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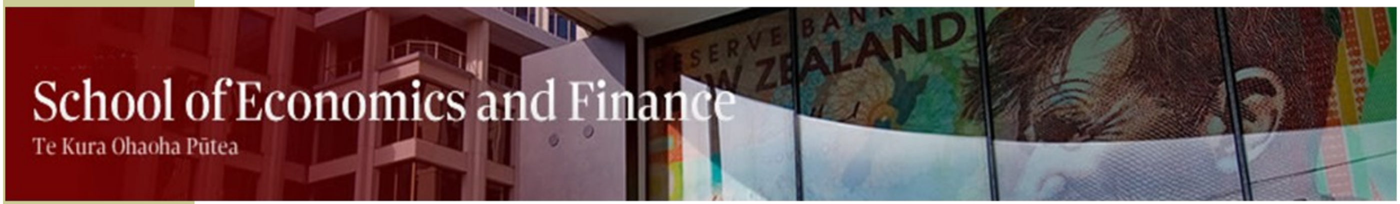


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# The Impact of Private Hospital Insurance on Utilization of Hospital Care in Australia: Evidence from the National Health Survey

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**Abstract**

We estimate the impact of private hospital insurance on utilization of hospital care services in Australia. We employ the two-stage residual inclusion approach to address the endogeneity of private insurance. We calculate moral hazard based on a difference-of-means estimator. Our three-stage estimation framework provides evidence of selection into private hospital insurance. We find strong evidence of moral hazard when we treat hospital insurance as exogenous. After controlling for the endogeneity of hospital insurance, we find robust evidence of substitution from public to private hospital care but no evidence of ex-post moral hazard in the number of nights spent in hospital.

**JEL Classification:** I11, I18, C35

**Keywords:** Health Insurance, Health Care Consumption, Moral Hazard

# 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, 1989). 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. Individuals cannot opt-out of Medicare; 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, however, enrolment in PHI fell dramatically until the late 1990s. This development alarmed policy-makers since there was strong support in

[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.

government circles for a balanced delivery of healthcare services involving both the public and the private sector. There was also concern that decreasing rates of PHI were causing an 'adverse selection death-spiral'. Barrett and Conlon (2002) used the NHSs to examine the health risk profile of the private insured population in 1989 and 1995. They found that while the insured population consisted of a heterogeneous mix of adversely-selected and positively-selected individuals in both time periods, decreasing insurance coverage over this period was associated with increasing adverse selection; coverage declined much more for younger individuals than for older ones. 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). The purpose of the latter is to weaken community rating rules and improve the average risk of the privately insured population, by encouraging younger people to purchase PHI. 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, and provide a strong motivation for re-examining the relationship between the demands for insurance and health services in Australia. Moreover, there is a lack of consensus in the literature on risk selection in Australia following these reforms; some papers find evidence of positive selection, while others find evidence suggestive of adverse selection.[5] Since optimal health policy depends crucially on the type of distortions afflicting health care markets, the differential findings in the empirical literature provide another motivation

[3]See Hall *et. al.* (1999) and Butler (2002) for a detailed summary of these reforms.

[4]See Butler (2002), Lu and Savage (2007), Savage *et.al.*(2009) and Vaithianathan (2004)

[5]These papers are reviewed in the following section.

for this paper. Australia's experience can offer valuable insights into risk-selection and moral hazard for other countries with similar health care institutions.

We take note of certain features of the Australian health care system that have implications for moral hazard in light of changing incentives for private insurance purchases. Over time, private hospitals in Australia have specialized in elective procedures while public hospitals continue to deal with the majority of emergency services.[6] Moreover, most elective surgery requires day-admission only, with no overnight stay (Vaithianathan (2004), Duckett (2005) and Cheng and Vahid (2010)). This relative specialization of services suggests that estimates of the impact of PHI status based purely 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. If the primary advantage afforded by PHI is speedier access to elective surgery, then seeking hospitalization as a private patient is an important aspect of moral hazard. With regards to non-elective treatment as well, private patients enjoy certain advantages like the option to choose their doctor and to enjoy certain facilities that are not offered to public patients, such as the use of a private room and special meals. Our method for estimating moral hazard therefore incorporates the predicted probability of seeking hospitalization as private or as Medicare patients as well as the the number of nights spent in hospital, in a multi-stage estimation framework.

Our paper makes three main contributions. Firstly, we correct for the endogeneity of private hospital insurance (PHoI) status in estimating medical service utilization, using the two-stage residual inclusion (2SRI) method. Among those who seek hospitalization, we distinguish between individuals who were admitted as private versus public patients, and estimate the intensity of their health care utilization, measured as the number of nights spent in hospital. Secondly, we estimate the 'average treatment effect' of PHoI on hospital utilization 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 from public patient care) and an 'expansion effect' (pure moral hazard). We underline the importance of this decomposition analysis in under-

[6] 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).

standing the factors that contribute to the estimated increase in medical services utilization due to supplementary health 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 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.[7] Medicare is supplemented by a private health insurance system. 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. PHI also provides cover for ancillary services not insured by Medicare such as dental care, optical services and chiropractic treatment. Essentially, PHI covers non-acute and elective medical services for which Medicare either provides no coverage or involves long waiting times.

The PHI 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

[7] 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 PHI can reduce or eliminate the remaining 25% of the fees (Savage and Wright, 2003).

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 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. 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.[8]

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 at least 30% for any private health insurance premium. 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.[9] 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). 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 (2002) 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 -0.23 suggests that the demand for private health insurance in Australia is price-inelastic. He also examined the

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

[9]The MLS is calculated at 1% of taxable income and is in addition to the 1.5% Medicare Levy.

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) used the 2001 wave of the NHS to estimate the demand for private health insurance. They found that the positive impact of income on private coverage, found in the pre-reform period, was reinforced by the insurance incentives. There was also a broadening in the age distribution of private health insurance, suggesting a reduction in adverse selection. Doiron *et.al.* (2008) examined the relationship between ex-ante risk and PHI using the 2001 wave of the NHS, and found evidence of advantageous selection into insurance. They found that controlling for age, people with PHI report higher self-assessed health on average, relative to people without. They also found that those engaging in risk-taking behaviours like smoking and drinking in excess, are less likely to be in good health and also less likely to buy insurance.

Buchmueller et.al. (2008) used the NHS 2004-'05 to construct an ex-post risk measure: the predicted probability of hospital admission in the previous 12 months. They interpret this as the empirical analogue of the risk variable in the Rothschild-Stiglitz model. They used a semi-parametric approach to estimate the relationship between insurance demand and predicted risk, and found evidence of advantageous selection into private health insurance in Australia.

Lu and Savage (2007) 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. They addressed the endogeneity of hospital insurance by using a propensity score matching method, and compared outcomes among the matched and unmatched samples. Among the recently insured (those who are 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 (2010) estimated the impact of private hospital insurance on the utilization of private hospital care services in Australia. They used the 2004-'05 wave of the Australian National Health Survey (NHS), the same data source used in this paper.[10] They addressed the endogeneity of private insurance and patient-type in the hospital admission decision. They used a full-information maximum likelihood 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 find no evidence of moral hazard in hospital use.

