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Denise Doiron
Denzil G. Fiebig
Agne Suziedelyte

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Denise Doiron, Denzil G. Fiebig and Agne Suziedelyte

School of Economics, University of New South Wales, Australia

Australian School of Business Building, Level 4, UNSW Sydney NSW 2052, Australia

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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.

*This research uses data from the 45 and Up Study which is managed by the Sax Institute in collaboration with major partner Cancer Council New South Wales; and partners the Heart Foundation (NSW Division); NSW Ministry of Health; *beyondblue: the national depression initiative*; Ageing, Disability and Home Care, NSW Family and Community Services; Australian Red Cross Blood Services; and UnitedCare Ageing. This project was undertaken by the University of Technology Sydney and utilised MBS and PBS data supplied by the Department of Human Services. Data linkage for the project was undertaken by the Centre for Health Record Linkage. The project has ethics approval from the NSW Population and Health Services Research Ethics Committee. The study findings are those of the authors and do not necessarily represent the views of the Commonwealth of Australia, represented in this instance by the Department of Health and Ageing and the Department of Human Services. The project is funded by an ARC Discovery Project grant (DP110100729).

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 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 exists, it will appear differentially across diverse health services. Thus, analyses at an aggregate level such as 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 267,000 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 demographics, socio-economic status and risk behaviours. It is still possible for heterogeneity in cognitive skills or risk preferences to be impacting on the estimated moral hazard effect, but the robustness of our results to a broad range of specification checks involving controls for preference heterogeneity and the fact that our sample is fairly homogenous to begin with will mitigate this impact.

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 0.67 percentage points, which corresponds to a 24 percent 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 the case of health insurance is arguable since health care may be perceived to be unpleasant and only to be sought in cases 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). 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.

The main advantages of private cover are greater choice over medical providers and shorter waiting times for many procedures. Uninsured patients treated in public hospitals can face long waiting times, are treated by specialists paid by the hospital and do not have access to a private ward. Hospital insurance is duplicate in that it can be used to fund hospital costs that are also provided free-of-charge in the public system. It is also complementary in that it can be used to cover excess medical fees over the legislated Medicare subsidy.

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.

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 percent 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 causal 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:

$$\begin{aligned} s^*_{ijt} &= \alpha PHI_{i,t-1} + X'_{i,t-1}\beta + u_{ijt}, \\ s_{ijt} &= 1[s^*_{ijt} > 0], \end{aligned} \tag{1}$$

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 measures the effect of having private health insurance in period t on the probability of having a surgery in the next period.

The vector $X_{i,t-1}$ contains two types of variables, measured at the same time as an individual's private health insurance status: (1) health measures and (2) risk preferences proxied by risk behaviours and socio-economic and demographic characteristics. 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 (and in the absence of excluded instrumental variables), the positive coefficient on the insurance status variable cannot be convincingly interpreted as a causal or 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. This data is used to construct an extensive list of objective and subjective health measures.

An individual's demand for private health insurance may also be positively correlated with his/her level of risk aversion. More risk averse individuals may also invest more in their health and, in turn, be in better health and have lower need for a surgery. Thus, omitting controls for an individual's risk preferences from equation (1) may lead to underestimation of the insurance effect. Following the literature, we use risk behaviours and socio-demographic characteristics such as age, sex, education and income, to proxy for an individual's preference and risk type.

As mentioned above, 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. As a sensitivity check, we also estimate the effect of private health insurance on the probability of having an emergency hospitalisation. We expect no causal effect of private health insurance on emergency hospitalisations. A patient can receive emergency treatment irrespective of his/her private health insurance status and has limited discretion in the decision regarding his/her admission to hospital in emergency situations. Therefore, this exercise can be treated as a falsification test. A significant positive (negative) effect of insurance on emergency hospitalisations would suggest that there may be adverse (advantageous) selection even after we control for the observed health measures and proxies for preference heterogeneity.

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 267,000 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 percent of those sent questionnaires participated and the full sample includes around 10 percent of the eligible population (45 and Up Study Collaborators 2008). The 45 and Up Study provides information about the respondents' socio-demographic characteristics, retirement status, lifestyle, diet, social connections, mental health, physical limitations, medical conditions, surgical procedures, medications and other health related factors.

The 45 and Up Study 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 individuals who were not chosen but volunteered to participate in the 45 and Up Study, as they may introduce selection bias (0.5 percent of the observations). 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 the dependent variables, ends in 2009. Thus, 3,604 individuals (1.4 percent) who completed the survey in 2009 and 2010 are excluded. Finally, the observations that have missing data on any of the dependent or key control variables cannot be used for the analysis. Thus, the size of the analysis sample varies between 196,187 and 240,502 observations depending on the specification used.

4.1 Variables

4.1.1 Dependent variables

The dependent variables used in the estimations of equation (1) 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 list of the indicator (most common) procedures performed in New South Wales hospitals provided by Australian Institute of Health and Welfare (2012*a*). For each of these surgeries, data on its distribution by urgency category is available. Thus, the classification of the procedures is exogenous to the data analysis.

All surgical procedures performed in Australian hospitals are classified into emergency that need to be performed within 24 hours and elective (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. In NSW, the following main categories are used (Baggoley et al. 2011):

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

As the urgency of the procedure depends on the health condition of the patient, the same procedure may be considered to be non-urgent in one case and semi-urgent or urgent in another case. Nonetheless, some procedures are usually classified either as urgent, or semi-urgent, or non-urgent. For example, most patients admitted for knee replacement have been assigned urgency category 3 (Australian Institute of Health and Welfare 2012*b*).

We begin with the case of elective procedures. Our definition of an elective surgery includes non-urgent elective procedures (category 3). Among the most common elective surgeries performed in NSW hospitals, the following procedures are usually considered to be non-urgent (the number in the parentheses indicates proportion of patients admitted for a given procedure that have been assigned urgency category 3) (Australian Institute of Health and Welfare 2012*b*):

- septoplasty or nasal surgery (88%),
- total knee replacement (87%),
- myringoplasty or eardrum surgery (86%),
- cataract extraction (85%),
- varicose vein stripping and ligation (79%),
- tonsillectomy or tonsil removal (73%) and
- total hip replacement (71%).

We construct a binary variable that takes the value one if an individual had any of these procedures in the *12 months* following the survey date and the value zero otherwise.

It would be interesting to look directly at the impact of insurance on waiting times as jumping the queue is one of the usual reasons given for insurance purchase in Australia. Unfortunately, we do not observe when patients were placed on the waiting list. Also, most of the non-urgent procedures (88.9 percent) are performed within 365 days in NSW hospitals (Baggoley et al. 2011). Therefore, a difference in the proportion of people who had an elective surgery within 12 months between the insured and uninsured is not likely to capture differences in waiting times.

