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Age penalties and take-up of private health insurance

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Abstract

Financial penalties for delayed enrollment could be useful tools to encourage people to enroll earlier in health insurance markets, but little is known about how effective they are. We use a large administrative dataset for a 10% random sample of all Australian tax-filers to study how people respond to a step-wise age-based penalty, and whether the effect has changed over time. Individuals must pay a 2% premium surcharge for each year they delay enrollment beyond age 31. The penalty stops after 10 years of continuous hospital cover. The age-based penalty creates discontinuities in the incentive to insure by age, which we exploit to estimate causal effects. We find that people respond as expected to the initial age-penalty, but not to subsequent penalties. The 2% premium loading results in a 0.78–3.69 percentage points (or 2.1%–9.0%) increase in the take-up rate at age 31. We simulate the penalty impact and implications of potential reforms, and conclude that modest changes around the policy make little difference in the age distribution of insured, premiums or take-up rates. Our study provides important evidence on an understudied area in the literature and offers insights for countries considering financial penalties.

KEYWORDS
age-based penalty, Australia, health insurance, private health insurance, regression discontinuity

JEL CLASSIFICATION
I13, I18, I12

1 | INTRODUCTION

Private health insurance (PHI) markets are heavily regulated in many countries. To reduce adverse selection and encourage more people to take up private insurance early, financial incentives are commonly used, mainly in two types: "carrots" such as subsidies for purchasing health insurance, and "sticks" such as penalties for not having insurance. Subsidies are more commonly used and have been widely studied worldwide (Cheng, 2014; Finkelstein, 2002; Frean et al., 2017; Gruber & Washington, 2005; Hinde, 2017; López Nicolás & Vera-Hernández, 2008; Rodríguez & Stoyanova, 2008). However, in comparison, financial penalties are under-studied, and their effects are less known. It is an important policy question to understand how individuals respond to financial penalties and whether it is an effective tool that could be used more commonly.

We study an age-based financial penalty—Lifetime Health Cover (LHC)—implemented in Australia to encourage people to buy PHI earlier in life. Starting from July 2000, if people do not have hospital cover before July 1 following their 31st birthday and decide to buy later, they must pay a 2% loading on top of their hospital premium for every year they are aged over 30. That is, if one joins when he is 31, he pays 2% loading, and if he joins when he is 50, he pays 40% [= 2% × (50 − 30)] loading. The loading is removed after one has held private hospital cover for 10 continuous years. Following Australia's suit, in 2015, the Irish government implemented a similar scheme—lifetime community rating, which increases PHI premiums by 2% per year for individuals aged 35 and over who postpone buying their PHI (Keegan, 2020).

Australia's LHC policy offers us a novel opportunity to examine how the age-based penalty affects demand for private insurance. LHC creates an incentive for those without insurance to purchase insurance just before the LHC base day (the July 1 following their birthday), when the loading increases each year.

We examine the effects of LHC for each age between 31 and 65, and for each year between 1999 and 2018, using rich administrative tax return data from a 10% random sample of Australian tax-filers. The penalty creates discontinuities in the incentives to insure by age, which we exploit to estimate causal effects using regression discontinuity design (RDD). We use an innovative new method to select a preferred RDD estimator for each year, which relies on data away from the discontinuity to select among many potential estimators, varying in bandwidth, polynomial order and controls (Kettlewell & Siminski, 2022). We also conduct numerous robustness tests.

We first conduct a simulation analysis guided by the theoretical predictions of the effects of LHC incentives. Our simulation suggests that even though the absolute value of the penalty is the same at each age threshold, the jump in take-up may be much larger at age 31 than other ages, because for each year LHC mainly affects those uninsured at the margin. As people age, more people sign up for PHI, and therefore for each subsequent age fewer marginally uninsured people are left.

We then turn to the data and find that people respond as expected to the initial age-penalty, but there is no response to subsequent penalties at later ages. The larger effect at age 31 is consistent with our simulation prediction. The 2% penalty results in a 0.78–3.69 percentage points (ppts) (or 2.1%–9.0%) increase in the take-up rate at age 31. The effects change over time, with the largest relative effect in the first year after LHC was introduced (between July 2000 and June 2001), before declining gradually and reaching the lowest level in 2006, and then rebounding back starting in 2008. This rebound coincides with a new policy in which people were sent letters if they were approaching 31, when the LHC penalty starts. This suggests the importance of behavioral nudges in supporting financial incentives. Between 2008 and 2018, the LHC effect has been fairly stable in the range of 4.6%–7.2%. In 2018, LHC increased insurance take-up at age 31 by 2.94 ppts (or 6.0%).

We are the first to cleanly estimate the causal effect of LHC, an age-based financial penalty incentive. This is an important contribution because this is an understudied area, and the effects of financial penalties are not well known. We are also the first to study the subsequent age penalty thresholds and an effect at age 31 only. We use large individual-level administrative data, improving on earlier work that primarily relied on older, much smaller restrictive datasets that did not observe age with the necessary detail to truly exploit the age discontinuities (e.g., Palangkaraya & Yong, 2005, 2007). Finally, we are also the first to estimate LHC's long-term impact post-introduction. This is important because the initial response to LHC does not seem to have been solely about the price incentive; instead, the advertising blitz probably played a substantial role (Ellis & Savage, 2008). In addition, earlier studies tell us little about the ongoing impact of LHC, especially in recent years when more young people have dropped PHI (Zhang, 2020), and there is a real concern about whether PHI is sustainable (Australian Government Department of Health, 2021a).

2 | PRIVATE HEALTH INSURANCE IN AUSTRALIA

Australia has a universal health insurance scheme known as Medicare, which covers free hospital treatment in public hospitals, subsidized medications and primary care doctors and specialist treatment (Australian Government Department of Health, 2021b).

In addition, a PHI market and private hospital system runs parallel to public care and provides users with more flexible treatment options. Premiums of PHI in Australia are subject to community rating, which do not change by individual characteristics such as age, gender or prior health condition. But premiums can vary by state, and benefit levels. There are four benefits levels: basic, bronze, silver, and gold. As of March 2021, 44% of Australians held PHI. People often buy private hospital insurance to access shorter or no waits for hospital care either in private or public hospitals, access to private rooms, and a greater ability to choose one's own doctor, and financial reasons in response to government regulations (Zhang & Prakash, 2021).[1] Despite free access to Medicare, the government encourages people to buy PHI with various "carrots" and "sticks" policies. The justification for these government interventions is that, if more people buy PHI and use the private system, it may take pressure off the public system.

Three main government regulations were initiated between 1997 and 2000 to encourage people to take up PHI. On July 1, 1997, the government introduced the Medicare Levy Surcharge (MLS), an income-based tax penalty, which imposes additional income tax for people who earn above a certain threshold and do not hold private hospital cover. In addition, the government offered rebate incentives to buy PHI for those with incomes below certain thresholds (max $150 discount per year for singles earning <$35,000, and $450 for families earning below $70,000). On July 1, 1999, the government increased the rebate to 30% of premiums for everyone regardless of income. Finally, on July 1, 2000, the government introduced LHC, an age-based financial penalty for delayed enrollment.

Since then, the Australian government has made some changes to the incentives. For example, age-specific rebates were introduced in 2005 to raise rebates for adults older than 65, rebates became means-tested and their growth capped in 2012, and MLS thresholds and levy rates increased in 2008 and 2012 respectively. For example, in 2007–2008 the MLS thresholds increased from $50,000 ($100,000) AUD to $70,000 ($140,000) for singles (families) and became indexed based on full-time adult average weekly ordinary time earnings. Nevertheless, these three incentives have largely maintained their structure, especially LHC, which has not experienced any major changes since 2000.

