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Hips and hearts: the variation in incentive effects of insurance across hospital procedures

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Abstract

The separate identification of effects due to incentives, selection and preference heterogeneity in insurance markets is the topic of much debate. In this paper, we investigate the presence and variation in moral hazard across health care procedures. The key motivating hypothesis is the expectation of larger causal effects in the case of more discretionary procedures. The empirical approach relies on an extremely rich and extensive dataset constructed by linking survey data to administrative data for hospital medical records. Using this approach we are able to provide credible evidence of large moral hazard effects but for elective surgeries only.

Keywords: health insurance; asymmetric information; moral hazard.
JEL: D82; I11; I13.

1 Introduction

A relationship between health insurance coverage and health care utilisation is easy to establish but more difficult to explain. Observing the typical positive correlation could be the result of adverse selection, where people with high expected usage of health services purchase (more) insurance or it could be moral hazard, where those who are insured face lower costs of health care leading to increased utilisation of health services (Arrow, 1963). Findings of negative correlations in certain markets has sparked research focussing on a third source of correlation, namely, that of preference heterogeneity; variation in

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risk aversion, cognitive skills, or bequest motives has been shown to lead to correlation between insurance purchase and outcomes. Institutional factors also play a role. For example, the information available to insurers and the degree with which they can design contracts based on this information vary substantially across markets and areas. In brief, the sign and magnitude of the correlation between insurance and utilisation is an empirical matter and disentangling each of these factors is difficult. It is perhaps not surprising to find quite different net effects both in sign and magnitude across markets and institutional environments. In this paper we focus on a different source of variation, that coming from differential incentives faced by consumers.

Our empirical approach starts with the hypothesis that if moral hazard is present in the case of health insurance, it will appear differentially across diverse health services. Thus, analyses at an aggregate level such as total hospital admissions, which is typical in the existing literature, will likely be subject to aggregation biases and hence mask the true situation. Using an extremely rich and extensive dataset we are able to provide credible evidence of variation in moral hazard effects. The data are constructed by linking a survey of older individuals to administrative data for hospital inpatient medical records. The survey is part of the Sax Institute's 45 and Up Study of over 265,000 residents of the state of New South Wales (NSW) in Australia. These data are sufficiently detailed to allow identification of relatively heterogeneous procedures and with the very large number of observations available there are a sufficient number of procedures to allow credible analyses of the insurance-utilisation relationships at a highly disaggregated level. The use of specific procedures allows us to address the issue of heterogeneity in the incentive effects of health insurance on hospitalisation. In particular, surgeries that are elective or non-urgent such as hip replacements are distinguished from non-elective or urgent procedures such as coronary artery bypass graft surgeries (CABG). As elective procedures are more discretionary in nature, the patient will be much more involved in whether to have the procedure or not as well as when to have it.

Selection and preference heterogeneity remain a threat for the identification and estimation of the causal impact of private health insurance on the demand for surgical procedures. One approach would be to exploit the panel nature of the administrative data, which in the case of hospital admissions, is available from 2000 to 2009. However, the survey, which is linked to the administrative data, was collected only once during this period and this is the source of the insurance status of individuals. Even with the availability of insurance information matching the time period corresponding to the administrative data, the lack of variation in the insurance status of older individuals would likely leave the effect unidentified in any analysis controlling for individual fixed effects.

The predominant approach in separating incentive effects from selection in the literature on private health insurance has been the use of instrumental variables. Finding good instruments has been challenging and in many cases, the identifying instrumental variables have not been convincing nor supported by strong empirical evidence. So while many of the instruments that have previously been used are available in our dataset, we do not actively pursue this approach.

Instead, our primary approach is to exploit the rich set of controls we have at our disposal, including extensive self-reported health measures obtained from the survey as well as past health care utilisations obtained from the administrative data. Thus, selection effects are dealt with by the use of proxies that form a comprehensive picture of an individual's health status and history thereby minimising the likelihood of any omitted health effects being a threat to inference. Some support for our approach is provided by Buchmueller et al. (2005) in their survey of the insurance-utilisation relationship in health. They do not find large differences in inferences across different econometric methods and they conclude that: "(...) there is a high degree of concordance among the results of studies that use extensive health status controls and demographic variables to control for the nonrandom assignment of insurance status and those using instrumental variables or quasi-experimental regression techniques." As for the potential confounding effect from preference heterogeneity, we follow most of the literature by using controls representing variation in risk behaviours.

The empirical results provide strong evidence of moral hazard in the case of elective surgeries, but not in the case of non-elective surgeries. Insurance increases the probability of having an elective surgery by 0.659 percentage points, which corresponds to a 21.7 per cent increase from the mean. The estimated insurance effect on non-elective surgeries is substantially smaller in magnitude and not statistically significant. These results are robust to additional specification checks.

2 Background

2.1 Literature review

The case for incentive effects in association with health insurance is arguable since health care may be perceived to be unpleasant and only to be sought in situations of necessity. Nevertheless, it is now generally accepted that health insurance has some causal impact on health care utilisation. As stated by Pauly (2006):

"there is one thing we do know: people do not just use medical care based on how sick they are and what doctors order is not just based on their medical training; in both cases, insurance matters."

Studies analysing the effects of insurance on utilisation span many different countries and different institutional environments. Empirical studies generally find positive correlations. However, there have been few large-scale health insurance experiments (the RAND experiment of the mid 1970's and the recent Oregon experiment), and the separation of causal effects has relied in many cases on exclusion restrictions that may be problematic (for example, socio-economic variables affecting utilisation only through insurance in studies with coarse information on health). The use of program changes in health insurance as natural experiments have also been widely applied in various contexts. Examples of studies estimating causal effects are: Ettner (1997), Vera-Hernandez (1999), Harmon and Nolan (2001) and Jones et al. (2006). Examples based on natural experiments are: Currie and Gruber (1996), Stabile (2001), Remler and Atherly (2003), Decker and Remler (2004), Currie and Fahr (2005), McWilliams et al. (2007), Grignon et al. (2008), Ketcham and Simon (2008), Card et al. (2009), Hullegie and Klein (2010) and Anderson et al. (2012). Studies using panel data that control for unobserved fixed effects are less common but include the recent work of Bolhaar et al. (2012) for Ireland where they find no evidence of moral hazard.

In their survey, Buchmueller et al. (2005) concentrate on US studies and do not find large differences in inferences about the insurance-utilisation relationship across different econometric methods. This suggests that variation in institutional contexts may be driving differences in empirical estimates. One other potential reason for the variation in estimated causal effects is the likely heterogeneity in impacts across types of medical problems and the amount of discretion the patient has. Due to data limitations, existing studies of the causal effects of insurance on health care have used aggregate measures of utilisation and so cannot distinguish between the different incentives across types of care. (One exception is the distinction between GP and specialist care; e.g. Jones et al. (2006).) Furthermore, aggregation weights and characteristics of the relevant population are likely to vary across institutional environments in ways that may reinforce the aggregation bias. To our knowledge, this paper is the first to study the variation in incentive effects of health insurance across the different types of hospital care.

Much of the recent empirical literature on insurance markets generally has focused on the presence of asymmetric information and selection effects. See Finkelstein and McGarry (2006), Cohen and Einav (2007), Fang et al. (2008) and Olivella and Vera-Hernndez (2013) for examples and Cohen and Siegelman (2010) for a survey. Interest in this literature was sparked by findings of advantageous selection in particular insurance markets. Heterogeneity in preferences is believed to lead to advantageous selection in certain markets; depending on the context, this heterogeneity in preferences can take the form of variation in risk aversion, cognitive skills or utility of wealth. Certain recent papers have focussed on the separation of the distributions of risk types from preference types and the estimation of correlation in these marginal distributions. This requires more stringent structural assumptions, but the argument is that identification of these distributions is needed for welfare analysis. See Einav et al. (2010) and Einav and Finkelstein (2011) for a discussion of this area. In most of these studies, moral hazard is ignored in order to focus on the identification of the two other sources of correlation between insurance and outcomes. (An exception to this is the paper on health insurance by Cardon and Hendel (2001).)

Previous Australian studies looking at the effects of insurance on utilisation have generally found positive effects although the magnitudes vary a lot across studies. This is perhaps not surprising given the variety of identification strategies used. Savage and Wright (2003) and Lu and Savage (2006) consider selection on observables only. Several studies have used instrumental variables to separate causal effects from selection. Examples include Cameron et al. (1988), Srivastava and Zhao (2008), Cheng and Vahid (2011) and Doiron (2012). Most of these studies rely to some extent on exclusion restrictions involving socio-economic or demographic variables and in some cases risk behaviours (smoking, drinking, exercise and BMI). Doiron (2012) is an exception to this; she looks at the effects of private health insurance on hospital utilisation for couples only. The identification strategy relies on the exclusion of partner's health and expectations regarding future children in one's hospital use (conditional on one's health and actual children).

2.2 The Australian institutional environment

Australia has a health care system that is a mix of public and private funding and delivery. Medicare is a universal public insurance system which provides all Australian citizens with free public hospital treatment, including services provided by emergency departments, and subsidised out-of-hospital medical services and pharmaceuticals. In addition to this public insurance, there exists a private health insurance sector. Patients covered by private insurance have access to private hospitals and private treatment in public hospitals. Individuals without private cover can also access private hospitals as self-funded patients. An important fact for our analysis is that elective and non-elective procedures are performed in both private and public hospitals.

Private health insurance can be used to cover the costs of hospital stays but not doctors' visits; this is true for general practitioners and for specialists. Private health insurance can also be used to cover other procedures and items such as prostheses and ancillary services which include dental care, allied health services and complementary care. Most individuals who purchase private health insurance buy hospital cover and may or may not purchase cover for ancillary services. Less than 5% of the insured have cover for ancillaries only. In this paper we consider hospital insurance only and if individuals do not have hospital cover they are considered as uninsured.

The cost sharing arrangements in the Australian hospital system are based on the insurance status of the patient as well as the type of hospital in which they are admitted. For public hospitals, Medicare covers 100% of hospital costs for public patients. For private patients (who could be self-insured or privately insured) in either public or private hospitals, Medicare covers 75% of the Medicare Scheduled fee. Private providers are not restricted to charging the Medicare Scheduled fee and so patients face a liability for any residual payment required (25% of the Scheduled fee plus charges above this). For private patients with private health insurance this may involve out-of-pocket expenses depending on the fees set by the private provider and the cost-sharing arrangements (co-payments and deductibles) of their particular policy. However, there has been an upward trend in no-gap policies that avoid such expenses and according to PHIAC (2008) the proportion of benefits paid for in-hospital medical services with no gap in New South Wales was 81.2 per cent in 2008. Note that individuals with private health insurance are not excluded from the public system; an individual always has a choice to use or not to use private health insurance.

