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DISCUSSION PAPER SERIES

IZA DP No. 14901

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ABSTRACT

Age Penalties and Take-up of Private Health Insurance*

Penalty mandates are used in many countries to encourage people to purchase health insurance. But are they effective? 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 mandate, and whether this has changed over time. The mandate creates discontinuities in the incentive to insure by age, which we exploit to estimate causal effects. People who do not insure before the penalty dates face higher premiums in the future, which should encourage them to bring forward purchases. We find that people respond as expected to the initial age-penalty, but not to subsequent penalties. The 2% premium loading results in a 1-4% increase in take-up, with effects increasing after an annual government letter campaign that reminds people approaching the penalty deadline about the policy. We discuss the impact of the mandate on the overall efficiency of the market, and implications of potential reforms.

JEL Classification: I13, I18, I12

Keywords: health insurance, age-based mandate, regression discontinuity, Australia

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1 Introduction

Private health insurance markets are heavily regulated in many countries. To reduce adverse selection and encourage more people to take out private insurance, individual penalty mandates are commonly used. For example, an individual mandate was one of the main provisions in the 2014 US Affordable Care Act (ACA), which required all Americans to obtain health insurance or pay a tax penalty. When the US Medicare prescription drug (Part D) program was first implemented in 2006, individuals who enrolled when they became eligible paid a community-rated premium, but those who delayed enrolment had to pay a penalty.

Another important example is in Australia, where the government uses an age-based penalty mandate – Lifetime Health Cover (LHC) – to encourage people to buy private insurance earlier in life. Starting from July 2000, if people do not have hospital cover before the 1 July 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. Following Australia's suit, in 2015, the Irish government implemented a similar scheme – lifetime community rating, which increases private health insurance (PHI) premiums by 2% per year for individuals aged 35 and over who postpone buying their PHI (Keegan, 2020).

Health insurance markets in many countries use community rating, which requires insurers to charge the same premiums to all members, regardless of health status or any other characteristic that predicts medical expenditures (Buchmueller, 2008). Community rating is to ensure those who are high risk and with pre-existing conditions can still have affordable private insurance, but it also makes PHI less attractive to the young and the healthy. If young and healthy consumers respond to these actuarially unfair prices by dropping out of the market, premiums must increase to cover the cost of insuring the remaining relatively higher risk pool. Then more low-risk people drop out, which results in further increases in premiums. This creates an "adverse selection death spiral." Key to stable community rating is the ability to attract and retain the young and healthy. An age-based penalty mandate is designed to solve this problem, but little is known about how effective it is, especially in recent years.

Australia's LHC policy offers us a novel opportunity to examine how age-based penalty mandates affect demand for private insurance and overall efficiency of insurance markets. LHC creates an incentive for those without insurance to purchase insurance just before the loading increases each year. If people are responding optimally to the policy, we should observe a discontinuous increase in the probability of insurance just after people's LHC base day (the 1 July following their birthday) because each year the penalty is increased by 2 percentage points on this date.

Previous research estimated effects after its initial introduction in July 2000, but they could not isolate the effect of LHC from two other major policies that were implemented around the same time (a tax penalty mandate for high income individuals and a 30% premium subsidy) (Palangkaraya and Yong, 2005; Buchmueller, 2008; Ellis and Savage, 2008). In addition, previous studies only focused on those aged around 31, and were limited by restrictive small survey data or highly aggregated administrative records unsuited to identify causal effects from age discontinuities (Palangkaraya and Yong, 2005, 2007; Ellis and Savage, 2008).

No studies have examined how LHC effects vary by age and whether its effects change over time, especially in recent years when more young people have dropped out from PHI (Zhang, 2020), and there is a real concern about whether PHI is sustainable (Australian Government Department of Health, 2021a).

We examine the effects of LHC for each age between 31 and 65, and for each year between 1999-2018, using rich administrative tax return data from a 10% random sample of Australian tax-filers. The mandate 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 of data away from the discontinuity to select among many potential estimators, varying in bandwidth, polynomial order and controls (Kettlewell and Siminski, 2021). We also conduct numerous robustness tests including using randomization inference and data perturbations.

We first conduct a simulation analyses 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 LHC mainly affects those uninsured at the margin and for each subsequent penalty threshold 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. The larger effect at age 31 is consistent with our simulation prediction. The 2% premium loading per year for 10 years results in a 0.89-3.88 percentage points (or 2.4%-10.0%) increase in take-up rate at age 31. The effects change over time, with largest 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 behavioural nudges in supporting financial incentives. Between 2008-2018, the LHC effect has been fairly stable in the range of 4.2%-6.6%. In 2018, LHC increased insurance take-up at age 31 by 2.69 ppts (or 5.6%). We also simulate the impact of LHC on premiums and the age distribution of enrolees, and conclude these effects are small.

We are the first to estimate causal effects of LHC on private insurance coverage for different age cohorts and to document how its effect changes over time. Previous studies using data pre- and post-LHC (around 2000) could not disentangle the effect of LHC alone so only estimated the combined effects from three policies that were implemented around the same time. We are the first to use a non-aggregated, large administrative dataset to study this policy effect; this is a substantial contribution to the small literature that primarily relied on older, much smaller restrictive data that did not observe age with the necessary detail to truly exploit the age discontinuities.

Our study addresses a key policy question relevant for many countries with government regulations on private health insurance. In addition, our study contributes to the small literature on penalty mandates in insurance markets. For example, several states in the US have demonstrated that individual mandates could be an effective tool to increase insurance coverage and reduce premiums (Hackmann et al., 2015; Fung et al., 2019). However, more recent research on the ACA suggests that the individual mandate meaningfully increased insurance coverage, but likely by less than was projected before its implementation (Frean et al., 2017; Collins et al., 2018; Fiedler, 2020).

The remainder of this paper is organized as follows. We describe the institutional context, LHC incentives, theoretical framework and simulation in Section 2. We describe data and econometric methods in Section 3. We present results in Section 4 and policy simulations in Section 5. Finally, Section 6 concludes and discusses policy implications.

2 Private health insurance in Australia

Australia has a universal health insurance scheme known as Medicare. Under Medicare, all Australians (and some overseas visitors) have access to a wide range of medical and hospital services at low or no cost (Australian Government Department of Health, 2021b). Specifically, Medicare covers free hospital treatment in public hospitals, subsidised medications and primary care doctors and specialist treatment.

Like many countries with universal public health insurance, non-urgent hospital treatment has a waiting list in public hospitals. A private hospital system runs parallel to public care and provides users with more flexible treatment options. People often buy private hospital insurance to access shorter waits for care in private hospitals and a greater ability to choose one's own doctor (Zhang and Prakash, 2021). However, private patients often need to pay high out-of-pocket expenses for the treatment either as a deductible or gap between what insurers cover and what doctors charge. There are no price regulations for private doctors.

In addition, reasons to buy PHI vary substantially by age. For example, 73% of those older than 65 said that they purchased PHI for a sense of security, protection or peace of mind, while for those aged 18-34, the most common reasons are 'I need it for a current health condition' (e.g., young women buy PHI when anticipating child birth) (Doiron and Kettlewell, 2020) or financial reasons in response to government regulations (Zhang and Prakash, 2021).

As of March 2021, 44% of Australians held PHI. This relatively high PHI rate results from considerable government interventions. The justification for these government interventions is that, if more people buy PHI and use the private system, it may alleviate pressure on the public system. Three main government regulations were initiated between 1997 and 2000 to encourage people to take out PHI. On July 1 1997, the government introduced the Medicare Levy Surcharge (MLS), an income-based tax incentive, 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 1 July 2000, the government introduced selective age-based premium increases for those enrolling after a deadline – Lifetime Health Cover (LHC). These three policies were effective in encouraging the uptake of PHI twenty years ago, resulting in higher PHI enrolment from 31% in 1999 to 45% in 2001 (Palangkaraya and Yong, 2007). Since then, the Australian government has made some changes to the incentives. For example, rebates became means-tested and their growth capped in 2012, and MLS thresholds and levy rates increased in 2008 and 2012 respectively. 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?

LHC is designed to encourage people to buy hospital cover earlier in life. People born on or before 1 July 1934 (87 years old in 2021) are exempt from LHC. If people do not have hospital cover before their base day (the later of July 1 2000 or the 1 July 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 1 July prior to joining (Commonwealth Ombudsman, 2021b). For example, if one joins when he is 31, he pays 2% loading, and if he joins when he is 40, he pays 20% (2%*(40-30)). The maximum LHC loading is 70%, and the loading stops after 10 years of continuous hospital cover. So if one joins when he is 65 or older, he pays 70% loading for 10 years. LHC loadings only apply to hospital cover, not for out-of-hospital care ('extras') including dental and optical care.

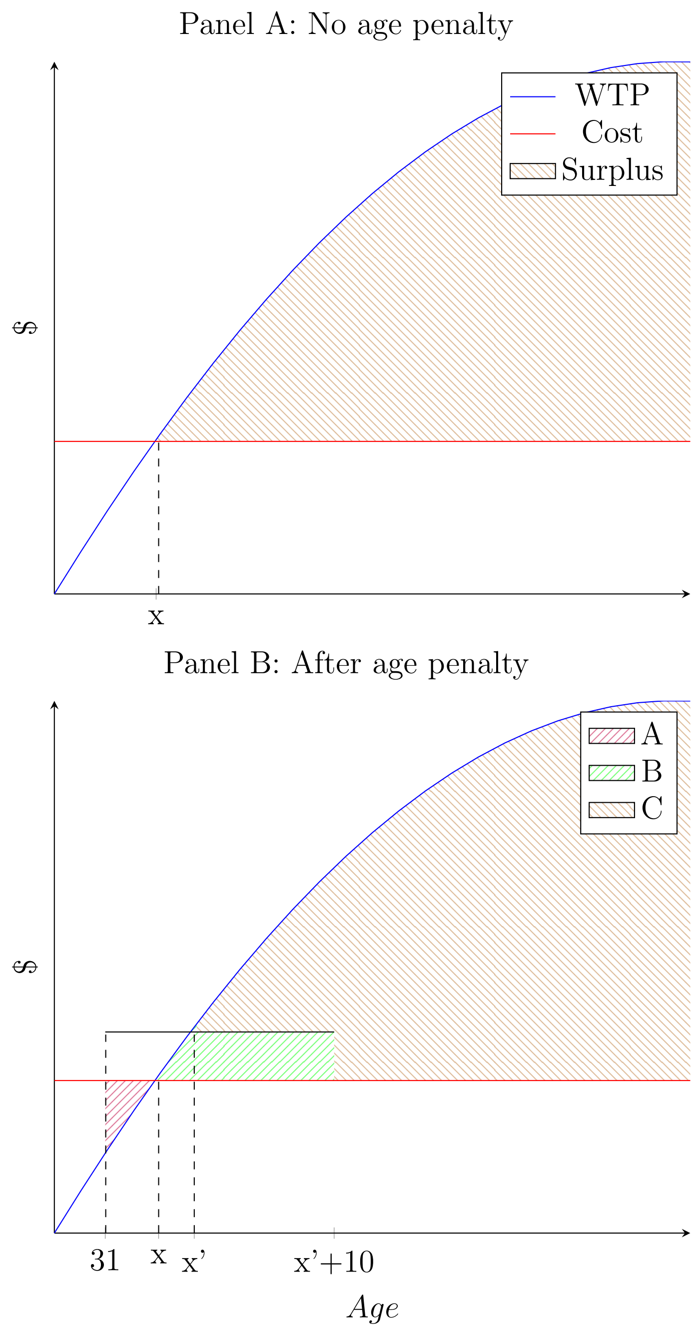
2.2 The incentive effects of LHC

Consider an individual with willingness to pay for PHI given by the function $WTP = f(age)$. Demand for PHI is assumed to be non-decreasing with age with $f^{'}(age) > 0$ and $f^{''}(age) < 0$. This relationship is shown in Figure 1. A non-decreasing WTP function makes it straightforward to solve the dynamic choice problem, as we show below in the simulation section, but it is not critical to the exercise. Because WTP is non-decreasing in age, we can assume once they insure they remain insured thereafter.

At each point in time, the person observes the price of PHI P and insures if the price is less than WTP. With a non-decreasing 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 1 Panel A, the person purchases insurance at age x.

The LHC threshold at age 31 (for people born on 1 July, such that their LHC reference date falls on their birthday) effectively creates a 10 year price increase at the point of the 31st birthday such that $P + LHC = P * 1.02$ between age 31 and 10 years after they first

Figure 1: Insurance decisions over the life-cycle



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 at this date.

Assume that people are utility maximizing, forward looking decision makers who know their WTP profile at all times. In the example in Figure 1 Panel B, 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 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.

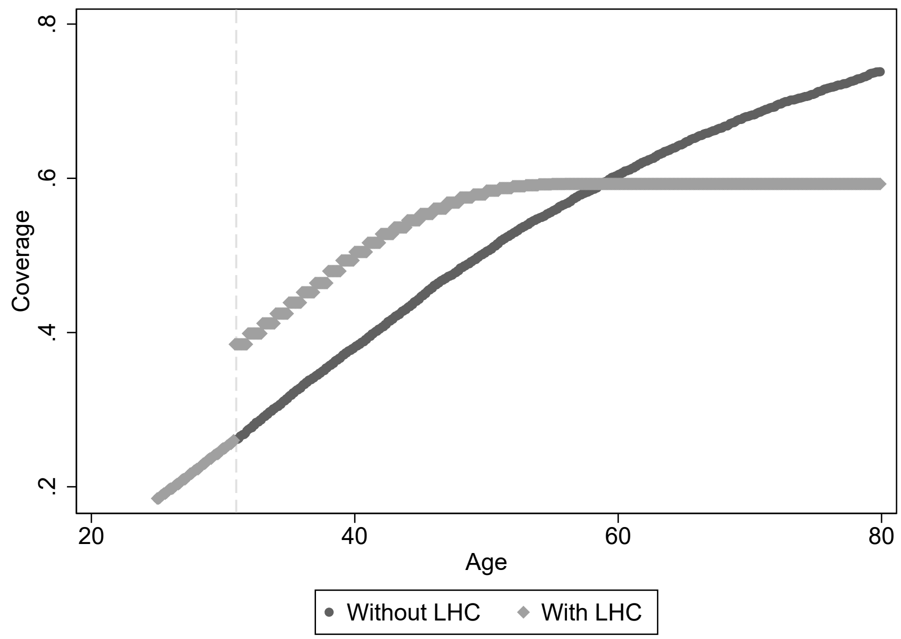
2.3 Simulation

To further explore the theoretical expectations we conduct a simple simulation. We assume WTP is linearly non-decreasing with age according to the function $WTP_i = \alpha_i + \beta_i Age_i$. 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. We further assume PHI costs P = \$2,000 in every year, which implies that $E[WTP] = P$ at age 50.[1]

[1] 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). However, we stress this is a theoretical exercise and our choice of parameters is highly arbitrary. Stata code to replicate the simulations is provided as Supplementary Material.

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.[2] This gives us an age profile of the insurance pool as shown in Figure 2.

