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The effect of income-based mandates on the demand for private hospital insurance and its dynamics[☆]

Thomas C. Buchmueller[a], Terence C. Cheng[b,*], Ngoc T.A. Pham[b], Kevin E. Staub[c]

[a] University of Michigan and NBER, United States
[b] University of Adelaide, Australia
[c] University of Melbourne, Australia

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ABSTRACT

We examine the effect of an income-based mandate on the demand for private hospital insurance and its dynamics in Australia. The mandate, known as the Medicare Levy Surcharge (MLS), is a levy on taxable income that applies to high-income individuals who choose not to buy private hospital insurance. Our identification strategy exploits changes in MLS liability arising from both year-to-year income fluctuations, and a reform where income thresholds were increased significantly. Using data from the Household, Income and Labour Dynamics in Australia longitudinal survey, we estimate dynamic panel data models that account for persistence in the decision to purchase insurance stemming from unobserved heterogeneity and state dependence. Our results indicate that being subject to the MLS penalty in a given year increases the probability of purchasing private hospital insurance by between 2 to 3 percent in that year. If subject to the penalty permanently, this probability grows further over the following years, reaching 13 percent after a decade. We also find evidence of a marked asymmetric effect of the MLS, where the effect of the penalty is about twice as large for individuals becoming liable compared with those going from being liable to not being liable. Our results further show that the mandate has a larger effect on individuals who are younger.

1. Introduction

Many countries use financial incentives to encourage the take-up of private health insurance (Colombo and Tapay, 2004). Perhaps the most notable example in recent years is the US's Affordable Care Act (ACA), which uses a mix of premium tax credits and a tax penalty for not having insurance — the "individual mandate" — to increase private health insurance coverage. Another important example is Australia, which since the late-1990s has taken a "carrot and stick" approach that incorporates subsidies and penalties (Hall et al., 1999). The "carrot" consists of premium subsidies, initially targeted at low-income households, but

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* Corresponding author.
E-mail address: terence.cheng@adelaide.edu.au (T.C. Cheng).

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soon replaced with a universal 30 percent premium rebate. Two types of "sticks" are used to incentivize take-up. One is an entry-age rating scheme, known as Lifetime Health Cover, which requires higher premiums for people who first purchase private insurance at an older age. The second is the Medicare Levy Surcharge (MLS), a tax on high-income Australians who choose not to purchase private insurance.

Overall, these policies, which were first implemented between 1997 and 2000, appear to have been effective. Between 1999 and 2001, the percentage of Australians with private insurance increased from 31 percent to more than 45 percent. However, because they were implemented within such a short period of time, it is difficult to disentangle the independent effects of the different policies. Several early studies attribute most of the coverage increase to the Lifetime Health Cover policy. There is no consensus in this literature on what effect, if any, the premium subsidies and the MLS had (Butler, 2002; Frech et al., 2003; Palangkaraya and Yong, 2005; Ellis and Savage, 2008).

When the MLS was established in 1997, it applied to single individuals with incomes above $50,000 and families with incomes above $100,000. Households with incomes above these thresholds that did not purchase private insurance covering hospital care were subject to a 1 percent tax surcharge on their *total* income. Because these income thresholds were not indexed for inflation, over time more and more Australians were subject to the MLS. For the 2008–09 financial year, the thresholds were increased to $70,000 for single individuals and $140,000 for families, causing a significant reduction in the number of people subject to the policy. Starting that year, the thresholds were also indexed for inflation.

Only one prior study has attempted to estimate the independent effect of the MLS on private health insurance coverage. Stavrunova and Yerokhin (2014) apply a regression discontinuity model to cross-sectional tax data of single Australians from 2007–08, just before the change in the MLS income thresholds. The analysis is complicated by tax avoidance behavior that results in a bunching of reported income just below the MLS threshold and by the fact that marital status is not accurately measured in the tax data. They find a significant discontinuity in private insurance coverage at the threshold. Their results suggest that the MLS increased the aggregate private insurance coverage rate among single individuals by 2.4 percentage points.

In this paper we examine the effect of the MLS on private health insurance coverage, using a different empirical strategy that exploits changes in MLS liability arising from both year-to-year income fluctuations and the change in the MLS threshold policy in 2008. Our analysis is based on longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey from 2004 to 2013. In addition to allowing for a different source of econometric identification, these data allow us to focus on important but hitherto unexplored issues in the empirical literature on the effects of policy incentives on health insurance demand.

First, there is evidence from a number of different contexts that consumers tend to maintain the same health insurance choices even as factors that influenced their original choices change.[1] The longitudinal feature of HILDA allows us to estimate dynamic panel data models that account for such persistence. Our main econometric specification includes both individual fixed effects, to account for persistence that is driven by time-constant preferences and circumstances, and lagged values of the dependent variable, to allow for demand dynamics.

Persistence in the decision to buy health insurance shapes the response to mandates and can therefore have important consequences for policy design. If demand is persistent, estimates from models that ignore dynamics are not fully informative because they do not convey any information about the duration of the policy effect and its trajectory over time. These estimates represent some weighted average of individual treatment effects at a certain point in time after implementation of the policy, and it is not possible to infer if the estimates represent a temporary or long-lasting effect. In contrast, our dynamic model allows us to estimate the effects of either transitory or permanent changes to MLS liability. We present two simulation experiments that illustrate the different aggregate effects that would arise from temporary or permanent changes in the MLS policy.

Another limitation of analyses based on cross-sectional data is that they implicitly assume that the effect of becoming subject to the MLS penalty is the same (in absolute value) as the effect of becoming not liable. Although this assumption of symmetric effects follows directly from a basic economic model of utility maximization, a growing body of research applying insights from behavioral economics finds that many consumer health insurance decisions deviate from the predictions of such a model.[2] As we discuss below, in the case of the MLS, there are several reasons to expect that the effect of becoming liable for the penalty will be larger than the effect of becoming not liable. With panel data, we are able to test this prediction.

A final advantage of the HILDA data relative to administrative data is that it includes proxies for individual health risk. Using these variables, we test for heterogeneous policy effects by conducting separate analyses for lower- and higher-risk individuals. Stratifying the data in this way sheds light on whether the MLS mitigates the problem of adverse selection by keeping lower-risk consumers in the market. Such an effect is a key rationale for insurance mandates.

Results from our main specification indicate a small but statistically significant initial effect of the MLS. Being subject to the MLS penalty increases the probability of purchasing private hospital insurance by between 2 to 3 percent that year. Due to state dependence, the probability is estimated to increase over the following years if the individual remains liable for the MLS penalty; for instance, an initial increase of 2 percent grows to an effect of almost 13

[1] See, for example, Royalty and Solomon (1999), Strombom et al. (2002), Dormont et al. (2009), Bolhaar et al. (2012) and Handel (2013).

[2] Baicker et al. (2012) provide a good discussion of how ideas from behavioral economics can be applied to health insurance demand, with specific reference to the ACA. Kettlewell (2020) considers suboptimal decision-making in the context of the Australian private health insurance market.

percent after a decade. We use our estimates to simulate the yearly share of Australians with private health insurance cover under two hypothetical alternative policies. We consider what would have happened had the MLS liability thresholds not been adjusted in 2008, as well as what would have happened if the MLS had been abolished altogether. The latter policy affects individuals' MLS liability permanently; under the former, affected individuals' liability can be more transient. While the share of the population affected by both experiments is roughly the same, we find that after five years the effect of the permanent change in MLS liability is over twice as large (in absolute value).

Other results suggest that the effect of the policy is asymmetric: becoming liable for the tax penalty initially increases private coverage by 3.5 percentage points, whereas going from being liable to not being liable is associated with an initial 1.4 percentage point decline in coverage. Tests for heterogeneous policy effects related to health risk produce mixed results. We find a larger effect of the MLS on individuals who are under age 40 than those who are over that age. However, differences related to self-reported health status and the presence of long-term chronic conditions are not statistically significant.

In addition to having direct implications for health policy in Australia, our analysis is relevant for understanding similar policies that have been enacted elsewhere, such as the ACA's individual mandate. When it went into effect in 2014, the individual mandate penalty for not having private insurance was the same as the MLS penalty: one percent of income. Research on the initial effect of the individual mandate has produced mixed results. In an analysis of all ACA coverage provisions, Frean et al. (2017) conclude that the individual mandate penalties had little impact on insurance coverage. In contrast, three studies focusing only on the individual mandate find a small, but statistically significant positive effect (Jacobs, 2018; Fiedler, 2018; Lurie et al., 2019). Legislation passed in 2017 effectively eliminated the individual mandate penalty, starting in the 2019 tax year. Early anecdotal evidence suggests that the effect of eliminating the penalty has been limited, which is consistent with our finding of an asymmetric effect of the MLS.

The paper is organized as follows. Section 2 describes the institutional context and the financial incentives for private health insurance in Australia. Section 3 describes the data used in the analyses. Section 4 presents the econometric framework, and discusses the estimation and identification strategy. The results are discussed in Section 5 followed by the policy experiments in Section 6. The paper concludes with a summary and discussion of the findings.

2. Private health insurance in Australia

Private health insurance is an integral component of Australia's health financing system. In 2018, roughly 45 percent of the population held private coverage (Australian Institute of Health and Welfare, 2015). Private insurance is mainly used to pay for hospital care, either in a private hospital or as a private patient in a public facility.[3] A primary benefit of choosing a private hospital is reduced wait times for elective procedures. In 2017–18, roughly two-thirds of elective surgeries were performed in private hospitals (Australian Institute of Health and Welfare, 2019). Private patients in public hospitals have greater ability to choose their own doctor and enjoy better amenities, such as a private room. Private health insurance can also be used to pay for other health services, such as dental care, allied health (e.g. dental, chiropractic, physiotherapy), and items such as eye glasses.