Depending on the particular insurance policy held by a private patient, the out-of-pocket costs for a specific procedure may be higher than if they were undergoing the hospital stay as a public patient. This is true regardless of the hospital in which the procedure is performed. The question is then why do patients buy and use health insurance for their hospital procedures? One answer is that private insurance allows you to jump queues and hence provides shorter waiting times. (We return to the issue of waiting times in the discussion of the results.) There are other benefits of private insurance the main one being a greater choice of doctor and hospital. Having access to an experienced surgeon working in a well-equipped and well-staffed private hospital is a major benefit of private health insurance. Incentive effects of insurance identified in this paper can be due to differences in the quality of care as well as differences in costs between public and private sectors. We would argue that this interpretation of moral hazard is not inconsistent with the literature as very few studies have any measure of, or control for, the quality of the insured services.

Two features of the Australian setting help simplify our analysis. First, private health insurance is not tied to employment as it is in many environments. This makes the modelling of the demand for insurance easier since accounting for selection into employment and employer-provided insurance cover is not needed. Second, the system is community-rated; insurers cannot refuse to insure or adjust premiums based on individual characteristics including any past usage of medical services. There are two exceptions to this: premiums increase by a fixed amount of two per cent per year of age for $30 \leq$ age ≤ 65 for those who purchased private health insurance after 2000, and insurers can impose waiting times of up to a year for insurance claims involving pre-existing conditions. Community rating implies that providers have limited opportunities to exclude or separate different risk types. Since insurers cannot base provision or features of the insurance contract on personal characteristics, the relationship between observed characteristics of the consumer and the decision to purchase insurance reflects consumer preferences and information rather than insurers' reaction to potential adverse selection. It is worth noting that in such a system, we expect adverse selection to be greater both because of community rating and due to the presence of a universal public insurance system (Vera-Hernandez, 1999).

Coverage of private health insurance in Australia has been high despite being limited largely to private in-hospital treatment and the availability of high-quality free public hospitals. A common argument presented by Australian policy makers is that a well-functioning private system is needed for the sustainability of a high-quality public system. Policy initiatives implemented around the year 2000 have created incentives for individuals, especially those with higher incomes to purchase private health insurance. But for the period under study the institutional environment remained stable and no major reforms were implemented. For additional details on the Australian private health insurance system, please see Colombo and Tapay (2003).

3 Empirical strategy

The aim of this paper is to identify the incentive effects of private health insurance on the demand for elective and non-elective surgeries. To disentangle these effects from selection and preference heterogeneity, we need to control for the confounding variables that may affect both the demand for private health insurance and the demand for surgeries. The baseline specification of the model is given by:

$$s^*_{ijt} = \alpha_j PHI_{i,t-1} + X'_{i,t-1}\beta_j + u_{ijt},$$
$$s_{ijt} = 1[s^*_{ijt} > 0], \tag{1}$$

where subscript t refers to the time period, j indicates the type of a surgery (elective or non-elective) and i refers to an individual. The variable s^*_{ijt} is the net benefit associated with having a surgery, which is unobserved. Instead, we observe s_{ijt}, that is, whether or not a person has a surgery in period t. This variable takes the value 1 if the net benefit s^*_{ijt} is positive and the value 0 otherwise. We assume that the error term u_{ijt} follows a standard normal distribution and estimate equation (1) by probit regression. To account for the possibility that an encounter with the health care system may affect an individual's demand for private health insurance and in turn lead to simultaneity bias, we estimate a prospective model. More specifically, the coefficient α_j measures the effect of having private health insurance in period t on the probability of having a particular type of surgery in the next period.

The vector $X_{i,t-1}$ contains two main types of variables, measured at the same time as an individual's private health insurance status: (1) health measures to capture expected future health usage and tastes for health and (2) risk preferences proxied by risk behaviours. The argument underlying adverse selection in insurance markets is that the demand for insurance is positively correlated with the expected health costs or usage in the next period; this is related to the health state in the next period which in turn is positively related to an individual's health in the current period. Therefore, if one fails to properly control for an individual's health status, the positive coefficient on the insurance status variable cannot be convincingly interpreted as a moral hazard effect of insurance. In this analysis, we have access to a very rich dataset constructed by linking survey data to administrative data for hospital medical records. These data are used to construct an extensive list of health measures; as detailed below, we use over 230 objective and subjective health variables to control for the person's health status.

An individual's demand for private health insurance may also be positively correlated with his/her level of risk aversion. Ceteris paribus, more risk averse individuals will be willing to pay more for insurance; they may also invest more in their health and, in turn, have lower need for surgery. Thus, omitting controls for an individual's risk preferences from equation (1) may lead to under-estimation of the insurance effect especially in cases where health status is poorly measured. In our case, better measurement of health through the use of extensive health controls will minimize these potential biases.

Nevertheless, it is possible that individual preferences affect utilization and insurance demand directly rather than through actual health status; for example, the so-called "worried-well" person may also be more likely to purchase cover. Another example is a case where more risk averse (and/or health conscious) individuals choose to have surgical procedures as preventive measures. We partly account for this by including past health care utilization measures, as such persons are likely to have had higher health service usage in the past. Following the literature, we also use measures of risk behaviours, including smoking, drinking, exercise, diet and use of preventive health care, to proxy for an individual's preference type.

The main premise of this paper is that we expect to find stronger evidence of moral hazard in the demand for elective surgeries than in the demand for non-elective procedures. For this reason, we estimate equation (1) separately for selected elective and non-elective surgeries. Making statements that these effects are causal normally requires the use of alternative strategies such as instrumental variables. In our case we simply do not believe that any of the instruments we have available are credible. Instead we argue that the use of an extremely rich set of controls gives us confidence that what we find is in fact causal. However, we cannot definitely rule out the possibility that residual omitted factors remain that may bias our results. To gauge how likely this is in our case, we rely on the extent to which the inclusion of variables, specifically designed to control for biases due to selection and risk attitudes, impact the magnitude of the estimated insurance coefficient. Such an approach is in the spirit of Altonji et al. (2005) who compare the impact of possible omitted variables with the impact of observed control variables. In doing so, we also exploit collateral information provided by conducting the analysis separately for elective and non-elective surgeries. While a priori there might be cases for biases going in either direction, we argue that if biases due to omitted variables (such as risk preferences) do exist they should be in the same direction for both elective and non-elective surgeries.

4 Data

We use a rich dataset constructed by merging survey data with administrative medical records. Access to these data enables us to control for many variables that are usually unobserved. The survey data come from the 45 and Up Study, a survey of over 265,000 individuals 45 years of age or over, who were randomly selected from the residents of New South Wales (NSW), the largest state of Australia. The sampling frame includes all individuals in the target age range who were covered by Medicare, Australia's universal public health insurance program. Medicare covers all Australian citizens and permanent residents. Mail questionnaires were used to collect information from the participants. Recruitment in the study started in early 2006 and the final questionnaires were received in the beginning of 2010, but most of the questionnaires were completed in 2008. Around 18 per cent of those sent questionnaires participated and the full sample includes around 10 per cent of the eligible population (45 and Up Study Collaborators, 2008). Johar et al. (2012) demonstrated that the 45 and Up sample is broadly representative of the populations of NSW and Australian in terms of most demographic and socio-economic characteristics (age, gender, marital status, and employment). On the other hand, there is some selection on household income and country of birth. To take this selection into account, we have controlled for country of birth, income and other variables that may be related to income (education and housing type) in our analysis.

The 45 and Up Study provides information about the respondents' socio-economic and demographic characteristics, medical conditions, physical limitations, mental health, surgical procedures, medications, lifestyle, diet, social connections and other health related factors. The survey data, with the consent of all the participants, are linked to the respondents' medical records. More specifically, we have information on the respondents' hospitalisations, emergency department visits and the use of medical services and prescription medicines. For this analysis, we mainly use the hospitalisation data that come from the NSW Admitted Patient Data Collection and cover all hospital admissions of the sample individuals from 2000 to 2009. Admissions to public and private hospitals and day procedure centres are included in the data. Detailed information is provided on each admission, including the exact time and date of admission and separation, diagnosed conditions and performed procedures.

The initial sample contained 266,804 individuals. The criteria for the inclusion of observations in the analysis sample are as follows. First, we exclude 1,330 individuals who were not chosen but volunteered to participate in the 45 and Up Study, as they may introduce selection bias. Second, a small number of invalid records (individuals younger than 45 years of age) are excluded from the sample (22 observations). Third, only individuals interviewed in 2006-2008 are used for the analysis, because we are estimating a prospective model and hospitalisation data, which is used to construct dependent variables, ends in 2009. Therefore, 3,604 individuals who completed the survey in 2009 and 2010 are excluded. Additionally, 5,490 observations with missing private health insurance status are deleted. We deal with missing data on other control variables in two ways. For the variables with more than 1 per cent of values missing, we create indicator variables for missing values. Observations with missing data on control variables with less than 1 per cent of values missing are dropped from the sample. The final analysis sample contains

249,273 observations (93.43 per cent of the initial sample). A comparison of our analysis sample with the full 45 and Up sample shows no substantial differences in the means of main demographic and socio-economic characteristics (details are available on request).

4.1 Variables

4.1.1 Main variables

They key variable of interest is an individual's private health insurance status, which is reported in the 45 and Up Survey. We construct a variable that takes the value one if an individual has private health insurance (with or without ancillary service coverage) and the value zero otherwise. Around 65 per cent of the sample reported having private health insurance cover.

The dependent variables used in the estimations are constructed using the hospital admission data. For each admission, the principal procedure performed on the patient is recorded. To define whether a procedure is elective or non-elective, we use the urgency category distribution by procedure provided by Australian Institute of Health and Welfare (2012b). This information is available for 15 indicator procedures, or most common surgeries performed in the Australian hospitals. Importantly, the classification of the procedures is exogenous to the data analysis. In Australia, surgical procedures are divided into emergencies that need to be performed within 24 hours and electives (planned or booked) that can be postponed for at least 24 hours or more. Patients that need an elective procedure are placed on a waiting list and assigned one of the urgency categories by their doctor (Baggoley et al., 2011):

1. Urgent - for a condition that has the potential to deteriorate quickly to the point that it may become an emergency (admission within 30 days is desirable);
2. Semi-urgent - for a condition which is not likely to deteriorate quickly or become an emergency (admission within 90 days is desirable); or
3. Non-urgent - for a condition which is unlikely to deteriorate quickly and which has little potential to become an emergency (admission within 365 days is acceptable).

We begin with the case of elective surgeries. Our definition of elective surgeries includes procedures that are usually classified as non-urgent. Panel A of Table 1 lists these procedures and presents their incidence rates by private health insurance status. The proportion of non-urgent cases varies from 71 per cent for hip replacement to 88 per cent for septoplasty (Australian Institute of Health and Welfare, 2012b). For the main analysis, we construct a binary variable that takes the value one if an individual had any of the listed elective procedures in the *12 months* following the survey date and the value zero otherwise. We also look separately at the effects of insurance on the demand for the three most prevalent elective procedures (cataract extraction, knee replacement and hip replacement). The incidence rates of most of the elective surgeries are higher in the insured sub-sample. On the other hand, the incidence rate of cataract extraction is higher among the uninsured. As a result, the overall incidence rate of elective surgeries is similar (around 3 per cent) in both sub-samples. Note that the zero correlation between insurance and elective surgeries may be explained by advantageous selection and does not imply that there is no incentive effect of insurance.