Figure 2: Simulated take-up of PHI



Note: The figure shows the simulated proportion of people ($n = 10,000$) with PHI at every age assuming $WTP_i = \alpha_i + \beta_i Age_i$ with with $\alpha \sim N(0, 1000)$ and $\beta \sim N(40, 20)$, truncated at zero. PHI is assumed to cost $P =$ \$2,000 in every year.

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.[3] It also shows the disincentive effects of LHC –

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

[3]This is not a general result, and with a more complicated set of WTP profiles this conclusion may

in our example LHC lowers the probability of insurance from age 58.8.

2.4 Literature review of the effect of LHC

Because LHC was introduced around the same time as the MLS and rebate (1997-2000), most earlier studies evaluated their joint effects on the take-up rates of PHI. For example, Ellis and Savage (2008) found that the three interventions increased PHI enrolment by 50% and reduced the average age of enrolees. They interpreted the major drivers of the increased enrolment from 1999-2001 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 polices by decomposition analysis using survey data before and after the reforms and comparing those aged above and below the LHC cut-off. They found that LHC could explain between 42-75% 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, using a kind of differences-in-difference strategy for people aged above and below the cut-off before and after the reforms (Palangkaraya and Yong, 2007).[4] 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.

Our contribution is to cleanly estimate the causal effect of LHC independently of other incentives using large detailed administrative data for the first time. 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 and Savage, 2008). In addition, earlier studies tell us little about the ongoing impact of LHC, or the likely effect of its

be different. However, modelling 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.

[4] 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.

withdrawal. Finally, the existing small literature primarily relied on older, much smaller restrictive data that did not observe age with the necessary detail to truly exploit the age discontinuities.

3 Data and methods

3.1 Data

We use the Australian Taxation Office's (ATO's) Alife data, which covers a 10% random sample of all Australian registered tax-filers across the years 1999-2018. 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, 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 enrol 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 with Alife.

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.[5] 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

[5]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 (30 June). 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.

status as of 30 June we use a custom indicator equal to one if the PHI details section of the tax return is not blank for years up to 2011-12. 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 2012-13 we have better information on insurance status. Since 2012-13, 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 30 June. We use the 'source tax return' PHI indicator for years up to 2012-13 and the 'source funds' indicator from that year onwards.[6]

3.2 Trends in coverage

Figure 3 shows how PHI coverage has evolved for tax-filers since 1999 – the year before LHC was introduced.[7] The effect of the policy on take-up is apparent in the 1999-00 and 2000-01 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% to 46% before steadily rising to a peak of around 56% in 2015-16. The flattening and subsequent decrease in coverage since 2015-16 – particularly for those aged 25-30 years – has continued into later years.[8]

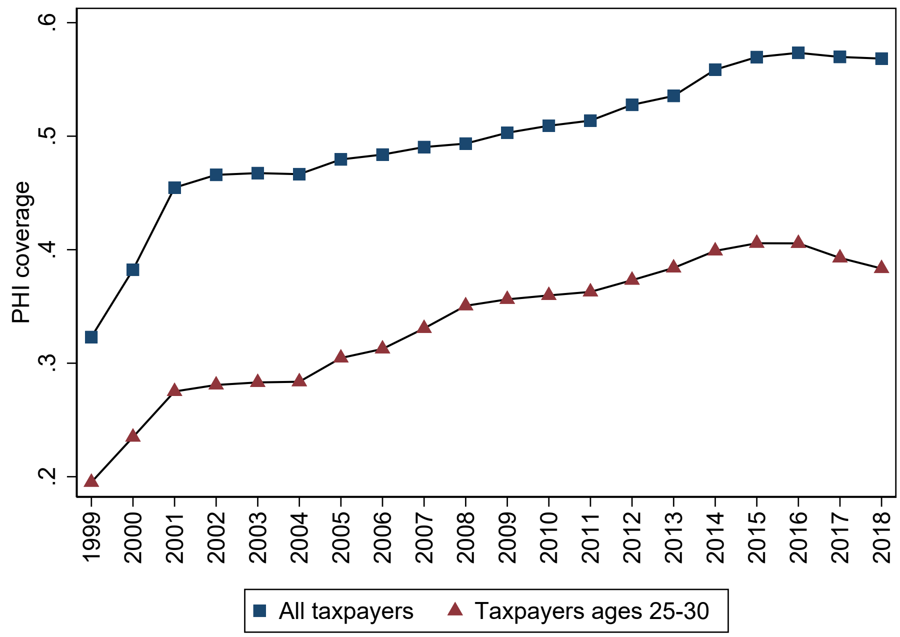
It is also informative to examine how the age profile of the insurance pool has changed over time. Figure 4 shows how following the introduction of LHC there was an increase in coverage among all age groups, as noted elsewhere (Ellis and Savage, 2008). By 2018, coverage was again higher for all age groups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

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

[7] 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 2012-13 using 'source funds'. The trends are similar but coverage is approximately 5 percentage points higher using the funds variable.

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

Figure 3: Trend in PHI coverage between 1999-2018



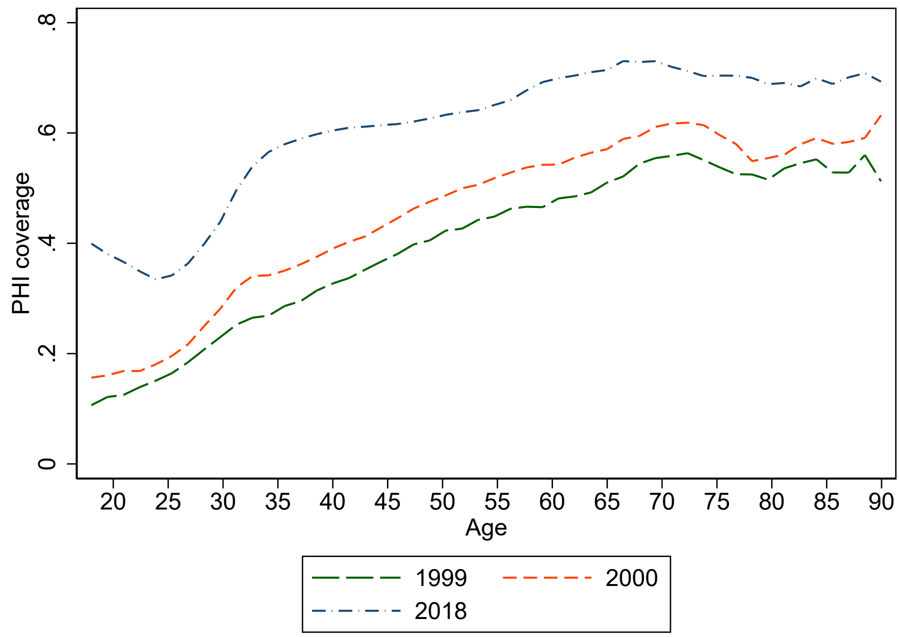
Note: Alife 2018 release version. We used tax return files between 1999-2018. Australians file taxes in financial years that run from July 1 to next June 30, so 2000 data covers July 1 1999 to June 30 2000, the first deadline for LHC. PHI coverage is calculated consistently using the indicator for non-blank private health insurance details in the tax return for each financial year ending 30 June.

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. Identifying the overall effect of LHC on demand is beyond the scope of this paper. Instead, we focus on one clear and unambiguous prediction. Namely, if people are responding optimally to the policy, we should observe a discontinuous increase in the probability of insurance just after people's birthday for each year the penalty is increased by 2 percentage points. If we do not observe this, it may indicate either that the policy is not effective, or that people are not timing their purchases optimally. 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

Figure 4: Changes in the age profile of insureds: 1999, 2000 and 2018



Note: 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, the first deadline for LHC. PHI coverage is calculated using an indicator for non-blank PHI details in the tax return for the financial year ending 30 June. Smoothed lines are based on local polynomial fits of the underlying data.

return covers the 12 months to 30 June, it can provide a snapshot of PHI status as of 1 July. 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 1 July still have another 12 months before they need to purchase insurance (since the LHC base date is the 1 July following the 31st birthday). This structure means we should observe a discontinuous increase in the probability of holding insurance at age 31, as well as other ages that the penalty increases.

To formally estimate the effect of LHC penalties on PHI take-up, we estimate regression discontinuity design (RDD) specifications. Our basic estimation equation is given by:

$$Y_i = \alpha_1 + \alpha_2.f(age_i) + \beta_1 T_i + \beta_2 T_i.f(age_i) + \epsilon_i \tag{1}$$

Y_i is the fraction of people born in month-year i who have PHI, $f(age_i)$ is a flexible function for age, T_i is an indicator for being older than the age penalty threshold (e.g. age

31 or older for the initial penalty threshold) and ϵ_i is a stochastic error term. $\hat{\beta}_2$ 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).

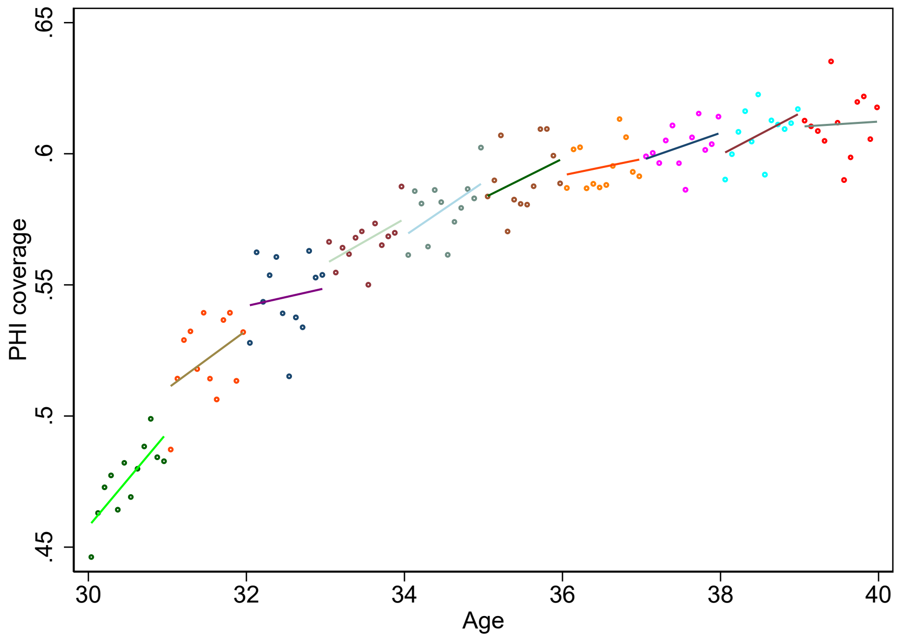
3.3.1 RDD model selection

Estimation of Eq. 1 requires several researcher choices. Importantly, we need to select a bandwidth around the threshold and a functional form for $f(age_i)$. Longer bandwidths increase bias but reduce variance. The choice of $f(.)$ also involves a trade-off between bias and variance (Pei et al., 2021) although in practice researchers often limit attention to linear and quadratic specifications since higher order polynomials can greatly distort boundary estimates (Gelman and 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 coveys 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 Figures A2-A5 we provide similar charts for every year between 2000-2018, and for ages 41-65 years. The pattern is the same in those years and for those ages.

To more formally test whether there are age discontinuities we estimate linear RDD models using one-year bandwidths around each age threshold from 31-64 years in every year from 2000-2018 (see Figure A6). Excluding age 31, only 11 out of 561 discontinuity

Figure 5: Private health insurance coverage by age in 2018



Note: Alife 2018 release. 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 30 June 2018.

estimates are statistically significant (which is less than expected by chance) and no other age discontinuity is significant more than once.

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 (2021) (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.[9] The method

[9]KS show this approach outperforms other popular methods for bandwidth selection in a variety of Monte

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 one year and the maximum to four years. We consider placebo thresholds and bandwidths in increments of one 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 and 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.

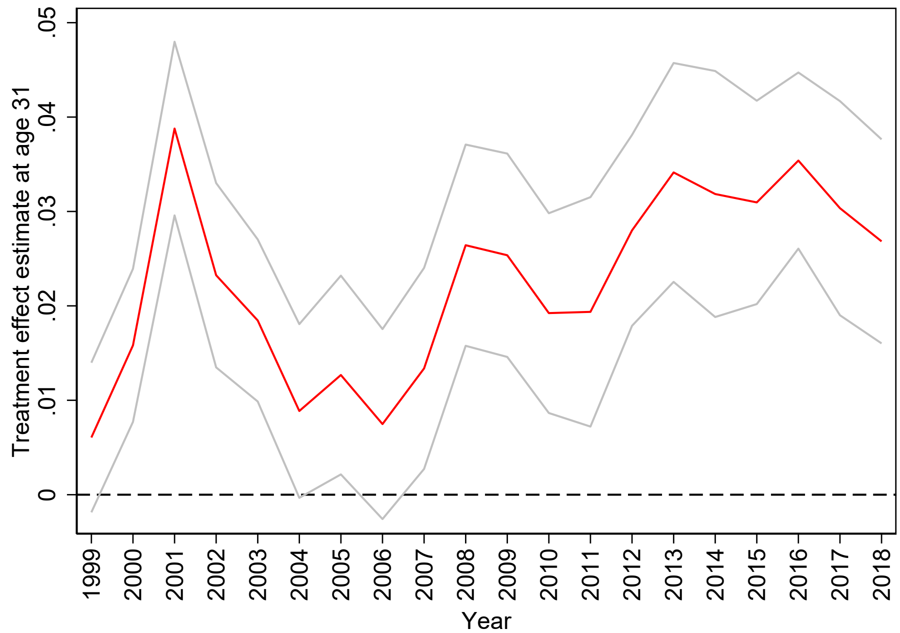
4 Results

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 the maximum allowed (four 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 10% (relative to the mean at age 31) in 2001 – before waning in the mid 2000s and then rebounding in 2008.

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 Figures 4 and A2-A5).

Figure 6: RDD estimates for each year: Age 31 penalty



Note: 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, the first deadline for LHC. Each year corresponds to a separate RDD estimate. Grey 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.

The policy effect generally trended upward since 2011. In 2011 the effect was 2.0 ppts (4.2%). In 2018 it was 2.7 ppts (5.6%). Because we use a different variable for PHI status from 2013, in Appendix Figure A7 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 2014-2018 the mean probability of having insurance at the age 31 threshold decreased from 55.8% to 48.3% (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 2006-07 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,

Table 1: RDD estimates for each year: Age 31 penalty

Year	Estimate	Std. Error	Mean	Est./Mean	BW	Obs.	Poly. order	Controls
1999	0.0061	0.0040	0.2618	0.0233	3.96	187201	1	No
2000	0.0159	0.0041	0.3038	0.0522	3.64	177951	1	No
2001	0.0388	0.0046	0.3873	0.1003	3.96	192884	1	No
2002	0.0307	0.0052	0.3703	0.0830	3.96	195980	1	Yes
2003	0.0191	0.0042	0.3637	0.0524	3.88	195192	1	Yes
2004	0.0089	0.0046	0.3779	0.0235	3.56	185310	1	No
2005	0.0127	0.0053	0.3715	0.0342	3.56	185736	1	No
2006	0.0075	0.0050	0.3966	0.0188	3.96	202691	1	Yes
2007	0.0134	0.0054	0.4248	0.0315	3.56	185378	1	No
2008	0.0265	0.0054	0.4210	0.0629	3.96	209612	1	No
2009	0.0254	0.0054	0.4534	0.0560	3.96	213258	1	No
2010	0.0193	0.0053	0.4466	0.0431	3.48	194637	1	No
2011	0.0194	0.0061	0.4597	0.0422	3.56	205809	1	No
2012	0.0280	0.0051	0.4743	0.0591	3.56	209706	1	No
2013	0.0342	0.0058	0.4939	0.0692	3.88	228830	1	No
2014	0.0306	0.0073	0.5582	0.0549	3.40	211076	1	Yes
2015	0.0321	0.0055	0.5556	0.0578	3.48	221090	1	Yes
2016	0.0354	0.0047	0.5339	0.0663	3.88	248103	1	No
2017	0.0304	0.0057	0.5045	0.0602	3.40	226739	1	No
2018	0.0269	0.0054	0.4828	0.0557	3.64	244535	1	No

Note: Alife 2018 release 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 30 June 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 one-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 + one 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.

encouraging them to consider purchasing PHI (Department of Health, 2010). Our results are consistent with this policy being effective and suggest that mandates are more effective when combined with information nudges.

