The Impact of Private Hospital Insurance on the Utilization of Hospital Care in Australia

Damien S. Eldridge*, Ilke Onur†, Malathi Velamuri‡and Cagatay Koç§

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*La Trobe University, Australia; email:d.eldridge@latrobe.edu.au
†(Corresponding author) University of South Australia, Australia; email: ilke.onur@unisa.edu.au
‡Independent Researcher; email: mala@wennersten.org
§Senior Economist, Cornerstone Research, USA; email:cagatay.koc@gmail.com

Abstract

We use the 2004-'05 wave of the Australian National Health Survey to estimate the impact of private hospital insurance on the propensity for hospitalization as a private patient. We employ instrumental-variable methods to account for the endogeneity of supplementary private hospital insurance purchases. We calculate moral hazard based on a difference-of-means estimator. We decompose the moral hazard estimate into a *diversion* component that is due to an insurance-induced substitution away from public patient care towards private patient care, and an *expansion* component that measures a pure insurance-induced increase in the propensity to seek private patient care. We find some evidence of self-selection into insurance but this finding is not robust to alternative specifications. Our results suggest that on average, private hospital insurance causes a sizable and significant increase in the likelihood of hospital admission as a private patient. However, there is little evidence of moral hazard; the treatment effect of private hospital insurance on private patient care is driven almost entirely by the substitution away from public patient care towards private patient care.

JEL Classification: I11, I18, C35

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1 Introduction

An extensive literature on markets characterized by asymmetric information between agents predicts that insurance markets will be prone to inefficient outcomes. According to theoretical models, the demands for health insurance and health care will be jointly determined since the insured individual no longer bears the full costs of health care, potentially leading to moral hazard (Arrow, 1963; Manning and Marquis, 1996). Similarly, individual choice among health insurance policies may induce risk-based sorting across plans, resulting in adverse selection (Rothschild and Stiglitz, 1976). These theoretical predictions, however, are mediated by institutional and regulatory features of the health care system prevalent in each market.

The Australian health care system is typical of most industrialized countries (with the notable exception of the United States) in that a private, health insurance market complements a universal, public health care system called Medicare. Medicare is the primary source of health insurance in Australia. Private health insurance (PHI) coverage is purely voluntary and does not affect Medicare entitlements. A large part of private health insurance therefore leads to duplication in coverage while only a small part comprises supplementary coverage (Paolucci *et.al.*, 2008).[1] Moreover, the private health insurance market is heavily regulated, mandating community rating and open enrolment.[2] These characteristics of the health care system have implications for the structure of private health insurance demand in Australia.

Cameron *et.al.* (1988) is one of the earliest papers to estimate the joint demands for health insurance and health services in Australia. Their analysis preceded the introduction of Medicare in 1984. They used a structural approach to modeling the demand for health care services while simultaneously addressing the issue of self-selection into health insurance. They estimated the model using the 1977-'78 wave of the Australian National Health Survey (NHS). Their findings indicated that both self-selection and moral hazard were important determinants of health care usage in Australia.

Following the introduction of Medicare in 1984, enrolment in PHI fell dramatically until the late 1990s. This development alarmed policy-makers since there was strong support in government circles for a balanced delivery of healthcare services involving both the public and private sectors. There was also concern that decreasing rates of PHI were causing an 'adverse selection death-spiral' (Buchmueller, 2008). Barrett and Conlon (2003) found

[1]Even in situations involving duplication of coverage, PHI does offer increased choice of doctors, shorter waiting times and higher quality of hospital services such as a private room or better meals.

[2]Strict community rating was relaxed in 1999, allowing premiums to be age-specific.

evidence in support of this view. Savage and Wright (2003) used the 1989-90 wave of the NHS to investigate whether individuals with private hospital insurance over-consumed private hospital services. They also found evidence of adverse selection, and substantial moral hazard effects.

Since the publication of these papers, the Australian government has introduced a number of policies, with the express intention of increasing the uptake of PHI and lowering insurance premiums. The objective of these policies was to reduce the pressure on the public health system while ensuring universal access, as well as offering more choice to consumers.[3] These policies comprise financial incentives for purchasing PHI and a lifetime community rating regulation called Lifetime Health Cover (LHC). These reforms led to variation in insurance premia across age and income groups, by family structure and over time, altering the structure of demand for insurance (Ellis and Savage, 2008).

The above policies remain controversial, with opinions sharply divided as to their effectiveness in increasing private insurance coverage, relieving the burden on the public health system and providing equitable access to health care.[4] For our purposes, however, these initiatives undoubtedly changed incentives for the purchase of private health insurance. Since optimal health policy depends crucially on the type of distortions afflicting health care markets, these changed incentives provide a strong motivation for re-examining the relationship between the demands for insurance and health services in Australia. Australia's experience can offer valuable insights into moral hazard for other countries with similar health care institutions.

Our paper makes three contributions. Firstly, we correct for the endogeneity of private hospital insurance ($PHoI$) status in estimating hospital utilization. Secondly, we estimate the 'average treatment effect' of $PHoI$ on hospital utilization (admission) by using a multi-stage estimation procedure that tracks the individual's decision process. Thirdly, we decompose the total moral hazard effect into a 'diversion effect' (substitution away from public patient care) and an 'expansion effect' (pure moral hazard). We emphasize the importance of this decomposition analysis in understanding the factors that contribute to the estimated increase in hospital utilization due to supplementary hospital insurance.

The rest of the paper is organized as follows: section 2 gives a brief description of the Australian health care system, highlighting the reforms introduced since the late 1990s, and reviews the literature in the post-reform period; section 3 describes the theoretical framework

[3]See Hall *et. al.* (1999) and Butler (2002) for a detailed summary of these reforms.
[4]See Butler (2002), Lu and Savage (2006) and Vaithianathan (2004).

employed; section 4 describes the NHS data and provides some descriptive statistics; in section 5, we explain the empirical approach adopted in the paper; section 6 presents the estimates; section 7 concludes.

2 Australia's Health Care Reforms and Related Literature

Australia's health system offers a comprehensive range of public and privately funded health services. Medicare, the tax-financed public health system introduced in 1984, provides universal, compulsory coverage for the full cost of being treated as a public patient in a public hospital. It also provides coverage for some of the costs of private medical services and pharmaceuticals through the Medicare Benefits Schedule (MBS) and Pharmaceutical Benefits Scheme (PBS) respectively. Medicare is supplemented by a private health insurance system. Private ancillary insurance provides cover for ancillary services not covered by Medicare such as dental care, optical services and chiropractic treatment. Private hospital insurance covers hospitalization either in private hospitals or in public hospitals for individuals choosing to be admitted as private patients. Private insurance for private hospital treatment may involve out-of-pocket costs but allows choice of medical practitioner and shorter waiting times for some procedures. Hospital and ancillary insurance may be purchased separately, however a majority of the insured population has both hospital and ancillary cover.[5]

The private health insurance sector is highly regulated. Until 2000, private insurance funds were required to apply strict community rating, whereby premiums were invariant by risk category. Open enrolment guarantees access to PHI coverage for all applicants, including continuous renewal of coverage over time (Colombo and Tapay, 2003). Community rating implies that the low-risks (younger and healthier individuals) subsidize the high-risks. This can result in the low-risks dropping cover because the premiums they pay exceed their true risk, thus worsening the risk pool of the insured and leading to adverse selection. Once Medicare was introduced in 1984, this is exactly what happened in Australia. Between 1984 and 1990, private hospital cover declined from 50% of the population to 44%, and

[5] The MBS fees are set by the government and reviewed periodically. Providers are not bound by the MBS fees and can charge patients a higher fee. The difference between the actual amount charged to patients and the MBS fee is referred to as the gap. Individuals admitted as private patients in public and private hospitals can get Medicare to cover 75% of the MBS fees for approved in-hospital services. Individuals with private health insurance can reduce or eliminate the remaining 25% of the fees (Savage and Wright, 2003).

by mid-2000, coverage had fallen to 31% of the population (Barrett and Conlon, 2002). Since support for private hospitals comes largely from PHI, the very viability of private hospitals was threatened (CDHA, 1999). In response to these developments, the Australian government introduced a mix of financial incentives and regulatory tools in the late 1990s to increase enrolment in PHI plans and reduce public health care costs.[6]

In 1997, a non-linear, income-based subsidy to purchase private health insurance was introduced (Ellis and Savage, 2008). This means-tested initiative was replaced in 1999 with a universal rebate of 30% for any private health insurance premium.[7] High-income individuals and households also face a penalty; beyond specified income thresholds, individuals without private patient hospital cover for themselves and for all dependants during any period of the income year, pay the Medicare Levy Surcharge (MLS) for that period.[8] Lifetime Health Cover (LHC) is a government initiative that started in July 2000. It is designed to weaken strict community-rating, thereby encouraging people to purchase hospital cover earlier in life and to maintain that cover. This improves the overall age profile of health insurance members, which contributes to making premiums more affordable for all members. To avoid paying a LHC loading, individuals need to purchase hospital cover by 1 July following their 31st birthday. Purchases made after the 31st birthday attract loading rates that increase with age (Vaithianathan, 2004).[9] These initiatives undoubtedly changed incentives for the purchase of private health insurance. A number of papers have studied the private insurance market and outcomes in Australia following these reforms.

Butler (1999) used aggregate time series data from the Health Insurance Commission (HIC) to examine the effectiveness of these policy changes in increasing private insurance coverage in Australia. He estimated the price elasticity of demand for health insurance, following the introduction of the 30% private insurance rebate introduced in 1999. His point estimate of

[6] See Butler (2002) for a description of these policies.

[7] New legislation to introduce means testing for the the private health insurance rebate came into effect on July 1, 2012. Under the new rules, individuals earning over AU$84,001 annually, or couples earning over AU$168,001 will receive a lower rebate rate. Australians aged 65 and over will receive a higher rebate rate, but this age benefit is also in proportion to their annual income rebate - with higher income earners losing a percentage of their rebate rate. For details, see http://www.health.gov.au/privatehealth.