Next, we turn to the definition of non-elective surgeries. Non-elective surgeries include procedures that are usually classified as emergency, urgent, or semi-urgent. The list and incidence of these procedures are provided in panel B of Table 1. Appendectomy and coronary angioplasty are emergency procedures (Australian Institute of Health and Welfare, 2012a). The proportion of urgent or semi-urgent cases varies from 68 per cent for myringotomy to 95 per cent for coronary artery bypass graft (Australian Institute of Health and Welfare, 2012b). For the analysis we use a binary variable that takes the value one if an individual had one of these procedures in the *12 months* following the survey date and the value zero otherwise. The difference in the overall incidence rate of non-elective surgeries between the uninsured (0.661 per cent) and insured (0.597 per cent) is not statistically significant. Note that the incidence of elective and especially non-elective surgeries is relatively small; large samples are needed for this type of analysis.

4.1.2 Control variables

As mentioned in Section 3, the baseline model controls for two main types of variables that are expected to affect an individual's demand for elective and/or non-elective surgeries and may also be correlated with his/her health insurance status. First, we control for a number of health measures obtained from the administrative and survey data. Hospital medical records are used to construct an individual's history of medical conditions in the past five years. The hospital data include principal and secondary diagnoses associated with each admission; these are coded using the World Health Organization's ICD-10 classification system. We have used Sightlines DxCG Risk Solutions software to aggregate these codes to a smaller number of condition categories. In total, 24 condition categories are included in the models (rare conditions are grouped into one category). Importantly, we include conditions that may be directly related to the demand for the elective and non-elective surgeries analysed in this paper. Past musculoskeletal, ophthalmic, vascular and ear, nose and throat diseases may increase the demand for related elective surgeries. A history of cardiovascular or hepatobiliary (related to liver or gallbladder) diseases may be linked to a higher likelihood of a non-elective surgery.

We also add binary variables that indicate whether or not an individual has been previously admitted to a hospital for an elective and non-elective surgery. A patient who had a surgery in the recent past may be less likely to need the same surgery within the next 12 months. Moreover, the removal of gall bladder and appendectomy can only be performed once. On the other hand, a patient who had a surgery recently may need a repeat surgery. For example, a patient who had a knee replacement operation on one knee may need an operation on the other knee in near future. Therefore, the direction of the relationship between past and future operations is unclear. The models also control for past hospitalisations for other reasons.

To control for less acute health conditions that may not require a hospital admission, hospitalisations outside our administrative data window and any other factors, we include self-reported health measures obtained from the survey data. The 45 and Up study contains a number of objective health measures, including diagnosed medical conditions, recent treatments for a number of conditions, medicines taken in the past 4 weeks, history of surgeries, family health history, long term illness/disability status, activity limitations[1], body mass index (BMI), teeth, bone and urinary health, hearing loss, incidence of falls and mental health. Additionally the respondents are asked to self-assess their general health, quality of life, vision, teeth health and memory. We refer to the latter variables as subjective health measures. In total, there are 198 health measures (233 variables) included in the model.

Second, we include an extensive list of proxies for unobserved individual preferences to the model (29 characteristics, 41 variables). Specifically, the regressions control for an individual's smoking status, alcohol consumption, exercise, time spent outdoors and on sedentary activities and use of preventative health care services (cancer screening tests). The survey data also include a number of questions on an individual's diet. The respondents report how many times per week they eat various types of food (meat, fish, cheese, bread, vegetables and fruit) and what type of milk they consume.

All regressions also control for year effects and demographic and socio-economic characteristics, such as age[2], sex, marital status, number of children, remoteness of the area

[1] The questions on activity limitations are used to construct The Medical Outcomes Study - Physical Functioning scale. This scale ranges from 0 to 100. A higher score indicates a higher level of physical activity.

[2] To allow for non-linear age effects, we include dummies for age-in-years. Individuals older than 84 years of age are grouped into one category due to small numbers of older individuals.

of residence[3], country of birth, ancestry, second language, education, income, and employment status. Type of housing is included as a proxy for household wealth. We also control for the SEIFA Index of Relative Socio-economic Advantage and Disadvantage, which measures the socio-economic status of the population in an individual's local area (Pink, 2006). Additionally, the survey data contains social capital variables. The respondents are asked about their social interactions and social network size. The full list and means of control variables are provided in Appendix A Table A.1. In total there are 245 controls (362 variables) included in the model.

To test the sensitivity of the results, we add an individual's total health care expenditure in the past calendar year to the model. Total health care expenditures include spending on hospitalisations, emergency department visits, GP and specialist visits, diagnostic tests, other medical services and prescription medicines. This information is obtained from the administrative data[4]. Controlling for the past hospitalisations, the total health care expenditure variable measures the use of other health care services and severity of hospital-based diagnoses.

5 Results

All tables in this section report probit average partial effects. Standard errors are estimated using the delta method (by Stata's "margins" command). Table 2 presents the main results. Column (1) reports the estimated effects of insurance on the demand for elective and non-elective surgeries in the full model specification. Private health insurance is found to increase the probability of having an elective surgery within the next 12 months by 0.659 percentage points, which is close to a 22 per cent increase from the mean. This effect is highly statistically significant. The effect of private health insurance compares to (or is larger than) the effects of other important determinants of the demand for elective surgeries, such as, recent history of musculoskeletal disorders, use of glucosamine (a supplement for osteoarthritis), having a long-term illness or disability, poor self-assessed health, or employment status. The effect of insurance is almost as large as a four year increase in age (at the average age of 63 years). This finding is interpreted as evidence of a substantial incentive effect of insurance in the case of elective surgeries.

As expected, we find that private health insurance has a substantially smaller effect on the probability of undergoing a non-elective surgery. It is estimated that health insurance

[3]Remoteness is measured by the Accessibility/Remoteness Index of Australia Plus (ARIA+) (Trewin, 2001). We create a dummy variable for individuals living in the major cities.

[4]We thank Meliyanni Johar for constructing and providing this variable.

cover increases this probability by 0.030 percentage points, which represents an increase of roughly 5 per cent from the mean. Relative to the mean, the average partial effect of insurance on non-elective surgeries is more than four times smaller than the average partial effect of insurance on elective surgeries. Moreover, this effect is statistically insignificant at the conventional significance levels despite a very large sample size. Thus, we do not find any evidence of an incentive effect of insurance in the case of non-elective surgeries.

As they stand, the results are consistent with our initial hypothesis that the incentive effects for elective surgeries are larger than for non-electives. Moreover, taken literally there is a large incentive effect of insurance for electives but no effect for non-electives. To be more confident in these conclusions we need to address the question of whether it is possible that these results are an artifact of selection on unobservables. We follow the arguments of Altonji et al. (2005) and use the results on selection on the extensive range of observables to gauge the consequences of potential selection effects from the unobservables.

In columns (2)-(6) of Table 2, we investigate how large the biases in the estimated effects of insurance would be if we did not include the extensive list of controls available in our data. Each column represents the estimated insurance effect after deleting a particular set of control variables. (Note that each set of controls is deleted from the specification with the full set of controls.) Turning first to elective procedures, we find that the effect of insurance is overestimated if we do not control for objective health (objective health includes all of our health related variables except self-assessed health measures). This result suggests that there is adverse selection on observed objective health, which is as expected. In contrast, omitting subjective health measures (self-assessed general health, quality of life, vision, teeth health and memory) leads to an underestimate of the insurance effect, suggesting that, controlling for the objective health variables, there is advantageous selection on self-assessed health. Finally, we do not find evidence of advantageous selection on risk behaviours once all the health measures are held constant, as omitting these variables reduces the estimated effect of insurance only slightly (from 0.659 to 0.656).

The exclusion of socio-economic characteristics also has practically no impact on the estimated effect of insurance on elective surgeries (the average partial effect drops from 0.659 to 0.654). On the other hand, we find that it is important to control for age as omitting the age dummies causes an upward bias in the average partial effect of insurance on elective surgeries. Age may be capturing unobserved aspects of health. Older people may have a higher probability of getting a surgery even conditional on observed health.

For example, doctors may be more likely to take health complaints of an older person seriously as future health consequences may be more severe.

In the case of non-elective surgeries, the pattern of results is similar to that found for elective surgeries indicating that biases move in the same direction. The main difference for non-elective surgeries is that the estimated effect of insurance remains small and insignificant in all of the specifications.

The results in Table 2 indicate that if there are any remaining biases, they are likely to move in tandem for the two types of surgeries and to be larger for electives. If there were remaining biases associated with advantageous selection, then the incentive effects would in fact be larger for both types of surgeries and the discrepancy between them would likely increase. Our conclusions would be strengthened. A more plausible threat to our core conclusions is the case of remaining biases associated with adverse selection. Because we believe the causal effect of insurance to be non-negative, the maximum bias in the estimated effect for non-electives can only be small. This leaves us with the question of whether a bias due to adverse selection could conceivably eliminate the entire effect that is currently observed for elective surgeries. Comparing the baseline estimate (column 1) to that associated with the exclusion of all objective health measures (column 2) provides an indication of possible bias resulting from adverse selection. While this estimated bias is economically large, if replicated by a set of unobservables it would not be sufficient to eliminate the baseline effect. Given the extensive list of controls obtained not only from the survey, but also from the administrative data, it is very unlikely that selection on the unobserved health-related variables would be more severe than selection on the currently observed variables. These arguments lead us to be confident in the baseline estimates of the incentive effect of insurance on surgeries.

Next, we look at what particular variables are driving selection in private health insurance cover. Table 3 presents the probit average partial effects of the main control variables (objective and subjective health measures and risk behaviours) on the demand for elective and non-elective surgeries and insurance cover. The results show that an important source of adverse selection is past hospitalizations, which are positively related to both the demand for elective and non-elective surgeries and the demand for insurance. Additionally, the variables that signal poor joint health (recent hospital-based treatment for musculo-skeletal disorders, consumption of glucosamine and earlier hip or knee replacements) increase both the probability of an elective surgery and the probability of insurance.

We find that a main driver of the finding of advantageous selection for subjective health is self-assessed vision. Better self-assessed vision is associated with increased probability of insurance cover and lower demand for elective surgeries. Some self-assessed health measures contribute to adverse selection; for example in the case of dental health and quality of life, better self-assessed health is related to more surgery and a higher incidence of cover. Although poor self-assessed health increases the probability of a non-elective procedure, it reduces the probability of an elective procedure. It may seem counterintuitive for individuals who rate their health as good or better to be more likely to undergo an elective surgery in the 12 months following the survey date. A possible explanation for this result is that the self-assessed health variable measures unobserved aspects of health which may make an individual more or less suitable for a surgery. An individual in poor health may choose to wait for an improvement before undergoing surgery if there is indeed scope for discretion in the scheduling of the procedure. Individuals in poor health may also have greater caregiving needs after a surgery and their choice of whether to undergo an elective surgery or not may be constrained by the availability of a caregiver. Alternatively, controlling for the objective health measures, self-assessed health may proxy for optimism or other personality factors that have positive effects on the demand for elective surgeries.

