Impacts of the 2012 'Fairer Private Health Insurance Incentives' reforms on membership and coverage in Australia

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Declaration

This thesis is submitted in fulfilment of the requirements of the degree of Master of Research (MRes) in the Faculty of Business and Economics, Macquarie University.

This thesis represents the original work and contribution of the author, except as acknowledged by general and specific references. I hereby certify that this thesis has not been submitted for a higher degree to any other university or institution.

Signed: Date:

10/10/2016

Abstract

This study estimates the impacts of the 2012 Fairer Private Health Insurance Incentives (FPHII) reforms, which encompassed means-testing private health insurance (PHI) rebates and increased rates of the Medicare levy surcharge (MLS) for higher income earners. The impacts of the reforms on changes in the probability of holding hospital cover and on downgrading in the treatment group (higher income earners directly affected by FPHII) were analysed using longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. This included analysis of PHI status variables and estimated household expenditure on PHI. A first-difference estimator and difference-in-difference analysis was employed to analyse a sample of approximately 6,500 individuals. The baseline analysis for the treatment group found that the reforms increased the probability of having hospital cover by 2.9% to 3.8%, and downgrading of hospital cover by 24.6% to 34.6%. The estimated effects on hospital cover and downgrading were relatively robust to all sensitivity analyses performed. The substantial downgrading impacts from the reforms hold important implications for health care use and equity in the current Australian PHI market, which is characterised by asymmetric information on the provider side and offers over 20,000 available policies with complex product features.

List of abbreviations

ABS	Australian Bureau of Statistics
ACCC	Australian Competition and Consumer Commission
APRA	Australian Prudential Regulation Authority
ATE	average treatment effect
ATT	average effect of the treatment on the treated
ATO	Australian Taxation Office
DID	difference-in-difference
FPHII	Fairer Private Health Insurance Incentives
HILDA	Household, Income and Labour Dynamics in Australia survey
LHC	Lifetime Health Cover
LPM	linear probability model
MLS	Medicare Levy Surcharge
NHS	National Health Survey
OLS	ordinary least squares
PHA	Private Healthcare Australia
PHI	private health insurance
PHIAC	Private Health Insurance Administration Council
PHIIS	Private Health Insurance Incentive Scheme
WTP	willingness-to-pay

1 Introduction

Nearly half (47%) of the Australian population is covered by private health insurance (PHI) for hospital treatment (AIHW, 2015). PHI plays an important role in facilitating health care access and financing, operating alongside the public health care system.

The PHI market has been seen as a vehicle for reducing public hospital cost pressures and waiting lists by government and industry (Colombo and Tapay, 2003). When Medicare was introduced in 1983, PHI membership declined persistently, leading to concerns around public hospital cost and resource pressures (OECD, 2004).

In order to arrest this decline, the government introduced a series of reforms to encourage PHI take-up. The Private Health Insurance Incentive Scheme (PHIIS) commenced in 1997, and offered tax subsidies to individuals and households with lower income to take up private health insurance. The Medicare Levy Surcharge (MLS), a flat tax levy of 1%, was also introduced in 1997 for higher income earners without PHI. In 1998, the PHIIS tax subsidy was replaced by a non-means tested, flat 30% rebate on private health insurance premiums (PHIAC, 2015). In July 2000, Lifetime Health Cover (LHC) was introduced, which allowed health funds to charge a 2% per annum premium loading on those who purchased PHI after the age of 30. Following the reforms, PHI coverage rose dramatically in 2000 to approximately 45% of the population.

Contention exists regarding the use of government financial incentives to foster PHI membership (Cheng, 2014). Government expenditure on rebates has grown rapidly in the past and currently amounts to over $6 billion (Commonwealth Government, 2016), which is a significant public investment. Furthermore, past Australian studies have attributed the bulk of the membership increase following the 1990s reforms to the LHC policy, and found the rebates to have had limited effect (Butler, 2003; Frech et al.., 2003; Walker et al.., 2005; Ellis and Savage, 2008). Since PHI coverage rates rise with higher income levels (ATO, 2016), this has meant that the previously flat 30% rebate was disproportionately received by higher income earners and this has been seen as inequitable (Smith, 2001).

Some contend that the rebates allowed higher income earners who would have purchased PHI anyway to enjoy windfall gains (Palangkaraya and Yong, 2009). Past findings of a relatively price-inelastic demand for PHI in Australia have been supported by a recent study which projects that reducing rebates would have limited impact on PHI membership and result in net cost savings for government (Cheng, 2014). These arguments coincide with broader equity concerns which have been voiced regarding the ability of privately insured patients, often higher income earners (Doiron et.al., 2008), to bypass waiting lists and access elective surgery sooner than public patients (Cheng, 2014), and access different mixes of health care to uninsured patients (Van Doorslaer et al.., 2008). If these inequalities translate into poorer health outcomes for uninsured patients, there would be cause for concern about equity.

New reforms were recently introduced under the Fairer Private Health Insurance Incentives (FPHII) package on 1 July 2012, which resulted in lower rebates and increased MLS rates for three tiers of higher income earners. Insured individuals in the top income tier ineligible to receive any PHI premium rebate. The MLS is also allowed to vary from 1% to 1.5% for uninsured individuals in these tiers (PHIAC, 2015).

The FPHII reforms were an attempt to both curb government expenditure on rebates, and ensure that those with a greater capacity to pay made a larger contribution to the cost of their PHI cover (Commonwealth of Australia, 2011), through reduced rebates at higher income levels. The simultaneous introduction of increased MLS rates at higher tiers aimed to maintain PHI membership and sustain the role of the PHI market in the health care system. Because the MLS and rebates affect PHI purchase through their influence on individual and household income and expenditure on PHI (that is, price), any changes to the MLS and rebates potentially affect PHI coverage in Australia.

Downgrading is another potential effect of policy-related changes, whereby higher income individuals may attempt to reduce the effects of price increases from reduced rebates by reducing their PHI coverage level. Whether or not downgrading occurs depends on the expected benefit these individuals derive from their PHI policy and their initial level of coverage compared to expected cost savings from downgrading.

While some initial pre-reform research reports projected large decreases in PHI membership would result from FPHII (Deloitte, 2011; ANOP, 2011), the reforms have not yet been examined empirically.

This paper is the first study to estimate the effects of the FPHII reforms. The potential effects of the reforms are estimated for the treatment group in terms of changes in probability of holding hospital cover and changes in the probability of downgrading hospital cover. Here, the treatment group constitutes those individuals in three tiers of higher income earners who faced reduced rebates and increased MLS rates due to the FPHI reforms. Downgrading has not been explored in previous studies on PHI reforms in Australia.

Empirical analysis was carried out using data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, which is an annual, household-based, longitudinal survey. A sub-sample of approximately 6,500 individuals in HILDA was analysed. The presence of questions and variables related to the PHI status of individuals in pre- and post-reform years provided a unique opportunity to analyse the reforms using longitudinal analysis. HILDA data on household expenditure on PHI, was used to construct a downgrading indicator to investigate effects on downgrading. Difference-in-difference (DID) analysis was carried out using a first-difference estimator to analyse the waves of data.

The study found that the FPHII reforms had a significant effect in increasing the probability of having hospital cover, and the probability of downgrading hospital cover, for individuals in the treatment group. In the baseline analysis for the treatment group, the FPHII reforms were found to have significantly:

- increased the probability of having hospital cover by 2.9 to 3.8 percentage points between the years 2008-09 and 2012-13; and
- increased the probability of downgrading hospital cover by 24.6 percentage points between the years 2008-09 and 2012-13 and 25.8% to 34.6% between the years 2011-12 and 2013-14.

The estimated overall effects on having hospital cover generally remained strongly significant (1% level) in the sensitivity analyses performed (changes in the income measure). The exception was with a 5% decrease in estimated MLS income, which caused the effect to become marginally significant (10% level). The downgrading results were found to be robust to both changes in the income measure and downgrading indicator used and remained strongly statistically significant (at the 1% level) for all sensitivity analyses.

Past PHI reforms in Australia have only ever been empirically analysed using cross-sectional or time series data (Section 3). Time series and cross-sectional analyses require strict assumptions to ensure comparability between treatment and control groups and pre and post-reform periods to ensure the construction of a valid counterfactual. This is the first Australian study in the PHI area to use longitudinal DID analysis to analyse HILDA data, which has empirical advantages by following the same individuals over time. Another advantage of the panel DID estimator over other estimators is that it allows for removal of time-constant individual-level unobservables which may be correlated with other explanatory variables and result in heterogeneity bias, which affect values of the outcome variable (Wooldridge, 2006). Pooled cross-sectional estimators may suffer from this heterogeneity bias. The comparison between the results obtained from panel DID and pooled OLS supports the benefits of removing heterogeneity bias in this context.

This study adds to the literature on the effects of PHI reforms in Australia (Butler, 2003, Cheng, 2014, Frech et al., 2003, Palangkaraya and Yong, 2005, Walker et al., 2005, Palangkaraya and Yong, 2004, Palangkaraya et al., 2005, Palangkaraya et al., 2009, Ellis and Savage, 2008, Stavrunova and Yerokhin, 2014). It examines a set of reforms which have not been looked at before. This study contributes to the current debate about the effectiveness of certain types of policy measures in the PHI market on membership levels in Australia, and provides insights into the effects of policy instruments on PHI membership and coverage.

The Federal government recently conducted a review and survey on the role of PHI in Australia, the value offered by PHI products and future reform options (DOH, 2016). The results of the survey found that consumers perceived complexity and little value in available PHI products (DOH, 2016). The Australian Competition and Consumer Commission (ACCC), in its most recent report on PHI (ACCC, 2015) discusses market failures in PHI including asymmetric information on the supplier side impeding consumer decision making regarding products offering the best value in the face of uncertain future health needs. In the context of the current analysis, the ACCC suggests that government intervention through rebates and the MLS has driven insurers to offer products to primarily reduce consumer tax liabilities (ACCC, 2015). Thus, the results of this analysis should also be viewed in the context of the overall perceived value offered by PHI to Australian consumers and how past and future reforms may have affected this.

Downgrading may have important implications for health care use and equity. Because PHI covers ancillary services and different mixes of hospital services, downgrades could result in potential inequity if it involves increasing the number of excluded services in policies. Additionally, downgrades that involve increasing excess levels may reduce access to private hospitals to due increased out-of-pocket costs. Downgrading coupled with the large number of existing PHI policies (>20,000), complexity in product features and asymmetric information on the insurer side (ACCC, 2015) could result in patients not being covered for services they need and/or facing longer waiting times for services by relying on public health care. This also holds potential implications for public health care costs and warrants attention in future studies. However, downgrading may also hold potential benefits for PHI holders, if individuals optimise their policies by excluding services that are rarely or never used. The PHI market in Australia exhibits significant inertia, in terms of relatively inelastic demand (Butler et al., 2003, Frech et al., 2003, Walker et al., 2005, Ellis and Savage, 2008) and very low levels of consumer switching between policies (PHIAC, 2015). If increased downgrading is a result of optimisation by consumers to ensure policies better suit their needs, downgrading may result in increased welfare.

2 The private health insurance market and government intervention

The private health insurance (PHI) market plays an important role in the Australian health care system, with nearly half (47%) of the Australian population covered by PHI for hospital treatment (PHIAC, 2015). PHI funded just over 8% of total health care expenditure in 2013-14 (AIHW, 2015).

PHI interacts with the Australian public health care system, Medicare, in several ways. While Medicare provides access to medical and public hospital services to all residents in Australia, PHI covers private hospital treatment but allows for choice of doctor and provides shorter waiting times for services such as elective surgery. The extent to which PHI hospital care duplicates or substitutes public hospital care depends on the extent to which it is viewed as a differentiated good in terms of 'quality'. In a strict economic sense, the extent to which hospital PHI substitutes publicly-covered hospital care is dependent on the positivity of cross-price elasticity of demand between the two. If an increase in the price of PHI-covered hospital care lead to an increase in the use of public hospital care, then the two would be said to substitute each other.

PHI also covers fees above the Medicare Benefits Schedule level for in-hospital medical services and provides partial cover for ancillary services not covered by Medicare such as dental, optical, chiropractic services and physiotherapy. In these two functions, PHI 'supplements' Medicare by providing additional services and coverage beyond what Medicare provides.

PHI plays an important role facilitating financing and access to health care in Australia and has potential effects on both access to health care and equity of health care use. Issues of equity surround the ability of privately insured patients to bypass waiting lists and access elective surgery sooner than public patients (Cheng, 2014) or access different mixes of health care to uninsured patients (Van Doorslaer et al., 2008), particularly if this is found to contribute to poorer health outcomes for the uninsured. The PHI market has also been seen as a vehicle for reducing public hospital cost pressures by government and the PHI industry (Colombo and Tapay, 2003), and past government intervention has sought to encourage PHI membership.

2.1 Regulatory context and PHI reforms

The PHI market in Australia is heavily regulated. Community-rating of premiums is legislated and annual premium increases must be submitted by insurers to the Health Minister for approval. Risk equalisation arrangements force insurers to share claim burden by pooling claims of high-cost claimants, and thus support community rating. Also, legal stipulations exist around insurance product offerings and portability requirements (PHIAC, 2015).

The Australian government substantially subsidises PHI expenditure by providing premium rebates to individuals holding a minimum level of PHI hospital cover. Current government expenditure for these rebates amounts to over $6 billion (Commonwealth Government, 2016). This is a significant investment and stems from late 1990s reforms to stop the persistent decline in PHI membership which followed the introduction of Medicare in 1983. PHI coverage of the population fell from 50% in 1984 to its lowest level of 30% in 1998 (PHIAC, 2015). There were concerns that the decrease in PHI membership would lead to negative impacts on private hospitals and unsustainable cost pressures on public hospitals (Colombo and Tapay, 2003).

A series of reforms aimed at increasing PHI coverage were introduced, starting with the *Private Health Insurance Incentive Scheme* (PHIIS) in 1997, which provided tax-subsidies to individuals and households with lower income to take up PHI in 1997. The *Medicare Levy Surcharge* (MLS), a tax levy of 1%, was also introduced in 1997 for higher income earners without PHI. In 1998, the tax subsidy was replaced by a non-means tested, flat 30% rebate on PHI premiums (PHIAC, 2015). In July 2000, *Lifetime Health Cover* (LHC) was introduced which allowed health funds to charge a 2% per annum premium loading on those who purchased PHI after the age of 30, and thus partially relaxed pure community rating arrangements. Following the reforms, PHI coverage rose dramatically in the year 2000 (Figure 1). In 2000, legislation was also introduced requiring insurers to offer at least one hospital policy with no gap or a known gap.

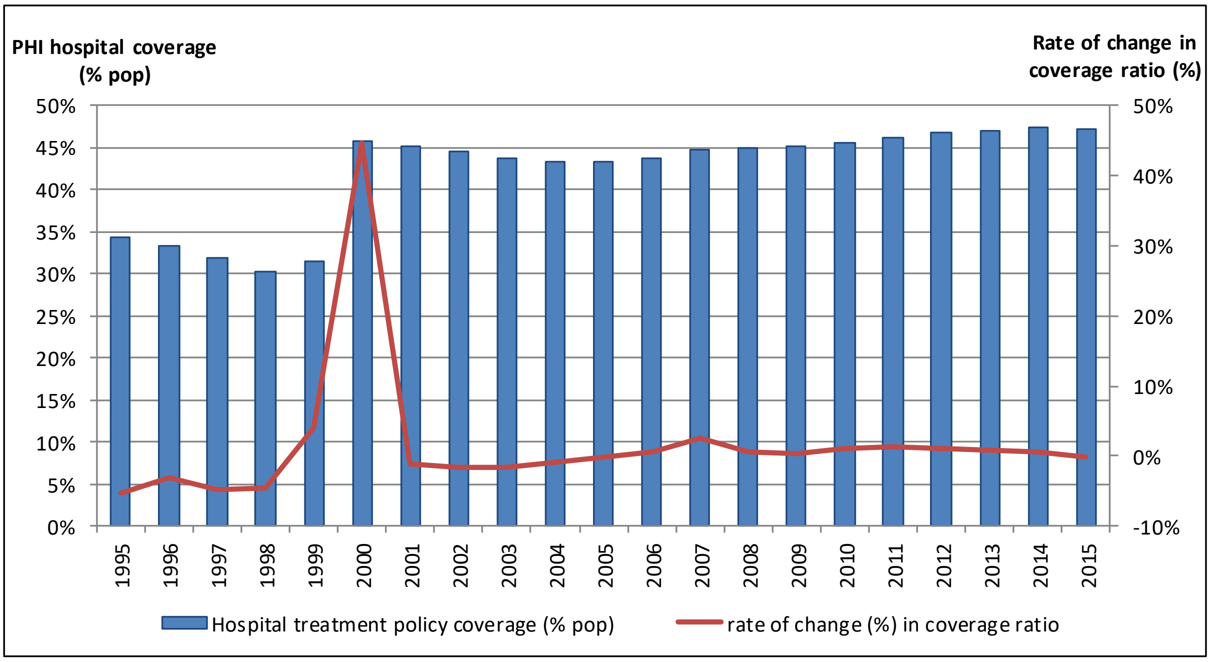

Figure 1: PHI coverage for hospital treatment in Australia

Source: Created from APRA data (2016)

Contention exists regarding the use of these incentives to foster PHI membership (Cheng, 2014). This involves the significant public investment in PHI rebates, particularly if these are found to be of limited effectiveness in encouraging uptake (see Section 3). The rebates have also been disproportionately received by higher income earners due to increasing coverage at higher income levels (Smith, 2001). The PHI market has been seen as a vehicle for reducing public hospital cost pressures and if those who take up PHI cover in response to financial incentives do not utilise private hospital care (Fiebig et al., 2006), questions arise over whether PHI alleviates this public burden. Recent research (Cheng, 2014) questions the current level of intervention by claiming reduced rebates would generate cost savings above any potential increase in expenditure on public hospital care.

New reforms were recently introduced under the *Fairer Private Health Insurance Incentives* (FPHII) package on 1 July 2012 which resulted in lower rebate rates and increased MLS rates for higher income earners. As part of FPHII, the government introduced means-testing for existing PHI rebates based on three income tiers. Individuals in these income tiers are now entitled to lower rebates with the top income tier ineligible to receive any PHI premium rebate. These income tiers were also applied to the MLS, which was allowed to vary from 1% to 1.5% based on income level (PHIAC, 2015).

The FPHII reforms were an attempt to balance efficiency and equity concerns, while also maintaining PHI membership. Reduced rebates were introduced to curb government rebate expenditure, and ensure that those with a greater capacity to pay made a larger contribution to the cost of their PHI cover (Commonwealth of Australia, 2011). The simultaneous introduction of increased MLS rates at higher tiers aimed to maintain PHI membership and sustain the role of the PHI market in the health care system.

The rebate from the LHC loading was removed from 1 July 2013 (PHIAC, 2015). From April 2014, PHI rebates were subject to discounting by a rebate adjustment factor based on the increase in consumer price index and the industry-weighted average premium increase (DOH, 2015). The government also announced a freeze on income thresholds for PHI rebates and the MLS at 2014-15 indexed rates until 2017-18 (ATO, 2016). In the most recent Federal Budget, this freeze was extended for three further years to 2020-21 (Commonwealth Government, 2016).

The current income thresholds and PHI rebates and MLS rates are presented in Table 2.1, along with the original income thresholds introduced on 1 July 2012.

Table 2.1 Means-tested PHI rebates, MLS rates and income thresholds

Status	Income thresholds introduced on 1 July 2012			
	Base tier	**Tier 1**	**Tier 2**	**Tier 3**
Single	$84,000 or less	$84,001-$97,000	$97,001-$130,000	$130,001 or more
Family	$168,000 or less	$168,001-$194,000	$194,001-$260,000	$260,001 or more
Status	**Income thresholds for 2014-15 to 2020-21 (current)**			
	Base tier	**Tier 1**	**Tier 2**	**Tier 3**
Single	$90,000 or less	$90,001-$105,000	$105,001-$140,000	$140,001 or more
Family*	$180,000 or less	$180,001-$210,000	$210,001-$280,000	$280,001 or more
Age	**Rebate for premiums paid, 1 April 2016 – 30 June 2016 (current)**			
Under 65 years	26.791%	17.861%	8.930%	0%
65-69 years	31.256%	22.326%	13.395%	0%
70 years and over	35.722%	26.791%	17.861%	0%
	MLS rate applying to income threshold			
MLS rate	0%	1%	1.25%	1.5%

* *The family income threshold is increased by $1,500 for each dependent under 21 years old or between 21-24 years old and a full-time student.*

Source: ATO (2016)

The introduction of different PHI reforms in Australia since 1997 is summarised in Table 2.2.

Table 2.2: Chronology of recent PHI reforms in Australia

Year	Reform
1997	- PHIIS offered tax-subsidies to lower income individuals and households to take up PHI - MLS tax levy of 1% imposed on higher income earners without PHI
1998	- PHIIS tax subsidy replaced by a non-means tested, flat 30% rebate on private health insurance premiums.
2000	- LHC introduced, allowing funds to charge premium loading for those purchasing PHI after the age of 30 (2% for each year above 30) - Legislation introduced requiring PHI funds to offer at least one no/known gap hospital insurance policy
2005	- Higher PHI premium rebates for older individuals.
2007	- BHC initiative introduced, allowing PHI funds to cover clinically appropriate substitutes to hospital treatment (for example, hospital substitute care at home or at community health care clinics) and programs to manage chronic diseases. - New risk equalisation arrangements supporting community rating under BHC introduced including provisions for differential pricing treatment of single parent families to two-parent families.
2008	- Legislation introduced requiring uniform safety and quality standards for facilities and providers offering PHI services.
2012	-Under the FPHII Act, means testing of existing age-related PHI rebates introduced based on three income tiers (individuals in these tiers entitled to reduced or zero rebates). - Increased MLS rates applied to top three income tiers – allowed to vary from 1% to 1.5% based on income level.
2013	- Rebate from the LHC loading removed from 1 July 2013
2014	- From April 2014, PHI rebates subject to discounting by a rebate adjustment factor - Government announced freeze on income thresholds for PHI rebates and the MLS at 2014-15 indexed rates until 2017-18

2.2 Trends in membership and downgrading since FPHII reforms

2.2.1 PHI membership

Figure 1 shows PHI hospital coverage rose dramatically in the year 2000, after the introduction of the PHIIS, MLS and LHC reforms. A distinct change in hospital coverage is not evident following the introduction of FPHII in 2012, but there is indication that growth in overall hospital coverage slowed slightly.

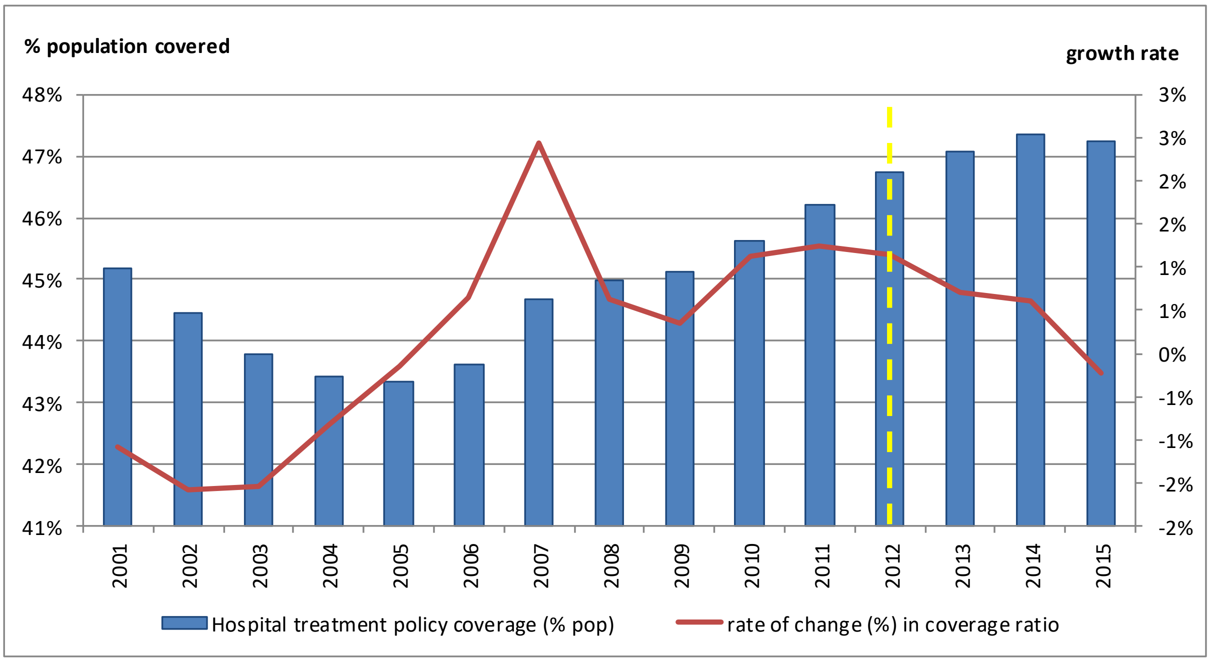

Figure 2: PHI coverage for hospital treatment in Australia

Source: Created from APRA data (2016)

Table 2.3 shows the growth in PHI policies recorded by the ATO (hospital and/or general treatment) by 'total income' group. This data are not all inclusive because it only shows policies recorded by the ATO through income tax return data. This data shows that there was a decrease in PHI policies recorded by the ATO for most income groups immediately following FPHII introduction in 2012-13. In 2013-14, there was positive growth in PHI policies for most income groups. Generally, the highest income groups had lower growth in PHI policies across all years, compared to lower income groups.

Table 2.3: Annual growth in PHI policies (hospital and/or general treatment), by total income, recorded by the ATO

Income group	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14
<$6000 to $50,000	3.5%	1.8%	-0.2%	3.6%	0.9%	6.7%
$50,001 to $80,000	-1.9%	-2.2%	-3.1%	-1.2%	-0.3%	3.1%
$80,001 to $100,000	0.5%	-0.2%	-1.6%	-1.4%	-1.4%	1.1%
$100,001 to $150,000	-1.2%	0.0%	-2.2%	0.0%	-0.8%	1.3%
$150,001 to $180,000	-0.5%	0.0%	-1.8%	0.0%	-1.4%	0.7%
$180,001 to $250,000	-0.2%	0.1%	-0.5%	0.0%	-1.0%	0.0%
$250,001 to $500,000	-0.1%	0.3%	0.0%	0.0%	-0.7%	0.0%
$500,001 to $1,000,000	-0.3%	0.5%	0.0%	0.0%	-0.7%	-0.3%
$1,000,001 or more	0.0%	0.4%	0.5%	0.0%	-0.4%	0.1%
Total	**2.1%**	**1.5%**	**4.0%**	**0.0%**	**1.4%**	**4.9%**

Source: ATO (2016) – special data request

2.2.2 PHI downgrading

The Australian Prudential and Regulation Authority (APRA) (2016a) compiles quarterly data on PHI hospital policies by coverage level, which is useful for analysing potential changes in downgrading of policies following FPHII reform introduction. This is presented in Figure 3 below. This data shows potential downgrading occurred since policy introduction, with a gradual decline in full cover policies over 2012-13 and 2013-14, and a switch towards reduced cover policies (both 'no lifetime exclusions' and 'some lifetime exclusions' policies). This data shows intensified downgrading occurring a bit later after policy introduction, towards the end of 2013-14 and into 2014-15, with a sharp switch from 'reduced cover but no lifetime exclusions' policies to 'reduced cover but some lifetime exclusions' policies.