Next, we turn to the description of non-elective procedures. In our analysis, a non-elective procedure refers to an emergency, urgent, or semi-urgent surgery. The most common emergency procedures are appendectomy and coronary angioplasty (Australian Institute of Health and Welfare 2012*a*). Among the most common procedures, the following are generally classified as urgent or semi-urgent (the number in parentheses indicates the proportion of patients admitted for a given procedure that have been assigned urgency category 1 or 2) (Australian Institute of Health and Welfare 2012*b*):

- coronary artery bypass graft (95%),
- cholecystectomy or removal of the gall bladder (70%) and
- myringotomy or repair of the perforated drum (68%).

The constructed binary variable 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.

We also construct a binary variable that indicates whether or not an individual had an emergency hospitalisation within the 12 months following the survey date. A hospitalisation is defined to be emergency if a patient was admitted to the hospital via the emergency department (ED). To construct this variable, we merge the hospital admission data with emergency department visit data (by personal identification number and date). More specifically, we define a hospitalisation to be emergency if a patient made an ED visit on the same day as he/she was admitted to the hospital. If a patient made a planned, return, outpatient, or pre-arranged visit to the ED on the same day as he/she was admitted to the hospital, such hospitalisation is not considered to be emergency.

Table 1 presents the descriptive statistics of the variables described above. Around 3 percent of the analysis sample (6,973 individuals) had at least one of the above listed elective procedures within the 12 months following the survey date. Some of these individuals had more than one surgery. Therefore, the total number of the procedures is higher (8,712). The most common elective procedure is cataract extraction. Slightly under 1 percent of the sample had their knee or hip replaced. The other elective procedures are less common. Less than 1 percent of the sample had one of the non-elective surgeries described above within the 12 months following the survey date. There were 1,505 such surgeries performed on 1,468 patients. The most common procedure was gall bladder removal, followed by coronary artery bypass graft surgery and coronary angioplasty. A larger proportion of the sample (6.5 percent) had an emergency hospital admission. The relatively small incidence of specific procedures highlights the need for large samples in this type of analysis.

4.1.2 Explanatory variables

They key variable of interest is an individual's private health insurance status. People self-report their health insurance status 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 two thirds of the sample (65.53 percent) reported having private health insurance cover.

As mentioned in Section 3, the baseline model controls for two types of variables that are expected to affect an individual's demand for an elective and/or non-elective surgery and may also be correlated with his/her health insurance status. First, we control for a number 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 includes principal and secondary diagnoses associated with each admission, which are coded using 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, 30 conditions are included in the models, with rare conditions grouped into one category. The incidence of these diagnoses (averaged over the past five years) for the insured and uninsured is presented in Appendix A Table A.1. 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 and connective tissue disorders, ophthalmic and vascular conditions and ear, nose and throat diseases may increase the demand for an elective surgery. History of cardiovascular diseases and hepatobiliary conditions (related to liver, gallbladder, bile ducts, or bile) may be linked to a higher likelihood of a non-elective surgery. The incidences of most of these conditions are higher among the uninsured.

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, gall bladder removal 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. As reported in Table A.2, a smaller proportion of insured individuals had an elective surgery in the past compared to the uninsured, whereas there are no differences in the incidence of the non-elective procedures by private health insurance status. The models also control for past hospitalisations for other reasons.

To control for less serious health conditions that may not require a hospital admission and any other factors, we include self-reported health measures obtained from the survey data. The 45 and Up study includes questions on chronic conditions, recent treatments for a number of conditions, long term illness/disability, activity limitations, body mass index (BMI), vitamins and medicines taken in the past 4 weeks, history of operations and self-assessed health status and eyesight. The full list, descriptions and means of the self-reported health measures are provided in Appendix A Table A.3. Insured individuals seem to be generally healthier than the uninsured. Insurance status is negatively correlated with most of the chronic conditions, medicine consumption, physical activity limitations, disability and BMI. More importantly, health insurance status is negatively correlated with health problems that may be associated with a higher need for the surgeries that are the focus of this analysis. Insured individuals are less likely to have been diagnosed and/or treated for heart disease, high blood pressure, high cholesterol, which may increase the likelihood of a CABG surgery or angioplasty. Insured individuals are also less likely to report having osteoarthritis and osteoporosis, which may signal a need for a hip or knee replacement. Additionally, individuals with private health insurance rate their health as better than individuals without insurance, which is consistent with the findings of the literature (Doiron et al. 2008). All in all, there seems to be suggestive evidence of advantageous selection into private health insurance. We investigate this issue further in the next section.

Second, we include proxies for unobserved individual preferences to the models. We control for an individual's smoking status, alcohol consumption, sex, age, marital status, country of birth, ancestry, language, education, income[1], employment status and remoteness of the area of residence[2]. Note that employment status can also act as a proxy for the opportunity costs associated with a surgery, which will be higher for employed people compared to the unemployed and those not in labour force. We also include the type of housing, which acts as as a proxy for wealth and 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[3]. The descriptions and means of the socio-economic and demographic variables are presented in Appendix A Table A.4. As expected, the insured are less likely to smoke than the uninsured. On the other hand, insurance status is positively correlated with alcohol consumption, which suggests that this variable may not be a good proxy for risk aversion in the population of interest. People who have private health insurance are slightly younger, are more likely to be currently married, live in less remote regions, are more likely to be Australian born, are less likely to speak another language than English at home, have a higher level of education, income and wealth, live in wealthier areas and are more likely to be employed than people without private health insurance.

As part of the sensitivity analysis, we include additional variables to the baseline specification. The first group of additional controls is obtained from the survey data. These variables, listed in Appendix B, may affect an individual's need for a surgery or act as proxies for an individual's risk attitudes, or both. The second group of additional controls is obtained from the administrative data and are expected to serve as proxies for an individual's health status. Specifically, we control for an individual's emergency department

[1]We also include a dummy variable for missing income in the regressions.

[2]Remoteness is measured by the Accessibility/Remoteness Index of Australia Plus (ARIA+). More details on this index are available in Trewin (2001).

[3]For more information on the SEIFA indexes see Pink (2006).

visits in the past two years and total health care expenditure in the past calendar year[4]. The total health care expenditure includes the expenditure on hospitalisations, emergency department visits, doctor visits, diagnostic tests and prescription medicines. More information on how this variable is constructed is provided in Ellis et al. (forthcoming).

5 Results

All tables in this section report probit average partial effects of private health insurance and other variables. Standard errors are estimated using the delta method (by Stata's `margins` command).