An alternative explanation is related to changes to the MLS thresholds; however, the data do not support this. In 2007-08 the MLS (income penalty mandate) thresholds increased from $50,000 ($100,000) AUD to $70,000 ($140,000) for singles (families) and became indexed on the basis of 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 A8 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 2007-08 is consistent with an MLS interaction effect (most people in this income range were liable for the MLS in 2006-07 but not in 2007-08). However, we also see a modest rebound for those below the MLS threshold, which suggests another factor (e.g., the LHC mailout) was also at play.

4.1 Robustness

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 A9 we plot the number of people by month-of-birth cohort in each year and find no systematic discontinuity at the age 31 threshold.

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 A10). 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.

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 than at other ages. Nevertheless, if people do respond to these other penalties our estimates may be biased in an uncertain way. 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 Figure A11). We conclude that ignoring incentive effects at other ages is not materially important to our estimates of the age 31 threshold.

Alternative inference. In Appendix Figure A12 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 one 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 A12 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.

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 2012-13 the TFT was more than tripled from \$6,000 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 A13 and Table A4).

5 Policy simulation

We use the estimates in the previous section 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.

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. We assume the maximum bring forward age is 35. For each month-of-birth bin we then estimate a counterfactual rate of PHI coverage by subtracting $k_i * 3.0$ 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, which creates a wedge in coverage, with the difference in the two curves reflecting take-up induced by LHC. We estimate that LHC increases overall coverage from 59.25% to 59.38% and lowers the average

age from 46.80 to 46.77. 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 $1.90 per year (average premium in our sample is $1,641.62).[10] [11] In Appendix Table A5 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 towards older ages in the insurance pool and the fact LHC only affects the young.

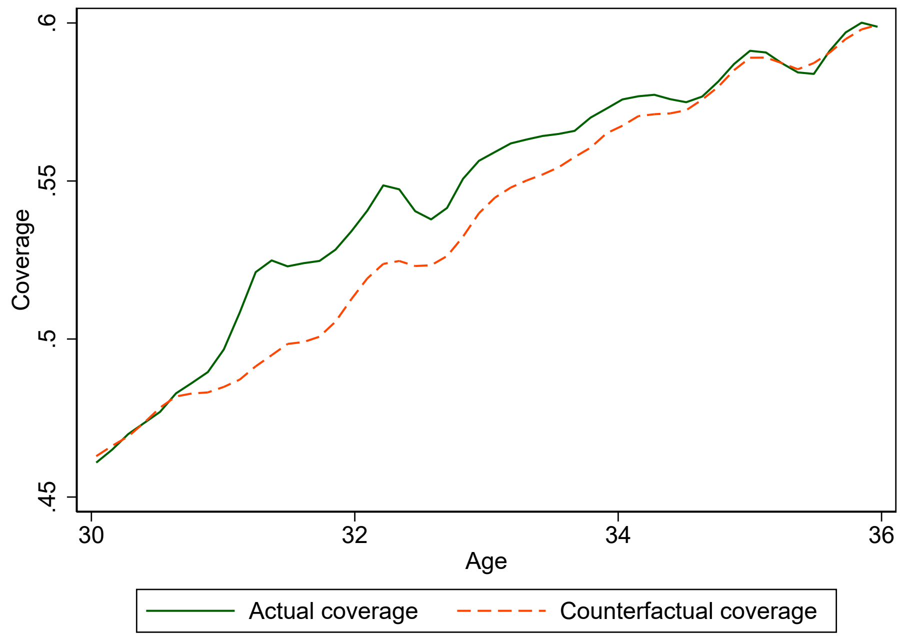
Because insurers get to keep loading penalties as additional revenue, LHC acts as a form of quasi-price discrimination. We do not observe people's premium loadings in our data, but the number of people paying each rate of loading is reported each quarter by the Australian Prudential Regulation Authority (APRA), an independent statutory authority that supervises insurance institutions. Using these data for the March 2018 quarter and assuming an average premium of $1,150 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 $1.90 lower premium effect due to people purchasing PHI to avoid the penalty.

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, it

[10] Since taxpayers may not be representative of the general population we did a crude calculation using counts of all people with insurance using the Australian Prudential Regulation Authority (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*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$1,150 each in premiums on average (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.

[11] 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.

Figure 7: Actual coverage with Lifetime Health Cover (LHC) and counterfactual coverage without LHC in 2018



Note: Alife 2018 dataset. Private health insurance coverage is calculated using an indicator for if a person holds a policy expiring after 30 June 2018. *Actual coverage* is a local polynomial fit of the unadjusted data. *Counterfactual coverage* is a local polynomial fit after subtracting $k_i * 3$ ppts from the actual data, where k_i is a triangular weight with $k_{31} = 1$ and $k_{35} = 0$.

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 (Doiron and

Kettlewell, 2020; Buchmueller et al., 2021), it is possible that a fraction of those induced to insure would have never insured otherwise. For them, the decision to insure would be welfare reducing compared to not insuring (since they cannot be optimizing), so it is not clear this would be a desirable policy outcome. 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.[12]

6 Discussion

The LHC mandate 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 insurance for those aged 31 by 3.9 percentage points (or 10.0% relative to the mean at age 31). The effect declined gradually reaching the lowest level in 2006, and then rebounded back in 2008. Between 2008-2018, the LHC effect has been fairly stable in the range of 4.2%-6.9%. In 2018, LHC increased the insurance take-up rate at age 31 by 2.69 ppts (or 5.6%).

The policy effect at age 31 roughly doubled from 2007 to 2008 (3.2% to 6.3%) and then maintained a higher level. This appears to be due to the 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.

Keegan (2020) studied a similar scheme in Ireland and concluded that the lifetime community rating increased the up-take of PHI by 2.5 percentage points on average among those

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

aged 35-69, but the effect concentrated in the 35-54 age cohort. But it is difficult to compare his results with ours. Keegan evaluated the initial implementation of lifetime community rating where there is a sudden large incentives 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.

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 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 and Tversky, 1979; Tversky and 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 documented consumer inertia in health insurance choices (Handel, 2013; Ericson, 2014; Handel and Kolstad, 2015; Abaluck and Gruber, 2016; Drake et al., 2021). 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.

In the past 5 years, rates of PHI enrolment dropped the fastest among young people aged 20–34 years (Zhang, 2020). Some speculate that LHC is no longer effective. We find this is not the case. In fact, although the probability of having insurance at age 31 has declined from 56% in 2014 to 48.3% in 2018 in our study sample, the LHC effects are fairly stable during this time. This implies that LHC has been equally effective as before. In addition, LHC should not affect take-up decisions for those younger than 30. For this group, the increase in wages has been much slower than the increase in premiums (Duckett et al., 2019), and this may partially explain why many young people have dropped PHI recently.

From April 2019, the Australian government allows insurers to offer people aged 18-29 years discounts. The allowable discounts range from 2% for those aged 29, 4% for 28, 6% for 27, 8% for 26 and 10% for 18-25 years old (Commonwealth Ombudsman, 2021a). The age-based discounts have not been shown to be effective in increasing the up-take rates among the young (Australian Prudential Regulation Authority, 2021), partially because discounts are relatively small and not all insurers offer these discounts. Also people younger than 24 living with parents can join their parents' PHI as dependents, which is much cheaper than buying separate PHI plans.[13]

The Australian Government is currently evaluating the effectiveness of LHC and whether any changes in this policy could improve value for consumers (Australian Government Department of Health, 2021a). Our findings suggest that the overall effect from LHC is small. Although the effectiveness of LHC remains over time, any modest changes around this policy, (or abolishing LHC) would unlikely make much difference in the age distribution of insured, premiums or up-take rates. Instead, focusing on increasing the value of private insurance, especially services useful to the young, may be a better approach to encourage the young to enrol. For example, the government could incentivize insurers to provide better preventive health benefits to help prevent illness and hospitalizations, and allow insurers more freedom to adjust premiums for the young and healthy if they pick up healthy behaviors and maintain good health.

Our findings are relevant for countries with mixed private and public universal health insurance coverage. In these countries, governments often struggle to find the balance in regulating and subsidizing PHI while funding the public system. Designing a novel strategy to improve the overall health system's efficiency and population health, instead of simply

[13] A PHI legislation amendment bill to increase maximum dependent age from 24 to 31 has recently passed in June 2021 (*Private Health Insurance Legislation Amendment (Age of Dependants) Bill 2021*) but has not been implemented by private insurers.

increasing PHI take-up, should be the ultimate goal.

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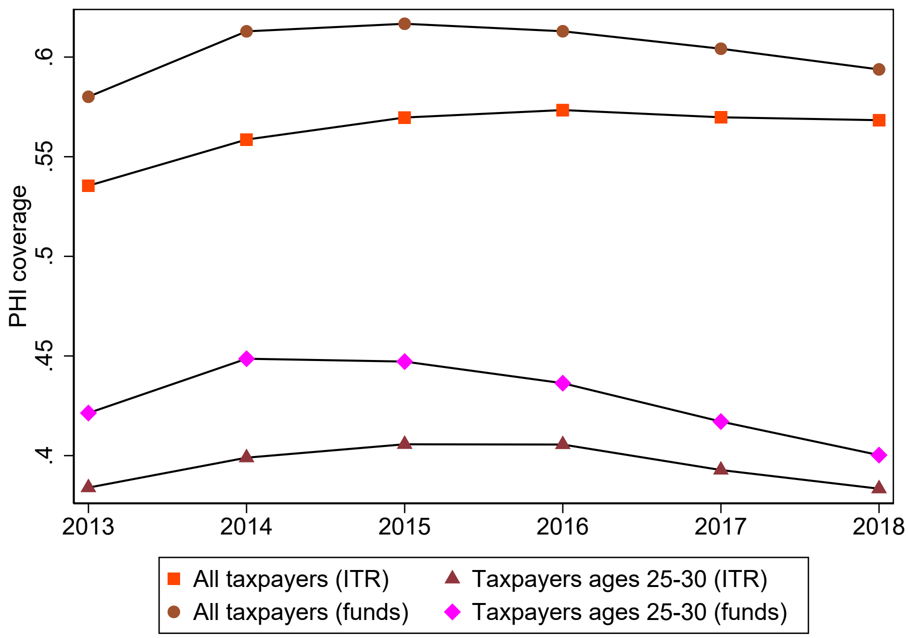
Online Appendix