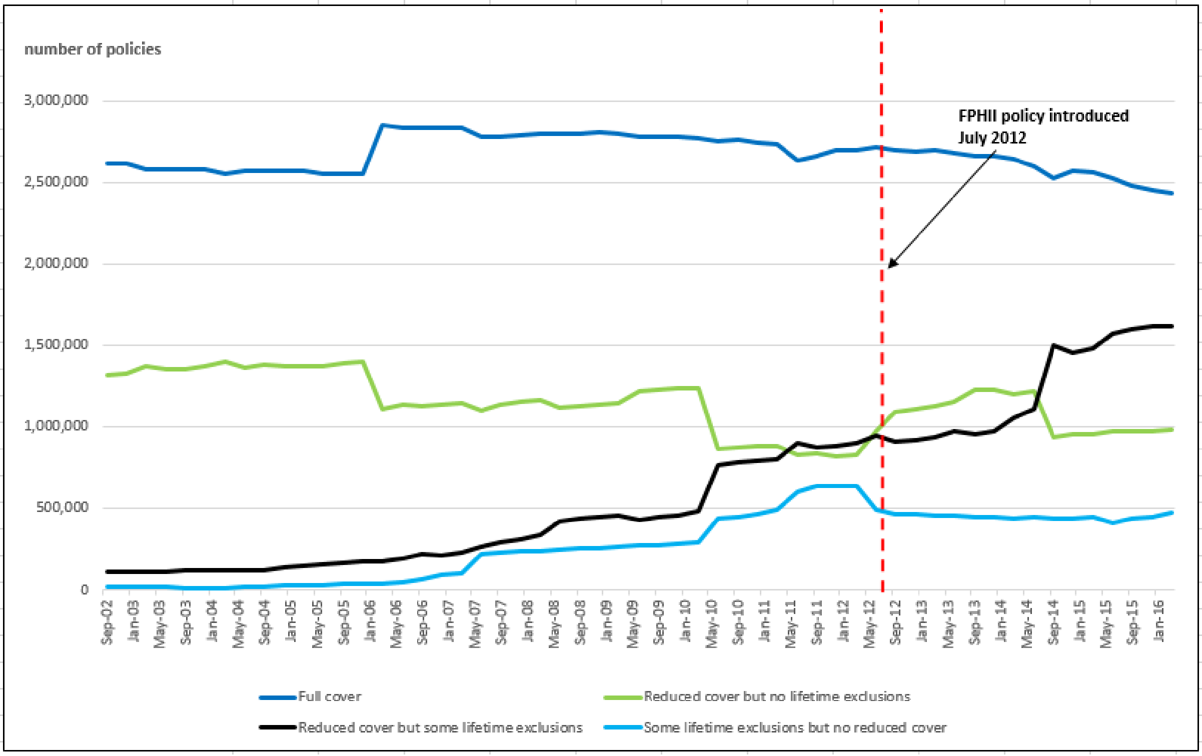

Figure 3: PHI hospital policies by coverage level

Source: Created from APRA data (2016a)

3 The effects of past PHI market reforms in Australia

Australian studies have analysed the effects of past PHI reforms on the probability of holding hospital cover. Literature review on past Australian studies assists the current investigation by analysing potential mechanisms through which past PHI reforms affected variables of interest. These findings may have some bearing on the potential effects of the FPHII reforms.

Exploring the methods and datasets used in past studies also allows the identification of datasets of interest and the strengths and limitations of past methods in this area. Additionally, it allows the identification of potential gaps in current understanding, and datasets and methods that have not been utilised in past studies.

3.1 Literature review

Early and recent studies have analysed the effects of specific reforms on the changes in PHI membership, including changes in coverage level and the membership profile by age and income group (Butler, 2003, Frech et al., 2003, Palangkaraya and Yong, 2005, Walker et al., 2005, Palangkaraya and Yong, 2004, Palangkaraya et al., 2005, Palangkaraya et al., 2009, Ellis and Savage, 2008, Stavrunova and Yerokhin, 2014). However, the primary challenge in isolating the effects of specific policies is that the PHIIS, MLS and LHC reforms were introduced in close succession over a short period of time.

Some have attributed the increase in PHI uptake that occurred post-2000 to primarily the 2000 LHC policy (Butler et al., 2003, Frech et al., 2003, Walker et al., 2005, Ellis and Savage, 2008). Butler (2003) analysed time series data to investigate changes in coverage after the introduction of policy reforms and concluded that LHC was the main contributor to the increase in PHI uptake. Based on this attribution, Butler estimated that demand for PHI was relatively price inelastic (point estimate of -0.23). A limitation of this paper was lack of econometric analysis to estimate a counterfactual and isolate a precise estimate of the policy effect. Butler's analysis was largely based on visual analysis of trends before and after successive policy changes, which ignores the possibility of earlier policies affecting PHI membership with a lag or of the total coverage increase being a result of the successive contribution of all reforms. There is also a possibility of confounding the policy effect with a time trend when using a simple pre- versus post- estimator of the policy effect on one group (here, the general population) (see Section 6.1).

Frech et al. (2003) conducted a more rigorous time series analysis of the reforms by fitting a deterministic trend to PHI coverage data from the earlier policy-stable period of 1987 to 1997 and then analysing differences between fitted and actual levels of coverage over the 1997 to 2000 reform period based on the timing of different reforms. The study estimated coverage increased 11% due to the rebate and derived a price elasticity of -0.37%, which is similar to the estimate by Butler et al. (2003). Coverage was estimated to have increased by 42.8% in the first three quarters of 2000, which the authors attributed entirely to enrolment due to the LHC deadline threat. The authors concluded that LHC was the primary contributor to the increase in coverage. Similar to Butler et al. (2003), a limitation is that this conclusion is based on the assumption of short-term effects following immediately after individual policy changes. If the rebate and MLS reforms had a longer-term impact on coverage, the effects of these reforms would be underestimated and the effect of LHC would be overestimated.

Walker et al. (2005) analysed Australian Bureau of Statistics' (ABS) PHI and National Health Survey (NHS) data in a time series spanning from 1983 to 2001 to conduct a simulation analysis of the reforms' effects on PHI coverage. After disaggregating population groups by age, sex and income, they used logistical regression to model the probability of coverage from 2002 to 2010. To investigate the contribution of individual reforms, the authors modelled three scenarios, a base scenario with no reforms, a 'current world' scenario with both rebate and LHC, and a 'removal of rebate' scenario with hypothetical removal of the rebate from 2004. The rebate removal scenario was based on historically observed responses of individuals to increases in their OOP costs for PHI. A 2% per annum real increase in PHI premiums was assumed in all scenarios, based on historical trends between 1994 and 2001. The study estimated that coverage would have declined to under 20% in the absence of any reform. Under the current world scenario, they estimated coverage would peak at 40% in 2010. The highest impacts on PHI coverage were estimated to have been for the 25-34 and 35-54 years age groups, with minimal impacts for those aged 75 and older. Under the rebate removal scenario, they estimated a modest drop in coverage following 2004, with PHI coverage just under 40% in 2010.

Hence, most of the coverage increase was attributed to LHC. Increases in PHI coverage were estimated to be higher among the most affluent 20% of the population. The initial rebate was replaced with a non-means tested rebate in 1998, while the MLS penalty was geared towards uninsured higher income earners. This arrangement may have led to the finding of higher income earners responding most to policy changes. However, the analysis did not isolate the effect of the MLS reform.

Similar to these studies, Ellis and Savage (2008) also attributed the increase in coverage primarily to LHC, not from the entry-age premium surcharges, but rather through the mass marketing campaign and deadline for LHC commencement. They exploited a series of questions on timing of PHI take-up in 2001 NHS cross-sectional data to isolate the effects of specific reforms. The data was broken up into a series of policy periods (before 1997 PHIIS reform, after PHIIS reform but before flat 30% rebate reform, after 30% rebate reform but before LHC and after LHC). The PHI choice process was modelled as a sequence of binary choices, with a choice made each period for those not insured in the previous period. Each of the reforms was modelled through effects on premiums and a policy dummy to reflect non-price related impacts. The LHC reform and associated advertising campaign around the LHC 'deadline' were modelled as affecting expected future premiums and a policy dummy. Clustered logit estimation simulated the effect of removing specific reforms on coverage. The authors found that removing the 30% rebate while leaving the other reforms intact would reduce overall coverage by 2% for singles and increase overall coverage for families by 2%. The result for families appears counter-intuitive. Similar to Walker et al. (2005), the authors found the reforms increased the propensity of high income earners to purchase PHI. This may have been due to the MLS, which was not isolated.

Ellis and Savage (2008) also found that removing the premium penalties ('price effects') associated with the 2000 LHC would reduce coverage by 2% for singles and 7% for families. Removing the 2000 policy dummy (non-price related aspects of LHC) was estimated to reduce coverage a further 4% for singles and 5% for families. By attributing the entire effect of the 2000 policy dummy to the LHC advertising campaign, they concluded the LHC deadline advertising campaign had had the greatest impact on the increase in coverage. This approach, however, ignores that other factors may have been behind the effect of the 2000 dummy. For example, the no/known-gap policy scheme was also introduced in 2000 (Section 2.1) which may have caused substitution towards private hospital services (Hopkins and Zweifel, 2005). As with earlier studies (Butler et al., 2003, Frech et al., 2003), Ellis and Savage (2008) assumed that immediate effects in the period following introduction of a reform were attributable to that reform. This ignores delayed impacts of the other reforms on coverage, and potential interaction effects between the individual policies.

Ellis and Savage (2008) found an implied elasticity of PHI demand with respect to current price of -0.6 for singles and -0.4 for families. This is somewhat more elastic than Butler's (2003) estimate of -0.23 but is still relatively inelastic. Because premium expenditures were imputed from Medibank data, the possibility of attenuation bias is noted. The estimated effects of current and future premiums on PHI purchase are a lower bound, suggesting that impacts from price-related rebate reform may have been underestimated.

Overall, these studies attributed the bulk of the membership increase to the LHC (Butler et al., 2003, Frech et al., 2003, Walker et al., 2005, Ellis and Savage, 2008). However, the trend analysis in these studies ignores the possibility of earlier policies affecting PHI membership with a lag or of the total coverage increase being due to interactions between policies. It is possible that the LHC may have been the 'tipping point' in affecting coverage in the broader package of reforms.

By attributing the bulk of the policy effect to LHC, these studies concluded the rebate reforms had limited effectiveness and that demand for PHI in Australia is relatively price-inelastic (Butler et al., 2003, Frech et al., 2003, Walker et al., 2005, Ellis and Savage, 2008). This is supported by a recent study (Cheng, 2014) which found price elasticity in the range of -0.36 to -0.41 and estimated that net cost savings would occur from reducing rebates for PHI.

A series of studies by Palangkaraya and Yong (2004, 2005, 2009) using a variety of estimation approaches on 1995 and 2001 NHS cross-sectional and found that the overall contribution of LHC may have been less than that estimated by earlier studies. Their earliest study (Palangkaraya and Yong, 2004) used a regression-discontinuity approach to isolate the impact of LHC, by exploiting the fact that LHC affected individuals in a certain age group (30 years and older) while the 30% rebate affected all individuals. They noted LHC introduced a discontinuity at age 30, which was particularly important during the grace period from September 1999 to July 2000 before the LHC premiums came into place. Because the ABS age-group classification for their treatment and control group distinction (25-29 and 35-39) was too coarse and introduced unobserved age-correlated factors, they compared estimates between 1995 (pre-LHC) and 2001 (post-LHC) to remove these. Using a linear probability model (LPM), they estimated that LHC significantly raised the coverage of singles by 4.7% with no control variables and 6.8% with control variables. They found the estimate differed by income group, with no statistically significant effect found for low-income individuals, and a significant estimated increase of 15.5% to 17.2% for high-income individuals. An estimated increase of 5.6% to 9.1% was found for middle-income individuals. A limitation of this study in terms of generalisability to the overall effect of LHC was the exclusion of families from the analysis.

Palangkaraya and Yong (2005) estimated the total effects of reforms on coverage for both singles and families by estimating demand models for 1995 and 2001 using logit estimation. They constructed a counterfactual scenario by applying the 2001 NHS data to the estimated 1995 estimated coefficients (which did not reflect policy changes), which enabled the estimation of the PHI decision under a hypothetical scenario with no policy effects. A household was estimated to be affected by the policies if it had no PHI under the counterfactual but was actually covered by PHI in 2001. The effects of LHC were isolated under the assumption that it affected households in the target age group of 30 to 69 years, while other non-LHC policies affected all households in a uniform manner. They found the reforms induced 15.5% of singles to take up PHI and 30.1% of families to take up PHI. For singles, they found 61% of the 15.5% PHI increase was from individuals aged 30 to 69 years (the LHC target group). Between 41 to 61% of the coverage increase for singles, and 42 to 78% of the coverage increase for families was attributed to LHC. However, the upper bound estimates for the LHC are unlikely because the authors attributed the entire coverage increase for the LHC target age group to LHC. Additionally, the assumption that consumers in younger age groups were not affected by the LHC ignores the potential for younger consumers to be forward-looking in early purchases of PHI to avoid the LHC.

In their most recent study, Palangkaraya and Yong (2009) applied probit modelling and created a counterfactual by applying 1995 coefficients to 2001 household characteristics and then applying a Blinder-Oaxaca decomposition to the change in PHI take-up to isolate policy effects. They estimated the reforms increased probability of coverage by 12.2% for singles and 12.8% for families. Their estimate for singles aligned with the confidence interval from their earlier study (Palangkaraya and Yong, 2005). Notably, Palangkaraya and Yong (2009) found many households from high income groups would have purchased PHI in the absence of reforms and thus enjoyed windfall gains from the 30% rebate.

A limitation across several studies was that none attempted to isolate the impact of the MLS reform on PHI coverage. This is particularly significant because several studies found that the increases in PHI coverage as a result of the reforms were more pronounced for higher income groups (Palangkaraya and Yong, 2004, 2009, Walker et al., 2005, Ellis and Savage, 2008). The MLS was the only reform geared specifically toward higher-income groups which may have had a bearing on these findings.

Stavrunova and Yerokhin (2014) addressed this limitation by estimating the effect of the MLS on PHI coverage using a regression discontinuity-type method. They analysed 2007-08 income tax data for single, childless individuals and PHI demand at the MLS threshold, after controlling for a bunching interval (where taxpayers were found to 'shift' income to avoid hitting the threshold). Unlike earlier studies, this analysis was not undertaken to analyse the immediate effects of PHI reforms when they were introduced. However, it does provide an indication of how the MLS contributes to Australian PHI coverage rates, from which the importance of the MLS in the earlier reform package can potentially be inferred. Stavrunova and Yerokhin (2014) found that the MLS increased coverage at the MLS threshold by 15.6% for the treated group. To estimate the total effect of the MLS on the treatment group (those above the MLS threshold), a constant MLS effect per dollar of the tax was assumed and this was extrapolated to PHI coverage rates at higher income levels. It was estimated that total PHI coverage increased by 7.2% for all singles above the threshold and concluded that the MLS had only a modest effect on coverage. In fact, the authors note their estimated MLS effect would be an upper bound because it might be expected that higher income earners would be less responsive to a tax of given size, as opposed to their constant effect assumption. Stavrunova and Yerokhin (2014) also found the oldest age group (50+) displayed the strongest increase in PHI coverage due to the MLS (9.2 percentage points). PHI coverage of the youngest age group increased by 7.4 percentage points while the middle age group was found to be least responsive to the MLS with a 5 percentage point increase. The authors suggest that older individuals are likely to have the highest net benefits from purchasing PHI which makes them most responsive to the policy. This is evidenced by the youngest age group being found to have the largest proportion of non-compliers with the MLS mandate.

Stavrunova and Yerokhin's (2014) study was limited to childless singles, thus is not generalisable to the entire population with PHI above the MLS threshold. This is important because earlier studies found that families are likely to be more responsive to PHI policies than singles (Palangkaraya and Savage, 2005, Ellis and Savage, 2008). Additionally, because the study analysed data from several years after the reform, it may not provide an accurate indication of the MLS' effectiveness in raising coverage shortly after it was introduced. The impact of the introduction of the MLS on the increase in coverage in the immediate post-reform period has not been isolated by any study.

No previous studies have attempted to empirically estimate the effects of the recent 2012 FPHII reforms which introduced reduced means-tested rebates and increased MLS rates for three tiers of high income earners. However, the findings of past literature on previous PHI reforms in Australia may have some bearing on the potential effects of FPHII. If, as earlier studies have found (Butler, 2003, Frech et al., 2003, Walker et al., 2005, Palangkaraya et al., 2009, Ellis and Savage, 2008, Cheng, 2014), demand for PHI in Australia is indeed relatively price-inelastic, reduced rebates may result in limited effects on overall coverage and result in net cost savings, as predicted by Cheng (2014). Additionally, if the contribution of the MLS on coverage is modest (Stavrunova and Yerokhin, 2014), the increased MLS rates may have little effect on PHI coverage and result in increased tax revenue.

Another channel through which the FPHII reforms may have effects on coverage is through the downgrading of policies by individuals, whose net benefits of PHI purchase would have been altered due to the reforms.

Downgrading has not been explored in previous studies but may have important implications, including for health care use and equity. Downgrading coupled with asymmetric information on the insurer side could result in consumers not being covered for services they need (ACCC, 2015), and/or facing longer waiting times for these services by relying on the public sector. Because PHI often covers ancillary services including dental care and different combinations of hospital services, downgrading could result in potential inequity the use of services which are dropped, such as dental cover.

Past studies have relied wholly on cross-sectional data from the ABS NHS to analyse insurance choices in response to policy reforms, which is not as empirically powerful as following the decisions of the same individuals over time.

These gaps present an important area for research investigation. Past studies have not employed longitudinal analysis or a difference-in-difference estimator to analyse the effects of PHI reforms in Australia. The difference-in-difference estimation method offers several unique advantages in isolating the effect of policy, and these are discussed in Section 6.1.

4 Conceptual framework

Demand for PHI can be analysed under an expected utility framework, where consumers analyse the expected net benefits of PHI purchase compared to non-purchase. This assists in understanding determinants which may factor into the PHI purchase decision. It also provides context for the current analysis, as government intervention in PHI affects consumer net benefits, thereby affecting the PHI purchasing or downgrading decision.

4.1 Determinants of the PHI purchase decision

Under the theoretical framework (Cameron and Trivedi, 1991, Barrett and Conlon, 2003, Ellis and Savage, 2008, Palangkaraya and Yong, 2005), households are assumed to purchase PHI when the expected utility of purchasing exceeds the expected utility of not purchasing. In other words, the decision to purchase PHI occurs when there are expected positive net benefits associated with making the PHI purchase.

Robson et al. (2011) note several factors that may influence the net benefits of PHI for an individual, and thus influence the purchase decision. These include:

- income;
- price;
- tastes (individual's attitude toward risk);
- risk factors (individual's subjective probability assessment of health risks); and
- characteristics of the insurance product.

Income

Income can influence the probability of purchasing PHI (Finn and Harmon, 2006). On the one hand, higher income earners can more easily afford to purchase PHI and have a lower opportunity cost of purchase than lower income earners, as PHI constitutes a smaller proportion of their total budget. Additionally, higher income earners have a higher opportunity cost of time (in terms of wage per hour). The cost of poor health would be greater, if it resulted in reduced productivity. Because use of public health care is associated with a longer waiting time to receive treatment than private health care, those on higher incomes and those employed would have a greater incentive to purchase PHI (Hopkins and Kidd, 1996).

The effect of income on insurance purchase is also governed by the degree of risk aversion (Feldstein, 1973), the source of the income change and consumer preferences (Ehrlich and Becker, 1973). At prices which are not at the actuarially fair level and when expected loss is positively related to initial income (as with a higher opportunity cost of time), an increase in initial income would shift the demand curve out at every price, while the slope of the demand curve would be affected by the degree of absolute risk aversion (Cleeton and Zellner, 1973). With declining risk aversion, higher income would lead to a decrease in PHI demand, while with increasing risk aversion, higher income would lead to an increase in PHI demand. Empirical studies in Australia find that higher income individuals have a greater propensity to purchase PHI (Barrett and Conlon, 2003, Hopkins and Kidd, 1996, Savage and Wright, 2003), which supports the premise of increasing risk aversion with higher income.

Price

Under actuarially fair prices, the demand for net PHI coverage (payout minus premium) would be a downward sloping function of price (Ehrlich and Becker, 1972, Folland, Goodman and Stano, 2007, Robson et al., 2011). Empirically, studies in Australia have found the demand for PHI in Australia to be relatively price-inelastic (Butler et al., 1999, Butler et al., 2003, Cheng, 2014, Frech et al., 2003, Walker et al., 2005, Ellis and Savage, 2008).

Tastes

'Tastes' refer to an individual's attitude toward assuming risk. Those exhibiting risk aversion have a diminishing marginal utility of wealth or income, whereby the utility from an extra dollar of wealth or income is worth more when one is relatively poorer, and vice versa. Risk aversion is one of the conditions required for insurance purchase (Ehrlich and Becker, 1972, Rothschild and Stiglitz, 1976).

Risk factors

Health risk affects the expected utility of PHI through its relation to expected medical need and through utility derived from health. Ultimately, individuals purchase PHI as they value their health. Individuals derive utility from health alone (as a consumption good) and also because it increases the number of healthy days available to work and earn income (as a capital good) (Grossman, 1972). Demand for health care is a derived demand, to a large extent, because consumers desire the final product of healthy days (Grossman, 1972). Similarly, demand for PHI, which facilitates health care access and financing, may also be seen as a derived demand, with the ultimate consumer desire being healthy days.

Individuals may face a greater risk of being ill due to their age, sex, health behaviours and pre-existing health conditions. Being older or female may lead to increased medical need (Hopkins and Kidd, 1996). Additionally, marital status and number of dependents are also related to medical need. Most studies find that marital status has a positive link to PHI purchase, while there are mixed findings on the effect of dependent children (Hopkins and Kidd, 1996). Health risk and medical need affect expected loss in the case of ill-health. Assuming a concave utility of wealth function (risk aversion), an increased expected loss would lead to an increased propensity to insure (Folland, Goodman and Stano, 2007).

Individuals with higher health risk (and expected losses) are more likely to insure and asymmetric information may exacerbate this situation, leading to adverse selection and potential crowding out of low-risk individuals in PHI markets (Rothschild and Stiglitz, 1976). Community-rating regulation, as in Australia, may potentially further aggravate such a situation, because younger, healthier individuals face higher premiums than they would in an unregulated market, which may cause them to drop out, leading to even higher prices, further drop out and an ‘adverse selection death spiral’ (Buchmueller, 2008).

Recent empirical studies, however, have found positive selection into PHI markets in Australia (Buchmueller et al., 2013, Doiron et al., 2008). These studies suggest a link between health risk and risk preferences can mean that more risk averse individuals (who are more likely to insure) also tend to be healthier (Doiron et al., 2008). Under this reasoning, individuals exhibiting risky behaviours (e.g. smoking) are less likely to be in good health and purchase PHI. Buchmueller et al. (2013), supported this finding in Australia via analysis of 2005 NHS data and found that those purchasing PHI were also more likely to purchase other types of insurance and be risk-averse. The authors suggest other reasons for positive selection in Australian PHI may be cognitive ability and income, which positively affect PHI status and negatively affect expected claims

Characteristics of the insurance product

Hopkins and Kidd (1996) note that quality differences between the public and private health care sectors and interstate differences in the mix of public and private health care services are other factors which may affect the PHI purchase decision in Australia. They note that historical differences in the interstate public provision of health care services has led to differences in the private sector's mix and size of services, across states.

4.2 Relative importance of determinants of PHI purchase

The expected utility of purchasing PHI is dependent on different factors, each of which is weighted differently by different individuals, and which may be weighted differently for the same individual over time. There has been limited empirical research on the demand for PHI and relative importance of factors in the PHI purchase decision. The ABS NHS contains a question asking individuals on their reasons for purchasing PHI. Analysing the responses to this question can provide insights into Australian consumers' demand determinants for PHI and how these are changing over time. Table 4.1 shows changes in the ranking of different factors behind PHI purchase, based on percentage of responses where the factor was selected as a reason for purchase. The data shows that the ranking of different factors has not changed much over time. The reason most related to risk aversion ("security/protection/peace of mind") remains the most cited reason for purchase while reasons related to insurance product characteristics ("choice of doctor", "treatment as private patient" and "benefits for ancillary services") also remain important.

The reason related to government benefits and avoiding the MLS ranks lower down the list of reasons at seventh, and has remained constant in rank. The responses are not disaggregated by income level here, which makes it difficult to see the potential effect of the FPHII reforms, as specific income groups were affected.

Table 4.1: Ranking of factors behind PHI purchase (ABS NHS)

Reason for PHI purchase	2008-09	2009-10	2010-11
Security/protection/peace of mind	1	1	1
Allows treatment as private patient in hospital	2	2	2
Choice of doctor	3	5	5
Shorter wait for treatment/concern over public hospital waiting lists	4	4	4
Provides benefits for ancillary services/"extras"	5	3	3
Always had it/parents pay it/condition of job	6	6	6
To gain government benefits/avoid extra Medicare levy	7	7	7
Lifetime cover/avoid age surcharge	8	8	8
Elderly/getting older/likely to need treatment	9	10	9
Has illness/condition that requires treatment	10	9	10
Other financial reasons	12	12	11
Other reason	11	11	12

Source: ABS (2009, 2013, 2016)

4.3 Graphical analysis on the potential effects of the FPHII reforms on PHI membership and coverage

The MLS and PHI premium rebates potentially affect a consumer's PHI purchase decision through their influence on individual and household income and expenditure on PHI (i.e., price). There may be a group of consumers who value PHI so highly that their purchase decision is unaffected by the MLS and rebates (Robson et al., 2011). However, a group of consumers may be amenable to changing their purchase decision through reforms based on financial incentives, such as FPHII. The ultimate effect of policy on a consumer's downgrading or purchase decision is influenced by the consumer's income level relative to the price of PHI, the initial level of PHI cover (because this influences the ability to downgrade), and expected future medical need.

4.3.1 Effects on PHI purchase

As noted by Robson et al. (2011), offering PHI premium rebates results in consumers being more able to afford PHI compared to other goods, with the same amount of income. This would lead to increased consumer welfare due to lower PHI costs. If PHI is assumed to be a normal good (as has been shown empirically in Hopkins and Kidd (1996), Barrett and Conlon (2003), and Savage and Wright, (2003)), then PHI rebates would increase the demand for PHI for those consumers amenable to influence.

Figure 4 shows a situation where consumers who would not necessarily purchase PHI (because their willingness-to-pay (WTP) would be less than the premium) might be influenced into purchasing PHI through premium rebates. If the premium rebate (P_S) is high enough, it would make the net benefits of PHI purchase positive (shift the net benefits curve to above the horizontal axis), and consequently lead to these consumers purchasing PHI. Figure 4 shows the situation where premium rebates are not means-tested, and where the entire group of consumers has the same WTP.