5.1 Insurance effects on elective and non-elective surgeries

Table 2 presents the estimated effects of private health insurance on the probabilities of having an elective and non-elective surgery. Controlling for the demographic and socio-economic characteristics and health measures obtained from the administrative data (column 1), private health insurance is found to increase the probability of having an elective surgery within the next 12 months by 0.577 percentage points, which is a 19.9 percent increase from the mean. This effect is highly statistically significant. Additionally controlling for the self-reported health measures (column 2) increases the estimated partial effect of insurance to 0.670 percentage points, which corresponds to a 24.3 percent increase from the mean[5]. The effect of private health insurance compares to the effects of other important determinants of the demand for elective surgeries, such as, a 5.5 year increase in age, recent history of musculoskeletal disorders, or use of glucosamine (a supplement for osteoarthritis). 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. Using the first specification (column 3), it is estimated that health insurance cover increases this probability only by 0.016 percentage points, which is a 2.7 percent increase from the mean. Moreover, this effect is statistically insignificant. In the specification with the full set of controls (column 4),

[4] In this analysis, a time period t does not correspond to a calendar year. The time is measured from the day an individual completed the 45 and Up survey. The health expenditures were calculated, however, by calendar year.

[5] Due to missing values in the survey data, the second specification is estimated using a smaller sample. However, re-estimating the first specification on this smaller sample gives similar results to those reported in column 1, as shown in Table 4.

the estimated effect of insurance on the demand for non-elective surgeries is somewhat larger, but still statistically insignificant. Relative to the mean, the average partial effect of insurance on non-elective surgeries is three times smaller than the average partial effect of insurance on elective surgeries. Thus, we do not find any evidence of an incentive effect of insurance in the case of non-elective surgeries. Moreover, the results reported in Table 2 suggest that the positive insurance effect on elective surgeries is unlikely to be driven by any remaining adverse selection. Otherwise, we would expect to find similar insurance effects across different types of hospitalisations.

To examine whether the results for the elective surgeries are driven by particular procedures, Table 3 presents the effects of private health insurance on selected individual surgeries (cataract extraction, hip replacement and knee replacement)[6]. The results show that private health insurance significantly increases the probability of all of these surgeries. Relative to the mean, private health insurance has larger effects on the demand for knee replacement and hip replacement than on the demand for cataract extraction. This is perhaps not surprising, given that cataract extraction is a less complicated procedure than knee or hip replacement. For this reason, the benefits of insurance may be smaller in the case of cataract surgery than in the case of knee or hip replacement.

It is also of interest to investigate whether there is any evidence of adverse or advantageous selection in private health insurance. For this purpose, we consecutively add the control variables in the two regressions a group at a time and check how this affects the average partial effect of insurance. In such an exercise, the order of the inclusion of variables usually affects results. In our case, the qualitative pattern of the results remains the same when we change the order in which different groups of variables are included in the regressions.

Results for elective surgeries are presented in panel A of Table 4. Starting with the model with no other controls besides age and time effects and adding the socio-economic and demographic characteristics and risk behaviours increases the estimated coefficient on the private health insurance variable, which suggests an advantageous selection on these characteristics. These variables would be available in most surveys. We further investigate how important it is to account for selection on health measures, which are included in our data, but may not be available in other studies. Comparing columns 2 and 5, it may appear that the addition of these health measures does not significantly affect the estimated effect of insurance on elective surgeries. However, further investigation of the results shows that this cannot be interpreted as an absence of selection effects.

[6] The numbers of tonsil removal, varicose vein, ear drum and nasal surgeries are too small to estimate the models for these procedures separately.

Instead, the results presented in columns 3-5 suggest that insurance status is correlated with both types of health measures, but selection on administrative health measures appears to be adverse, whereas selection on self-reported health variables appears to be advantageous (holding administrative measures fixed). It is especially important to control for the subjective health measures (self-assessed general health and eyesight), as omitting these variables results in substantial underestimation of the effect of insurance on the demand for elective surgeries.

Results for non-elective surgeries are presented in panel B of Table 4. The pattern of these results is similar to the case of elective surgeries. We observe suggestive evidence of adverse selection on the health measures obtained from the administrative data and advantageous selection on the self-reported health measures. Insurance status is, however, not statistically significant in either of the specifications.

Next, we briefly discuss average partial effects of the other variables. The average partial effects of the selected variables[7] are presented in Appendix A Table A.5. These estimates are based on the specification with the full set of controls. Some of the findings are as expected. The probability of having both types of surgery increases with related health conditions. Specifically, the probability of an elective surgery is positively correlated with recent musculoskeletal disorders, eye diseases, ear, nose and throat conditions, osteoarthritis and consumption of glucosamine. Individuals with worse self-assessed eyesight are also more likely to have an elective surgery. The probability of a non-elective surgery is positively associated with recent gall bladder conditions and heart attack. The likelihood of a non-elective surgery also increases with worse self-reported health.

On the other hand, some of the results are somewhat unexpected. We find that worse self-assessed general health is negatively associated with the probability of an elective surgery. A possible explanation for this result is that individuals in poor health may not be fit for such a major surgery as knee or hip replacement, which often requires general anesthesia and has a long recovery period. It is also found that controlling for health status, other variables, such as country of birth and ancestry, are significantly correlated with the probability of an elective surgery, which suggests that the demand for elective surgeries may not be solely explained by health risk.

Finally, we turn to the variables describing an individual's hospitalisation history in the past five years. Note that the models also include the self-reported indicators of selected operations. Thus, the coefficients on the self-reported operations measure the effects of ever having had a particular surgery, whereas the utilisation variables obtained from the

[7]Due to large number of variables, the average partial effects of past diagnoses are not reported, but are available from the authors upon request.

administrative data can be interpreted as the additional effects of the recent surgeries and/or other procedures, for which we do not have self-reported indicators. Looking at elective surgeries, self-reported past hip and knee operations are found to increase the probability of having an elective surgery in the future. As to the utilisation measures obtained from the administrative data, it is found that only the most recent elective surgeries have additional explanatory power. Turning to non-elective surgeries, a past gall bladder operation decreases the probability of a non-elective surgery in the future, which is not surprising, because gall-bladder removal can be only done once. Past non-elective surgeries are mainly positively correlated with the probability of a non-elective surgery in the future. Controlling for the self-reported indicator of a past gall bladder operation, these results are possibly driven by coronary artery bypass graft surgery and coronary angioplasty, suggesting persistence in heart problems.

5.2 Sensitivity analysis

To address a possibility of remaining selection effects, we first examine whether the results are affected by the inclusion of the additional control variables described in Subsection 4.1.2. Due to missing values for these variables, the sample sizes are substantially smaller in these estimations than in the main analysis. For this reason, we also present estimates of the baseline model (with full set of main controls) for each of the sub-samples. Column 1 of Table 5 presents the estimated effects of private health insurance in the models with additional controls available in the survey data. The results presented in column 2 show how the estimated effects of private health insurance are affected by the inclusion of the binary variables that indicate whether or not an individual visited the emergency department (ED) in the past two years. As the emergency department data starts on 1 July 2005, for these estimations we can only use individuals who completed the survey from 1 July 2007 to 31 December 2008. Finally, column 3 controls for an individual's total health care expenditure in the past calendar year. Due to data availability, the sample is restricted to the surveys completed in 2007 and 2008.