Australia's universal health insurance program, Medicare, was established in 1984. At that time, private health insurance went from being a primary source of financing health care services to a complementary one. In the next decade or so, the percentage of Australians purchasing private health insurance declined steadily. In response to this trend, the government introduced several policies aimed at increasing private coverage, with the ultimate goal of taking pressure of the public hospital system. A means-tested premium subsidy for low-income households was introduced in 1997, but in 1998 was replaced with a 30 percent premium subsidy available to all households regardless of income. In 2000, the government introduced the Lifetime Health Cover policy, which allows private health insurers to charge higher premiums for people who entered the market at later ages. Specifically, premiums are allowed to increase by 2 percent relative to a community-rated premium for each year of age above 30 years that an individual is without approved private health insurance.[4] This design was intended to increase take-up by younger consumers in order to mitigate the problem of adverse selection (Buchmueller, 2008).

The Medicare Levy Surcharge requires consumers with incomes above a certain level to purchase a private health insurance plan that covers hospital care or pay a supplemental tax on all of their income. As noted in the introduction, when it was established in 1997, the income thresholds were set at $50,000 for singles, and $100,000 for families and the tax rate was 1 percent. Because they were set in nominal terms, the real value of the thresholds declined over time, causing more households to be faced with the choice of buying private insurance or paying the penalty. In financial year 2008–09, the income thresholds for the MLS were increased to $70,000 for singles and $140,000 for families and the percentage of households subject to the MLS fell to 24 percent, down from 38 percent prior to the change. Since then, the thresholds have been indexed for inflation (see Table A1 in the appendix).

Starting in financial year 2012–13, the second-to-last year in our sample period, income levels above the thresh-

[3] In 2019, 83 percent of Australians with private health insurance had hospital treatment coverage, in the form of either combined hospital and general treatment coverage, or hospital treatment only coverage. Hospital services account for roughly three-quarters of total private insurance expenditures (Australian Prudential Regulatory Authority, 2019).

[4] In Australia, there is mandatory community rating on PHI premiums which stipulates that insurers must charge the same premium for a given insurance plan regardless of individuals' age, gender, health status, or claims history.

olds were divided into three tiers. Single individuals with incomes between $84,000 and $97,000 face an MLS tax rate of 1 percent (Tier 1). The tax rate is 1.25 percent for those with incomes between $97,000 and $130,000 (Tier 2), and 1.5 percent for those with incomes greater than $130,000 (Tier 3). For families, the income thresholds corresponding to the three tiers are $168,001 to $194,000 (Tier 1), $194,001 to 260,000 (Tier 2) and greater than $260,000 (Tier 3).

Alone, the introduction of these tiers would have increased the financial incentive for very high income households to have private health insurance. However, at the same time the government reduced the tax rebate that higher income households could claim for purchasing private coverage. For households not subject to the MLS, the subsidy rate remained at 30 percent. The subsidy was reduced to 20 percent for households in Tier 1, 10 percent in Tier 2 and zero in Tier 3. For individuals and families in Tier 1, the incentive to purchase private insurance decreased. For the other two tiers, the net effect of the higher MLS penalty and lower premium subsidy could go in either direction, depending on the household's exact income and the premium for their preferred plan. However, in most cases the change would be small.[5] Therefore, we do not attempt to capture the effect of these reforms. Rather, we simply distinguish between people who are and are not subject to any MLS penalty.

3. Data

Our study uses ten years of data (2004–2013) from the Household, Income and Labour Dynamics in Australia (HILDA) survey. HILDA is a nationally representative longitudinal survey that commenced in 2001. Each year, the survey collects extensive information on household and family formation, labour force and income, health insurance, health status and household expenditures. Every member of the household age 15 and over is surveyed via a face-to-face interview and is requested to fill in a self-completion questionnaire. From 2004 to 2010, each year of data contains over 17,000 person-observations; for 2011 to 2013 the sample sizes are larger with over 23,000 person-observations due to the inclusion of a top-up sample in 2011. In constructing the analysis sample, as there are households with multiple income units, we retain in the sample respondents that make up the primary income unit and excluded 18,198 respondents (9754 households) from non-primary income units.[6] Out of the 191,136 respondent-year observations recorded in the full sample from waves 4 to 13, respondents from single income unit households comprise 76.4 percent (146,662 respondent-years) of all observations. We further exclude observations of 46,668 respondents under the age of 18. After excluding observations with missing or ambiguous responses, we have an unbalanced panel of 101,670 observations on 18,407 individuals.

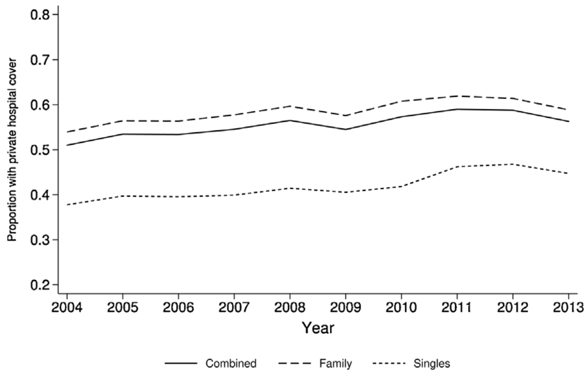

Fig. 1. Proportion with private hospital insurance. *Note*. Proportions in 2004, 2009 and 2013 show the observed percentage of the sample with private hospital insurance. Percentages in the other years show the imputed values. All percentages are weighted to be representative of the population using cross-sectional survey weights available in the HILDA data.

3.1. Private hospital insurance coverage

There are two main sources of information on health insurance coverage in HILDA. Each year starting in 2005, respondents were asked to report their expenditures on private health insurance as part of the self-completed questionnaire. This part of the survey does not ask whether the insurance covers hospital care, though premiums for general treatment only plans are quite low and therefore stand out in the data. In addition to this expenditure data, three HILDA waves (2004, 2009 and 2013) include a detailed battery of questions about health insurance. These questions directly identify the type of coverage (hospital, general or combined) and whether it is a single or family plan. Combining these questions about health insurance with the expenditure information allows us to measure whether an individual had private hospital insurance each year. A detailed description on how PHI status is constructed is provided in the Appendix.

Fig. 1 shows the proportion of the sample with private hospital insurance for the full sample and by household type. Over half of the sample has private health insurance, with higher coverage rates for family households compared with singles. From 2004 the overall coverage rate had been gradually increasing up until 2008 where it decreased by approximately 2 percentage points. The decrease comes after the revision of the MLS income thresholds that came into effect. The reduction was temporary and the overall coverage rate continued to grow gradually before falling again from 2011.

3.2. Medicare Levy Surcharge liability

We use income information collected in the HILDA to derive an indicator of liability for the MLS. To do this, we first adjust data on individuals' gross (pre-tax) total

[5] The offsetting nature of these two changes can be illustrated with a simple example. Consider a family with income of $227,000, which is the midpoint of the initial Tier 2 range. The reform caused their potential MLS penalty to increase by $576.50 per year. In our data, the average private insurance premium paid by families in Tier 2 was approximately $2800, which means that the average premium subsidy fell by $560.

[6] Examples of households with multiple income units are couples or lone parent with non-dependent children or extended family members.

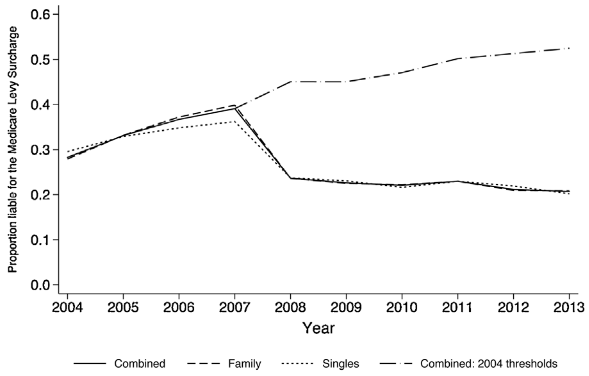

Fig. 2. Proportion liable for Medicare Levy Surcharge (2004–13). *Note*. The figure shows the percentage of the sample liable for the Medicare Levy Surcharge (MLS) for the combined sample, and by income units. The line "Combined (2004 threshold)" shows what percentage of the combined sample would be liable for the MLS if the MLS thresholds remain at their 2004 levels.

income in the HILDA survey to correspond with the definition of income for MLS purposes that is determined by the Australian Tax Office.[7] We then construct a MLS liability indicator variable which takes the value of 1 if individuals' income are above the income thresholds (see Table A1) in a given year, and 0 otherwise.

Fig. 2 depicts the proportion of the sample liable for the MLS for the full sample and by household type. Between 2004 and 2008, the share of the sample subject to the MLS increased by 10 percentage points, from 28 percent to 38 percent. This figure fell to 24 percent in 2009 after the MLS income thresholds were increased to $70,000 for individuals and $140,000 for families. Liability rates stabilized thereafter due to annual indexation of the thresholds.