The Lu and Savage (2007) and the Cheng and Vahid (2010) papers are closest in spirit to ours; they study the same question that we address in this paper. However, the methodological approach varies considerably among the three. Lu and Savage (2007) tackled self-selection using the propensity score matching method that matches individuals based on observable characteristics. Observable characteristics like health status and income explain some of the heterogeneity among individuals with respect to insurance purchase. Yet theoretically, much of the heterogeneity arises from attitudes towards risk and is likely to be unobserved by the researcher. Both Cheng and Vahid (2010) and our paper address unobserved heterogeneity. But we use a flexible approach; we employ a sequential, multi-stage approach that does not require us to completely specify the joint distribution function as Cheng and Vahid (2010) do. While this method is likely to involve some efficiency loss, the large sample sizes we use to estimate our model can mitigate any such losses. We describe the method in detail in Section 5.

Our estimates offer evidence of selection into private hospital insurance. Our 'treatment effect' of private hospital insurance on hospital utilization is positive, sizable and significant. Consistent with Cheng and Vahid (2010), we find no evidence of moral hazard in the intensity of hospital care services. However, our multi-stage estimation procedure offers robust evidence that private hospital insurance causes a sizable substitution away from public patient care towards private patient care. Thus, the treatment effect of insurance is driven primarily by this substitution of private care for public care. This is an important finding that has significant implications for the efficacy of the

[10] However, Cheng and Vahid used the smaller 'Basic Confidentialised Unit Record File' version of the NHS 2004-'05 dataset while we use the larger 'Expanded Confidentialised Unit Record File' version of the same dataset in this paper.

insurance incentive policies introduced in Australia.

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. It is this intuition which seems to provide a potential justification for the private health insurance rebate policy in Australia. If the policy increases the number of people who have private hospital insurance (PHoI), it 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 characterised 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 utilisation 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 underlines 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.

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 for private patient hospital care is given by $D_Y$ (PHoI). The new equilibrium quantity of private patient hospital care 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 inwards 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 inwards shift in the demand curve for public patient care 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 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 impute 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.[11]

## 3.2 The endogeneity of private hospital insurance

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

[11] 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.

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. Conditional on this decision, they decide how many nights to stay in hospital.

We can thus summarize the agent's decision problem as follows:

- At time period $t = 1$, the agent decides whether or not to purchase private hospital insurance;
- At $t = 2$, Nature chooses the patient's disease state. The agent observes the realized disease state, and decides on what type of care to seek. The agent either chooses not to seek care ($j = 0$), to seek care as a public patient ($j = 1$) or to seek care as a private patient ($j = 2$);
- At $t = 3$, conditional on type of care chosen at $t = 2$, the agent decides on length of hospital stay.

The agent's insurance purchase decision is endogenous; it depends on the probability distribution over health states in period 2, insurance premiums, the net prices of private hospital services (given insurance), the waiting time for free medical services in public hospitals, and other socio-economic variables. While we have data on some socio-economic variables and self-reported health status variables for the individuals in our sample, we do not observe many of the other variables that influence the insurance decision. To address this issue, we employ the two-stage residual inclusion (2SRI) method that purges the estimates of bias due to endogeneity. We describe this method in more detail in Section 5.

# 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-based 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.[12] This is the fourth in the 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.[13] We use the expanded version of the data for this paper.

Like all other papers that use this data source, we are hampered by a lack of data on insurance premiums, net prices of medical services, and waiting times for various treatments facing patients who are contemplating using the public health system. In our regression analysis, we control for a detailed set of health conditions to overcome this weakness. We also control for state of residence to capture variation in insurance prices, institutional features 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, weighted by the person weights provided in the survey.

Respondents in the NHS are asked whether they are covered by PHI, 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

[12]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.

[13]For example, the 'Personal gross weekly cash income' is reported as a continuous item in the expanded version but only in deciles in the basic file. Similarly, 'Age' is reported in discreet bands in the basic version but the expanded version reports exact age in years.

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

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. The average individual in the sample is 48 years old and around 43% of the sample has at least a high-school diploma. The employment rate in the sample is 64%, with 52% employed in the private sector. Over 70% of the sample is Australian-born, with another 10% declaring New Zealand or the United Kingdom as their country of birth. 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% are single-parent households while 24% are single households.

The NHS collects information on the prevalence of over 100 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. Those who were admitted to hospital over the previous 12 months are also asked how many nights they spent in hospital during their last admission. The responses range from 0 (indicating day admission only) to 29 and more nights. We transform this range by adding 1 to each of the responses, such that 1 now indicates day admission only, and the maximum number of recorded nights is 30. Those admitted spent less than 1 night in hospital on average, which implies that most of these admissions were day-admissions only.

In Table 2 , we compare the characteristics of the insured and uninsured samples. The insured population is slightly younger, wealthier, more educated and more likely to be employed compared to the uninsured. They are also more likely to be Australian-born, working in the private sector and self-employed. 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. Among the hospitalized, those without insurance spent slightly longer in hospital relative to those with insurance, though on average, both groups spent less than a day in hospital. We seek to explain these differences in behavior in our empirical analysis below.

## 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 and health care services by consumers are discrete in nature; health insurance choice data is in a form that recommends the use of indicator variables to represent different choices, while health care data comes in the form of counts. 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, and a count data model for the health care service utilization component of the model.

We tackle the endogeneity arising out of self-selection into private hospital insurance (PHoI) using the two-stage residual inclusion (2SRI) method. The 2SRI method is an instrumental-variable based approach to dealing with endogenous regressors. It is an extension of the two-stage least squares method (2SLS) to non-linear models.[15] This approach allows us to estimate the causal impact of private hospital insurance on the propensity to be admitted to hospital as a private or a

[15] Terza *et. al.* (2008) demonstrate the consistency of the 2SRI estimator in a generic, parametric framework.

public patient, and on the demand for medical services (measured by the number of nights spent in hospital) - we refer to these two effects as moral hazard at the extensive margin and at the intensive margin respectively.

When we estimate the impact of PHoI on the intensity of medical services utilization, the 'patient-type' decision in the second-stage - whether to be admitted to hospital as a public or private patient - is also potentially endogenous; having PHoI influences the choice of patient type, which in turn can have an impact on the number of days spent in hospital. We do not explicitly address this second source of endogeneity in estimating our intensive measure of moral hazard. We instead surmise that this patient-type decision is influenced by individuals' latent health status, which is unobserved. The NHS collects detailed information on the health status of respondents, including the prevalence of an extensive list of long-term conditions and self-assessed overall health status, which we described in Section 4. Collectively, this rich set of health conditions are likely to proxy for the latent health status which we do not observe. In our estimation procedure, we also control for these health variables. This approach, in our view, mitigates the endogeneity bias in our estimates of moral hazard on the intensive margin.

### 5.1 Stages in the Estimation Process

The units of observation in this study are consumers. The different consumers are indexed by $i \in \{1, 2, ....I\}$. Corresponding to the steps in the individual's decision process, as described in section 3, we first estimate the propensity that an individual has private hospital insurance (PHoI) as a function of exogenous covariates, $X_o$ and six instrumental variables (IVs) using probit analysis:

$$Y_{ins} = \mathbf{1}(X\beta + u > 0), \tag{1}$$

where $X = [X_o \;\; X_p]$, $X_p$ is the vector of instrumental variables, and $(u/X)$ follows a standard normal distribution. We assume that the error term from the probit regression defined by Equation 1 comprises all the unobservables that confound the effect of $Y_{ins}$ on hospital utilization.