There is also evidence of advantageous selection into insurance for some of the risk behaviours. The demand for private health insurance is correlated with smoking, fruit consumption, choice of the type of milk, and cancer screening in expected directions. On the other hand, the insured have higher alcohol consumption and are not more likely to exercise, eat vegetables or choose healthier sources of protein or carbohydrates than the uninsured. Most of the risk behaviours do not significantly affect the demand for surgeries, which explains why the exclusion of these behaviours from the models does not change our main results (see Table 2). This finding is not surprising given that we control for numerous subjective and objective health measures. There is also no strong support in our data for the hypothesis that individuals choose elective surgery as a preventive measure. The probability of an elective surgery is positively correlated with only a few health-enhancing behaviours (the number of hours spent outdoors on weekend, fruit consumption and breast/prostate cancer screening).

The effects of demographic and socio-economic variables are presented in Appendix A Table A.2. Once the health measures are fixed, most of these variables have no effect on the probabilities of elective and non-elective surgeries. Given that Australia has a universal health care system and all Australian residents are eligible for free public hospital treatment, this result is not surprising. Some results are worth noting. Employed individuals are found to have lower demand for elective surgeries, perhaps because the time cost of a surgery is higher for them. We also find that people living in aged care facilities have a lower probability of an elective surgery. Remoteness of the area of residence is not found to be a barrier to health care access; if anything, individuals living in regional or remote areas are slightly more likely to have an elective surgery compared to individuals living in the city. The demographic variables are correlated with the demand for insurance as expected; similarly, the demand for insurance increases with higher socio-economic status, as measured by education, income, SEIFA and employment.

As shown in Table 2 and unlike other demographic and socio-economic variables, the controls for age have a large impact on our main results. The predicted probabilities of elective and non-elective surgeries and private health insurance by age are presented in Figure 1. The conditional probability of an elective surgery increases with age, whereas the probability of a non-elective surgery does not vary significantly by age. The probability of having private health cover is increasing with age until around 65 years and slightly decreases afterwards. (Age-in-year dummies are jointly statistically significant in the insurance and elective surgery equations at the 0.1% level while in the non-elective surgery equation, age dummies are only statistically significant at the 10% level.) The most striking aspect of Figure 1 is the strength of the relationship between age and the probability of elective surgery even with extensive health controls. Nevertheless, it is still the case that the effect of age on electives is smaller than the effects of the most relevant health variables. If we calculate the average effect of a one year increase in age across all ages, this average age effect is smaller than the effects of such health measures as past diagnosis of musculo-skeletal disorders or eye disease, recent treatment for arthritis, use of supplements for arthritis, or poor self-assessed vision. For example, a change from excellent to poor vision increases the probability of an elective surgery by as much as a nine year change in age from the sample average (63 years).

To address the possibility of remaining selection effects, in Table 4 we examine whether our main results are affected by the inclusion of an individual's total health care expenditures in the past year. Specifically, we include a binary variable indicating whether or not an individual had any health care expenditures, dummies for expenditure quintiles as well as a 3rd order polynomial in continuous expenditures (in thousand dollars). Note that the sample size is smaller in these models, because this information is only available for the respondents who completed the 45 and Up survey in 2007 and 2008. For this reason, columns (1) and (3) present the estimates of the baseline model using this smaller sample. Columns (2) and (4) report the estimated effects of insurance with the health care expenditure variables added to the model. Having positive health care expenditures significantly increases the probability of an elective surgery in the next year by 0.711 percentage points. Being in a higher health care expenditure quintile also increases the likelihood of both types of surgeries. Controlling for health care expenditures reduces the average partial effects of private health insurance status only slightly. The estimated effect of insurance on the probability of an elective surgery changes from 0.679 to 0.657 percentage points. Statistically insignificant effects of insurance on the probability of a non-elective surgery remain in both specifications. We have also repeated this analysis excluding outliers (the top 1 per cent in the distribution of expenditures) and obtained very similar results to those presented in Table 4[5].

We examine next the question of heterogeneity in the effect of insurance across specific procedures and also look at the effect of insurance on hospitalizations as a whole. Columns (1) - (3) of Table 5 present the effects of private health insurance on the most common elective surgeries: cataract extraction, hip replacement and knee replacement. Relative to the mean, private health insurance cover has the largest effect on the probability of hip replacement (29 per cent) followed by the probability of knee replacement (26 per cent). The probability of having a cataract extraction is least affected by private health insurance status (16 per cent). The latter finding may be explained by the fact that cataract extraction is a less complicated procedure than knee or hip replacement; therefore, the benefits of insurance may be smaller. Additionally, the price of cataract surgery is lower than the price of the other two surgeries.

The last column of Table 5 reports the estimated effect of insurance cover on the probability of having a hospitalization for any reason. This estimate aggregates over the insurance effects on the elective and non-elective surgeries, as defined above, and hospitalizations for other purposes. This aggregate measure of health care utilization is often used in the

[5] As an added check on the robustness of our results, we also estimated 2SLS regressions instrumenting insurance status with a subset of instrumental variables used by Cameron et al. (1988) and Srivastava and Zhao (2008) (marital status, country of birth, a dummy for metro areas, education, past hospitalizations for purposes other than elective and non-elective surgeries, a dummy for having a child under 18 years old, as well as its interaction with marital status (to indicate single parent households), smoking status, a dummy for being a heavy drinker, a dummy for being overweight, and a dummy for not exercising). Using the full set of instrumental variables, we reject the null hypothesis that the instruments are uncorrelated with the error term based on overidentification tests for both elective and non-elective surgeries. Following this, we used a reduced set of identifying instruments that we believe are less likely to violate the exogeneity assumption (marital status, country of birth, urban, education, children under 18 years of age and an interaction of the children variable with marital status). With this reduced set of instrumental variables, we pass the overidentification tests for both elective and non-elective surgeries but only marginally so in the case of elective surgeries (the p-value is 2%). Qualitatively, the results from the latter specification are comparable to the probit average partial effects presented in Table 2 in the sense that (1) we find no evidence of moral hazard in the case of non-elective surgery (the 2SLS estimate is in fact negative but highly imprecise) and (2) we find evidence of a positive causal effect of insurance in the case of electives but again the 2SLS estimate is very imprecise.

literature. Relative to the mean, the estimated effect of insurance on any hospitalization is roughly 16 per cent; this lies between the effect on non-elective surgeries and that on elective surgeries. This finding illustrates that the use of aggregate measures of health care utilization may mask larger effects of insurance on some services as well as zero impact on other services.

We conclude this section with a discussion of waiting times for procedures. Jumping the queue is one of the usual reasons given for insurance purchase in Australia. The importance of differential waiting times for insured and uninsured patients is particularly relevant when using data collected over a fixed window of observation. This potential problem is that of right hand side (RHS) censoring of the data and refers to a window of observation which is too short relative to the standard waiting time for a procedure. The potential effect of RHS censoring in our context would be to exaggerate the size of the incentive effect of insurance as we may be excluding uninsured patients who undergo a surgery further in the future. Although we do not observe when patients were placed on a waiting list, we have looked at other evidence related to waiting times and we do not believe that censoring is driving our results.

First, we provide statistics on average waiting times for procedures in NSW public hospitals. During the analysis period, 88.9 per cent of the non-urgent procedures were performed within 365 days (Baggoley et al., 2011). For the main elective procedures studied in the paper, the median waiting times are 131 days for hip replacement, 163 days for cataract surgery and 226 days for knee replacements (Australian Institute of Health and Welfare, 2013). If differences in waiting times between the insured and uninsured were indeed driving our results, we would expect to find larger insurance effects on the demand for cataract extraction and especially knee replacement than on the demand for hip replacement. To the contrary, we find that the insurance cover has the largest effect on the probability of hip replacement (relative to the mean), as shown in Table 5.

We also exploit information on specialist services which is available in our dataset to compare the relationship between the use of specialist services and the incidence of surgery for the insured and uninsured. The underlying hypothesis is that, if waiting times for procedures are driving our main results, the probability of a procedure conditional on having seen a specialist would be lower for an uninsured individual relative to a comparable person covered by private insurance. Note that hospital procedures can only be scheduled by specialists hence patients must consult a specialist before undergoing any of these procedures.

We estimate these conditional probabilities using all observations with the required information. Since the data on specialist visits is not available for the 2006 respondents, the sample is restricted to the respondents who completed the survey in 2007 or 2008. (The resulting subsample represents 86% of the full analysis sample.) Given the small incidence of the procedures, we also estimate the conditional probabilities for those individuals who are more likely to need the procedures. Specifically, we estimate the incidence of elective surgery in the next 12 months on all controls including insurance status. We then calculate the predicted probability of having a surgery setting insurance status at 1 for everyone and we select individuals who have a predicted probability that exceeds the average predicted probability in the subsample of individuals who actually received a surgery (equal to 8.84 per cent).

For the full 2007-8 sample and the restricted high probability of surgery sample we perform the following exercise. We regress the incidence of elective surgery on all the controls (including insurance) plus a variable measuring the number of specialists visits in the past 12 months and an interaction of specialists visits with insurance status. Given our definition of elective surgery, we restrict attention to two types of specialist services: orthopaedic surgeons and eye specialists/optometrists. In Table 6, we present the effects of the number of specialists visits in a given year on the incidence of surgery in the following year by insurance status. To illustrate the results, we use an example. Take an uninsured individual with characteristics that make him/her a high risk for elective surgery in the coming year. Suppose this individual has one more visit with an orthopaedic surgeon during the year, then he/she has a probability of undergoing elective surgery which is 2.152 percentage points higher in the following year than a comparable person who does not have the additional visit. A comparable individual with insurance has a probability of surgery which is 1.910 percentage points higher. Hence insurance cover does not increase the probability that a specialist visit leads to a procedure. If censoring was indeed driving our results, we would expect the effects of insurance to increase the probability of a procedure following a specialist visit. What we see instead is either no effect of insurance or a negative effect in the case of eye specialists.

6 Conclusion

Using a unique data set we have examined the relationship between insurance status and health care utilisation at a disaggregated level. By comparing results for particular elective surgeries with those from non-elective surgeries and by exploiting a comprehensive set of controls for an individual's health and past health care utilisation we are able to provide evidence that an average incentive effect (due to the use of aggregate data) can mask a large variability. Specifically, in the case of elective surgeries, we find incentive effects of around 22 per cent relative to the mean, while for non-elective procedures, there is no evidence of any moral hazard.

These results must be placed in the context of a mixed private-public system. In a different system where non-elective services are not available without private insurance, we would expect perhaps less variation in the incentive effects but we would still expect more discretionary services to also involve greater moral hazard. The Australian system is also characterised by community-rating so that insurers are not able to design contracts that price insurance according to risk type. This feature would be expected to lead to more extensive selection problems in private health insurance. However, our extensive dataset and sensitivity analysis suggests that we have dealt with selection on risk types in a satisfactory manner. Finally our data refer to an older population (45 years of age or more) but it is this older subpopulation that consumes the majority of health services and will be the major source of future growth in health expenditures making research of the type presented here even more important in terms of understanding the impact of incentives on the use of health services.