The smooth trends in the aggregate data belies substantial intertemporal variation in MLS liability at the household level. Table 1 summarizes year-to-year changes in MLS liability that are the basis for our econometric identification. Before the policy change, roughly 14 percent of observations that were not liable in year *t* experienced an increase in income that caused them to be liable in year *t+1* (NY). This figure fell to 4 percent in 2008, before stabilizing at roughly 8 percent in subsequent years. After the policy change, there was also an increase in the percentage of households that were liable in year *t* but not liable in year *t+1*. Prior to 2008, between 16 and 18 percent of households experienced such a transition because of a decrease in income (YN). In 2008, nearly 50 percent of households that were liable the year before were no longer subject to the tax penalty.

Table 1
Transition matrices for Medicare Levy Surcharge.

Year	NN	NY	YN	YY
2005	86.32	13.68	17.92	82.08
2006	85.38	14.62	18.72	81.28
2007	85.85	14.15	16.86	83.14
2008	95.94	4.06	46.86	53.14
2009	92.10	7.90	30.46	69.54
2010	91.80	8.20	27.59	72.41
2011	91.28	8.72	26.40	73.60
2012	92.92	7.08	29.22	70.78
2013	92.99	7.01	27.37	72.63
2004–2013	90.62	9.38	28.96	71.04

Notes. Transition matrices show Medical Levy Surcharge (MLS) liability in a given year compared with that of the preceding year. In these matrices, percentages add up to 100% for each pair based on the status in the preceding year (e.g. NN% + NY% = 100).

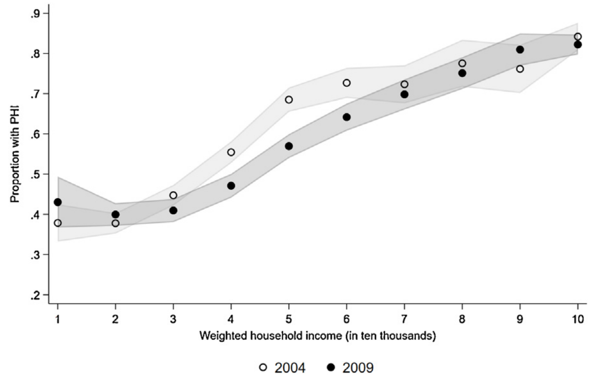

Fig. 3. Proportion with private hospital insurance by household income in 2004 and 2009. *Note*. Each dot shows the average proportion with private hospital insurance by household income for Medicare Levy Surcharge purposes in the 2004 and 2009 surveys. Reported incomes for families are divided by two given that thresholds for families are two times those for singles. Shaded bands denote 95 percent confidence intervals.

To provide a preliminary sense of how the change in the MLS threshold affected the take-up of private insurance, Fig. 3 shows the average proportion with private hospital insurance by household income in the 2004 and 2009 survey years. The sample used to generate this figure combines single and family households. Because thresholds for families are always two times those of singles, we divide incomes in half for families. In both years, there is a strong positive coverage gradient with respect to income. If the MLS has a causal effect on private insurance coverage, we should expect to see a decline in coverage among consumers with incomes between $50,000 and $70,000, as individuals with incomes in this range would have been liable for the MLS in 2004, but not in 2009. Indeed, this is what we see. In contrast, there was no change over time among individuals with lower incomes, who were not liable for the MLS penalty in either year, or among individuals with higher incomes, who would have been subject to the penalty in either year. This pattern suggests that the decline in coverage in 2009 that is evident in Fig. 1 was caused by the increase in the MLS income threshold.

[7] Gross total income is calculated as the sum of regular market income (wages and salary, business income, investment income, income from private pensions), regular private transfers, government welfare benefits, and income from irregular sources. To arrive at an estimate of income for MLS purposes, we deduct total irregular income other than redundancy and severance income from the reported gross total income. These irregular income components, which comprise of inheritance, bequests, and irregular transfers, are non-taxable and hence not included in the calculation of income for MLS purposes. The definition of income for MLS is described here: https://www.ato.gov.au/individuals/medicare-levy/medicare-levy-surcharge/ (Accessed on 27 November 2020).

3.3. Other covariates

In our regressions, we control for an extensive set of characteristics that are commonly used in studies of health insurance demand (e.g. Cheng (2014) and Doiron et al. (2008); also see Kiil (2012) for a review) but which are often unavailable in administrative data such as tax returns. Most importantly, because MLS liability depends on income, which has an independent effect on the demand for insurance, in all our analyses we control for income and income squared. We further interact income with household type to flexibly account for differences in the effect of income for families and singles. The demand for insurance is also likely to be correlated with demographic and socioeconomic characteristics (age, marital status, education, occupation) and health status (number of health conditions, self-assessed health status). In addition to controlling for age and age squared, we include an indicator of whether respondents are over the age of 30 because that is the age at which they become subject to the Lifetime Health Cover policy. The HILDA survey includes several questions on health behaviors (daily alcohol consumption, smoking), which can be interpreted as proxies for risk preferences, as well as information on where respondents live (state/territories, remoteness).

Summary statistics for these individual characteristics are presented in Table 2. Women make up over 54 percent of the sample. The average age of the sample is 48 years, with individuals who are privately insured being slightly older (48.8 vs. 46 years). The average annual household income is \$96,745, and is considerably higher for those with insurance (\$121,276) compared to the non-insured (\$66,151). Consistent with prior research on Australia (Doiron et al., 2008; Buchmueller et al., 2013), we see that privately insured individuals are more likely to report being in better health, are less likely to have a long-term health condition, and are less likely to be a regular smoker.

4. Econometric model

Longitudinal data allows us to account for the high degree of persistence in purchase decisions, a key feature of the demand for health insurance. There are two main sources of persistence: unobserved individual-specific heterogeneity and state dependence.

Unobserved preferences, such as risk tolerance or attitudes toward public and private hospitals, are likely to be correlated with both MLS liability and the demand for private health insurance and are thus a potential source of bias. If preferences are constant over time—as economists have traditionally assumed (Stigler and Becker, 1977)—conditioning on individual fixed effects will eliminate this bias. However, this will not be true if preferences change in a way that is correlated with changes in MLS liability. The empirical literature on the stability of preferences suggests that in our context, any potential bias will be small.[8]

The possibility of state dependence, due to switching costs or status quo bias, suggests the use of a dynamic specification in which current purchase decisions depend directly on past decisions. Therefore, similar to previous research on the demand for supplemental private health insurance (Bolhaar et al., 2012), our main econometric specification is a linear dynamic panel data model, which can be written as

$$PHI_{it} = \rho PHI_{it-1} + \gamma MLS_{it} + x_{it}'\beta + \alpha_i + \delta_t + \varepsilon_{it}. \quad (1)$$

PHI_{it} is an indicator variable representing the decision of individual i to purchase private hospital insurance in year t. The first term on the right hand side, PHI_{it-1}, is a one-period lagged private hospital insurance status, with autoregressive parameter ρ. For brevity, Eq. (1) includes only a single lag, though in our empirical analysis we determine the optimal lag length in a data-driven way through specification testing, which indicates that a model with three lags best fits the data.

The second term, MLS_{it}, is the policy variable of interest: an indicator variable that equals 1 if the individual's income in year t is greater than the MLS threshold, making them subject to the tax penalty if they do not purchase hospital insurance. The vector x_{it} consists of time-varying individual characteristics, the most important of which are income and income squared, and β is a conformable vector of coefficients. The individual fixed effects are represented by α_i. Because important variation in MLS liability comes from the change in thresholds introduced in 2008–09, it is important to also control for year fixed effects, which are represented by δ_t. Our assumption is that these year effects will capture the effect of other shocks to the market that affect all consumers, regardless of whether their incomes are close to the MLS threshold. Examples of such factors would include increases in private insurance premiums or changes in public hospital waiting lists. Finally, ε_{it} is the regression error, assumed to be uncorrelated to MLS_{it}, x_{it}, α_i, and δ_t.

The main parameters of interest in model (1) are γ and ρ. If the MLS policy has the intended effect of increasing take-up of private insurance, the parameter γ will be positive. It represents the ceteris paribus percentage point difference in the likelihood for individual i to purchase private insurance in year t if she is subject to the MLS tax penalty in that year. This interpretation holds regardless of the purchase decision being subject to persistence due to state dependence ($\rho \neq 0$) or not ($\rho = 0$). However, if there is positive state dependence in insurance purchasing decisions

[8] Two studies that use multiple years of longitudinal survey data are particularly relevant to our work. Sahm (2012) examines the variation of risk preferences over time using data from the Health and Retirement Survey. She finds no relationship between risk preferences and shocks to health, income, wealth or employment. Although risk tolerance decreases slightly with age and increases with improvements in macroeconomic conditions, she concludes that time-constant attributes are substantially more important than measurable time-varying factors in explaining interpersonal variation in risk preferences. Kettlewell (2019) conducts a similar investigation using HILDA data. He finds that individual fixed effects account for roughly 60 percent of the variance in risk preferences. Changes in individual finances are correlated with significant changes in risk aversion, but these effects are economically small and transitory. Risk preferences are generally not correlated with health shocks.

Table 2
Sample characteristics.