Second, we use a multinomial logit analysis to estimate the likelihood of the following events: (i) individual $i$ is not admitted to hospital; (ii) individual $i$ is admitted to hospital as a Medicare patient; and (iii) individual $i$ is admitted to hospital as a private patient. We include the hospital insurance variable (PHoI), other observed covariates (excluding the IVs from the first stage), and the residual from the first-stage probit regression as regressors in the multinomial analysis. The residual is calculated using the following formula:[16]

$$Y_u \equiv \frac{(Y_{ins} - \Phi(X\beta))\phi(X\beta)}{\Phi(X\beta)[1 - \Phi(X\beta)]} \tag{2}$$

Third, we estimate the number of nights spent in hospital conditional on hospital admission, on the same set of variables as in the second stage using a negative binomial analysis, that allows us to test for overdispersion in the count data. We denote the probability mass function as:

$$h(Hos\_nights_i) = \frac{\Gamma(Hos\_nights_i + \theta)}{\Gamma(\theta)\Gamma(Hos\_nights_i + 1)}\left(\frac{\theta}{\lambda_i + \theta}\right)^{\theta}\left(\frac{\lambda_i}{\lambda_i + \theta}\right)^{Hos\_nights_i}, \tag{3}$$

where $Hos\_nights$ refers to the number of nights spent in hospital, $\Gamma(.)$ denotes the gamma function, $\lambda_i = exp(\beta' x_i)$ is the conditional mean of number of nights in hospital, and the conditional variance is given by $\lambda_i[1 + (1/\theta)\lambda_i]$. The null hypothesis for the absence of overdispersion is $\theta = 0$.

Since the set of regressors includes the residual $Y_u$, we control for the endogeneity of private hospital insurance in estimating the intensity of hospitalization as well, using the 2SRI method. The 2SRI method serves to alleviate the endogeneity bias due to self-selection into PHoI, in the estimates from stages two and three.

Our approach to estimating the demand for hospital utilization in Australia is similar to that used by Shea *et.al.* (2007). We define the moral hazard effect of private hospital insurance in Australia as the average difference in hospital utilization in the population from two counterfactual scenarios: one where all individuals in the population are given private hospital insurance and the other where no one is given insurance.

$$MH = E[N_1] - E[N_0],$$

where $N_1$ and $N_0$ correspond to hospital utilization in the two counterfactual scenarios respectively. However, in our survey data we only observe $N_1$ for those who have purchased hospital insurance and $N_0$ for those who have not. Taking the simple difference in these observed outcomes, $\{(\overline{N}|PHoI = 1) - (\overline{N}|PHoI = 0)\}$ is likely to give us a biased estimate of moral hazard, as those who purchase insurance may be different in unobservable ways to those who do not purchase insurance. To

[16]See Chesher and Irish (1987), and Shea *et.al.* (2007)

overcome this 'selection bias', we combine the second and third-stage results to derive the following difference-of-means (DOM) estimator of moral hazard on the intensive margin:

$$\widehat{MH} = \frac{\sum_{i=1}^{n}\{\widehat{N}_{1(i)} - \widehat{N}_{0(i)}\}}{n} \tag{4}$$

where $\widehat{N}_{1(i)}$ and $\widehat{N}_{0(i)}$ are the predicted values of hospital utilization for individual $i$ in the two counterfactually-determined scenarios. These predicted values are obtained from the second and third stages of the estimation process described above. We describe the procedure in the following subsection.

### 5.2 Measures of Moral Hazard

We estimate the following measures of moral hazard:

1. The treatment effect of private hospital insurance on medical service utilization. We denote this as the 'total moral hazard effect', or simply the 'total effect'. This measures the total insurance-induced change in the quantity of hospital utilization caused by private patients increasing their utilization for hospital services. We use the coefficients of the negative binomial regression estimated using the sample admitted as private patients. For each individual $i$ in the sample, we predict the number of nights spent in hospital in the two counterfactual scenarios: one where she has PHoI, and one where she does not. For each individual, we estimate the following:

$$TE = [Pr_i^{1*}(Private) \times E^{1*}(HospitalNights)] - [Pr_i^{0*}(Private) \times E^{0*}(HospitalNights)] \tag{5}$$

   where the $1*$ and $0*$ indicate the two counterfactual scenarios respectively. The probabilities $Pr_i^{1*}$ and $Pr_i^{0*}$ are calculated from the second stage and the expected hospital use from the third stage. We then take the sample average to estimate the 'total effect'.

2. The total effect can be decomposed into two components: the 'diversion effect' and the 'expansion effect', as described in section 3. The method for estimating the diversion effect is similar to the one above, where the probability of being admitted as public patient is calculated from the second stage and the expected hospital use is calculated from the third stage negative binomial regression on the sample of individuals admitted as public patients.

The corresponding difference for each individual $i$ in the sample is:

$$DE = [Pr_i^{1*}(Public) \times E^{1*}(HospitalNights)] - [Pr_i^{0*}(Public) \times E^{0*}(HospitalNights)], \quad (6)$$

The sample average gives the 'diversion effect'.

The difference between the total effect and the diversion effect gives us the imputed 'expansion effect' (EE).

These are ex-post measures of moral hazard, arising from the fact that policy holders' healthcare consumption increases with insurance coverage. Ideally, given the amount of insurance cover purchased, insurance companies would like to restrict the quantity consumed to the optimal level given the true marginal cost of provision, and just pay the costs associated with that level of treatment. However, the true demand curve for treatment is not known. As such, the lower price of health care due to insurance is likely to induce 'excessive' use of treatment. The relationship between asymmetric information and ex-post moral hazard in the health insurance industry is due to the fact that with ex-post moral hazard, it is not the action (medical care demand) that is hidden, but the motivation behind the action (health status).

### 5.3 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 which take this sample design into consideration. There are two commonly-used replication methods for calculating variances and sampling errors: jackknife and bootstrap estimation. 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 $v(\hat{\theta})$ of an estimate $\theta$, based on the jackknife replication method is:

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

where $\hat{\theta}$ is the estimate of $\theta$ based on the full sample, $\hat{\theta}_s$ is the estimate of $\theta$ based on observations from the $s^{th}$ strata and $S$ is the total number of strata (S=60 for the NHS sample).[17]

# 6 Results

## 6.1 Stage 1: Probit Estimates of Propensity to Purchase PHoI

In Table 3, we report marginal effects and standard errors from the first-stage probit estimation of the propensity to have private hospital insurance.[18] As Heckman (2000) points out, even in non-linear models, exclusion restrictions offer robust identification of the parameters of interest. We use five categorical variables that denote the individual's country of birth, and a variable that indicates the individual's English language proficiency, as exclusion restrictions. Institutional arrangements for health care delivery vary substantially across countries. Also, proficiency in English is an important indicator of assimilation into Australia for most immigrants, which includes access to information and familiarity with the health care system. It is therefore reasonable to assume that country of birth and proficiency in the English language impact the decision to purchase supplementary health insurance. Table 2 offers some evidence to support this claim; there is extensive variation in insurance coverage by country of birth, and some difference by English proficiency. At the same time, while there is likely to be substantial *individual* heterogeneity in the decision to seek medical care in the event of illness, there is no reason to expect this heterogeneity to vary systematically by country of origin or English language proficiency.[19] These variables are therefore good candidates to serve as instruments.