2.1 | What is Lifetime Health Cover and what do we know about its effects?

LHC is designed to encourage people to buy hospital cover earlier in life. People born on or before July 1, 1934 (89 years old in 2023) are exempt from LHC. If people do not have hospital cover before their base day (the later of July 1, 2000 or the July 1 following their 31st birthday) and decide to buy after, they have to pay a 2% loading on top of their hospital premium for every year they are aged over 30, based on their age on the July 1 prior to joining (Commonwealth Ombudsman, 2021). The maximum LHC loading is 70% ($2\% \times (65 - 30)$), so if one joins when he is 65 or older, he pays 70% loading. In addition, the loading stops after 10 years of continuous hospital cover. However, if one cancels hospital cover after the loading is removed, he may become liable to pay a LHC loading again if he takes out another hospital cover.

Because LHC was introduced around the same time as the MLS and rebate (1997–2000), most earlier studies evaluated their joint effects on PHI take-up. For example, Ellis and Savage (2008) found that the three interventions increased PHI enrollment by 50% and reduced the average age of enrollees. They interpreted the major drivers of the increased enrollment from 1999 to 2001 as a response to the LHC deadline and an advertising blitz, rather than a pure price response. Palangkaraya and Yong (2005) tried to isolate the effects of LHC from the other two tax and rebates policies by decomposition analysis using survey data before and after the reforms. They found that LHC could explain between 42% and 75% of the increase in take-up. A second study by the same authors concluded that LHC may only account for 22%–32% of the combined effects, accounting for about 3–4.5 ppts increase in the PHI take-up from 1999 to 2001 (Palangkaraya & Yong, 2007).[2] T. Buchmueller (2008) compared the degree of adverse selection in Australian PHI, before and after the implementation of LHC in 2000, and concluded that LHC induced a greater number of younger consumers into the market and resulted in lower average premiums.

2.2 | The incentive effects of LHC

Consider an individual with willingness to pay for PHI given by the function WTP $= f(\text{age})$ (other determinants of WTP are assumed fixed for this exercise). Demand for PHI is assumed to be increasing with age with $f'(\text{age}) > 0$. This assumption seems strong, but it is not essential to this exercise. We choose it so it is straightforward to solve the dynamic choice problem, as shown below in the simulation section.

At each point in time, the person observes the premium for PHI P and insures if the premium is less than WTP. With an increasing WTP function in age, and a fixed cost of PHI, there will be a single "switch" point where the person purchases cover and maintains it indefinitely (assuming at some age WTP $> P$). In Figure 1a, the person purchases insurance at age x.

The LHC threshold at age 31 (for people born on July 1, such that their LHC base day falls on their birthday) effectively creates a 10-year premium increase at the point of the 31st birthday such that $P + \text{LHC} = P \times 1.02$ between age 31 and 10 years after they first purchase cover. This can be avoided by purchasing and retaining insurance just before this date. LHC makes the decision to purchase a dynamic rather than static one on this date, while having no influence on insurance choice before this.

Assume that people are utility maximizing, forward looking decision makers who always know their WTP profile. In the example in Figure 1b, if the person purchases insurance just before their birthday, they receive a lifetime net surplus equal to the area $C + B - A$. If instead they do not purchase, they will delay purchasing PHI until age x' and will receive a net surplus equal to C. The decision rule for whether to purchase insurance at age 31 is therefore whether $B > A$.

Whether LHC acts as an incentive or disincentive depends on the WTP profile of the given person. In the example above, LHC causes the person to bring forward their purchase. All else equal, the penalty (for people with a concave profile) is more likely to incentivize people who would have purchased insurance near the penalty date anyway. For people who accept the

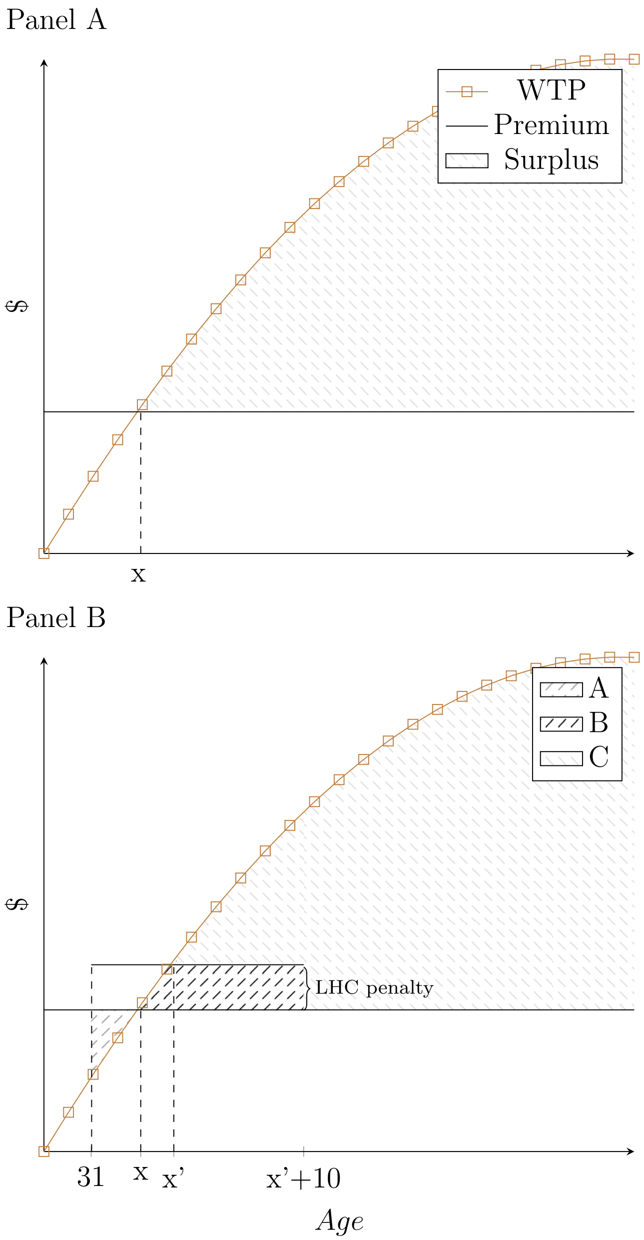

FIGURE 1 Insurance decisions over the life-cycle. (a) No age penalty. (b) After age penalty. In panel (a), it is optimal to purchase private health insurance at age x. In panel (b), purchasing at age 31 will result in net surplus $B + C -$ A. Purchasing at age x' will result in net surplus C. Therefore, if $A < C$, the LHC age penalty will cause the person to purchase sooner (at age 31). LHC, Lifetime Health Cover.

penalty, it will cause them to delay taking up PHI, and in some cases they may never take up PHI at all. This is more likely to be the case for those who would otherwise first purchase at an older age, so may have the effect of lowering the average age of people with insurance.