Variable	Combined $N = 101{,}670$ Mean (sd)	PHI = No $N = 46{,}249$ Mean (sd)	PHI = Yes $N = 55{,}421$ Mean (sd)	
Female	0.540 (0.498)	0.543 (0.498)	0.538 (0.499)	
Age	47.578 (16.952)	46.068 (17.827)	48.838 (16.078)	***
Age (>30)	0.815 (0.388)	0.766 (0.423)	0.857 (0.350)	***
Single	0.210 (0.407)	0.268 (0.443)	0.161 (0.368)	***
Household size	0.248 (0.432)	0.134 (0.341)	0.342 (0.474)	***
Married	0.575 (0.494)	0.463 (0.499)	0.668 (0.471)	***
Household income	96.745 (93.095)	66.151 (52.687)	122.276 (110.225)	***
Tertiary education	0.248 (0.432)	0.134 (0.341)	0.342 (0.474)	***
Occupation				
Manager	0.095 (0.293)	0.056 (0.229)	0.128 (0.334)	***
Professional	0.169 (0.375)	0.091 (0.288)	0.235 (0.424)	***
Blue collar	0.170 (0.376)	0.221 (0.415)	0.127 (0.334)	***
Sale/admin	0.217 (0.412)	0.213 (0.409)	0.221 (0.415)	***
Unemployed/not in labor force	0.348 (0.476)	0.420 (0.493)	0.289 (0.453)	***
Has long-term health condition	0.282 (0.450)	0.324 (0.468)	0.247 (0.431)	***
Excellent or v.good health	0.461 (0.498)	0.394 (0.489)	0.517 (0.500)	***
Daily alcohol	0.081 (0.273)	0.074 (0.262)	0.087 (0.282)	***
Daily smoking	0.162 (0.368)	0.251 (0.434)	0.087 (0.282)	***
State/Territories				
New South Wales	0.294 (0.456)	0.295 (0.456)	0.294 (0.456)	
Victoria	0.244 (0.430)	0.230 (0.421)	0.257 (0.437)	***
Queensland	0.211 (0.408)	0.242 (0.428)	0.184 (0.388)	***
South Australia	0.093 (0.290)	0.096 (0.295)	0.090 (0.286)	***
Western Australia	0.097 (0.296)	0.079 (0.269)	0.113 (0.316)	***
Tasmania	0.032 (0.177)	0.040 (0.196)	0.026 (0.160)	***
Northern Territory	0.007 (0.084)	0.006 (0.078)	0.008 (0.088)	***
Australian Capital Territory	0.021 (0.144)	0.013 (0.112)	0.029 (0.166)	***
Remoteness				
Major city	0.648 (0.478)	0.579 (0.494)	0.706 (0.456)	***
Regional	0.335 (0.472)	0.404 (0.491)	0.278 (0.448)	***
Remote	0.017 (0.128)	0.017 (0.129)	0.016 (0.127)	

Notes. Standard deviations are reported in parenthesis.
*** $p < 1\%$ denotes statistical significance from the two-sample t-test of difference between means.

($0 < \rho < 1$), the increased likelihood of buying insurance in t due to the MLS liability also increases the likelihood in t+1 by $\gamma\rho$, in t+2 by $\gamma\rho^2$, etc. If state dependence is strong, such long-run effects can be substantially larger than the contemporaneous effect, γ. In the next section, we explore two possible long-run effects in more detail, one stemming from a temporary change in tax liability and the other from a permanent change in liability.

To estimate the model, we use the *system* generalized method of moments (GMM) approach proposed by Arellano and Bond (1991) and Blundell and Bond (1998). Taking the first difference of (1), we obtain

$$\Delta PHI_{it} = \rho \Delta PHI_{it-1} + \gamma \Delta MLS_{it} + \Delta x'_{it}\beta + \Delta\delta_t + \Delta\varepsilon_{it}, \quad (2)$$

where Δ denotes first difference, and $i = 1, \ldots, N;\quad t = 2, \ldots, T$. The lagged first-difference variable ΔPHI_{it-1} is endogenous given that $PHI_{it-1} - PHI_{it-2}$ is mechanically correlated with $\varepsilon_{it} - \varepsilon_{it-1}$. The second lag (i.e., PHI_{it-2}) and all subsequent lags are likely to be correlated with ΔPHI_{it-1}, but, if ε_{it} are serially uncorrelated, uncorrelated with $\Delta\varepsilon_{it}$. Therefore, all PHI_{it-k} for $k \geq 2$ can potentially be used as instruments for ΔPHI_{it-1}. However, the first-difference of other right-hand side variables, ΔMLS_{it} and Δx_{it}, may not act as their own instruments if they are correlated with past error term (i.e., these variables are *predetermined*). In this case, the parameters of (2) are inconsistent even if PHI_{it-k} are valid instruments for ΔPHI_{it-1}. Arellano and Bond (1991) and Blundell and Bond (1998) show that one can consistently estimate model (1) by including additional moment conditions that current and lagged MLS_{it} and x_{it} are uncorrelated with ε_{it} in the estimation. This method is called *system* GMM.

There are two important issues related to the use of system GMM. The first is that the error terms may be serially correlated. Serial correlation of the errors can be reduced by including further lags of the dependent variable in the specification. Thus, it is important to select an appropriate number of lags. The second specification issue concerns the selection of instruments. Since the number of available instruments increases exponentially with the number of time periods, the set of available instruments is very large. This can be problematic because in such a situation the Hansen's J test for instrument validity can result in implausible perfect p-values of 1.000, failing to detect the invalidity of the instruments (Roodman, 2009). We deal with these two specification issues jointly by letting the data choose the optimal model: we select the most parsimonious model which passes both the Arellano-Bond test for serial correlation in the errors and Hansen's J test for instrument validity, where we use Roodman (2009) collapsed instrument matrix to reduce the number

Table 3
Estimates of linear probability models of private health insurance (PHI).

	OLS			Fixed-effects			Dynamic model		
	Combined (1)	Family (2)	Single (3)	Combined (4)	Family (5)	Single (6)	Combined (7)	Family (8)	Single (9)
MLS_{it}	0.127***	0.135***	0.113***	0.012***	0.012***	0.016**	0.013***	0.015***	0.011
	(0.005)	(0.006)	(0.012)	(0.003)	(0.003)	(0.007)	(0.003)	(0.004)	(0.010)
PHI_{it-1}							0.488***	0.559***	0.259
							(0.180)	(0.210)	(0.456)
PHI_{it-2}							0.359**	0.307*	0.553
							(0.142)	(0.166)	(0.351)
PHI_{it-3}							0.082***	0.070**	0.139
							(0.028)	(0.031)	(0.089)
Mean PHI	0.545	0.579	0.419	0.545	0.579	0.419	0.568	0.608	0.436
Individual FEs	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,670	80,335	21,335	101,670	80,335	21,335	54,002	40,856	9063
Number of instruments							43	41	41
F *p*-values							0.000	0.000	0.000
AB 2 *p*-values							0.098	0.265	0.266
AB 3 *p*-values							0.427	0.804	0.588
Hansen *p*-values							0.710	0.761	0.314
Method							2 lags of internal IVs		

Notes. Cluster-robust standard errors are reported in the parenthesis; standard errors are clustered at individual level. MLS_{it} is the coefficient estimate on the Medicare Levy Surcharge liability. PHI_{it-1}, PHI_{it-2} and PHI_{it-3} are the parameter estimates of the one-, two-, and three-period lagged dependent variables. The dynamic model is estimated using System GMM and the static model using within-individual estimation. All models control for household income, income squared, income × household type, household size, age, age squared, marital status, tertiary education, occupation, health conditions, daily drinking and smoking, state/territories and remoteness.

* Significance: 10%.
** Significance: 5%.
*** Significance: 1%.

of instruments.[9] This leads to a model with three lags in the dependent variable. However, our results are robust to using a specification with only one lag in the dependent variable.[10]

5. Results

Table 3 presents results from our main specification as well as two simpler static models, which are presented to highlight the effect for the estimate of γ of accounting for persistence in health insurance purchases by conditioning on individual fixed effects and lagged values of the dependent variable. In columns 1–3, we treat the data as a repeated cross-section, dropping the individual fixed effects and lagged measures of insurance coverage. This model is estimated by OLS. In columns 4–6 we add the individual fixed effects. Individual characteristics that do not vary over time, such as gender, are included in the basic OLS specification, but not in the model with fixed effects. The results reported in the last three columns are from a specification that includes both individual fixed effects and lagged values of the dependent variable.

In the "naive" OLS specification, the estimate of γ is large and statistically significant. The estimated coefficient on the MLS indicator is 0.127 for the full sample, 0.135 for families and 0.113 for single individuals. However, as noted above, we believe that this estimate overstates the causal effect of the MLS penalty since higher socioeconomic status households that are subject to the MLS penalty are likely to have a stronger demand for private health care and thus private health insurance, even in the absence of the policy. Indeed, when we add individual fixed effects to the model, the estimated coefficient on the MLS indicators are smaller by an order of magnitude. The estimate of γ is 0.012 for both the full sample and family subsample, and 0.016 for the single subsample. Relative to the sample means, these estimates imply that being subject to the MLS penalty increases the probability of purchasing private hospital insurance by between 2 and 4 percent.

Moving on to the dynamic fixed effects model, the coefficients on the lagged values of the dependent variable are large and statistically significant, indicating strong state dependence in insurance purchase decisions. The estimates on the one- and two-year lagged dependent variables are 0.49 and 0.36 respectively. The former estimate indicates that having private health insurance in a given year increases the probability of being privately insured in the next year by 0.49. In addition, having private health insurance in two consecutive years (e.g. year t and $t+1$), increases the probability of being privately insured in the year following $(t+2)$ by 0.85 compared to someone without PHI coverage during the last two years.

[9] For inference, we use the finite-sample correction for the two-step covariance matrix of Windmeijer (2005) to minimize the occurrence of bias in small samples.