[17]See Brick et.al. (2000) for a discussion of various replication methods.

[18]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.

[19]In support of this claim, the average number of nights spent in hospital was less than 1 for each sub-sample stratified by country of birth, ranging from 0.48 for those from Asia to 0.87 for those born in Western Europe.

The first specification controls for a parsimonious set of health status variables while the second specification includes a more detailed set of variables. Household income has a sizeable and significantly positive impact on the probability of having private hospital insurance; an increase of AU$1,000 in household income increases the probability of hospital insurance coverage by 32%, in both specifications.[20] This is consistent with the findings of other papers cited in Section 2. Other things equal, individuals who are older, female, better educated, living in urban areas, Australian-born and belonging to couple-households are more likely to purchase hospital insurance. Individuals who have a government health card are less likely to purchase insurance. Controlling for occupation at the 1-digit level, we find that individuals who are employed are less likely to have hospital insurance.

Those who report being in good health are more likely to be insured relative to those in poor health - by 17% and 18% in the two specifications respectively. This suggests that there might be advantageous selection into insurance.[21] Individuals with a higher likelihood of having a mental disorder, as indicated by higher scores on the kessler psychological distress scale, are less likely to have hospital insurance; an increase in this score by 1 unit reduces the propensity of insurance coverage by 1%, in both specifications. However, the propensity to be insured also increases with the number of long-term conditions.

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

Table 4 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. The first two columns pertain to the parsimonious specification that includes only three health status variables - a dummy variable for good health, kessler score and the number of long-term conditions, while the third and fourth column report estimates based on the more detailed specification of health variables.[22]

[20] All percentages are calculated as the ratio of the corresponding marginal effect to the predicted probability of having private hospital insurance at the mean levels of all control variables, which is 0.4602 and 0.4601 in specifications 1 and 2 respectively.

[21] Recall that from Table 1, nearly 83% of our sample report being in good health.

[22] Of the 14,520 observations that comprise our estimation sample, 107 observations had missing values for the 'hospital admission' question. We are therefore left with 14,413 observations.

Those in good health are about 5-6% 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 marginally more likely to be admitted as private patients. 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% and 4% in the two specifications, according to Table 3. However, the multinomial estimates indicate that having an additional long-term health condition increases the likelihood of seeking admission as a *public* patient by about 1%.

The positive and significant estimate of the residual variable on the admission as public patient outcome suggests that hospital insurance status is endogenous with respect to the hospital admission decision. However, this estimate is precisely estimated only in the public admission choice, and only for the parsimonious specification. One plausible interpretation of the positive and marginally significant estimate on the residual variable is that individuals are negatively selected into insurance, and these same individuals are more likely to seek treatment in the public healthcare system when they fall sick because it is better equipped to deal with the treatment of chronic conditions and emergency cases.[23] This latter explanation, if true, would suggest that Australia's 'carrots-and-sticks' policies might have succeeded in increasing hospital insurance coverage in the country as desired by policy-makers, but without achieving the larger objective of easing the pressure on the public health system.

On the other hand, the positive and significant estimate of the insurance variable in the private admissions case suggests that patients with insurance who are seeking elective surgery are likely to admit themselves as private patients, to avoid the waiting lines in the public system. This would suggest that the incentive policies have eased the pressure on the public hospital system. We discuss this point further when we discuss the moral hazard estimates. Note that after controlling for the endogeneity of PHoI, having insurance increases the probability of hospital admission as a private patient relative to not being admitted, by about 13%. This result indicates strong moral hazard effects of insurance on the decision to be admitted to hospital as a private patient.

[23] The estimates of the number of long-term conditions, discussed in the previous paragraph, support this view.

### 6.3 Stage 3: Negative Binomial Estimates of Intensity of Hospital Use

The third-stage results from the negative binomial estimation are presented in Table 5, separately by patient-type at time of last admission.[24] The coefficient of the residual variable from the first stage is imprecisely estimated for both public and private patients. There is thus no evidence of endogeneity of the hospital insurance variable on the number of nights spent in hospital. This contrasts with the evidence of endogeneity in the patient-type outcome in the multinomial logit specification in stage two. The PHoI variable is also imprecisely estimated in both columns, again suggesting that the insurance variable, PHoI, has no influence on the intensity of medical services usage. This implies that hospital insurance affects the patient-type decision, but has no direct influence on the number of days spent in hospital. Being in good health has a negative and significant effect on the number of nights spent in hospital, for both types of patients. The estimates of the dispersion parameter, 0.577 and 0.4243 for public and private patients respectively, suggest over-dispersion and hence support the use of the negative binomial model over the Poisson model.

We also attempt to address the endogeneity of the patient-type decision, as mentioned earlier. We do so by adding controls for a number of chronic health conditions, those listed under long-term conditions in Table 1. We assume that these extensive set of health status variables serve as a suitable proxy for the individual's latent health status, which influences their decision to get admitted to hospital as public or private patients. Once again, we estimate coefficients separately for public and private patients, by running two negative binomial specifications. We have already discussed the estimates from the first two stages for this specification, as reported in Table 3 and Table 4, under specification 2. Estimates from the third-stage negative binomial regression are described in Table 6. Again, the estimates of PHoI are imprecisely estimated for both the public patients sample and the private patients sample.

The estimates in Table 5 and Table 6 do not reflect the multi-stage approach to estimating moral hazard, as described in Sections 5.1 and 5.2. In Table 7, we report estimates of moral hazard based on the intensity of hospital use, estimated according to Equation 5 and Equation 6, for both specifications. These measure the average difference in the number of nights spent in hospital in two counterfactual scenarios: one where everyone has insurance and one where no one has insurance.

[24]The coefficient measures the impact of a one-unit increase in the independent variable on the predicted number of nights in hospital.

We report two effects: (1) the *diversion effect*, an estimate based on Equation 6; and (2) the *total effect*, an estimate based on Equation 5. The probabilities $Pr_i^{1*}$ and $Pr_i^{0*}$ are calculated from the second stage and the expected hospital use from the third stage. We then take the sample averages to estimate the total effect and the diversion effect respectively. The difference between the total effect and the diversion effect gives us the imputed expansion effect (EE).

The estimates in Table 7 also present no evidence of moral hazard in either specification; the expansion effect is imprecisely estimated. The total effect is sizable and significant, largely due to the diversion effect. The diversion effect is negative, as expected; insurance induces an increase in the probability of seeking treatment as a private patient, and simultaneously a decrease in the time spent in hospital (recall from Table 2 that on average, individuals without PHoI stay longer in hospital). Relative to the average number of nights spent in hospital among the hospitalized (0.6707, from Table 1), the total effect and the diversion effect measure a 82% increase and a 75% decrease in the intensity of hospital use respectively for specification 1. In specification 2, the total effect is about 80% bigger relative to the average number of nights spent by hospitalized individuals (0.6707 in Table 1), while the diversion effect is 72% smaller.

