.16)
Rural areas	-13.69***	-12.38**	-14.26***	-13.16***	-13.77***	-12.52**
	(4.92)	(4.93)	(4.94)	(4.94)	(4.94)	(4.94)
Victoria [d]	-4.66	-4.63	-4.83	-4.91	-4.69	-4.72
	(4.86)	(4.90)	(4.87)	(4.90)	(4.88)	(4.91)
Queensland [d]	-16.27***	-9.79**	-15.45***	-9.20*	-15.50***	-9.25*
	(4.95)	(4.98)	(4.97)	(4.99)	(4.97)	(5.00)
South Australia [d]	-4.37	-5.65	-3.30	-4.60	-3.40	-4.79
	(5.22)	(5.23)	(5.23)	(5.24)	(5.23)	(5.24)
Western Australia [d]	19.88***	22.23***	18.82***	20.99***	19.05***	21.28***
	(5.38)	(5.36)	(5.40)	(5.38)	(5.41)	(5.39)
Tasmania [d]	-8.47	-7.58	-6.51	-5.91	-6.44	-5.75
	(5.74)	(5.77)	(5.75)	(5.77)	(5.76)	(5.78)
Northern Territory [d]	4.69	-5.17	5.27	-4.80	5.21	-4.89
	(6.86)	(6.84)	(6.89)	(6.86)	(6.90)	(6.87)
Australian Capital Territory [d]	-13.17**	-7.32	-12.70**	-6.95	-12.82**	-7.06
	(5.68)	(5.70)	(5.71)	(5.71)	(5.72)	(5.73)
Linkage quality	0.05	0.38*	0.06	0.39*	0.06	0.39*
	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
Sample mean	61.18	56.01	61.18	56.01	61.18	56.01
F statistic	21.28	36.95	77.95	68.41	48.67	51.51

Notes: Results (multiplied by 100) in each column are from a separate instrumental variable bivariate probit regression, with instrument(s) listed on the top row. [a], [b], [c], and [d] denotes "Year 12 or under", "Single", "Full-time employed", and "New South Wales" as the base group, respectively. Other control variables include state dummies and survey month-year dummies. "F statistic" from a Wald-type test for a null hypothesis that the estimate(s) of instrument(s) from the coverage equation is (are) zero. Robust standard errors are in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Appendix Table A6: Determinants of health care use