2.3 | Simulation

To further explore the theoretical expectations, we conduct a simple simulation. We assume WTP is linearly non-decreasing with age according to the function $\text{WTP}_{it} = \alpha_i + \beta_i \text{Age}_{it}$. Because WTP is non-decreasing in age, we can assume once people insure, they remain insured thereafter. α and β are random variables with $\alpha \sim N(0, 1000)$ and $\beta \sim N(40, 20)$, truncated at zero. These parameters were chosen because they give rise to a similar age-coverage profile to what we see in our analysis data, and the degree of heterogeneity is similar to that assumed in similar simulations by Sowa et al. (2018) (doubling or halving the standard deviations does not qualitatively affect our results). We further assume PHI premium $P = \$2000$ in every year, which implies that in expectation, 50% of people will be insured at age 50.[3]

With this set-up, we simulate the WTP profiles for 10,000 individuals who live from age 25–80. For each age (in 0.1 steps) we calculate the total lifetime surplus from buying insurance at that age and identify the optimal age to join insurance as the age where surplus is maximized.[4] This gives us an age profile of the insurance pool as shown in Figure 2.

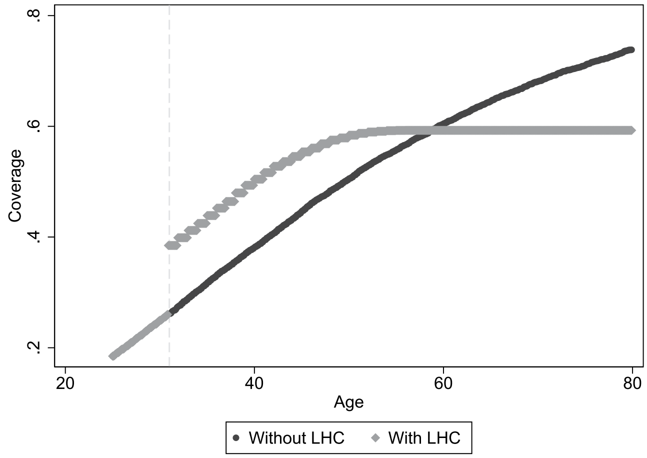

FIGURE 2 Simulated take-up of private health insurance. The figure shows the simulated proportion of people (n = 10,000) with PHI at every age assuming $\text{WTP}_{it} = \alpha_i + \beta_i Age_{it}$ with $\alpha \sim N(0, 1000)$ and $\beta \sim N(40, 20)$, truncated at zero. PHI is assumed to cost P = \$2000 in every year, and loading is added to those who are subject to Lifetime Health Cover (LHC). PHI, private health insurance.

Up to age 31, the take-up rate is the same with or without LHC. Because of LHC there is a large concentration of people who insure just before age 31, creating a large discontinuity. There are also discontinuities at other ages, but these are markedly smaller and gradually disappear. This pattern can be explained by the fact that at age 31, marginally-uninsured people join the pool. This means that at the next penalty threshold (32) there are fewer marginally uninsured people (and so on). Our simulation therefore suggests that even though the absolute value of the penalty is the same at each age threshold, the jump in take-up may be much larger at age 31 than other ages.[5] It also shows the disincentive effects of LHC—in our example LHC lowers the probability of insurance from age 58.8.

To close out this section, we note some behavioral biases that could affect the predictions above. First, researchers have documented the presence of inertia in PHI markets (Drake et al., 2022; Ericson, 2014; Handel, 2013; Polyakova, 2016). If people suffer from inertia due to inattention and switching costs, they are more likely to remain status quo. For those who do not have PHI, they are less likely to buy PHI so the incentive effects will be smaller. On the other hand, for those who have PHI, they are less likely to switch or drop when their situations change and do not need PHI any more. Second, if people view the LHC penalty as a loss and are loss averse, this could lead to an even stronger response at age 31 than predicted by utility maximizing behavior.

3 | DATA AND METHODS

3.1 | Data

We use the Australian Taxation Office's ALife data, which covers a 10% random sample of all Australian registered tax-filers across the years 1999–2018 (our estimation sample sizes differ slightly across years, but range from about 180,000 to 250,000). Australians file taxes in financial years that run from July 1 to next June 30, so 2000 data covers July 1, 1999 to June 30, 2000, which is the first deadline by which people needed to be insured to avoid LHC (so constitutes the first "policy year"). ALife tracks individuals' tax and superannuation records and includes detailed information on all their income sources, such as salary and wages, government pension and allowances, annuities and superannuation, interests, and dividends. Because the Australian government uses tax incentives to encourage people to enroll in PHI, ALife also tracks PHI coverage each year. Taxes are levied at the individual level in Australia and it is not currently possible to link household members.

Because we are interested in discontinuities by age, we require more granular date-of-birth information than in the standard ALife release. We also require more detailed indicators for PHI status.[6] We therefore use a custom release of ALife. To allow for more granularity in age, our datasets for each financial year are collapsed at the month-year-of-birth level. We then use frequency weights in all our analyses. Collapsing the data in this way provides detailed information on age while satisfying privacy concerns for the ATO. To capture PHI status as of June 30 we use a custom indicator equal to one if the PHI details section of the tax return is not blank for years up to 2011–2012. One drawback is that we also classify people who drop insurance mid-year as insured. Since we focus primarily on age 31, which is a period people are generally taking-up insurance, we do not expect this to greatly affect the results. Moreover, from 2012 to 2013 we have better information on insurance status. Since 2012–2013, insurance funds provide details to the ATO on start and end date for each policy held, which allows us to create an indicator for if the person at any time held a policy ending after June 30. We use the "source tax return" PHI indicator for years up to 2012–2013 and the "source funds" indicator from that year onwards.[7]

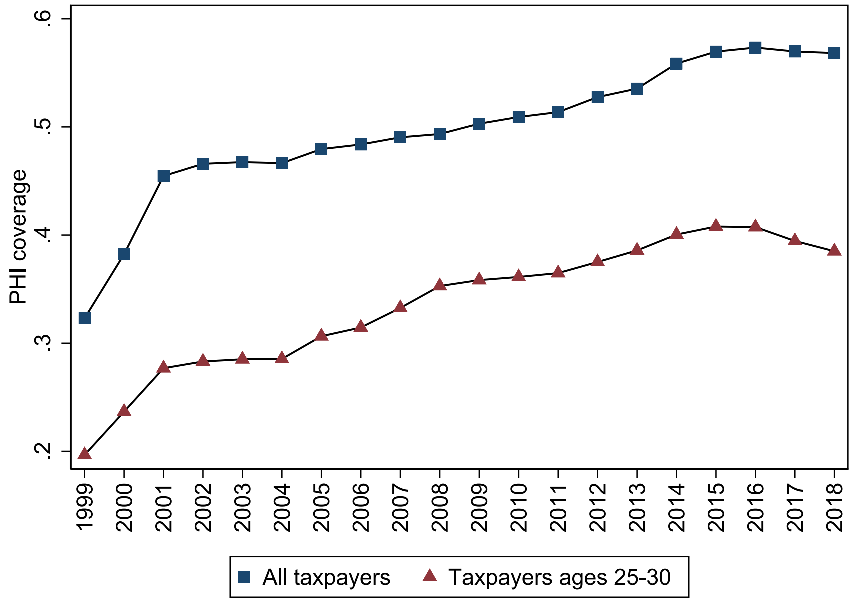

FIGURE 3 Trend in private health insurance coverage between 1999 and 2018. Data are from the ALife 2018 release version. We used tax return files between 1999 and 2018. Australians file taxes in financial years that run from July 1 to next June 30, so 2000 data covers July 1, 1999 to June 30, 2000, right before the first deadline for LHC on July 1 2000. PHI coverage is calculated consistently using the indicator for non-blank private health insurance details in the tax return for each financial year ending June 30. LHC, Lifetime Health Cover; PHI, private health insurance.