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Figure 1: Predicted probabilities of elective and non-elective surgeries and private health insurance.

Table 1: Incidence rates of elective and non-elective surgeries by PHI status

	No PHI	PHI	z-stat
A. Elective surgeries			
Any elective surgery	3.109	3.000	1.510
Cataract extraction	2.186	1.812	6.280
Knee replacement	0.480	0.569	-2.951
Hip replacement	0.361	0.415	-2.118
Varicose vein stripping and ligation	0.068	0.121	-4.270
Septoplasty (repair of septum)	0.039	0.096	-5.613
Tonsillectomy	0.008	0.012	-1.072
Myringoplasty (repair of eardrum)	0.007	0.009	-0.501
B. Non-elective surgeries			
Any non-elective surgery	0.661	0.597	1.901
Cholecystectomy (removal of gall bladder)	0.414	0.310	4.049
Coronary artery bypass graft (CABG)	0.137	0.126	0.698
Coronary angioplasty	0.064	0.076	-1.116
Appendectomy	0.035	0.047	-1.399
Myringotomy (opening of eardrum)	0.014	0.038	-3.933
Observations	87,652	161,621	

Notes: Incidence rates are presented in percentages. The last column presents z-statistics for the equality of means test.

Table 2: Estimated effect of PHI in the full model and alternative specifications

		Excluded variables				
	Full model	Obj. health	Subj. health	Risk beh.	SES	Age
	(1)	(2)	(3)	(4)	(5)	(6)
A. Elective surgeries						
Average partial effect, ppt	0.659***	0.842***	0.604***	0.656***	0.654***	0.824***
	(0.077)	(0.077)	(0.078)	(0.077)	(0.073)	(0.076)
Change from mean, %	21.695	27.716	19.891	21.593	21.537	27.136
Bias, % of mean		6.020	−1.804	−0.102	−0.158	5.441
Pseudo R-squared	0.145	0.106	0.133	0.144	0.143	0.126
B. Non-elective surgeries						
Average partial effect, ppt	0.030	0.042	0.030	0.031	0.032	0.038
	(0.038)	(0.037)	(0.038)	(0.037)	(0.036)	(0.037)
Change from mean, %	4.892	6.861	4.843	4.924	5.118	6.200
Bias, % of mean		1.970	−0.048	0.032	0.226	1.308
Pseudo R-squared	0.058	0.025	0.056	0.057	0.055	0.054
Control variables:						
Objective health	Yes	No	Yes	Yes	Yes	Yes
Subjective health	Yes	Yes	No	Yes	Yes	Yes
Risk behaviours	Yes	Yes	Yes	No	Yes	Yes
Socioeconomic status	Yes	Yes	Yes	Yes	No	Yes
Age	Yes	Yes	Yes	Yes	Yes	No
Demographic variables	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample size is 249,273. Standard errors are reported in parentheses. All regressions include time effects. Symbol *** denotes statistical significance at the 0.1% level.

Table 3: Effects of health measures and risk behaviours on elective and non-elective surgeries and PHI

	Elective surgeries		Non-elective surgeries		PHI	
	APE, ppt.	S.E.	APE, ppt.	S.E.	APE, ppt.	S.E.
Surg_el_1yago	1.897***	(0.276)	0.172	(0.141)	0.350	(0.713)
Surg_el_2yago	0.077	(0.221)	−0.044	(0.115)	1.460*	(0.727)
Surg_el_3yago	−0.156	(0.228)	0.269	(0.177)	0.783	(0.762)
Surg_el_4yago	−0.139	(0.236)	0.151	(0.150)	1.282	(0.785)
Surg_el_5yago	−0.307	(0.241)	0.344	(0.200)	0.961	(0.816)
Surg_nel_1yago	0.204	(0.392)	−0.158	(0.113)	2.641*	(1.047)
Surg_nel_2yago	−0.300	(0.338)	0.589*	(0.253)	2.076*	(1.045)
Surg_nel_3yago	−0.196	(0.357)	0.507*	(0.252)	4.707***	(1.030)
Surg_nel_4yago	0.282	(0.394)	0.079	(0.189)	4.808***	(1.029)
Surg_nel_5yago	−0.179	(0.362)	0.075	(0.203)	2.741*	(1.093)
Hosp_oth_1yago	0.519***	(0.126)	0.203**	(0.064)	3.268***	(0.339)
Hosp_oth_2yago	0.539***	(0.131)	−0.019	(0.060)	3.669***	(0.347)
Hosp_oth_3yago	0.255	(0.134)	0.163*	(0.071)	4.021***	(0.358)
Hosp_oth_4yago	0.333*	(0.138)	0.162*	(0.072)	5.191***	(0.360)
Hosp_oth_5yago	0.358*	(0.142)	0.159*	(0.075)	3.259***	(0.376)
Hdiag_infec_1	0.122	(0.260)	−0.119	(0.106)	−1.413	(0.777)
Hdiag_maneo_1	0.169	(0.258)	−0.072	(0.108)	1.966**	(0.711)
Hdiag_beneo_1	0.190	(0.164)	0.094	(0.080)	2.041***	(0.464)
Hdiag_diabet_1	−0.150	(0.212)	0.111	(0.116)	0.709	(0.668)
Hdiag_metabol_1	−0.131	(0.188)	0.220*	(0.108)	−3.141***	(0.604)
Hdiag_hepabil_1	0.339	(0.456)	1.465***	(0.422)	−1.576	(1.244)
Hdiag_gastro_1	0.052	(0.129)	0.131	(0.067)	1.139**	(0.379)
Hdiag_musskel_1	0.769***	(0.172)	−0.064	(0.071)	2.871***	(0.456)
Hdiag_hematol_1	−0.384	(0.238)	0.055	(0.130)	−1.274	(0.823)
Hdiag_psychi_1	−0.005	(0.417)	−0.186	(0.145)	−0.683	(1.168)
Hdiag_neuro_1	0.144	(0.254)	0.056	(0.129)	2.357**	(0.743)
Hdiag_cardio_1	−0.124	(0.151)	0.060	(0.080)	−0.912	(0.488)
Hdiag_vascu_1	−0.420	(0.221)	−0.044	(0.114)	1.271	(0.769)
Hdiag_pulmo_1	−0.121	(0.224)	−0.089	(0.100)	−1.561*	(0.719)
Hdiag_ophthal_1	2.891***	(0.320)	−0.057	(0.107)	0.511	(0.711)
Hdiag_ENT_1	−0.334	(0.276)	0.238	(0.162)	3.826***	(0.839)
Hdiag_urinar_1	−0.206	(0.189)	−0.153	(0.079)	−0.333	(0.609)
Hdiag_genital_1	0.173	(0.254)	0.102	(0.122)	0.503	(0.674)
Hdiag_derma_1	−0.164	(0.241)	−0.067	(0.115)	0.031	(0.770)
Hdiag_injury_1	−0.345	(0.254)	−0.001	(0.139)	−0.786	(0.829)
Hdiag_screen_1	−0.032	(0.120)	−0.143**	(0.050)	0.239	(0.364)
Hdiag_compli_1	0.075	(0.231)	−0.049	(0.109)	−1.577*	(0.748)
Hdiag_lcom_1	−0.086	(0.242)	0.062	(0.124)	0.068	(0.754)
Hdiag_lwdef_1	−0.233	(0.133)	0.086	(0.069)	−0.127	(0.409)
Diag_cancer	−0.005	(0.093)	−0.029	(0.046)	−0.056	(0.244)
Diag_hrtdis	−0.129	(0.112)	0.116	(0.062)	−0.156	(0.332)
Diag_highbp	0.290**	(0.099)	0.036	(0.047)	0.385	(0.252)
Diag_stroke	−0.059	(0.160)	0.093	(0.089)	−1.489**	(0.488)
Diag_diabet	−0.030	(0.158)	−0.024	(0.074)	−1.969***	(0.425)
Diag_bldclot	0.239	(0.150)	0.145	(0.083)	−0.786	(0.415)
Diag_asthmhayf	−0.162	(0.092)	−0.030	(0.043)	0.773***	(0.224)

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	Elective surgeries		Non-elective surgeries		PHI	
	APE, ppt.	S.E.	APE, ppt.	S.E.	APE, ppt.	S.E.
Diag_Parkin	0.225	(0.350)	−0.282*	(0.129)	2.335*	(0.998)
Treat_cancer	−0.441*	(0.172)	−0.025	(0.091)	−2.969***	(0.549)
Treat_hrtattack	−0.164	(0.174)	0.539***	(0.124)	−2.764***	(0.557)
Treat_othhrtdis	−0.200	(0.172)	0.084	(0.090)	0.560	(0.530)
Treat_highbp	−0.191	(0.103)	−0.037	(0.050)	−0.138	(0.283)
Treat_cholest	−0.081	(0.100)	0.019	(0.049)	−0.008	(0.276)
Treat_bldclot	−0.117	(0.204)	−0.176*	(0.082)	0.334	(0.625)
Treat_asthma	0.183	(0.182)	−0.029	(0.082)	−0.545	(0.470)
Treat_arthrit	1.248***	(0.128)	−0.058	(0.056)	−1.457***	(0.327)
Treat_thyroid	0.025	(0.191)	0.004	(0.096)	0.264	(0.511)
Treat_osteop	−0.370**	(0.122)	−0.073	(0.068)	0.189	(0.389)
Vitamins	−0.013	(0.083)	−0.076*	(0.038)	1.684***	(0.200)
Suppl_omega3	0.150	(0.078)	−0.023	(0.037)	0.343	(0.193)
Suppl_glucosam	0.622***	(0.088)	−0.039	(0.041)	3.040***	(0.213)
Drugs_hrtdis	−0.407**	(0.147)	−0.055	(0.078)	0.111	(0.502)
Drugs_bldclot	0.024	(0.087)	0.073	(0.046)	0.533*	(0.247)
Drugs_diabet	0.239	(0.187)	0.119	(0.094)	0.049	(0.488)
Drugs_asthma	0.258	(0.165)	0.086	(0.084)	−1.775***	(0.430)
Drugs_thyroid	−0.028	(0.190)	0.017	(0.099)	1.329**	(0.514)
Drugs_osteop	0.050	(0.106)	0.009	(0.057)	2.268***	(0.290)
Drugs_hrtburn	−0.090	(0.088)	0.252***	(0.051)	−0.007	(0.251)
Drugs_kidney	0.425**	(0.165)	−0.010	(0.077)	0.203	(0.453)
Surg_knee	0.945***	(0.158)	0.012	(0.079)	3.987***	(0.430)
Surg_hip	1.109***	(0.175)	−0.066	(0.082)	4.727***	(0.465)
Surg_gallbladder	−0.131	(0.103)	−0.306***	(0.039)	−0.178	(0.285)
Surg_heart	0.133	(0.150)	0.028	(0.071)	0.644	(0.430)
Surg_reprodorg	0.133	(0.072)	0.025	(0.034)	0.734***	(0.175)
Surg_skinca	−0.194*	(0.094)	−0.019	(0.047)	0.189	(0.254)
FHH_cancer	−0.014	(0.071)	−0.038	(0.034)	−0.505**	(0.172)
FHH_hrtdis	0.076	(0.073)	0.038	(0.035)	0.697***	(0.177)
FHH_highbp	−0.183*	(0.076)	−0.011	(0.036)	0.430*	(0.184)
FHH_stroke	0.002	(0.078)	−0.108**	(0.036)	0.074	(0.194)
FHH_diabet	0.155	(0.088)	0.029	(0.040)	−0.280	(0.204)
FHH_arthrit	0.134	(0.086)	−0.051	(0.040)	−0.410	(0.212)
FHH_osteop	0.151	(0.106)	−0.052	(0.048)	0.940***	(0.251)
FHH_hipfrac	−0.050	(0.112)	−0.047	(0.055)	0.663*	(0.289)
FHH_Parkin	0.134	(0.161)	−0.096	(0.072)	−0.191	(0.397)
FHH_Alzh	0.035	(0.093)	−0.060	(0.044)	0.486*	(0.232)
FHH_depress	−0.006	(0.115)	−0.054	(0.051)	−1.170***	(0.265)
Disability	−0.724***	(0.120)	−0.157*	(0.061)	−1.178**	(0.428)
Phys_func	−0.031***	(0.002)	−0.002	(0.001)	0.046***	(0.005)
BMI	0.021**	(0.007)	0.010**	(0.003)	−0.035*	(0.017)
Teethnum_1_9	0.192	(0.137)	0.114	(0.075)	2.420***	(0.359)
Teethnum_10_19	0.309*	(0.127)	0.020	(0.063)	5.707***	(0.315)
Teethnum_20mo	0.013	(0.120)	−0.042	(0.061)	8.256***	(0.340)
Broken_bone	−0.188	(0.100)	−0.057	(0.049)	−1.264***	(0.268)
Urinel_1tl	0.139	(0.097)	0.008	(0.046)	0.575*	(0.235)
Urinel_2_3t	−0.015	(0.124)	0.024	(0.062)	0.388	(0.322)
Urinel_4_6t	0.162	(0.179)	−0.004	(0.088)	0.178	(0.465)