[10] A further specification issue is that because the conditional mean which we model is a probability, the linear model is necessarily misspecified and represents a linear approximation to the true nonlinear conditional mean. This induces heteroskedasticity, which affects the GMM estimator's efficiency, but not its consistency (in terms of the parameters of the linear approximation).

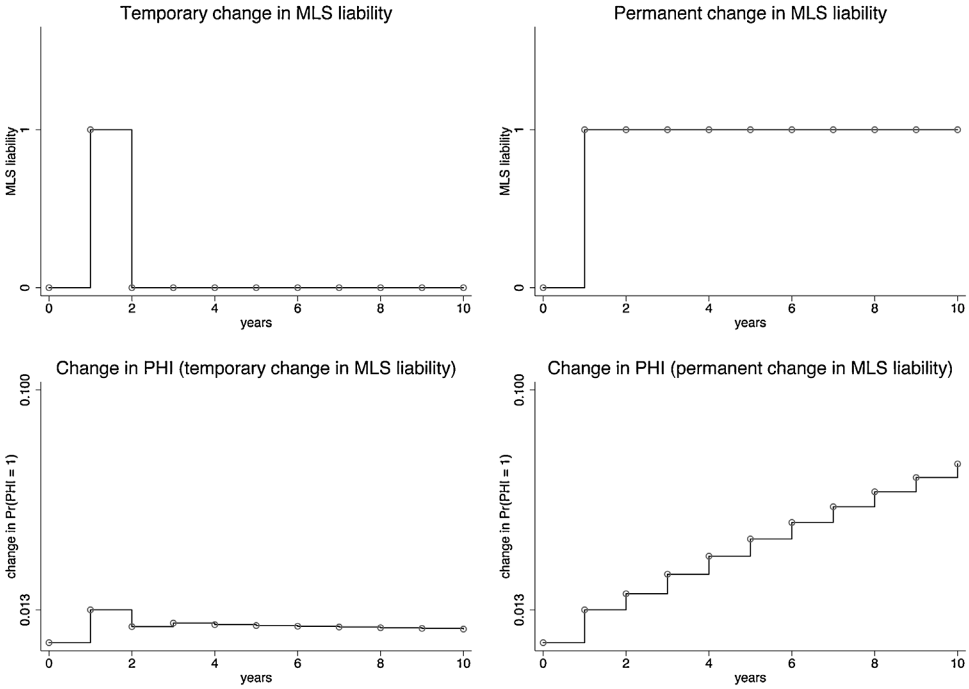

Fig. 4. Change in the probability of having private health insurance for a temporary and a permanent change in Medicare Levy Surcharge liability. *Note*. The figures show changes in the probability of having private health insurance following for a temporary change (left) and a permanent change (right) in liability for the Medicare Levy Surcharge. The estimates are calculated using estimates of γ_M and of the lagged dependent variables from the combined (family and single) sample in Table 3.

For the full sample and the sub-sample of families, the estimates of γ from the dynamic model imply that being liable for the MLS penalty in a given year increases the probability of purchasing private hospital insurance by 1.3 and 1.5 percentage points that year, respectively. Relative to the sample means, these estimates imply that becoming liable for the MLS penalty increases the probability of being privately insured by between 2 and 3 percent. For singles, we obtain a similar, but less precise estimate of γ. These dynamic estimates are very close to the estimates from the static fixed effects model. This means that after controlling for contemporaneous covariates and persistence from time-invariant unobserved heterogeneity, the remaining persistence in PHI from past covariates and past shocks to the propensity to buy PHI is largely unrelated to current MLS status. This similarity of coefficients is a known theoretical result. The within estimator of a static fixed effects model, when the true model is dynamic, is biased towards the short run effect (Pirotte, 1999), and this bias can be quite severe in settings, such as ours, where persistence due to state dependence is substantial (Egger and Pfaffermayr, 2005). Indeed, in such settings, as T becomes very large, the within estimator of γ converges to the true γ, the short run effect of the dynamic model.

The dynamic adjustment towards the long-run effect of private health insurance demand that is implied by the results for the full sample is shown in Fig. 4. We consider how the demand for private health insurance changes following a change in MLS liability under two scenarios. The first is a temporary change where individuals become liable for the MLS in year 1, and switch back to not being liable from year 2. In this scenario, demand for private health insurance first increases by 1.3 percentage points in the year of becoming liable, before decreasing gradually from year 2 onward. The projections, which are presented in Table 4, show that at year 10, the demand for private health insurance still remains 0.54 percentage points higher than baseline suggesting that there is a small but persistent effect even for a temporary change in MLS liability. The second scenario is a permanent change in MLS liability. Demand for private health insurance increases by 1.3 percentage points in year 1 following the tax change, and gradually increase at a decreasing rate over time. At year

Table 4
Changes in private health insurance ownership for a temporary and a permanent change in Medicare Levy Surcharge liability.

Year	ΔPHI: temporary change in MLS liability	ΔPHI: permanent change in MLS liability
1	0.013	0.013
2	0.006	0.019
3	0.008	0.027
4	0.007	0.034
5	0.007	0.041
6	0.006	0.048
7	0.006	0.054
8	0.006	0.060
9	0.006	0.065
10	0.005	0.071

Notes. Estimates show year-on-year changes in the probability of having private health insurance (PHI) following for a temporary change and a permanent change in liability for the Medicare Levy Surcharge. The estimates are calculated using estimates of γ_M and of the lagged dependent variables in Table 3.

Table 5
Estimates of linear probability models of private health insurance (PHI): 2007–2011.

	OLS			Fixed-effects			Dynamic model		
	Combined (1)	Family (2)	Single (3)	Combined (4)	Family (5)	Single (6)	Combined (7)	Family (8)	Single (9)
MLS_{it}	0.115***	0.120***	0.105***	0.006*	0.007*	0.005	0.018***	0.025***	0.026*
	(0.006)	(0.007)	(0.015)	(0.004)	(0.004)	(0.009)	(0.006)	(0.007)	(0.015)
PHI_{it-1}							0.898***	0.858***	0.940***
							(0.040)	(0.049)	(0.076)
Mean PHI	0.551	0.585	0.422	0.551	0.585	0.422	0.557	0.595	0.428
Individual FEs	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,354	39,040	10,314	49,354	39,040	10,314	34,761	26,961	6674
Number of instruments							38	36	36
F *p*-values							0.000	0.000	0.000
AB 2 *p*-values							0.004	0.002	0.357
Hansen *p*-values							0.608	0.877	0.913
Method							2 lags of internal IVs		

Notes. Cluster-robust standard errors are reported in the parenthesis; standard errors are clustered at individual level. MLS_{it} is the coefficient estimate on the Medicare Levy Surcharge liability. PHI_{it-1} is the parameter estimate of the one-lagged dependent variable. The dynamic model is estimated using System GMM and the static model using within-individual estimation. All models control for household income, income squared, income × household type, household size, age, age squared, marital status, tertiary education, occupation, health conditions, daily drinking and smoking, state/territories and remoteness.
* Significance: 10%.
*** Significance: 1%.

10, the increase in demand for private health insurance is 7.1 percentage points, an effect that is considerably larger than the size of the initial increase.[11] Relative to the sample mean, the effect after ten years corresponds to an increase of 13 percent.

Estimated coefficients for our control variables are reported in Table D1 in the appendix. In addition to a positive effect of age, we find that private insurance coverage increases discretely at age 31, when individuals become subject to the Lifetime Health Cover policy. This is consistent with the results of prior studies that conclude that the introduction of Lifetime Health Cover significantly increased private health insurance coverage (Butler, 2002; Frech et al., 2003; Palangkaraya and Yong, 2005; Ellis and Savage, 2008). We also find that insurance coverage increases with income, though at a decreasing rate.

The estimated policy effects in Table 3 are identified by two sources of variation: year-to-year changes in income that move households from one side of the MLS liability threshold to the other and the change in the threshold resulting from the reform that was put in place in 2008. Arguably, the variation arising from the change in the threshold provides for a "cleaner" estimate of the causal effect. Therefore, we re-estimated the models limiting the analysis period to the years 2007 to 2011, i.e., from just before to shortly after the policy change. The estimates are shown in Table 5.[12] With this shorter panel, we estimate the dynamic model with only a single lag. Limiting the sample in this way yields slightly larger estimates of the effect of the MLS. The combined sample results from the dynamic model implies that MLS liability initially increases the probability of purchasing private hospital insurance by 1.8 percentage points, a 3.2 percent effect relative to the sample mean.

5.1. Testing for asymmetric effects

The models reported in Table 3 assume that the effect of crossing the MLS income threshold is symmetric – i.e., the positive effect of becoming liable for the tax penalty is comparable in absolute value to the effect of transitions in the opposite direction. However, this might not be the case. There may be an asymmetry in terms of salience. Consumers may be very aware of the MLS when they first become liable – and strongly motivated to avoid paying a tax (Olivola and Sussman, 2015) – but less aware when they become not liable because their income falls below the MLS threshold. Consumer learning may also contribute to an asymmetric response: individuals who initially purchase insurance to avoid the MLS penalty may learn that they value that coverage more than they anticipated, making them less likely to drop it when they are no longer subject to the penalty. In light of these considerations, we hypothesize that the positive effect of becoming liable for the MLS penalty will be larger in absolute value than the negative effect of becoming not liable.