[8] The MLS, when introduced, was calculated at 1% of taxable income and is in addition to the 1.5% Medicare Levy. Single individuals with annual household income greater than $50,000 and couples (both married and defacto) with annual household income grater than $100,000 are liable for the MLS amounting to one percent of their taxable income if they do not have private health insurance. The Medicare levy surcharge (MLS) income test also changed on 1 July 2012. For details, see http://www.health.gov.au/privatehealth.

[9] Specifically, individuals have to pay a surcharge of 2 per cent for every year that they delay initial purchase beyond age 30. LHC applies up to age 65, implying a maximum possible penalty of 70 per cent. Individuals purchasing private coverage after age 65 for the first time, face no penalty (Buchmueller, 2008).

-0.23 suggests that the demand for private health insurance in Australia is price-inelastic. He also examined the effectiveness of the LHC in increasing insurance coverage. There was a sharp increase in coverage immediately following the introduction of the LHC in 2000, implying an alleviation of the adverse selection problem associated with the previous community rating regime. However, the average age of the insured population increased in the following years. In Butler's (2002) interpretation, these findings suggest that the effectiveness of the LHC in easing the problem of adverse selection was short-lived.

Ellis and Savage (2008) found an increase in insurance coverage following the reforms. There was also a broadening in the age distribution of private health insurance, suggesting a reduction in adverse selection. Lu and Savage (2006) assessed the impact of Australia's insurance incentives on the demand for the public and private hospital systems using the 2001 wave of the NHS. They modeled the probability of the type of hospital care (public versus private), if any, and estimated the conditional (among the admitted) and unconditional length of hospital stay among individuals stratified by insurance status and duration. From their results, they inferred the existence of self-selection in insurance choice. Among the recently insured (those who were likely to have purchased supplementary insurance after the incentives were introduced), they found evidence of significant moral hazard. Moreover, they found that increased usage of private care far outweighed the reduction in public care, and concluded that the insurance reforms were not very effective in lowering the pressure on the public health system.

Cheng and Vahid (2011) estimated the impact of private hospital insurance on the utilization of private hospital care services in Australia. They used a simultaneous equation approach to model the joint demand for private hospital insurance, type of hospital care (private versus public patient) and number of nights spent in hospital. They used wave 4 of the Household Income and Labour Dynamics in Australia (HILDA) data to estimate their model. They found no evidence of self-selection into insurance but some evidence of moral hazard in the propensity of insured individuals to seek private patient care.

Our paper most closely resembles the work of Lu and Savage (2006) and Cheng and Vahid (2011); they studied questions similar to those that we address in this paper though all three papers use different data sets for estimating their respective models - Lu and Savage (2006) use the 2001 wave of NHS, we use the 2004-'05 wave of NHS while Cheng and Vahid (2011) use the HILDA data. Moreover, the methodological approach varies considerably among the three. Lu and Savage (2006) tackled self-selection using the propensity score matching method that matches individuals based on observable characteristics. Both Cheng and Vahid

(2011) and our paper addresses unobserved heterogeneity. But again, the approaches are different. Cheng and Vahid use a semi-structural econometric approach to estimating moral hazard, while accounting for the heterogeneity of insurance. We use a bivariate probit model to test for endogeneity and also a sequential, multi-stage approach for estimating moral hazard. This latter method does not require us to completely specify the joint distribution function, as Cheng and Vahid (2011) do. While this flexibility is likely to involve some efficiency loss, the large sample sizes we use to estimate our model can mitigate any such losses. Importantly, Cheng and Vahid (2011) estimate their model on the sub-sample of those hospitalized at least for one night, while we include the non-hospitalized in our sample. Our bivariate probit estimates offer no evidence of endogeneity of private hospital insurance while our multi-stage method suggests mixed evidence of self-selection into insurance. We therefore present moral hazard estimates from methods that correct for the endogeneity of insurance, as well as those that treat this variable as exogenous.

We estimate the insurance-induced moral hazard in the propensity to seek hospital care as a private patient, using a difference-of-means estimator. We refer to this as the total moral hazard effect, or simply the total effect. Our principal contribution lies in decomposing this total effect into a *diversion effect* and an *expansion effect.* The diversion effect measures the component of total moral hazard that is due to substitution away from the use of public hospital care towards the use of private hospital care. The expansion effect is the component that measures the net increase in the use of hospital care due to private hospital insurance. We refer to this latter effect as the *pure moral hazard effect.* In our view, such a decomposition offers crucial information to policy-makers on the possible impact of private insurance expansion. For instance, if the total moral hazard effect is substantially due to the diversion effect, the implication is that an expansion in coverage will be successful in lowering the pressure on the public health system. On the other hand, if the diversion effect is negligible, then the total moral hazard effect simply measures the insurance-induced increase in health services utililization, and suggests that expansion of private insurance is likely to lead to cost increases without achieving the objective of reducing the waiting lines in public hospitals. To our knowledge, our paper is the first to attempt such a decomposition analysis.

Our 'treatment effect' of private hospital insurance on hospital utilization is positive, sizable and significant. Our estimation procedure offers robust evidence that this effect is driven predominantly by the diversion effect - substitution away from public patient care towards private patient care. The expansion effect (pure moral hazard), is small. This is an important finding that potentially has significant implications for the efficacy of the insurance incentive

policies introduced in Australia. Such implications, of course, are only relevant when these incentives increase insurance coverage rates. We discuss these implications in Section 7.
In the following section, we briefly describe the decision process underlying our estimation strategy.

3 Theoretical Framework

Our objective is to measure the impact of private hospital insurance on the utilization of both private patient hospital care services and public patient hospital care services. Clearly, these two groups of services are related and can, moreover, be seen as imperfect substitutes. Presumably, it is this intuition that provides a potential justification for the private health insurance rebate policy and the medicare levy surcharge in Australia. If these policies increase the number of people who have private hospital insurance ($PHoI$), they will reduce the price for private patient hospital care services that is faced by these people. This will, in turn, reduce the demand for public patient hospital care. It is hoped that this reduction in the demand for public patient care will relieve pressure on a public hospital system that appears to be characterized by excess demand and the associated quantity rationing in the form of waiting lists.
In this section, we outline the theoretical framework that we use to measure the impact of $PHoI$ on the utilization of hospital care services. First, we provide a simple short-run partial equilibrium analysis of the markets for public patient and private patient hospital care services. This analysis is used to motivate the various measures of the impact of $PHoI$ on the utilization of hospital care that we estimate. Second, we consider the nature of the decision problem that faces a consumer who is thinking about purchasing $PHoI$, given the possibility that he might want to utilize hospital care services in the future. This underscores the need to control for the potential endogeneity of the decision to purchase $PHoI$.

3.1 The markets for hospital care

The market for public patient hospital care is illustrated in Figure 1 while the related market for private patient hospital care is illustrated in Figure 2. In order to simplify the analysis, we assume that the supply of public patient hospital care is perfectly elastic up until a capacity constraint of X_0 is reached. Beyond this point, it is perfectly inelastic. We also assume that the supply of private patient hospital care is perfectly elastic over the entire range of output that is relevant for this analysis.

We are interested in the average treatment effect of private hospital insurance on the demand for hospital care. Suppose that initially, nobody in the population has $PHoI$. In this case, the demand for public patient hospital care is given by the demand curve D_X (No PHoI) in Figure 1, while the demand for private patient hospital care is given by the demand curve D_Y (No PHoI) in Figure 2. The actual quantity of public patient hospital care that is intially provided is limited to X_0 because of the capacity constraint. This leaves an excess demand of $(X_1 - X_0)$ units of public patient hospital care at the prevailing, and regulated price. The equilibrium quantity of private patient hospital care services that is initially provided is Y_0 units.

Suppose now that everybody in this economy has $PHoI$. This reduces the effective price that people face for private patient hospital care for any given 'sticker' price. As such, the presence of $PHoI$ shifts the demand curve for private patient hospital care to the right in Figure 2. The new demand curve is given by D_Y (PHoI). The new equilibrium quantity that is provided is Y_1 units. Note that Y_1 is greater than Y_0. Since public patient and private patient hospital care are substitutes, the decrease in the effective price of private patient care induced by the presence of $PHoI$ results in a decrease in the demand for public patient care. This involves an inward shift of the demand curve for this type of service. The new demand curve for public patient hospital care is given by D_X (PHoI) in Figure 1. In the case that is illustrated in Figure 1, the inward shift in demand is large enough to induce a fall in the actual quantity of public patient care that is provided to X_2 units. Since this amount is less than the capacity constraint, there is no excess demand and the waiting list is completely eliminated. If the inward shift in the demand curve had not been large enough for the desired demand at the regulated price to fall below this capacity constraint, then there would have been no reduction in the quantity of services provided; the waiting list would have been reduced, but not eliminated.

Assume that the impact of $PHoI$ on the markets for private patient and public patient hospital care is as illustrated in Figures 1 and 2. In this case, we can decompose the total impact of $PHoI$ on the utilization of private patient hospital care (the *total effect*) into two components. The first of these components is a *diversion effect*. The diversion effect is the insurance-induced change in the quantity of medical services utilization caused by individuals switching away from seeking treatment as public patients to seeking treatment as private patients. The second of these effects is an *expansion effect*. The expansion effect measures the insurance-induced net expansion in private patient care that remains after the reduction in public patient care has been removed.