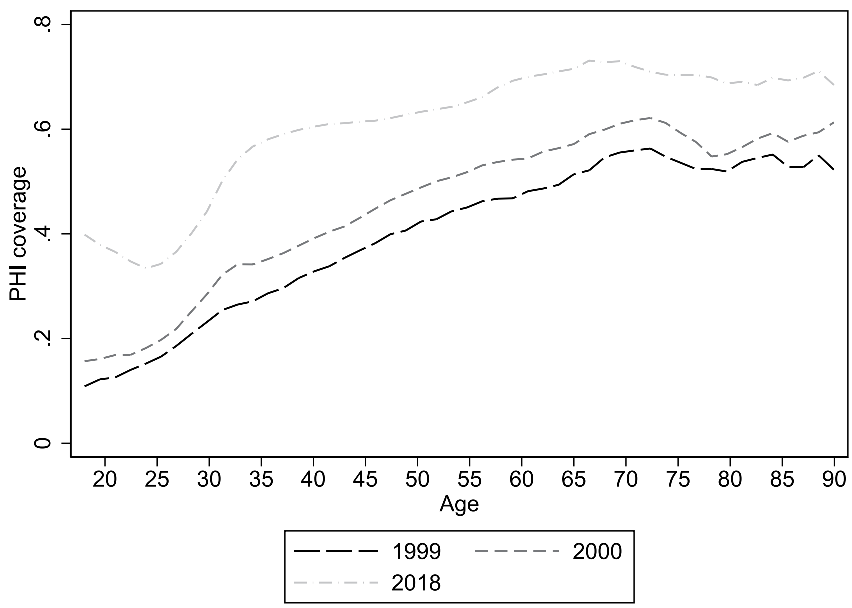

FIGURE 4 Changes in the age profile of insured people: 1999, 2000, and 2018. Data are from the ALife 2018 release version. We only use tax return files in 1999, 2000, 2018 to generate this figure. Australians file taxes in financial years that run from July 1 to next June 30, so 2000 data covers July 1, 1999 to June 30, 2000. PHI coverage is calculated using an indicator for non-blank PHI details in the tax return for the financial year ending June 30. Smoothed lines are based on local polynomial fits of the underlying data. LHC, Lifetime Health Cover; PHI, private health insurance.

3.2 | Trends in coverage

Figure 3 shows how PHI coverage has evolved for tax-filers since 1999—the year before LHC was introduced.[8] The effect of the policy on take-up is apparent in the 1999–2000 and 2000–2001 financial years, even for those aged 25–30 years who were not directly affected by the penalty but were affected by two other policies that were implemented around the same time. During this period, coverage increased from around 32%–46% before steadily rising to a peak of around 56% in 2015–2016. The flattening and subsequent decrease in coverage since 2015–2016—particularly for those aged 25–30 years—has continued into later years.[9]

It is also informative to examine how the age profile of the insurance pool has changed over time. Figure 4 shows how following the introduction of LHC there was an increase in coverage among all age groups, as noted elsewhere (Ellis & Savage, 2008). By 2018, coverage was again higher for all age groups but with notable differences in the structure, with much steeper take-up between ages 25–35 than the earlier years.

3.3 | Econometric model

While it is evident that LHC (or the advertising campaign associated with it) successfully pushed people into insurance in 2000, it is less clear how strongly the policy has continued to incentivize people thereafter. As discussed in Section 2, the incentive effects are complicated and go in both directions. We focus on one clear and unambiguous prediction. Namely, if people are responding to the policy, we should observe a discontinuous increase in the probability of insurance just before the base day each year when the penalty is increased by 2 ppts. Our simulations also suggest the effect is likely to be largest at age 31.

To understand this prediction in the context of our data, note that because the tax return covers the 12 months to June 30, it can provide a snapshot of PHI status as of July 1. People who turn 31 by this date will be subject to the LHC penalty if they have not purchased insurance. People who are aged 30 as of July 1 still have another 12 months before they need to purchase insurance (because the LHC base date is the July 1 following the 31st birthday).

To formally estimate the effect of LHC penalties on PHI take-up, we estimate RDD specifications. Our basic estimation equation is the canonical local-linear RDD specification, given by:

$$Y_g = \beta_0 + \tau T_g + \beta_1 \left(\text{Age}_g - c\right) + T_g \beta_2 \left(\text{Age}_g - c\right) + \epsilon_g \tag{1}$$

Y_g is the fraction of people born in month-year g who have PHI, T_g is the fraction of people subject to the LHC penalty (e.g., age 31 or older for the initial penalty threshold, given the end of the tax year is June 30), c is the age at which the LHC penalty kicks in, and ϵ_g is a stochastic error term. $\hat{\tau}$ is the causal effect of LHC on the probability of insuring for those at the age threshold provided the continuity assumption is satisfied (Hahn et al., 2001). This requires there are no other discontinuous changes in outcomes at the age threshold which could affect take-up, and no sorting into treatment or control groups at the threshold (which is unlikely since age is difficult to manipulate). While ultimately untestable, we provide supportive evidence below that these assumptions seem to hold in our context (see Section 4.1).

3.3.1 | RDD model selection

Estimation of Equation (1) requires several researcher choices. Importantly, we need to select a bandwidth around the threshold and decide whether to include additional polynomial terms for the control function. Larger bandwidths increase bias but reduce variance. The choice of polynomial also involves a trade-off between bias and variance (Pei et al., 2021) although in practice researchers often limit attention to linear (as in Equation (1)) and quadratic specifications since higher order polynomials can greatly distort boundary estimates (Gelman & Imbens, 2019).

In our application, we are seemingly constrained to bandwidths of 12 months for each threshold since the penalty increases every 12 months. We first follow usual practice and in Figure 5 plot coverage by age for the most recent tax year available (2018). To aid the detection of discontinuities we include linear fit lines for each 12-month age group. This figure succinctly conveys our first main finding. While there is a clear discontinuity at age 31, where the initial penalty kicks in, there is no evidence for discontinuities at any other age. In other words, people respond as expected to the initial LHC penalty but do not respond as expected to additional penalties. This result is not limited to 2018 or ages 30–40 years. In Appendix Figure A2 we provide similar charts for ages 41–65 years in 2018 and find no strong visual evidence of discontinuities.[10]

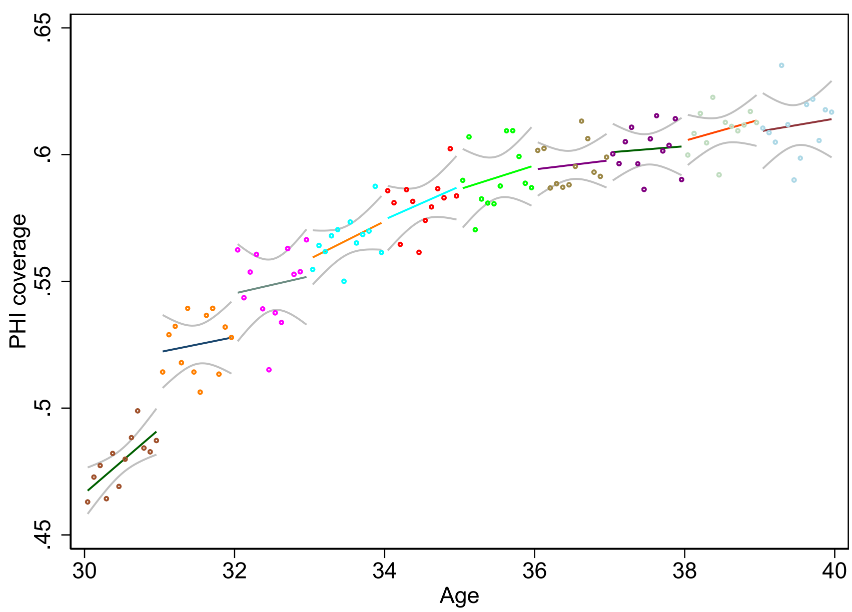

FIGURE 5 Private health insurance coverage by age in 2018. Data are from the ALife 2018 release version. We only use the 2018 tax return file in this figure. PHI coverage is calculated using an indicator for if a person holds a policy expiring after June 30, 2018. Each scatter point corresponds to the mean PHI coverage for that age (month level) and linear fit lines (with 95% confidence intervals) are for 1 year intervals. PHI, private health insurance.