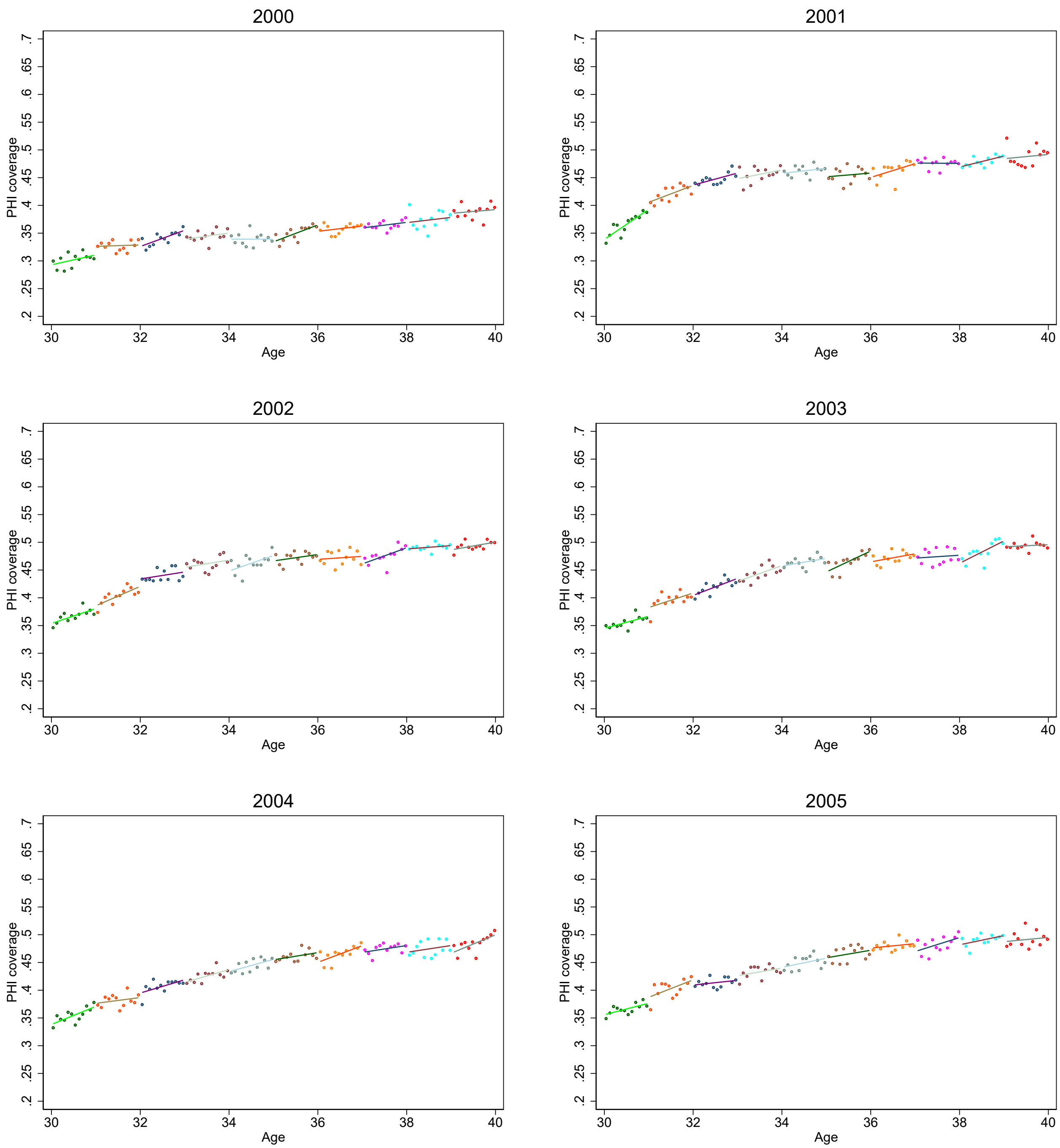
A Additional tables and figures

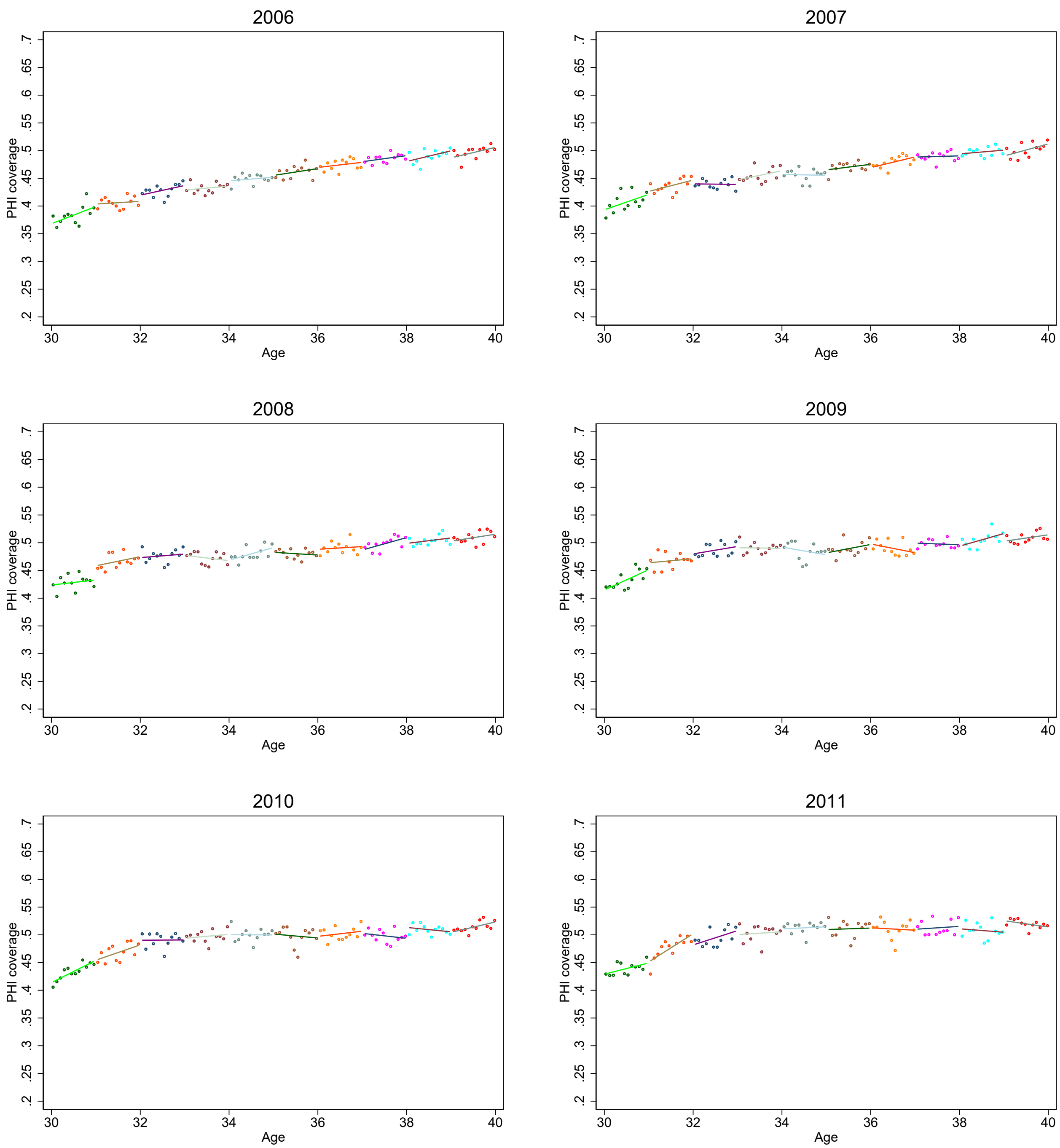
Figure A1: Trend in PHI coverage between 2013-2017



Note: Alife 2018 release version. We used tax return files between 2013-2018. Australians file taxes in financial years that run from July 1 to next June 30, so 2013 data covers July 1 2012 to June 30 2013. PHI coverage is calculated using an indicator for non-blank PHI details in the tax return (ITR) or if the person holds a policy expiring after June 30 (funds) for the financial year ending 30 June (x-axis).

Figure A2: Coverage by age: Ages 30-40




2006
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PHI coverage
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Age
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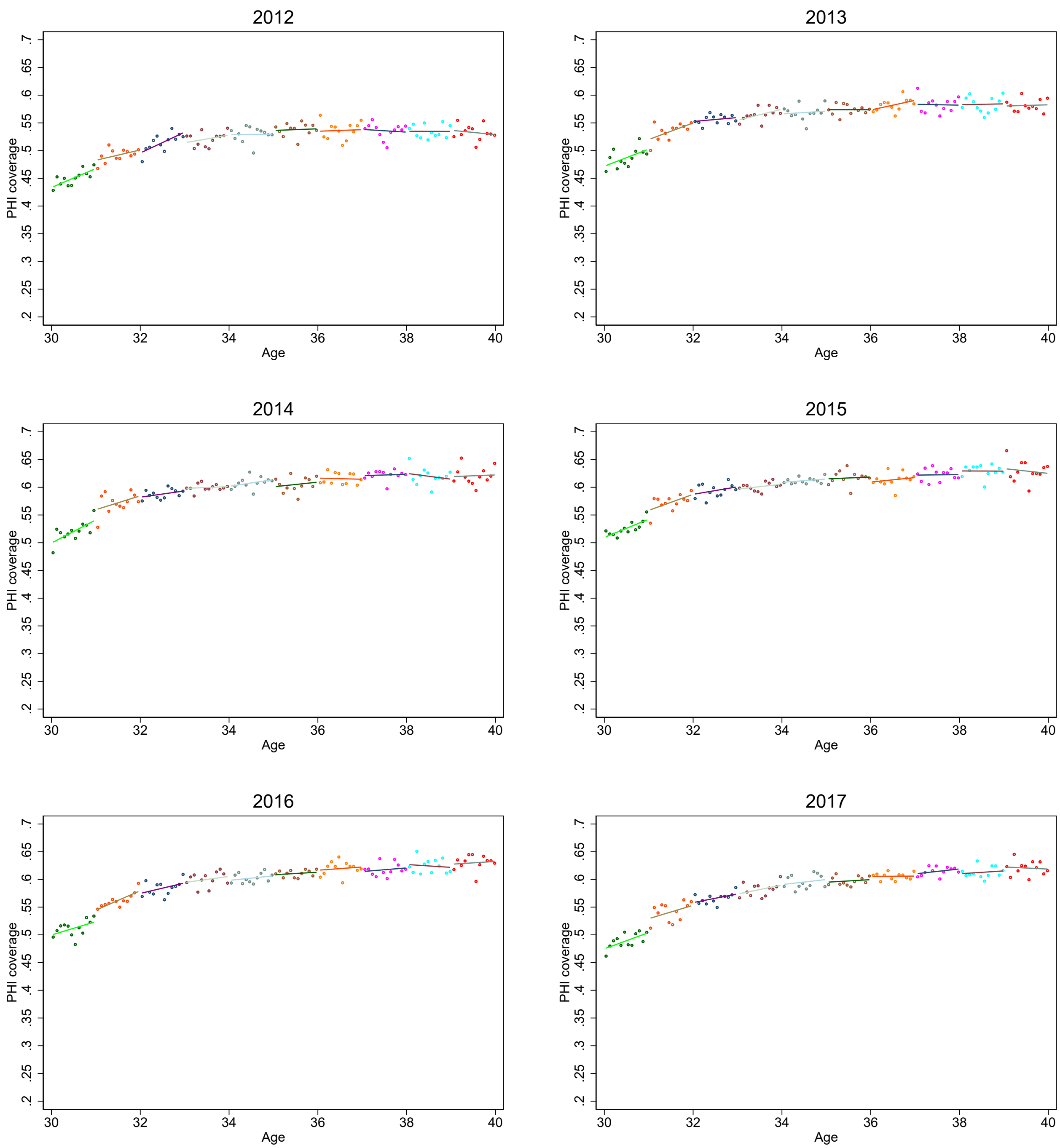
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2015
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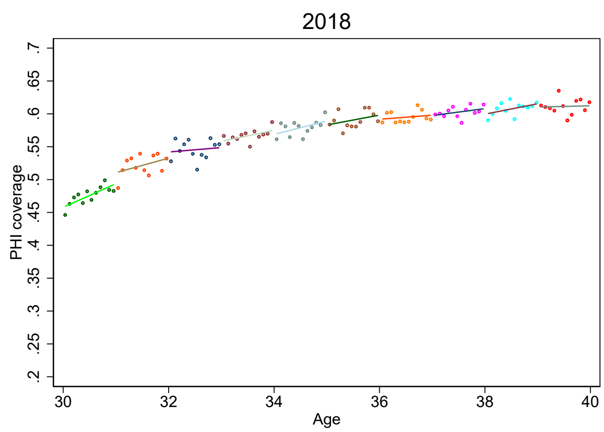
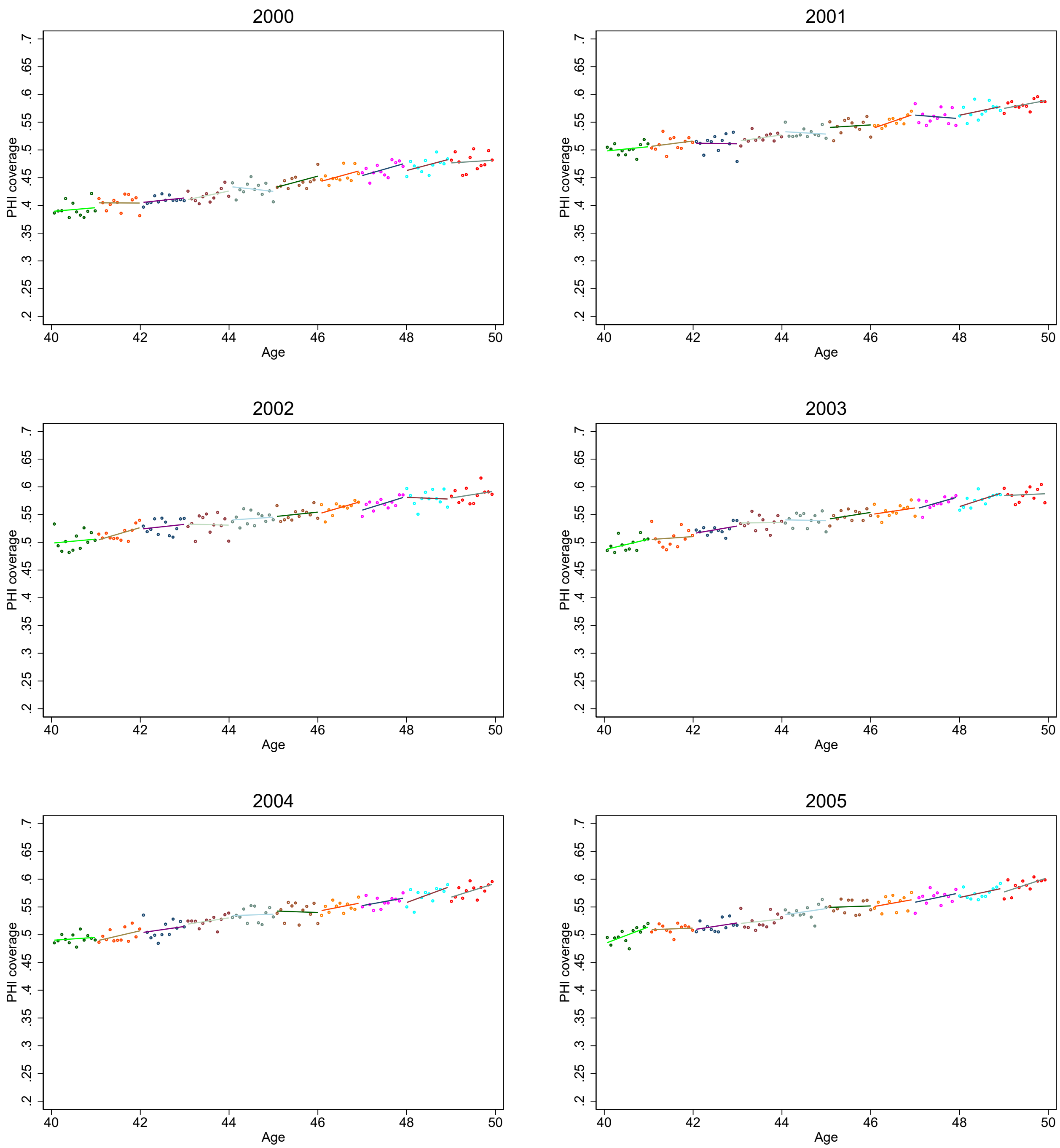
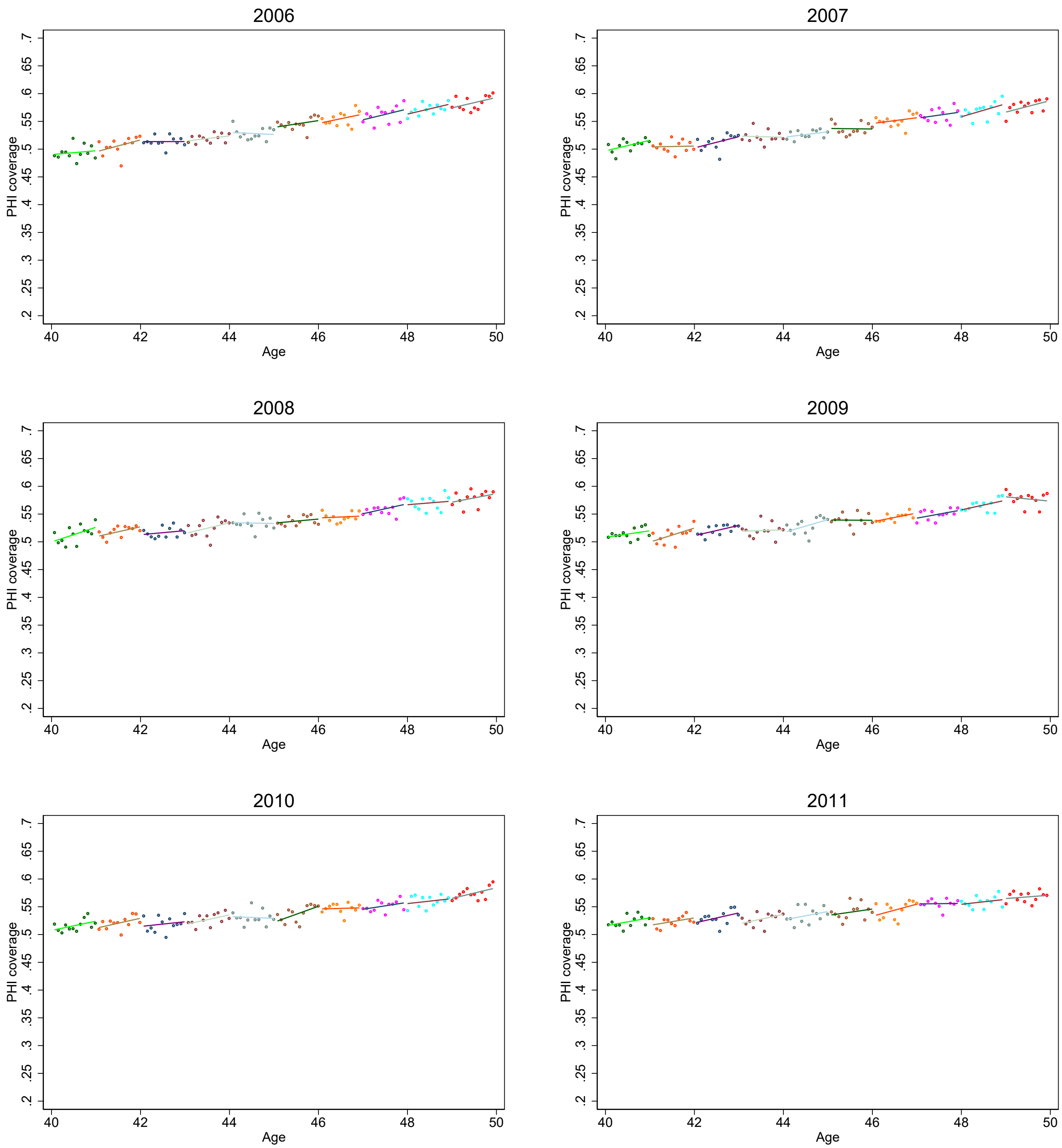
2017
PHI coverage
Age
.2 .25 .3 .35 .4 .45 .5 .55 .6 .65 .7
30 32 34 36 38 40