The total increase in the utilization of private patient hospital care due to the presence of $PHoI$ is equal to $(Y_1 - Y_0)$ units. The diversion effect is the total decrease in the pressure facing public patient hospital care due to the presence of $PHoI$. It is equal to $(X_2 - X_1)$ units of public patient hospital care. Unfortunately, because we do not observe the size of the waiting list for public hospital care, we are not able to measure this effect. Instead, we can impute the actual decrease in the utilization of public patient hospital care due to the presence of $PHoI$. This effect is equal to $(X_2 - X_0)$ units . Note that this is a lower bound for the size of the diversion effect, because $(X_2 - X_0)$ is necessarily less than or equal to $(X_2 - X_1)$. Finally, we can impute the expansion effect by calculating the residual that is left after we subtract the diversion effect from the total effect. The true expansion effect is equal to $\{(Y_1 - Y_0) - (X_2 - X_1)\}$. We can impute a measured expansion effect as $\{(Y_1 - Y_0) - (X_2 - X_0)\}$. Since $(X_2 - X_0)$ is a lower bound for $(X_2 - X_1)$, we know that the measured expansion effect will be an upper bound for the true expansion effect.[10]

Our framework implicitly involves risk-averse agents who have preferences over a composite commodity and health status. They have private information about their health status which is not observed by the insurer. In the initial period, agents decide whether to purchase private hospital insurance, without knowledge of their future health status which will determine their demand for services in the second period. In the second period, faced with a health shock that requires hospitalization, the 'net' prices for private in-patient medical services and waiting time for the required treatment, they decide whether to be admitted to hospital as a public patient or a private patient.

The agent's insurance purchase decision is likely to be endogenous; it potentially depends on the probability distribution over health states in period 2, insurance premia, the net prices of private hospital services (given insurance), the waiting time for free medical services in

[10] Policy arrangements designed to encourage people to purchase PHoI were introduced, and in one case further modified, over the period from 1 July 1997 to 15 July 2000 (Butler 2002). These policies may have provided an incentive for changes in the structure of supply for hospital care in Australia, in addition to any impact that they might have had on the demand for hospital care services. If private providers believe that these policies will be sustained over a long period of time, it is possible that more private hospitals would be willing to enter the industry and existing private hospitals might choose to expand. Similarly, if the policies result in reduced pressure on public hospitals, then it is possible that the number and size of public hospitals might be reduced over time. Given the substantial infrastructure involved in the construction and expansion of hospitals, it seems reasonable to suppose that any supply effects are going to take place over a reasonably long period of time. As such, it is not possible to either detect or analyze the significance of any such supply changes using a cross-sectional data set. In our estimation strategy, we therefore assume away any supply-side effects.

public hospitals, and other socio-economic variables. While we have data on socio-economic variables and self-reported health status variables for the individuals in our sample, we do not observe some of the other variables that might influence the insurance decision - for example, the insurance premia. To address the endogeneity issue, we employ an instrumental variable-based approach. We describe this method in more detail in Section 5.

3.2 Measures of Moral Hazard

Our objective is to obtain estimates of the total effect, the diversion effect and the expansion effect as described in Section 3.1. While we will be estimating an econometric version of the individual choice model for hospital insurance and hospital care, the three effects were derived from the partial equilibrium model of the market for health care. As such, we will need to relate the individual choice model to the partial equilibrium model. We outline such a relationship below.

There are two measures of hospital utilization that one can use to test for the presence and extent of moral hazard. One is the duration of stay (number of days) in hospital and the other is admission to hospital as a private patient. Lu and Savage (2006) and Cheng and Vahid (2011) estimate moral hazard using the first measure. However, there are a number of reasons why this measure may not be appropriate for the purpose. Over time, private hospitals in Australia have specialized in elective procedures while public hospitals continue to deal with the majority of emergency services. According to the Australian Hospital Statistics, in 2007-08, over 90% of Emergency admissions involving overnight stay were treated in the public sector and 61% of Elective admissions were treated in the private sector. For same-day separations, the public sector handled 96% of Emergency admissions while 55% of Elective admissions were treated in the private sector (AIHW, 2009). Most elective surgery requires day-admission only, with no overnight stay (Vaithianathan (2004) and Duckett (2005)). The relative specialization of services suggests that estimates of the impact of hospital insurance based on the intensity of hospital utilization (as measured by number of nights of hospitalization) are likely to understate the moral hazard effects associated with insurance. This is compounded by the fact that the 2004-'05 wave of the NHS that we use provides no information on the reason for hospital admission. If the disease-composition of patients admitted to public and private hospitals differs considerably (a likely situation considering the relative specialization of services referred to above), then a simple comparison of the intensity of utilization would give misleading results. Moreover, awareness of the threat of infections acquired in hospitals is increasing all over the world. This development makes it harder to make an unequivocal claim that individuals would prefer a longer stay in hospital, all else equal. Perhaps the greatest objection to using the duration measure is that it requires the assumption that the individual (or her family) makes the decision on how many nights to spend in hospital. While individuals might use some discretion over whether or not to go to hospital (for an elective procedure) and whether to receive treatment as a private or public patient, the decision regarding how long they will remain hospitalized is often influenced by the treating physician.

If the primary advantage afforded by private hospital insurance is speedier access to elective surgery, then seeking hospitalization as a private patient is the important behavioral dimension for estimating moral hazard. Our focus is therefore on estimating the impact of insurance on the propensity to seek hospital admission as a private patient. Towards this end, we suppose that the presence or absence of private hospital insurance only affects the type of hospital admission (private or public) and not the duration of treatment.

Consider an individual potential patient, $i \in \{1, 2, \cdots I\}$. Let λ_i^{j1} denote individual i's probability of admission into hospital as a public patient ($j = 1$) or a private patient ($j = 2$), conditional on having private hospital insurance ($PHoI = 1$). We define λ_i^{j0} analogously for the case when i has no hospital insurance, ($PHoI = 0$).

The total effect, as defined in Section 3.1, is the treatment effect of private hospital insurance on the propensity to seek private patient hospital care. It is thus the following sum:

$$TE = \Sigma_i(\lambda_i^{21} - \lambda_i^{20})$$

The diversion effect is the treatment effect of private hospital insurance on the propensity to seek public patient hospital care, and is given by

$$DE = \Sigma_i(\lambda_i^{11} - \lambda_i^{10}),$$

We expect $TE \geq 0$ and $DE \leq 0$.

We will assume that a transfer of treatment to private patient hospital care by individual i, following the purchase of private hospital insurance, is responsible for the decrease in public patient hospital care. The expansion (or pure moral hazard) effect is then simply the extent to which any increase in the utilization of private patient hospital care following the purchase of private hospital insurance exceeds this decrease in the utilization of public patient hospital care. This is given by

$$
\begin{aligned}
EE &= TE + DE \text{ (recall that } DE \leq 0) \\
&= \Sigma_i(\lambda_i^{21} - \lambda_i^{20} + \lambda_i^{11} - \lambda_i^{10})
\end{aligned}
$$

The sign and magnitude of the EE indicate the presence and severity of insurance-induced moral hazard, if any.

4 Data and Descriptives

The joint estimation of health insurance and health care demands requires detailed information on the health-status and utilization of health care services, as well a rich set of socio-economic and demographic characteristics. The main objectives of the NHS surveys are to obtain information on a range of health-related issues in Australia and to monitor trends in health over time. The NHSs are household surveys based on a (weighted) random sample of Australians. One person aged 18 years and over in each dwelling was selected and interviewed about their own health characteristics. An adult resident, nominated by the household, was interviewed about all children aged 0-6 years and one selected child aged 7-17 years in the dwelling.

We use the 2004-'05 wave of the NHS.[11] This is the fourth in a series of cross-sectional surveys. Beginning with the 2001 survey, the survey is now conducted every 3 years. The data are available in two formats: basic and expanded files. The basic data are available in a CD-ROM while access to the expanded dataset is through the Remote Access Data Laboratory. These two versions contain similar information but some items have more detailed information in the expanded version.[12] We use the expanded version of the data for this paper.

The NHS surveys collect information on a detailed set of health status variables - self-assessed health status, kessler score for mental health,[13] number of long-term (chronic) health

[11] The 2007-'08 wave of the NHS is currently available for use but in this wave, questions about hospitalization in the previous year were not asked. We are therefore unable to use this wave for our analysis.

[12] For example, the actual 'Personal gross weekly cash income' is reported in the expanded version, but only in deciles in the basic file. Similarly, 'Age' is reported in discrete bands in the basic version but the expanded version reports exact age in years.

[13] The Kessler Psychological Distress Scale (K10) is a measure of non-specific psychological distress based on 10 questions about the level of nervousness, agitation, psychological fatigue and depression. Scores range from 10 to 50, with higher scores indicating higher levels of mental distress (Andrews and Slade, 2001).

conditions, as well as information on whether the individual suffers from any among a long list of individual long-term conditions. In our regression analysis, we control for these conditions. However, like all other papers that use this survey, we are hampered by a lack of data on insurance premia, net prices of medical services, claims and waiting times for various treatments facing patients who are contemplating using the public health system. We control for state of residence to capture some of the variation in insurance prices, and waiting times across states.

Our sample consists of individuals who were over 21 years of age when the survey was conducted.[14] We consider the income unit as the decision-making unit, and restrict our sample to 'single family households' that comprise family members only. This way, we avoid dealing with households that have multiple, unrelated income units. After imposing these restrictions, we are left with 17,731 individuals from these single family units. Table 1 presents basic descriptive statistics for this sample, weighted by the person weights provided in the survey.

Respondents in the NHS are asked whether they are covered by private health insurance, and if so, what type of cover they possess - ancillary cover only, hospital cover only, both ancillary and hospital cover, or none. Since our measure of health care utilization is hospitalization, the relevant insurance measure is hospital cover. Accordingly, we classify all those individuals as having private hospital insurance (PHoI) if they responded as having either private hospital insurance only or having both private ancillary and hospital cover. Those who claim to have only ancillary cover, or no private insurance at all, are classified as not having private hospital insurance. When respondents were unsure of their private insurance status, the corresponding values were classified as missing. Table 1 reveals that nearly half the sample had private hospital insurance.