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	Elective surgeries		Non-elective surgeries		PHI	
	APE, ppt.	S.E.	APE, ppt.	S.E.	APE, ppt.	S.E.
Urinel_eveday	−0.175	(0.131)	0.009	(0.069)	−0.186	(0.370)
Hear_loss	−0.096	(0.072)	0.092**	(0.034)	−0.042	(0.177)
SAH_g	0.421***	(0.122)	−0.083	(0.053)	0.587	(0.310)
SAH_vg	0.598***	(0.155)	−0.196**	(0.063)	−0.445	(0.370)
SAH_exc	0.439*	(0.217)	−0.325***	(0.060)	−1.395**	(0.467)
QoL_g	0.227	(0.132)	0.068	(0.065)	1.301***	(0.340)
QoL_vg	0.375*	(0.155)	0.091	(0.076)	2.801***	(0.387)
QoL_exc	0.140	(0.187)	0.158	(0.099)	2.719***	(0.446)
Vision_g	−1.776***	(0.089)	−0.031	(0.046)	1.929***	(0.245)
Vision_vg	−2.601***	(0.089)	−0.041	(0.053)	3.062***	(0.284)
Vision_exc	−2.334***	(0.081)	0.014	(0.075)	3.259***	(0.376)
Teethh_g	0.340***	(0.092)	0.015	(0.043)	4.926***	(0.215)
Teethh_vg	0.620***	(0.125)	−0.012	(0.053)	6.972***	(0.265)
Teethh_exc	0.908***	(0.203)	0.120	(0.087)	7.726***	(0.367)
Memory_g	0.342***	(0.099)	0.017	(0.048)	−0.034	(0.248)
Memory_vg	0.652***	(0.123)	0.114	(0.058)	−0.982***	(0.285)
Memory_exc	0.681***	(0.170)	0.091	(0.077)	−2.874***	(0.370)
Drinks_pwk	0.007	(0.006)	−0.012***	(0.003)	0.224***	(0.014)
Smoked_before	0.199*	(0.078)	0.039	(0.037)	−4.395***	(0.188)
Smokes_now	−0.084	(0.167)	0.122	(0.078)	−8.850***	(0.368)
Exer_walk	0.006	(0.004)	0.002	(0.002)	−0.089***	(0.011)
Exer_vigour	−0.015	(0.011)	−0.005	(0.006)	−0.030	(0.021)
Exer_mod	0.000[a]	(0.004)	−0.004	(0.003)	−0.030**	(0.009)
Out_hrswd	−0.010	(0.013)	−0.002	(0.006)	−0.130***	(0.029)
Out_hrswe	0.031*	(0.013)	0.012*	(0.006)	−0.042	(0.029)
Hrs_sleep	−0.028	(0.018)	0.003	(0.009)	0.023	(0.049)
Hrs_sit	−0.010	(0.011)	0.000[a]	(0.005)	0.040	(0.028)
Hrs_screen	−0.009	(0.015)	0.004	(0.007)	−0.061	(0.036)
Hrs_stand	−0.005	(0.011)	0.001	(0.005)	−0.082**	(0.025)
Pro_redmeat	0.032*	(0.013)	−0.003	(0.007)	0.467***	(0.034)
Pro_chicken	−0.020	(0.022)	0.019	(0.010)	0.105	(0.054)
Pro_sausages	0.013	(0.022)	0.003	(0.010)	−0.106*	(0.054)
Pro_fish	0.005	(0.023)	−0.012	(0.012)	−0.121*	(0.057)
Pro_cheese	−0.011	(0.014)	−0.015*	(0.007)	0.006	(0.035)
Carbs_brbread	−0.002	(0.004)	0.002	(0.002)	−0.063***	(0.009)
Carbs_cereal	−0.023	(0.013)	0.001	(0.006)	0.428***	(0.030)
Veg_cooked	0.013	(0.021)	0.025**	(0.010)	0.090	(0.052)
Veg_raw	−0.023	(0.024)	0.009	(0.011)	0.094	(0.061)
Fruit_raw	0.056*	(0.024)	−0.023	(0.012)	0.242***	(0.062)
Fruit_juice	0.040	(0.032)	0.029	(0.015)	−0.208*	(0.083)
Milk_whole	−0.044	(0.122)	−0.055	(0.056)	−4.065***	(0.300)
Milk_lowfat	−0.010	(0.119)	0.036	(0.056)	2.874***	(0.287)
Milk_skim	−0.207	(0.121)	0.031	(0.059)	0.629*	(0.299)
Milk_soy	−0.205	(0.141)	0.001	(0.069)	−1.384***	(0.355)
Milk_other	−0.104	(0.230)	−0.015	(0.110)	−2.680***	(0.585)
Test_psamam	0.242*	(0.099)	0.010	(0.045)	4.273***	(0.234)
Test_bowelca	0.034	(0.075)	0.003	(0.035)	3.114***	(0.183)
Pseudo R-squared	0.145		0.058		0.243	
Wald test Chi^2 stat	3760.740		862.200		14982.560	

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	Elective surgeries		Non-elective surgeries		PHI	
	APE, ppt.	S.E.	APE, ppt.	S.E.	APE, ppt.	S.E.
Wald test p-value	0.000		0.000		0.000	
Mean of dep var, %	3.038		0.056		64.837	

Notes: Sample size is 249,273. All regressions additionally control for hospital-based diagnoses 5, 4, 3 and 2 years ago, socio-economic and demographic characteristics and time effects. The bottom panel presents Chi-square statistics and p-values for Wald test of joint significance of all health and health risk variables. Symbols *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively. Symbol [a] indicates that the absolute value of the coefficient is less than 0.0005.

Table 4: Sensitivity of results to adding total health care expenditure in the past year, probit average partial effects (ppt)

	Elective surgeries		Non-elective surgeries	
	Baseline	HC expend. added	Baseline	HC expend. added
	(1)	(2)	(3)	(4)
Private health insurance	0.679***	0.657***	−0.013	−0.018
	(0.084)	(0.084)	(0.040)	(0.040)
Total HC expenditure > 0		0.711*		0.089
		(0.307)		(0.124)
Total HC expenditure quintile:				
2nd		0.341*		0.153*
		(0.137)		(0.061)
3rd		0.545***		0.094
		(0.136)		(0.060)
4th		0.909***		0.139*
		(0.144)		(0.064)
5th		0.881***		0.083
		(0.183)		(0.082)
Total HC expenditure, thousand AUD		−0.036**		0.008
		(0.012)		(0.006)
Mean of dep var, %	3.042	3.042	0.578	0.578
Pseudo R-squared	0.144	0.145	0.061	0.062
Sample size	214,601	214,601	214,601	214,601

Notes: Standard errors are reported in parentheses. All regressions control for objective and subjective health measures, risk behaviours, socio-economic and demographic characteristics and time effects. Symbols *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively.

Table 5: Effects of PHI on most common procedures and any hospitalization

	Cataract extraction	Knee replacement	Hip replacement	Any hospitalization
	(1)	(2)	(3)	(4)
Average partial effect, ppt	0.319***	0.138***	0.114***	4.080***
	(0.062)	(0.033)	(0.028)	(0.195)
Change from mean, %	16.402	25.632	28.712	15.988
Pseudo R-squared	0.193	0.227	0.202	0.118
Sample size	249,273	249,273	249,273	249,273

Notes: Standard errors are reported in parentheses. All regressions control for the objective and subjective health measures, socio-economic and demographic characteristics, risk behaviours and time effects. Symbol *** denotes statistical significance at the 0.1% level.

Table 6: Effects of the number of specialist services on probabilities of elective surgery, probit average partial effects (ppt)

	Full 2007-08 Sample		High Predicted Prob of Surgery	
	Uninsured	Insured	Uninsured	Insured
Orthopaedic	0.574***	0.558***	2.152***	1.910***
surgeon	(0.063)	(0.052)	(0.236)	(0.177)
Eye specialist	0.192***	0.115***	0.721***	0.392***
or optometrist	(0.017)	(0.019)	(0.064)	(0.064)
Sample size	214,601		18,177	

Notes: Standard errors are reported in parentheses. In addition to insurance cover and specialist visits, all regressions control for the objective and subjective health measures, socio-economic and demographic characteristics, risk behaviours and time effects. Symbol *** denotes statistical significance at the 0.1% level.