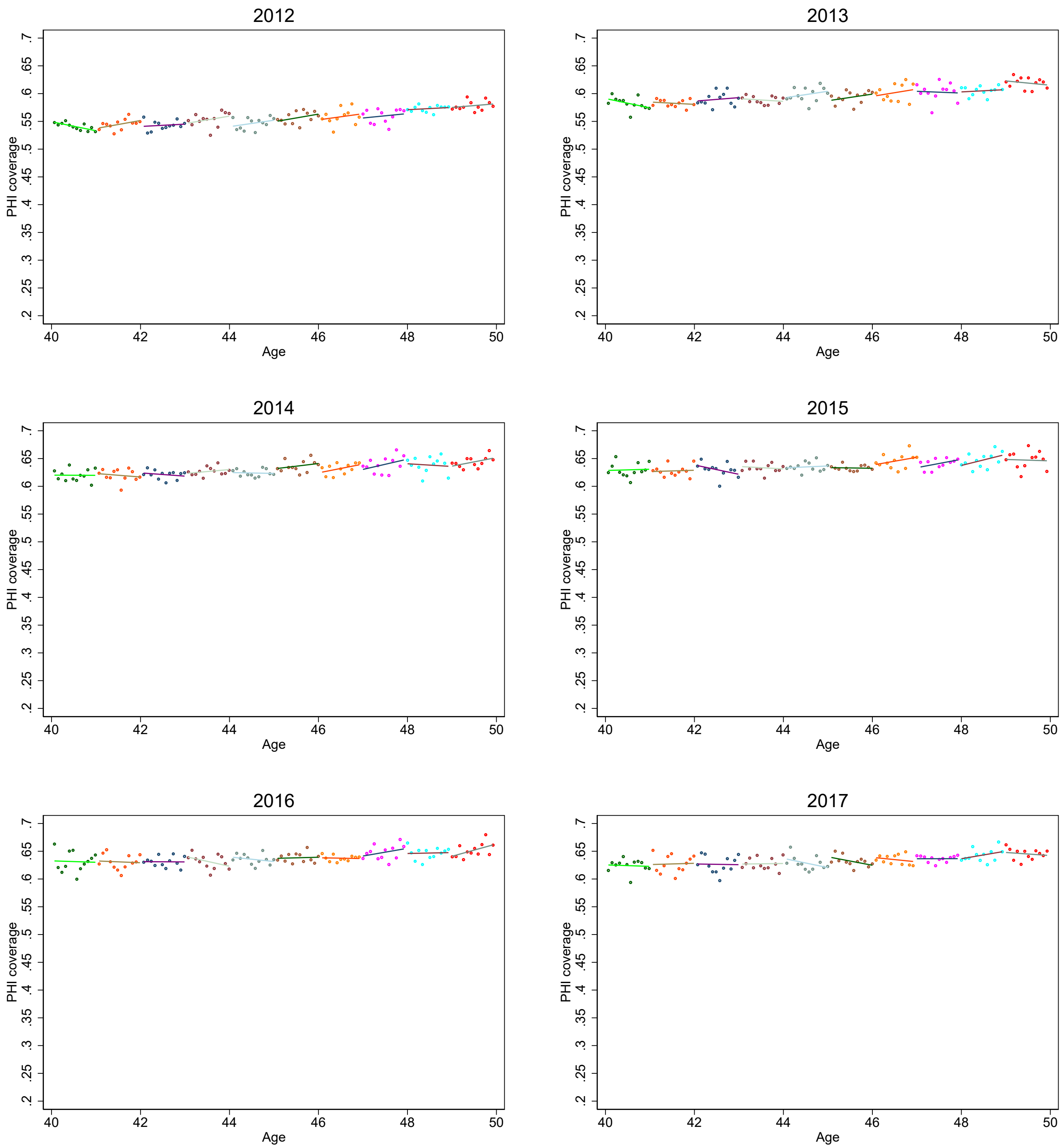


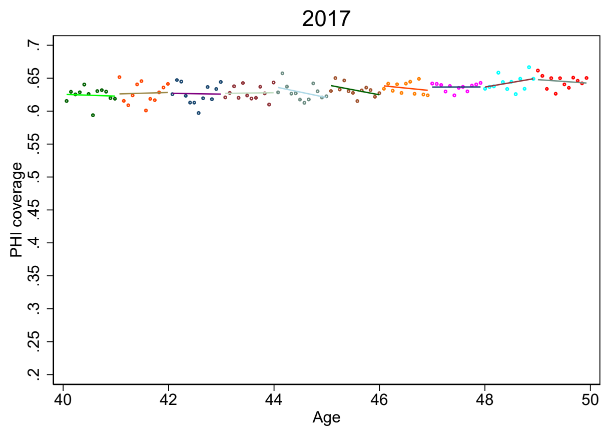
Note: Alife 2018 release. Australians file taxes in financial years that run from July 1 to next June 30, so Alife 1999 data covers from July 1 1998 to June 30 1999; 2000 data covers July 1 1999 to June 30 2000, the first deadline for LHC. PHI coverage is calculated using an indicator for if a person holds a policy expiring after 30 June 2018.

Figure A3: Coverage by age: Ages 40-50



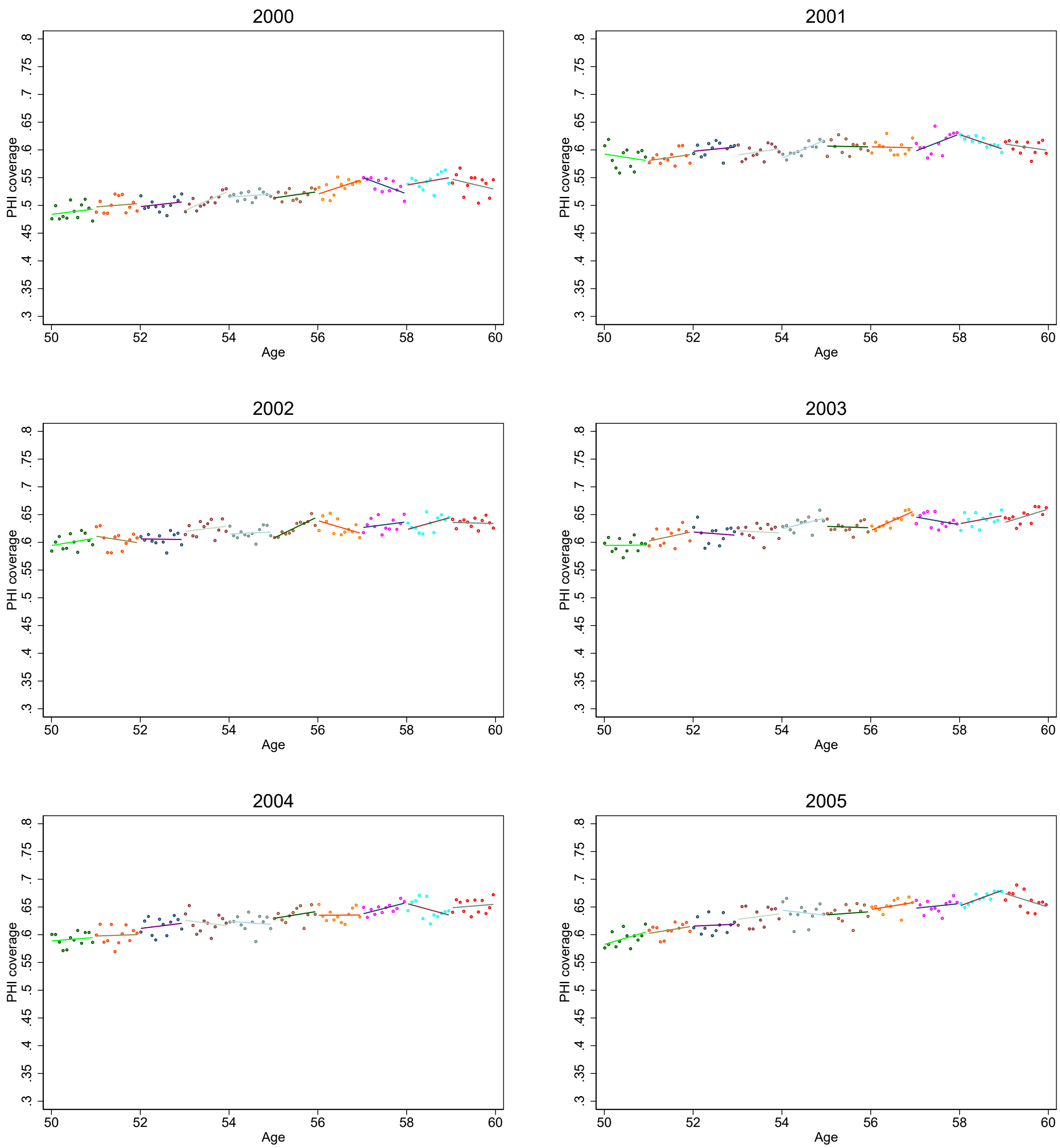

2006
2007
2008
2009
2010
2011
PHI coverage
Age
.2
.25
.3
.35
.4
.45
.5
.55
.6
.65
.7
40
42
44
46
48
50

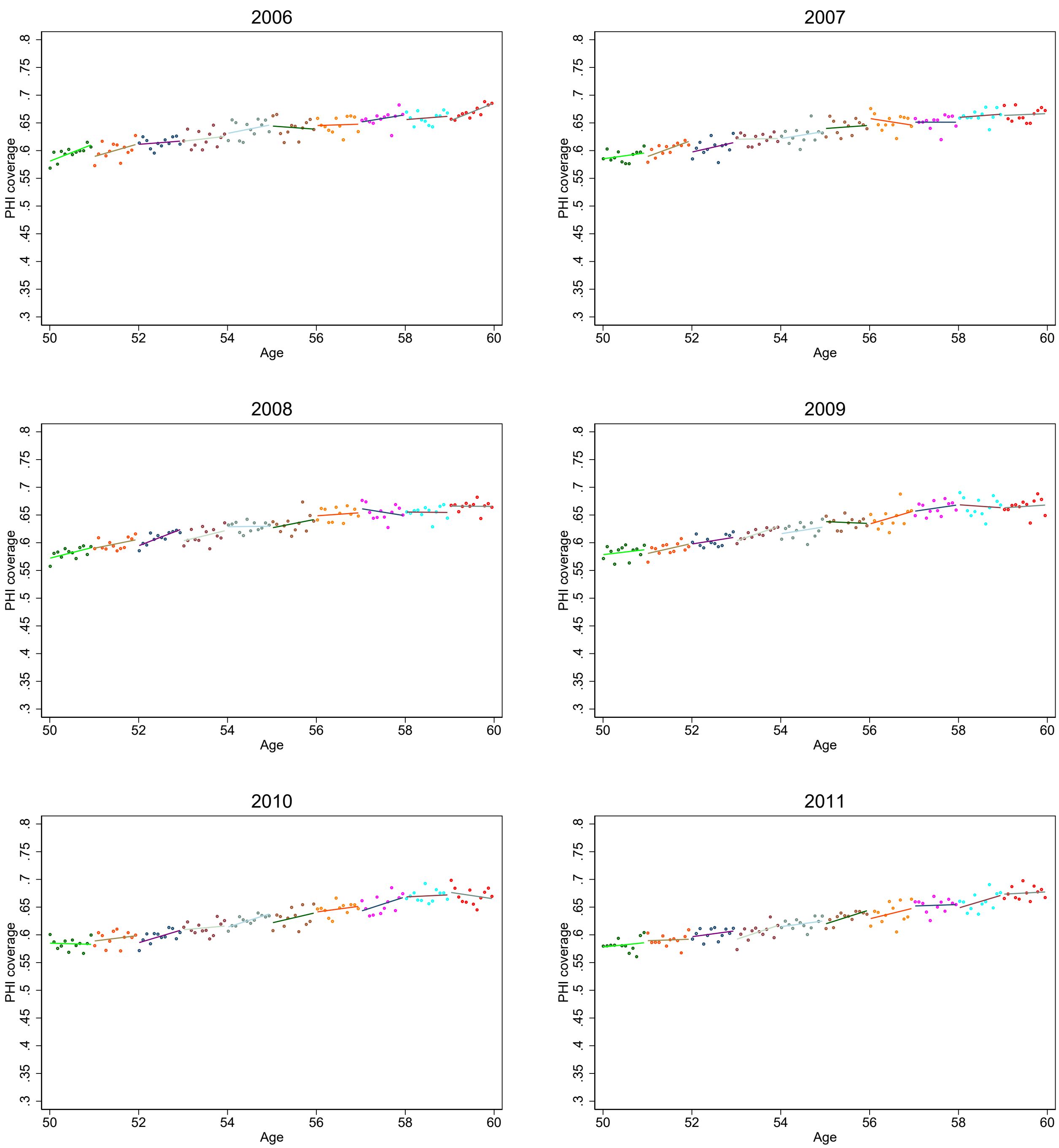

2012
2013
2014
2015
2016
2017
PHI coverage
.2
.25
.3
.35
.4
.45
.5
.55
.6
.65
.7
40
42
44
46
48
50
Age

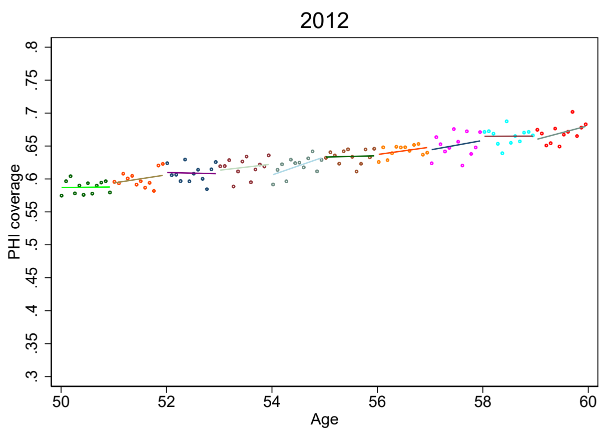


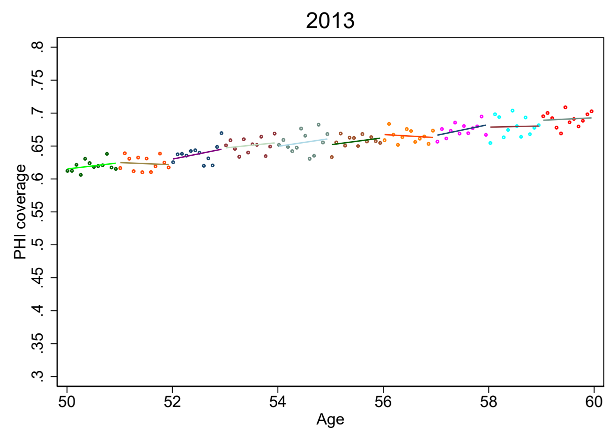
Note: Alife 2018 release. Australians file taxes in financial years that run from July 1 to next June 30, so Alife 1999 data covers from July 1 1998 to June 30 1999; 2000 data covers July 1 1999 to June 30 2000, the first deadline for LHC. PHI coverage is calculated using an indicator for if a person holds a policy expiring after 30 June 2018.