Nearly 49% of the sample is male and the average individual in the sample is 48 years old. The LHC variable is defined as 1 for those who are at least 31 years of age, and 0 for those below 31. Over 82% of the sample is over the age of 31. Around 46% of the sample has at least a high-school diploma. The employment rate in the sample is 64%. Over 10% of the sample is born in New Zealand or the United Kingdom, with another 19% born in other countries; the rest are Australian-born. Almost 97% of the sample profess to be proficient in the English language. Of the 17,731 individuals in the sample, about 39% belong to couple households without children, 33% belong to couple households with children, 4%

[14] An unmarried individual can have health coverage under her parent's health insurance policy until the age of 21.

are single-parent households while 24% are single-person households. The MLS variable is an indicator variable, defined as 1 for single individuals whose annual household income exceeds AU$50,000 or for couples whose household income exceeds AU$100,000, and 0 for all other individuals. Households in this category (for whom MLS=1) are required to pay the Medicare Levy Surcharge (MLS) of 1% of taxable income for the tax period over which they do not purchase hospital insurance for themselves and for all their dependents. Around 13% of the sample belong to this category.

The NHS collects information on the prevalence of a number of long-term health conditions. As Table 1 reveals, the average number of long-term conditions in the sample is about 3. Similarly, 83% of the sample is in good health, based on a dummy variable that equals 1 if respondent's subjective general health assessment is 'good', 'very good' or 'excellent' as opposed to 'fair' or 'poor'. About 17% of the sample was hospitalized at least once in the previous 12 months. The NHS also asks whether individuals who were hospitalized in the previous 12 months were admitted as private patients or Medicare patients on their last hospital admission. Around 7% of the sample were admitted as private patients on their last admission.

In Table 2, we compare the characteristics of the insured and uninsured samples. The insured population is slightly older, more educated, more likely to be employed and wealthier, compared to the uninsured. They are also more likely to be Australian-born. Couple households have higher rates of insurance coverage relative to single-headed households. Single parents have the lowest coverage rates. Moreover, 88% of the insured sample report being in good health compared to 78% among the uninsured. All these characteristics are suggestive of positive selection into insurance. At the same time, the average Kessler score is lower among the insured sample, and the individual long-term conditions present a mixed picture; for some conditions, the share of the insured sample is bigger than the non-insured, while for others it is the reverse. Overall, these descriptive statistics indicate that the population of individuals with hospital insurance are a heterogeneous mix of positively and adversely selected individuals.

There is also significant variation in insurance coverage across states. This is likely to reflect differences in waiting times for surgery, institutional differences, as well as variation in insurance prices across states (Barrett and Conlon, 2003). Hospitalization rates by insurance status were quite similar but type of patient care was different; a little over 1% of the uninsured population and about 14% of those with insurance were admitted as private patients during their last hospital admission.

5 Empirical Approach

The joint estimation of health insurance purchases and health care utilization requires taking account of the data generating processes underlying the observations on the variables of interest. In most health surveys, including the NHS that we use, information on the health insurance choices of, and health care utliization by consumers, are discrete in nature. This suggests the use of discrete choice models for estimating the determinants of private health insurance and the choice of admission to hospital as private or public patients.

We employ two methods to account for the potential endogeneity of private hospital insurance status among individuals. The first is a bivariate probit model, estimated solely on the sub-sample of those admitted to hospital at least once in the previous 12 months of the survey. The second method is a two-stage procedure based on the sample of all individuals, including those not admitted to hospital. We describe these methods below.

5.1 Estimation using a bivariate probit model

We are interested in estimating the impact of private hospital insurance ($PHoI$) on the probability of seeking hospital admission as a private patient for the sub-sample of those hospitalized at least once in the previous 12 months. However, this estimate is likely to be biased if there are unobservable characteristics that are correlated with both $PHoI$ and with the probability of seeking private-patient hospital care.

We have two binary dependent variables, $y_j, j = 1, 2$. For our purposes, y_1 represents private hospital insurance ($PHoI$) status ($y_{1i} = 1$ if individual i has $PHoI$, and $y_{1i} = 0$ if she does not), while y_2 records whether the individual was admitted to hospital as a private patient ($y_{2i} = 1$) or a Medicare patient ($y_{2i} = 0$). We specify a bivariate probit model as follows[15]:

$$\begin{aligned} y_1^* &= x_1\beta_1 + \epsilon_1,\ \ y_1 = 1 \text{ if } y_1^* \geq 0 \\ y_2^* &= x_2\beta_2 + \beta_3 y_1 + \epsilon_2,\ \ y_2 = 1 \text{ if } y_2^* \geq 0 \\ (\epsilon_1, \epsilon_2) &\sim N_2(0, 0, 1, 1, \rho) \end{aligned} \tag{1}$$

The model is identified by imposing exclusion restrictions; for identification purposes, we require that there is at least one variable in the insurance equation y_1 that is excluded from

[15] See Arendt and Holm, 2006

the type of hospital care equation y_2.
The advantage of using the bivariate probit model is that it allows us to directly test for the endogeneity of private hospital insurance in the y_2 equation; the likelihood ratio (LR) test provides a basis for testing wether ϵ_1 and ϵ_2 are indeed correlated. A weakness in using the bivariate probit model for estimating the impact of insurance on the probability of seeking hospital care as a private patient is that we exclude the non-hospitalized from the model. This group represents 83% of our total sample, and 82% of those with private hospital insurance. Clearly, the characteristics of this group are an important source of variation for our outcome of interest. For this reason, we next use a method that allows us to include the non-hospitalized into the procedure.

5.2 Estimation using a two-stage residual inclusion (2SRI) model

For our second method, we include all individuals in our sample - hospitalized as well as non-hospitalized.
Following Terza *et.al.* (2008), we employ the following nonlinear framework. We assume that

$$E[Admit/x_o, x_p, x_u] = M(x_o\beta_o + x_p\beta_p + x_u\beta_u), \tag{2}$$

where $Admit_i$ is 0 if individual i does not seek hospital admission, 1 if she seeks hospital admission as a private patient, and 2 if she seeks admission as a Medicare patient; x_o is an indicator variable that equals 1 if individual i has private hospital insurance ($PHoI$), and 0 otherwise, x_p is a $1 \times K$ vector of control variables (exogenous regressors) and x_u is a set of unobservable, latent variables that influence the outcome, $Admit$, and are possibly correlated with x_o. $M(.)$ is a known nonlinear function. We tackle the endogeneity through the instrumental-variable based two-stage residual inclusion (2SRI) approach. This method has been used frequently in applied health research.[16]
The regression model corresponding to Equation 2 is

$$Admit = M(x_o\beta_o + x_p\beta_p + x_u\beta_u) + e, \tag{3}$$

with $\beta' = [\beta_o', \beta_p', \beta_u']$ being the corresponding column vector of coefficients and e being the

[16]See for instance, DeSimone (2002), Shea *et.al.* (2007) and Terza *et.al.* (2008).

regression error term, with $E(e/x_o, x_p, x_u] = 0$.
We deal with the correlation between x_o and x_u by means of instrumental variable techniques. To this end, we define the following reduced-form equation:

$$x_o = k(r\alpha) + x_u, \tag{4}$$

where $r = [x_p \;\; r*], r* = [r_1*, ...r_s*]$ is a $1 \times s$ vector of instrumental variables (IVs) and α is a $[K + s] \times 1$ column vector of parameters. The elements of $r*$ are required to satisfy the following conditions: (1) no correlation with x_u; (2) sufficiently correlated with x_o; and (3) $s \geq 1$ - there must be at least as many elements in $r*$ as there are endogenous regressors in Equation 3.
In the first stage of the 2SRI approach, we employ a Probit specification for Equation 4 and estimate α. In the second stage, we apply a multinomial logit specification for Equation **??** and estimate the vector of parameters.
Thus,

$$Pr[Admit_i = j] = \frac{e^{x_o\beta_o + x_p\beta_p + \hat{x_u}\beta_u}}{1 + \sum_{j=0}^{2} e^{x_o\beta_o + x_p\beta_p + \hat{x_u}\beta_u}}$$

where $j = 0$ if individual i does not seek hospital admission, $j = 1$ if she seeks hospital admission as a private patient, and $j = 2$ if she seeks admission as a Medicare patient. The endogenous regressor x_o is included in the second-stage regression and we replace the unobserved variables x_u with the residuals from the auxiliary regression $\hat{x_u}$.[17] Then, since the set of regressors includes the residual $\hat{x_u}$, we can estimate Equation 3 directly without any endogeneity bias.[18]

5.3 Estimates of moral hazard

We define the moral hazard effect of private hospital insurance on the extensive margin, as the average difference in probabilities of admission as a private patient in the population from two counterfactual scenarios: one where all individuals in the population are given

[17]The following formula gives the generalized residuals: $\hat{x_u} = \frac{(x_o - \Phi(r\hat{\alpha}))\phi(r\hat{\alpha})}{\Phi(r\hat{\alpha})[1-\Phi(r\hat{\alpha})]}$

[18]The 2SRI method is a special case of the control function approach to address endogeneity. Its application remains controversial however, since the theory only demonstrates that *some function* of the residuals is the appropriate control function. It is not clear that using a linear function of the residuals is the appropriate functional form (see Garrido *et.al.*, 2012). Nevertheless, this approach has gained popularity recently, especially in applied health research.

private hospital insurance and the other where no one is given insurance.

$$MH = E[p_1] - E[p_0], \tag{5}$$

where p_1 and p_0 correspond to hospital admission as a private patient in the two counterfactual scenarios respectively. However, in our survey data we only observe p_1 for those who have purchased hospital insurance and p_0 for those who have not. Taking the simple difference in these observed outcomes, $\{(\overline{p}|PHoI = 1) - (\overline{p}|PHoI = 0)\}$ is likely to give us a biased estimate of moral hazard for 2 reasons: (1) those who purchase insurance may be different in unobservable ways to those who do not purchase insurance; and (2) we need to take account of the likely behavior of the non-hospitalized, who constitute a large share of the sample and comprise both insured and non-insured individuals. For these reasons, we derive the following difference-of-means (DOM) estimator of moral hazard:

$$\widehat{MH} = \frac{\sum_{i=1}^{n}\{\widehat{p}_{1(i)} - \widehat{p}_{0(i)}\}}{n} \tag{6}$$

where $\widehat{p}_{1(i)}$ and $\widehat{p}_{0(i)}$ are the predicted values of hospital admission as a private patient for individual i in the two counterfactually-determined scenarios. This gives us 4 probability estimates that we use to estimate the total effect (TE) and the diversion effect (DE). We then estimate the expansion effect (EE) by differencing these 2 effects.