In Table 8, we compare the moral hazard estimates from the two specifications we have described thus far, with those from a specification that treats the PHoI variable as exogenous. We calculate the latter estimates without implementing the 2SRI procedure. We estimate a multinomial logit model for type of hospital admission, if any, to estimate predicted probabilities, and then run negative binomial estimations separately for public and private patients, and then do a counterfactual analysis as before, to estimate the total moral hazard effect (TE) and the diversion effect (DE) according to equations 5 and 6. The difference between these two gives us the expansion effect.

Table 8 highlights the importance of controlling for the endogenity of private insurance; both specifications under the exogenous case show evidence of moral hazard. The estimates indicate an increase of about 26% in the utilization of hospital services due to private insurance. But as discussed above, there is no evidence of moral hazard once we control for the endogeneity of private insurance. Comparing within specifications, we find that the total effect is overestimated when we treat PHoI as exogenous. The magnitude of the bias is about 8% and 11% for specifications 1 and 2 respectively, relative to the average number of nights spent in hospital in our sample (0.6707). In contrast, the diversion effect is underestimated, with the magnitude of the bias being 11% and 6% for the two specifications respectively.[25]

Given these estimates, 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.[26] We are unable to offer a categorical response to this question because of lack of data on all relevant factors. Crucially, we have no data on prices. This prevents us from drawing welfare implications of the policy reforms. In drawing out the implications of our findings, we also make two assumptions: (i) that the incentive policies increased private insurance take-up among the population; and (ii) that there is substitution between private patient care and public patient care; at the margin, individuals formerly seeking care as public patients will switch to seeking care as private patients, when given insurance. There is evidence to suggest that both these assumptions are reasonable. 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.[27] Regarding substitutability between private and public patient care, 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.[28]

With the above limitations in mind, the increased propensity of those with insurance to be admitted as private patients, as well as the sizable estimates of the diversion effect found in this paper suggest that increased insurance take-up may have cut down waiting times in public hospitals substantially. We find no evidence of moral hazard in hospital utilization. Thus, the treatment effect of private hospital insurance on private patient care is driven entirely by the substituion

[25] As a robustness check, we also used the following, alternate set of instrumental variables in our estimation: two indicator variables for employment in the private sector and for self-employment, as well as nine indicator variables denoting occupation. The results from this alternative specification are qualitatively similar to those reported in Tables 3 through 7. These estimates are reported in Table A1 in the appendix.

[26] Lu and Savage (2007) express the view that the policies might have had only a modest impact in this regard.

[27] 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).

[28] As mentioned earlier, private insurance offers coverage for a number of services covered by Medicare. Thus, there is bound to be some switching from Medicare towards private care, once insurance is purchased.

away from public patient care towards private patient care. These results suggest that Australia's policies with regard to private health insurance might have achieved the intended objective of policy-makers to reduce the pressure on the public hospital system in terms of reducing waiting times for treatments. We cannot, however, conclude that this led to a concomitant reduction in costs. Increased insurance take-up might have exacerbated the tendency of public hospitals to specialize in costly emergency and chronic care, with private hospitals dealing predominantly with elective treatment; the evidence in this paper offers some support for this hypothesis. If this is indeed the case, then the distributional impacts of these outcomes remain beyond the scope of this paper.

## 7 Conclusions

We use the 2004-'05 wave of the Australian National Health Survey to examine the impact of private hospital insurance on the utilization of both public patient hospital care services and private patient hospital care services in Australia. This involves estimating a three stage econometric model. The first stage consists of a probit model for the purchase of private hospital insurance. The second stage consists of a multinomial logit model for the type of hospital care, if any, that is used. The third stage consists of a negative binomial count data model for the number of nights spent in hospital.

In order to control for the potential endogeneity of private hospital insurance, we employ the two-stage residual inclusion technique that is advocated by Terza *et. al.* (2008). In addition to this, 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 hospital care. These estimation results are then used in a counterfactual analysis to calculate difference-of-means estimates of the treatment effect of private hospital insurance on hospital utilization 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 sum of the total effect, which is positive in our case, and the diversion effect, which is negative in our case. The latter effect is our measure of ex-post moral hazard.

The multi-stage approach we have employed in this paper is a conceptually sound and empirically powerful method for estimating the causal impact of private hospital insurance on the consumption of hospital care services, when there is self-selection in the insurance purchase decision and when the intensity of hospital services is mediated by the decision to seek hospital care. The 2SRI method mitigates the endogeneity bias due to self-selection into insurance in the estimated coefficients in stages two and three of our method. The counterfactual analysis facilitates estimation of the relevant moral hazard measures based on a difference-in-means estimator that incorporates the impact of insurance on both the extensive margin of healthcare (hospitalization, in our case) as well as the intensive margin (number of days spent in hospital).

Our results offer evidence of negative selection into private hospital insurance in Australia. After controlling for the endogeneity of health insurance, we find no evidence of moral hazard in the number of nights spent in hospital. However, 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 almost entirely due to the substitution of private patient care for public patient care. We cautiously conclude that increased take-up of private hospital insurance in Australia caused a reduction in waiting times for treatment in public hospitals.

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 effect of PHoI 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.