The estimated effect of insurance on the demand for elective surgeries remains statistically and economically significant when these additional controls are included to the regression, as shown in Panel A of Table 5. The inclusion of the additional survey variables decreases the estimated effect of insurance on the probability of an elective surgery, but only slightly. The estimate of the insurance effect is practically not affected by the addition of past ED visits and total health care expenditure. Across different model specifications, the average partial effect of health insurance on the demand for elective surgeries varies from 25.6 to

30.3 percent relative to the mean. The results of the sensitivity analysis further support the hypothesis that private health insurance does not significantly affect the demand for non-elective surgeries. These results are reported in panel B of Table 5.

As a second check, we estimate a model in which the dependent variable indicates whether or not an individual has been admitted to a hospital via emergency department in the 12 months following the survey date. This acts as a falsification test, as we do not expect private health insurance status to affect an individual's probability to be admitted to the hospital in an emergency situation. Therefore, a significant positive (negative) coefficient on the insurance would suggest possible adverse (advantageous) selection into insurance. We find that health insurance coverage decreases the probability of being admitted to a hospital via emergency department by 0.943 percentage points, or 15.6 percent relative to the mean. The average partial effect is statistically significant at conventional levels. (Detailed results are available upon request.) This result suggests that insurance status may be negatively correlated with unobserved health problems. Thus, we may under-estimating incentive effects of insurance.

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 24 percent while for urgent 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 urgent 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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Table 1: Description and means of the dependent variables

Variable	Description	Mean
A. Elective surgeries		
s_nurg_365d	=1 if had an elective surgery in the next 12 months	0.0290
p_eye_365d_y	=1 if had cataract surgery in the next 12 months	0.0188
p_knee_365d_y	=1 if had knee replacement in the next 12 months	0.0050
p_hip_365d_y	=1 if had hip replacement in the next 12 months	0.0035
p_vvein_365d_y	=1 if had varicose vein surgery in the next 12 months	0.0010
p_nose_365d_y	=1 if had nasal surgery in the next 12 months	0.0008
p_tons_365d_y	=1 if had tonsillectomy in the next 12 months	0.0001
p_ear_365d_y	=1 if had ear drum surgery in the next 12 months	0.0001
B. Non-elective surgeries		
s_urg_365d	=1 if had a non-elective surgery in the next 12 months	0.0061
p_gallbl_365d_y	=1 if had gall bladder removal in the next 12 months	0.0034
p_cabg_365d_y	=1 if had coronary artery bypass graft surgery in the next 12 months	0.0013
p_ptca_365d_y	=1 if had coronary angioplasty in the next 12 months	0.0007
p_append_365d_y	=1 if had appendectomy in the next 12 months	0.0004
p_perfear_365d_y	=1 if had perforated ear drum repair in the next 12 months	0.0003
C. Emergency hospitalisations		
ed_snd_365d_y	=1 if was admitted to hospital via ED in the next 12 months	0.0650
Observations		240,502

Table 2: Effects of health insurance on elective and non-elective procedures

	Elective		Non-elective	
	(1)	(2)	(3)	(4)
Average partial effect, ppt.	0.577***	0.670***	0.016	0.046
	(0.077)	(0.083)	(0.038)	(0.042)
Change from mean, %	19.908	24.255	2.670	7.763
Pseudo R-squared	0.114	0.145	0.040	0.057
Sample size	240,502	196,187	240,502	196,187
Control variables:				
Socio-demographic	Y	Y	Y	Y
Risk behaviours	Y	Y	Y	Y
Health (admin data)	Y	Y	Y	Y
Health (survey data)	N	Y	N	Y
Number of controls	201	268	201	268

Notes: 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 insurance on individual elective procedures

	(1) Any	(2) Cataract	(3) Knee	(4) Hip
Average partial effect, ppt.	0.670***	0.298***	0.157***	0.106***
	(0.083)	(0.067)	(0.035)	(0.029)
Change from mean, %	24.255	16.584	33.067	32.958
Pseudo R-squared	0.144	0.197	0.231	0.202
Sample size	196,187	196,187	196,187	196,187

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

Table 4: Variation in effects of insurance across model specifications

Add...	(1) Age	(2) Socio-dem. & risk behaviours	(3) Health (admin. data)	(4) Obj. health (survey data)	(5) Subj. health (survey data)
A. Elective surgeries					
Average partial effect, ppt.	0.507***	0.718***	0.549***	0.577***	0.670***
	(0.075)	(0.083)	(0.084)	(0.084)	(0.083)
Change from mean, %	18.359	25.993	19.879	20.875	24.255
Pseudo R-squared	0.086	0.091	0.116	0.132	0.145
B. Non-elective surgeries					
Average partial effect, ppt.	−0.019	0.065	0.026	0.044	0.046
	(0.037)	(0.041)	(0.042)	(0.042)	(0.042)
Change from mean, %	−3.203	10.865	4.343	7.378	7.763
Pseudo R-squared	0.009	0.019	0.043	0.055	0.057
Sample size	196,187	196,187	196,187	196,187	196,187

Notes: Standard errors are reported in parentheses. All regressions include time effects. Symbol *** denotes statistical significance at the 0.1% level. Variables are added to the regressions consecutively.

Table 5: Sensitivity of results to adding other covariates, effects of insurance

	(1)		(2)		(3)	
Add...	Base	Oth vars	Base	ED hist	Base	Tot HC exp hist
A. Elective surgeries.						
Average partial effect, ppt.	0.636***	0.589***	0.708***	0.711***	0.707***	0.711***
	(0.127)	(0.130)	(0.090)	(0.090)	(0.090)	(0.090)
Change from mean, %	30.304	28.032	25.627	25.765	25.618	25.759
Pseudo R-squared	0.164	0.175	0.144	0.144	0.144	0.144
B. Non-elective surgeries						
Average partial effect, ppt.	0.030	0.043	−0.007	0.003	−0.007	−0.008
	(0.070)	(0.071)	(0.045)	(0.045)	(0.045)	(0.045)
Change from mean, %	5.942	8.468	−1.318	0.481	−1.301	−1.425
Pseudo R-squared	0.099	0.119	0.056	0.057	0.056	0.056
Sample size	64,542	64,542	168,846	168,846	168,899	168,899

Notes: Standard errors are reported in parentheses. All regressions control for administrative and self-reported 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: Incidence of hospital-based diagnoses averaged over past five years