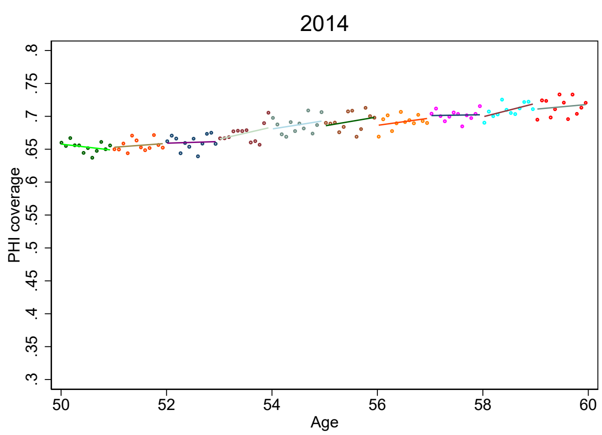
Figure A4: Coverage by age: Ages 50-60

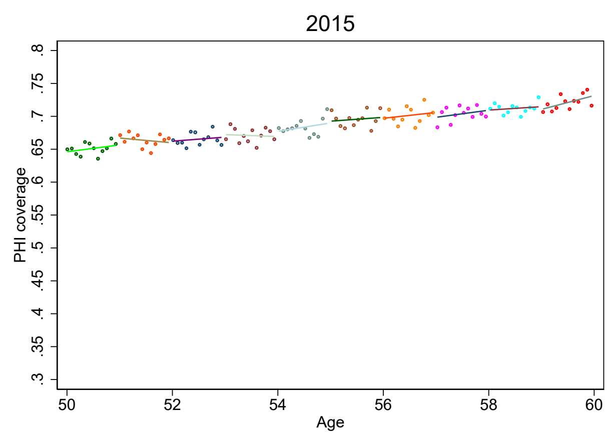


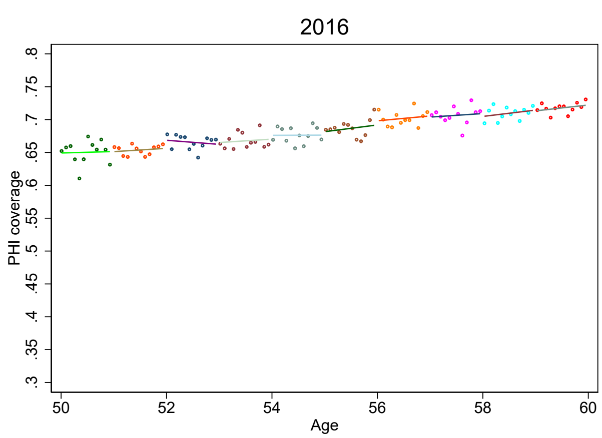

2006
2007
2008
2009
2010
2011
PHI coverage
Age
.3 .35 .4 .45 .5 .55 .6 .65 .7 .75 .8
50 52 54 56 58 60