A Additional tables

Table A.1: Description and means of control variables

Variable name	Description	Mean	Observations
A. Demographic characteristics			
Age[a]	Age in years	62.644	249,273
Male	=1 if male	0.461	249,273
Married	=1 if married/lives with partner	0.757	249,273
Children	Number of children	2.456	249,273
Loc_city[b]	=1 if lives city	0.450	249,273
Loc_remotreg	=1 if lives in a remote/regional area	0.550	249,273
CoB_Au	=1 if born in Australia	0.759	247,088
CoB_ES	=1 if born in English speaking country	0.126	247,088
CoB_NES[b]	=1 if born in non-English speaking country	0.116	247,088
Ances_Au	=1 if Australian ancestry	0.523	246,682
Ances_En	=1 if English/Irish/Scottish ancestry	0.591	246,682
Ances_othEu	=1 if other European ancestry	0.121	246,682
Ances_oth	=1 if other ancestry	0.134	246,682
Oth_lang	=1 if speaks other language than English at home	0.093	249,273
Educ_lths[b]	=1 if hasn't completed high school	0.341	245,543
Educ_hs	=1 if has high school diploma	0.099	245,543
Educ_trade	=1 if did trade/apprenticeship	0.112	245,543
Educ_cert	=1 if has certificate/diploma	0.212	245,543
Educ_univ	=1 if has university degree	0.236	245,543
Inc_lt5k[b]	=1 if HH income is less then $5000 per year	0.019	196,209
Inc_5_10k	=1 if HH income is $5000-$9999 per year	0.050	196,209
Inc_10_20k	=1 if HH income is $10000-$19999 per year	0.176	196,209
Inc_20_30k	=1 if HH income is $20000-$29999 per year	0.123	196,209
Inc_30_40k	=1 if HH income is $30000-$39999 per year	0.101	196,209
Inc_40_50k	=1 if HH income is $40000-$49999 per year	0.093	196,209
Inc_50_70k	=1 if annual HH income is $50000-$69999	0.134	196,209
Inc_mt70k	=1 if annual HH income >= $70000	0.304	196,209
SEIFA_1dec[b]	=1 if in 1st decile of SEIFA Index of rel soc-econ adv/disadv	0.024	249,273
SEIFA_2dec	=1 if in 2nd decile of SEIFA Index of rel soc-econ adv/disadv	0.074	249,273
SEIFA_3dec	=1 if in 3th decile of SEIFA Index of rel soc-econ adv/disadv	0.067	249,273
SEIFA_4dec	=1 if in 4th decile of SEIFA Index of rel soc-econ adv/disadv	0.109	249,273
SEIFA_5dec	=1 if in 5th decile of SEIFA Index of rel soc-econ adv/disadv	0.091	249,273
SEIFA_6dec	=1 if in 6th decile of SEIFA Index of rel soc-econ adv/disadv	0.151	249,273
SEIFA_7dec	=1 if in 7th decile of SEIFA Index of rel soc-econ adv/disadv	0.120	249,273
SEIFA_8dec	=1 if in 8th decile of SEIFA Index of rel soc-econ adv/disadv	0.091	249,273
SEIFA_9dec	=1 if in 9th decile of SEIFA Index of rel soc-econ adv/disadv	0.081	249,273
SEIFA_10dec	=1 if in 10th decile of SEIFA Index of rel soc-econ adv/disadv	0.193	249,273
Employed	=1 if full-time, part-time or self- employed	0.476	246,864
Housing_agedc[b]	=1 if lives in an aged care facility	0.044	249,273
Housing_flat	=1 if lives in a flat	0.107	249,273
Housing_farm	=1 if lives in a house on farm	0.078	249,273
Housing_house	=1 if lives in a house	0.771	249,273
Socap_visit	Spends time with friends/family, times/week	4.364	246,036
Socap_phone	Talks to someone on phone, times/week	6.608	246,036
Socap_group	Goes to meetings of social groups, times/week	1.403	246,036

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Variable name	Description	Mean	Observations
Socap_ppl	Number of people nearby on which can depend on	7.128	239,924
B. Objective health measures from administrative data			
Surg_el_1yago	=1 if had an elective surgery 1 year(s) ago	0.029	249,273
Surg_el_2yago	=1 if had an elective surgery 2 year(s) ago	0.027	249,273
Surg_el_3yago	=1 if had an elective surgery 3 year(s) ago	0.025	249,273
Surg_el_4yago	=1 if had an elective surgery 4 year(s) ago	0.022	249,273
Surg_el_5yago	=1 if had an elective surgery 5 year(s) ago	0.020	249,273
Surg_nel_1yago	=1 if had a non-elective surgery 1 year(s) ago	0.008	249,273
Surg_nel_2yago	=1 if had a non-elective surgery 2 year(s) ago	0.009	249,273
Surg_nel_3yago	=1 if had a non-elective surgery 3 year(s) ago	0.008	249,273
Surg_nel_4yago	=1 if had a non-elective surgery 4 year(s) ago	0.008	249,273
Surg_nel_5yago	=1 if had a non-elective surgery 5 year(s) ago	0.008	249,273
Hosp_oth_1yago	=1 if admitted for other reasons 1 year(s) ago	0.227	249,273
Hosp_oth_2yago	=1 if admitted for other reasons 2 year(s) ago	0.211	249,273
Hosp_oth_3yago	=1 if admitted for other reasons 3 year(s) ago	0.195	249,273
Hosp_oth_4yago	=1 if admitted for other reasons 4 year(s) ago	0.183	249,273
Hosp_oth_5yago	=1 if admitted for other reasons 5 year(s) ago	0.175	249,273
Hdiag_infec_1[c]	=1 if diagnosed with infectious and parasitic disease 1 year ago	0.014	249,273
Hdiag_maneo_1[c]	=1 if diagnosed with malignant neoplasm 1 year ago	0.016	249,273
Hdiag_beneo_1[c]	=1 if diagnosed with benign/in situ neoplasm 1 year ago	0.042	249,273
Hdiag_diabet_1[c]	=1 if diagnosed with diabetes 1 year ago	0.025	249,273
Hdiag_metabol_1[c]	=1 if diagnosed nutritional/metabolic disease 1 year ago	0.026	249,273
Hdiag_hepabil_1[c]	=1 if diagnosed with hepatobiliary disorder 1 year ago	0.006	249,273
Hdiag_gastro_1[c]	=1 if diagnosed with gastrointestinal disease 1 year ago	0.080	249,273
Hdiag_musskel_1[c]	=1 if diagnosed with musculoskeletal disease 1 year ago	0.046	249,273
Hdiag_hematol_1[c]	=1 if diagnosed with hematological disease 1 year ago	0.011	249,273
Hdiag_psychi_1[c]	=1 if diagnosed with psychiatric disease 1 year ago	0.005	249,273
Hdiag_neuro_1[c]	=1 if diagnosed with neurological disorder 1 year ago	0.013	249,273
Hdiag_cardio_1[c]	=1 if diagnosed with cardiovascular disease 1 year ago	0.055	249,273
Hdiag_vascu_1[c]	=1 if diagnosed with vascular disease 1 year ago	0.012	249,273
Hdiag_pulmo_1[c]	=1 if diagnosed with pulmonary disease 1 year ago	0.015	249,273
Hdiag_ophthal_1[c]	=1 if diagnosed with ophthalmic disease 1 year ago	0.027	249,273
Hdiag_ENT_1[c]	=1 if diagnosed with ears/nose/throat disease 1 year ago	0.010	249,273
Hdiag_urinar_1[c]	=1 if diagnosed with urinary disease 1 year ago	0.023	249,273
Hdiag_genital_1[c]	=1 if diagnosed with genital disease 1 year ago	0.018	249,273
Hdiag_derma_1[c]	=1 if diagnosed with dermatological disorder 1 year ago	0.013	249,273
Hdiag_injury_1[c]	=1 if admitted for injury, poisoning 1 year ago	0.010	249,273
Hdiag_screen_1[c]	=1 if admitted for screening/history 1 year ago	0.102	249,273
Hdiag_compli_1[c]	=1 if admitted for complications of care 1 year ago	0.014	249,273
Hdiag_lcom_1[c]	=1 if diagnosed with less-common conditions 1 year ago	0.014	249,273
Hdiag_lwdef_1[c]	=1 if diagnosed with less-well defined conditions 1 year ago	0.059	249,273
C. Objective health measures from survey data			
Diag_cancer	=1 if diagnosed with cancer	0.360	249,273
Diag_hrtdis	=1 if diagnosed with heart disease	0.119	249,273
Diag_highbp	=1 if diagnosed with high blood pressure	0.357	249,273
Diag_stroke	=1 if diagnosed with stroke	0.031	249,273
Diag_diabet	=1 if diagnosed with diabet	0.089	249,273
Diag_bldclot	=1 if diagnosed with blood clot	0.046	249,273
Diag_asthmhayf	=1 if diagnosed with asthma/hay fever	0.215	249,273

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Variable name	Description	Mean	Observations
Diag_Parkin	=1 if diagnosed with Parkinson's disease	0.006	249,273
Treat_cancer	=1 if treated for cancer in the last month	0.028	249,273
Treat_hrtattack	=1 if treated for heart attack in the last month	0.026	249,273
Treat_othhrtdis	=1 if treated for other heart disease in the last month	0.028	249,273
Treat_highbp	=1 if treated for high blood pressure in the last month	0.244	249,273
Treat_cholest	=1 if treated for high cholesterol in the last month	0.152	249,273
Treat_bldclot	=1 if treated for blood clotting problems in the last month	0.019	249,273
Treat_asthma	=1 if treated for asthma in the last month	0.047	249,273
Treat_arthrit	=1 if treated for osteoarthritis in the last month	0.080	249,273
Treat_thyroid	=1 if treated for thyroid problems in the last month	0.050	249,273
Treat_osteop	=1 if treated for osteoporosis in the last month	0.057	249,273
Treat_depranx	=1 if treated for depression/anxiety in the last month	0.082	249,273
Vitamins	=1 if has taken vitamins in the past 4 weeks	0.247	249,273
Suppl_omega3	=1 if took fish oil/Omega 3 in the past 4 weeks	0.327	249,273
Suppl_glucosam	=1 if took glucosamine in the past 4 weeks	0.222	249,273
Drugs_hrtdis	=1 if took drugs for heart disease in the past 4 weeks	0.028	249,273
Drugs_highbp	=1 if took drugs for hypertension in the past 4 weeks	0.218	249,273
Drugs_cholest	=1 if took drugs for cholesterol in the past 4 weeks	0.218	249,273
Drugs_bldclot	=1 if took drugs for blood clot in the past 4 weeks	0.198	249,273
Drugs_diabet	=1 if took drugs for diabetes in the past 4 weeks	0.049	249,273
Drugs_asthma	=1 if took drugs for asthma in the past 4 weeks	0.055	249,273
Drugs_thyroid	=1 if took drugs for thyroid in the past 4 weeks	0.048	249,273
Drugs_osteop	=1 if took drugs for osteoporosis in the past 4 weeks	0.108	249,273
Drugs_hrtburn	=1 if took drugs for heart burn in the past 4 weeks	0.137	249,273
Drugs_kidney	=1 if took drugs for kidney disease in the past 4 weeks	0.034	249,273
Surg_knee	=1 if had knee replacement operation	0.042	249,273
Surg_hip	=1 if had hip replacement operation	0.032	249,273
Surg_gallbladder	=1 if had gall bladder removal operation	0.102	249,273
Surg_heart	=1 if had heart or coronary bypass surgery	0.059	249,273
Surg_reprodorg	=1 if had reproductive organ operation	0.413	249,273
Surg_skinca	=1 if had skin cancer removal operation	0.267	249,273
FHH_cancer	=1 if family history of cancer	0.459	228,689
FHH_hrtdis	=1 if family history of heart disease	0.474	228,689
FHH_highbp	=1 if family history of high blood pressure	0.526	228,689
FHH_stroke	=1 if family history of stroke	0.270	228,689
FHH_diabet	=1 if family history of diabetes	0.239	228,689
FHH_arthrit	=1 if family history of arthritis	0.222	228,689
FHH_osteop	=1 if family history of osteoporosis	0.153	228,689
FHH_hipfrac	=1 if family history of hip fracture	0.100	228,689
FHH_Parkin	=1 if family history of Parkinson's disease	0.048	228,689
FHH_Alzh	=1 if family history of Alzheimer's disease	0.169	228,689
FHH_depress	=1 if family history of depression	0.129	228,689
Disability	=1 if has a long-term illness/disability	0.056	237,987
Phys_func	Physical Functioning scale, 0(low)-100(high)	82.104	225,630
BMI	Body mass index	27.085	232,135
Teethnum_no[b]	=1 if has no teeth left	0.092	242,383
Teethnum_1_9	=1 if has 1-9 teeth left	0.099	242,383
Teethnum_10_19	=1 if has 10-19 teeth left	0.201	242,383
Teethnum_20mo	=1 if has >= 20 teeth left	0.609	242,383