Aggregated condition category	No PHI	PHI	z-stat
Infectious and Parasitic	0.014	0.010	18.959
Malignant Neoplasm	0.012	0.013	-2.844
Benign/In Situ/Uncertain Neoplasm	0.027	0.039	-30.181
Diabetes	0.026	0.016	23.874
Nutritional and Metabolic	0.029	0.018	30.687
Hepatobiliary	0.007	0.005	11.995
Gastrointestinal	0.063	0.072	-16.976
Musculoskeletal and Connective Tissue	0.042	0.041	0.337
Hematological	0.011	0.007	15.480
Psychiatric	0.008	0.004	21.981
Neurological	0.012	0.010	8.031
Cardiovascular	0.059	0.038	37.740
Vascular	0.012	0.009	12.637
Pulmonary	0.020	0.009	34.078
Ophthalmic	0.024	0.019	14.603
Ears, Nose and Throat	0.008	0.009	-5.852
Urinary	0.022	0.017	14.232
Genital	0.014	0.018	-14.132
Dermatologic	0.011	0.010	4.296
Injury, Poisoning	0.011	0.007	18.135
Symptoms, Signs and Ill-Defined Conditions	0.060	0.045	28.414
Screening/History	0.080	0.082	-3.793
Complications of Care	0.013	0.011	9.324
Other	0.016	0.008	29.239
Invalid code	0.005	0.003	14.294
Observations	82,897	157,605	

The last column presents z-statistics for the equality of means test.

Table A.2: Incidence of past surgeries

Variable	Description	No PHI	PHI	z-stat
s_nurg_h1_y	=1 if had an elective surgery 1 year(s) ago	0.029	0.027	2.473
s_nurg_h2_y	=1 if had an elective surgery 2 year(s) ago	0.027	0.025	3.736
s_nurg_h3_y	=1 if had an elective surgery 3 year(s) ago	0.025	0.022	4.494
s_nurg_h4_y	=1 if had an elective surgery 4 year(s) ago	0.023	0.020	5.164
s_nurg_h5_y	=1 if had an elective surgery 5 year(s) ago	0.022	0.018	5.741
s_urg_h1_y	=1 if had a non-elective surgery 1 year(s) ago	0.008	0.008	-0.234
s_urg_h2_y	=1 if had a non-elective surgery 2 year(s) ago	0.009	0.008	1.692
s_urg_h3_y	=1 if had a non-elective surgery 3 year(s) ago	0.009	0.008	0.926
s_urg_h4_y	=1 if had a non-elective surgery 4 year(s) ago	0.009	0.008	2.752
s_urg_h5_y	=1 if had a non-elective surgery 5 year(s) ago	0.009	0.008	2.088
hoth_h1_y	=1 if admitted for other reasons 1 year(s) ago	0.209	0.234	-14.485
hoth_h2_y	=1 if admitted for other reasons 2 year(s) ago	0.195	0.217	-12.840
hoth_h3_y	=1 if admitted for other reasons 3 year(s) ago	0.181	0.201	-11.911
hoth_h4_y	=1 if admitted for other reasons 4 year(s) ago	0.171	0.187	-9.518
hoth_h5_y	=1 if admitted for other reasons 5 year(s) ago	0.167	0.177	-6.291
Observations		82,897	157,605	

The last column presents z-statistics for the equality of means test.

Table A.3: Description and means of self-reported health measures

Variable	Description	No PHI	PHI	z-stat
skin	=1 if diagnosed with skin cancer	0.247	0.273	-12.277
melan	=1 if diagnosed with melanoma	0.058	0.054	3.421
prostbr	=1 if diagnosed with prostate/breast cancer	0.057	0.057	0.185
otherca	=1 if diagnosed with other cancer	0.073	0.058	12.726
hrt	=1 if diagnosed with heart disease	0.143	0.106	22.899
highbld	=1 if diagnosed with high blood pressure	0.388	0.343	19.417
stroke	=1 if diagnosed with stroke	0.043	0.022	23.716
diabet	=1 if diagnosed with diabetes	0.115	0.071	30.878
bldclot	=1 if diagnosed with blood clot	0.053	0.041	11.901
asthmhayf	=1 if diagnosed with asthma/hay fever	0.212	0.226	-7.026
Parkin	=1 if diagnosed with Parkinson's disease	0.007	0.005	5.114
trtcancer	=1 if treated for cancer in the last month	0.032	0.025	8.981
trthrtattack	=1 if treated for heart attack in the last month	0.037	0.017	24.006
trtothheart	=1 if treated for other heart disease in the last month	0.034	0.024	11.713
trthighbld	=1 if treated for high blood pressure in the last month	0.272	0.229	20.639
trthighchol	=1 if treated for high cholesterol in the last month	0.166	0.149	9.479
trtbloodclott	=1 if treated for blood clotting problems in the last month	0.024	0.015	12.278
trtasthma	=1 if treated for asthma in the last month	0.057	0.041	14.794
trtarthritis	=1 if treated for osteoarthritis in the last month	0.097	0.066	22.552
trtthyroid	=1 if treated for thyroid problems in the last month	0.054	0.047	6.380
trtosteop	=1 if treated for osteoporosis in the last month	0.063	0.050	11.449
trtdepranx	=1 if treated for depression/anxiety in the last month	0.108	0.070	27.099
mospf	Physical Functioning scale, 0(low)-100(high)	76.624	86.561	-81.380
disabled	=1 if has a long-term illness/disability	0.091	0.033	47.505
medic4multivmin	=1 if took multivitamins & minerals in the past 4 weeks	0.196	0.235	-19.904
medic4multivonly	=1 if took multivitamins alone in the past 4 weeks	0.034	0.039	-5.116
medic4fishoil	=1 if took Fish oil in the past 4 weeks	0.280	0.323	-19.910
medic4gluco	=1 if took glucosamine in the past 4 weeks	0.184	0.241	-29.422
medic4omega3	=1 if took Omega 3 in the past 4 weeks	0.071	0.078	-5.723
medic4paracetamol	=1 if took paracetamol in the past 4 weeks	0.268	0.228	19.251
medic4aspirinhrt	=1 if took aspirin for the heart in the past 4 weeks	0.184	0.157	14.941
medic4spirinother	=1 if took aspirin for other reasons in the past 4 weeks	0.060	0.049	10.306
medic4lipitor	=1 if took Lipitor in the past 4 weeks	0.153	0.136	10.282
medic4avapro	=1 if took Avapro/Karvea in the past 4 weeks	0.076	0.068	6.018
medic4warfarin	=1 if took warfarin/Coumadin in the past 4 weeks	0.036	0.025	12.423
medic4Pravachol	=1 if took Pravachol in the past 4 weeks	0.025	0.021	6.116
medic4Coversyl	=1 if took Coversyl in the past 4 weeks	0.074	0.057	14.514
medic4Lasix	=1 if took Lasix/frusemide in the past 4 weeks	0.039	0.018	24.326
medic4Zocor	=1 if took Zocor/Lipex in the past 4 weeks	0.062	0.052	9.041
medic4Cardizem	=1 if took Cardizem/Vasocordol in the past 4 weeks	0.020	0.014	10.285
medic4Nexium	=1 if took Nexium in the past 4 weeks	0.061	0.052	7.645
medic4Norvasc	=1 if took Norvasc in the past 4 weeks	0.033	0.028	6.181
medic4Fosamax	=1 if took Fosamax in the past 4 weeks	0.032	0.025	8.163
medic4Somac	=1 if took Somac in the past 4 weeks	0.045	0.034	10.867
medic4Tritace	=1 if took Tritace in the past 4 weeks	0.040	0.032	8.563
medic4Caltrate	=1 if took Caltrate in the past 4 weeks	0.074	0.094	-15.668
medic4Losec	=1 if took Losec/Acimax/omeprazole in the past 4 weeks	0.049	0.039	9.992
medic4Noten	=1 if took Noten/Tenormin/atenolol in the past 4 weeks	0.047	0.036	11.731
medic4Oroxine	=1 if took Oroxine/thyroxine in the past 4 weeks	0.049	0.046	2.401