To test for such an asymmetry, we limit our sample to the first occurrence of a switch in liability status, including observations prior to and after this switching occurs. Separate linear dynamic models are estimated for each sub-sample comprising of individuals switching in and out. The estimated asymmetric effects are presented in Table 6 for individuals becoming liable (column 1) and those who became not liable (columns 2) for the MLS.[13]

[11] In the case of a model with a single lag, as in Eq. (1), as $t \to \infty$ the long-run effect of a permanent change in liability leads to an increase of $\gamma/(1-\rho)$.
[12] Full regression estimates are shown in Table D2 in the Appendix.
[13] Full regression estimates are shown in Table D3 in the appendix.

Table 6
Estimates of linear probability models of private health insurance (PHI): asymmetric effects of the Medicare Levy Surcharge (MLS).

	Becoming liable (MLS: $N \rightarrow Y$) (1)	Becoming not liable (MLS: $Y \rightarrow N$) (2)
MLS_{it}	0.035***	0.014***
	(0.008)	(0.005)
PHI_{it-1}	0.502***	0.549***
	(0.182)	(0.165)
PHI_{it-2}	0.337**	0.301**
	(0.143)	(0.131)
PHI_{it-3}	0.092***	0.092***
	(0.030)	(0.026)
Mean PHI	0.466	0.521
Individual FEs	Yes	Yes
Year FEs	Yes	Yes
Observations	31,556	34,662
Number of instruments	43	43
F *p*-values	0.000	0.000
AB 2 *p*-values	0.191	0.296
AB 3 *p*-values	0.768	0.262
Hansen *p*-values	0.700	0.437

Notes. Cluster-robust standard errors are reported in the parenthesis; standard errors are clustered at individual level. MLS_{it} is the coefficient estimate on the Medicare Levy Surcharge liability. PHI_{it-1}, PHI_{it-2} and PHI_{it-3} are the parameter estimates of the one-, two-, and three-period lagged dependent variables. Estimates are from the combined (family and single) samples. The dynamic model is estimated using System GMM using two lags of interval IVs. All models control for household income, income squared, income × household type, household size, age, age squared, marital status, tertiary education, occupation, health conditions, daily drinking and smoking, state/territories and remoteness.
** Significance: 5%.
*** Significance: 1%.

For both samples, our estimate of γ is positive and statistically significant, though the magnitudes of the estimates differ, as hypothesized. Becoming liable for the MLS penalty leads to a 3.5 percentage point increase in the probability of purchasing private hospital insurance, which represents roughly an 8 percent effect relative to the mean for this sample. In comparison, going from being liable for the penalty to not being liable reduces the private insurance take up by 1.4 percentage points, a 2.7 percent effect relative to the mean for that sample. In contrast to the differences in γ, the estimated coefficients on lagged insurance coverage are very similar for the two models. This means that the differences implied by the two estimates of γ will persist over time. To test whether the coefficient on MLS differs for the two groups, we pool the observations for both sub-samples and run specifications with interactions using an indicator variable representing the "becoming not liable" subsample. The test using the most flexible specification (interactions in MLS and all covariates) has a *p*-value of 0.09 and the simplest one (interaction only in MLS) has a *p*-value smaller than 0.01, indicating that the effects are statistically significantly different.

5.2. Differences by risk status

It is important to understand not only how the MLS affects the number of people with private hospital insurance but also how the policy affects the composition of the risk pool. Previous studies using data from a variety of settings have found that younger, healthier consumers have a more price-elastic demand for health insurance.[14] To the extent that this relationship between health risk and price sensitivity holds, the MLS penalty could have the effect of increasing the share of lower-risk consumers in the private insurance risk pool.

To shed some light on this, we test for heterogeneous treatment effects related to individuals' risk status. We divide the sample into two groups based on three different risk proxies: age (under 40 vs. over 40 at wave 4), self-assessed health status (very good/excellent vs. good/fair/poor), and whether or not respondents reported having a long-term health condition. We then estimate three separate regressions where the MLS variable is interacted with the different risk proxies. For the models using the two health status measures, we include only respondents who did not report a change in the measure between waves 4 to 13.[15]

The estimates from these models are shown in Table 7; full regression results are reported in Appendix Table D4. When we allow the effect of the MLS to vary by age, we find stronger effects on younger individuals: being liable for the MLS increases the probability of having private hospital insurance by 1.9 percentage points for individuals age 40 years and under (3.5 percent of the sample mean for this group), and 0.6 percentage points for those age over 40 years (a 1.1 percent effect). The difference between these two estimates is statistically significant at the.05 level. This pattern is slightly different from what Stavrunova and Yerokhin (2014) find in their analysis of tax data on single individuals. They estimate separate effects for three age categories. They find a stronger effect for the youngest group (under age 33) than for their middle age group (33 to 50), though they find that the effect of the MLS is strongest for adults over age 50.

When we allow for the effect of the policy to vary with self-assessed health, the estimated effect is larger for individuals in very good or excellent health than for those in good, fair or poor health (0.022 vs. 0.013) though the t-statistic for the interaction term coefficient, which represents the difference in the effect of the MLS for the two groups, is only 0.90. Similarly, the estimates reported in column 3 imply that individuals with long-term conditions are not significantly less sensitive to the MLS penalty than individuals without such conditions.

5.3. Robustness checks

In general, dynamic panel data models may be sensitive to the model specification and the type and number of instruments. This is not the case in our application. The estimates of the effect of being liable for the MLS are robust to how we model the lag structure. For example, when we include only a single lag, the estimates of γ are

[14] See, for example, Royalty and Solomon (1999), Strombom et al. (2002), Schut et al. (2003), van Dijk et al. (2008) and Handel (2013).
[15] Roughly half of the analysis sample (49.7 percent) of individuals reported having the same self-assessed health status for all waves between 4 and 13. A slightly higher percentage (52.7 percent) reported having no change in the presence of a long-term health condition.

Table 7
Estimates of linear probability models of private health insurance (PHI): coefficient estimates of the Medicare Levy Surcharge by risk factors

	Age (1)	Self assessed health status (2)	Long-term (LT) health condition (3)
MLS_{it}	0.006*	0.013*	0.011**
	(0.004)	(0.007)	(0.005)
$MLS_{it} \times < 40$ years	0.013**		
	(0.006)		
$MLS_{it} \times$ Ex/VG health		0.009	
		(0.010)	
$MLS_{it} \times$ Has LT conds			−0.000
			(0.012)
Mean PHI	0.545	0.537	0.549
Individual FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Observations	101,670	32,543	36,384

Notes. Cluster-robust standard errors are reported in the parentheses; standard errors are clustered at individual level. MLS_{it} is the coefficient estimate on the Medicare Levy Surcharge liability. The estimating model is the fixed-effect "within" estimator. Age, self-assessed health status (excellent, very good, and otherwise) and presence of a long-term health condition are based on observations in Wave 4. Age is individuals' age observed in Wave 4. In the analyses by health status, we include only respondents who did not report a change in self-assessed health status (excellent, very good, and otherwise) and whether they have a long-term health condition over waves 4 to 13. All regressions control for household income, income squared, income × household type, household size, age, age squared, occupation, marital status, tertiary education, self-assessed health status and health conditions (where relevant), daily drinking and smoking, individual and year fixed-effects.

* Significance: 10%.

** Significance: 5%.

0.012 (s.e. = 0.003) for the combined sample (compared to 0.013 in the baseline), 0.017 (s.e. = 0.003) for the family subsample (0.015 in the baseline) and 0.011 (s.e. = 0.007) for the single subsample (0.011 in the baseline). The dynamic model results are also not sensitive to the number of lagged values of the dependent variable that are used as instruments. Table B1 in the Appendix shows how our estimates vary when three and four lags of interval IVs were used. These estimates are very similar in magnitude to our baseline results shown in Table 3.

While our approach to specification and estimation has the advantage of being standard in the literature, some recent approaches to dynamic panels where N is large and T is short address the order-T bias resulting from the lagged dependent variable by means other than through instrumental variables, such as analytical or jackknife bias-reduction methods (Hahn and Newey, 2004). The results are robust to using one of the most widely used of such methods, the split-panel jackknife estimator (Table B2). Finally, given that our dependent variable is binary and its conditional mean therefore is nonlinear, binary response models are a natural alternative way of specifying the model. However, using a dynamic probit model with fixed effects, too, does not change the estimates substantially (Table B3).[16]

We further assess the sensitivity of our estimates to potential reporting errors in respondents' income. Liability for the MLS is defined based on income information that is self-reported, and misreporting may introduce measurement-error bias on our estimates. To this end, we ran additional regressions with two alternative definitions of MLS liability. In the first specification, we recoded MLS status as liable (not liable) if reported incomes are \$1000, \$2500 and \$5000 below (above) the threshold. In the second specification, we excluded observations from the estimation sample if the reported income are \$1000, \$2500 and \$5000 above and below the threshold. The estimates from these alternative definitions of MLS liability are shown in Tables B4 and B5 . These estimates are very similar in magnitude to our baseline results shown in Table 3.

Our econometric model described in Eq. (2) implicitly assumes that the effect of the MLS is constant – i.e., the MLS has the same effect for all income levels above the threshold. To assess the sensitivity of our results to this assumption, we perform an additional robustness check by substituting the binary MLS indicator with quartiles of MLS liability in dollar terms. We re-estimated (2) using four dummy variables representing each quartile, with the reference category being individuals not liable for the MLS. These estimates are presented in Table B6. The estimated coefficient on the MLS indicator is 0.08 for individuals in the first quartile, and are in the range of 0.14 to 0.16 for the other quartiles. These results indicate that while the MLS has a smaller effect on the probability of being insured for individuals whose incomes are slightly above the threshold, the magnitude of the effect is similar for individuals in higher income levels.