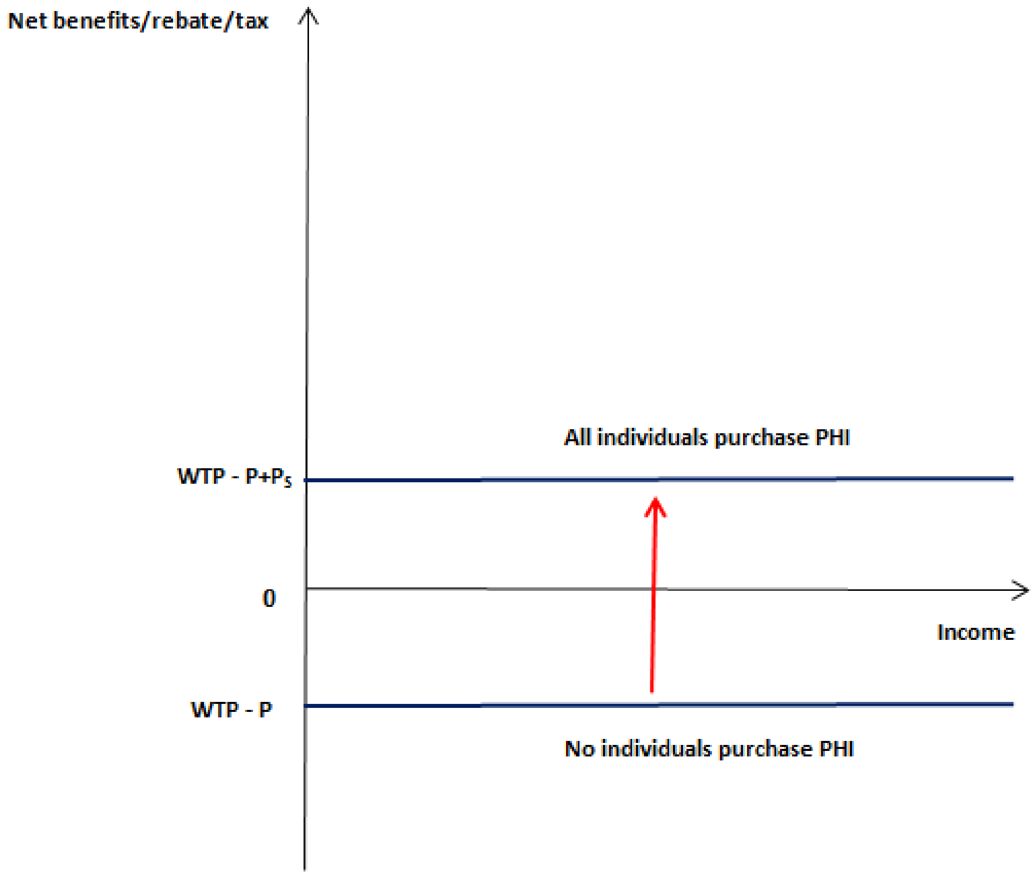

Figure 4: Potential effects of non-means tested premium rebates on PHI purchase

Source: adapted from Robson et al. (2011) and Robson and Paolucci (2012)

Figure 5 shows the potential effects of means-testing rebates at three different income tier levels, with the highest tier getting no premium rebate (as in the FPHII reforms). This either decreases purchases of PHI (as shown below) or has no effect (if consumers' WTP below the price, even with the rebates). Prior to the policy change, all consumers would purchase PHI, with the availability of the flat rebate. With means-testing for tiers Y_1, Y_2 and Y_3, the net benefits curve would shift from W_1 to W_2. This would result in some consumers not purchasing PHI, as their WTP would now be less than PHI price.

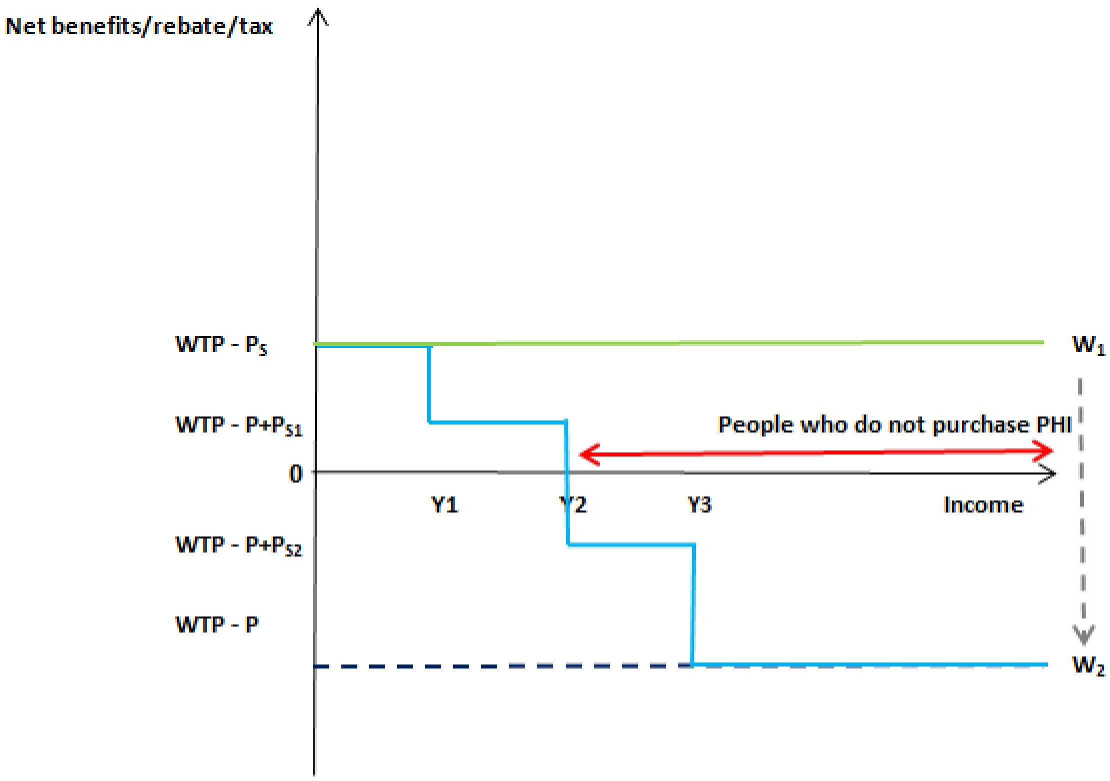

Figure 5: Potential effects of means testing the PHI rebate on PHI purchase

Source: adapted from Robson et al. (2011) and Robson and Paolucci (2012)

Because the MLS is a flat tax on consumer income, its impact on PHI purchase (for consumers above the MLS threshold) depends on the consumer's initial income level relative to the price of PHI.

Figure 6 shows the situation where non-means tested premium rebates on their own are not high enough to influence consumers to purchase PHI, but the introduction of the MLS causes the net benefits curve to kink upwards at the income threshold, Y*, with some consumers now purchasing PHI. The increasing slope of the curve after the kink represents increasing benefits from avoiding the MLS at higher income levels, as the MLS is proportional to income.

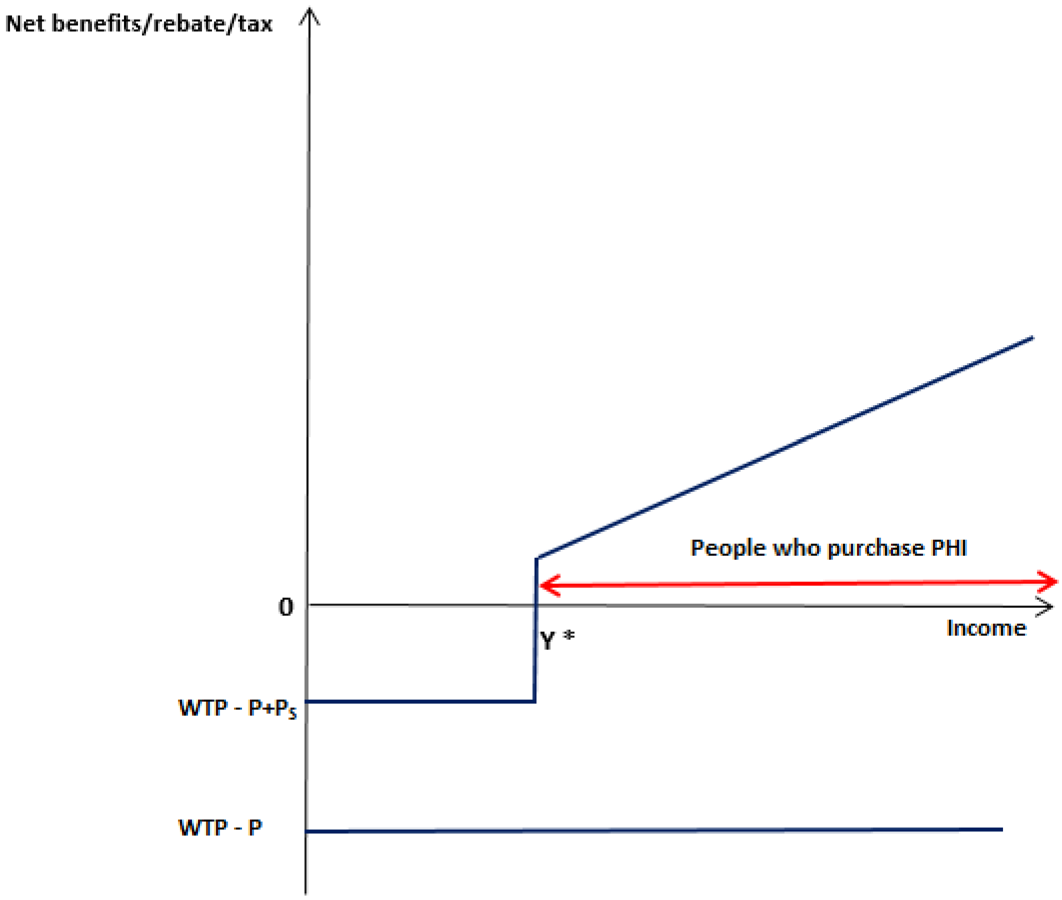

Figure 6: Potential effects of the MLS on PHI purchase

Source: adapted from Robson et al. (2011) and Robson and Paolucci (2012)

Increased MLS rates would impact individuals differently across FPHII income tiers. If a large proportion of individuals in higher income tiers already have PHI cover, an increased MLS would have a greater ability to influence individuals in lower income tiers.

Figure 7 shows the potential differential impact of an increased MLS across income tiers. An increased MLS rate would steepen the WTP curve at the income threshold (Y1) where it starts applying. Prior to the policy change, all individuals in the higher income tiers, Y2 to Y3, and Y3 and over already purchased PHI cover. The increased MLS rate would thus influence only individuals in tier Y1 to Y2 by increasing the number purchasing PHI cover.

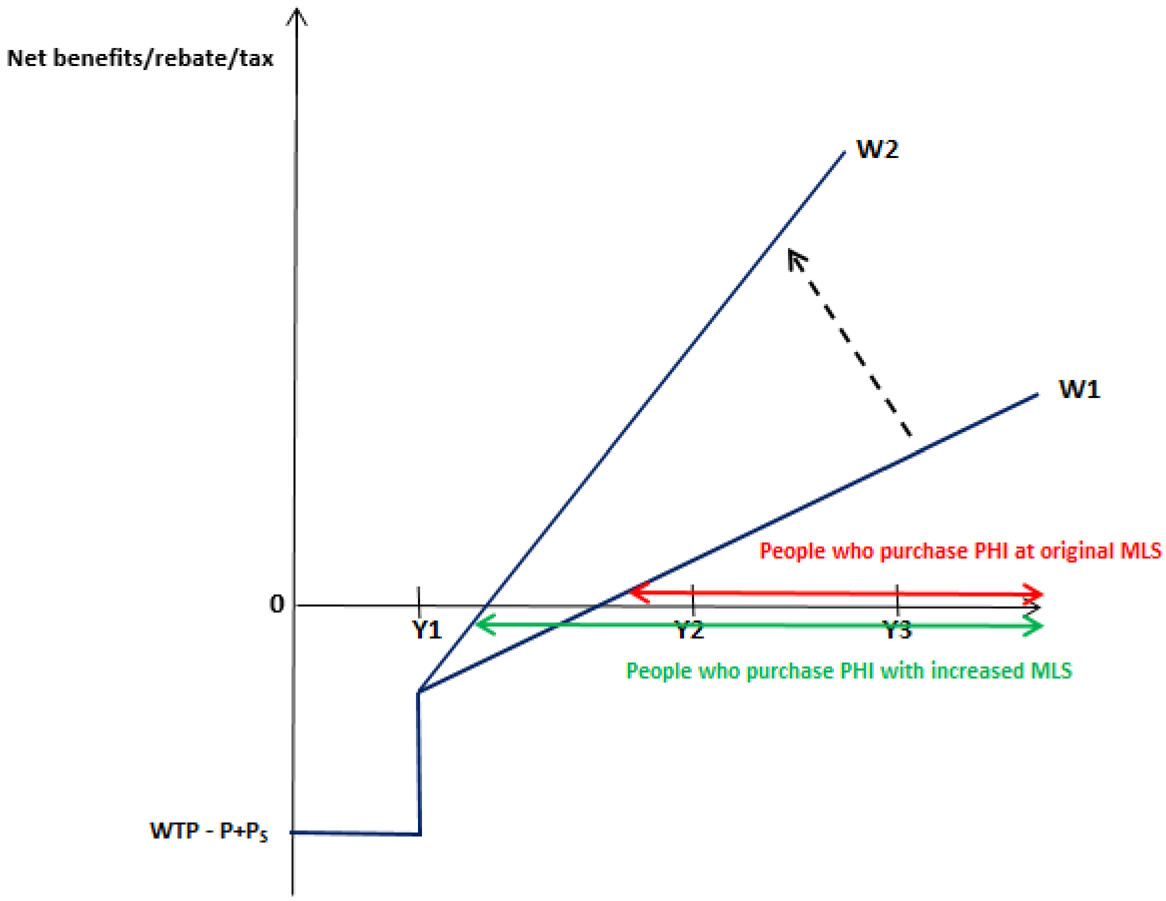

Figure 7: Potential effects of an increased MLS on PHI purchase across income tiers

Source: adapted from Robson et al. (2011) and Robson and Paolucci (2012)

Figure 8 shows the potential effects of the introduction of successively increased MLS rates for income tiers Y1 to Y2, Y2 to Y3, and Y3 and higher, as encompassed in the FPHII reforms. With a flat MLS rate applying from Y_1, the WTP curve is W_1. Increased MLS rates kink and steepen the WTP curve at the income level where they start applying. With three different MLS rates (means-testing), there are three kinks in the MLS curve at Y1, Y2 and Y3, with the curve, W_2 becoming successively steeper. Under a means-tested MLS with successively increasing rates by income level, the number of people purchasing PHI would increase. Here, the effect occurs in the lower income tier, Y2 to Y3, as the top tier Y3 and higher, would purchase PHI under both scenarios.

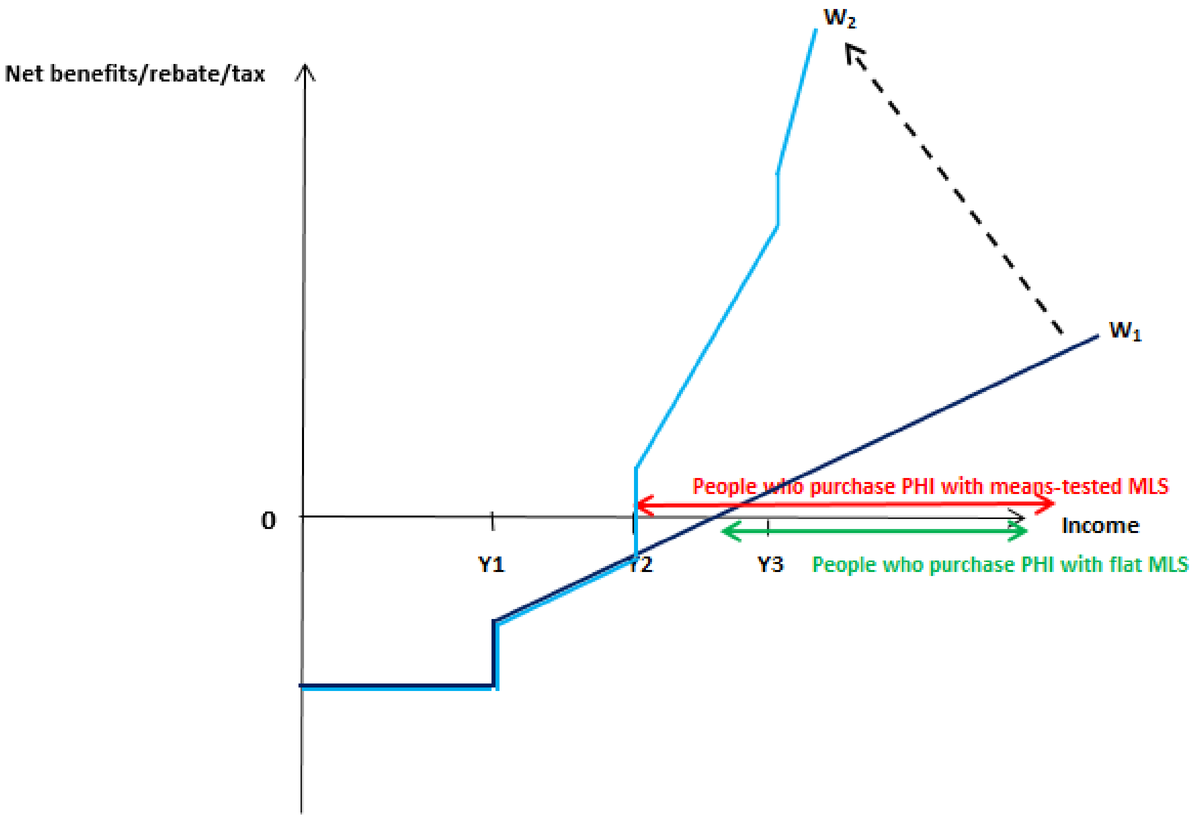

Figure 8: Potential effects of means testing the MLS on PHI purchase

Source: adapted from Robson et al. (2011) and Robson and Paolucci (2012)

Data from the ATO (2016) from the year 2011-12 shows very high proportions of individuals with PHI cover at higher income levels, which supports the premise that an increased MLS would be more likely to induce those in lower income tiers above the MLS threshold to purchase PHI. Additionally, the distribution of income in the Australian system supports the premise that there would be relatively small numbers of people in the higher income tiers, meaning the absolute impact on PHI membership would be low. The lower number of insured people in lower income tiers combined with the higher number of uninsured people in these tiers, would support that that greatest impact of an increased MLS would most likely to influence membership in these tiers.

Table 4.2 Proportion of individuals with PHI (hospital and/or general treatment), by income level, recorded by the ATO

Income level	Proportion of individuals with PHI cover
Less than or equal to $6,000	38%
$6,001 to $10,000	40%
$10,001 to $18,200	39%
$18,201 to $25,000	41%
$25,001 to $30,000	43%
$30,001 to $37,000	44%
$37,001 to $40,000	44%
$40,001 to $45,000	45%
$45,001 to $50,000	47%
$50,001 to $55,000	50%
$55,001 to $60,000	53%
$60,001 to $70,000	58%
$70,001 to $80,000	66%
$80,001 to $90,000	74%
$90,001 to $100,000	77%
$100,001 to $150,000	83%
$150,001 to $180,000	90%
$180,001 to $250,000	94%
$250,001 to $500,000	96%
$500,001 to $1,000,000	97%
$1,000,001 or more	97%
Total	**53%**

Source: ATO (2016)

4.3.2 Effects on PHI downgrading

The MLS affects consumers with income over the MLS threshold, by creating a discontinuous kink in the consumer's budget line at the level of minimum hospital cover required to avoid the MLS (Robson et al., 2011). The impact of the MLS depends on the consumer's initial income level (and hence, amount of MLS tax faced) relative to the price of a policy offering the minimum level of hospital cover required to avoid the MLS. Figure 9 shows how the introduction of the MLS may induce a consumer to increase their level of PHI coverage. Without an MLS, the consumer would have purchased PHI at the level PHI*. With the introduction of the MLS, if the consumer purchases PHI at a level lower than the required level of cover, 'min PHI', then the consumer's income would be reduced by the MLS rate multiplied by their income level, resulting in reduced consumer welfare (lower indifference curve). Hence, the consumer would rationally increase their level of coverage to the minimum level of required cover, because they would be worse off at their original PHI purchase level (Robson et al., 2011).

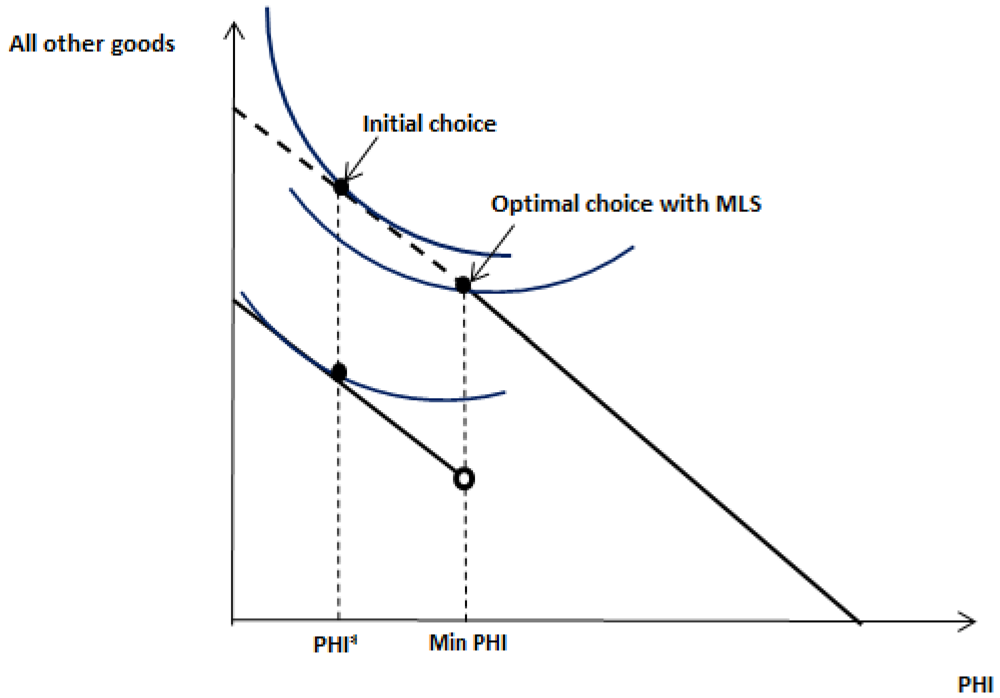

Figure 9: Potential effects of the MLS on a consumer above the MLS threshold

Source: adapted from Robson et al. (2011) and Robson and Paolucci (2012)

For insured individuals in the FPHII income tiers, reduced rebates (as encompassed by FPHII) would mean an increased PHI price (ΔP_{PHI}) and lowered welfare. If an individual with more cover than the minimum required level (to avoid the MLS), downgraded their policy in response to this price rise, this would be an attempt to recover these increased costs (ΔP_{PHI}).

The decision to downgrade is based on comparing the reduction in expected benefits from downgrading existing PHI cover (ΔEB_{PHI}) to the price savings from a downgrade (ΔP_{PHI}). Here, expected benefits from PHI (EB_{PHI}) depend on factors discussed in Section 4.1, such as future medical need (e.g. age, illness), risk aversion and product characteristics.

The ability to downgrade and associated price savings (ΔP_{PHI}) would also be dependent on an individual's initial level of PHI cover (Cov). If a consumer was already at the minimum level of PHI cover to avoid the MLS (Cov_{min}), this would reduce their ability to downgrade in response to a price increase.

If price savings exceeded the reduction in expected benefits from downgrading, then an individual would choose to downgrade.

$$[(\Delta P_{PHI} > \Delta EB_{PHI}) \mid Cov > Cov_{min}] \rightarrow downgrade$$

If, however, the reduction in expected benefits from PHI exceeded the price savings from downgrading, an individual would choose to maintain cover.

$$[(\Delta P_{PHI} < \Delta EB_{PHI}) \mid Cov > Cov_{min}] \rightarrow maintain\ cover$$

For consumers downgrading to levels below the minimum cover needed to avoid the MLS (Cov_{min}), price savings from downgrading net of the increase in MLS tax paid (ΔMLS) would exceed the reduction in expected benefits from PHI.

$$(\Delta P_{PHI} - \Delta MLS < \Delta EB_{PHI}) \rightarrow downgrade$$

4.3.3 Theoretical predictions

This analysis suggests means-testing PHI rebates would potentially have a negative impact on the demand for PHI by increasing price. The magnitude of this effect would be dependent on the degree of price elasticity of PHI demand.

Means-testing the MLS (with successively higher rates at higher income tiers) would have a positive effect on the demand for PHI. However, the impact is likely to be differential across FPHII income tiers, with more potential for impact among lower tiers of high income earners, due to existing high levels of PHI coverage at higher income levels. Because the FPHII reforms introduced both these changes together at the same income tiers, the ultimate impact would be based on which effect would be stronger. If price elasticity of demand for PHI is relatively low, as estimated in previous studies (Butler et al., 1999, Butler et al., 2003, Cheng, 2014, Frech et al., 2003, Walker et al., 2005, Ellis and Savage, 2008), the MLS effect may outweigh the reduced rebate effect, and the FPHII reforms would increase the probability of having hospital cover.

Downgrading of hospital cover may occur in response to reduced rebates (price increases) for those in the FPHII income tiers. Because the FPHII reforms introduced different levels of rebates across income tiers (with the highest tier receiving no rebate), the downgrading effect is likely to be differential across FPHII income tiers. The largest downgrading impact may occur for individuals in higher income tiers, due to the higher PHI price increases faced.

The downgrading effect also depends on individuals' initial level of PHI cover, and expected benefits from PHI. Thus, a potential downgrading effect may differ across different population segments.

5 Data and preliminary analysis

This section describes the division of the data into treatment and control groups and the dependent and explanatory variables used in the study. This section also presents the descriptive statistics on the dependent variables and some preliminary analysis on downgrading.

5.1 Household, Income and Labour Dynamics in Australia (HILDA) sample

Empirical analysis on the effects of the FPHII reforms in this study was carried out using data from the Household, Income and Labour Dynamics in Australia (HILDA) survey (Melbourne Institute, 2016). This is a household-based, longitudinal survey which commenced in 2001, and is conducted annually in the July to August period. Wave 1 contained information on 7,683 households and 19,914 individuals. Because HILDA is retrospective, questions and imputations on financial information from each wave apply to the previous financial year (for example, wave 1 questions apply to financial information from the 2000-01 financial year). However, other variables in the HILDA survey including on PHI status apply to the point of time the survey was conducted.

Because the purpose of this study is to examine the effects of the FPHII reforms on presence of PHI hospital coverage and downgrading of hospital cover, information in HILDA on PHI status and expenditure on PHI is of particular interest. Waves 2003-04, 2008-09 and 2012-13 contained questions on the PHI coverage of individuals. Additionally, the HILDA has collected total household expenditure on PHI premiums since 2004-05. The HILDA imputes household expenditure on PHI for missing cases.[1]

For this study, a balanced panel of individuals aged 15 years or older was analysed for the years 2003-04, 2008-09 and 2012-13 to look at the effects of the FPHII reforms on PHI status. Additionally, the years 2011-12, 2012-13 and 2013-14 were employed to analyse impacts on downgrading. Here, 2003-04, 2008-09 and 2011-12 constitute pre-FPHII reform years, and 2012-13 and 2013-14 constitute post-FPHII reform years.

[1] The proportion of missing cases for household expenditure on PHI ranged from 15.6% to 19.8% between waves 5 to 14 (Summerfield et al, 2015). Imputation was performed using either the nearest neighbour regression method for imputation of zeros, and nearest neighbour regression or Little and Su imputation for the imputation of non-zero amounts (Summerfield et al, 2015). Where possible, preference was given to Little and Su imputation, which could only be performed for cases enumerated over more than one wave with at least one wave of non-zero data.