To more formally test whether there are age discontinuities we estimate linear RDD models using 1-year bandwidths around each age threshold from 31 to 64 years in every year from 2000 to 2018 (see Appendix Figure A3). Excluding age 31, only 14 out of 594 (2.4%) discontinuity estimates are statistically significant (which is less than expected by chance if estimates are independent) and only one discontinuity is significant more than once (age 46, which is significant twice). In contrast, the discontinuity estimate for age 31 is positive and significant in 11/18 regressions.

An alternative to estimating a separate regression for each year and age threshold is to pool the data and estimate RDD models for each age threshold controlling for the year. This can improve statistical power but might hide effects that are significant in some years only. We present results from this exercise in Appendix Figure A4. Again, we only find evidence LHC increases take-up at age 31. Somewhat surprisingly, there is a small (0.3–0.35 ppts) but significant drop in take-up at ages 48 and 60–63. The latter may be due to retirement decisions. Regardless, the magnitudes are negligible (note in 2018 around 70% of people aged 60–63 in this age group had PHI) and it is not consistent with the incentives created by LHC.

Based on the preceding evidence we hereafter focus on the age 31 threshold and proceed as if there is no discontinuity at any other age thresholds. We then rigorously estimate the behavioral response to the age 31 threshold, and map out dynamics in this response over time. We deal with the problem of RDD model selection by adopting the method in Kettlewell and Siminski (2022) (KS). Their method uses a "placebo zone" of the running variable (age) as a training ground to inform the choice of estimator at the true policy threshold. The intuition is as follows. In the placebo zone we know the policy effect is zero at any threshold. We can therefore estimate any number of models (varying in dimensions like bandwidth and polynomial order) in this zone across the different "placebo thresholds" and compare them on our preferred criterion (root mean squared error, RMSE). The model with the lowest RMSE is the preferred estimator for the true treatment effect.[11] The method allows us to deal with the problems of bandwidth and polynomial selection simultaneously and lends itself to an intuitive randomization inference approach in the spirit of Ganong and Jäger (2018), which serves as a useful robustness exercise for hypothesis testing using conventional standard errors.

To operationalize the KS model selection algorithm, we use ages 31–65 as our placebo zone. We stop at age 65 as Age Pension eligibility kicks in for many people at 65. We set the minimum (symmetric) bandwidth to 1 year and the maximum to 4 years. We consider placebo thresholds and bandwidths in increments of 1 month. So, our first placebo threshold is at age 35 ($= 31 + 4$), our second is at age 35 and one month and so on up to age 61 ($= 65 - 4$). Given well-known issues with higher order polynomials in RDD (Gelman & Imbens, 2019), we only consider linear and quadratic specifications. We also consider these with and without controls. Controls include total tax deductions, taxable income, sex, self-employment flag, Accessibility/Remoteness Index of Australia classification (five levels) and State dummies. These variables were selected because financial circumstances, sex and region are known to predict PHI take-up.

The Office of Research Ethics and Integrity at the University of Melbourne has approved this study.

4 | RESULTS

Figure 6 plots the RDD estimates across the years 1999–2018. These are generated from separate regressions using the model selected by the KS algorithm as described above. Precise details on the models (bandwidth, polynomial, controls) are provided in Table 1. For almost every year, the preferred bandwidth is close to the maximum allowed (4 years) with a linear control function (polynomial order one), sometimes with and sometimes without controls.

The effect in 1999 (the placebo year) is close to zero and statistically insignificant, as we expected. The policy effect is moderate—peaking at 9% (relative to the mean at age 31) in 2001—before waning in the mid 2000s and then rebounding in 2008.

The policy effect generally trended upward since 2011. In 2011 the effect was 2.5 ppts (5.7%). In 2018 it was 2.9 ppts (6.0%). Because we use a different variable for PHI status from 2013, in Appendix Figure A5 we report estimates using the same specifications but replacing the PHI variable with the one used pre-2013 (source tax return). The estimates are similar to those in Figure 6.

Between 2014 and 2018 the mean probability of having insurance at the age 31 threshold decreased from 52.8% to 48.7% (Table 1). However, during the same period, the LHC policy effect is fairly stable. This implies that the decline in PHI participation in recent years is more likely due to other factors, instead of LHC becoming less effective over time.

The apparent weakening of the incentive effect up to 2006–2007 is curious. It may be that people's awareness of the penalty waned. From July 1, 2007, the Department of Health began a policy of mailing letters to people approaching their first LHC penalty deadline, encouraging them to consider purchasing PHI (Department of Health and Ageing, 2010). We acknowledge that we do not directly evaluate the effects from mailing campaign, but our results are consistent with this policy being effective and suggest that financial penalties are more effective when combined with information nudges.

FIGURE 6 RDD estimates for each year: Age 31 penalty. Data are from the ALife 2018 release version that include tax return files from 1999 to 2018. Australians file taxes in financial years that run from July 1 to next June 30, so ALife 1999 data covers from July 1, 1998 to June 30, 1999; 2000 data covers July 1, 1999 to June 30, 2000, right before the first deadline for LHC on July 1 2000. Each year corresponds to a separate RDD estimate. Gray lines are 95% asymptotic confidence intervals with standard errors clustered at the month of birth level. Further details on the estimates are in Table 1. LHC, Lifetime Health Cover; RDD, regression discontinuity design.

An alternative explanation is related to changes to the MLS thresholds; however, the data do not completely support this. In 2007–2008 the MLS (income tax penalty) thresholds increased from $50,000 ($100,000) AUD to $70,000 ($140,000) for singles (families) and became indexed based on full-time adult average weekly ordinary time earnings. The MLS may have been crowding out the effect of LHC before this change. In Appendix Figure A6 and Tables A1–A3 we report estimates for three sub-groups of tax filers—those with wage price adjusted income for MLS purposes below $50,000 AUD-2005 (always below MLS threshold), those above $88,000 AUD-2014 (always above MLS threshold) and those between these amounts. We double the thresholds for people identified as having a spouse. Most people (around 2/3) are in the always below MLS threshold group. The overall trends are similar for each group, although the effect sizes are much larger for the middle- and high-income groups in the early 2000s. The sharp rebound for the middle group in 2007–2008 is consistent with an MLS interaction effect (most people in this income range were liable for the MLS in 2006–2007 but not in 2007–2008). However, we also see a modest rebound for those below the MLS threshold, which suggests another factor (e.g., the LHC mail-out) was also at play. Apart from a dip just before the mail-out, the trend for the high income group is fairly flat. However, given the MLS already provides this group with a strong financial incentive to insure, it is plausible that the mail-out would have had a limited effect.