6 Results

6.1 Testing for endogeneity of insurance: Bivariate Probit estimates

Table 3 presents coefficients and corresponding standard errors of variables of interest from the bivariate probit estimation.[19] We use exclusion restrictions to identify the model, as

[19] *A Note on the Standard Errors:* As in many household surveys, in the NHS, selection into the sample occurs at the level of geographical units called primary sampling units (PSUs). However, grouping respondents into PSUs significantly increases the risk of a respondent being identified and as such, the Australian Bureau of Statistics (ABS) does not release this information. The sample selection process involves an overall grouping of PSUs into 'strata', representing non-random sets of PSUs that are grouped together according to various geographic and socio-economic variables. The NHS is structured around 60 such strata. To enable researchers to produce accurate variance estimates, the ABS releases 60 sets of replicate weights

described in Section 5.2. In specification 1, the following variables are included in the insurance equation, but not in the type of hospital care (private or public) equation: (i) LHC is a dummy variable that equals 1 if the individual is at least 31 years old, and 0 otherwise; and (ii) household income. These variables are natural candidates to serve as instrumental variables; as described in Section 1, to weaken strict community rating and encourage people to buy insurance early, the Australian government introduced the Lifetime Health Cover (LHC) policy in 2000 that requires individuals to purchase hospital cover by the 1st of July following their 31st birthday if they want to avoid a LHC loading factor. Similarly, households over a certain annual household income level are penalized for not purchasing hospital insurance, by having to pay a Medicare levy surcharge (MLS). Thus, the incentives introduced by the government to increase insurance purchases depend directly on these variables. In specification 2, we include two indicator variables denoting the individual's country of birth (with the reference category as Australia) in the insurance equation but not in the patient-type equation - the first of these is an indicator for whether or not the individual was born in New Zealand or England (both being English-speaking nations with a public healthcare system similar to that of Australia), and the second is an indicator for all other countries (except Australia). This choice is based on the assumption that individuals born in Australia and in countries with institutional mechanisms for health care delivery similar to Australia, are likely to be better aware of these mechanisms than those born elsewhere.

The results in Table 3 reveal that men are less likely to purchase insurance compared to women, those who report being is good health are more likely to purchase insurance while

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which take this sample design into consideration. There are two commonly-used replication methods for calculating variances and sampling errors: jackknife and bootstrap estimation (See Brick et.al. (2000) for a discussion of various replication methods). In this paper, we use a jackknife variance estimator to calculate the standard errors of our estimates (Maré and Dixon, 2007). This allows us to not only take the complex survey design features of the NHS into consideration but to also take account of the multi-stage estimation technique employed in the paper; we need to correct the standard errors to reflect the fact that estimates from each stage are used in subsequent stages of the estimation procedure. The jackknife variance estimator adjusts for this.

The estimated variance $v(\hat{\theta}_i)$ of an estimate θ_i, based on the jackknife replication method is:

$$v(\hat{\theta}_i) = \frac{S-1}{S} \sum_{s=1}^{S} (\theta_{i,(\hat{S-1}),s} - \theta_{\hat{i,S}})^2,$$

where $\hat{\theta}_i$ is the i'th component of $\hat{\theta}$, $\theta_{i,(\hat{S-1}),s}$ is the i'th component of $\theta_{(\hat{S-1}),s}$ and $\theta_{\hat{i,S}}$ is the i'th component of $\hat{\theta_S}$ (S=60 for the NHS sample). We also use this procedure for all the joint tests of significance reported in the paper.

those who have a government health card are less likely to do so. Employed individuals are more likely to purchase insurance, though this effect is not statistically significant in specification 1, perhaps because this variable is highly correlated with household income. In specification 1, the instrumental variables are both individually and jointly significant; individuals older than 31 are more likely to purchase insurance, as are those with higher household incomes. Specification 2 reveals that individuals in Australia whose country of birth is either New Zealand or England are less likely to purchase supplementary insurance, relative to the Australian-born. Those with private hospital insurance are much more likely to seek hospital care as private patients. This effect is similar across the two specifications. The coefficient of the correlation parameter ρ is negative but statistically insignificant in both specifications and from the Wald test, we cannot reject the hypothesis of no correlation between the 2 equations. This implies that there is no evidence of endogeneity of private hospital insurance in the decision to seek hospital care as a private or public patient. As discussed in Section 5.2 however, restricting the sample to those that were hospitalized at least once in the previous year, may at best limit our analysis, and at worst, provide misleading results. In our overall sample, only 17% of those who purchased private hospital insurance were hospitalized in the previous year (see Table 2). Thus, we also need to analyze the likely behavior of the non-hospitalized to test for evidence of endogeneity, if any, and to then estimate moral hazard effects.

6.2 Two-stage Residual Inclusion (2SRI) estimates

We now include both the hospitalized and non-hospitalized individuals in our sample and employ the 2SRI method to test for endogeneity of hospital insurance, and to estimate moral hazard effects. In Table 4, we report marginal effects and standard errors from the first-stage probit estimation of the propensity to have private hospital insurance.[20] We use the same exclusion restrictions as in the bivariate probit estimations - the LHC dummy and household income variables in specification 1, and two country of birth dummy variables in specification 2.

Estimates from the two specifications suggest that men are between 3%-4% less likely to purchase hospital insurance compared to women. Other things equal, older individuals and those in good health are more likely to purchase hospital insurance. Individuals who

[20]For continuous variables, marginal effects are calculated at the mean levels of the variables. For the dummy variables, marginal effects denote the change in probability from changing the dummy variable from 0 to 1.

have a government health card are about 21% to 35% less likely to purchase insurance, according to the two specifications respectively. Individuals with a higher likelihood of having a mental disorder, as indicated by higher scores on the Kessler psychological distress scale, are marginally less likely to have hospital insurance, while those with more number of long-term conditions are about 2% more likely to purchase insurance. The two instrumental variables in specification 1, LHC and household income, both have a positive, sizable and significant effect on private hospital insurance coverage. In specification 2 also, the two IVs are both economically and statistically significant, though they both affect the dependent variable negatively; relative to being Australian born, individuals born in any other country are less likely to have private hospital insurance. In each specification, the IVs are also jointly significant.

6.3 Stage 2: Multinomial Estimates of Decision to Seek Type of Hospital Care

Table 5 reports summary results from the multinomial logit estimation. Marginal effects are reported for the following two outcomes: admission to hospital as a public (Medicare) patient and admission to hospital as a private patient, relative to no hospital admission.

Estimates of the impact of the health variables are similar in both specifications. Those in good health are about 4%-5% less likely to be admitted as public patients and about 1% less likely to seek treatment as private patients, relative to not being hospitalized. Those with mental disorders are more likely to seek hospital treatment, either as public or private patients, though the effect is very small. The coefficient on the number of long-term conditions variable is notable - having an additional long-term condition increases the likelihood of purchasing hospital insurance by 3% in specification 1, according to Table 4. However, the multinomial estimates indicate that a unit change in this variable increases the likelihood of seeking admission as a *public* patient by about 1%, in both specifications. This variable does not appear to affect the likelihood of hospital admission as a private patient.

On average, those with private hospital insurance are about 11%-12% less likely to be admitted to hospital as public patients and about 11% more likely to be admitted as private patients. The signs on the coefficients accord with expectations. Measured as a percentage of the predicted probability of admission as a private patient (0.0343 and 0.0335 for specifications 1 and 2 respectively), having hospital insurance increases the probability of hospitalization as a private patient by over 300%. These are significant effects. The evidence on the endogeneity of hospital insurance, however, is mixed.

The coefficient of the residual variable is positive and significant (at the 1% and 5% levels, for specification 1 and 2 respectively) in the hospitalization as public patient outcome. In the private patient outcome equation, the residual, while also positive, is marginally significant for specification 1 and statistically indistinguishable from zero in specification 2. This latter effect is consistent with the results from the bivariate probit estimation. One plausible interpretation for the positive sign on the residual variable is that individuals are negatively selected into insurance, and are therefore more likely to be hospitalized.[21] However, controlling for such negative selection, they are less likely to be hospitalized as public patients if they own private hospital insurance and more likely to seek hospital care as private patients. [22]

In summary, the bivariate probit analysis provides no evidence of endogeneity and there is little suggestion of endogeneity in the private patient outcome using the 2SRI method. These results are consistent with Cheng and Vahid (2011), who find no evidence of endogeneity of insurance in the decision to seek hospitalization as a private/public patient. We therefore present estimates from a single-stage multinomial logit specification of the patient-type outcome in columns (5) and (6) of Table 5, that treats insurance as exogenous. Notably, the marginal effects of the variables are very similar to those from the 2SRI analysis; the presence of insurance now reduces the likelihood of admission as a public patient by about 10% (compared to 12% and 11% in specification 1 and specification 2 of the 2SRI results) and increases the probability of admission as a private patient by 12% (compared to about 11% in both specifications of the 2SRI results). This similarity of results also suggests that endogeneity is either not an issue or, if it is, the bias in ignoring the endogeneity is negligible. Other estimates are also qualitatively similar to the 2SRI estimates.

Our preferred interpretation of our results is that they do not reveal evidence of endogeneity

[21] The bivariate probit analysis cannot identify such selection effects since it is based solely on the sample of the hospitalized population.