After restricting the sample to individuals who answered questions on PHI and the other explanatory variables included in the model, the HILDA sample was reduced to approximately 6,520 individuals for the analysis using the 2003-04, 2008-09 and 2012-13 waves, and nearly 6,550 individuals for the 2011-12, 2012-13 and 2013-14 waves.

5.2 Division into treatment and control groups

When FPHII reforms were introduced on 1 July 2012, they affected those in income tiers 1, 2 and 3 in Table 2.1 as presented in Section 2.1. These tiers faced both reduced premium rebates and increased MLS rates, compared to the base tier.

Those in tiers 1, 2 and 3 constitute the treatment group for this analysis, while those in the base tier constitute the control group. The Australian Taxation Office (ATO, 2016) has a specific method for calculating 'income for MLS purposes' as the sum of:

- taxable income;
- reportable fringe benefits;
- total net investment losses (including net financial and net rental property losses);
- reportable super contributions;
- any net trust income not included in taxable income; and
- exempt foreign employment income.

In addition, for families, income thresholds increase by $1,500 for each dependent child after the first.

To estimate income for MLS purposes using HILDA data, household income variables were matched to components in the ATO MLS income definition. This was not a straightforward process, as HILDA income variables are not collected in a form exactly amenable to the ATO calculation. The MLS income calculation is outlined in Table 5.1 below.

Table 5.1 Calculation of income for MLS purposes using HILDA variables

Step	Description	HILDA variables utilised
1) Estimate taxable income	Estimated gross regular household income from HILDA includes elements such as wages and salaries, business income, investment income, pensions and government transfers (Wilkins, 2014). Estimated deductions were calculated by multiplying gross household income by rates noted in Wilkins (2014) (deductions as a % of gross income). These estimated deductions as well as household-level regular private pensions, private transfers, Disability Support Pension, parental leave and Family Tax Benefit payments (non-taxable payments) were all subtracted from gross household income to obtain an estimate of household taxable income.	- Gross regular household income (hifefp – hifefn) - Household Family Tax Benefit (hifftb) - Household Maternity Payments (hifmat) - Disability Support Pension payments (bnfdspa) - Household private pensions (hifppi) - Household private transfers (hifpti)
2) Calculate net investment losses	Subtract household-level estimated investment losses from household level investment gains.	- Household financial year investments - positive values (hifinip) - Household financial year investments - negative values (hifinin)
3) Estimate income for MLS purposes	Add components (1) and (2)	- All of the above variables

Source: ATO (2016) and Wilkins (2014)

As noted by Ellis and Savage (2008), the calculation rules linking the MLS and premiums to family structure and income are complicated and non-linear. Measurement error is noted here, as a possibility. However, this is the first study to attempt to isolate individuals' MLS income components and match them to variables in the collected dataset. Ellis and Savage (2008) included 'annual income' in their model, but did not note whether this included all of the components in the ATO definition. Because the estimated income for MLS in this study is amenable to measurement error, sensitivity analysis was conducted in the modelling to check the potential impact on results from the accuracy of the income measure (see Section 6.2.5).

Those in the treatment group in wave 13 (2012-13) were identified based on their estimated income for MLS purposes compared to the FPHII income tier thresholds in Section 2.1. These thresholds were increased by $1,500 for each child after the first, for those individuals who noted they had dependents, using HILDA variables on dependents aged 0 to 24 (hhd0_4, hhd5_9, hhd1014, hhd1524). Those individuals indicating they had a partner and/or child were compared against family income thresholds, while the remaining individuals were compared against single-income thresholds. Additionally, the treatment group was divided into tier 1, tier 2 and tier 3, corresponding to the thresholds in Section 2.1. The estimated treatment group was carried over to other years (before and after 2012-13) to conduct the empirical analyses.

Table 5.2 presents the percentage of estimated individuals in the treatment and control groups in the HILDA sample, using this method. Those in estimated treatment group comprised 17.6% of the sample or 1,147 individuals.

Table 5.2 Estimated individuals in treatment and control groups

	Control group	Treatment group				Total
	Base tier	**Tier 1**	**Tier 2**	**Tier 3**	**Total**	**All**
number of individuals	5,387	338	459	350	1,147	6,534
% of total	82.4	5.2	7.0	5.4	17.6	100

5.3 Dependent variables

The HILDA questions and imputations relating to PHI, which are relevant to this study, are summarised in Table 5.3. These were used to construct the outcome (dependent) variables for the study.

Table 5.3 HILDA questions and imputations on PHI relevant to current study

HILDA question and variable code	Waves available
"Apart from Medicare, are you currently covered by private health insurance?" (phpriin)	2003-04, 2008-09, 2012-13
"What type of health insurance do you have? Hospital cover only, extras cover only, or both hospital and extras cover?" (phctype)	2003-04, 2008-09, 2012-13
Covered by private patient hospital (insurance) cover for the whole of last year-imputed (phlfyi)	2011-12, 2012-13, 2013-14
Household annual expenditure - Private health insurance ($) [imputed] (hxyphii)	2004-05 to 2013-14

Source: Melbourne Institute (2016)

The effects on PHI status were examined by constructing a dependent variable using the 2003-04, 2008-09 and 2012-13 waves. Variables on financial information (including household income) in HILDA from each wave are retrospective while other variables in HILDA survey including PHI status apply to the point of time the survey was conducted. It is noted that this is a potential limitation of the analysis (using previous financial year information to predict current PHI status) but this approach was taken due to data constraints.

While the 2011-12, 2012-13 and 2013-14 waves contained an indicator variable for PHI hospital cover over the whole of last year (phlfyi), this was not used as a dependent variable due to potential for measurement error with using a variable imputed using the Nearest Neighbour regression method (Summerfield et al., 2015). Additionally, the 2003-04, 2008-09 and 2012-13 waves provided more spacing between pre-reform and post-reform time periods, which potentially avoids the policy effect being confounded by pre-emptive anticipatory actions by individuals close to policy introduction. However, the 2011-12, 2012-13 and 2013-14 indicator variable for PHI hospital cover over the whole of last year was used as a secondary variable in constructing the downgrading dependent variable (Section 5.3.2). This is because downgrading was defined as reduced expenditure on PHI while maintaining hospital cover over the time period analysed.

5.3.1 PHI status

The first dependent variable constructed was the presence of PHI hospital cover for the analysis using the 2003-04, 2008-09 and 2012-13 waves. This dummy variable was constructed using HILDA questions on presence of PHI cover combined with whether this PHI included a hospital cover component (phpriin, phctype).

5.3.2 Downgrading and constructing a downgrading indicator

The analysis of PHI policy trends in Section 2.2 and reporting by Private Healthcare Australia (PHA) suggests that increased downgrading of PHI cover has occurred following the introduction of the FPHII reforms. PHA[2] define five types of downgrading of PHI cover:

- downgrading from a product with no excess to one with an excess;
- downgrading from a product with an excess to one with a higher excess;
- downgrading from a product with no exclusions to one with exclusions;
- downgrading from a product with exclusions to one with a greater number of exclusions; and
- downgrading from hospital and general treatment cover to hospital-only cover.

Downgrading has not been previously investigated as a dependent variable in other Australian studies. For individuals in the FPHII income tiers holding PHI cover, potential downgrading may occur as a response to an increase in the price of PHI through reduced rebates. Here, a downgrade would be an attempt to recover the net benefits of PHI. Such individuals would be those for whom the price of a minimum-level hospital cover policy would be less than the amount of potential MLS tax faced, thus they would still have an incentive to maintain at least the minimum level of hospital cover.

It is assumed here that downgrading involves a switch to a cheaper health insurance product, because moving to a product with higher excesses and/or more exclusions would result in a lower price faced, ceteris paribus.

Under legislation, private health insurers in Australia apply annually to the Minister for Health for approval of premium increases above inflation (PHIAC, 2015). While the level of actual price increase in premiums varies across insurers, the annual average industry price increase since 2006-07 is presented in Figure 10. This varied between 4.5% to just over 6% over the last decade, with the highest increases being for the last two financial years.

[2] Personal communication with PHA (teleconference with David, R. and Lim, J. of PHA on Wednesday 6 July 2016).

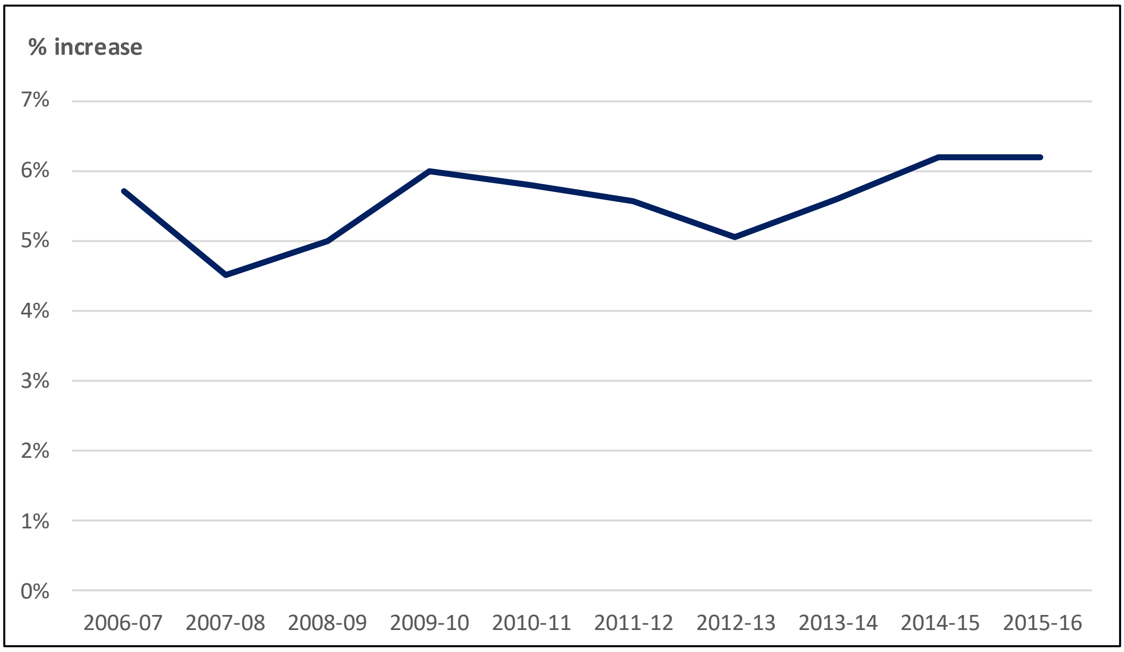

Figure 10: Annual average weighted industry increase in PHI premiums

Source: Biggs (2009) and DOH (2016)

It would be expected that a household's annual expenditure on PHI would rise in line with the average weighted industry increase in PHI premiums, with the maintenance of a constant level of PHI cover. If annual household expenditure grew by less than the average industry increase, this could indicate a possible downgrade in cover.

However, to be more conservative, downgrading in this study is defined as a *decrease* in annual household expenditure on PHI from one year to the next, while maintaining PHI hospital coverage. Because HILDA contains information on household expenditure on PHI premiums, a dummy variable to represent downgrading was constructed using the HILDA variable on household expenditure on PHI premiums (hxyphii) and presence of hospital cover. This was constructed to equal 1 with a decrease in annual PHI expenditure from one year to the next, while maintaining hospital cover, and 0 otherwise.

It is noted that a decrease in household expenditure on PHI from one year to the next may indicate that an individual has 'shopped around' and obtained a cheaper equivalent policy from another insurer. However, data indicates the level of switching in the Australian PHI industry is very low, at only 4% of total policies in 2013 (PHIAC, 2015). Hence, it is contended here that the majority of decreases in PHI expenditure are related to downgrading rather than switching between insurers.

Because those in the treatment group (above the FPHII income threshold) faced reduced premium rebates after 1 July 2012, they essentially faced a PHI price increase because of the FPHII reforms. For a valid comparison with average industry price increases and individuals in the control group, a downward adjustment was needed to the expenditure of those in the treatment group to remove the effect of the reforms on expenditure in post-reform years (2012-13 and 2013-14).

Table 5.4 shows the price increases due to reduced rebates faced by those in the FPHII income tiers, and the downward adjustments for household expenditure on PHI for individuals in the treatment group (by age group and income tier). Adjusted household expenditure on PHI was calculated as:

$$Adjusted\ expenditure = (1 - \%\ price\ rise) \times unadjusted\ expenditure$$

The downgrading analysis was restricted to the years 2008-09, 2011-12, 2012-13 and 2013-14 since household expenditure on premiums was not collected for 2003-04.

Table 5.4 PHI rebates, price increases and adjusted PHI expenditure levels for different age groups and income tiers post-FPHII reforms

Pre-reform rebate level			
Age group	**Income tier 1**	**Income tier 2**	**Income tier 3**
<65 years	30%	30%	30%
65-69 years	35%	35%	35%
70+ years	40%	40%	40%
Post-reform rebate level			
Age group	**Income tier 1**	**Income tier 2**	**Income tier 3**
<65 years	20%	10%	0%
65-69 years	25%	15%	0%
70+ years	30%	20%	0%
Price increase faced by tier (pre-reform rebate minus post-reform rebate)			
Age group	**Income tier 1**	**Income tier 2**	**Income tier 3**
<65 years	10%	20%	30%
65-69 years	10%	20%	35%
70+ years	10%	20%	40%
Adjusted household PHI expenditure (as a % of unadjusted expenditure)			
Age group	**Income tier 1**	**Income tier 2**	**Income tier 3**
<65 years	90%	80%	70%
65-69 years	90%	80%	65%
70+ years	90%	80%	60%

5.4 Explanatory variables

The literature review on the demand for PHI identified the explanatory variables to be included in the model (Barrett and Conlon, 2001, Cameron and Trivedi, 1991, Cheng, 2014, Savage and Wright, 2003). Section 4.1 contained a detailed discussion of factors that may influence PHI demand. Downgrading is another form of the PHI demand decision, where instead of determining whether or not to purchase PHI hospital cover, the individual decision is about whether to reduce the amount of coverage. It is contended, therefore, that the downgrading decision would have the same determinants as the PHI purchase decision.

Explanatory variables identified from the literature were matched to variables in the HILDA dataset. The list of explanatory variables is presented in the Appendix. The majority of explanatory variables included in the model were binary variables.

Due to the choice of a first-difference estimator model form, only explanatory variables expected to vary over time and between individuals were included. This resulted in exclusion of variables that do not vary over time or vary by the same amount for each individual such as age, gender and country of birth (Wooldridge, 2006).

Variables indicating the presence of type 1 or type 2 diabetes were not available for the years 2012 and 2014. Hence, for the 2012/2013/2014 analysis, another explanatory variable (otherhealthcond) indicating the presence of a long-term condition including diabetes was included.

Variables on body mass index (BMI) group were not available for waves earlier than 2006. Additionally, there were no variables available indicating body weight in HILDA for these years. Studies have found higher levels of physical activity have been associated with lower body weight (Jeffery et al., 2003). Hence, to proxy weight, a dummy variable indicating a high level of physical activity (physact) was included in the analysis for 2004, 2009 and 2013.

A health care use variable, number of hospital admissions in the last twelve months, was included as an explanatory variable. Because the analysis is focused on PHI hospital cover only, hospital admissions was the only health care use type included in the model. As noted by Cameron et al. (1998), expected future demand for health care use can affect the decision to purchase PHI but the presence of PHI cover can also influence the probability of health care use, due to moral hazard (Cameron et al., 1998). Hence, there is potential endogeneity between the determination of PHI status and health care utilisation. However, since most hospital admissions in Australia are for acute care (94% of all hospital separations in 2014-15) (AIHW, 2016), it is contended that the ability of PHI status to influence the vast majority of hospital admissions would be weak. A recent study supports this premise, finding no significant evidence of moral hazard in Australian emergency or urgent hospitalisations (Doiron et al., 2014).

5.5 Descriptive statistics

5.5.1 Dependent variables

Table 5.5 includes a summary of the mean values and standard deviations for the dependent variables, by wave, for the treatment and control groups. This includes the presence of hospital cover and the presence of downgrading by relevant wave. The HILDA sample, on average, has a higher proportion of individuals covered by PHI hospital cover than the general population (see Section 2.2). As expected, those in the treatment group (comprising higher income earners) had a higher proportion of people covered than the control group across all years. PHI hospital coverage has risen for both the treatment and control groups over time, but appears to have risen more steeply for the treatment group. The proportion of people estimated to be downgrading cover has generally been higher in the treatment group, across years. The proportion estimated to downgrade has increased in both treatment and control groups over time, but far more steeply for the treatment group.

Table 5.5 Mean values of presence of hospital cover and downgrading by treatment group (TG) and control group (CG)

Variable	2003-04			2008-09			2012-13		
	TG	CG	Total	TG	CG	Total	TG	CG	Total
hospital cover	0.71 (0.45)	0.47 (0.50)	0.51 (0.50)	0.78 (0.41)	0.49 (0.50)	0.55 (0.50)	0.84 (0.37)	0.51 (0.50)	0.57 (0.50)
downgrading	-	-	-	0.30 (0.46)	0.22 (0.41)	0.24 (0.43)	0.68 (0.47)	0.35 (0.48)	0.43 (0.50)
Variable	**2011-12**			**2012-13**			**2013-14**		
	TG	CG	Total	TG	CG	Total	TG	CG	Total
downgrading	0.30 (0.46)	0.32 (0.47)	0.31 (0.46)	0.68 (0.47)	0.35 (0.48)	0.43 (0.50)	0.59 (0.49)	0.35 (0.48)	0.41 (0.49)

n = 6,522 individuals for 2003-04/2008-09/2012-13 analysis

n= 6,547 individuals for 2011-12/2012-13/2013-14 analysis

Standard deviations in parentheses

5.5.2 Explanatory variables

Mean values of the explanatory variables for all waves are presented in the Appendix, for treatment and control groups. On average, the treatment group had higher levels of household wages than the control group across all years, as expected. The treatment group was generally also more likely to have higher qualification levels (higher proportion with postgraduate qualifications), be employed, have higher self-assessed health, to be married and have children. Those in the treatment group were also less likely than the control group to be regular smokers, drink alcohol daily and have diabetes or other health condition, and had less hospital admissions over the past year on average.

5.6 Preliminary analysis on downgrading

Figure 11 below shows average household expenditure on PHI in HILDA for those in the control group mapped against the average industry price increase. Annual expenditure on PHI for the control group generally increased in line with the industry trend, including after the policy change.

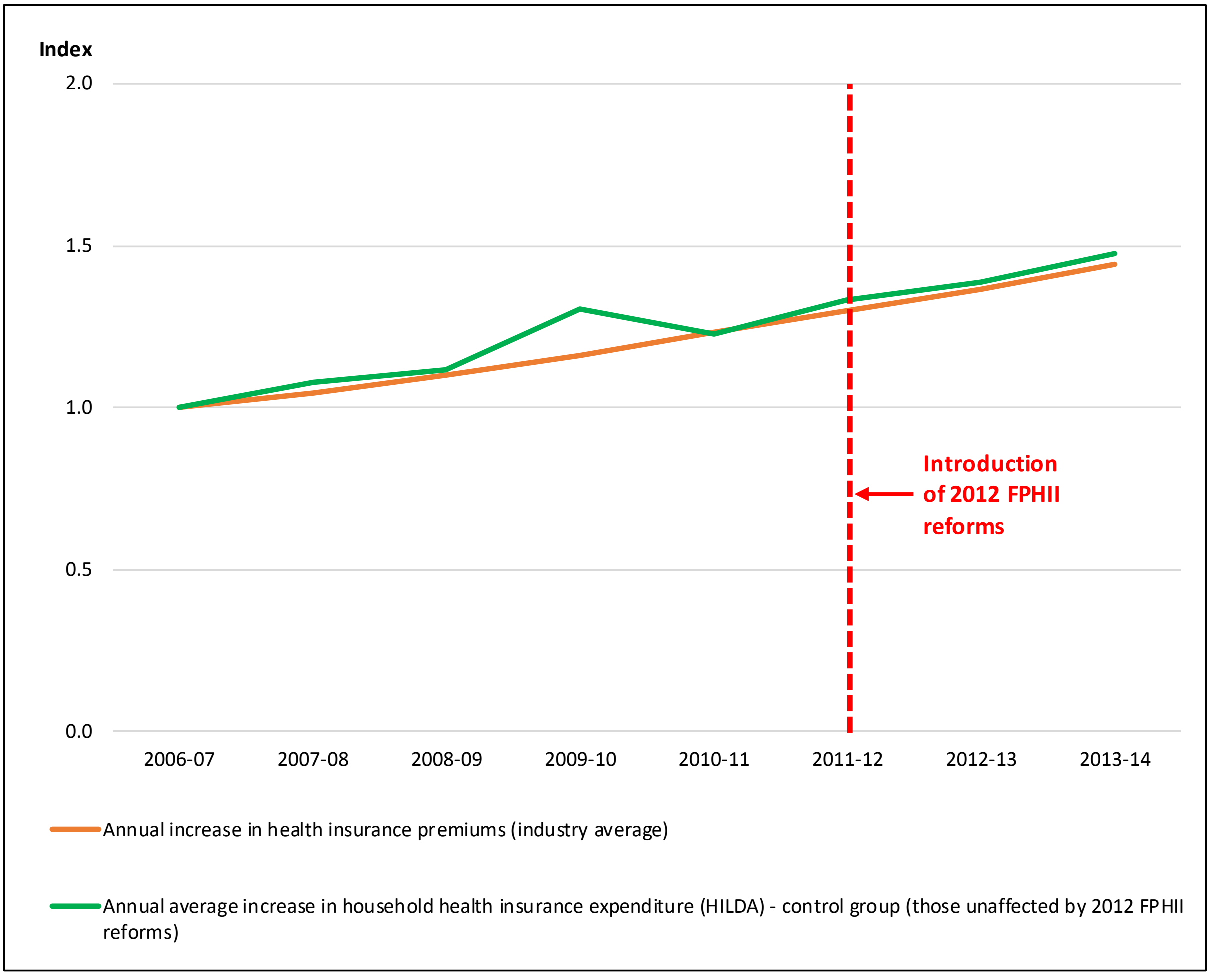

Figure 11: Annual average industry increase in premiums versus growth in household expenditure on PHI for HILDA control group

Figure 12 shows average household expenditure on PHI in HILDA for those in the treatment group mapped against the average industry price increase. Adjusted household expenditure (to take out the effects of reduced rebate rates) after 2012-13 is mapped as a dashed line. Household expenditure on PHI for the treatment group tended to grow faster than the industry trend over the entire policy period. However, Figure 12 shows evidence of increased potential downgrading immediately after the policy change, with growth in adjusted expenditure for the treatment group falling below the industry trend in 2012-13. However, this seems to adjust back to higher than industry level in 2013-14, but it is still substantially lower than unadjusted expenditure. Compared to the APRA data discussed in Section 2.2, Figure 12 shows intensified downgrading potentially occurring immediately after the introduction of the FPHII reforms, with this slowing down in 2013-14. APRA data showed a potential downgrading occurring after policy introduction, with a gradual decline in full cover policies over 2012-13, and a switch towards reduced cover policies (both 'no lifetime exclusions' and 'some lifetime exclusions' policies). However, APRA data potentially shows further intensified downgrading occurring a bit later after the policy impact, towards the end of 2013-14 and into 2014-15, with a sharp switch from 'reduced cover but no lifetime exclusions' policies to 'reduced cover but some lifetime exclusions' policies. Because this switch occurred towards the end of 2013-14, it does not seem to have been picked up by the HILDA household expenditure data in wave 2013-14. Future HILDA waves (2014-15 and onwards) would be needed to investigate whether intensified downgrading occurred in later years.

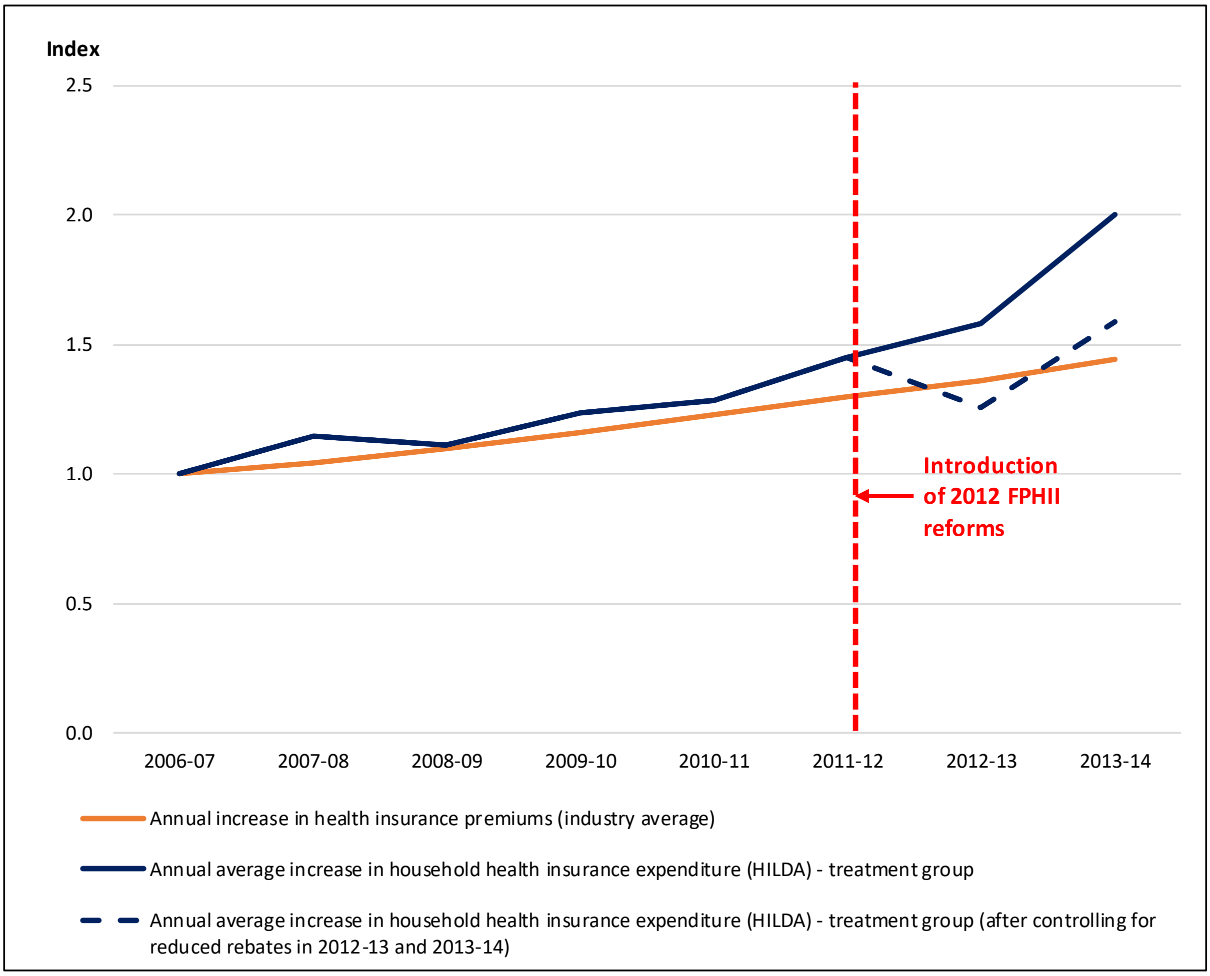

Figure 12: Annual average industry increase in premiums versus growth in household expenditure on PHI for HILDA treatment group

6 Modelling framework

To empirically estimate the effect of the FPHII reforms on the presence of PHI hospital cover and downgrading of hospital cover, a panel difference-in-difference estimator was chosen. This offers advantages in exploiting the longitudinal nature of the HILDA dataset and countering some of the limitations associated with cross-sectional and time-series estimators used in past PHI studies. The strength and weaknesses of using this approach are discussed, and compared to features of other potential estimators.