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Variable	Description	No PHI	PHI	z-stat
medic4Ventolin	=1 if took Ventolin/salbutamol in the past 4 weeks	0.068	0.045	20.012
medic4Zyloprim	=1 if took Zyloprim/alloputinol in the past 4 weeks	0.038	0.032	7.233
medic4Diabex	=1 if took Diabex/Diaformin/metfotmin in the past 4 weeks	0.062	0.039	20.769
bmi	Body mass index	27.383	26.930	17.145
opskin	=1 if had skin cancer removal operation	0.262	0.283	-9.812
opreprod	=1 if had reproductive organ operation	0.411	0.421	-4.112
opkneereplac	=1 if had knee replacement operation	0.041	0.038	3.605
ophipreplac	=1 if had hip replacement operation	0.030	0.030	0.014
opgallb	=1 if had gall bladder removal operation	0.114	0.092	14.755
opheart	=1 if had heart or coronary bypass surgery	0.070	0.052	15.166
ratehealth_exc[a]	=1 if self-rated health is excellent	0.116	0.184	-41.246
ratehealth_vg	=1 if self-rated health is very good	0.319	0.413	-41.135
ratehealth_g	=1 if self-rated health is good	0.360	0.311	21.367
ratehealth_f	=1 if self-rated health is fair	0.168	0.081	52.447
ratehealth_p	=1 if self-rated health is poor	0.038	0.011	33.304
ratevision_exc[a]	=1 if self-rated vision is excellent	0.083	0.131	-33.551
ratevision_vg	=1 if self-rated vision is very good	0.268	0.363	-43.610
ratevision_g	=1 if self-rated vision is good	0.427	0.386	17.416
ratevision_f	=1 if self-rated vision is fair	0.183	0.106	44.389
ratevision_p	=1 if self-rated vision is poor	0.039	0.014	30.011
Observations		64,468	131,719	

Notes: [a] indicates omitted category in the regressions.
The last column presents z-statistics for the equality of means test.

Table A.4: Description and means of risk behaviours and demographic and socio-economic characteristics

Variable	Description	No PHI	PHI	z-stat
alcdrinksperweek	Number of alcoholic drinks per week	6.492	7.304	-18.745
smokestat_1	= 1 if smokes now	0.119	0.045	59.345
smokestat_2	=1 if smoked before, not now	0.388	0.341	22.655
smokestat_3[a]	=1 if never smoked	0.493	0.613	-56.697
male	=1 if male	0.462	0.465	-1.386
age	Age in years	64.095	61.546	52.248
ms_single	=1 if single	0.081	0.048	30.632
ms_married[a]	=1 if married	0.587	0.764	-87.706
ms_partner	=1 if living with partner	0.062	0.051	11.501
ms_widowed	=1 if widowed	0.124	0.063	46.810
ms_divorced	=1 if divorced	0.116	0.058	46.222
ms_separated	=1 if separated	0.042	0.021	27.203
childrennum	Number of children	2.587	2.372	32.614
ARIA_plus_mean	Accessibility/Remoteness Index, 0(accessible)-15(remote)	1.492	1.109	50.858
CofO_Au	=1 if born in Australia	0.724	0.781	-30.631
CofO_es	=1 if born in English speaking country	0.141	0.118	15.993
CofO_nes[a]	=1 if born in non-English speaking country	0.135	0.101	24.121
ancesAust	=1 if has Australian ancestry	0.504	0.528	-11.061
ancesEnglish	=1 if has English ancestry	0.427	0.426	0.583
ancesIrish	=1 if has Irish ancestry	0.164	0.167	-1.863
ancesScot	=1 if has Scottish ancestry	0.143	0.151	-5.262
ancesEuro	=1 if has other European ancestry	0.118	0.111	5.425
ancesOth	=1 if has other ancestry	0.152	0.128	16.101
otherlanghomeyn	=1 if speaks other language than English at home	0.110	0.078	25.254
highestqual_1	=1 if doesn't have any qualifications	0.202	0.067	87.851
highestqual_2	=1 if has school/intermediate certificate	0.263	0.203	32.685
highestqual_3	=1 if has higher school certificate	0.100	0.099	0.661
highestqual_4	=1 if has trade/apprenticeship	0.139	0.098	29.079
highestqual_5	=1 if has certificate/diploma	0.180	0.231	-29.747
highestqual_6[a]	=1 if has university degree	0.117	0.302	-115.538
currenthousing_1[a]	=1 if lives in a house	0.725	0.798	-39.511
currenthousing_2	=1 if lives in a flat	0.133	0.092	29.788
currenthousing_3	=1 if lives in a house on farm	0.076	0.080	-3.557
currenthousing_o	=1 if lives in other housing	0.067	0.031	37.156
income_1	=1 if HH income is less then $5000 per year	0.025	0.009	26.865
income_2	=1 if HH income is $5000-$9999 per year	0.077	0.017	60.459
income_3	=1 if HH income is $10000-$19999 per year	0.256	0.074	110.117
income_4	=1 if HH income is $20000-$29999 per year	0.129	0.079	36.727
income_5	=1 if HH income is $30000-$39999 per year	0.080	0.081	-0.440
income_6	=1 if HH income is $40000-$49999 per year	0.065	0.079	-13.222
income_7	=1 if HH income is $50000-$69999 per year	0.075	0.124	-39.514
income_8[a]	=1 if HH income is $70000 or more per year	0.077	0.333	-169.668
income_miss	=1 if refused to answer	0.216	0.203	7.106
seifa_1	=1 if in 1st decile of SEIFA Index of rel soc-econ adv/disadv	0.038	0.015	30.743
seifa_2	=1 if in 2nd decile of SEIFA Index of rel soc-econ adv/disadv	0.108	0.055	43.328
seifa_3	=1 if in 3th decile of SEIFA Index of rel soc-econ adv/disadv	0.085	0.057	24.647
seifa_4	=1 if in 4th decile of SEIFA Index of rel soc-econ adv/disadv	0.142	0.091	35.734
seifa_5	=1 if in 5th decile of SEIFA Index of rel soc-econ adv/disadv	0.106	0.082	19.380