[22] In other specifications that we estimated, the marginal effect on the residual variable was significant at the 1% level for the public patient care outcome, while it was statistically insignificant for the private patient care outcome. The first of these alternative specifications is a variation of specification 1 presented in the paper. It uses as IVs, the LHC variable and an indicator variable MLS, defined as 1 for single individuals whose annual household income exceeds AU$50,000 or for couples whose household income exceeds AU$100,000, and 0 for all other individuals. As mentioned in Section 1, households over a certain annual household income level are penalized for not purchasing hospital insurance, by having to pay a Medicare levy surcharge (MLS). In 2003-'04, these thresholds were AU $50,000 for single households and AU$100,000 for couple households. The second alternative specification uses the LHC, the MLS and the country of birth variables (that is, all the IVs used in the paper) as IVs. These results are not presented in the paper.

of insurance in the type of patient care decision. The 2SRI method indicates some evidence of endogeneity however, in the public patient outcome. Given this ambiguity, in the next subsection, we present moral hazard estimates for both cases - where we treat private hospital insurance as endogenous, and where we treat it as exogenous.

6.4 Stage 3: Estimates of Moral Hazard in the Probability to Seek Hospital Care as a Private Patient

We present estimates of moral hazard in the probability of seeking hospital care as a private patient, in Table 6. These are based on Equation 6, and correspond to two counterfactual scenarios - one scenario where everyone has hospital insurance, and the other when no one does. The total effect, diversion effect and expansion effect, based on these scenarios, are defined in Section 3.2. We present estimates for both cases: where we assume that private hospital insurance is endogenous, and where we assume it is exogenous. Estimates presented under specifications 1 and 2 derive from the corresponding specifications in Table 4 and Table 5. Similarly, for the exogenous case, we estimate moral hazard effects based on the multinomial logit estimates for the exogenous case, presented in Table 5.

Estimates of the total effect (TE) based on the endogeneity assumption indicate that private hospital insurance induces a 12-13 percentage point increase in the probability of hospital admission as a private patient. This is a sizable effect, relative to the 3% predicted probability of admission as a private patient (Table 4). In comparison, the TE for the exogenous case is marginally bigger at about 13.5 percentage points. Interestingly, the TE in all cases is largely due to the diversion effect (DE); under the endogeneity assumption, in specification 1, the DE overwhelms the TE, while in specification 2, it measures 94% of the TE. In the exogenous case, it is 82% of the TE. This implies that insurance induces those seeking hospitalization to switch from treatment as Medicare patients to treatment as private patients. The expansion effect (EE) is therefore a very small fraction of the total effect - it is -2 percentage points in specification 1 and less than 1 percentage point in specification 2, while it is about 2 percentage points when we assume insurance to be exogenous. Note however, that under the endogeneity assumption, the EE is not statistically significant in either specification, implying that we cannot reject the hypothesis that there is no pure moral hazard. When we assume that insurance is exogenous, however, the EE suggests that insurance induces an increase in private patient hospital care, net of the DE, of 2 percentage points, or about 29% measured as a proportion of the average private hospital admission rate of 7% in the sample. In either case, according to these estimates, the treatment effect of private hospital insurance on private patient care is driven almost entirely by the substitution away from public patient care towards private patient care.

7 Conclusions and Discussion

We use the 2004-'05 wave of the Australian National Health Survey to examine the impact of private hospital insurance on the propensity to seek hospital care as a private patient. We test for the endogeneity of private hospital insurance by employing two methods: a bivariate probit model and a two-stage residual inclusion (2SRI) technique. We incorporate a number of control variables that are related to an individual's health status in an attempt to mitigate any potential endogeneity associated with the type of patient care. Estimates from the bivariate probit analysis imply that there is no endogeneity; the type of patient care (private versus public patient) equation is uncorrelated with the insurance equation. Evidence from the 2SRI method is mixed; there is some evidence of endogeneity but this evidence is not robust to alternative specifications.

We use the 2SRI estimates to do a counterfactual analysis for calculating difference-of-means estimates of the treatment effect of private hospital insurance on type of patient care in Australia. We decompose this treatment effect into a diversion effect and an expansion effect. The diversion effect is the impact of private hospital insurance on the utilization of public patient hospital care services. The expansion effect is the total effect, net of the diversion effect. The expansion effect is our measure of ex-post moral hazard.

Estimates of moral hazard based on specifications controlling for the endogeneity of hospital insurance offer no evidence of moral hazard, while those based on the assumption that insurance is exogenous suggest that insurance induces an expansionary increase in private patient hospital care of about 29%. In all cases, we find that having private hospital insurance significantly increases the likelihood of seeking treatment in hospitals as a private patient. The diversion effect - which is a measure of the impact that increased take-up of private hospital insurance has on switching people from the public to the private healthcare system - is substantial and robust across specifications. Our findings therefore imply that the treatment effect of private hospital insurance in Australia is predominantly due to the substitution of private patient care for public patient care.

Our estimates highlight the importance of the decomposition analysis used in this paper, not only in the Australian context but more generally in markets where there is a mix of public and private financing of healthcare, and where at least some of the coverage offered through private health insurance is duplicate coverage for what is available through the public healthcare system. In such settings, estimates of the total moral hazard effect, or the treatment effects of private hospital insurance on private patient care, convey limited information on the role of insurance, and are likely to overstate the true moral hazard. At the same time, focusing solely on the ex-post moral hazard (or the expansion effect) completely ignores the role of insurance in switching individuals from the public, to the private sector. We contend that the decomposition analysis is crucial in evaluating the role of supplementary insurance in Australia, and in other countries with a similar healthcare structure.

Given our results, the question arises whether the 'carrots-and-sticks' policies introduced to substantially increase the take-up of private health insurance in Australia was effective in lowering the pressure on the public health system. Butler (2002), and Lu and Savage (2007) provide evidence of sharp increases in private insurance coverage following the introduction of the policy changes, especially the Lifetime Health Cover.[23] Our results also suggest that private hospital insurance induces individuals to seek hospital care as private patients. This effect is sizable and significant. Buchmueller *et.al.* (2008) document that private hospitals perform the majority of procedures with relatively long public hospital waiting lists, such as endoscopy and knee replacement surgeries. This fact is also consistent with our finding of a substantial diversion effect.

Our results however, do not allow us to conclude that increased insurance take-up had an impact on waiting times for surgery in public hospitals. This is because an individual can seek treatment as a private patient in either private or public hospitals.[24] In some states (for example, New South Wales), the practice of block funding of hospitals creates financial incentives for both physicians and the public hospital administrators to increase the number of private patients treated in these public hospitals (Johar *et.al.*, 2013). Thus, it is possible for private insurance to increase the rate of private patient hospital care, without leading to a concomitant reduction in public hospital waiting lists.[25] And in fact, there is evidence that this has been the case.

Fiebig *et.al.* (2006) and Lu and Savage (2006) find that increased private insurance coverage

[23]Both papers argue that the observed increase in 2000 was not fully sustained. Nevertheless, relative to the 30% rate in 1998, private insurance rates have remained well above 40% since 2000. In our sample, private hospital insurance coverage measures 49% (see Table 1).

[24]Individuals admitted as private patients in public hospitals have to pay for their treatment and care either out-of-pocket or through private health insurance, whereas those admitted as public patients receive free care.

[25]Vaithianathan (2002) presents a theoretical model to illustrate these effects.

has not been accompanied by a decrease in the use of public hospitals in Australia. Both papers find that individuals who purchased insurance to take advantage of financial incentives and to avoid penalties (in other words, those who purchased insurance after the introduction of the government's policy reforms in relation to private health insurance) are more likely to continue using the public health system despite having private insurance. On the other hand, those who purchased insurance to avail of the choices afforded by private insurance (for example, choice of doctor) are more likely to seek treatment in private hospitals.

Recent policy changes by the Australian government also indicate a sharp shift in focus away from subsidizing private health insurance towards providing funding for the expansion of capacity in the public hospital system. From July 2012, the universal health insurance subsidy became means-tested; the level of subsidy now depends on income thresholds or 'tiers', and these tiers attract corresponding increases in the Medicare Levy Surcharge as well. This implies that the cost of private insurance has increased for a large share of the population. A report commissioned by the Australian Health Insurance Association (Deloitte, 2011) concludes that the impact of this increased cost of insurance on the public health system will be substantial and will, over time, outweigh the savings to government from the means testing of the rebate. Cheng (2012) estimates the effect of removing the insurance subsidy altogether, on public sector expenditure for hospital care and reaches the opposite conclusion. He finds that the increased public expenditure from eliminating the insurance subsidy is likely to be much lower than the cost of subsidizing insurance. While our results do not inform this debate directly, our sizable estimate of the diversion effect suggests that a significant decrease in private insurance rates following from an increase in the cost of insurance is likely to result in a large switch in demand away from private patient care towards public patient care. But further research is required to shed light on this very important issue.