6. Policy simulations

We use the baseline econometric estimates in a simulation analysis to predict how the aggregate PHI coverage rates would change under two hypothetical scenarios. In the first scenario, we kept the MLS thresholds at their pre-2008 levels and predict PHI coverage in the years

[16] The split-panel jackknife estimates presented in Table B2 correspond to the estimator of Dhaene and Jochmans (2015). The estimates from the dynamic panel probit model with fixed effects of Appendix Table B3 are based on the bias-reduction estimator of Kosmidis and Firth (2009). In the context of a panel probit model, this estimator not only reduces the order-T bias arising from fixed effects and lagged dependent variables (e.g. Bester and Hansen, 2009), but in addition avoids reducing the sample size as a consequence of the perfect prediction problem in binary responses (Kunz et al., 2019).

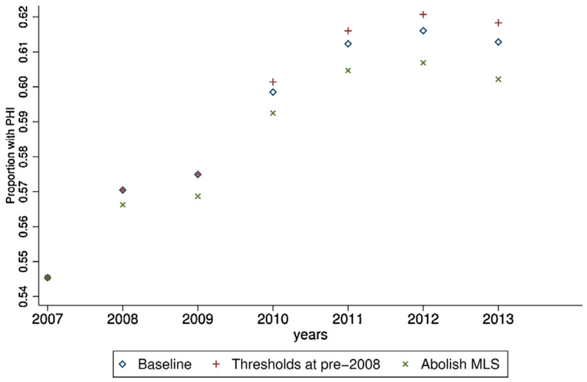

Fig. 5. Simulated proportion of population with private health insurance. *Notes*. The figures show the simulated proportion of the population with private health insurance under two simulation scenarios. Scenario 1 sets the MLS income thresholds at the pre-reform (2008) levels. Scenario 2 simulates the abolishing of the MLS where income thresholds are effectively set to infinity. All estimates are weighted to the population using sample weights. In the simulation, all individual characteristics (e.g. age, income) are allowed to vary over time.

2008 to 2013. In the second scenario, we predict how PHI coverage rates change if MLS were to be abolished completely in 2008 (or, technically, set to infinity). For each of these simulations, we use our estimates to predict how the PHI purchase decision for each observation in our sample would change in response to the hypothetical policy change. These predictions take into account dynamic effects of PHI holding, in which current purchase decisions depend on past decisions, as well changes over time in the characteristics (e.g. income, age) of our sample. Simulation estimates are weighted to the population using sample weights.

The simulation results are presented in Fig. 5. The full simulation estimates are shown in Table C1 in the Appendix. Under the first scenario where thresholds are kept at their pre-2008 levels, we predict a small increase in the proportion of the population with PHI by 0.1 percentage points in 2010, up from the baseline of 60 percent coverage if thresholds increased as they did in 2008. By 2013, the proportion of privately insured individuals is predicted to rise to 61.8 percent, an increase of 0.5 percentage points relative to the baseline.

Under the second scenario where the MLS is abolished in 2008, we predict a 0.4 percentage point reduction in the privately insured population in the first year of the policy change compared to the baseline of 57 percent. By 2013, 5 years after MLS income thresholds were removed, the proportion of the insured population is predicted to be 60.2 percent, a decrease of 1.1 percentage points relative to a baseline of 61.3 percent if thresholds were to remain as they were.

These policy estimates can be contrasted to the pure ceteris paribus estimates presented in Fig. 4 using simple back-of-the-envelope calculations. For instance, becoming permanently liable for MLS is associated with a 4.8 percentage point increase in the probability of having private insurance five years later, ceteris paribus. Both policy experiments affect about 20 percent of the population, as can be seen from Fig. 2. Thus, a permanent liability change to 20 percent of the population is predicted to change aggregate rates by about 1 percentage point, a number very close to the predicted reduction under the second experiment of abolishing the MLS. By contrast, the increase associated with the first experiment of keeping the thresholds at their 2008 levels is only about half of the ceteris paribus benchmark. The reason is that such a policy is subject to the income dynamics of the affected population, resulting in heterogenous MLS liability patterns and shorter average liability durations.

7. Summary and conclusions

For decades, Australia has had financial incentives designed to encourage the purchase of private health insurance. Although the enactment of these policies in the late 1990s and early 2000s reversed a long-run decline in private insurance coverage, evidence on the effects of specific policies has been limited. In this paper, we provide new evidence on the effect of one of these policies, the Medicare Levy Surcharge. Despite differences in data and research design, our main results are broadly consistent with the one prior study on the MLS (Stavrunova and Yerokhin, 2014). Overall, we find moderate, statistically significant effects of the policy on the probability of purchasing private health insurance. Interestingly, this result is also consistent with the results of recent studies on the effect of the Affordable Care Act's individual mandate penalty (Jacobs, 2018; Fiedler, 2018; Lurie et al., 2019).

Incentives for private health insurance in Australia and in other countries where private insurance coexist with a universal public health insurance system have been justified on arguments that a private health care market can relieve cost and capacity pressures off the public system and improve the responsiveness of the system to patients needs and preferences. The extent to which the MLS helps to achieve these goals is an important question that is beyond the scope of this study. One recent study on health insurance rebates in Australia concludes that the fiscal cost of rebates is substantially larger than the reduction in public healthcare expenditures caused by increased private insurance coverage (Cheng, 2014). Research from Spain (López Nicolás and Vera-Hernández, 2008) and the UK (Emmerson et al., 2001) also finds that the cost of subsidizing private health insurance exceeds the potential public healthcare savings.

Beyond the relevance to specific policy questions, our analysis contributes to a more general research literature on the effect of incentives on the demand for health insurance. As in other countries, there is a strong persistence in insurance purchase decisions in Australia. Estimates from our dynamic panel data models indicate that this persistence is driven by both unobserved individual heterogeneity and state dependence. Two other studies estimate dynamic models for private health insurance, but they do not consider long-run, dynamic effects of financial incentives. However, it is reassuring that our estimates of the state dependence are broadly similar with the ones presented in these studies. In an analysis of Irish data, Bolhaar et al. (2012) find that having insurance in a given year increases the probability of having insurance in the next year by 0.24. Our corresponding estimate is 0.49. The weaker state dependence in the Irish study is likely due to the fact that the models include lags of key covariates such as health status and healthcare expenditures. Since our interest lies in calculating the dynamic adjustment process, these are channels through which persistence in PHI operates and which should not be held fixed when calculating the long-run effect. In another Australian study, Doiron and Kettlewell (2020) find that being insured three years prior increases the probability of having insurance by 0.25. As their data is roughly triennial, this would imply a one-year autoregressive coefficient of about 0.6, which is close to our estimate of 0.49. Our finding of strong and long-lasting state dependence in PHI has implications for other policies related to insurance purchases as well, as it implies that estimates of policy effects from static models might be biased towards short-run effects. Understanding the fundamental causes of persistence in health insurance demand remains an important research topic.

Authors' contributions

All authors (Thomas Buchmueller, Terence C Cheng, Ngoc A Pham and Kevin E Staub) were involved in the Conceptualization of the study, development of Methodology, Formal analysis, and Writing – Original draft and Review and Editing of the manuscript.

Appendix A. Medicare Levy Surcharge income thresholds

Table A1

Appendix B. Robustness checks

Table A1
Medicare Levy Surcharge income thresholds, by year.

Year	Thresholds by household type		Medicare Levy Surcharge rate
	Family	Single	
2004 to 2008	$100,000	$50,000	1%
2008–09	140,000	70,000	1%
2009–10	146,000	73,000	1%
2010–11	154,000	77,000	1%
2011–12	160,000	80,000	1%
2012–13			1%
Tier 1	168,001–194,000	84,001–97,000	1%
Tier 2	194,001–260,000	97,001–130,000	1.25%
Tier 3	>260,000	>130,000	1.5%

Notes. The family income threshold is increased by $1500 for each Medicare levy surcharge dependent child after the first child.

Table B1
Dynamic models of private health insurance – 3 or 4 lags of internal IVs.

	3 lags of internal IVs			4 lags of internal IVs		
	Combined (1)	Family (2)	Single (3)	Combined (4)	Family (5)	Single (6)
MLS_{it}	0.013***	0.015***	0.014	0.013***	0.014***	0.010
	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.008)
PHI_{it-1}	0.516***	0.633***	0.092	0.574***	0.623***	0.709***
	(0.139)	(0.153)	(0.375)	(0.127)	(0.153)	(0.275)
PHI_{it-2}	0.333***	0.244**	0.696**	0.286***	0.257**	0.216
	(0.109)	(0.120)	(0.295)	(0.100)	(0.122)	(0.215)
PHI_{it-3}	0.072***	0.053**	0.168**	0.063***	0.059***	0.046
	(0.021)	(0.024)	(0.080)	(0.020)	(0.023)	(0.068)
Mean PHI	0.568	0.608	0.436	0.568	0.608	0.436
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54,002	40,856	9063	54,002	40,856	9063
Number of instruments	49	47	47	55	53	53
F *p*-values	0.000	0.000	0.000	0.000	0.000	0.000
AB 2 *p*-values	0.054	0.294	0.088	0.099	0.266	0.646
AB 3 *p*-values	0.663	0.896	0.456	0.799	0.993	0.822
Hansen *p*-values	0.447	0.738	0.564	0.671	0.578	0.544

Notes. Cluster-robust standard errors are reported in the parenthesis; standard errors are clustered at individual level. MLS_{it} is the coefficient estimate on the Medicare Levy Surcharge liability. PHI_{it-1}, PHI_{it-2} and PHI_{it-3} are the parameter estimates of the one-, two- and three-period lagged dependent variables. The dynamic model is estimated using System GMM and the static model using within-individual estimation. All regressions control for state/territories and remoteness.