4.1 | Robustness

4.1.1 | Manipulation of running variable

Since age cannot be directly manipulated, we do not expect sorting into treatment in our application. However, policy decisions like availability of contraception and family benefits may alter the density of births. In Appendix Figure A7, we plot the number of people by month-of-birth cohort in each year and find no systematic discontinuity at the age 31 threshold.

4.1.2 | Discontinuities in other variables

To test the continuity assumption we estimated our RDD models against a number of other variables: self-employment, income, total tax deductions, government transfer payments;, and claims against the net medical expenses tax offset (Appendix Figure A8). In most years the effects are statistically insignificant. The few instances where they are not is expected given the number of hypotheses being tested and those effect sizes are small. Altogether our results support the causal interpretation of our estimates in Table 1.

4.1.3 | Undetected penalty effects

Our main results assume there are no discontinuous jumps in take-up of PHI at any age threshold other than 31, which is supported visually and by statistical tests. Our simulations in Section 2 also suggest that the jump at 31 should be much larger

TABLE 1 RDD estimates for each year: Age 31 penalty.

Year	Estimate	Std. error	Mean	Est./mean	BW	Obs.	Poly. order	Controls
1999	0.0055	0.0038	0.2430	0.0228	3.96	191,226	1	No
2000	0.0139	0.0041	0.3263	0.0425	3.72	181,819	1	No
2001	0.0365	0.0049	0.4052	0.0900	3.88	192,836	1	No
2002	0.0311	0.0051	0.3737	0.0833	3.96	199,923	1	Yes
2003	0.0221	0.0036	0.3569	0.0620	3.72	191,379	1	Yes
2004	0.0078	0.0046	0.3733	0.0209	3.64	189,509	1	No
2005	0.0163	0.0047	0.3649	0.0446	3.56	186,221	1	No
2006	0.0079	0.0048	0.3949	0.0201	3.96	207,590	1	Yes
2007	0.0126	0.0052	0.4403	0.0285	3.96	208,283	1	No
2008	0.0238	0.0053	0.4539	0.0525	3.96	214,232	1	No
2009	0.0228	0.0056	0.4682	0.0487	3.96	217,949	1	No
2010	0.0208	0.0055	0.4504	0.0462	3.48	194,516	1	No
2011	0.0246	0.0052	0.4293	0.0573	3.48	200,808	1	No
2012	0.0288	0.0045	0.4678	0.0615	3.72	219,004	1	No
2013	0.0359	0.0049	0.5002	0.0719	3.8	228,500	1	No
2014	0.0346	0.0056	0.5279	0.0656	3.4	210,719	1	Yes
2015	0.0369	0.0041	0.5353	0.0690	3.88	246,227	1	Yes
2016	0.0344	0.0050	0.5463	0.0629	3.8	248,112	1	No
2017	0.0315	0.0053	0.5121	0.0614	3.4	226,601	1	No
2018	0.0294	0.0046	0.4872	0.0604	3.8	255,529	1	No

Note: Data are from the ALife 2018 release version including tax files 1999–2018. Each row corresponds to a separate RDD estimate. Australians file taxes in financial years that run from July 1 to next June 30; 2000 data covers July 1, 1999 to June 30, 2000, the first deadline for LHC. The dependent variable is an indicator for non-blank PHI details in the tax return (1999–2012) or an indicator for if the person holds a policy expiring after June 30 for the corresponding year (2013–2018). Columns *BW*, *Poly. order* and *Controls* are the bandwidth, polynomial order and whether controls were used for the RDD estimator selected by the KS algorithm. The algorithm considered models with bandwidths 1–4 years in 1-month increments, linear and quadratic control function, and with/without controls. The controls are total tax deductions, taxable income, sex, self-employment flag, Accessibility/Remoteness Index of Australia classification (five levels) and State dummies. The column *Mean* is the average PHI coverage for people aged 31–31 + 1 month years. The column *Obs.* is the underlying number of individuals in the month-of-birth collapsed estimation sample. Standard errors are clustered at the month-of-birth level.

Abbreviations: LHC, Lifetime Health Cover; PHI, private health insurance; RDD, regression discontinuity design.

than at other ages. Nevertheless, if people do respond to these other penalties our estimates may be biased in an uncertain way, both because our local-linear regressions are biased, and because the KS model selection algorithm is invalid due to non-zero treatment effects in the placebo zone. To gauge whether such bias is likely to be serious in practice, we conduct a kind of permutation test by adding a treatment effect of 3 ppts to each age threshold and then re-run the KS algorithm on the transformed data. Even with such an extreme transformation of the data, our estimates are similar (see Appendix Figure A9). We also re-estimate models using only ages 35–60 for the placebo zone, considering that undetected effects are most likely to be in the years close to age 31, and our earlier finding of small drops in PHI at ages 60–63 years. Again, our estimates are similar (see Appendix Figure A10). We conclude that potentially undetected incentive effects at other ages is not materially important to our main findings.

4.1.4 | Alternative inference

In Appendix Figure A11, we present the distributions of the placebo treatment effect estimates for each year (i.e., estimates at each of the placebo thresholds, which are ages 35–61 years in steps of 1 month). Statistics for the placebo estimates serve several purposes. The coverage rate (percentage of times we fail to reject zero) serves as a kind of falsification test for inference based on our preferred specification. Each year coverage is close to (and often exceeds) 95%, which bodes well for the standard errors in Table 1. Nevertheless, we also use Appendix Figure A11 for an alternate type of inference (randomization inference). Specifically, we compare our estimate at age 31 to the 97.5th percentile of the placebo distribution, which is suggested by Ganong and Jäger (2018). Our results are robust to this. We also use the parametric approach suggested by KS, which adjusts the degrees of freedom to account for serial correlation in the placebo estimates but also assumes the estimates belong to a normal distribution. The p-values from this approach are reported for each year and again our conclusions are robust. Finally, the mean of the placebo estimates informs the magnitude of any bias from our approach. The implied bias is always negligible.

4.1.5 | Sample selection and the tax-free threshold

People with income below the tax-free threshold (TFT) who do not have withholdings throughout the year are not required to file a tax return, and therefore are not in our sample. Changes in the fraction of people with incomes above the TFT may affect the comparability of our estimates across years. In particular, in 2012–2013 the TFT was more than tripled from $6000 to $18,200. As a robustness exercise we therefore restrict our sample to people earning more than $18,200 (for other years we use the wage adjusted value of $18,200 in 2013). Our estimates are very similar to those in Table 1 (see Appendix Figure A12 and Table A4).

5 | POLICY SIMULATION

We use the estimates in Section 4 to provide indicative back-of-the-envelope calculations for the "marginal" effect of LHC on total PHI uptake, the age profile, and premiums. These effects are marginal in that they only speak to what the situation would be like if there was no uptake at age 31 each year; coverage induced by the introduction of LHC in 2000 is part of the baseline. It is important to recognize that our goal in this exercise is to provide indicative figures only, with the hope of better contextualizing our RDD estimates. To truly capture the equilibrium effects of LHC we would need data on claims and premium setting, and estimates of both the incentive and disincentive effects associated with LHC.