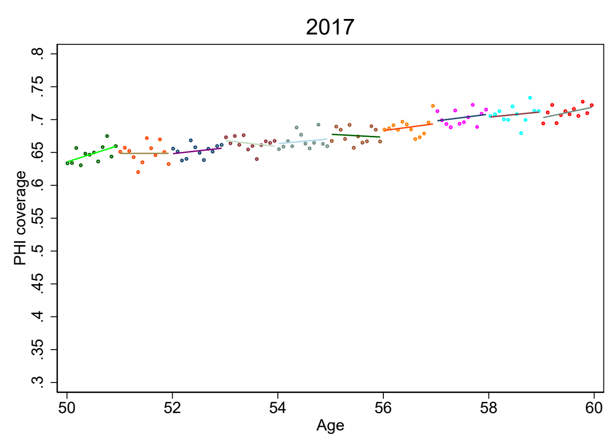

2012
PHI coverage
.3
.35
.4
.45
.5
.55
.6
.65
.7
.75
.8
50
52
54
56
58
60
Age

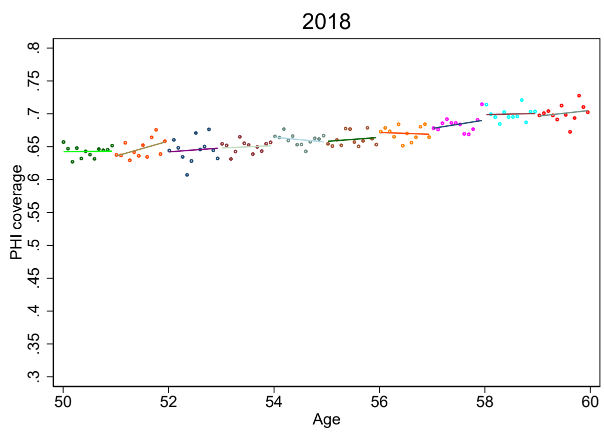

2013
PHI coverage
.3
.35
.4
.45
.5
.55
.6
.65
.7
.75
.8
50
52
54
56
58
60
Age


2014
PHI coverage
.3
.35
.4
.45
.5
.55
.6
.65
.7
.75
.8
50
52
54
56
58
60
Age


2015
PHI coverage
.3
.35
.4
.45
.5
.55
.6
.65
.7
.75
.8
50
52
54
56
58
60
Age

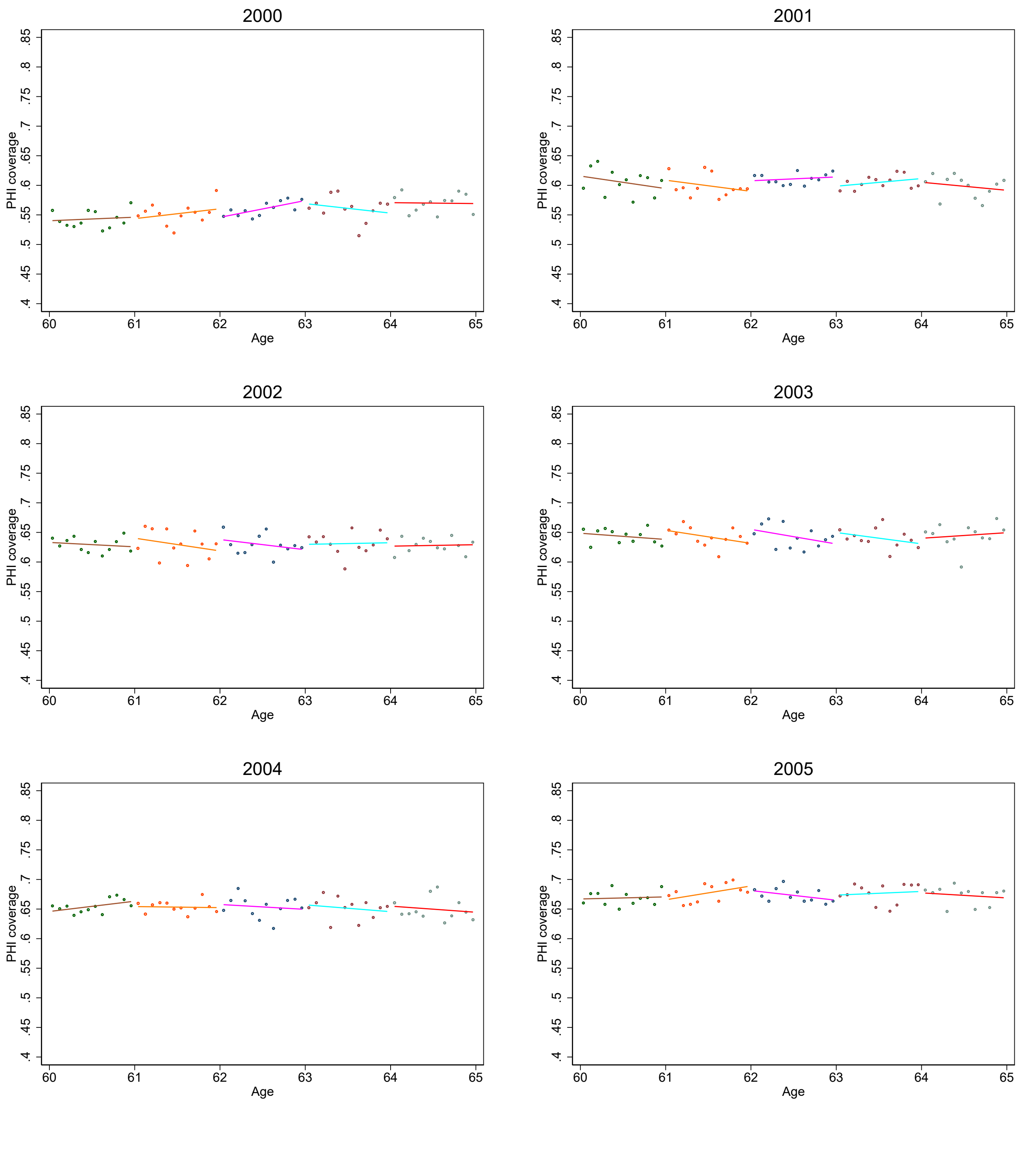

2016
PHI coverage
.3
.35
.4
.45
.5
.55
.6
.65
.7
.75
.8
50
52
54
56
58
60
Age

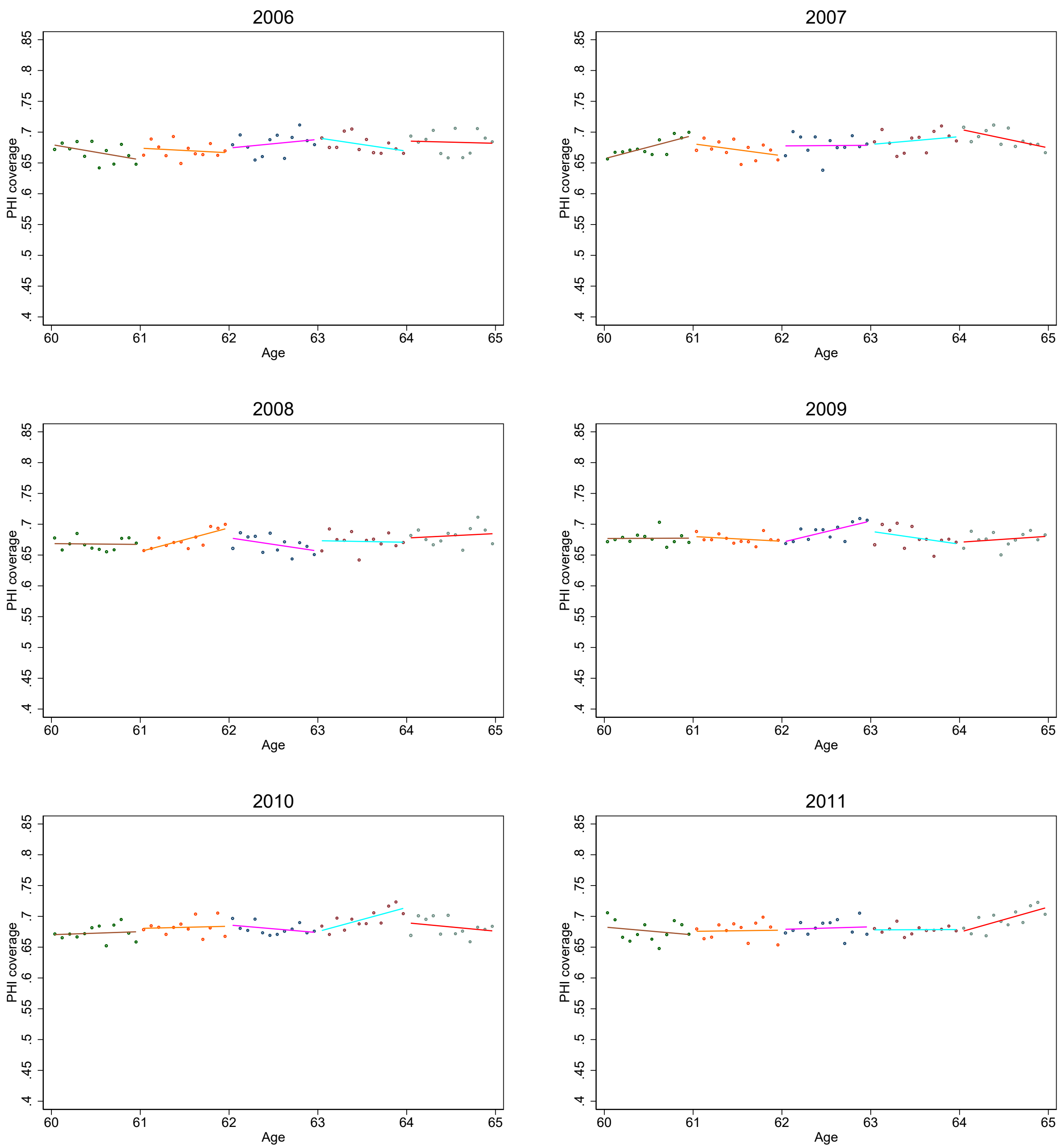

2017
PHI coverage
.3
.35
.4
.45
.5
.55
.6
.65
.7
.75
.8
50
52
54
56
58
60
Age

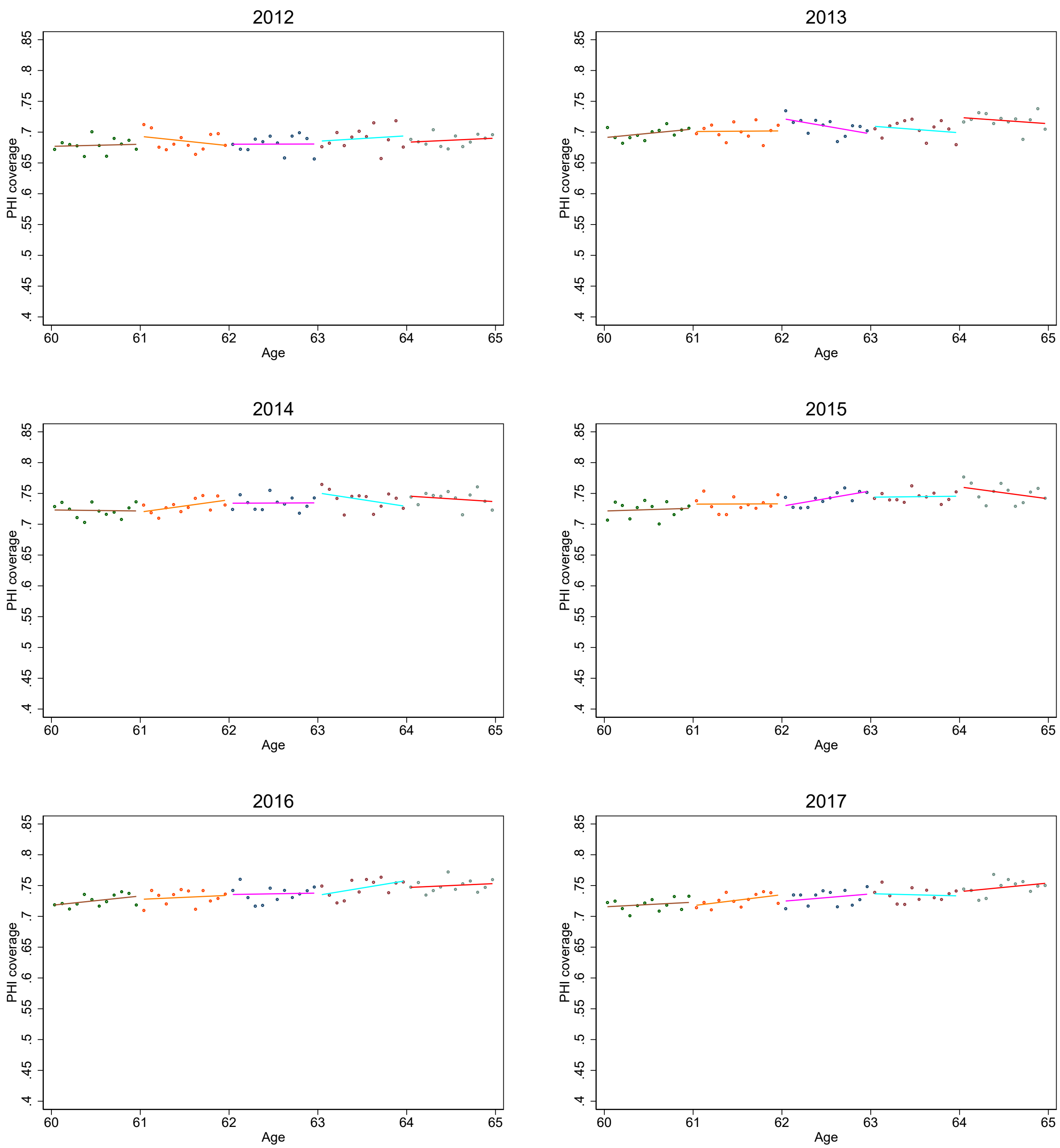


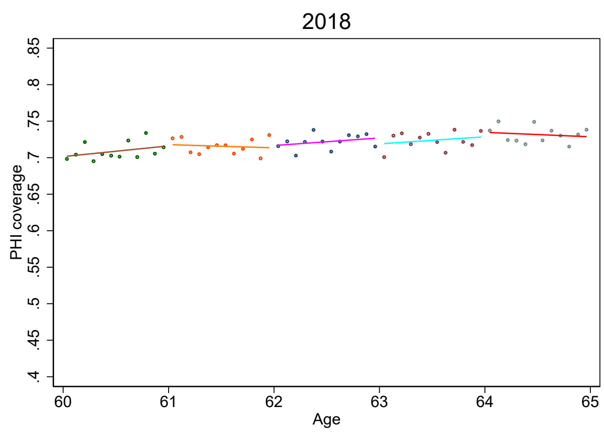
Note: Alife 2018 release. Australians file taxes in financial years that run from July 1 to next June 30, so Alife 1999 data covers from July 1 1998 to June 30 1999; 2000 data covers July 1 1999 to June 30 2000, the first deadline for LHC. PHI coverage is calculated using an indicator for if a person holds a policy expiring after 30 June 2018.

Figure A5: Coverage by age: Ages 60-65



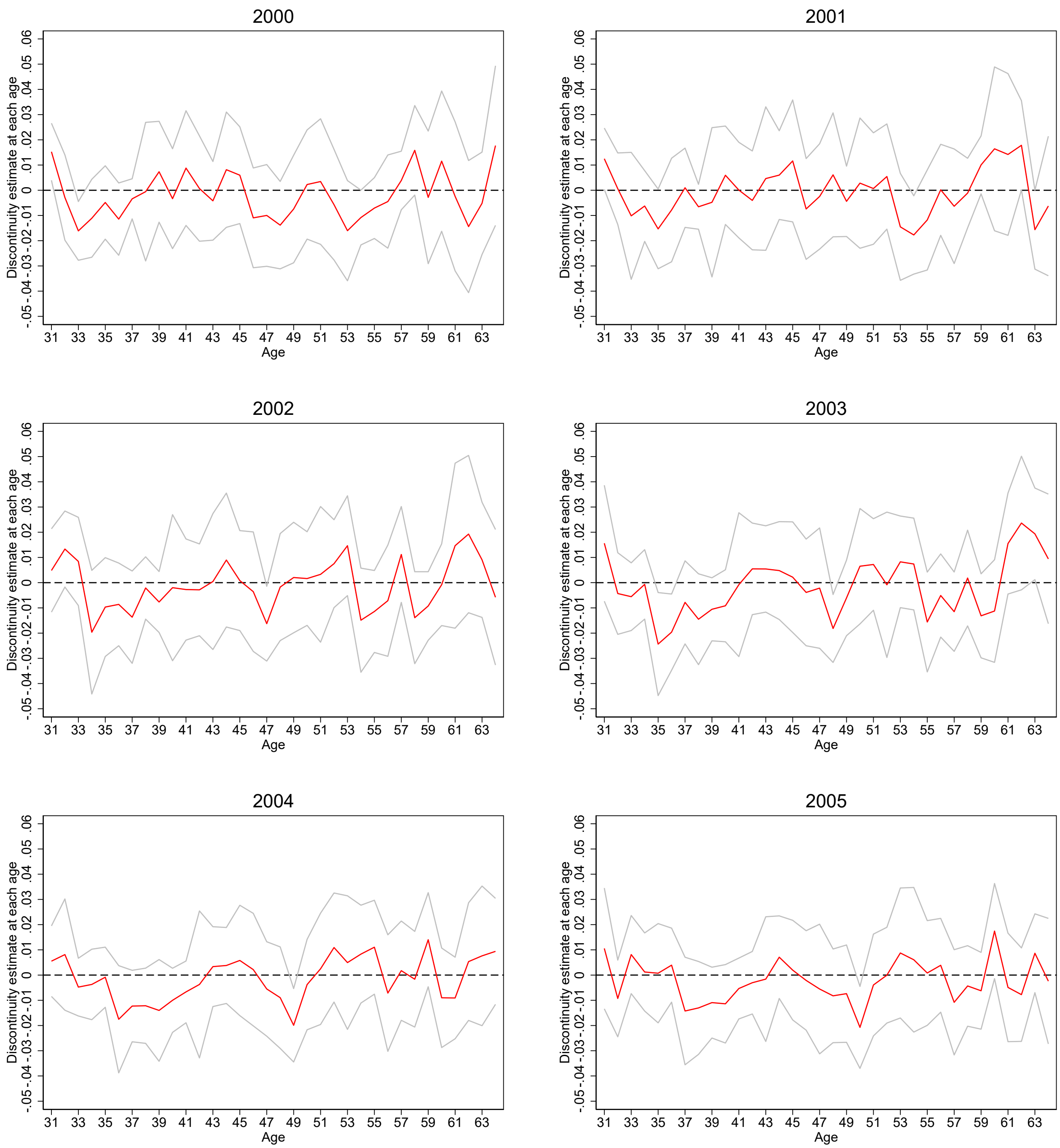

2006
2007
2008
2009
2010
2011
PHI coverage
.4
.45
.5
.55
.6
.65
.7
.75
.8
.85
60
61
62
63
64
65
Age

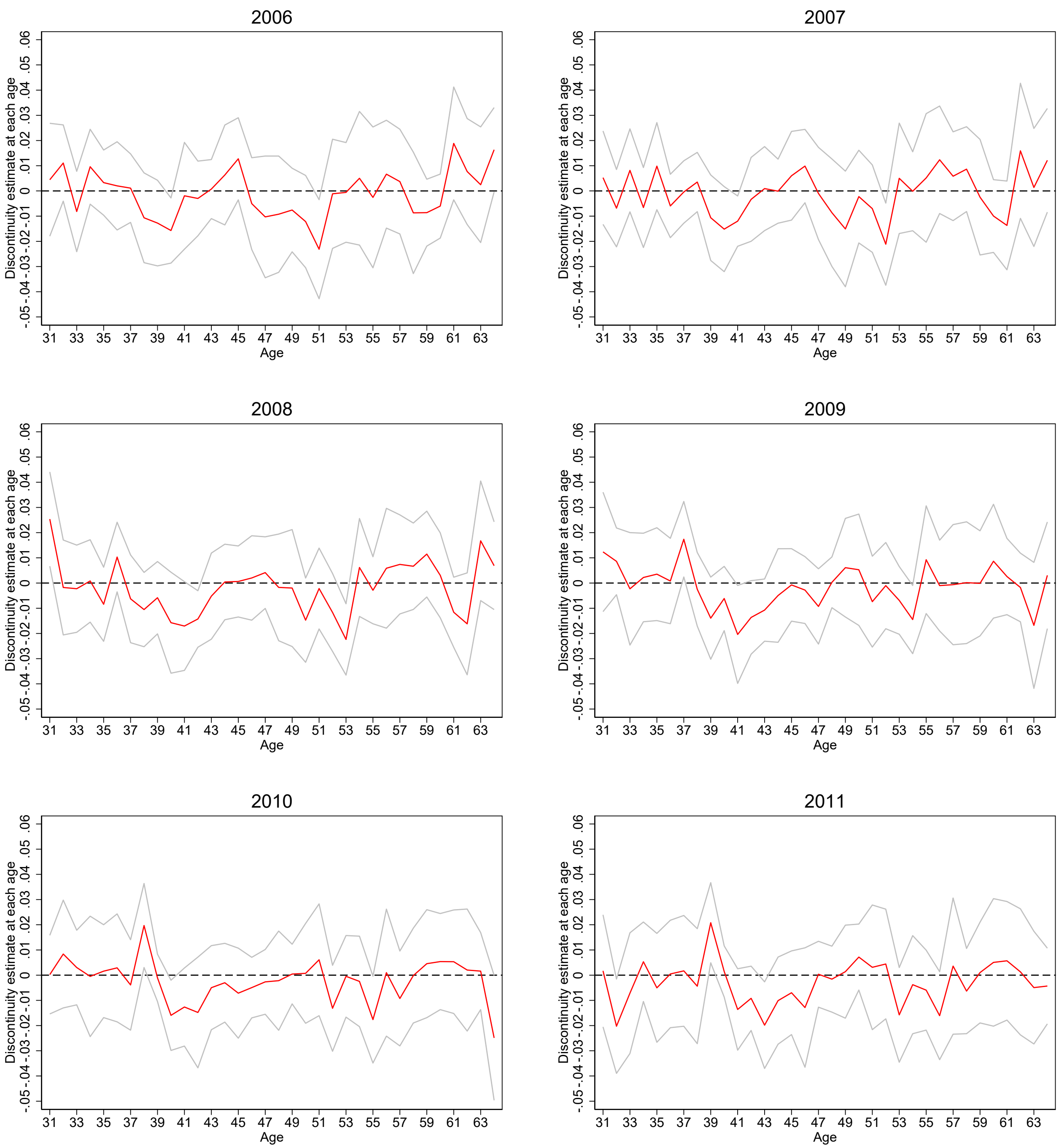

2012
2013
2014
2015
2016
2017
PHI coverage
Age
.4
.45
.5
.55
.6
.65
.7
.75
.8
.85
60
61
62
63
64
65