6.1 Difference-in-difference approach

This study aims to estimate the effect of the 2012 FPHII reforms on the presence of PHI hospital cover and downgrading of PHI hospital cover, for those individuals affected (the treatment group). Thus, the main effects of interest this study attempts to measure for the treatment group are:

- the change in the probability of having PHI hospital cover due to the FPHII reforms; and
- the change in the probability of downgrading PHI hospital cover, due to the FPHII reforms.

These estimates would represent the average effect of the 'treatment' (that is, the FPHII reforms) on the 'treated' (that is, those in the FPHII income tiers) or the ATT. One could also estimate the population average treatment effect (ATE), which represents the expected effect of the treatment on the entire population (treated and untreated) on average. The ATE can be useful in situations where the aim is to look at potential expansion of a treatment or intervention to the untreated population (Cobb-Clark and Crossley, 2003). However, for our purposes of post-reform evaluation and where the treatment (FPHII) has been tightly targeted to higher income tiers, the ATT is the primary effect of interest.

As noted in Section 4, the decision to purchase PHI occurs if the net benefit (expected utility) of PHI purchase is positive. Policy interventions such as the MLS and premium rebates affect PHI demand through their influence on price and income determinants. Downgrading is another form of the PHI demand decision, where instead of determining whether or not to purchase PHI hospital cover, the individual decision is about whether to reduce the amount of coverage. It is contended, therefore, that the downgrading decision would have the same determinants as the PHI purchase decision, and would also potentially amenable to influence by the MLS and rebate policies.

Each decision can be observed as a discrete choice, and structured as a binary variable, Y, equal to 1 with the presence of PHI hospital cover, or occurrence of a downgrade, or 0 otherwise. The observed PHI cover or downgrade decision for individual i can be formulated as (Albuoy, 2004):

$$Y_i = \alpha + \beta TG_i + \Upsilon t_i + \delta TG.t_i + \varepsilon_i \quad (1)$$

where TG is a variable equal to 1 when individual i is in the treatment group (income tiers affected by FPHII) and 0 otherwise;

t is a variable equal to 1 when individual i is in the post-reform time period (after 1 July 2012) and 0 otherwise, and represents the common time trend faced by both treatment and control groups;

TG.t is an interaction term indicating if individual i is in the treatment group in the post-reform time period; and

ε is the error term.

The coefficient, δ, on the interaction term captures the true ATT of the policy and is the coefficient of interest. This format has been referred to as the cross-sectional difference-in-difference (DID) estimator (Wooldridge, 2006). Using the terminology, $(Y_{t=0,1}^{TG/CG} | D = 0,1)$, where TG or CG indicates whether an individual is in the treatment or control group and D indicates whether 'treatment' was actually received (whether the individual was subject to reduced rates of the rebate and increased rates of the MLS), an unbiased estimator of the effect size could be specified as:

$$\tilde{\delta} = (\bar{Y}_1^{TG} | D = 1) - (\bar{Y}_1^{TG} | D = 0)$$

This represents the average impact on the treated from the FPHII reforms. The coefficient would represent the change in the probability of having or downgrading hospital cover for this group, due to the reforms. The second term in this equation represents a counterfactual scenario, which cannot be observed, because all individuals in the FPHII tiers were definitively subject to the reforms in t=1. Thus, we face a missing data problem, and the task of evaluation is to construct a valid counterfactual to proxy $(\bar{Y}_1^{T} | D = 0)$ (Blundell and Costa-Dias, 2000).

A simple pre- versus post- estimator comparing outcomes for the treatment group before and after the reforms, as below, would produce a biased expected estimate if a time trend existed in outcomes, as below (Albuoy, 2004):

$$\hat{\delta} = (\bar{Y}_1^{TG}|D = 1) - (\bar{Y}_0^{TG}|D = 0)$$

$$E[\hat{\delta}] = E[\bar{Y}_1^{TG}|D = 1] - E[\bar{Y}_0^{TG}|D = 0]$$

$$E[\hat{\delta}] = (\alpha + \beta + \Upsilon + \delta) - (\alpha + \beta) = \Upsilon + \delta \quad \text{from (1)}$$

Here, ϒ in the estimator above represents bias from a potential time trend in PHI cover, unrelated to policy changes. Another option may be to use the post-reform outcome for the control group to proxy the treatment group's counterfactual outcome in the absence of treatment (Albuoy, 2004):

$$\hat{\delta} = (\bar{Y}_1^{TG}|D = 1) - (\bar{Y}_1^{CG}|D = 0)$$

This could be estimated using post-reform cross-sectional data on outcomes for a treatment and control group. An unbiased estimate from this estimator would require an assumption of strict independence to hold:

$$(\bar{Y}_1^{TG}|D = 0) = (\bar{Y}_1^{CG}|D = 0)$$

However, this would require treatment to be completely randomly assigned to individuals. With a randomised allocation of treatment, a simple comparison of outcomes between the treatment and control group would enable unbiased estimation of the ATT (Cobb-Clark and Crossley, 2003). Unfortunately, this scenario is extremely rare in the case of policy reforms and the above estimator would be generally subject to selectivity bias, as below. The term β represents selectivity bias present in the estimator from inherent differences between the treatment and control groups:

$$E[\hat{\delta}] = E[\bar{Y}_1^{TG}|D = 1] - E[\bar{Y}_1^{CG}|D = 0]$$

$$E[\hat{\delta}] = (\alpha + \beta + \Upsilon + \delta) - (\alpha + \Upsilon) = \beta + \delta$$

For the FPHII reforms, treatment and control groups are based on income tiers, and preliminary analysis of the HILDA data in Section 5 shows there are clear differences in the PHI purchasing behaviour, health-related actions and health status between the treatment and control groups. Because the treatment is not randomly assigned, selectivity bias would lead to violation of one of the standard regression assumptions of no correlation between the random error term and treatment, $cov(\varepsilon_{i,}D) \neq 0$ required for estimates to be unbiased and have the lowest variance (Cobb-Clark and Crossley, 2003).

As noted by Cobb-Clark and Crossley (2003), selectivity bias can be based on selection on observables or unobservables. Potential estimators exist that try to account for the heterogeneity in untreated outcomes between treatment and control groups. Regression-based approaches attempt to control for selectivity bias on observables by adding control variables to equation (1). This would result in a weakening of the strict independence requirement to one of conditional independence. Conditional independence would not require random assignment of treatment, but rather would require that potentially untreated outcomes between treatment and control groups do not systematically vary, after controlling for differences in observable characteristics.

Richer datasets with more control variables make the conditional independence assumption more plausible (Cobb-Clark and Crossley, 2003). In particular, data on pre-treatment outcomes could eliminate the selectivity bias on observables inherent in a single-cross section of data, by identifying and controlling for observable differences between treatment and control groups (Moffitt, 1991). Some studies on the effects of the 1990s PHI reforms have used cross-sections of data before and after the reform to isolate the policy impacts (Ellis and Savage, 2008, Palangkaraya and Yong, 2005, Palangkaraya and Yong, 2009). However, this approach would still not correct for potential selectivity bias on individual-specific unobservables.

Estimators can also attempt to control for selectivity bias by making comparisons between treatment and control groups more valid, by ensuring treatment and control groups are as similar as possible. A regression-discontinuity approach would control for selectivity bias by assuming those individuals very close to, but on opposite sides of the reform thresholds would have very similar observable and unobservable characteristics. If this were true, comparisons between the treatment and control group in untreated outcomes would be less likely to suffer from bias. However, this method would require very definitive and clear information in the data on the income measures needed to divide individuals into treatment and control groups based on the reform thresholds. Stavrunova and Yerokhin (2014), for example, used reported income tax return data which reported whether an individual paid the MLS or not. The FPHII reforms are based on a complicated income definition (as described in Section 5.2) which has strong informational requirements. A regression-discontinuity approach may not be as effective when combined with the HILDA dataset, which has rich information on valuable individual observable characteristics, but for which division into strict treatment and control groups close to the thresholds is difficult.

Another approach to avoid selection bias is to use a matching estimator that is based on the idea that the best estimate of the counterfactual untreated outcome for an individual in the treatment group would be the untreated outcome of an individual in the control group who is most like them, in terms of observable characteristics (Cobb-Clark and Crossley, 2003). Thus, matching attempts to control for bias resulting from selection on observables, and requires the conditional independence assumption to hold for matched individuals. A limitation of matching is that a finite dataset may make it difficult to control for numerous individual characteristics on which individuals may differ. Matching on a propensity score (propensity to be subject to treatment, given observable characteristics) may overcome this limitation. Propensity score matching has been employed in a past Australian study looking at the impact of past PHI reforms on the use of hospital care (Lu and Savage, 2006). Matching also requires the common-support assumption to hold, which is that, for an individual in the treatment group, the probability of treatment must be 0<P<1 after controlling for observables, to ensure that all individuals have a counterpart in the control group and all individuals constitute potential treatment participants (Blundell and Costa-Dias, 2000). As noted by Blundell and Costa-Dias (2009), this is only possible if observable characteristics do not predict program participation or treatment exactly. This makes matching less appropriate to the FPHII context, where treatment has been directed to a tightly specified income group.

As noted earlier, the availability of pre and post-reform data on the treatment and control group can make the conditional independence assumption more plausible by inclusion of more information. Panel or longitudinal data such as the HILDA offers further advantages for strengthening analysis by following the same individuals and their actions over time. A first-difference DID estimator can be constructed using panel data by subtracting pre-reform values of variables from post-reform values. From equation (1), this estimator would have an unbiased expectation of the estimate of the effect size, δ (Albuoy, 2004):

$$\hat{\delta} = [(\bar{Y}_1^{TG}|D = 1) - (\bar{Y}_0^{TG}|D = 0)] - [(\bar{Y}_1^{CG}|D = 0) - (\bar{Y}_0^{CG}|D = 0)]$$

$$E[\hat{\delta}] = [(\alpha + \beta + \Upsilon + \delta) - (\alpha + \beta)] - [(\alpha + \Upsilon) - \alpha] = \delta$$

An advantage of a panel DID estimator over other estimators is that it allows for removal of time-invariant individual-level unobservables which may be correlated with other explanatory variables and affect values of the outcome variable (Wooldridge, 2006). In the PHI context, some potential time-invariant factors that are difficult to control for, and may influence the PHI purchase decision, may be risk attitudes, financial numeracy, cognitive ability and mental health (Buchmueller et al., 2013).

Buchmueller et al. (2013), supported this finding in Australia via an analysis of 2005 NHS data and found those purchasing PHI were also more likely to purchase other types of insurance and thus be risk-averse. The authors suggest other reasons for positive selection in Australian PHI may be cognitive ability and income, which have both been found to positively affect PHI status and negatively affect expected claims.

This is identical to the advantage offered by time-demeaning of observations with a panel fixed-effects model with two waves of data (Wooldridge, 2006). In contrast, a pooled cross-sectional estimator may potentially suffer from heterogeneity bias from omission of a time-constant variable that may be correlated with explanatory variables. In the PHI context, this may be useful if, for example, time-constant observable individual characteristics that influence PHI demand (for example, risk aversion attitude, personality, cognitive ability) are difficult to control for in the model.

6.1.1 Limitations with the DID estimator

In its construction of a counterfactual, the DID estimator implicitly assumes a parallel trend in the pre-treatment values of the outcome variable for the treatment and control groups (Moffitt, 1991). This assumption requires time effects and macro shocks, including changes in PHI markets, to be identical for treatment and control groups (Blundell and Costa-Dias, 2000). PHI regulation in Australia such as community rating and mandated increases in premiums for all individuals have allowed the PHI market to be relatively uniform for both control and treatment groups prior to the FPHII reforms, and supports this assumption to some extent.

As noted by Albuoy (2004), DID analysis can be limited by the failure of this parallel trends assumption and result in a biased estimate of the treatment effect. If the control group has a different time trend, ϒ, to the treatment group, ϒ+Δ (Albuoy, 2004), from equation (1), the DID estimator would result in a biased estimate:

$$\hat{\delta} = [(\bar{Y}_1^{TG}|D = 1) - (\bar{Y}_0^{TG}|D = 0)] - [(\bar{Y}_1^{CG}|D = 0) - (\bar{Y}_0^{CG}|D = 0)$$

$$E[\hat{\delta}] = [(\alpha + \beta + \Upsilon + \Delta + \delta) - (\alpha + \beta)] - [(\alpha + \Upsilon) - \alpha] = \delta + \Delta$$

It may be possible to check for support of the common trends assumption using HILDA data for the pre-reform period. Unfortunately, for the analysis on presence of hospital cover, the common-trends assumption cannot be tested due to availability of only two pre-reform time periods and due to available time periods being spaced out. The common-trends assumption could have been checked here, with the availability of year by year changes in PHI hospital cover membership, which is not available in HILDA.

This assumption can be better tested for with the data on household expenditure on PHI premiums, which is available from wave 5 onwards in the HILDA dataset and can be used to examine trends in potential downgrading between the treatment and control group. The exact downgrading indicator used in the analysis, downgrading of hospital cover, cannot be constructed for all waves from 5 to 14, because PHI hospital cover status is only reported in selected waves. However, Figure 13 shows individuals whose household expenditure on PHI *decreased* from one year to the next in the treatment and control groups. PHI expenditure for those in the treatment group after 2013 is adjusted as per the adjustment in described in Section 5.3.2. Figure 13 shows some potential support for the common-trends assumption holding because the number of individuals with decreased expenditure from one year to the next remained roughly constant for both the treatment and control groups prior to the FPHII reforms. However, after the reforms, the number of individuals with decreased expenditure in the treatment group kinked upward in 2012-13, and moderated in 2013-14 but still remained higher than the pre-reform trend.

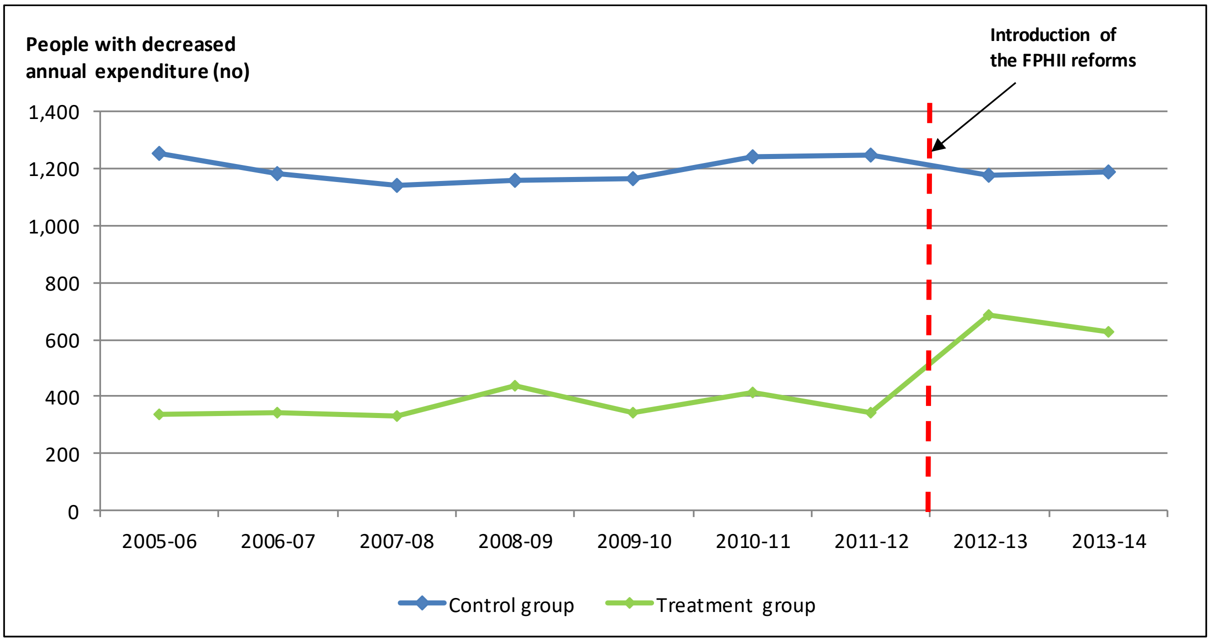

Figure 13: Individuals with decreased annual expenditure on PHI in HILDA

Note: Expenditure for those in the treatment group adjusted using method detailed in Section 5.3.2

More data are needed to check the common-trends assumption holding for presence of PHI cover between treatment and control groups. The failure of the common-trends assumption for PHI cover presence and downgrading would mean that DID would not consistently estimate the true effect of the FPHII policy on these variables for the treatment group.

Another potential limitation with DID analysis is its inability to control for temporary, unobserved individual-specific shocks that may influence an individual's being in the treatment group (Blundell and Costa-Dias, 2009). In the current context, this may mean anticipatory actions in response to the FPHII policy before its implementation, which could influence whether an individual is in the treatment group. Stavrunova and Yerokhin (2014) found individuals do engage in income 'shifting' in a certain interval around the MLS threshold to avoid paying the MLS. It has not been examined to what extent the introduction of the FPHII reforms would have exacerbated such a phenomenon. In this case, potential 'income shifting' before the introduction of the reforms could have occurred by individuals to avoid being in the reforms' treatment group, and thus avoid paying either higher MLS rates with the absence of PHI hospital cover, or receiving reduced rebates with the presence of PHI hospital cover. Sensitivity analysis was conducted around the DID results in this paper to examine the effect of altering estimated income on policy effects (see Section 6.2.5).

There are difficulties with combining the DID model with a non-linear specification, because this leads to an inconsistent estimator if the common trends assumption is upheld (Lechner, 2010). Blundell and Costa-Dias (2009) note that this can be overcome using a linear index model, but this causes the DID estimator to lose its simplicity of interpretation. For the analyses in this paper, DID is combined with a linear probability model, as detailed in Section 6.2.1.

Bertrand et al. (2003) note that the DID form combined with long time-series and dependent variables subject to persistence may lead to problems with serial correlation. This can lead to underestimation of standard errors and misinterpretation of significance of effect sizes. Their survey of 92 papers using DID analysis found the vast majority did not correct for serial correlation, leading to potential misinterpretation of the significance of treatment effects. PHI coverage status is a variable that may be subject to persistence (Finn and Harmon, 2006). Bertrand et al. (2003) note that collapsing time periods to two (pre and post-reform) periods and estimating corrected errors can help to counter concerns with inference. The majority of the analyses in this paper focus on two time periods. Additionally, clustered robust standard errors are estimated for all analyses.

6.2 Estimation

6.2.1 Choice of a linear probability model

The outcome variables for the analysis (represented by Y) are both structured as a binary variable equal to 1 with presence of hospital cover or downgrading, and 0 otherwise. The specific definitions of the outcome variables constructed from HILDA are elaborated on in Section 5.3.

With a discrete binary variable as the outcome variable, the natural inclination would be to use a non-linear model form such as the probit or logit model to avoid the generation of predicted probabilities outside the unit interval and to allow for non-constant marginal effects of explanatory variables (Wooldridge, 2006).

However, an LPM form was employed to conduct the analyses in this paper for several reasons. Lechner (2010) notes that there are issues with using non-linear models in the DID context. By construction, estimation of a DID model with a standard specification of a non-linear model form would lead to an inconsistent estimator if the common-trends assumption (which is required for DID analysis) is upheld (Lechner, 2010).

Additionally, the LPM's weaknesses, namely the generation of predicted probabilities outside the unit interval, and the inability of probabilities to be linearly related to all possible values of explanatory variables, are limited in the current context, because most included covariates in the model are also binary variables (Section 5.4). DID analysis of mostly dummy variables is focused on analysing mean differences between treatment and control groups, leading to reduced probability of over- or under-prediction.

Finally, the LPM can often generate good estimates of partial effects on response probability near the centre of the distribution of covariates. In particular, when the aim is to estimate the partial effect of a covariate on the response probability, averaged across the distribution of covariates, the generation of predicted values lying outside the unit interval may not be as important (Wooldridge, 2002).

Past papers from the United States analysing effects of reforms on the probability of health insurance cover have used the LPM form to attain estimates (Buchmueller and DiNardo, 2002, Monheit and Schone (2004), Ham and Shore-Sheppard, 2005, Cawley et al., 2006, Monheit et al., 2011). In particular, Cawley et al. (2006) analysed longitudinal data using a similar approach to the one employed here. They used a LPM first-difference estimator and conducted DID analysis to examine the impact of welfare reform in the US on the change in probability of health insurance coverage of women and children.

6.2.2 Model specification

A pooled cross-section DID model is presented below for each individual i at time t. This model was then first-differenced and applied to the HILDA data to estimate the effects of the FPHII reforms on the outcome variables:

$$Y_{it} = \alpha + \beta TG_{it} + \Upsilon t_i + \delta TG.t_{it} + \Phi X_{it} + \alpha_i + u_{it} \quad (2)$$

Other time-varying explanatory variables impacting the PHI demand decision, identified in Section 5.4, represented by X_{it}, were included as control variables in the model. The model's error term has been broken up into two components, where α_i represents time-constant individual unobservables and u_{it} represents an idiosyncratic error term. The first-differenced form of this model removes the time-constant component of the error term (α_i) and is presented below:

$$\Delta Y_i = \Upsilon + \delta \Delta TG.t_i + \Phi \Delta X_i + \Delta u_i \qquad (3)$$

The terms for treatment group, TG_{it}, also drops out as the same group of individuals in the treatment group is analysed over time, and so this term does not vary over time. Here, the coefficient on the time trend term, ϒ, in equation (2), becomes the constant term in the first-differenced equation (3).

The analyses conducted are listed below:

(1) Changes in probability of having PHI hospital cover
   a. 2008-09 and 2012-13 waves
   b. 2003-04, 2008-09 and 2012-13 waves
(2) Changes in the probability of downgrading hospital cover
   a. 2008-09 and 2012-13 waves
   b. 2011-12 and 2012-13 waves
   c. 2011-12 and 2013-14 waves

For the analysis involving three waves of data (1b), the observations were double-differenced, with the inclusion of time dummies for the years 2008-09 and 2012-13 to capture time trends. This analysis may offer further advantages over two-wave estimation, because additional pre-treatment observations of the outcome enable weaker assumptions of common change in growth rates of the outcome variable (as opposed to common trends) (Moffitt, 1991). Inclusion of more pre-treatment observations allows estimates of treatment effects to potentially approach those available with a randomised allocation of treatment.

By construction, the LPM model form violates the Gauss-Markov assumption of homoscedasticity (Wooldridge, 2002). Hence, for valid inference, standard errors must be corrected for heteroscedasticity. Heteroscedasticity-robust standard errors, clustered at the household level, are estimated for all analyses in this paper, to assist inference.

6.2.3 Estimate of policy effect and accounting for heterogeneity of policy effect in the treatment group

The estimated ATT of the FPHII policy on the probability of having hospital cover and probability of downgrading hospital cover is identified through the coefficient, δ, on the interaction term, $TG.t_i$.

To identify potential variation in the policy effect within the treatment group, additional estimation was carried out using interaction terms with the three FPHII income tiers (TG1, TG2 and TG3 in order of ascending income), and the post reform time period, as below:

$$\Delta Y_i = \Upsilon + \delta_1 \Delta TG1.t_i + \delta_2 \Delta TG2.t_i + \delta_3 \Delta TG3.t_i + \Phi \Delta X_i + \Delta u_i \qquad (4)$$

6.2.4 Comparison with estimates from a fixed-effects and pooled cross-section estimator

Estimates from the differenced DID analyses were compared to estimates from the pooled cross-section DID estimator presented in Section 6.2.2 (equation (2)). This was to ascertain the benefits of panel data estimation and in particular, the removal of heterogeneity bias through the differencing out of time-constant individual unobservables, $\alpha_{i,}$

Wooldridge (2006) notes potential differences between a fixed-effects and first-difference estimator with more than two waves of data, based on serial correlation in idiosyncratic errors. With no serial correlation or substantial negative serial correlation, a fixed-effects estimator may be more efficient. With substantial positive serial correlation, Wooldridge notes a first-difference estimator may perform better. Hence, for the analysis involving three waves of data (2b), serial correlation was tested for and results from the first-difference estimator were compared to those from a fixed-effects estimator below. This includes time-demeaned explanatory variables and two post-reform time-period dummy variables, $2t_i$ and $3t_i$:

$$\ddot{Y_{it}} = \alpha + \beta \ddot{TG}_{it} + \Upsilon \ddot{2t}_i + \eta \ddot{3t}_i + \delta \ddot{TG.t}_{it} + \Phi \ddot{X}_{it} + \ddot{u}_{it} \qquad (5)$$

6.2.5 Sensitivity analyses

Estimated income for MLS purposes

As noted in Section 5.2, the calculation of income for MLS purposes by the ATO is not straightforward, and HILDA income variables are not collected in a form exactly amenable to the ATO calculation. This leads to the possibility of measurement error. To check the potential impact on results from the accuracy of the income measure, sensitivity analysis was carried out by inflating and deflating estimated income for MLS purposes by 5%.

Downgrading definition

The downgrading analyses define the downgrading variable as a decrease in household expenditure on PHI (or adjusted household expenditure on PHI for the treatment group) from one year to the next, while still maintaining hospital cover. This is an approximate, not exact, measure of downgrading, since HILDA does not collect data on downgrading. To check the potential impact on results from the changes in the definition of the downgrading indicator, sensitivity analysis was carried out by alternatively defining the indicator as:

(1) Any change in household expenditure on PHI below the annual average industry increase in PHI premiums (including no change), while maintaining hospital cover.
(2) A decrease in household expenditure on PHI by more than 5% from one year to the next, while still maintaining hospital cover.

7 Empirical analysis and results

Estimates of the FPHII policy effect on the dependent variable are presented and analysed, including estimates from first-difference, ordinary least squares (OLS) using pooled cross-section data and fixed effects models (for the three-wave analysis). Sensitivity analysis around the FPHII income definition and the definition of downgrading was conducted, to examine the impacts on estimates of the policy effect. The estimated coefficients for explanatory variables are presented in the Appendix.

Results are presented for two model forms:

(i) one with the overall policy effect estimated by one interaction term, $TG.t_i$; and

(ii) one with the policy effect broken up into the three FPHII income tiers, estimated through three interaction terms, $TG1.t_i$, $TG2.t_i$ and $TG3.t_i$.

In the first-difference estimator, the estimated constant term represents the time trend in the dependent variable (see Section 6.2), while in the pooled OLS estimator, this is represented by the estimated coefficient on the post-reform year dummy variable.

7.1 The effects of the FPHII reforms on PHI hospital cover

Using first-difference estimation, the FPHII reforms were estimated to have increased the probability of having hospital cover by 2.9 percentage points for those in the treatment group (Table 7.1). This effect was found to be statistically significant at the 1% significance level. The ordinary least squares (OLS) results from pooled cross-section data estimated the overall policy effect to be negative and insignificant. This indicates the potential benefits of removing heterogeneity bias with panel data, which confounds the policy effect estimate in cross-sectional analysis. The majority of error variance (84.6%) was due to time-constant, individual-specific unobservables, indicating the advantage of using a panel estimator in this context.