** Significance: 5%.

*** Significance: 1%.

Table B2
Split-panel-jackknife (SPJ) estimates of linear dynamic fixed effects models of private health insurance (PHI), Combined sample.

	Uncorrected estimates			SPJ bias-corrected estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
MLS_{it}	0.009***	0.006**	0.006*	0.012***	0.008**	0.007**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
PHI_{it-1}	0.426***	0.464***	0.442***	0.655***	0.747***	0.741***
	(0.011)	(0.013)	(0.015)	(0.011)	(0.013)	(0.015)
PHI_{it-2}		0.047***	0.040***		0.108***	0.110***
		(0.009)	(0.012)		(0.009)	(0.012)
PHI_{it-3}			−0.026**			−0.042***
			(0.009)			(0.009)
Mean PHI	0.562	0.566	0.572	0.562	0.566	0.572
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,652	62,634	50,919	75,652	62,634	50,919

Notes. Cluster-robust standard errors are reported in the parenthesis; standard errors are clustered at individual level. MLS_{it} is the coefficient estimate on the Medicare Levy Surcharge liability. PHI_{it-1}, PHI_{it-2} and PHI_{it-3} are the parameter estimates of the one-, two-, and three-period lagged dependent variables. Columns (1)–(3) estimated by OLS using the within-estimator, columns (4)–(6) estimated using Dhaene and Jochmans (2015) split-panel-jackknife bias-corrected estimator. All models control for a linear time trend, household income, income squared, income × household type, household size, age, age squared, marital status, tertiary education, occupation, health conditions, daily drinking and smoking, state/territories and remoteness.
* Significance: 10%.
** Significance: 5%.
*** Significance: 1%.

Table B3
Biased-corrected estimates of dynamic fixed effects probit models of private health insurance (PHI).

	Combined (1)	Family (2)	Single (3)	Combined (4)	Family (5)	Single (6)
MLS_{it}	0.063***	0.067***	0.030	0.052***	0.057***	0.031
	(0.009)	(0.010)	(0.024)	(0.010)	(0.011)	(0.027)
PHI_{it-1}	1.214***	1.188***	1.103***	1.171***	1.158***	0.995***
	(0.011)	(0.012)	(0.034)	(0.016)	(0.018)	(0.041)
PHI_{it-2}				0.234***	0.240***	0.227***
				(0.018)	(0.020)	(0.048)
PHI_{it-3}				−0.051**	−0.054**	0.161***
				(0.017)	(0.019)	(0.046)
AME of MLS_{it}	0.009***	0.010***	0.005	0.007***	0.008***	0.005
	(0.001)	(0.001)	(0.004)	(0.001)	(0.002)	(0.004)
Mean PHI	0.554	0.588	0.433	0.568	0.608	0.436
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83,222	65,855	11,159	54,002	40,856	9063

Notes. Standard errors are reported in parenthesis. MLS_{it} is the coefficient estimate on the Medicare Levy Surcharge liability. PHI_{it-1}, PHI_{it-2} and PHI_{it-3} are the parameter estimates of the one-, two-, and three-period lagged dependent variables. AME of MLS_{it} is the average marginal effect of MLS_{it}. All models estimated using the biased-reduced generalized linear model estimator of Kosmidis and Firth (2009) adapted to the panel probit model with fixed effects (Kunz et al., 2019). All models control for household income, income squared, household size, age squared, marital status, tertiary education, occupation, health conditions, daily drinking and smoking, state/territories and remoteness.
** Significance: 5%.
*** Significance: 1%.

Table B4
Robustness checks: allowing for measurement errors in reporting income (I).

	Combined (1)	Family (2)	Single (3)
Panel A: Liable for MLS if income is $1K below threshold			
MLS_{it}	0.014***	0.015***	0.015
	(0.003)	(0.003)	(0.010)
Panel B: Liable for MLS if income is $2.5K below threshold			
MLS_{it}	0.014***	0.015***	0.016*
	(0.003)	(0.003)	(0.009)
Panel C: Liable for MLS if income is $5K below threshold			
MLS_{it}	0.014***	0.015***	0.021**
	(0.003)	(0.003)	(0.010)
Panel D: Liable for MLS if income is $1K above threshold			
MLS_{it}	0.013***	0.014***	0.012
	(0.003)	(0.003)	(0.010)
Panel E: Liable for MLS if income is $2.5K above threshold			
MLS_{it}	0.012***	0.014***	0.012
	(0.003)	(0.003)	(0.009)
Panel F: Liable for MLS if income is $5K above threshold			
MLS_{it}	0.012***	0.013***	0.013
	(0.003)	(0.004)	(0.010)
Mean PHI	0.568	0.608	0.436
Method		2 lags of internal IVs	

Notes. Cluster-robust standard errors are reported in the parenthesis; standard errors are clustered at individual level. MLS_{it} is the coefficient estimate on the Medicare Levy Surcharge liability. PHI_{it-1}, PHI_{it-2} and PHI_{it-3} are the parameter estimates of the one-, two- and three-period lagged dependent variables. The dynamic model is estimated using System GMM. All regressions control for state/territories and remoteness.

* Significance: 10%.
** Significance: 5%.
*** Significance: 1%.

Table B5
Robustness checks: allowing for measurement errors in reporting income (II).

	Combined (1)	Family (2)	Single (3)
Panel A: Excluding individuals whose income are above/below MLS threshold by $1K			
MLS_{it}	0.014***	0.016***	0.009
	(0.004)	(0.004)	(0.009)
Mean PHI	0.563	0.603	0.429
Panel B: Excluding individuals whose income are above/below MLS threshold by $2.5K			
MLS_{it}	0.016***	0.018***	0.005
	(0.004)	(0.005)	(0.009)
Mean PHI	0.555	0.594	0.422
Panel B: Excluding individuals whose income are above/below MLS threshold by $5K			
MLS_{it}	0.014***	0.015***	−0.005
	(0.005)	(0.005)	(0.012)
Mean PHI	0.546	0.585	0.410
Method		2 lags of internal IVs	

Notes. Cluster-robust standard errors are reported in the parenthesis; standard errors are clustered at individual level. MLS_{it} is the coefficient estimate on the Medicare Levy Surcharge liability. PHI_{it-1}, PHI_{it-2} and PHI_{it-3} are the parameter estimates of the one-, two- and three-period lagged dependent variables. The dynamic model is estimated using System GMM. All regressions control for state/territories and remoteness.

*** Significance: 1%.

Table B6
Effect heterogeneity by quartiles of MLS liability in dollar terms.

	Combined (1)	Family (2)	Single (3)
Ref: Not liable for the MLS			
MLS liability Q1	0.008*	0.009**	0.010
	(0.004)	(0.004)	(0.010)
MLS liability Q2	0.016***	0.017***	0.028
	(0.003)	(0.004)	(0.024)
MLS liability Q3	0.014***	0.015***	0.012
	(0.004)	(0.005)	(0.023)
MLS liability Q4	0.015***	0.018***	−0.004
	(0.005)	(0.005)	(0.027)
PHI_{it-1}	0.485***	0.557***	0.268
	(0.181)	(0.211)	(0.454)
PHI_{it-2}	0.361**	0.310*	0.545
	(0.142)	(0.167)	(0.349)
PHI_{it-3}	0.082***	0.070**	0.137
	(0.028)	(0.031)	(0.089)
Mean PHI	0.568	0.608	0.436
Individual FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Observations	54,002	40,856	9063
Number of Instruments	46	44	44
F *p*-values	0.000	0.000	0.000
AB 2 *p*-values	0.096	0.261	0.271
AB 3 *p*-values	0.426	0.800	0.603
Hansen *p*-values	0.713	0.765	0.316
Method		2 lags of internal IVs	

Notes. Cluster-robust standard errors are reported in the parenthesis; standard errors are clustered at individual level. MLS liability Q1–Q4 refers to the quartiles of MLS liability in dollar terms. The reference category are individuals who are not liable for the MLS. PHI_{it-1}, PHI_{it-2} and PHI_{it-3} are the parameter estimates of the one-, two- and three-period lagged dependent variables. The dynamic model is estimated using System GMM. All regressions control for state/territories and remoteness.

* Significance: 10%.
** Significance: 5%.
*** Significance: 1%.

Table C1
Simulated proportion of population with private health insurance.

Year	Baseline	Thresholds at pre-2008 levels	Abolishing MLS
2007	0.545	0.545	0.545
2008	0.570	0.570	0.566
2009	0.575	0.575	0.569
2010	0.600	0.601	0.592
2011	0.612	0.616	0.605
2012	0.616	0.621	0.607
2013	0.613	0.618	0.602

Notes. Estimates show simulated proportion with private health insurance (PHI). Scenario 1 sets the MLS income thresholds at the pre-reform (2008) levels. Scenario 2 simulates the abolishing of the MLS, where income thresholds are effectively set to infinity. All estimates are weighted to the population using sample weights. In the simulation, all individual characteristics (e.g. age, income) are allowed to vary over time.

Appendix C. Counterfactual simulation results

Appendix D. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jhealeco.2020.102403.

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