**Figure 1: The market for public hospital care**

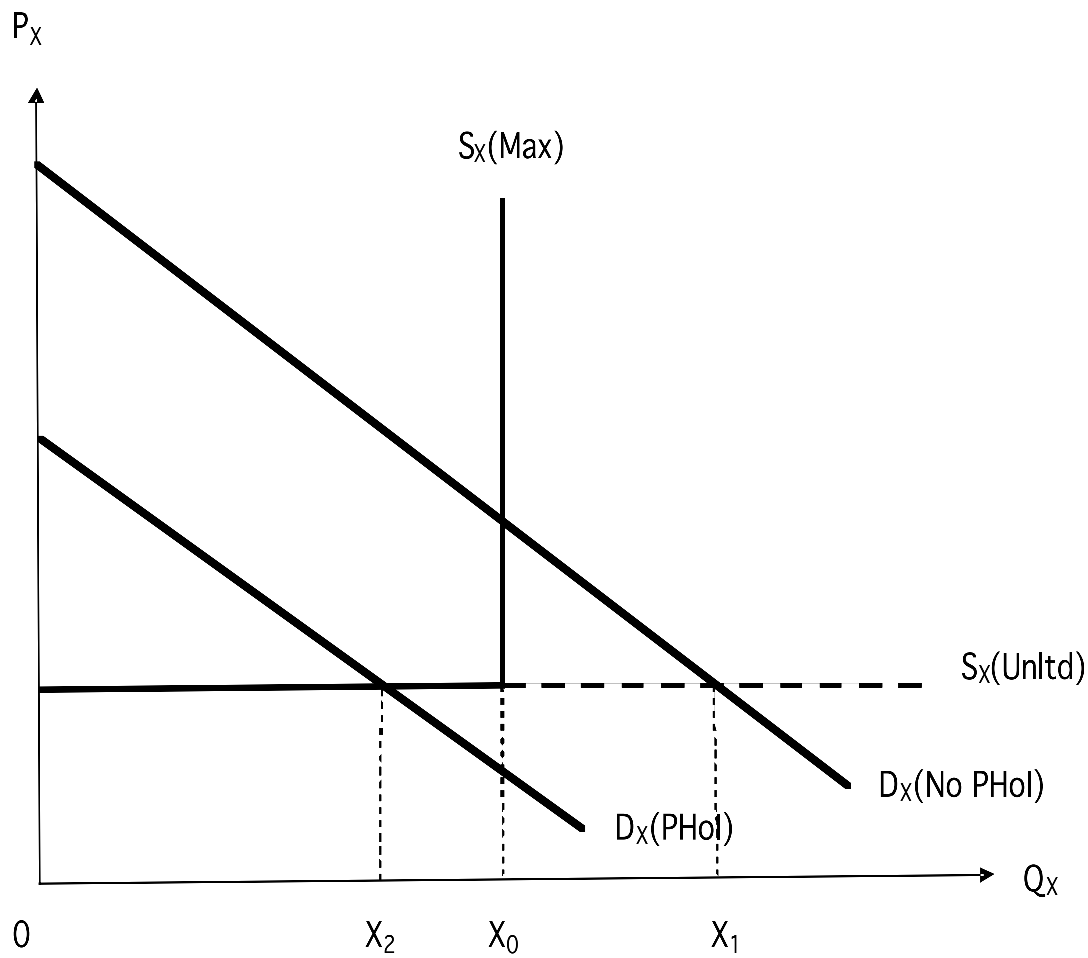

**Figure 2: The market for private hospital care**

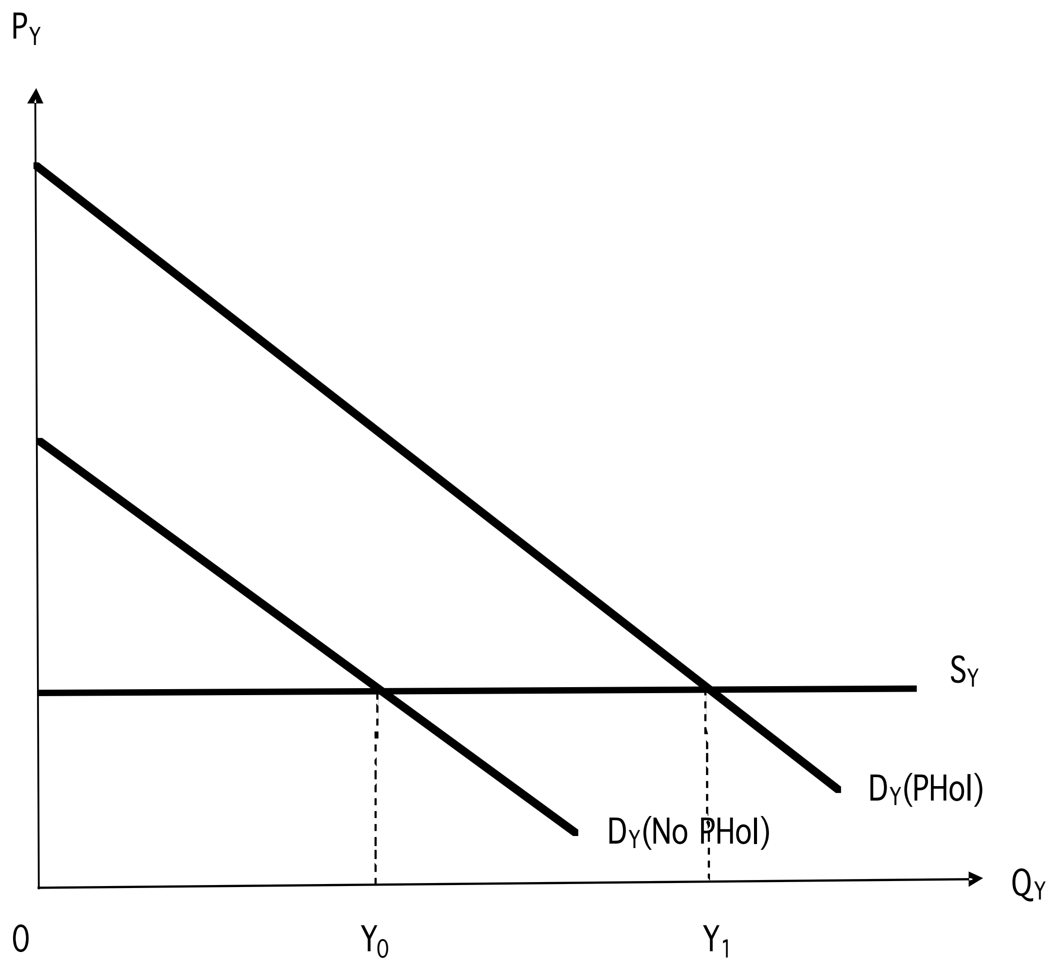

Table 1: Sample Characteristics

| 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 |
| Education | 0.4327 | 0.4955 | 0 | 1 |
| Employed | 0.6364 | 0.4810 | 0 | 1 |
| Private Sector | 0.5162 | 0.4998 | 0 | 1 |
| Self-Employed | 0.1505 | 0.3575 | 0 | 1 |
| Country of Origin: | | | | |
| NZUK | 0.1045 | 0.3059 | 0 | 1 |
| SEU | 0.0502 | 0.2185 | 0 | 1 |
| WEU | 0.0236 | 0.1519 | 0 | 1 |
| ASIA | 0.0608 | 0.2390 | 0 | 1 |
| OTHER | 0.0506 | 0.2192 | 0 | 1 |
| English Proficiency | 0.9685 | 0.1746 | 0 | 1 |
| 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 |
| #People in Household | 2.7889 | 1.3385 | 1 | 8 |
| Household Income*$10^{-3}$ | 1.2923 | 1.1652 | -0.5020 | 22.4750 |
| Good Health | 0.8278 | 0.3776 | 0 | 1 |

Continued on next page

**Table 1 – continued from previous page**

| Variable | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|
| 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 |
| 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 |
| Admitted as Private Patient | 0.0720 | 0.2584 | 0 | 1 |
| # Hospital Nights | 0.6707 | 2.5755 | 0 | 30 |

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 |
| Education | 0.3642 | 0.4812 | 0.5049 | 0.5000 |
| Employed | 0.5642 | 0.4959 | 0.7138 | 0.4520 |
| Private Sector | 0.4774 | 0.4995 | 0.5578 | 0.4967 |
| Self-Employed | 0.1159 | 0.3201 | 0.1872 | 0.3901 |
| Country of Origin: | | | | |
| NZ_UK | 0.1065 | 0.3085 | 0.1022 | 0.3029 |
| S.E.Europe | 0.0606 | 0.2387 | 0.0395 | 0.1949 |
| W.Europe | 0.0232 | 0.1505 | 0.0241 | 0.1532 |
| Asia | 0.0709 | 0.2567 | 0.0494 | 0.2167 |
| Other | 0.0609 | 0.2391 | 0.0400 | 0.1959 |
| English Proficiency | 0.9541 | 0.2093 | 0.9845 | 0.1234 |
| 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 |
| Occupation: | | | | |
| Managers, Administrators | 0.0365 | 0.1875 | 0.1093 | 0.3121 |