For our calculations we assume a policy effect of 3.0 ppts at age 31 and no effects for any other age. Our calculations are for 2018, and the estimated policy effect in this year and the preceding few years was close to this value. Drawing on our discussions in Section 2, we also assume that this discontinuity is from people bringing forward insurance purchase, by which we mean that they would have purchased PHI at some stage in the future, but LHC causes them to purchase just before the penalty kicks in instead. We assume the maximum bring forward age is 35 (i.e., anyone who purchases PHI due to LHC would have purchased PHI by age 35 anyway). For each month-of-birth bin we then estimate a counterfactual rate of PHI coverage by subtracting $k_i \times 3.0$ ppts where k_i is a triangular weight with $k_{31} = 1$ and $k_{35} = 0$. That is, the probability of bringing forward is decreasing linearly between ages $\in (31, 35)$. For each month-of-birth bin we calculate total premiums paid using average premium per person (supplied by insurers to the ATO) multiplied by the number of people.

Figure 7 shows the actual and counterfactual age profile of coverage in 2018 for ages 30–36. Our assumption that people bring forward between ages 31–35 creates a wedge in coverage, with the difference in the two curves reflecting take-up induced by LHC. We estimate that this wedge increases overall coverage from 59.25% to 59.38% and lowers the average age from 46.67 to 46.64 due to the joining incentive. If we make the generous assumption that insurers retain 60% of premiums from those joining because of LHC as profits and then pass those profits on evenly through lower premiums, premiums would decrease by a negligible $1.91 per year (average premium in our sample is $1641.62).[12,13] In Table 2 we vary the parameters in our calculation, but under no reasonable assumptions does the policy make a significant impact on coverage or premiums, which reflects the skew toward older ages in the insurance pool and the fact LHC only encourages the young to take-up PHI.

Because insurers get to keep loading penalties as additional revenue, LHC acts as a form of quasi-price discrimination. We do not observe people's premium loadings in our data, but the number of people paying each rate of loading is reported each quarter by the Australian Prudential Regulation Authority (APRA), an independent statutory authority that supervises insurance institutions. Using these data for the March 2018 quarter and assuming an average premium of $1150 for people aged 31 and an increase of 1.5% for each additional year of age up to 65 (where the LHC penalty reaches the 70% maximum), we estimate that additional revenue is equal to $30.60 per person per year. While still modest, this is notably larger than the estimated $1.91 lower premium effect due to people purchasing PHI to avoid the penalty.

5.1 | Limitations

While some of our assumptions mean we may overestimate the potential effect of LHC, there are some reasons why we may be underestimating effects. First, we assume that people who purchase before age 30 are not influenced by LHC. Theoretically,

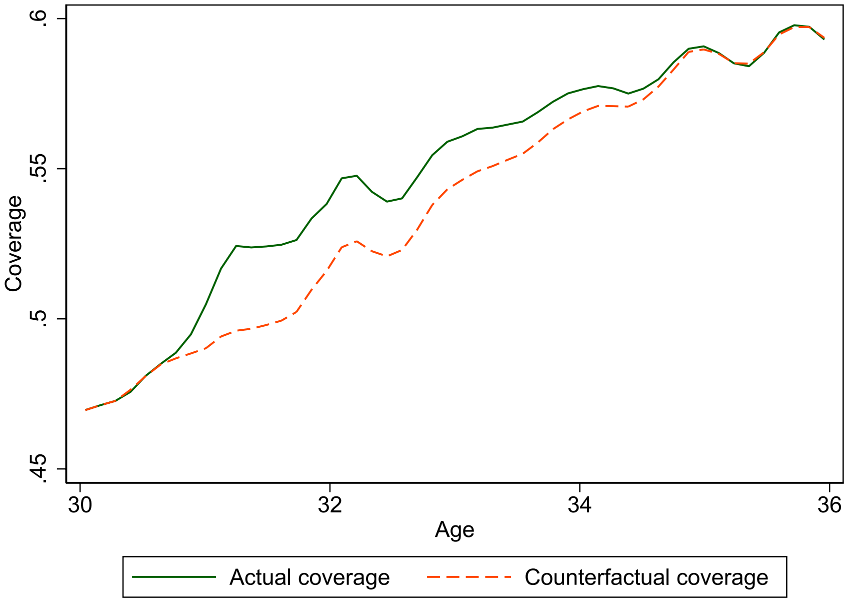

FIGURE 7 Actual coverage with Lifetime Health Cover (LHC) and counterfactual coverage without LHC in 2018. Data are from the ALife 2018 release version. Private health insurance coverage is calculated using an indicator for if a person holds a policy expiring after June 30, 2018. *Actual coverage* is a local polynomial fit of the unadjusted data. *Counterfactual coverage* is a local polynomial fit after subtracting $k_i \times 3$ ppts from the actual data, where k_i is a triangular weight with $k_{31} = 1$ and $k_{35} = 0$.

TABLE 2 Policy simulations.

Treatment effect (ppts)	3	3.5	5
Max age bring forward	35	40	40
Revenue passed on	60%	60%	60%
Actual coverage	59.38%	59.38%	59.38%
Counterfactual coverage	59.25%	59.08%	58.88%
Actual mean age	46.64	46.64	46.64
Counterfactual mean age	46.67	46.71	46.75
Mean premium reduction	$1.91	$4.48	$7.50

Note: Data are from the ALife 2018 release version. Counterfactual values are if there was no uptake at age 31 each year. We assume that this discontinuity is from people bringing forward insurance purchase. We assume the maximum bring forward age is "max age bring forward." For each month-of-birth bin we then estimate a counterfactual rate of private health insurance coverage by subtracting k_i* "treatment effect" ppts where k_i is a triangular weight with $k_{31} = 1$ and $k_{\text{max age bring forward}} = 0$. For each month-of-birth bin we calculate total premiums paid using average premium per person (supplied by insurers to the Australian Taxation Office) multiplied by the number of people. We assume that insurers retain "revenue passed on" of premiums from those joining because of Lifetime Health Cover as profits and then pass those profits on evenly through lower premiums, which gives the "mean premium reduction."

it would be sub-optimal for people to bring forward this far given the penalty does not kick in until age 31. People aged 25–29 comprise a relatively small fraction of the insurance pool so even if some of their coverage is due to LHC, the impact on the market is likely small. Second, we assume there is no bringing forward at other age penalty thresholds. This is supported by results in Section 3; however, it is possible people bring forward in a way that does not show up as discontinuities (which would indicate sub-optimal behavior). Given the fairly flat rate of coverage from age 35 onwards we expect any effects from this to be small. Third, we do not capture spill-over effects (e.g., people who purchase because their spouse turned 31). However, even if we doubled the number of people who purchase PHI due to LHC, the impact on premiums would still be modest. Fourth, we assume that all people who purchase PHI due to LHC would have purchased PHI eventually absent the incentive. Given that preferences and risks are dynamic, and insurance is subject to state dependence (T. C. Buchmueller et al., 2021; Doiron & Kettlewell, 2020), it is possible that a fraction of those induced to insure would have never insured otherwise. Finally, our estimates do not capture discouragement effects from people who would have purchased at an older age but do not because their penalty is too high. Depending on their expected claims, such discouragement effects could either decrease or increase insurer profits (and in turn put upward or downward pressure on premiums). While we do not know the magnitude of these discouragement effects, it is worth noting that such effects do not seem to be part of the intended goals of LHC.[14]

It is also worth acknowledging that our estimates do not capture the effect of LHC on the overall allocative efficiency of hospital care services. There is evidence that PHI increases hospital admission due to moral hazard in Australia, although this effect seems to be stronger for older age groups (Doiron et al., 2014; Doiron & Kettlewell, 2018). If moral hazard represents healthcare utilization where marginal benefits exceed marginal costs, this would be a welfare cost of the policy not captured in our analysis of premiums and take-up. A moral hazard effect could also reduce any welfare losses due to discouragement effect from LHC among the older uninsured.