Health care use measure:	Any GP visit		Any specialist visit		Any inpatient treatment		Any outpatient treatment		Any ED visit		Any day clinic visit		Any dental consultation	
PHI indicator from:	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
PHI coverage	49.18**	36.84*	46.20***	29.78*	-35.71*	-27.46	-25.90	-32.08	-39.37*	-26.42	-15.45	-5.70	58.90***	54.65***
	(20.16)	(20.71)	(16.40)	(15.93)	(20.02)	(21.62)	(24.98)	(24.78)	(22.49)	(25.32)	(29.57)	(35.09)	(17.65)	(16.93)
Age	-3.94***	-4.17***	-0.73	-0.94	-4.21***	-4.06***	0.97	1.16	-4.10***	-3.94***	1.18	1.21	1.29**	0.94
	(0.84)	(0.86)	(0.58)	(0.59)	(0.69)	(0.72)	(0.82)	(0.82)	(0.71)	(0.73)	(0.86)	(0.89)	(0.57)	(0.57)
Age squared	0.05***	0.05***	0.01**	0.02***	0.04***	0.04***	-0.01	-0.01	0.04***	0.04***	-0.01	-0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Male	-42.75***	-42.89***	-15.80***	-15.96***	-14.04***	-14.35***	-16.51***	-16.83***	-5.70	-5.76	-10.94**	-10.88**	-15.82***	-15.33***
	(3.74)	(3.75)	(2.94)	(2.95)	(3.63)	(3.67)	(4.19)	(4.20)	(3.71)	(3.77)	(4.39)	(4.49)	(2.84)	(2.86)
Born in Australia	5.88	6.51	12.21***	13.40***	13.56***	13.40***	4.55	5.58	11.35**	10.65**	15.93***	15.23**	1.79	1.38
	(4.46)	(4.64)	(3.67)	(3.72)	(4.37)	(4.62)	(5.19)	(5.35)	(4.65)	(5.03)	(5.62)	(6.22)	(3.60)	(3.68)
Poor English proficiency	-14.16**	-12.19*	-25.09***	-23.83***	-23.03***	-25.56***	-27.83***	-30.56***	-33.00***	-34.67***	-9.85	-9.72	-18.92***	-14.94***
	(5.97)	(6.57)	(5.94)	(6.26)	(7.91)	(8.49)	(9.56)	(10.02)	(8.82)	(9.46)	(9.40)	(10.70)	(5.27)	(5.65)
Diploma/Certificate [(a)]	12.44***	12.93***	9.53***	9.94***	12.78***	12.64***	12.83***	13.03***	11.40***	11.18***	7.39	7.14	7.66**	7.53**
	(4.24)	(4.25)	(3.44)	(3.44)	(4.20)	(4.23)	(4.83)	(4.82)	(4.26)	(4.31)	(5.09)	(5.16)	(3.31)	(3.30)
Bachelor or higher [(a)]	4.68	7.04	19.80***	22.47***	18.50***	17.37***	14.61**	15.11**	10.24*	8.32	5.62	4.18	21.19***	22.32***
	(5.35)	(5.29)	(4.39)	(4.21)	(5.03)	(5.11)	(6.14)	(5.98)	(5.46)	(5.62)	(6.72)	(7.13)	(4.31)	(4.14)
Widowed [(b)]	5.64	4.83	-2.11	-3.14	-5.51	-4.81	-18.14	-17.53	0.06	0.97	-29.99**	-29.75**	-10.32	-11.67
	(13.26)	(13.31)	(8.91)	(8.92)	(10.98)	(11.04)	(12.71)	(12.67)	(11.43)	(11.48)	(14.02)	(14.07)	(8.81)	(8.77)
Divorced [(b)]	28.71***	28.10***	11.13**	10.22*	16.15**	16.80**	10.35	10.38	12.91*	13.78**	0.70	1.16	5.41	4.58
	(6.90)	(6.93)	(5.34)	(5.34)	(6.78)	(6.79)	(7.40)	(7.35)	(6.79)	(6.80)	(7.87)	(7.88)	(5.23)	(5.19)
Separated [(b)]	21.62**	20.50**	9.91	8.65	27.38***	28.36***	14.54	14.54	25.50***	26.82***	-7.17	-6.29	-4.82	-6.02
	(8.73)	(8.75)	(7.11)	(7.09)	(8.67)	(8.68)	(9.68)	(9.62)	(8.61)	(8.60)	(10.99)	(10.99)	(6.91)	(6.87)
Married [(b)]	12.11**	12.03**	10.35**	10.27**	22.99***	23.62***	9.75*	10.39*	7.31	7.59	4.67	4.50	-5.10	-6.01
	(4.80)	(4.88)	(4.06)	(4.10)	(5.12)	(5.18)	(5.90)	(5.93)	(5.17)	(5.24)	(6.15)	(6.37)	(3.91)	(3.93)

Notes: Results (multiplied by 100) in each column are from a separate instrumental variable bivariate probit regression, with two instruments: MLS income and LHC cutoff instruments. [(a)], [(b)], [(c)], and [(d)] denotes "Year 12 or under", "Single", and "Full-time employed" as the base group, respectively. Other control variables include state dummies and survey month-year dummies. Robust standard errors are in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Appendix Table A6: Determinants of health care use (continued)