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**Table 2 – continued from previous page**

| Variable | No PHoI | | PHoI | |
|---|---|---|---|---|
| | **Mean** | **Std.Dev.** | **Mean** | **Std.Dev.** |
| Professionals | 0.0790 | 0.2698 | 0.1866 | 0.3896 |
| Associate Professionals | 0.0639 | 0.2446 | 0.1055 | 0.3072 |
| Tradespersons and Related Workers | 0.0842 | 0.2777 | 0.0655 | 0.2474 |
| Advanced Clerical,Service Workers | 0.0148 | 0.1208 | 0.0315 | 0.1747 |
| Intermediate Clerical, Sales, Sevice Workers | 0.0997 | 0.2997 | 0.1051 | 0.3068 |
| Intermediate Production,Transport Workers | 0.0663 | 0.2488 | 0.0425 | 0.2018 |
| Elementary Clerical, Sales, Service Workers | 0.0468 | 0.2112 | 0.0338 | 0.1808 |
| Labourers and Related Workers | 0.0687 | 0.2530 | 0.0276 | 0.1638 |
| #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 |
| 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 |
| 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 |

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**Table 2 – continued from previous page**

| Variable | No PHoI | | PHoI | |
|---|---|---|---|---|
| | **Mean** | **Std.Dev.** | **Mean** | **Std.Dev.** |
| 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 |
| Private Patient | 0.0119 | 0.1084 | 0.1359 | 0.3428 |
| # Hospital Nights | 0.7180 | 2.7298 | 0.6205 | 2.3897 |

**Table 3: Probit Estimates of Private Hospital Insurance: Marginal Effects and Standard Errors**

| Variables | Specification 1 Marginal Effect | Specification 1 Replicate Std. Error | Specification 2 Marginal Effect | Specification 2 Replicate Std. Error |
|---|---|---|---|---|
| Male | -0.0358*** | 0.0134 | -0.0307** | 0.0130 |
| Age | 0.0269*** | 0.0043 | 0.0253 | 0.0034*** |
| Age$^2$ | -0.0002*** | 0.0000 | -0.0002*** | 0.0000 |
| Education | 0.1291*** | 0.0143 | 0.1275*** | 0.0138 |
| Employed | -0.1580*** | 0.0326 | -0.1556*** | 0.0333 |
| Country of Origin: | | | | |
| NZ_UK | -0.1305*** | 0.0174 | -0.1311*** | 0.0165 |
| S.E. Europe | -0.1260*** | 0.0294 | -0.1248*** | 0.0283 |
| W. Europe | -0.1267*** | 0.0336 | -0.1265*** | 0.0363 |
| Asia | -0.1224*** | 0.0266 | -0.1263*** | 0.0260 |
| Other | -0.1163*** | 0.0351 | -0.1183*** | 0.0286 |
| English Proficiency | 0.0464 | 0.0489 | 0.0452 | 0.0423 |
| Scaled Income | 0.1487*** | 0.0175 | 0.1478*** | 0.0161 |
| Good Health | 0.0797*** | 0.0177 | 0.0834*** | 0.0162 |
| Kessler Score | -0.0048*** | 0.0011 | -0.0045*** | 0.0012 |
| #Long-Term Conditions | 0.0147*** | 0.0026 | 0.0189*** | 0.0064 |
| Govt. Health Card | -0.2664*** | 0.0202 | -0.2657*** | 0.0189 |
| Predicted Probability at $\overline{X}$ | 0.4602 | | 0.4601 | |
| Observations | 14,520 | | 14,520 | |

*Note:* Specification 1 includes three health status variables - indicator for good health, kessler score and number of long-term conditions, while specification 2 includes, in addition, the following health status variables: 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 occupation, 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 4: Marginal Effects From Multinomial Logit Estimation of Patient-Type in Hospital Admissions (Base Outcome: No Admission)**

| | **Specification 1** | | **Specification 2** | |
|---|---|---|---|---|
| Variables | Marginal Effect | Replicate Std. Error | Marginal Effect | Replicate Std. Error |
| *1. Admitted to Hospital as Public Patient* | | | | |
| PHoI | -0.1101*** | 0.0112 | -0.1077*** | 0.0110 |
| Residual | 0.0324* | 0.0184 | 0.0298 | 0.0186 |
| Good Health | -0.0554*** | 0.0092 | -0.0492*** | 0.0092 |
| Kessler Score | 0.0007 | 0.0004 | 0.0007 | 0.0004 |
| # Long-Term Conditions | 0.0083*** | 0.0010 | 0.0088*** | 0.0024 |
| Predicted Probability | 0.0692 | | 0.0672 | |
| *2. Admitted to Hospital as Private Patient* | | | | |
| PHoI | 0.1304*** | 0.0133 | 0.1257*** | 0.0126 |
| Residual | -0.0049 | 0.0081 | -0.0043 | 0.0079 |
| Good Health | -0.0142*** | 0.0052 | -0.0102** | 0.0048 |
| Kessler Score | 0.0006** | 0.0003 | 0.0008*** | 0.0003 |
| # Long-Term Conditions | 0.0009 | 0.0008 | 0.0013 | 0.0016 |
| Predicted Probability | 0.0343 | | 0.0335 | |
| Observations | 14,413 | | 14,413 | |

*Note:* Specification 1 includes three health status variables - indicator for good health, kessler score and number of long-term conditions, while specification 2 includes, in addition, the following health status variables: 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 age, the square of age, gender, education, employment status, occupation, family type, household income, 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 5: Negative Binomial Estimates of Nights Spent in Hospital, by Patient Type**

**Specification 1**

| Variables | Public Patients | | Private Patients | |
|---|---|---|---|---|
| | Coefficient | Replicate Std. Error | Coefficient | Replicate Std. Error |
| Male | -0.0699 | 0.0839 | -0.1248 | 0.1185 |
| Age | -0.0415** | 0.0233 | -0.0778*** | 0.0246 |
| Education | 0.0207 | 0.0799 | 0.159 | 0.1084 |
| Employed | 0.0643 | 0.2315 | -0.0673 | -0.2645 |
| Private Sector | -0.4034*** | 0.2053 | -0.2044 | 0.1468 |
| Self-Employed | 0.2338 | 0.1711 | 0.1814* | 0.1085 |
| Household Income*$10^{-3}$ | 0.0093 | 0.0573 | -0.0443 | 0.0592 |
| Good Health | -0.194*** | 0.0854 | -0.2596*** | 0.1158 |
| Kessler Score | 0.0091 | 0.0059 | -0.0025 | 0.0074 |
| #Long-Term Conditions | -0.024 | 0.0221 | -0.0159 | 0.0238 |
| Urban Residence | 0.0763 | 0.0823 | -0.169 | 0.119 |
| Government Health Card | 0.3373*** | 0.1212 | -0.0659 | 0.2119 |
| PHoI | 0.1361 | 0.196 | 0.1251 | 0.3471 |
| Residual | -0.0462 | -0.3014 | 0.3848 | 0.531 |
| $\alpha$ (dispersion) | 0.577*** | .0303 | 0.4243*** | .0444 |
| Observations | 1,503 | | 1,032 | |