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Variable	Description	No PHI	PHI	z-stat
seifa_6	=1 if in 6th decile of SEIFA Index of rel soc-econ adv/disadv	0.170	0.142	17.753
seifa_7	=1 if in 7th decile of SEIFA Index of rel soc-econ adv/disadv	0.119	0.121	-1.793
seifa_8	=1 if in 8th decile of SEIFA Index of rel soc-econ adv/disadv	0.085	0.093	-6.506
seifa_9	=1 if in 9th decile of SEIFA Index of rel soc-econ adv/disadv	0.060	0.092	-29.222
seifa_10[a]	=1 if in 10th decile of SEIFA Index of rel soc-econ adv/disadv	0.087	0.251	-111.676
workfulltime	=1 if in full time paid work	0.159	0.290	-76.384
workparttime	=1 if in part time paid work	0.126	0.142	-11.503
workfullyretired	=1 if completely retired or pension	0.459	0.336	58.267
workpartretired	=1 if partially retired	0.038	0.068	-32.053
workdisabledsick	=1 if disabled or sick	0.081	0.019	61.686
workselfemployed	=1 if self-employed	0.090	0.147	-42.813
workunpaid	= 1 if doing unpaid work	0.059	0.059	-0.308
workstudyonly	=1 if studying	0.019	0.014	9.329
workhomefamily	=1 if looking after home or family	0.102	0.105	-2.290
workunemployed	=1 if unemployed	0.042	0.015	36.003
workother	=1 if work status is other	0.021	0.012	15.545
yr_2006[a]	=1 if completed survey in 2006	0.150	0.131	12.389
yr_2007	=1 if completed survey in 2007	0.074	0.073	1.135
yr_2008	=1 if completed survey in 2008	0.776	0.796	-11.248
Observations		82,897	157,605	

Notes: [a] indicates omitted category in the regressions.
The last column presents z-statistics for the equality of means test.

Table A.5: Average partial effects of selected other variables

	Elective surgeries		Non-elective surgeries	
	APE, ppt.	Standard error	APE, ppt.	Standard error
male	0.018	(0.097)	0.046	(0.046)
age	0.127***	(0.005)	0.005	(0.003)
ms_single	−0.082	(0.171)	−0.034	(0.079)
ms_partner	−0.258	(0.186)	−0.056	(0.080)
ms_widowed	−0.034	(0.117)	−0.146*	(0.059)
ms_divorced	−0.060	(0.142)	0.069	(0.072)
ms_separated	−0.213	(0.235)	−0.060	(0.105)
childrennum	−0.036	(0.025)	0.010	(0.013)
ARIA_plus_mean	−0.028	(0.028)	−0.016	(0.014)
CofO_Au	0.405*	(0.175)	0.066	(0.083)
CofO_es	0.276	(0.214)	0.124	(0.108)
ancesAust	−0.018	(0.103)	0.060	(0.050)
ancesEnglish	−0.099	(0.083)	−0.004	(0.040)
ancesIrish	−0.088	(0.101)	0.026	(0.052)
ancesScot	−0.035	(0.105)	−0.064	(0.050)
ancesEuro	−0.001	(0.135)	0.014	(0.064)
ancesOth	−0.343**	(0.127)	0.022	(0.065)
otherlanghomeyn	−0.099	(0.179)	0.056	(0.089)
highestqual_1	−0.157	(0.136)	0.109	(0.078)
highestqual_2	−0.054	(0.117)	0.075	(0.062)
highestqual_3	−0.316*	(0.136)	0.019	(0.072)
highestqual_4	0.053	(0.140)	0.121	(0.075)
highestqual_5	−0.024	(0.115)	0.046	(0.058)
currenthousing_2	0.050	(0.117)	−0.015	(0.058)
currenthousing_3	−0.064	(0.154)	−0.147*	(0.063)
currenthousing_o	−0.486***	(0.136)	−0.099	(0.076)
income_1	0.253	(0.327)	−0.092	(0.141)
income_2	−0.142	(0.206)	0.059	(0.112)
income_3	0.083	(0.158)	−0.012	(0.076)
income_4	0.085	(0.160)	0.073	(0.081)
income_5	−0.167	(0.157)	0.122	(0.085)
income_6	−0.324*	(0.159)	0.024	(0.080)
income_7	0.014	(0.153)	−0.008	(0.068)
income_miss	0.045	(0.140)	−0.015	(0.064)
seifa_1	−0.348	(0.243)	−0.045	(0.121)
seifa_2	−0.212	(0.175)	0.030	(0.093)
seifa_3	−0.153	(0.168)	−0.022	(0.085)
seifa_4	−0.318*	(0.143)	−0.039	(0.074)
seifa_5	−0.009	(0.151)	0.084	(0.082)
seifa_6	−0.299*	(0.122)	0.011	(0.064)
seifa_7	−0.221	(0.129)	0.003	(0.067)
seifa_8	−0.263	(0.137)	0.130	(0.079)
seifa_9	−0.262	(0.140)	−0.025	(0.072)
workfulltime	−0.123	(0.168)	0.012	(0.075)
workparttime	−0.264	(0.154)	−0.055	(0.069)
workfullyretired	0.150	(0.139)	0.067	(0.069)
workpartretired	0.008	(0.170)	0.100	(0.092)