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Variable name	Description	Mean	Observations
Broken_bone	=1 if had broken bone in the past 5 yrs	0.118	240,349
Urinel_never[b]	=1 if never troubled by leaking urine	0.673	240,495
Urinel_1tl	=1 if troubled by leaking urine <= 1 time/wk	0.162	240,495
Urinel_2_3t	=1 if troubled by leaking urine 2-3 times/wk	0.074	240,495
Urinel_4_6t	=1 if troubled by leaking 4-6 times/wk	0.033	240,495
Urinel_eveday	=1 if troubled by leaking urine everyday	0.057	240,495
Hear_loss	=1 if has hearing loss	0.421	242,015
Falls	Number of falls in the past 5 years	0.507	237,049
K10_score	Kessler psychological distress scale (K10)	13.814	214,685
D. Subjective health measures			
SAH_fp[b]	=1 if self-rated health is fair/poor	0.139	241,080
SAH_g	=1 if self-rated health is good	0.337	241,080
SAH_vg	=1 if self-rated health is very good	0.372	241,080
SAH_exc	=1 if self-rated health is excellent	0.152	241,080
QoL_fp[b]	=1 if self-rated quality of life is fair/poor	0.104	236,953
QoL_g	=1 if self-rated quality is good	0.281	236,953
QoL_vg	=1 if self-rated quality is very good	0.376	236,953
QoL_exc	=1 if self-rated quality is excellent	0.239	236,953
Vision_fp[b]	=1 if self-rated vision is fair/poor	0.165	241,056
Vision_g	=1 if self-rated vision is good	0.406	241,056
Vision_vg	=1 if self-rated vision is very good	0.320	241,056
Vision_exc	=1 if self-rated vision is excellent	0.109	241,056
Teethh_fp[b]	=1 if self-rated teeth and gums are fair/poor	0.270	237,025
Teethh_g	=1 if self-rated teeth and gums are good	0.382	237,025
Teethh_vg	=1 if self-rated teeth and gums are very good	0.259	237,025
Teethh_exc	=1 if self-rated teeth and gums are excellent	0.089	237,025
Memory_fp[b]	=1 if self-rated memory is fair/poor	0.172	241,496
Memory_g	=1 if self-rated memory is good	0.381	241,496
Memory_vg	=1 if self-rated memory is very good	0.316	241,496
Memory_exc	=1 if self-rated memory is excellent	0.130	241,496
E. Proxies for preference heterogeneity			
Drinks_pwk	Number of alcoholic drinks per week	6.995	244,618
Smoked_never	=1 if never smoked	0.574	249,273
Smoked_before	=1 if smoked before, not now	0.355	249,273
Smokes_now	= 1 if smokes now	0.071	249,273
Exer_walk	Walking at least 10min, times/week	5.392	244,733
Exer_vigour	Vigorous exercise, times/week	1.429	244,733
Exer_mod	Moderate exercise, times/week	4.194	244,733
Out_hrswd	Time spent outdoors on weekday, hrs/day	3.193	244,351
Out_hrswe	Time spent outdoors on weekend, hrs/day	4.492	244,351
Hrs_sleep	Time spent sleeping, hrs/day	7.612	245,716
Hrs_sit	Time spent sitting, hrs/day	5.223	245,716
Hrs_screen	Time spent watching TV/using computer, hrs/day	4.105	245,716
Hrs_stand	Time spent standing, hrs/day	4.228	245,716
Pro_redmeat	Red meat, times/week	3.386	244,885
Pro_chicken	Chicken, times/week	2.265	244,885
Pro_sausages	Sausages, times/week	1.345	244,885
Pro_fish	Fish, times/week	1.771	244,885
Pro_cheese	Cheese, times/week	3.286	244,885

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Variable name	Description	Mean	Observations
Carbs_brbread	Slices of brown/wholemeal bread per week	10.174	242,833
Carbs_cereal	Bowls of breakfast cerel per week	4.529	242,833
Veg_cooked	Serves of cooked vegetables per day	2.510	244,298
Veg_raw	Serves of raw vegetables per day	1.416	244,298
Fruit_raw	Serves of fruit per day	1.914	243,859
Fruit_juice	Glasses of fruit juice per day	0.616	243,859
Milk_whole	=1 if drinks whole milk	0.313	243,487
Milk_lowfat	=1 if drinks reduced fat milk	0.370	243,487
Milk_skim	=1 if drinks skim milk	0.219	243,487
Milk_soy	=1 if drinks soy milk	0.080	243,487
Milk_other	=1 if drinks other milk	0.024	243,487
Test_psamam	=1 if had PSA test/mammogram	0.818	243,996
Test_bowelca	=1 if had bowel cancer test	0.505	243,752

Notes:
Analysis sample size is 249,273 observations.
[a] Regressions control for age-in-years dummies.
[b] Omitted category in regressions.
[c] Conditions diagnosed 5, 4, 3 and 2 years ago are also included in regressions.

Table A.2: Effects of demographic and socio-economic variables on elective and non-elective surgeries and PHI

	Elective surgeries		Non-elective surgeries		PHI	
	APE, ppt.	S.E.	APE, ppt.	S.E.	APE, ppt.	S.E.
Male	0.053	(0.097)	0.012	(0.045)	−0.955***	(0.232)
Married	0.046	(0.082)	0.015	(0.041)	6.989***	(0.217)
Children	−0.033	(0.022)	0.002	(0.011)	−1.252***	(0.057)
Loc_remotreg	0.170*	(0.087)	0.011	(0.040)	−2.715***	(0.210)
CoB_Au	0.266	(0.165)	−0.010	(0.079)	4.117***	(0.406)
CoB_ES	0.135	(0.194)	0.095	(0.095)	−3.979***	(0.452)
Ances_Au	−0.010	(0.091)	0.082	(0.044)	−0.543*	(0.223)
Ances_En	−0.029	(0.084)	−0.005	(0.039)	−1.045***	(0.205)
Ances_othEu	−0.104	(0.122)	0.024	(0.058)	0.139	(0.287)
Ances_oth	−0.306*	(0.120)	0.004	(0.059)	−1.719***	(0.301)
Oth_lang	−0.077	(0.163)	0.026	(0.077)	−1.395***	(0.385)
Educ_hs	−0.266*	(0.119)	−0.008	(0.058)	4.784***	(0.280)
Educ_trade	0.091	(0.115)	0.010	(0.054)	1.405***	(0.275)
Educ_cert	−0.069	(0.097)	−0.010	(0.046)	5.908***	(0.225)
Educ_univ	0.054	(0.109)	−0.053	(0.049)	10.080***	(0.251)
Inc_5_10k	−0.224	(0.270)	−0.007	(0.140)	−7.212***	(0.782)
Inc_10_20k	−0.096	(0.254)	−0.051	(0.122)	−5.165***	(0.693)
Inc_20_30k	−0.089	(0.261)	0.092	(0.144)	3.261***	(0.641)
Inc_30_40k	−0.305	(0.257)	0.141	(0.156)	9.495***	(0.605)
Inc_40_50k	−0.379	(0.259)	0.039	(0.144)	11.652***	(0.594)
Inc_50_70k	−0.090	(0.274)	−0.011	(0.134)	15.012***	(0.566)
Inc_mt70k	−0.118	(0.269)	0.022	(0.136)	25.223***	(0.560)
SEIFA_2dec	0.183	(0.263)	0.053	(0.128)	1.189*	(0.567)
SEIFA_3dec	0.270	(0.271)	0.081	(0.134)	4.591***	(0.553)
SEIFA_4dec	0.053	(0.247)	0.099	(0.129)	3.957***	(0.530)
SEIFA_5dec	0.475	(0.272)	0.193	(0.143)	6.386***	(0.522)
SEIFA_6dec	0.153	(0.245)	0.103	(0.125)	7.242***	(0.501)
SEIFA_7dec	0.261	(0.256)	0.155	(0.134)	8.689***	(0.502)
SEIFA_8dec	0.113	(0.258)	0.279	(0.156)	10.768***	(0.499)
SEIFA_9dec	0.272	(0.272)	0.109	(0.138)	12.604***	(0.501)
SEIFA_10dec	0.643*	(0.272)	0.161	(0.135)	18.720***	(0.477)
Employed	−0.360***	(0.101)	−0.053	(0.046)	3.951***	(0.241)
Housing_flat	0.586**	(0.182)	0.065	(0.092)	−1.297**	(0.458)
Housing_farm	0.290	(0.212)	−0.030	(0.096)	6.796***	(0.456)
Housing_house	0.440***	(0.132)	0.064	(0.071)	4.220***	(0.405)
Socap_visit	0.006	(0.006)	0.002	(0.003)	0.058***	(0.015)
Socap_phone	0.000[a]	(0.004)	−0.001	(0.002)	0.079***	(0.009)
Socap_group	0.020	(0.014)	−0.001	(0.007)	0.119**	(0.038)
Socap_ppl	−0.001	(0.003)	0.001	(0.001)	0.027***	(0.008)
2007	0.110	(0.156)	−0.056	(0.061)	−0.088	(0.379)
2008	0.181	(0.098)	−0.298***	(0.053)	0.088	(0.240)
Wald test Chi2 stat	1663.050		99.670		27825.950	
Wald test p-value	0.000		0.149		0.000	
Mean of dep var, %	3.038		0.056		64.837	

Notes: Sample size is 249,273. All regressions control for objective and subjective health measures and risk behaviours. The bottom panel presents Chi-square statistics and p-values for Wald test of joint significance of all demographic and socio-economic variables (including age). Symbols *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively. Symbol ^{a} indicates that the absolute value of the coefficient is less than 0.0005.