The first-difference estimator attributed most of this significant policy effect to those in FPHII income tier 1. The effect for those in Tier 2 was found to be only significant at a 10% level of significance, while the effect was found to be non-significant for Tier 3. This matches the theoretical predictions in Section 4.3.1 on the differential effects of the MLS across income tiers. Because the majority of income earners in higher tiers may have already been potentially driven by the MLS to purchase PHI cover, the FPHII reforms potentially had more ability to influence those in lower income tiers above the threshold without hospital cover.

Table 7.1: The effect of reforms on probability of having hospital cover, 2008-09 and 2012-13

Variable	First-difference		OLS	
	(i)	(ii)	(i)	(ii)
constant	0.014***	0.014***	0.280***	0.280***
	(0.004)	(0.004)	(0.018)	(0.018)
2012-13 year dummy	-	-	0.014	0.014
			(0.011)	(0.011)
overall policy effect	0.029***	-	-0.019	-
	(0.011)		(0.021)	
policy effect tier 1	-	0.063***	-	0.011
		(0.020)		(0.029)
policy effect tier 2	-	0.029*	-	-0.013
		(0.015)		(0.026)
policy effect tier 3	-	-0.011	-	-0.061
		(0.016)		(0.029)
treatment group	-	-	0.138***	0.135***
			(0.017)	(0.017)
N	**6,522**		**13,065**	

Robust standard errors in parentheses, clustered at household level. All specifications include a full set of controls. The full results are available from the author.

*p<0.1**

*p<0.05***

*p<0.01****

Because there are differences in efficiency between a fixed-effects and first-difference estimation with three-wave analysis, the results of both are presented in Table 7.2, in addition to the pooled OLS estimates. Tests indicated the presence of significant negative serial correlation, lending support to the use of a fixed-effects estimator for the three wave analysis (see Section 6.2.4).

The three wave fixed-effects estimator found that the FPHII reforms significantly increased the probability of having hospital cover by 3.8 percentage points for those in the treatment group. In contrast to the two-wave analysis, the policy effect here was found to be strongly significant (at the 1% level for significance), for both income Tiers 1 and 2 (7.7 percentage point increase for Tier 1 and 4.3 percentage point increase for Tier 2). The effect for Tier 3 remains insignificant.

Again, this supports the premise that FPHII reforms potentially had more ability to influence those in lower income tiers above the threshold to purchase hospital cover because the majority of individuals in the highest tier may have already been driven by the MLS to previously purchase hospital cover.

Table 7.2: The effects of reforms on the probability of having hospital cover, 2003-04, 2008-09 and 2012-13 (three waves)

	First difference		Fixed effect		OLS	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
constant	0.021***	0.021***	0.403***	0.403***	0.267***	0.268***
	(0.005)	(0.005)	(0.023)	(0.023)	(0.015)	(0.015)
2008-09 dummy	-	-	0.022***	0.021***	-0.001	-0.001
			(0.004)	(0.004)	(0.010)	(0.010)
2012-13 year dummy	-0.006	-0.006	0.035***	0.035***	0.013	0.012
	(0.006)	(0.006)	(0.005)	(0.005)	(0.011)	(0.011)
overall policy effect	0.024**	-	0.038***	-	-0.025	-
	(0.011)		(0.010)		(0.019)	
policy effect tier 1	-	0.059***	-	0.077***	-	0.012
		(0.020)		(0.018)		(0.027)
policy effect tier 2	-	0.027*	-	0.043***	-	-0.019
		(0.015)		(0.014)		(0.024)
policy effect tier 3	-	-0.017	-	-0.012	-	-0.075***
		(0.276)		(0.465)		(0.008)
treatment group	-	-	-	-	0.120***	0.119***
					(0.012)	(0.012)
N	**13,067**		**19,596**		**19,572**	

Robust standard errors in parentheses, clustered at household level. All specifications include a full set of controls. The full results are available from the author.

*p<0.1**

*p<0.05***

*p<0.01****

7.2 The effects of the FPHII reforms on downgrading PHI hospital cover

The effects on the probability of downgrading were estimated across three analyses using different pre and post-reform waves. Results are presented in Table 7.3, Table 7.4 and Table 7.5. The 2008-09 and 2012-13 analysis estimated the FPHII reforms significantly increased the probability of downgrading by 24.6 percentage points for those in the treatment group. This increased to 34.6 percentage points for the analysis between 2011-12 and 2012-13, and 25.8 percentage points for the analysis between 2011-12 and 2013-14. All three analyses indicated strongly significant positive effects across all three income tiers, with the effect increasing with successively higher income tiers. This intuitively makes sense, as the highest income tier, Tier 3, faced the greatest increase in price of PHI due to complete removal of rebates (30%-40% price increase in PHI).

The estimates from the pooled OLS analyses are close to the first-difference estimates, and also indicate a strong, positive and significant effect on downgrading, across all three income tiers. It was estimated that 38.9% to 41.6% of the error variance was due to time-constant, individual-specific unobservables, indicating fewer advantages of using a panel estimator here, compared to the probability of hospital cover analyses. This may be due to individual-specific unobservable factors that potentially do not vary over time such as risk attitudes, financial numeracy, cognitive ability and mental health (Buchmueller et al., 2013) not being as relevant to the PHI downgrading decision as to the initial decision to purchase PHI. This is particularly so if downgrading is more of a response to changes in price of PHI than other variables.

Table 7.3: Modelling results – effects on probability of downgrading hospital cover – 2008-09 and 2012-13

	First-difference estimator		OLS	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**
constant	-0.012	-0.013	0.350***	0.348***
	(0.018)	(0.018)	(0.029)	(0.029)
2012-13 year dummy	-	-	0.003	0.003
			(0.017)	(0.017)
overall policy effect	0.246***	-	0.230***	-
	(0.035)		(0.034)	
policy effect tier 1	-	0.157***	-	0.180***
		(0.059)		(0.047)
policy effect tier 2	-	0.239***	-	0.209***
		(0.046)		(0.043)
policy effect tier 3	-	0.348***	-	0.309***
		(0.057)		(0.043)
treatment group	-	-	0.089***	0.093***
			(0.026)	(0.026)
N	**3,381**		**6,772**	

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*p<0.01****

Table 7.4: Modelling results – effects on probability of downgrading hospital cover – 2011-12 and 2012-13

	First-difference estimator		OLS	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**
constant	-0.004	-0.004	0.379***	0.378***
	(0.018)	(0.018)	(0.028)	(0.028)
2013-14 year dummy	-	-	-0.004	-0.005
			(0.016)	(0.016)
overall policy effect	0.346***	-	0.338***	-
	(0.038)		(0.033)	
policy effect tier 1	-	0.291***	-	0.270***
		(0.062)		(0.045)
policy effect tier 2	-	0.335***	-	0.324***
		(0.056)		(0.041)
policy effect tier 3	-	0.417***	-	0.423***
		(0.059)		(0.042)
treatment group	-	-	-0.0005	0.007
			(0.025)	(0.025)
N	**3,555**		**7,110**	

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*p<0.01**

Table 7.5: Modelling results – effects on probability of downgrading hospital cover – 2011-12 and 2013-14

	First-difference estimator		OLS	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**
constant	-0.011	-0.011	0.367***	0.366***
	(0.017)	(0.017)	(0.027)	(0.027)
2013-14 year dummy	-	-	-0.008	-0.008
			(0.017)	(0.017)
overall policy effect	0.258***	-	0.259***	-
	(0.033)		(0.033)	
policy effect tier 1	-	0.177***	-	0.169***
		(0.053)		(0.047)
policy effect tier 2	-	0.280***	-	0.273***
		(0.049)		(0.041)
policy effect tier 3	-	0.304***	-	0.325***
		(0.053)		(0.044)
treatment group	-	-	-0.030	-0.025
			(0.026)	(0.026)
N	**3,506**		**7,012**	

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*p<0.01****

7.3 Robustness checks

7.3.1 Varying the estimated income measure

Sensitivity analysis was carried out by estimating the effects on results from altering the estimated MLS income measure (from Section 5.2) by 5% (increase and decrease), for all analyses. Results are presented in Sections A.5 and A.6 in the Appendix.

Effects on hospital cover analysis

The estimated overall effects on having hospital cover generally remained strongly significant (1% level) with changes in the income measure. The exception was with a 5% decrease in estimated MLS income, which caused it to become marginally significant (10% level). The estimated effect varied between 2.1 to 4.8 percentage point probability increase in the sensitivity analyses (compared to 2.9 to 3.8 percentage point increase for the baseline analyses).

Effects on downgrading analysis

The overall estimated policy effect on downgrading, in terms of effect size and statistical significance, was relatively robust to changes in the income measure of 5%. It remained significant at the 1% level for all analyses. The estimated effect varied between 26.2 to 36.6 percentage point probability increase in the sensitivity analyses (compared to 24.6% to 34.6% for the baseline analyses).

The finding of relatively larger downgrading effects with higher income tiers was preserved in the sensitivity analyses.

7.3.2 Changing the downgrading definition

The baseline downgrading analyses defined the downgrading variable as a decrease in household expenditure on PHI (or adjusted household expenditure on PHI for the treatment group) from one year to the next, while still maintaining hospital cover. To check the potential impact on estimates from changes in the definition of the downgrading indicator, sensitivity analysis was carried out by alternatively defining the indicator as:

(1) Any change in household expenditure on PHI below the annual average industry increase in PHI premiums (including no change), while maintaining hospital cover.

(2) A decrease in household expenditure on PHI by more than 5% from one year to the next, while still maintaining hospital cover.

The overall estimated policy effect on downgrading, was relatively robust to the alternative definitions of the downgrading indicator, in terms of both effect size and statistical significance. It remained significant at the 1% level for all sensitivity analyses around the downgrading definition.

The estimated effect varied between 23.8 to 34.7 percentage point probability increase in the sensitivity analyses (compared to 24.6 to 34.6 percentage point increase for the baseline analyses).

The finding of relatively larger downgrading effects with higher income tiers was preserved and robust to changes in the downgrading definition.

8 Conclusions

The objective of this study was to estimate the effects of the FPHII reforms on the treatment group in terms of changes in the probability of having PHI hospital cover and changes in the probability of downgrading PHI hospital cover. It is the first empirical study to look at the FPHII reforms.

There is a history of government intervention in the Australian PHI market, with current government financial incentives and penalties stemming from attempts to stop declining PHI membership after the introduction of Medicare. PHI plays a substantial role in facilitating health care access and financing for half of all Australians, and has been perceived as a vehicle for reducing public hospital cost pressures and waiting lists by government and industry (Colombo and Tapay, 2003).

Contention has been expressed over both cost and equity issues related to PHI and government intervention. Government expenditure on PHI rebates has grown rapidly over time and currently amounts to $6 billion (Commonwealth Government, 2016). Furthermore, some past studies have concluded that rebates have had limited effectiveness in encouraging PHI uptake (Butler, 2003, Frech et al., 2003, Walker et al., 2005, Ellis and Savage, 2008). Recent research (Cheng, 2014) questions the current level of intervention by claiming reduced rebates would generate cost savings above any potential increase in expenditure on public hospital care.

Since PHI coverage rates rise with higher income levels (ATO, 2016), this has meant that the previously flat 30% rebate was disproportionately received by higher income earners and this has been labelled inequitable (Smith, 2001). Some contend that the rebate allowed higher income earners who would have purchased PHI anyway to enjoy windfall gains (Palangkaraya and Yong, 2009). Equity concerns have also been voiced regarding the ability of privately insured patients to bypass waiting lists and access elective surgery sooner than public patients (Cheng, 2014), and access different mixes of health care to uninsured patients (Van Doorslaer et al.., 2008).

The introduction of the FPHII reform package on 1 July 2012 was an attempt by government to balance both efficiency and fairness objectives, while sustaining the role of the PHI market in the Australian health care system. Means testing rebates for higher income earners was an attempt to curb rapidly growing government expenditure on rebates, while ensuring those with a greater capacity to pay made a larger contribution to the cost of their PHI cover (Commonwealth of Australia, 2011). Increasing MLS rates targeted at uninsured higher income earners was an attempt to maintain PHI membership, and recognise and sustain the role PHI plays alongside the public health care system.

The results of this study indicate that the FPHII reforms had a small but significant impact in increasing the probability of having hospital cover for those in the treatment group (2.9% to 3.8%). These results suggest that the FPHII reforms have met their objective of maintaining PHI membership.

This study was the first to look at potential impacts on downgrading from PHI reforms, and found the FPHII package has led to substantial downgrading. The FPHII reforms are estimated to have significantly increased the probability of downgrading hospital cover by 24.6 to 34.6 percentage points for those in the treatment group. Downgrading has not been empirically explored in any other Australian studies, but other data sources support that increased downgrading has been occurring following the FPHII reforms (Section 2.2).

This is significant as downgrading may have important implications for vertical equity in health care use. Because PHI covers ancillary services and different mixes of hospital services, downgrades could result in potential inequity in health care use if it involves increases the number of excluded services in policies. Recent APRA (2016) data indicates that this type of downgrading has been occurring since FPHII introduction, with a sharp switch from 'no lifetime exclusions' policies to 'some lifetime exclusions' policies (Section 2.2.2). Additionally, downgrades that involve increasing excess levels may reduce access to private hospitals to due increased out-of-pocket costs.

These issues combined with the large number of existing PHI policies, complexity in product features and asymmetric information on the insurer side (ACCC, 2015) could potentially exacerbate patients not being covered for services they need and/or facing longer waiting times for services by relying on public health care. The potential public health care cost implications of downgrading have not yet been estimated.

However, downgrading may also hold potential benefits for PHI holders, if individuals optimise their policies by excluding services that are rarely or never used. If increased downgrading is a result of optimisation by consumers to ensure policies better suit their needs, downgrading may result in increased welfare.

In terms of government costs, increased downgrades may have resulted in further savings on rebate expenditure for the government. A downgraded policy can result in cost savings for government since it would involve a reduction in policy price and consequently, a lower absolute level of rebate paid by government. The amount of government cost saving from a downgrade depends on the extent of the downgrade and what income tier an individual is in (i.e. those in FPHII income Tier 3 no longer receive a rebate).

Whether the FPHII reforms have met their objective of reducing government costs is dependent on the extent to which cost savings from means-testing rebates and reduced rebates on downgraded policies exceed cost increases from any potential increases in the use of public health care. The effects of the FPHII reforms on the public system is a potential research area for future studies. Additionally, the responses of insurers to the reforms is another topic which could be further investigated. In particular, the potential effects of the FPHII reforms (lower rebates) on product offerings and pricing by insurers could be analysed and estimated.

There are several other directions for expanding this research in the future. The first is to examine the longer-term impacts of the FPHII reforms using later waves of HILDA data. This would be particularly useful for investigating the increased downgrading effects in 2014-15 which have been picked up in other data sources (see Section 2.2).

It is noted that the introduction of the FPHII reforms coincided with a number of other significant policy changes that may have impacted individuals affected by FPHII, such as the introduction of the carbon tax (*Clean Energy Act 2011)* and reforms to improve access to aged care. These may have acted as potential confounders to the estimated policy effect, which is acknowledged as a limitation of this analysis.

The estimates of the policy effects obtained from HILDA could be compared to other datasets such as ATO income tax data. This would assist in examining the robustness of estimated policy effects. The implications of the downgrading effect found in this study for health care use, equity in health care use and costs could be further explored and estimated. The HILDA survey contains va1riables on health care use and health status in pre- and post-reform periods, which could assist this potential research investigation.

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Appendix

A.1 Explanatory variables list

Table A.1 List of explanatory variables

Variable	Description
y9	dummy for year 2009 (0/1)
y13	dummy for year 2013 (0/1)
y14	dummy for year 2014 (0/1)
treatmentgroup	is in the treatment group (one of the FPHII income tiers) (0/1)
policy	interaction dummy between treatmentgroup and post-reform period year (0/1)
T1policy	interaction dummy between and post-reform period year and being in FPHII income tier 1 (0/1)
T2policy	interaction dummy between and post-reform period year and being in FPHII income tier 2 (0/1)
T3policy	interaction dummy between and post-reform period year and being in FPHII income tier 3 (0/1)
wages	household wages $10,000s
alcoholdaily	drinks alcohol daily (0/1)
children	has children (0/1)
married	is married (0/1)
lthealthcond	has a long term health condition (0/1)
employed	is employed (0/1)
unemployed	is unemployed (0/1)
nilf*	is not in labour force (0/1)
postgrad	has postgrad qualifications (0/1)
bachelors	has a Bachelors degree (0/1)
diploma	has Diploma qualifications (0/1)
cert	has Certificate qualifications (0/1)
nopostschool*	Year 12 or lower education (0/1)
regsmoker	Is a regular smoker - daily or weekly (0/1)
SAHex	self-assessed health status excellent (0/1)
SAHvg	self-assessed health status very good (0/1)
SAHg	self-assessed health status good (0/1)
SAHf*	self-assessed health status fair (0/1)
SAHp	self-assessed health status poor (0/1)
diabetes	type 1 or type 2 diabetes (0/1)

otherhealthcond	presence of long-term condition such as Alzheimer's, asthma, heart disease, dementia etc (0/1)
NSW*	resides in NSW (0/1)
VIC	resides in VIC (0/1)
QLD	resides in QLD (0/1)
SA	resides in SA (0/1)
WA	resides in WA (0/1)
NT	resides in NT (0/1)
TAS	resides in TAS (0/1)
ACT	resides in ACT (0/1)
hospital	number of hospital admissions in last 12 months
bmiobese	BMI obese (0/1)
bmiover	BMI overweight (0/1)
bminorm*	BMI normal (0/1)
bmiunder	BMI underweight (0/1)
physact	participates in physical activity more than 3 days a week (0/1)
major city*	resides in major city (0/1)
innerregional	resides in inner regional area (0/1)
outerregional	resides in outer regional area (0/1)
remote	resides in remote or very remote area (0/1)

Table note: * indicates base dummy variable excluded in regression equation

A.2 Descriptive statistics for explanatory variables

Table A.2: Mean values for explanatory variables - by treatment/control group and year

Variable	Treatment group		Control group		Total	
	mean	std.dev	mean	std.dev	mean	std.dev
2003-04						
wages	9.698	6.195	4.380	4.553	5.308	5.280
alcoholdaily	0.067	0.250	0.084	0.277	0.081	0.273
children	0.560	0.497	0.348	0.476	0.385	0.487
married	0.617	0.486	0.595	0.491	0.599	0.490
lthealthcond	0.168	0.374	0.274	0.446	0.255	0.436
employed	0.869	0.337	0.622	0.485	0.665	0.472
unemployed	0.017	0.128	0.024	0.152	0.022	0.148
nilf	0.114	0.318	0.355	0.478	0.313	0.464
postgrad	0.178	0.383	0.077	0.266	0.094	0.292
bachelors	0.245	0.430	0.105	0.307	0.130	0.336
diploma	0.109	0.312	0.094	0.292	0.096	0.295
cert	0.161	0.367	0.200	0.400	0.193	0.395
nopostschool	0.307	0.462	0.524	0.499	0.486	0.500
regsmoker	0.124	0.329	0.200	0.400	0.187	0.390
SAHex	0.130	0.336	0.083	0.276	0.091	0.288
SAHvg	0.410	0.492	0.344	0.475	0.355	0.479
SAHg	0.310	0.463	0.360	0.480	0.352	0.478
SAHf	0.094	0.292	0.135	0.342	0.128	0.334
SAHp	0.006	0.078	0.031	0.174	0.027	0.162
diabetes	0.000	0.000	0.000	0.000	0.000	0.000
otherhealt~d	0.054	0.227	0.107	0.309	0.098	0.297
NSW	0.307	0.462	0.292	0.455	0.295	0.456
VIC	0.266	0.442	0.249	0.433	0.252	0.434
QLD	0.183	0.387	0.210	0.407	0.205	0.404
SA	0.072	0.259	0.102	0.303	0.097	0.296
WA	0.112	0.316	0.090	0.286	0.094	0.291
NT	0.011	0.106	0.007	0.086	0.008	0.090
TAS	0.020	0.141	0.034	0.180	0.031	0.174
ACT	0.028	0.165	0.016	0.125	0.018	0.133
hospital	0.098	0.371	0.182	0.616	0.167	0.582

physact	0.295	0.456	0.324	0.468	0.319	0.466
majorcity	0.743	0.437	0.613	0.487	0.635	0.481
innerregio~l	0.168	0.374	0.250	0.433	0.236	0.425
outerregio~l	0.069	0.254	0.119	0.323	0.110	0.313
remote	0.020	0.141	0.018	0.134	0.019	0.135

Variable	**Treatment group**		**Control group**		**Total**	
	mean	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**
			2008-09			
wages	14.002	8.228	5.253	5.324	6.785	6.803
alcoholdaily	0.051	0.219	0.087	0.281	0.080	0.272
children	0.516	0.500	0.331	0.471	0.363	0.481
married	0.652	0.477	0.606	0.489	0.614	0.487
lthealthcond	0.183	0.387	0.358	0.479	0.327	0.469
employed	0.884	0.321	0.594	0.491	0.645	0.479
unemployed	0.011	0.106	0.020	0.141	0.019	0.135
nilf	0.105	0.307	0.386	0.487	0.336	0.473
postgrad	0.209	0.407	0.090	0.286	0.111	0.314
bachelors	0.251	0.434	0.111	0.314	0.136	0.342
diploma	0.115	0.319	0.099	0.299	0.102	0.302
cert	0.172	0.378	0.224	0.417	0.215	0.411
nopostschool	0.253	0.435	0.476	0.499	0.437	0.496
regsmoker	0.098	0.297	0.157	0.364	0.147	0.354
SAHex	0.157	0.364	0.084	0.278	0.097	0.296
SAHvg	0.384	0.487	0.327	0.469	0.337	0.473
SAHg	0.286	0.452	0.341	0.474	0.332	0.471
SAHf	0.080	0.271	0.134	0.340	0.124	0.330
SAHp	0.014	0.117	0.031	0.172	0.028	0.164
diabetes	0.035	0.184	0.070	0.255	0.064	0.244
otherhealt~d	0.064	0.245	0.163	0.370	0.146	0.353
NSW	0.305	0.461	0.287	0.452	0.290	0.454
VIC	0.260	0.439	0.249	0.432	0.251	0.434
QLD	0.188	0.391	0.217	0.412	0.212	0.409
SA	0.070	0.255	0.101	0.302	0.096	0.294
WA	0.113	0.316	0.090	0.286	0.094	0.291
NT	0.013	0.114	0.006	0.080	0.008	0.087
TAS	0.020	0.140	0.033	0.178	0.031	0.172

ACT	0.031	0.172	0.017	0.129	0.019	0.138
hospital	0.115	0.380	0.207	0.671	0.191	0.631
physact	0.303	0.460	0.325	0.469	0.322	0.467
majorcity	0.756	0.430	0.601	0.490	0.629	0.483
innerregio~l	0.161	0.368	0.264	0.441	0.246	0.431
outerregio~l	0.067	0.251	0.119	0.324	0.110	0.313
remote	0.016	0.125	0.016	0.125	0.016	0.125

Variable	**Treatment group**		**Control group**		**Total**	
	mean	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**
2012-13						
wages	19.059	10.960	5.104	5.420	5.104	5.420
alcoholdaily	0.056	0.230	0.082	0.275	0.082	0.275
children	0.431	0.495	0.310	0.462	0.310	0.462
married	0.655	0.476	0.602	0.490	0.602	0.490
lthealthcond	0.224	0.417	0.409	0.492	0.409	0.492
employed	0.869	0.337	0.530	0.499	0.530	0.499
unemployed	0.011	0.106	0.020	0.140	0.020	0.140
nilf	0.119	0.324	0.450	0.498	0.450	0.498
postgrad	0.238	0.426	0.098	0.298	0.098	0.298
bachelors	0.237	0.426	0.110	0.313	0.110	0.313
diploma	0.119	0.324	0.104	0.305	0.104	0.305
cert	0.171	0.377	0.234	0.424	0.234	0.424
nopostschool	0.235	0.424	0.453	0.498	0.453	0.498
regsmoker	0.085	0.278	0.134	0.340	0.134	0.340
SAHex	0.122	0.327	0.063	0.243	0.063	0.243
SAHvg	0.395	0.489	0.302	0.459	0.302	0.459
SAHg	0.309	0.462	0.358	0.479	0.358	0.479
SAHf	0.103	0.304	0.162	0.368	0.162	0.368
SAHp	0.011	0.106	0.043	0.203	0.043	0.203
diabetes	0.052	0.223	0.089	0.285	0.089	0.285
otherhealt~d	0.083	0.276	0.197	0.398	0.197	0.398
NSW	0.306	0.461	0.286	0.452	0.286	0.452
VIC	0.262	0.440	0.250	0.433	0.250	0.433
QLD	0.188	0.391	0.217	0.412	0.217	0.412
SA	0.071	0.256	0.099	0.299	0.099	0.299
WA	0.114	0.318	0.090	0.287	0.090	0.287

NT	0.011	0.106	0.007	0.081	0.007	0.081
TAS	0.017	0.131	0.035	0.184	0.035	0.184
ACT	0.030	0.170	0.016	0.125	0.016	0.125
hospital	0.151	0.524	0.250	0.864	0.250	0.864
physact	0.317	0.466	0.318	0.466	0.318	0.466
majorcity	0.759	0.428	0.597	0.490	0.597	0.490
innerregio~l	0.169	0.375	0.266	0.442	0.266	0.442
outerregio~l	0.060	0.238	0.122	0.327	0.122	0.327
remote	0.011	0.106	0.015	0.120	0.015	0.120

Table A.3: Mean values for explanatory variables - by treatment/control group and year

Variable	Treatment group		Control group		Total	
	mean	std.dev	mean	std.dev	mean	std.dev
2011-12						
wages	17.932	9.734	6.337	6.194	9.328	8.867
alcoholdaily	0.049	0.216	0.097	0.296	0.085	0.278
children	0.478	0.500	0.301	0.459	0.346	0.476
married	0.719	0.450	0.714	0.452	0.715	0.451
lthealthcond	0.154	0.361	0.339	0.473	0.291	0.454
employed	0.889	0.315	0.578	0.494	0.659	0.474
unemployed	0.009	0.093	0.013	0.114	0.012	0.109
nilf	0.103	0.303	0.408	0.492	0.329	0.470
postgrad	0.262	0.440	0.145	0.352	0.175	0.380
bachelors	0.267	0.443	0.146	0.353	0.177	0.382
diploma	0.121	0.326	0.119	0.323	0.119	0.324
cert	0.150	0.358	0.205	0.404	0.191	0.393
nopostschool	0.200	0.400	0.385	0.487	0.337	0.473
regsmoker	0.063	0.244	0.072	0.258	0.069	0.254
SAHex	0.143	0.350	0.076	0.265	0.093	0.291
SAHvg	0.397	0.490	0.344	0.475	0.358	0.479
SAHg	0.322	0.467	0.381	0.486	0.365	0.482
SAHf	0.076	0.266	0.129	0.336	0.116	0.320
SAHp	0.007	0.081	0.025	0.157	0.021	0.142
otherhealt~d	0.059	0.236	0.164	0.370	0.137	0.344
NSW	0.314	0.464	0.277	0.448	0.287	0.452
VIC	0.253	0.435	0.271	0.445	0.267	0.442