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Figure 1: The market for public hospital care

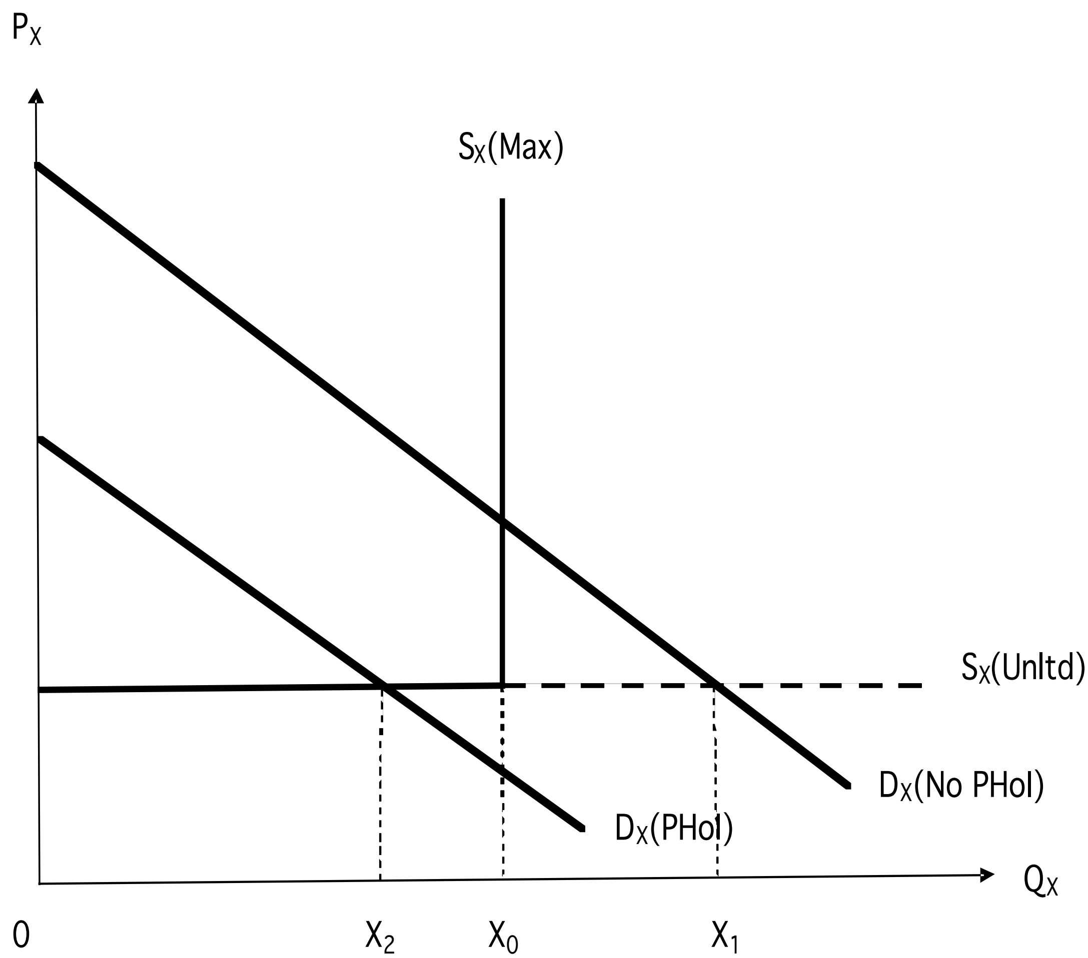

Figure 2: The market for private hospital care

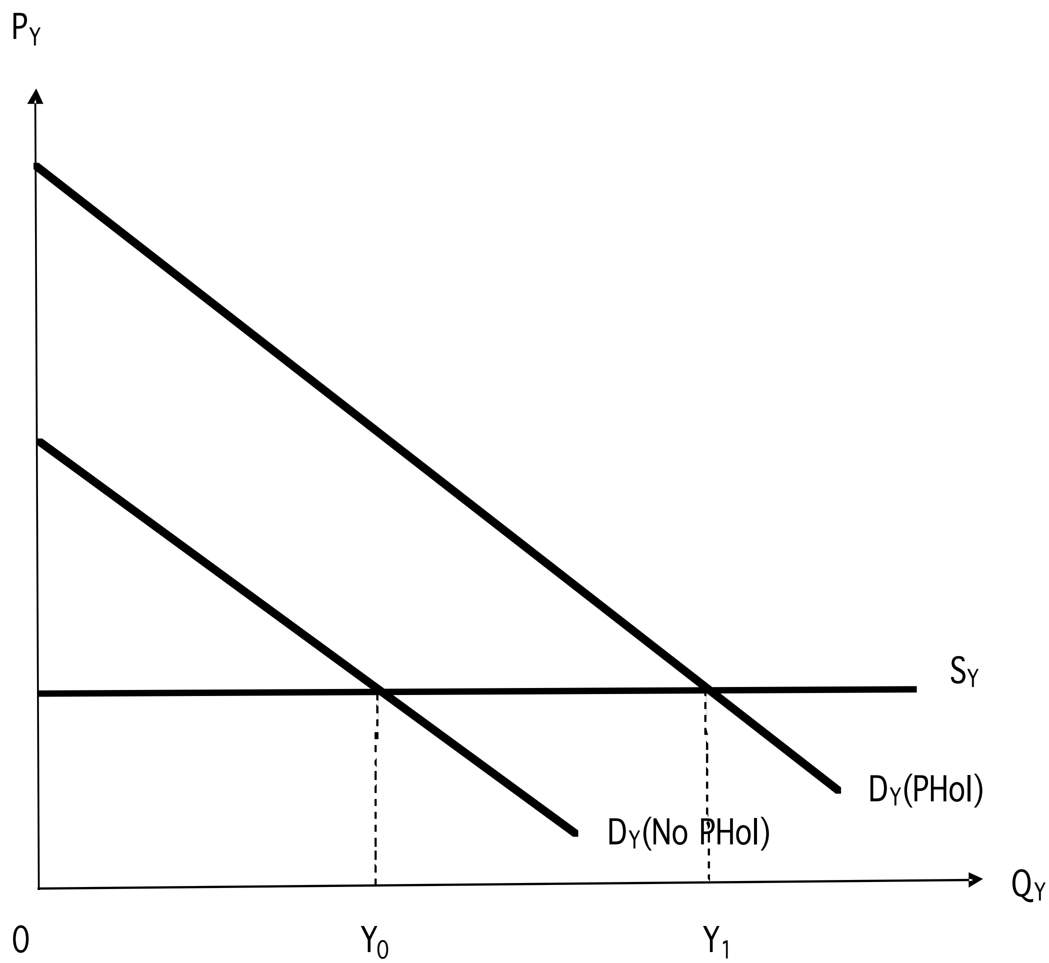

Table 1: Sample Characteristics

Variable	Mean	Std.Dev.	Min	Max
PHoI	0.4855	0.4998	0	1
Male	0.4852	0.4998	0	1
Age	48.18	16.30	22	85
LHC	0.8255	0.3795	0	1
Education:				
School only	0.4557	0.4980	0	1
Basic Vocation	0.0786	0.2692	0	1
Skilled Vocation	0.1491	0.3562	0	1
Diploma	0.1172	0.3217	0	1
Bachelors	0.1247	0.3304	0	1
Employed	0.6364	0.4810	0	1
Country of Origin:				
NZ_UK	0.1045	0.3059	0	1
Other	0.1852	0.3885	0	1
English Proficiency	0.9685	0.1746	0	1
#People in Household	2.7889	1.3385	1	8
Household Income*10^{-3}	1.2923	1.1652	-0.5020	22.4750
MLS	0.1322	0.3387	0	1
Good Health	0.8278	0.3776	0	1
Kessler Score	15.3193	5.9121	0	50
#Long-Term Conditions	3.1025	2.2076	0	7
Long-Term Conditions:				
Infectious	0.0109	0.1040	0	1
Neoplasms	0.0278	0.1644	0	1
Blood	0.0211	0.1436	0	1
Endocrine	0.1685	0.3743	0	1
Mental	0.1192	0.3240	0	1
Nerves	0.1004	0.3006	0	1
Eye	0.6784	0.4671	0	1
Ear	0.1678	0.3737	0	1

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Table 1 – continued from previous page

Variable	Mean	Std.Dev.	Min	Max
Circulatory	0.2553	0.4360	0	1
Respiratory	0.3170	0.4653	0	1
Digestive	0.0925	0.2897	0	1
Skin	0.0414	0.1993	0	1
Muscular	0.4221	0.4939	0	1
Urinary	0.0431	0.2030	0	1
Congenital	0.0089	0.0940	0	1
Family Type:				
Couple only	0.3919	0.4882	0	1
Couple with dependent children	0.3273	0.4692	0	1
One parent with dependent children	0.0410	0.1982	0	1
Single Person	0.2398	0.4270	0	1
Government Health Card	0.3614	0.4804	0	1
Hospitalized in last 12 months	0.1702	0.3758	0	1
of which:				
Admitted as Private Patient	0.0720	0.2584	0	1
# Hospital Nights	0.6707	2.5755	0	30
State:				
New S.Wales	0.3373	0.4728	0	1
Victoria	0.2495	0.4327	0	1
Queensland	0.1905	0.3927	0	1
S.Australia	0.0785	0.2689	0	1
W.Australia	0.0968	0.2957	0	1
Tasmania	0.0243	0.1539	0	1
Northern Territory	0.0071	0.0842	0	1
ACT	0.0160	0.1253	0	1

Table 2: **Sample Characteristics by Private Hospital Insurance (PHoI) Status**

	No PHoI		PHoI	
Variable	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**
Male	0.4878	0.4999	0.4828	0.4997
Age	47.08	17.42	49.35	14.89
LHC	0.7762	0.4168	0.8793	0.3257
Education:				
School only	0.5299	0.4991	0.3752	0.4842
Basic Vocation	0.0808	0.2726	0.0764	0.2656
Skilled Vocation	0.1585	0.3652	0.1398	0.3468
Diploma	0.1042	0.3056	0.1314	0.3379
Bachelors	0.0808	0.2726	0.1714	0.3769
Employed	0.5642	0.4959	0.7138	0.4520
Country of Origin:				
NZ_UK	0.1065	0.3085	0.1022	0.3029
Other	0.2156	0.4112	0.1529	0.3599
English Proficiency	0.9541	0.2093	0.9845	0.1234
#People in Household	2.7911	1.3999	2.7866	1.2702
Family Type:				
Couple only	0.3404	0.4739	0.4474	0.4973
Couple with dependent children	0.3060	0.4608	0.3514	0.4774
One parent with dependent children	0.0629	0.2427	0.0181	0.1334
Single Person	0.2908	0.4541	0.1830	0.3867
Household Income*10^{-3}	0.9720	0.7539	1.6502	1.4135
MLS	0.1048	0.3063	0.1584	0.3651
Good Health	0.7801	0.4142	0.8794	0.3257
Kessler Score	16.1340	6.5748	14.4419	4.9389
#Long-Term Conditions	3.1005	2.2833	3.1071	2.1232
Long-Term Conditions:				
Infectious	0.0133	0.1144	0.0085	0.0921
Neoplasms	0.0250	0.1560	0.0311	0.1735
Blood	0.0229	0.1495	0.0194	0.1379