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	Elective surgeries		Non-elective surgeries	
	APE, ppt.	Standard error	APE, ppt.	Standard error
workdisabledsick	−0.162	(0.201)	−0.009	(0.095)
workselfemployed	−0.149	(0.151)	0.014	(0.071)
workunpaid	0.086	(0.153)	−0.039	(0.073)
workstudyonly	0.535	(0.384)	−0.063	(0.147)
workhomefamily	−0.095	(0.130)	0.108	(0.070)
workunemployed	−0.265	(0.264)	−0.052	(0.118)
workother	0.013	(0.306)	0.047	(0.154)
alcdrinksperweek	0.007	(0.006)	−0.012***	(0.003)
smokestat_1	−0.272	(0.174)	0.118	(0.086)
smokestat_2	0.205*	(0.082)	0.048	(0.040)
s_nurg_h1_y	1.835***	(0.313)	0.269	(0.179)
s_nurg_h2_y	−0.100	(0.240)	−0.018	(0.138)
s_nurg_h3_y	−0.303	(0.243)	0.357	(0.221)
s_nurg_h4_y	0.162	(0.289)	0.228	(0.190)
s_nurg_h5_y	−0.468	(0.261)	0.377	(0.246)
s_urg_h1_y	0.308	(0.432)	−0.024	(0.151)
s_urg_h2_y	−0.323	(0.360)	0.568*	(0.276)
s_urg_h3_y	−0.060	(0.398)	0.372	(0.264)
s_urg_h4_y	0.812	(0.485)	0.144	(0.226)
s_urg_h5_y	−0.117	(0.402)	0.165	(0.244)
hoth_h1_y	0.460***	(0.137)	0.210**	(0.072)
hoth_h2_y	0.532***	(0.144)	−0.071	(0.065)
hoth_h3_y	0.128	(0.145)	0.224**	(0.083)
hoth_h4_y	0.382*	(0.152)	0.105	(0.078)
hoth_h5_y	0.467**	(0.158)	0.159	(0.085)
skin	0.027	(0.116)	−0.016	(0.058)
melan	−0.333*	(0.140)	−0.002	(0.077)
prostbr	0.155	(0.144)	0.010	(0.075)
otherca	−0.042	(0.138)	0.039	(0.074)
hrt	−0.064	(0.122)	0.113	(0.069)
highbld	0.170	(0.106)	0.027	(0.052)
stroke	0.073	(0.179)	0.038	(0.096)
diabet	0.139	(0.179)	−0.052	(0.082)
bldclot	0.092	(0.159)	0.110	(0.090)
asthmhayf	−0.102	(0.098)	−0.048	(0.047)
Parkin	0.200	(0.388)	−0.236	(0.158)
trtcancer	−0.388*	(0.189)	−0.066	(0.098)
trthrtattack	−0.357*	(0.180)	0.436***	(0.132)
trtothheart	−0.274	(0.180)	0.136	(0.105)
trthighbld	−0.060	(0.113)	−0.013	(0.057)
trthighchol	−0.120	(0.105)	0.032	(0.055)
trtbloodclott	−0.064	(0.229)	−0.107	(0.104)
trtasthma	0.121	(0.195)	−0.016	(0.093)
trtarthritis	1.308***	(0.143)	−0.067	(0.061)
trtthyroid	0.094	(0.217)	−0.073	(0.101)
trtosteop	−0.496***	(0.133)	−0.089	(0.079)
trtdepranx	−0.054	(0.133)	0.006	(0.064)
mospf	−0.031***	(0.002)	−0.002	(0.001)
disabled	−0.870***	(0.124)	−0.164*	(0.068)

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	Elective surgeries		Non-elective surgeries	
	APE, ppt.	Standard error	APE, ppt.	Standard error
medic4multivmin	−0.001	(0.093)	−0.078	(0.043)
medic4multivonly	−0.167	(0.189)	0.048	(0.098)
medic4fishoil	0.033	(0.085)	−0.054	(0.042)
medic4gluco	0.566***	(0.094)	−0.010	(0.046)
medic4omega3	0.067	(0.136)	−0.101	(0.065)
medic4paracetamol	0.138	(0.087)	0.043	(0.043)
medic4aspirinhrt	0.050	(0.097)	0.113*	(0.054)
medic4spirinother	0.198	(0.152)	0.130	(0.084)
medic4lipitor	0.203	(0.109)	−0.014	(0.052)
medic4avapro	0.098	(0.128)	0.018	(0.066)
medic4warfarin	0.410*	(0.205)	−0.090	(0.090)
medic4Pravachol	−0.115	(0.198)	−0.068	(0.095)
medic4Coversyl	−0.042	(0.135)	0.043	(0.071)
medic4Lasix	−0.361*	(0.165)	−0.102	(0.085)
medic4Zocor	0.227	(0.144)	−0.055	(0.067)
medic4Cardizem	0.136	(0.231)	0.129	(0.126)
medic4Nexium	0.043	(0.137)	0.151	(0.078)
medic4Norvasc	0.114	(0.181)	0.052	(0.095)
medic4Fosamax	0.245	(0.201)	−0.173	(0.093)
medic4Somac	−0.100	(0.154)	0.207*	(0.095)
medic4Tritace	0.091	(0.175)	0.164	(0.096)
medic4Caltrate	−0.034	(0.119)	0.060	(0.069)
medic4Losec	−0.349*	(0.137)	0.171	(0.088)
medic4Noten	0.129	(0.159)	0.098	(0.085)
medic4Oroxine	−0.193	(0.204)	0.039	(0.118)
medic4Ventolin	0.223	(0.181)	0.060	(0.092)
medic4Zyloprim	0.456*	(0.179)	0.006	(0.086)
medic4Diabex	0.123	(0.202)	0.140	(0.112)
bmi	0.021**	(0.007)	0.013***	(0.003)
opskin	−0.156	(0.116)	−0.024	(0.059)
opreprod	0.160*	(0.077)	0.011	(0.037)
opkneereplac	0.759***	(0.174)	−0.105	(0.079)
ophipreplac	0.679***	(0.184)	−0.049	(0.093)
opgallb	−0.037	(0.113)	−0.263***	(0.045)
opheart	0.182	(0.163)	0.000	(0.077)
ratehealth_vg	0.078	(0.136)	0.123	(0.069)
ratehealth_g	−0.283*	(0.142)	0.219**	(0.077)
ratehealth_f	−0.874***	(0.148)	0.285*	(0.114)
ratehealth_p	−0.01163***	(0.187)	0.692**	(0.250)
ratevision_vg	0.419**	(0.162)	−0.040	(0.063)
ratevision_g	1.392***	(0.168)	−0.063	(0.064)
ratevision_f	3.832***	(0.297)	−0.017	(0.074)
ratevision_p	6.129***	(0.564)	−0.263**	(0.087)
yr_2007	0.029	(0.164)	−0.034	(0.069)
yr_2008	0.134	(0.104)	−0.253***	(0.057)
Pseudo R-squared	0.145		0.057	
Mean of dep var	0.0276		0.0060	

Notes: Sample size is 196,187 observations. Symbols *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level.

B Additional variables

In this model specification, we additionally control for the self-rated quality of life, memory and teeth; a dummy for having hearing loss; the number of teeth left; the number of falls in the past 12 months; a dummy for having a broken bone in the past 12 months; the number of times an individual is troubled by leaking urine; mental health measures (The Kessler Psychological Distress Scale (K10), whether emotional problems interfere with a person's daily activities and family history of Alzheimer's); exercise; the number of hours spent outdoors; exposure to someone else's smoking; diet; time use; and social connections. Additionally, we include family history of the diseases that may affect the need for some of the surgeries. These diseases include arthritis, osteoporosis, hip fracture, heart disease, high blood pressure, stroke and diabetes. Finally, dummies for having had a prostate/breast cancer test and bowel cancer test are included in this specification. It is expected that more risk averse individuals may be more likely to have been tested than less risk averse individuals.