QLD	0.177	0.382	0.186	0.389	0.184	0.387
SA	0.067	0.249	0.098	0.298	0.090	0.286
WA	0.123	0.329	0.110	0.313	0.113	0.317
NT	0.013	0.114	0.008	0.089	0.009	0.096
TAS	0.017	0.131	0.029	0.167	0.026	0.159
ACT	0.036	0.186	0.020	0.140	0.024	0.154
bmiobese	0.206	0.405	0.228	0.420	0.222	0.416
bmiover	0.387	0.487	0.361	0.480	0.367	0.482
bminorm	0.328	0.470	0.332	0.471	0.331	0.471
bmiunder	0.014	0.118	0.013	0.113	0.013	0.114
majorcity	0.768	0.423	0.650	0.477	0.680	0.466
innerregio~l	0.155	0.362	0.245	0.430	0.221	0.415
outerregio~l	0.062	0.242	0.088	0.284	0.082	0.274
remote	0.015	0.123	0.017	0.131	0.017	0.129

Variable	**Treatment group**		**Control group**		**Total**	
	mean	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**
2012-13						
wages	19.754	11.269	5.957	5.953	9.516	9.771
alcoholdaily	0.059	0.236	0.099	0.298	0.088	0.284
children	0.469	0.499	0.299	0.458	0.343	0.475
married	0.716	0.451	0.710	0.454	0.711	0.453
lthealthcond	0.204	0.403	0.376	0.484	0.332	0.471
employed	0.883	0.321	0.559	0.497	0.642	0.479
unemployed	0.010	0.099	0.012	0.108	0.011	0.105
nilf	0.107	0.309	0.429	0.495	0.346	0.476
postgrad	0.267	0.443	0.147	0.354	0.178	0.382
bachelors	0.263	0.440	0.145	0.352	0.175	0.380
diploma	0.124	0.330	0.121	0.326	0.122	0.327
cert	0.148	0.356	0.204	0.403	0.190	0.392
nopostschool	0.197	0.398	0.383	0.486	0.335	0.472
regsmoker	0.060	0.238	0.066	0.248	0.064	0.245
SAHex	0.134	0.341	0.071	0.257	0.087	0.283
SAHvg	0.415	0.493	0.359	0.480	0.374	0.484
SAHg	0.297	0.457	0.360	0.480	0.344	0.475
SAHf	0.095	0.293	0.129	0.335	0.120	0.325
SAHp	0.010	0.099	0.030	0.169	0.024	0.155

otherhealt~d	0.072	0.259	0.181	0.385	0.153	0.360
NSW	0.315	0.465	0.277	0.448	0.287	0.452
VIC	0.253	0.435	0.271	0.445	0.267	0.442
QLD	0.178	0.383	0.187	0.390	0.185	0.388
SA	0.067	0.249	0.098	0.297	0.090	0.286
WA	0.123	0.329	0.110	0.313	0.114	0.317
NT	0.012	0.109	0.008	0.087	0.009	0.093
TAS	0.017	0.131	0.029	0.167	0.026	0.159
ACT	0.035	0.184	0.020	0.140	0.024	0.153
bmiobese	0.214	0.410	0.233	0.423	0.228	0.420
bmiover	0.402	0.491	0.364	0.481	0.374	0.484
bminorm	0.313	0.464	0.323	0.468	0.320	0.467
bmiunder	0.011	0.104	0.012	0.108	0.012	0.107
majorcity	0.768	0.423	0.651	0.477	0.681	0.466
innerregio~l	0.158	0.365	0.245	0.430	0.223	0.416
outerregio~l	0.061	0.240	0.087	0.282	0.080	0.272
remote	0.013	0.114	0.017	0.128	0.016	0.125

Variable	**Treatment group**		**Control group**		**Total**	
	mean	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**
2013-14						
wages	18.951	10.799	6.271	6.702	9.558	9.714
alcoholdaily	0.058	0.234	0.092	0.289	0.083	0.276
children	0.461	0.499	0.287	0.453	0.332	0.471
married	0.723	0.448	0.704	0.456	0.709	0.454
lthealthcond	0.184	0.387	0.379	0.485	0.329	0.470
employed	0.853	0.355	0.543	0.498	0.624	0.485
unemployed	0.010	0.099	0.008	0.092	0.009	0.094
nilf	0.138	0.345	0.448	0.497	0.368	0.482
postgrad	0.274	0.446	0.147	0.355	0.180	0.384
bachelors	0.256	0.437	0.145	0.352	0.174	0.379
diploma	0.124	0.330	0.121	0.327	0.122	0.327
cert	0.145	0.353	0.203	0.402	0.188	0.391
nopostschool	0.200	0.400	0.383	0.486	0.336	0.472
regsmoker	0.061	0.239	0.063	0.243	0.062	0.242
SAHex	0.122	0.328	0.062	0.242	0.078	0.268
SAHvg	0.383	0.486	0.343	0.475	0.353	0.478

SAHg	0.343	0.475	0.361	0.480	0.356	0.479
SAHf	0.088	0.283	0.146	0.353	0.131	0.337
SAHp	0.011	0.104	0.032	0.176	0.027	0.161
otherhealt~d	0.075	0.263	0.186	0.389	0.157	0.364
NSW	0.317	0.465	0.273	0.446	0.285	0.451
VIC	0.251	0.434	0.272	0.445	0.267	0.442
QLD	0.180	0.385	0.187	0.390	0.185	0.388
SA	0.066	0.248	0.098	0.297	0.090	0.286
WA	0.123	0.329	0.112	0.316	0.115	0.319
NT	0.011	0.104	0.008	0.092	0.009	0.095
TAS	0.017	0.127	0.030	0.170	0.026	0.160
ACT	0.035	0.184	0.019	0.137	0.023	0.151
bmiobese	0.222	0.416	0.228	0.419	0.226	0.418
bmiover	0.394	0.489	0.353	0.478	0.364	0.481
bminorm	0.310	0.463	0.327	0.469	0.323	0.468
bmiunder	0.007	0.081	0.014	0.117	0.012	0.109
majorcity	0.766	0.424	0.643	0.479	0.675	0.469
innerregio~l	0.163	0.369	0.254	0.435	0.230	0.421
outerregio~l	0.058	0.234	0.085	0.280	0.078	0.269
remote	0.013	0.114	0.018	0.132	0.017	0.128

A.3 Modelling results: full set of estimated coefficients

Changes in the probability of having hospital cover

Table A.4: The effect of the reforms on having hospital cover, 2008-09 and 2012-13

	Coefficient	Robust standard error	t	p-value
First-difference estimator - model (i)				
policy***	0.029	0.011	2.720	0.007
wages***	0.003	0.001	3.670	0.000
hospital	0.004	0.003	1.440	0.151
alcoholdaily***	-0.037	0.013	-2.760	0.006
children	-0.005	0.015	-0.320	0.751
married***	0.051	0.017	2.920	0.004
lthealthcond	0.000	0.008	0.060	0.954
employed	0.001	0.011	0.130	0.896
unemployed	0.023	0.020	1.110	0.269
postgrad*	0.107	0.055	1.940	0.052
bachelors	0.090	0.060	1.510	0.132
diploma	0.029	0.049	0.590	0.553
cert	0.001	0.039	0.040	0.970
regsmoker	-0.014	0.015	-0.930	0.353
SAHex	-0.004	0.016	-0.260	0.794
SAHvg	-0.013	0.010	-1.270	0.205
SAHg	-0.010	0.009	-1.120	0.264
SAHp	-0.018	0.017	-1.030	0.303
diabetes	0.001	0.018	0.060	0.950
VIC	0.048	0.066	0.730	0.467
QLD	-0.011	0.054	-0.210	0.835
SA	0.081	0.095	0.850	0.397
WA	0.003	0.084	0.030	0.974
TAS	0.039	0.113	0.340	0.731
NT	0.077	0.093	0.830	0.409
ACT	-0.009	0.073	-0.130	0.897
bmiobese*	0.024	0.012	1.950	0.051
bmiover	0.009	0.008	1.080	0.278
bmiunder	0.008	0.029	0.270	0.789
outerregional***	-0.092	0.033	-2.760	0.006
innerregional	-0.007	0.025	-0.270	0.786
remote	-0.023	0.056	-0.400	0.686
_cons***	0.014	0.004	3.190	0.001
N		**6,522**		

	Coefficient	Robust standard error	t	p-value
First-difference estimator - model (ii)				
T1policy***	0.063	0.020	3.170	0.002
T2policy*	0.029	0.015	1.930	0.053
T3policy	-0.011	0.016	-0.720	0.470

Dwages***	0.003	0.001	4.140	0.000
Dhospital	0.004	0.003	1.390	0.165
Dalcoholdaily***	-0.037	0.013	-2.740	0.006
Dchildren	-0.006	0.015	-0.390	0.693
Dmarried***	0.049	0.017	2.830	0.005
Dlthealthcond	0.000	0.008	0.050	0.962
Demployed	0.001	0.011	0.080	0.935
Dunemployed	0.022	0.020	1.090	0.277
Dpostgrad*	0.105	0.055	1.920	0.055
Dbachelors	0.090	0.060	1.510	0.131
Ddiploma	0.028	0.049	0.580	0.564
Dcert	0.001	0.038	0.030	0.980
Dregsmoker	-0.014	0.015	-0.930	0.350
DSAHex	-0.004	0.016	-0.240	0.813
DSAHvg	-0.013	0.010	-1.230	0.218
DSAHg	-0.009	0.009	-1.050	0.292
DSAHp	-0.017	0.017	-0.990	0.323
Ddiabetes	0.002	0.018	0.130	0.896
DVIC	0.048	0.066	0.720	0.470
DQLD	-0.010	0.054	-0.190	0.852
DSA	0.079	0.096	0.820	0.412
DWA	0.004	0.084	0.040	0.965
DTAS	0.036	0.113	0.320	0.749
DNT	0.075	0.092	0.820	0.414
DACT	-0.008	0.072	-0.110	0.911
Dbmiobese**	0.024	0.012	1.970	0.049
Dbmiover	0.009	0.008	1.070	0.284
Dbmiunder	0.009	0.028	0.300	0.764
Douterregional***	-0.093	0.033	-2.780	0.005
Dinnerregional	-0.008	0.025	-0.330	0.742
Dremote	-0.025	0.056	-0.450	0.655
_cons***	0.014	0.004	3.190	0.001
N		**6,522**		

	Coefficient	**Robust standard error**	**t**	**p-value**
		OLS - model (i)		
y13	0.014	0.011	1.280	0.201
treatmentgroup***	0.138	0.017	8.040	0.000
policy	-0.019	0.021	-0.880	0.377
wages***	0.009	0.001	10.670	0.000
alcoholdaily***	0.069	0.015	4.480	0.000
children***	-0.115	0.011	-10.580	0.000
married***	0.167	0.010	16.560	0.000
lthealthcond	0.015	0.010	1.490	0.137
employed	0.008	0.011	0.690	0.490
unemployed***	-0.099	0.028	-3.580	0.000
postgrad***	0.210	0.013	15.870	0.000
bachelors***	0.165	0.013	12.560	0.000
diploma***	0.115	0.014	8.260	0.000
cert	-0.002	0.011	-0.160	0.871
regsmoker***	-0.192	0.012	-15.780	0.000
SAHex***	0.106	0.017	6.150	0.000
SAHvg***	0.130	0.012	10.460	0.000

SAHg***	0.081	0.012	6.950	0.000
SAHp	-0.019	0.024	-0.800	0.422
diabetes	-0.010	0.016	-0.610	0.540
VIC	0.021	0.013	1.640	0.101
QLD	-0.020	0.014	-1.460	0.143
SA	0.023	0.018	1.270	0.205
WA***	0.084	0.017	4.850	0.000
NT***	0.138	0.051	2.700	0.007
TAS	0.037	0.029	1.300	0.194
ACT	0.047	0.032	1.440	0.149
hospital**	0.012	0.006	2.060	0.040
bmiobese	-0.011	0.011	-1.020	0.310
bmiover*	0.018	0.009	1.920	0.055
bmiunder	-0.052	0.032	-1.590	0.111
innerregional***	-0.044	0.012	-3.660	0.000
outerregional***	-0.110	0.017	-6.630	0.000
remote	0.001	0.043	0.010	0.990
_cons***	0.280	0.018	15.490	0.000
N		**13,067**		

	Coefficient	Robust standard error	t	p-value
		OLS - model (ii)		
y13	0.014	0.011	1.270	0.205
treatmentgroup***	0.135	0.017	7.890	0.000
T1policy	0.011	0.029	0.370	0.710
T2policy	-0.013	0.026	-0.510	0.607
T3policy**	-0.061	0.029	-2.070	0.038
wages***	0.009	0.001	11.040	0.000
alcoholdaily***	0.068	0.015	4.420	0.000
children***	-0.116	0.011	-10.670	0.000
married***	0.166	0.010	16.390	0.000
lthealthcond	0.015	0.010	1.500	0.135
employed	0.006	0.011	0.540	0.592
unemployed***	-0.100	0.028	-3.630	0.000
postgrad***	0.211	0.013	15.910	0.000
bachelors***	0.165	0.013	12.570	0.000
diploma***	0.115	0.014	8.230	0.000
cert	-0.002	0.011	-0.210	0.837
regsmoker***	-0.192	0.012	-15.820	0.000
SAHex***	0.107	0.017	6.180	0.000
SAHvg***	0.130	0.012	10.460	0.000
SAHg***	0.082	0.012	6.980	0.000
SAHp	-0.019	0.024	-0.780	0.438
diabetes	-0.008	0.016	-0.490	0.622
VIC	0.021	0.013	1.610	0.107
QLD	-0.021	0.014	-1.490	0.136
SA	0.022	0.018	1.220	0.222
WA***	0.085	0.017	4.880	0.000
NT***	0.137	0.051	2.660	0.008
TAS	0.037	0.029	1.280	0.199
ACT	0.046	0.032	1.410	0.158
hospital**	0.012	0.006	2.040	0.041
bmiobese	-0.012	0.011	-1.100	0.270

bmiover*	0.018	0.009	1.890	0.059
bmiunder*	-0.054	0.033	-1.650	0.099
innerregional***	-0.044	0.012	-3.630	0.000
outerregional***	-0.110	0.017	-6.610	0.000
remote	0.002	0.043	0.050	0.961
_cons***	0.280	0.018	15.520	0.000
N		**13,067**		

*p<0.1**

*p<0.05***

*p<0.01****

Table A.5: The effect of the reforms on having hospital cover, 2003,04, 2008-09 and 2012-13

	Coefficient	Robust standard error	t	p-value
		First-difference estimator - model (i)		
y13	-0.006	0.006	-0.970	0.333
policy**	0.024	0.011	2.270	0.023
wages***	0.004	0.001	5.850	0.000
hospital	0.003	0.002	1.360	0.174
alcoholdaily**	-0.021	0.010	-2.210	0.027
children	0.010	0.010	1.010	0.313
married***	0.079	0.012	6.450	0.000
lthealthcond	-0.003	0.006	-0.490	0.624
employed	0.011	0.008	1.470	0.143
unemployed*	0.026	0.015	1.770	0.076
postgrad***	0.107	0.041	2.600	0.009
bachelors*	0.072	0.037	1.940	0.052
diploma	0.043	0.038	1.140	0.255
cert	-0.016	0.022	-0.740	0.458
regsmoker***	-0.032	0.011	-2.860	0.004
SAHex	-0.007	0.012	-0.580	0.561
SAHvg	-0.007	0.007	-1.000	0.315
SAHg	-0.006	0.006	-0.890	0.375
SAHp	0.000	0.013	0.020	0.988
otherhealthcond	0.008	0.007	1.090	0.274
VIC	0.017	0.033	0.530	0.598
QLD	-0.026	0.029	-0.890	0.371
SA	0.075	0.054	1.390	0.164
WA	-0.003	0.064	-0.040	0.966
TAS	0.091	0.082	1.100	0.271
NT	0.074	0.079	0.930	0.355
ACT	0.001	0.044	0.030	0.975
physact	-0.008	0.005	-1.620	0.106
outerregional	-0.034	0.025	-1.370	0.170
innerregional	-0.005	0.016	-0.290	0.774
remote	0.004	0.043	0.100	0.923
_cons***	0.021	0.005	4.630	0.000
N		**13,067**		

	Coefficient	Robust standard error	t	p-value
First-difference estimator - model (ii)				
y13	-0.006	0.006	-0.920	0.355
T1policy***	0.059	0.020	2.950	0.003
T2policy*	0.027	0.015	1.780	0.075
T3policy	-0.017	0.016	-1.090	0.276
wages***	0.004	0.001	6.100	0.000
hospital	0.003	0.002	1.320	0.186
alcoholdaily**	-0.021	0.010	-2.200	0.028
children	0.010	0.010	0.960	0.335
married***	0.078	0.012	6.390	0.000
lthealthcond	-0.003	0.006	-0.500	0.617
employed	0.011	0.008	1.420	0.155
unemployed*	0.026	0.015	1.760	0.079
postgrad***	0.106	0.041	2.570	0.010
bachelors*	0.071	0.037	1.940	0.053
diploma	0.043	0.038	1.130	0.260
cert	-0.017	0.022	-0.750	0.453
regsmoker***	-0.032	0.011	-2.870	0.004
SAHex	-0.007	0.012	-0.570	0.570
SAHvg	-0.007	0.007	-0.980	0.328
SAHg	-0.005	0.006	-0.840	0.400
SAHp	0.001	0.013	0.040	0.965
otherhealthcond	0.008	0.007	1.110	0.266
VIC	0.017	0.033	0.530	0.596
QLD	-0.026	0.029	-0.880	0.378
SA	0.075	0.054	1.380	0.168
WA	-0.002	0.064	-0.030	0.972
TAS	0.089	0.082	1.080	0.279
NT	0.073	0.079	0.920	0.359
ACT	0.002	0.043	0.040	0.965
physact	-0.008	0.005	-1.590	0.111
outerregional	-0.034	0.025	-1.380	0.168
innerregional	-0.005	0.016	-0.320	0.750
remote	0.003	0.043	0.070	0.942
_cons***	0.021	0.005	4.570	0.000
N		**13,067**		

	Coefficient	Robust standard error	t	p-value
Fixed effects - model (i)				
y9***	0.022	0.004	5.400	0.000
y13***	0.035	0.005	6.950	0.000
policy***	0.038	0.010	3.860	0.000
wages***	0.004	0.001	6.800	0.000
alcoholdaily	-0.006	0.010	-0.560	0.573
children*	0.017	0.009	1.840	0.065
married***	0.086	0.012	7.400	0.000
lthealthcond	-0.005	0.006	-0.760	0.447
employed***	0.023	0.008	2.820	0.005
unemployed**	0.034	0.016	2.110	0.034

postgrad**	0.091	0.039	2.350	0.019
bachelors	0.055	0.036	1.550	0.122
diploma	0.045	0.035	1.260	0.207
cert	-0.027	0.021	-1.260	0.207
regsmoker***	-0.034	0.011	-3.060	0.002
SAHex	-0.011	0.012	-0.900	0.371
SAHvg	-0.001	0.008	-0.100	0.923
SAHg	0.003	0.007	0.390	0.699
SAHp	0.003	0.014	0.200	0.838
otherhealthcond	0.005	0.007	0.770	0.444
VIC	0.032	0.030	1.100	0.272
QLD	-0.027	0.026	-1.030	0.302
SA	0.058	0.052	1.110	0.268
WA	0.033	0.048	0.690	0.492
NT	0.073	0.067	1.100	0.271
TAS	0.051	0.048	1.060	0.290
ACT	0.038	0.045	0.840	0.402
hospital	0.003	0.002	1.190	0.235
physact	-0.008	0.005	-1.430	0.154
innerregional	0.003	0.015	0.170	0.862
outerregional	-0.025	0.023	-1.110	0.269
remote	0.012	0.039	0.320	0.747
_cons***	0.403	0.023	17.830	0.000
N		**19,596**		

	Coefficient	**Robust standard error**	**t**	**p-value**
		Fixed effects - model (ii)		
y9***	0.021	0.004	5.250	0.000
y13***	0.035	0.005	6.860	0.000
T1policy***	0.077	0.018	4.230	0.000
T2policy***	0.043	0.014	3.000	0.003
T3policy	-0.012	0.016	-0.730	0.465
wages***	0.004	0.001	7.320	0.000
alcoholdaily	-0.006	0.010	-0.560	0.573
children*	0.016	0.009	1.800	0.073
married***	0.085	0.012	7.270	0.000
lthealthcond	-0.005	0.006	-0.730	0.463
employed***	0.022	0.008	2.700	0.007
unemployed**	0.033	0.016	2.060	0.039
postgrad**	0.091	0.039	2.360	0.018
bachelors	0.056	0.036	1.560	0.118
diploma	0.044	0.035	1.260	0.209
cert	-0.027	0.021	-1.260	0.208
regsmoker***	-0.034	0.011	-3.060	0.002
SAHex	-0.011	0.012	-0.880	0.380
SAHvg	-0.001	0.008	-0.080	0.935
SAHg	0.003	0.007	0.440	0.662
SAHp	0.003	0.014	0.230	0.817
otherhealthcond	0.005	0.007	0.700	0.483
VIC	0.032	0.029	1.070	0.283
QLD	-0.027	0.026	-1.040	0.299
SA	0.054	0.052	1.030	0.301
WA	0.033	0.048	0.700	0.487

NT	0.073	0.067	1.090	0.275
TAS	0.049	0.048	1.010	0.311
ACT	0.038	0.045	0.830	0.405
hospital	0.003	0.002	1.120	0.263
physact	-0.007	0.005	-1.330	0.182
innerregional	0.002	0.015	0.130	0.896
outerregional	-0.025	0.023	-1.110	0.269
remote	0.012	0.038	0.310	0.760
_cons***	0.403	0.023	17.890	0.000
N		**19,596**		

	Coefficient	**Robust standard error**	**t**	**p-value**
		OLS - model (i)		
y9	-0.001	0.010	-0.070	0.947
y13	0.013	0.011	1.200	0.232
treatmentgroup***	0.120	0.012	9.640	0.000
policy	-0.025	0.019	-1.320	0.186
wages***	0.011	0.001	14.240	0.000
alcoholdaily***	0.077	0.013	6.100	0.000
children***	-0.108	0.009	-12.270	0.000
married***	0.171	0.008	20.630	0.000
lthealthcond	0.008	0.009	0.810	0.420
employed**	0.019	0.009	2.180	0.029
unemployed***	-0.099	0.021	-4.660	0.000
postgrad***	0.200	0.011	17.920	0.000
bachelors***	0.157	0.011	14.560	0.000
diploma***	0.112	0.011	9.710	0.000
cert	-0.003	0.009	-0.390	0.695
regsmoker***	-0.185	0.010	-19.340	0.000
SAHex***	0.091	0.014	6.300	0.000
SAHvg***	0.118	0.010	11.290	0.000
SAHg***	0.081	0.010	8.330	0.000
SAHp	-0.033	0.020	-1.610	0.107
otherhealthcond	0.014	0.012	1.200	0.230
VIC	0.017	0.011	1.630	0.103
QLD***	-0.032	0.011	-2.850	0.004
SA	0.024	0.015	1.640	0.102
WA***	0.078	0.014	5.380	0.000
NT**	0.093	0.045	2.070	0.038
TAS*	0.039	0.023	1.710	0.087
ACT***	0.071	0.027	2.580	0.010
hospital***	0.018	0.005	3.290	0.001
physact**	0.015	0.007	2.030	0.042
innerregional***	-0.046	0.010	-4.640	0.000
outerregional***	-0.107	0.014	-7.800	0.000
remote	-0.006	0.033	-0.180	0.858
_cons***	0.267	0.015	17.860	0.000
N		**19,596**		

	Coefficient	**Robust standard error**	**t**	**p-value**
		OLS - model (i)		

y9	-0.001	0.010	-0.120	0.908
y13	0.012	0.011	1.150	0.251
treatmentgroup***	0.119	0.012	9.500	0.000
T1policy	0.012	0.027	0.450	0.655
T2policy	-0.019	0.024	-0.800	0.424
T3policy***	-0.075	0.028	-2.670	0.008
wages***	0.011	0.001	14.670	0.000
alcoholdaily***	0.076	0.013	6.000	0.000
children***	-0.109	0.009	-12.350	0.000
married***	0.170	0.008	20.450	0.000
lthealthcond	0.008	0.009	0.870	0.384
employed**	0.018	0.009	2.000	0.045
unemployed***	-0.102	0.021	-4.790	0.000
postgrad***	0.200	0.011	17.950	0.000
bachelors***	0.157	0.011	14.580	0.000
diploma***	0.111	0.011	9.670	0.000
cert	-0.004	0.009	-0.490	0.622
regsmoker***	-0.185	0.010	-19.410	0.000
SAHex***	0.091	0.014	6.340	0.000
SAHvg***	0.118	0.010	11.260	0.000
SAHg***	0.081	0.010	8.350	0.000
SAHp	-0.032	0.020	-1.590	0.111
otherhealthcond	0.014	0.012	1.180	0.240
VIC	0.017	0.011	1.630	0.103
QLD***	-0.032	0.011	-2.860	0.004
SA	0.024	0.015	1.590	0.113
WA***	0.078	0.014	5.420	0.000
NT**	0.092	0.045	2.060	0.040
TAS*	0.039	0.023	1.710	0.088
ACT**	0.070	0.027	2.550	0.011
hospital***	0.018	0.005	3.280	0.001
physact**	0.015	0.007	2.100	0.035
innerregional***	-0.046	0.010	-4.610	0.000
outerregional***	-0.107	0.014	-7.840	0.000
remote	-0.005	0.033	-0.160	0.874
_cons***	0.268	0.015	17.890	0.000
N		**19,596**		

$p<0.1$*

$p<0.05$**

$p<0.01$***

Changes in the probability of downgrading hospital cover

Table A.6: The effect of the reforms on downgrading hospital cover, 2008-09 and 2012-13

	Coefficient	Robust standard error	t	p-value
	First-difference estimator - model (i)			
policy***	0.246	0.035	6.950	0.000
wages	-0.002	0.002	-0.770	0.442
hospital	-0.004	0.014	-0.300	0.766
alcoholdaily**	0.114	0.045	2.560	0.011
children**	-0.098	0.045	-2.170	0.030
married**	-0.108	0.048	-2.250	0.025
lthealthcond	-0.009	0.029	-0.310	0.754
employed**	-0.083	0.036	-2.300	0.021
unemployed**	-0.168	0.091	-1.840	0.065
postgrad	0.073	0.154	0.480	0.633
bachelors	0.111	0.155	0.720	0.474
diploma	0.072	0.150	0.480	0.633
cert	0.027	0.129	0.210	0.834
regsmoker	0.009	0.067	0.130	0.893
SAHex**	-0.102	0.045	-2.280	0.023
SAHvg*	-0.063	0.036	-1.770	0.077
SAHg*	-0.052	0.031	-1.660	0.097
SAHp	0.017	0.074	0.230	0.821
diabetes	0.093	0.070	1.320	0.187
VIC*	-0.271	0.150	-1.810	0.070
QLD	0.064	0.115	0.560	0.577
SA	0.140	0.243	0.570	0.566
WA	-0.005	0.153	-0.030	0.973
TAS*	-0.380	0.214	-1.780	0.075
NT	0.219	0.215	1.020	0.310
ACT	0.108	0.187	0.580	0.564
bmiobese	-0.002	0.043	-0.040	0.966
bmiover	0.024	0.029	0.820	0.413
bmiunder	-0.068	0.101	-0.670	0.500
outerregional	-0.073	0.112	-0.650	0.517
innerregional	-0.075	0.092	-0.810	0.417
remote	-0.202	0.130	-1.550	0.122
_cons	-0.012	0.018	-0.710	0.479
N		**3,381**		