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Table 2 – continued from previous page

Variable	No PHoI Mean	No PHoI Std.Dev.	PHoI Mean	PHoI Std.Dev.
Endocrine	0.1654	0.3715	0.1717	0.3772
Mental	0.1434	0.3505	0.0925	0.2897
Nerves	0.1036	0.3048	0.0970	0.2960
Eye	0.6283	0.4833	0.7325	0.4427
Ear	0.1790	0.3834	0.1562	0.3631
Circulatory	0.2571	0.4371	0.2546	0.4357
Respiratory	0.3162	0.4650	0.3182	0.4658
Digestive	0.0966	0.2954	0.0880	0.2833
Skin	0.0410	0.1984	0.0421	0.2008
Muscular	0.4359	0.4959	0.4083	0.4916
Urinary	0.0421	0.2009	0.0442	0.2056
Congenital	0.0086	0.0921	0.0092	0.0953
Urban Residence	0.8616	0.3453	0.8759	0.3297
Government Health Card	0.4876	0.4999	0.2244	0.4172
Admitted	0.1692	0.3750	0.1722	0.3776
of which:				
Private Patient	0.0119	0.1084	0.1359	0.3428
# Hospital Nights	0.7180	2.7298	0.6205	2.3897
State:				
New S.Wales	0.3396	0.4736	0.3357	0.4722
Victoria	0.2470	0.4313	0.2502	0.4332
Queensland	0.2003	0.4003	0.1810	0.3851
S.Australia	0.0760	0.2650	0.0817	0.2739
W.Australia	0.0926	0.2899	0.1017	0.3022
Tasmania	0.0255	0.1575	0.0231	0.1501
Northern Territory	0.0063	0.0794	0.0074	0.0857
ACT	0.0128	0.1123	0.0193	0.1376

Table 3: Bivariate Probit Estimates: Testing for Endogeneity of Private Hospital Insurance

	Specification 1		Specification 2	
Equation 1: Insurance				
Variable	Coefficient	Replicate S.E.	Coefficient	Replicate S.E
Male	-0.2165***	0.0754	-0.2382***	0.0722
Age			0.0254***	0.0036
Employed	0.0854	0.1041	0.2884***	0.0950
Self-reported Health	0.3666***	0.0798	0.3275***	0.0820
Govt. Health Card	-0.5519***	0.1088	-0.9593***	0.1055
LHC - Age>31 (IV)	0.5380***	0.1266		
Household Income*10^{-3} (IV)	0.3496***	0.0798		
Country of birth:				
NZUK (IV)			-0.4024***	0.1064
OTHER (IV)			0.0228	0.1025
Joint Test of Significance of IVs				
$\chi^2(2)$	51.59		19.85	
Prob> χ^2	0.00		0.00	
Equation 2: Patient-type				
Insurance dummy	2.4957***	0.2702	2.3195***	0.2445
Tests for Endogenity				
ρ	-0.1005	0.1874	-0.0208	0.1433
Wald test of $\rho = 0$				
$\chi^2(1)$	0.4639		0.0240	
P-value> χ^2	0.4958		0.8768	
Observations	2,535		2,831	

Note: In Specification 1, we use the 2 variables: LHC (a dummy variable that takes value 1 if the individual is at least 31 years old) and Household Income as instrumental variables. In specification 2, we use 2 dummy variables representing individuals' countries of birth (the first one takes value 1 if the individual was born in New Zealand or the U.K., and 0 otherwise, while the second one takes value 1 if the individual was born in any country other than New Zealand or U.K. The base category refers to those born in Australia). Other control variables include detailed health status variables, gender, education, employment status, family type, government health card status, urban status and state of residence. The replicate standard errors are calculated using a jackknife estimator.

*** - significant at the 99% level; ** - significant at the 95% level;* - significant at the 90% level

Table 4: Probit Estimates of Private Hospital Insurance

Variables	Specification 1 Marginal Effect	Specification 1 Replicate Std. Error	Specification 2 Marginal Effect	Specification 2 Replicate Std. Error
Male	-0.0276**	0.0128	-0.0439***	0.0123
Age			0.0096***	0.0005
Employed	-0.0349**	0.0171	0.0653***	0.0151
Good Health	0.0793***	0.0185	0.0802***	0.0171
Kessler Score	-0.0067***	0.0012	-0.0048***	0.0012
#Long-Term Conditions	0.0245***	0.0071	0.0157**	0.0066
Govt. Health Card	-0.2105***	0.0221	-0.3499***	0.0156
LHC (IV)	0.2079***	0.0170		
Household Income*10^{-3} (IV)	0.1599***	0.0172		
Country of birth			Base category: Australia	
New Zealand/England (IV)			-0.1009***	0.0159
Other countries (IV)			-0.1358***	0.0167
Predicted Probability at $\overline{X}$	0.4646		0.4796	
Joint test of significance of IVs ($\chi^2(2)$)	242.35		87.59	

Note: In specification 1, we use the following 2 variables as instruments for the endogenous PHoI (private hospital insurance) dummy in the second-stage multinomial regression of hospitalization outcomes: lifetime health cover (LHC, an indicator variable that equals 1 if the individual is at least 31 years old, and 0 otherwise) and household income. In specification 2, two country-of-birth indicator variables serve as instruments: born in New Zealand or the UK, and any other country (the reference category is Australian born).

In addition to the health variables in the table, we also control for a rich set of health variables that include the following: indicator variables for certain infectious/parasitic diseases, neoplasms, diseases of blood/blood-forming organs, endocrine/nutritional/metabolic diseases, mental/behavioural problems, diseases of nervous system, diseases of eye/ear/circulatory/respiratory/digestive systems, diseases of skin/musculoskeletal system/genito-urinary systems, congenital malformations. Both specifications also control for education, family type, urban status and state of residence. The replicate standard errors are calculated using a jackknife estimator.

*** - significant at the 99% level; ** - significant at the 95% level;* - significant at the 90% level

Table 5: Marginal Effects From Multinomial Logit Estimation of Patient-Type in Hospital Admissions (Base Outcome: No Admission)

Variables	**Insurance is endogenous**				**Insurance is exogenous**	
	Specification 1		*Specification 2*			
	Marginal Effect	Replicate Std. Error	Marginal Effect	Replicate Std. Error	Marginal Effect	Replicate Std. Error
	1. Admitted to Hospital as Public Patient					
Insurance	-0.1220***	0.0114	-0.1081***	0.0098	-0.0959***	0.0060
Residual	0.0464***	0.0167	0.0332**	0.0136		
Good Health	-0.0473***	0.0081	-0.0432***	0.0071	-0.05027***	0.0092
Kessler Score	0.0009**	0.0004	0.0007*	0.0004	0.0008*	0.0004
# Long-Term Conditions	0.0078***	0.0025	0.0079***	0.0023	0.0083***	0.0025
Predicted Probability	0.0692		0.0672		0.0698	
	2. Admitted to Hospital as Private Patient					
Insurance	0.1062***	0.0103	0.1133***	0.0113	0.1177***	0.0074
Residual	0.0127*	0.0076	0.0013	0.009		
Good Health	-0.0089*	0.0047	-0.0141**	0.0054	-0.0100**	0.0049
Kessler Score	0.0006**	0.0003	0.0008***	0.0003	0.0008***	0.0003
# Long-Term Conditions	0.0017	0.0017	0.0019	0.0016	0.0013	0.0016
Predicted Probability	0.0343		0.0335		0.0343	
Observations	14,413		14,413		14,413	

Note: In Specification 1, we use the 2 variables: LHC (a dummy variable that takes value 1 if the individual is at least 31 years old) and Household Income as instrumental variables. In specification 2, we use 2 dummy variables representing individuals' countries of birth (the first one takes value 1 if the individual was born in New Zealand or the U.K., and 0 otherwise, while the second one takes value 1 if the individual was born in any country other than New Zealand or U.K. The base category refers to those born in Australia). Other control variables include detailed health status variables, gender, education, employment status, family type, government health card status, urban status and state of residence. The replicate standard errors are calculated using a jackknife estimator.

*** - significant at the 99% level; ** - significant at the 95% level;* - significant at the 90% level

Table 6: Estimates of Moral Hazard in Probability of Hospitalization as Private Patient

	Insurance is endogenous				Insurance is exogenous	
	Specification 1		**Specification 2**			
	Patient-Type		*Patient-Type*		*Patient-Type*	
Counterfactual Scenario	Private	Public	Private	Public	Private	Public
PHoI=1	0.1342	0.0312	0.1183	0.0238	0.1470	0.0373
PHoI=0	0.0124	0.1686	0.0101	0.1137	0.0118	0.1476
Difference	$\widehat{TE}$= 0.1219***	$\widehat{DE}$= -0.1374***	$\widehat{TE}$= 0.1320***	$\widehat{DE}$= -0.1242***	$\widehat{TE}$= 0.1352***	$\widehat{DE}$= -0.1103***
Replicate standard error	(0.0105)	(0.0124)	(0.0124)	(0.0108)	(0.0065)	(0.0062)
$\widehat{EE} = \widehat{TE}$ - $\lvert\widehat{DE}\rvert$ =	-0.0155		0.0078		0.0249***	
Replicate standard error	(0.0152)		(0.0156)		(0.0089)	

Note: In Specification 1, we use the 2 variables: LHC (a dummy variable that takes value 1 if the individual is at least 31 years old) and Household Income as instrumental variables. In specification 2, we use two dummy variables representing individuals' countries of birth (the first one takes value 1 if the individual was born in New Zealand or the U.K., and 0 otherwise, while the second one takes value 1 if the individual was born in any country other than New Zealand or U.K. The base category refers to those born in Australia). Other control variables include detailed health status variables, gender, education, employment status, family type, government health card status, urban status and state of residence. The replicate standard errors are calculated using a jackknife estimator.

*** - significant at the 99% level; ** - significant at the 95% level;* - significant at the 90% level

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