6 | DISCUSSION

The LHC penalty creates discontinuities in the incentive to insure by age, which we exploit to estimate causal effects. Our estimates suggest there is only an effect at age 31. This effect was the largest in the first year after LHC was introduced, increasing the rate of PHI for those aged 31 by 3.7 ppts (or 9.0% relative to the mean at age 31). The effect declined gradually reaching the lowest level in 2006, and then rebounded back in 2008. Between 2008 and 2018, the LHC effect has been fairly stable in the range of 4.6%–7.2%. In 2018, LHC increased the insurance take-up rate at age 31 by 2.94 ppts (or 6.0%).

The largest effect from the first year of LHC implementation could be partially due to non-price aspects such as heavy advertising run by the government in 2000, which is consistent with the findings from an early study by Ellis and Savage (2008). They concluded that the major driver of the increased enrollment in 2000 was due to a deadline response and advertising blitz (4% for singles and 5% for families), rather than a pure price response (2% for singles and 7% for families). Our findings also indicate small price responses in later years with estimates at similar levels to Ellis and Savage (2008).

Keegan (2020) studied a similar scheme in Ireland and concluded that lifetime community rating increased the take-up of PHI by 2.5 ppts on average among those aged 35–69, but the effect concentrated in the 35–54 age cohort. It is difficult to compare his results with ours. Keegan evaluated the initial implementation of lifetime community rating where there is a sudden large incentive for people over 35 to join insurance—the penalty is in fact higher for the older groups. Instead, we evaluate a policy already existing since 2001 and examine its marginal effects at age 31 each year.

Our estimates tell us that LHC explains a relatively small percentage of PHI coverage for people aged around 31 years. We use our estimates to conduct some indicative back-of-the-envelope calculations for the wider market impact of LHC, considering the rate of PHI coverage, age profile of the insured, and premiums. We conclude the impact is likely small, which is partly due to our assumption that people who respond to the LHC penalty would have purchased insurance at some point anyway.

The policy effect at age 31 almost doubled from 2007 to 2008 (2.9%–5.3%) and then maintained a higher level. While we cannot rule out other explanations, we have provided evidence this is due to the Australian Department of Health mailing letters to people approaching the penalty deadline from July 2007, which speaks to the importance of informational nudges in supporting financial incentives. This is consistent with the growing literature on how behavioral nudges affect health plan take-up in health insurance markets (Domurat et al., 2021; Goldin et al., 2020; Myerson et al., 2022).

We only observe an effect of LHC at the initial age-penalty, not for subsequent penalties. Our simulation exercise predicted a bigger response at age 31 because the fraction of "marginal uninsured" gets smaller at each subsequent age threshold. In addition, there may be two behavioral biases at play related to decisions under risk; loss aversion and inertia in health insurance choices. First, loss aversion, first coined by Kahneman and Tversky, states that people by nature are aversive to losses and their responses to losses are stronger than the responses to corresponding gains (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). If individuals view the LHC penalty as a loss, they may be particularly sensitive to the initial threshold. However, once they incur the loss it may be less of a motivating factor, explaining a greatly weakened response to subsequent penalty increases. Second, several recent studies document consumer inertia in health insurance choices (Drake et al., 2022; Handel, 2013). Once people make their health plan choices, they tend to stick with their original choices even though their situations change and their original plans become dominated by new plans. If people make their decisions not to buy PHI when they turn 31, it is less likely for them to re-evaluate again in subsequent years.

Our findings suggest that the take-up effect from LHC is small. While our analysis does not quantify the discouragement effects due to higher premiums for those who purchase PHI later in life, several studies find that the price elasticity for PHI is low, including specifically for older people (Kettlewell et al., 2018). Together with our results, this suggests that modest changes around the LHC policy, (or abolishing LHC) may make little difference in the age distribution of insured, premiums or up-take rates. Our study provides important evidence on an understudied area in literature and offers insights to countries currently evaluating the effectiveness of financial penalties.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Australian Taxation Office. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from https://alife-research.app/ with the permission of Australian Taxation Office.

ETHICS STATEMENT

The Office of Research Ethics and Integrity at the University of Melbourne has approved this study.

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ENDNOTES

[1] Perceived differences in the quality of healthcare between public and private may also encourage some people to purchase PHI, although in practice many doctors work across both systems and the quality of treatment is likely to be similar.

[2] An important assumption in both studies is that higher coverage among younger people after the reform was due to the MLS and rebate, and not the advertising blitz, as suggested by Ellis and Savage (2008). The studies are also limited by the fact age is only observed in 5-year groupings.

[3] This is a theoretical exercise and our choice of parameters is highly arbitrary. Stata code to replicate the simulations is available on request.

[4] Once they insure they remain insured thereafter because WTP is non-decreasing in age.

[5] This is not a general result, and with a more complicated set of WTP profiles this conclusion may be different. However, modeling WTP as a non-decreasing linear function of age seems like a reasonable approximation to reality. Results are qualitatively similar if we assume instead a log-linear relationship with age.

[6] Specifically, the standard release includes an indicator for if a person is insured for the whole of the previous financial year, whereas we are interested in whether they are insured on the last day of the financial year (June 30). While these variables will be strongly correlated, the “full year” indicator cannot pick up people who purchase insurance just before their birthday, which is precisely the behavior we are interested in.

[7] We also show results using the “source tax return” indicator for the later periods to assess the potential bias caused by using this indicator.

[8] We use the “source tax return” PHI variable since it is available for all years. In Appendix Figure A1 we show the same trend from 2012 to 2013 using “source funds.” The trends are similar but coverage is approximately 5% points higher using the funds variable.

[9] Quarterly statistics on PHI membership are published at https://www.apra.gov.au/quarterly-private-health-insurance-statistics.

[10] Graphs for other years show the same pattern and are available on request.

[11] KS show this approach outperforms other popular methods for bandwidth selection in a variety of Monte Carlo simulations in terms of picking estimators with the lowest error. This is especially the case for data generating processes that are linear or quadratic, which closely resembles the relationship between PHI and age in our data (see Figure 4 and Figure A2).

[12] Since taxpayers may not be representative of the general population we did a crude calculation using counts of all people with insurance using the APRA data. APRA is an independent statutory authority that supervises institutions across banking, insurance and superannuation. In the June 2018 quarter there were 767,616 people with PHI aged 30–34 (APRA data are in 5-year age groupings). If we assume coverage would be $0.5\% \times 5.5\%$ lower for this age group absent LHC (based on Column 5 of Table 1, where multiplying by 0.5 approximates the triangular weights), then there would be 21,109 fewer people with insurance. Assume they pay AUD$1150 each in premiums on average in 2018 (approximately the mean for this age group in the ALife data) and insurers retain 60% of their premiums as extra profits. If this was then fully passed on, premiums would be $1.29 lower—similar to our estimate using the ALife data.

[13] APRA data suggest a benefit/premium ratio of around 60% for people aged 30–34. We chose a conservative figure (40%) because marginally insured people may have lower expected medical expenses than the general insured population.

[14] According to minister responsible, LHC “encourages people to join a fund early in life and to maintain their membership and discourages hit-and-run behavior” (Wooldridge, 1999).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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