	Coefficient	Robust standard error	t	p-value
	First-difference estimator - model (ii)			
T1policy***	0.157	0.059	2.640	0.008
T2policy***	0.239	0.046	5.140	0.000
T3policy***	0.348	0.057	6.110	0.000
wages	-0.003	0.002	-1.260	0.206
hospital	-0.003	0.014	-0.240	0.809
alcoholdaily**	0.113	0.045	2.520	0.012
children**	-0.092	0.045	-2.050	0.040

married**	-0.103	0.048	-2.140	0.033
lthealthcond	-0.009	0.028	-0.320	0.752
employed**	-0.082	0.036	-2.300	0.022
unemployed*	-0.163	0.092	-1.780	0.074
postgrad	0.086	0.152	0.570	0.572
bachelors	0.113	0.154	0.730	0.464
diploma	0.078	0.149	0.520	0.603
cert	0.034	0.128	0.260	0.794
regsmoker	0.007	0.067	0.110	0.912
SAHex**	-0.103	0.045	-2.300	0.021
SAHvg*	-0.064	0.036	-1.810	0.071
SAHg*	-0.053	0.031	-1.710	0.087
SAHp	0.014	0.074	0.180	0.854
diabetes	0.089	0.071	1.270	0.205
VIC*	-0.269	0.150	-1.790	0.073
QLD	0.050	0.115	0.440	0.662
SA	0.141	0.241	0.590	0.557
WA	-0.014	0.151	-0.090	0.927
TAS*	-0.361	0.204	-1.770	0.077
NT	0.215	0.216	0.990	0.321
ACT	0.106	0.180	0.590	0.556
bmiobese	-0.004	0.043	-0.090	0.926
bmiover	0.026	0.029	0.870	0.383
bmiunder	-0.071	0.101	-0.700	0.485
outerregional	-0.067	0.111	-0.610	0.545
innerregional	-0.066	0.092	-0.720	0.470
remote	-0.208	0.131	-1.590	0.111
_cons	-0.013	0.018	-0.740	0.460
N		**3,381**		

	Coefficient	Robust standard error	t	p-value
		OLS - model (i)		
y13	0.003	0.017	0.180	0.854
treatmentgroup***	0.089	0.026	3.470	0.001
policy***	0.230	0.034	6.690	0.000
wages	0.001	0.001	1.030	0.305
alcoholdaily**	0.054	0.023	2.330	0.020
children	-0.015	0.018	-0.830	0.408
married	-0.010	0.016	-0.670	0.505
lthealthcond	-0.008	0.015	-0.520	0.604
employed	0.019	0.017	1.160	0.246
unemployed	-0.002	0.059	-0.040	0.968
postgrad	-0.014	0.019	-0.700	0.483
bachelors	0.013	0.018	0.730	0.465
diploma	-0.009	0.020	-0.440	0.658
cert	-0.007	0.017	-0.410	0.683
regsmoker	0.020	0.024	0.800	0.424
SAHex	-0.030	0.026	-1.160	0.248
SAHvg	-0.027	0.019	-1.400	0.163
SAHg	-0.019	0.019	-1.000	0.317
SAHp	0.023	0.043	0.540	0.587
diabetes	-0.008	0.024	-0.350	0.728
VIC	0.011	0.020	0.550	0.580

QLD	-0.031	0.022	-1.400	0.161
SA	-0.003	0.029	-0.090	0.926
WA	-0.017	0.026	-0.670	0.506
NT	0.055	0.089	0.620	0.533
TAS	0.034	0.050	0.670	0.502
ACT	-0.031	0.048	-0.650	0.518
hospital	-0.004	0.010	-0.360	0.717
bmiobese	-0.005	0.017	-0.280	0.778
bmiover	-0.008	0.013	-0.600	0.551
bmiunder	0.038	0.056	0.670	0.504
innerregional**	0.038	0.019	1.980	0.048
outerregional	0.035	0.030	1.200	0.230
remote	0.022	0.062	0.350	0.724
_cons***	0.350	0.029	11.970	0.000
N		**6,772**		
	Coefficient	**Robust standard error**	**t**	**p-value**
		OLS - model (ii)		
y13	0.003	0.017	0.150	0.879
treatmentgroup***	0.093	0.026	3.630	0.000
T1policy***	0.180	0.047	3.850	0.000
T2policy***	0.209	0.043	4.890	0.000
T3policy***	0.309	0.043	7.130	0.000
wages	0.000	0.001	0.400	0.692
alcoholdaily**	0.055	0.023	2.400	0.016
children	-0.012	0.018	-0.670	0.500
married	-0.009	0.016	-0.540	0.586
lthealthcond	-0.008	0.015	-0.520	0.600
employed	0.024	0.017	1.430	0.153
unemployed	0.005	0.059	0.080	0.935
postgrad	-0.014	0.019	-0.720	0.472
bachelors	0.013	0.018	0.720	0.471
diploma	-0.009	0.020	-0.430	0.666
cert	-0.005	0.017	-0.320	0.750
regsmoker	0.019	0.024	0.780	0.437
SAHex	-0.031	0.026	-1.190	0.234
SAHvg	-0.027	0.019	-1.410	0.160
SAHg	-0.019	0.019	-1.010	0.311
SAHp	0.022	0.043	0.510	0.611
diabetes	-0.009	0.024	-0.370	0.715
VIC	0.012	0.020	0.590	0.557
QLD	-0.030	0.022	-1.350	0.176
SA	0.000	0.029	-0.020	0.987
WA	-0.018	0.026	-0.690	0.489
NT	0.059	0.088	0.670	0.506
TAS	0.035	0.050	0.690	0.490
ACT	-0.030	0.048	-0.620	0.535
hospital	-0.003	0.010	-0.320	0.751
bmiobese	-0.004	0.017	-0.270	0.790
bmiover	-0.007	0.013	-0.530	0.596
bmiunder	0.043	0.057	0.760	0.447
innerregional**	0.039	0.019	1.990	0.047
outerregional	0.035	0.030	1.190	0.233

remote	0.021	0.062	0.340	0.732
_cons***	0.348	0.029	11.920	0.000
N		**6,772**		

*p<0.1**

*p<0.05***

*p<0.01****

Table A.7: The effect of the reforms on downgrading hospital cover, 2011-12 and 2012-13

	Coefficient	Robust standard error	t	p-value
		First-difference estimator - model (i)		
policy***	0.346	0.038	9.170	0.000
wages	-0.004	0.003	-1.130	0.257
alcoholdaily	0.078	0.051	1.530	0.125
children	-0.015	0.070	-0.210	0.831
married	-0.094	0.104	-0.900	0.368
lthealthcond*	-0.060	0.035	-1.700	0.089
employed	-0.011	0.057	-0.200	0.844
unemployed	-0.125	0.097	-1.290	0.197
postgrad	-0.236	0.520	-0.450	0.650
bachelors	-0.044	0.474	-0.090	0.926
diploma	-0.336	0.344	-0.980	0.329
cert	-0.322	0.306	-1.050	0.292
regsmoker	0.074	0.089	0.830	0.409
SAHex	-0.025	0.058	-0.440	0.662
SAHvg	-0.015	0.042	-0.360	0.721
SAHg	0.000	0.035	0.010	0.991
SAHp	-0.021	0.088	-0.240	0.809
otherhealthcond	0.029	0.040	0.730	0.464
VIC	0.311	0.408	0.760	0.446
QLD	0.366	0.310	1.180	0.238
SA	0.929	0.607	1.530	0.126
WA	0.151	0.491	0.310	0.759
TAS	0.000	(omitted)		
NT	-0.272	0.406	-0.670	0.504
ACT	0.312	0.561	0.560	0.579
bmiobese*	-0.085	0.052	-1.650	0.099
bmiover	-0.034	0.035	-0.950	0.340
bmiunder	-0.049	0.112	-0.430	0.664
outerregional	-0.054	0.227	-0.240	0.813
innerregional	0.062	0.141	0.440	0.661
remote	0.138	0.446	0.310	0.757
_cons	-0.004	0.018	-0.210	0.830
N		**3,555**		
	Coefficient	**Robust standard error**	**t**	**p-value**
		First-difference estimator - model (ii)		
T1policy***	0.291	0.062	4.690	0.000

T2policy***	0.335	0.056	5.990	0.000
T3policy***	0.417	0.059	7.060	0.000
wages	-0.004	0.003	-1.380	0.168
alcoholdaily	0.078	0.051	1.540	0.124
children	-0.010	0.070	-0.150	0.881
married	-0.095	0.104	-0.910	0.364
lthealthcond*	-0.059	0.035	-1.690	0.092
employed	-0.014	0.057	-0.240	0.808
unemployed	-0.121	0.097	-1.240	0.214
postgrad	-0.222	0.520	-0.430	0.670
bachelors	-0.036	0.475	-0.080	0.939
diploma	-0.317	0.348	-0.910	0.364
cert	-0.316	0.307	-1.030	0.305
regsmoker	0.073	0.090	0.810	0.417
SAHex	-0.026	0.058	-0.450	0.651
SAHvg	-0.016	0.042	-0.400	0.692
SAHg	-0.002	0.035	-0.050	0.960
SAHp	-0.023	0.089	-0.260	0.791
otherhealthcond	0.029	0.040	0.730	0.463
VIC	0.308	0.412	0.750	0.456
QLD	0.359	0.313	1.150	0.252
SA	0.931	0.609	1.530	0.127
WA	0.139	0.491	0.280	0.776
TAS	0.000	(omitted)		
NT	-0.295	0.407	-0.720	0.469
ACT	0.320	0.560	0.570	0.567
bmiobese*	-0.086	0.052	-1.670	0.096
bmiover	-0.032	0.035	-0.900	0.367
bmiunder	-0.050	0.112	-0.440	0.657
outerregional	-0.046	0.226	-0.200	0.838
innerregional	0.070	0.142	0.490	0.624
remote	0.153	0.447	0.340	0.733
_cons	-0.004	0.018	-0.240	0.811
N		**3,555**		

	Coefficient	**Robust standard error**	**t**	**p-value**
		OLS - model (i)		
y13	-0.004	0.016	-0.270	0.787
policy***	0.338	0.033	10.360	0.000
treatmentgroup	0.000	0.025	-0.020	0.985
wages	-0.001	0.001	-0.620	0.534
alcoholdaily	0.019	0.022	0.860	0.387
children	-0.011	0.017	-0.670	0.504
married*	-0.026	0.015	-1.670	0.095
lthealthcond	-0.018	0.017	-1.080	0.279
employed	0.013	0.017	0.800	0.422
unemployed	-0.007	0.053	-0.130	0.897
postgrad	-0.014	0.018	-0.780	0.435
bachelors	0.003	0.018	0.160	0.876
diploma	0.003	0.020	0.150	0.883
cert	0.012	0.017	0.740	0.457
regsmoker	0.005	0.024	0.200	0.839
SAHex	-0.034	0.026	-1.330	0.184

SAHvg	-0.008	0.019	-0.410	0.682
SAHg	0.007	0.018	0.400	0.693
SAHp	0.056	0.041	1.350	0.177
otherhealthcond	0.004	0.021	0.200	0.839
VIC	-0.004	0.019	-0.230	0.818
QLD	0.012	0.021	0.580	0.562
SA	0.018	0.028	0.630	0.531
WA	-0.004	0.024	-0.170	0.862
NT	-0.097	0.086	-1.130	0.257
TAS	0.020	0.047	0.420	0.673
ACT	0.003	0.044	0.070	0.942
bmiobese*	-0.028	0.016	-1.790	0.074
bmiover	-0.019	0.013	-1.450	0.147
bmiunder	-0.040	0.052	-0.770	0.440
innerregional	0.023	0.019	1.250	0.212
outerregional	0.025	0.028	0.890	0.374
remote	-0.020	0.059	-0.330	0.741
_cons***	0.379	0.028	13.740	0.000
N		**7,110**		

	Coefficient	**Robust standard error**	**t**	**p-value**
OLS - model (ii)				
y13	-0.005	0.016	-0.280	0.779
T1policy***	0.270	0.045	6.030	0.000
T2policy***	0.324	0.041	7.880	0.000
T3policy***	0.423	0.042	10.060	0.000
treatmentgroup	0.007	0.025	0.260	0.794
wages	-0.001	0.001	-1.280	0.200
alcoholdaily	0.020	0.022	0.880	0.376
children	-0.009	0.017	-0.500	0.617
married	-0.023	0.015	-1.510	0.131
lthealthcond	-0.018	0.017	-1.090	0.278
employed	0.018	0.017	1.080	0.279
unemployed	0.001	0.053	0.010	0.992
postgrad	-0.016	0.018	-0.850	0.395
bachelors	0.003	0.018	0.140	0.888
diploma	0.002	0.019	0.120	0.904
cert	0.013	0.017	0.800	0.422
regsmoker	0.004	0.024	0.160	0.873
SAHex	-0.035	0.026	-1.360	0.173
SAHvg	-0.008	0.019	-0.430	0.670
SAHg	0.007	0.018	0.380	0.705
SAHp	0.054	0.041	1.320	0.188
otherhealthcond	0.004	0.021	0.210	0.837
VIC	-0.004	0.019	-0.180	0.856
QLD	0.014	0.021	0.670	0.504
SA	0.020	0.028	0.700	0.486
WA	-0.005	0.024	-0.190	0.853
NT	-0.091	0.086	-1.060	0.288
TAS	0.022	0.048	0.470	0.639
ACT	0.005	0.044	0.110	0.914
bmiobese*	-0.028	0.016	-1.770	0.077
bmiover	-0.018	0.013	-1.380	0.167

bmiunder	-0.040	0.052	-0.760	0.448
innerregional	0.023	0.019	1.240	0.217
outerregional	0.023	0.028	0.830	0.407
remote	-0.019	0.059	-0.330	0.745
_cons***	0.378	0.028	13.710	0.000
N		**7,110**		

*p<0.1**

*p<0.05***

*p<0.01****

Table A.8: The effect of the reforms on downgrading hospital cover, 2011-12 and 2013-14

	Coefficient	Robust standard error	t	p-value
	First-difference estimator - model (i)			
policy***	0.258	0.033	7.800	0.000
wages	0.003	0.002	1.380	0.169
alcoholdaily	0.047	0.053	0.880	0.379
children	-0.025	0.056	-0.450	0.655
married	-0.047	0.076	-0.620	0.538
lthealthcond	-0.002	0.030	-0.060	0.950
employed	-0.012	0.041	-0.290	0.772
unemployed	-0.098	0.088	-1.120	0.265
postgrad	-0.260	0.280	-0.930	0.354
bachelors	-0.453	0.297	-1.520	0.127
diploma	-0.106	0.268	-0.400	0.693
cert	-0.330	0.237	-1.390	0.164
regsmoker	0.015	0.079	0.190	0.852
SAHex	-0.051	0.053	-0.960	0.336
SAHvg	-0.038	0.037	-1.040	0.298
SAHg	-0.016	0.031	-0.520	0.600
SAHp	-0.051	0.064	-0.800	0.423
otherhealthcond	0.012	0.036	0.330	0.742
VIC	-0.214	0.180	-1.190	0.235
QLD	-0.062	0.182	-0.340	0.733
SA	-0.097	0.208	-0.470	0.642
WA	-0.160	0.193	-0.830	0.407
TAS	0.013	0.101	0.130	0.898
NT	0.065	0.250	0.260	0.796
ACT*	-0.432	0.252	-1.720	0.086
bmiobese	-0.045	0.043	-1.060	0.289
bmiover	-0.015	0.029	-0.520	0.601
bmiunder	0.114	0.086	1.320	0.187
outerregional	-0.105	0.127	-0.830	0.406
innerregional	0.056	0.104	0.530	0.595
remote	0.061	0.212	0.290	0.772
_cons	-0.011	0.017	-0.660	0.508
N		**3,506**		
	Coefficient	**Robust standard error**	**t**	**p-value**

First-difference estimator - model (ii)				
T1policy***	0.177	0.053	3.310	0.001
T2policy***	0.280	0.049	5.670	0.000
T3policy***	0.304	0.053	5.770	0.000
wages	0.003	0.002	1.310	0.191
alcoholdaily	0.047	0.053	0.880	0.377
children	-0.024	0.056	-0.420	0.673
married	-0.047	0.076	-0.620	0.536
lthealthcond	-0.001	0.030	-0.050	0.963
employed	-0.012	0.041	-0.310	0.759
unemployed	-0.097	0.088	-1.100	0.269
postgrad	-0.226	0.282	-0.800	0.422
bachelors	-0.439	0.298	-1.470	0.141
diploma	-0.091	0.272	-0.330	0.739
cert	-0.325	0.239	-1.360	0.175
regsmoker	0.015	0.079	0.190	0.849
SAHex	-0.052	0.053	-0.990	0.324
SAHvg	-0.040	0.037	-1.080	0.282
SAHg	-0.018	0.031	-0.570	0.571
SAHp	-0.051	0.064	-0.800	0.426
otherhealthcond	0.012	0.036	0.340	0.731
VIC	-0.219	0.181	-1.210	0.227
QLD	-0.072	0.183	-0.390	0.695
SA	-0.101	0.208	-0.480	0.628
WA	-0.168	0.192	-0.880	0.380
TAS	-0.018	0.099	-0.190	0.853
NT	0.029	0.255	0.110	0.910
ACT*	-0.427	0.249	-1.710	0.086
bmiobese	-0.046	0.043	-1.080	0.282
bmiover	-0.014	0.029	-0.490	0.626
bmiunder	0.110	0.086	1.270	0.204
outerregional	-0.105	0.126	-0.830	0.408
innerregional	0.061	0.105	0.580	0.565
remote	0.075	0.209	0.360	0.720
_cons	-0.011	0.017	-0.670	0.503
N		**3,506**		

	Coefficient	**Robust standard error**	**t**	**p-value**
OLS - model (i)				
y14	-0.008	0.017	-0.490	0.626
treatmentgroup1	-0.030	0.026	-1.160	0.245
policy***	0.259	0.033	7.810	0.000
wages*	0.002	0.001	1.700	0.089
alcoholdaily	0.002	0.024	0.090	0.929
children	0.004	0.018	0.220	0.830
married	-0.002	0.015	-0.130	0.896
lthealthcond	-0.027	0.017	-1.560	0.120
employed	-0.009	0.016	-0.580	0.562
unemployed	-0.005	0.060	-0.090	0.928
postgrad	-0.008	0.019	-0.410	0.683
bachelors	-0.012	0.018	-0.630	0.526
diploma**	-0.044	0.020	-2.250	0.024

cert	-0.015	0.017	-0.870	0.384
regsmoker	0.012	0.025	0.490	0.624
SAHex	-0.010	0.026	-0.390	0.699
SAHvg	0.001	0.019	0.030	0.979
SAHg	0.014	0.017	0.790	0.428
SAHp	0.048	0.041	1.180	0.240
otherhealthcond	0.020	0.021	0.960	0.339
VIC	-0.008	0.020	-0.420	0.678
QLD	0.012	0.022	0.560	0.573
SA	-0.009	0.027	-0.320	0.751
WA	0.027	0.026	1.040	0.301
NT	-0.117	0.072	-1.620	0.105
TAS	0.011	0.051	0.220	0.823
ACT	-0.016	0.048	-0.330	0.743
bmiobese	-0.023	0.016	-1.460	0.144
bmiover	-0.022	0.013	-1.600	0.110
bmiunder	0.001	0.050	0.010	0.991
innerregional	0.012	0.019	0.660	0.508
outerregional	0.007	0.029	0.260	0.797
remote	-0.022	0.057	-0.390	0.693
_cons***	0.367	0.027	13.440	0.000
N		**7,012**		

	Coefficient	Robust standard error	t	p-value
		OLS - model (ii)		
y14	-0.008	0.017	-0.480	0.631
treatmentgroup1	-0.025	0.026	-0.970	0.332
T1policy***	0.169	0.047	3.630	0.000
T2policy***	0.273	0.041	6.600	0.000
T3policy***	0.325	0.044	7.380	0.000
wages	0.001	0.001	1.230	0.221
alcoholdaily	0.002	0.024	0.090	0.927
children	0.005	0.018	0.300	0.761
married	0.000	0.015	-0.010	0.995
lthealthcond	-0.027	0.018	-1.540	0.123
employed	-0.006	0.016	-0.370	0.714
unemployed	-0.004	0.059	-0.070	0.947
postgrad	-0.009	0.019	-0.490	0.624
bachelors	-0.012	0.018	-0.670	0.501
diploma**	-0.045	0.020	-2.290	0.022
cert	-0.014	0.017	-0.820	0.414
regsmoker	0.011	0.025	0.450	0.652
SAHex	-0.011	0.026	-0.430	0.664
SAHvg	0.000	0.019	0.010	0.992
SAHg	0.014	0.017	0.790	0.429
SAHp	0.048	0.041	1.180	0.239
otherhealthcond	0.020	0.021	0.940	0.348
VIC	-0.007	0.020	-0.380	0.706
QLD	0.015	0.022	0.680	0.494
SA	-0.006	0.027	-0.220	0.828
WA	0.027	0.026	1.030	0.303
NT	-0.112	0.071	-1.580	0.115
TAS	0.013	0.051	0.260	0.793

ACT	-0.015	0.048	-0.320	0.750
bmiobese	-0.024	0.016	-1.480	0.139
bmiover	-0.022	0.013	-1.610	0.107
bmiunder	-0.001	0.050	-0.020	0.987
innerregional	0.012	0.019	0.660	0.509
outerregional	0.005	0.029	0.180	0.861
remote	-0.021	0.056	-0.370	0.714
_cons***	0.366	0.027	13.410	0.000
N		**7,012**		

*p<0.1**

*p<0.05***

*p<0.01****

A.4 Sensitivity analysis – Altering income measure

Probability of having hospital cover

Table A.9: Sensitivity analysis – income measure on probability of having hospital cover – 2008-09 and 2012-13 (first-difference estimator) (n=6,552)

	Baseline		5% decrease in estimated income for MLS		5% increase in estimated income for MLS	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
overall policy effect	0.029*** (0.011)	-	0.021* (0.011)	-	0.037*** (0.010)	-
policy effect tier 1	-	0.063*** (0.020)	-	0.061*** (0.021)	-	0.075*** (0.019)
policy effect tier 2	-	0.029* (0.015)	-	0.013 (0.015)	-	0.033** (0.014)
policy effect tier 3	-	-0.011 (0.016)	-	-0.017 (0.018)	-	-0.003 (0.016)

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*<0.01****

Table A.10: Sensitivity analysis – income measure on probability of having hospital cover – 2003-04, 2008-09 and 2012-13 (three wave fixed-effects estimator) (n=19,596)

	Baseline		5% decrease in estimated income for MLS		5% increase in estimated income for MLS	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
overall policy effect	0.038*** (0.010)	-	0.032*** (0.010)	-	0.048*** (0.009)	-
policy effect tier 1	-	0.077*** (0.018)	-	0.081*** (0.019)	-	0.086*** (0.017)
policy effect tier 2	-	0.043*** (0.014)	-	0.025* (0.015)	-	0.051*** (0.013)
policy effect tier 3	-	-0.012 (0.465)	-	-0.016 (0.017)	-	-0.001 (0.016)

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*p<0.01****

Probability of downgrading hospital cover

Table A.11: Sensitivity analysis – income measure on probability of downgrading – 2008-09 and 2012-13 (first-difference estimator) (n=3,381)

	Baseline		5% decrease in estimated income for MLS		5% increase in estimated income for MLS	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
overall policy effect	0.246*** (0.035)	-	0.273*** (0.036)	-	0.262*** (0.034)	-
policy effect tier 1	-	0.157*** (0.059)	-	0.207*** (0.059)	-	0.199*** (0.059)
policy effect tier 2	-	0.239*** (0.046)	-	0.272*** (0.048)	-	0.268*** (0.045)
policy effect tier 3	-	0.348*** (0.057)	-	0.346*** (0.061)	-	0.321*** (0.053)

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*p<0.01****

Table A.12: Sensitivity analysis – income measure on probability of downgrading – 2011-12 and 2012-13 (first-difference estimator) (n=3,555)

	Baseline		5% decrease in estimated income for MLS		5% increase in estimated income for MLS	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
overall policy effect	0.346*** (0.038)	-	0.366*** (0.039)	-	0.351*** (0.036)	-
policy effect tier 1	-	0.291*** (0.062)	-	0.315*** (0.064)	-	0.302*** (0.058)
policy effect tier 2	-	0.335*** (0.056)	-	0.356*** (0.059)	-	0.329*** (0.055)
policy effect tier 3	-	0.417*** (0.059)	-	0.435*** (0.062)	-	0.429*** (0.054)

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*p<0.01****

Table A.13: Sensitivity analysis – income measure on probability of downgrading – 2011-12 and 2013-14 (first-difference estimator) (n=3,506)

	Baseline		5% decrease in estimated income for MLS		5% increase in estimated income for MLS	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
overall policy effect	0.258*** (0.033)	-	0.269*** (0.034)	-	0.283*** (0.032)	-
policy effect tier 1	-	0.177*** (0.053)	-	0.215*** (0.057)	-	0.234*** (0.053)
policy effect tier 2	-	0.280*** (0.049)	-	0.272*** (0.051)	-	0.314*** (0.048)
policy effect tier 3	-	0.304*** (0.053)	-	0.318*** (0.055)	-	0.290*** (0.049)

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*p<0.01****

A.5 Sensitivity analysis – Changing the downgrading definition

Table A.14: Sensitivity analysis – Downgrading definition on probability of downgrading – 2008-09 and 2012-13 (first-difference estimator) (n=3,381)

	Baseline		Downgrade defined as greater than 5% decrease in annual premium expenditure		Downgrade defined as slower than average annual industry increase in premiums	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
overall policy effect	0.246*** (0.035)	-	0.241*** (0.035)	-	0.238*** (0.035)	-
policy effect tier 1	-	0.157*** (0.059)	-	0.139** (0.059)	-	0.152*** (0.059)
policy effect tier 2	-	0.239*** (0.046)	-	0.240*** (0.047)	-	0.242*** (0.047)
policy effect tier 3	-	0.348*** (0.057)	-	0.346*** (0.057)	-	0.321*** (0.057)

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*p<0.01****

Table A.15: Sensitivity analysis – Downgrading definition on probability of downgrading – 2011-12 and 2012-13 (first-difference estimator) (n=3,555)

	Baseline		Downgrade defined as greater than 5% decrease in annual premium expenditure		Downgrade defined as slower than average annual industry increase in premiums	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
overall policy effect	0.346*** (0.038)	-	0.347*** (0.038)	-	0.337*** (0.038)	-
policy effect tier 1	-	0.291*** (0.062)	-	0.305*** (0.062)	-	0.269*** (0.062)
policy effect tier 2	-	0.335*** (0.056)	-	0.315*** (0.056)	-	0.032*** (0.055)
policy effect tier 3	-	0.417*** (0.059)	-	0.434*** (0.059)	-	0.426*** (0.059)

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*p<0.01****

Table A.16: Sensitivity analysis – Downgrading definition on probability of downgrading – 2011-12 and 2013-14 (first-difference estimator) (n=3,506)

	Baseline		Downgrade defined as greater than 5% decrease in annual premium expenditure		Downgrade defined as slower than average annual industry increase in premiums	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
overall policy effect	0.258*** (0.033)	-	0.278*** (0.032)	-	0.254*** (0.033)	-
policy effect tier 1	-	0.177*** (0.053)	-	0.236*** (0.050)	-	0.153*** (0.054)
policy effect tier 2	-	0.280*** (0.049)	-	0.260*** (0.049)	-	0.263*** (0.049)
policy effect tier 3	-	0.304*** (0.053)	-	0.332*** (0.053)	-	0.335*** (0.053)

Robust standard errors in parentheses, clustered at household level

*p<0.1**

*p<0.05***

*p<0.01****