*Note:* This table reports estimates from negative binomial regressions run separately on the samples of public (Medicare) and private patients. Also included are controls for the square of age, occupation, family type 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: Negative Binomial Estimates of Nights Spent in Hospital, by Patient Type**

**Specification 2**

| | **Public Patients** | | **Private Patients** | |
|---|---|---|---|---|
| Variables | Coefficient | Replicate Std. Error | Coefficient | Replicate Std. Error |
| Male | -0.0846 | 0.0777 | -0.0983 | 0.1314 |
| Age | -0.0447** | 0.0232 | -0.0804*** | 0.0262 |
| Education | 0.0345 | 0.0736 | 0.1611 | 0.1037 |
| Employed | 0.0483 | 0.2238 | -0.0239 | 0.2568 |
| Private Sector | -0.3547** | 0.1939 | -0.2019 | 0.1582 |
| Self-Employed | 0.2549* | 0.1701 | 0.1666 | 0.1221 |
| Household Income*$10^{-3}$ | -0.0042 | 0.0460 | -0.0421 | 0.0580 |
| Good Health | -0.1742*** | 0.0793 | -0.2622*** | 0.1144 |
| Kessler Score | 0.0077 | 0.0059 | -0.0043 | 0.0088 |
| #Long-Term Conditions | -0.0499 | 0.0379 | -0.0243 | 0.0374 |
| Urban Residence | 0.0686 | 0.0827 | -0.1328 | 0.1241 |
| Government Health Card | 0.3507*** | 0.1191 | -0.0239 | 0.1961 |
| PHoI | 0.1791 | 0.1858 | 0.0990 | 0.3513 |
| Residual | -0.1721 | 0.2891 | 0.4399 | 0.5610 |
| $\alpha$ (dispersion) | 0.5496*** | | 0.4026*** | |
| Observations | 1,480 | | 1,032 | |

*Note:* This table reports estimates from negative binomial regressions run separately on the samples of public (Medicare) and private patients. Also included are controls for the square of age, occupation, family type, state of residence and the following health status variables: 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. 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 7: Estimates of Moral Hazard in Intensity of Hospital Use**

| | **Specification 1** | | **Specification 2** | |
|---|---|---|---|---|
| | *Patient-Type* | | *Patient-Type* | |
| Counterfactual Scenario | Private | Public | Private | Public |
| ***PHoI=1*** | 0.5868 | 0.1523 | 0.5708 | 0.1568 |
| ***PHoI=0*** | 0.0350 | 0.6569 | 0.0362 | 0.6400 |
| Difference | $\widehat{TE}$= 0.5518*** | $\widehat{DE}$= -0.5046*** | $\widehat{TE}$= 0.5346*** | $\widehat{DE}$= -0.4832*** |
| | (0.0545) | (0.0345) | (0.1515) | (0.0724) |
| $\widehat{EE} = \widehat{TE} - \lvert\widehat{DE}\rvert =$ | 0.0472 | | 0.0514 | |
| | (0.0664) | | (0.1624) | |

*Note:* This table reports estimates based on Equation 5 and Equation 6, where the third stage negative binomial regression is run separately on the samples of public (Medicare) and private patients; the total effect is based on the former and the diversion effect on the latter. Specification 1 includes only three health status variables - indicator for good health, kessler score and number of long-term conditions. In addition to the above three, specification 2 controls for a more detailed set of health status variables: 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 include controls for age, gender, education, employment status, occupation, family type, household income, government health card status, urban status and state of residence. Replicate standard errors in parentheses.

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

**Table 8: Moral Hazard in Intensity of Hospital Use**

**Comparison of Alternate Specifications**

| | **Status of PHoI Variable** | | | |
|---|---|---|---|---|
| | Exogenous | | Endogenous | |
| | Specification 1 | Specification 2 | Specification 1 | Specification 2 |
| Total Effect (TE) | 0.6075*** | 0.6067*** | 0.5518*** | 0.5346*** |
| | (0.0550) | (0.0545) | (0.1507) | (0.1515) |
| Diversion Effect (DE) | -0.4323*** | -0.4438*** | -0.5046*** | -0.4832*** |
| | (0.0350) | (0.0345) | (0.0794) | (0.0724) |
| Expansion Effect (EE) | 0.1752** | 0.1629** | 0.0472 | 0.0514 |
| | (0.0652) | (0.0664) | (0.1641) | (0.1624) |

*Note:* Replicate standard errors in parentheses.

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

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# 8 Appendix

**Table A1: Results Using Alternative Set of Instrumental Variables (IVs)**

| **I. First-Stage Probit Estimates** | | | | |
|---|---|---|---|---|
| | Specification 1 | | Specification 2 | |
| | Marginal Effect | Replicate S.E. | Marginal Effect | Replicate S.E. |
| Occupation 1 | 0.2939*** | 0.02911 | 0.2916*** | 0.0291 |
| Occupation 2 | 0.2450*** | 0.0311 | 0.2411*** | 0.0.0315 |
| Occupation 3 | 0.2152*** | 0.0269 | 0.2110*** | 0.0273 |
| Occupation 4 | 0.1130*** | 0.0336 | 0.1129*** | 0.0336 |
| Occupation 5 | 0.2723*** | 0.0361 | 0.2662*** | 0.0368 |
| Occupation 6 | 0.1626*** | 0.0339 | 0.1580*** | 0.0343 |
| Occupation 7 | 0.0991*** | 0.0367 | 0.0968*** | 0.0368 |
| Occupation 8 | 0.0801** | 0.0374 | 0.0762** | 0.0375 |
| Self-Employed | 0.0350* | 0.0212 | 0.0351* | 0.0231 |
| Private Sector | -0.0117 | 0.0197 | -0.0100 | 0.0212 |
| **II. Multinomial Logit Estimates of Patient-Type in Hospital Admissions (Base Outcome: No Admission)** | | | | |
| | Specification 1 | | Specification 2 | |
| | Public Patient | Private Patient | Public Patient | Private Patient |
| PHoI | -1.6482*** | 2.5511*** | -1.6562*** | 2.5406*** |
| Replicate S.E. | (0.1774) | (0.2216) | (0.1765) | (0.2120) |
| Residual | 0.5871*** | 0.1568 | 0.5559* | 0.1536 |
| Replicate S.E. | (0.2807) | (0.2245) | (0.2910) | (0.2212) |
| **III. Estimates of Moral Hazard in Intensity of Hospital Use** | | | | |
| | Specification 1 | | Specification 2 | |
| | Estimate | Replicate S.E. | Estimate | Replicate S.E. |
| Total Effect | 0.5497*** | 0.1296 | 0.5286*** | 0.1318 |
| Diversion Effect | -0.5327*** | 0.0757 | -0.5140*** | 0.0702 |
| Expansion Effect | 0.0170 | 0.1461 | 0.0147 | 0.1010 |

*Note:* This table reports estimates from a specification using an alternative set of instrumental variables - 9 occupation dummies, and indicator variables for self-employment and private-sector employment. The other control variables are the same as those used in the main tables.

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