Health care use measure:	Any GP visit		Any specialist visit		Any inpatient treatment		Any outpatient treatment		Any ED visit		Any day clinic visit		Any dental consultation	
PHI indicator from:	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin	Survey	Admin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Poor health	37.30***	36.89***	44.00***	43.45***	35.80***	36.40***	31.31***	31.05***	26.72***	27.54***	20.76***	21.26***	-6.58	-6.87
	(7.05)	(7.09)	(4.65)	(4.67)	(5.34)	(5.35)	(5.83)	(5.83)	(5.43)	(5.44)	(6.34)	(6.37)	(4.61)	(4.59)
Mental distress	27.64***	26.94***	35.48***	34.59***	19.60***	20.45***	21.83***	21.53***	25.84***	26.83***	13.51**	14.11**	3.46	2.97
	(7.06)	(7.09)	(4.84)	(4.85)	(5.70)	(5.70)	(6.22)	(6.21)	(5.66)	(5.65)	(6.82)	(6.86)	(4.82)	(4.79)
Disable	32.64***	32.73***	41.68***	41.91***	24.09***	24.39***	36.19***	36.29***	31.36***	31.62***	27.54***	27.49***	7.23**	7.00**
	(4.21)	(4.22)	(3.08)	(3.06)	(3.76)	(3.77)	(4.21)	(4.20)	(3.83)	(3.83)	(4.44)	(4.46)	(3.04)	(3.04)
Smoker	-9.15	-11.29**	-10.15**	-12.83***	-6.80	-5.60	-13.04*	-13.99**	2.26	4.39	-8.76	-7.22	-10.96**	-11.54**
	(5.73)	(5.74)	(4.84)	(4.76)	(5.83)	(6.04)	(6.90)	(6.89)	(6.02)	(6.29)	(7.64)	(8.29)	(4.74)	(4.65)
Part-time employed [(c)]	0.97	0.26	7.87**	7.15**	5.30	5.54	8.19	8.21*	-0.51	-0.05	7.48	7.90	2.05	1.57
	(4.39)	(4.39)	(3.50)	(3.50)	(4.37)	(4.39)	(4.99)	(4.97)	(4.49)	(4.51)	(5.40)	(5.42)	(3.42)	(3.39)
Unemployed [(c)]	-1.27	-2.46	13.49	11.85	15.76	16.57	7.30	6.44	1.25	2.44	25.26*	26.56**	-2.86	-3.01
	(11.55)	(11.61)	(9.44)	(9.49)	(11.11)	(11.25)	(12.73)	(12.77)	(11.19)	(11.33)	(13.01)	(13.34)	(9.24)	(9.23)
Not in the labour force [(c)]	-1.99	-1.17	13.91***	14.82***	18.82***	18.33***	14.52**	14.51**	2.92	2.15	20.93***	20.69***	8.47*	9.10*
	(6.37)	(6.38)	(4.81)	(4.77)	(5.65)	(5.67)	(6.53)	(6.48)	(6.17)	(6.20)	(6.68)	(6.70)	(4.77)	(4.73)
Number of adults in household	2.99	3.45	-0.74	-0.25	-1.25	-1.65	-1.00	-1.19	-0.09	-0.54	0.30	0.09	1.00	1.61
	(2.36)	(2.35)	(1.97)	(1.96)	(2.50)	(2.49)	(2.91)	(2.88)	(2.48)	(2.48)	(3.02)	(3.00)	(1.90)	(1.88)
Number of children in household	-0.25	-0.72	-5.50***	-6.11***	0.85	1.11	-3.07	-3.11	0.34	0.78	-6.66***	-6.46**	0.12	-0.18
	(1.91)	(1.90)	(1.62)	(1.59)	(1.94)	(1.94)	(2.30)	(2.27)	(1.98)	(1.99)	(2.49)	(2.52)	(1.54)	(1.51)
Household income for MLS purposes (100,000$)	-7.40*	-6.19	-0.78	1.70	10.45**	9.51*	1.14	2.93	8.51	6.24	2.94	1.81	0.63	0.47
	(4.03)	(4.30)	(4.11)	(3.85)	(4.91)	(5.47)	(6.87)	(7.16)	(6.69)	(7.60)	(4.52)	(5.67)	(4.54)	(4.64)
Household income squared	0.25	0.19	0.26	0.11	-0.94*	-0.85	-0.56	-0.70	-1.63*	-1.39	0.00	0.04	0.35	0.36
	(0.29)	(0.27)	(0.35)	(0.29)	(0.54)	(0.56)	(0.82)	(0.86)	(0.96)	(0.98)	(0.19)	(0.22)	(0.42)	(0.43)
Rural areas	-1.45	-2.29	-5.47	-6.27	4.23	4.79	-6.85	-6.99	5.15	5.94	-7.96	-7.45	-10.26**	-10.62**
	(6.07)	(6.08)	(4.98)	(4.96)	(5.89)	(5.92)	(6.97)	(6.94)	(6.08)	(6.11)	(7.54)	(7.59)	(4.80)	(4.78)
Linkage quality	1.14***	1.11***	0.61***	0.59***	0.78***	0.82***	0.58*	0.61*	0.95***	0.98***	0.81**	0.81**	0.20	0.15
	(0.26)	(0.26)	(0.23)	(0.23)	(0.29)	(0.29)	(0.33)	(0.33)	(0.29)	(0.30)	(0.35)	(0.35)	(0.21)	(0.22)

Notes: Results (multiplied by 100) in each column are from a separate instrumental variable bivariate probit regression, with two instruments: MLS income and LHC cutoff instruments. [(a)], [(b)], [(c)], and [(d)] denotes "Year 12 or under", "Single", and "Full-time employed" as the base group, respectively. Other control variables include state dummies and survey month-year dummies. Robust standard errors are in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.