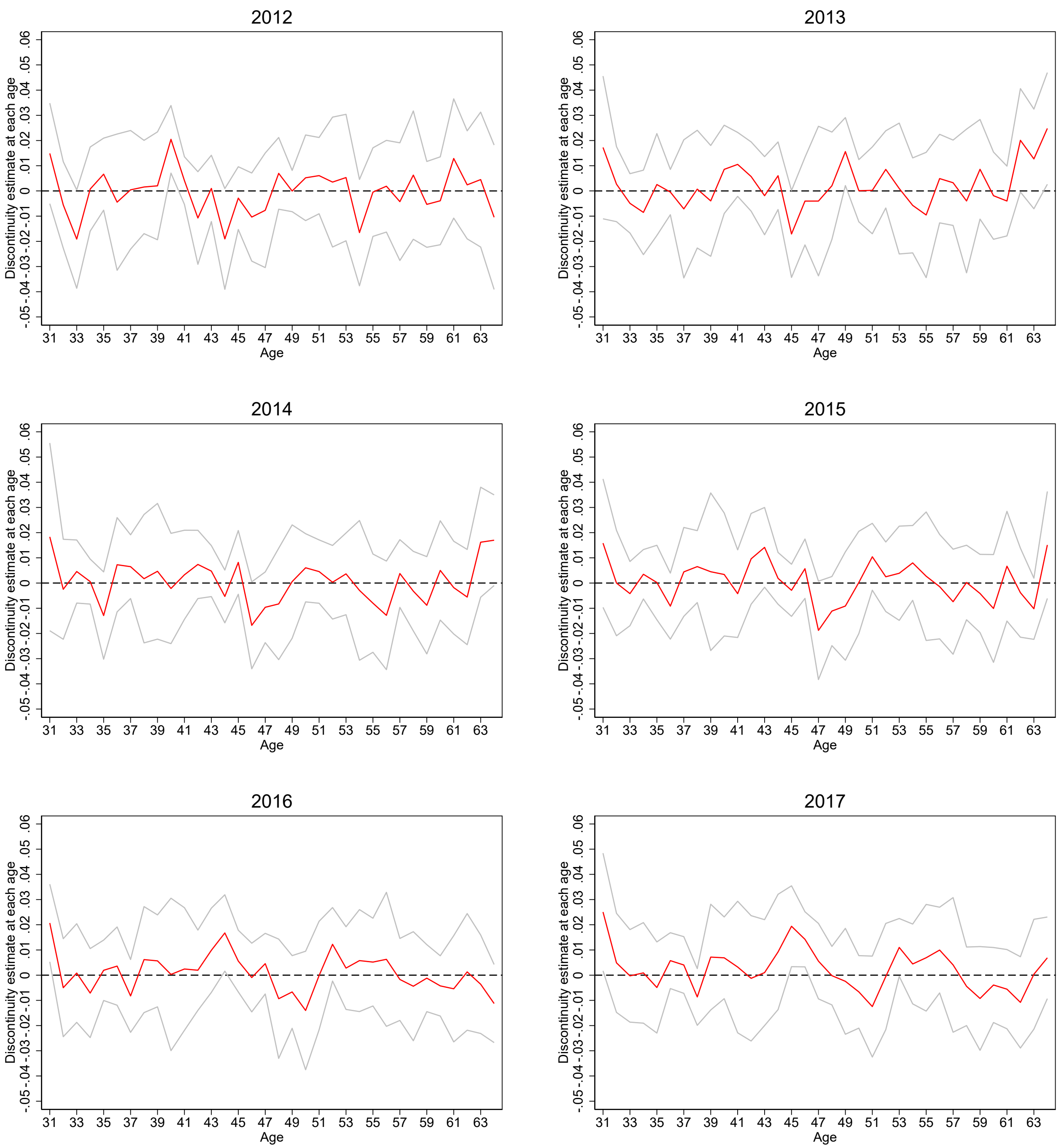


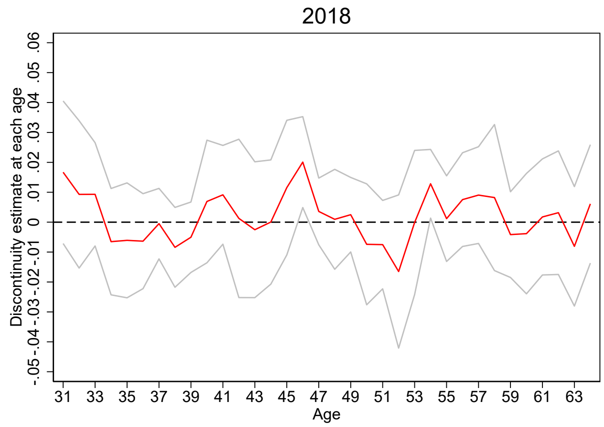
Note: Alife 2018 release. Australians file taxes in financial years that run from July 1 to next June 30, so Alife 1999 data covers from July 1 1998 to June 30 1999; 2000 data covers July 1 1999 to June 30 2000, the first deadline for LHC. PHI coverage is calculated using an indicator for if a person holds a policy expiring after 30 June 2018.

Figure A6: RDD estimates by age penalty



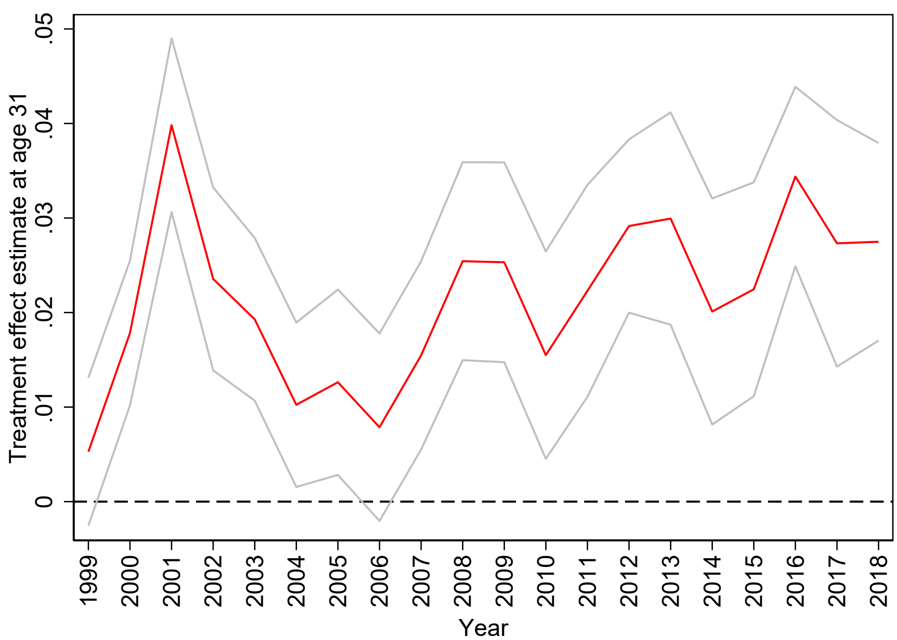

2006
2007
2008
2009
2010
2011
Discontinuity estimate at each age
-.05 -.04 -.03 -.02 -.01 0 .01 .02 .03 .04 .05 .06
31 33 35 37 39 41 43 45 47 49 51 53 55 57 59 61 63
Age


2012
2013
2014
2015
2016
2017
Discontinuity estimate at each age
-.05 -.04 -.03 -.02 -.01 0 .01 .02 .03 .04 .05 .06
31 33 35 37 39 41 43 45 47 49 51 53 55 57 59 61 63
Age



Note: 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, the first deadline for LHC. Each age corresponds to a separate RDD estimate for that age using a linear control function and 1-year bandwidth.b Dependent variable is an indicator for non-blank PHI details in the tax return (ITR) or if the person holds a policy expiring after June 30 (funds) for the financial year ending 30 June (after 2012). Grey lines are 95% asymptotic confidence intervals with standard errors clustered at the month of birth level.

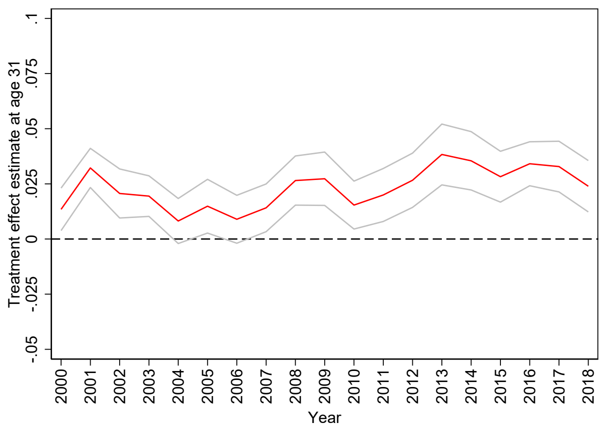
Figure A7: RDD estimates for each year using tax return PHI status variable: Age 31 penalty



Note: 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, the first deadline for LHC. Each year corresponds to a separate RDD estimate. Grey 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.

Figure A8: RDD estimates for each year by income sub-group: Age 31 penalty

(a) Below MLS threshold



(b) Between MLS threshold

(c) Above MLS threshold

Note: 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, the first deadline for LHC. Each year corresponds to a separate RDD estimate. Grey lines are 95% asymptotic confidence intervals with standard errors clustered at the month of birth level. In Panel (a) the sample is restricted to people whose wage adjusted income is below \$50,000 AUD-2005. In Panel (c) the sample is restricted to people whose wage adjusted income is above \$88,000 AUD-2014. In Panel (b) the sample is restricted to people whose wage adjusted income is between these thresholds. Wage inflation data are from the Australian Bureau of Statistics. Further details on the estimates are in Table 1.

Table A1: RDD estimates for each year for people with income below the MLS threshold: Age 31 penalty

Year	Estimate	Std. Error	Mean	Est./Mean	BW	Obs.	Poly. order	Controls
2000	0.0135	0.0048	0.2445	0.0550	3.64	132472	1	No
2001	0.0322	0.0045	0.3143	0.1025	3.96	147253	1	No
2002	0.0206	0.0056	0.2988	0.0691	3.96	150330	1	Yes
2003	0.0194	0.0046	0.2808	0.0693	3.88	151492	1	Yes
2004	0.0082	0.0051	0.2825	0.0289	3.56	141014	1	No
2005	0.0149	0.0061	0.2703	0.0550	3.56	139915	1	No
2006	0.0090	0.0055	0.2904	0.0308	3.96	151460	1	Yes
2007	0.0141	0.0054	0.2972	0.0476	3.56	136889	1	No
2008	0.0265	0.0056	0.2873	0.0923	3.96	152318	1	No
2009	0.0273	0.0061	0.3283	0.0832	3.96	154062	1	No
2010	0.0154	0.0055	0.3256	0.0472	3.48	138363	1	No
2011	0.0200	0.0060	0.3363	0.0593	3.56	144189	1	No
2012	0.0266	0.0062	0.3421	0.0779	3.56	144775	1	No
2013	0.0383	0.0069	0.3759	0.1020	3.88	145650	1	No
2014	0.0355	0.0066	0.4367	0.0812	3.40	136344	1	Yes
2015	0.0282	0.0058	0.4298	0.0657	3.48	143795	1	Yes
2016	0.0341	0.0050	0.4215	0.0809	3.88	161465	1	No
2017	0.0328	0.0058	0.3924	0.0837	3.40	149584	1	No
2018	0.0239	0.0059	0.3714	0.0644	3.64	160462	1	No

Note: Alife 2018 release including tax files 1999-2018. The sample is restricted to people whose wage adjusted income is below $50,000 AUD-2005. 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 30 June 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 one-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 + one 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.

Table A2: RDD estimates for each year for people with income between the MLS threshold: Age 31 penalty

Year	Estimate	Std. Error	Mean	Est./Mean	BW	Obs.	Poly. order	Controls
2000	0.0205	0.0098	0.4058	0.0506	3.64	30374	1	No
2001	0.0793	0.0132	0.5407	0.1467	3.96	29674	1	No
2002	0.0439	0.0104	0.5000	0.0879	3.96	29736	3	Yes
2003	0.0194	0.0128	0.5211	0.0372	3.88	29904	3	Yes
2004	0.0130	0.0134	0.6094	0.0214	3.56	28640	1	No
2005	0.0033	0.0122	0.5955	0.0055	3.56	29368	1	No
2006	0.0164	0.0101	0.6445	0.0254	3.96	32622	3	Yes
2007	0.0045	0.0102	0.6871	0.0065	3.56	29387	1	No
2008	0.0402	0.0092	0.6901	0.0582	3.96	34888	1	No
2009	0.0391	0.0105	0.6658	0.0588	3.96	36448	1	No
2010	0.0379	0.0112	0.6871	0.0551	3.48	34053	1	No
2011	0.0226	0.0117	0.6806	0.0332	3.56	37303	1	No
2012	0.0476	0.0083	0.6694	0.0712	3.56	39080	1	No
2013	0.0283	0.0107	0.7017	0.0403	3.88	45194	1	No
2014	0.0428	0.0120	0.7751	0.0552	3.40	41382	3	Yes
2015	0.0484	0.0086	0.7235	0.0669	3.48	42572	3	Yes
2016	0.0493	0.0092	0.7470	0.0659	3.88	47496	1	No
2017	0.0299	0.0092	0.7158	0.0417	3.40	43155	1	No
2018	0.0480	0.0085	0.6463	0.0743	3.64	48215	1	No

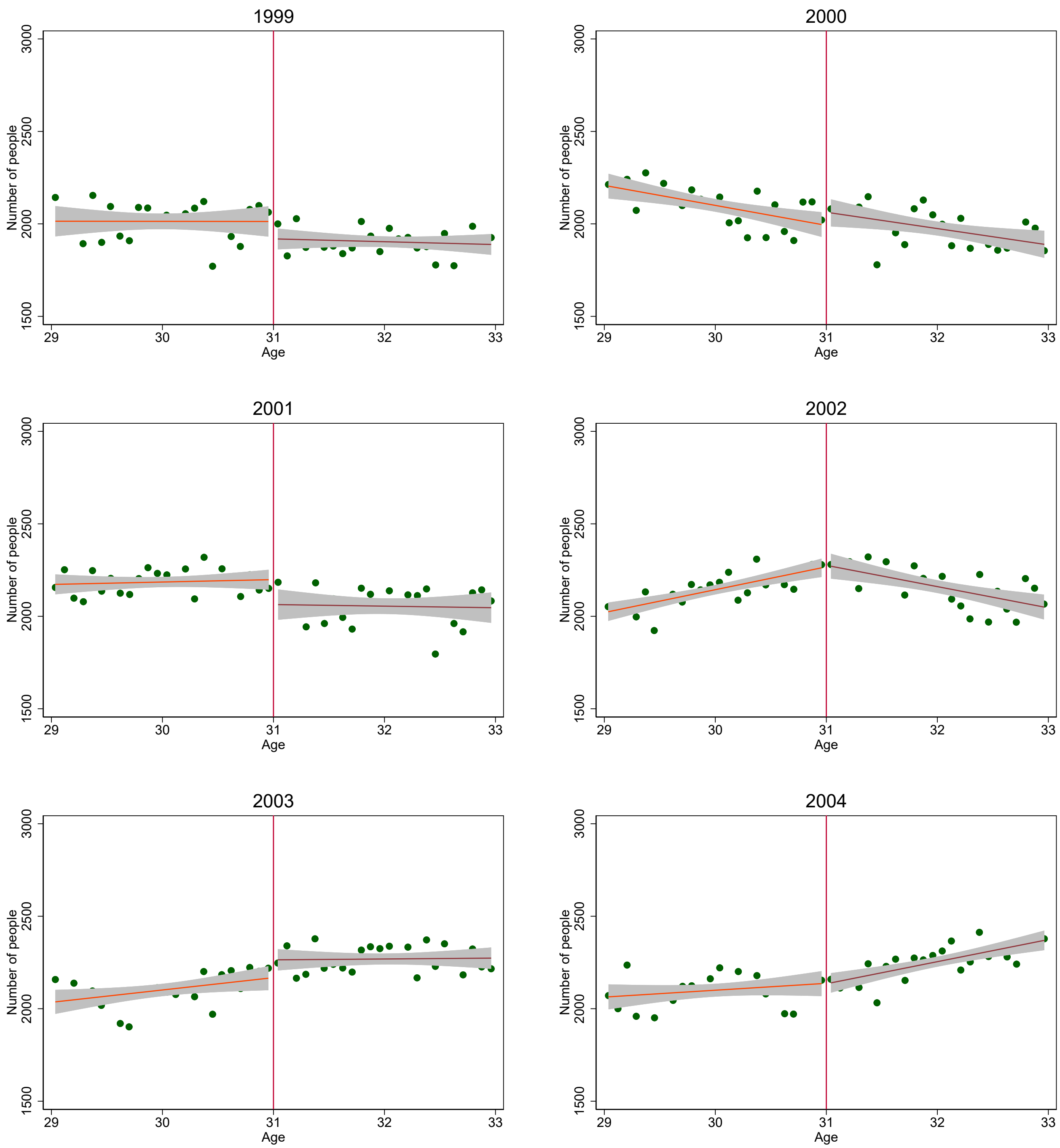
Note: Alife 2018 release including tax files 1999-2018. The sample is restricted to people whose wage adjusted income is between $50,000 AUD-2005 and $88,000 AUD-2014. Each row corresponds to a separate RDD estimate. Australians file taxes in financial years that run from July 1 to next June 30; 2000 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 30 June 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 one-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 + one 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.

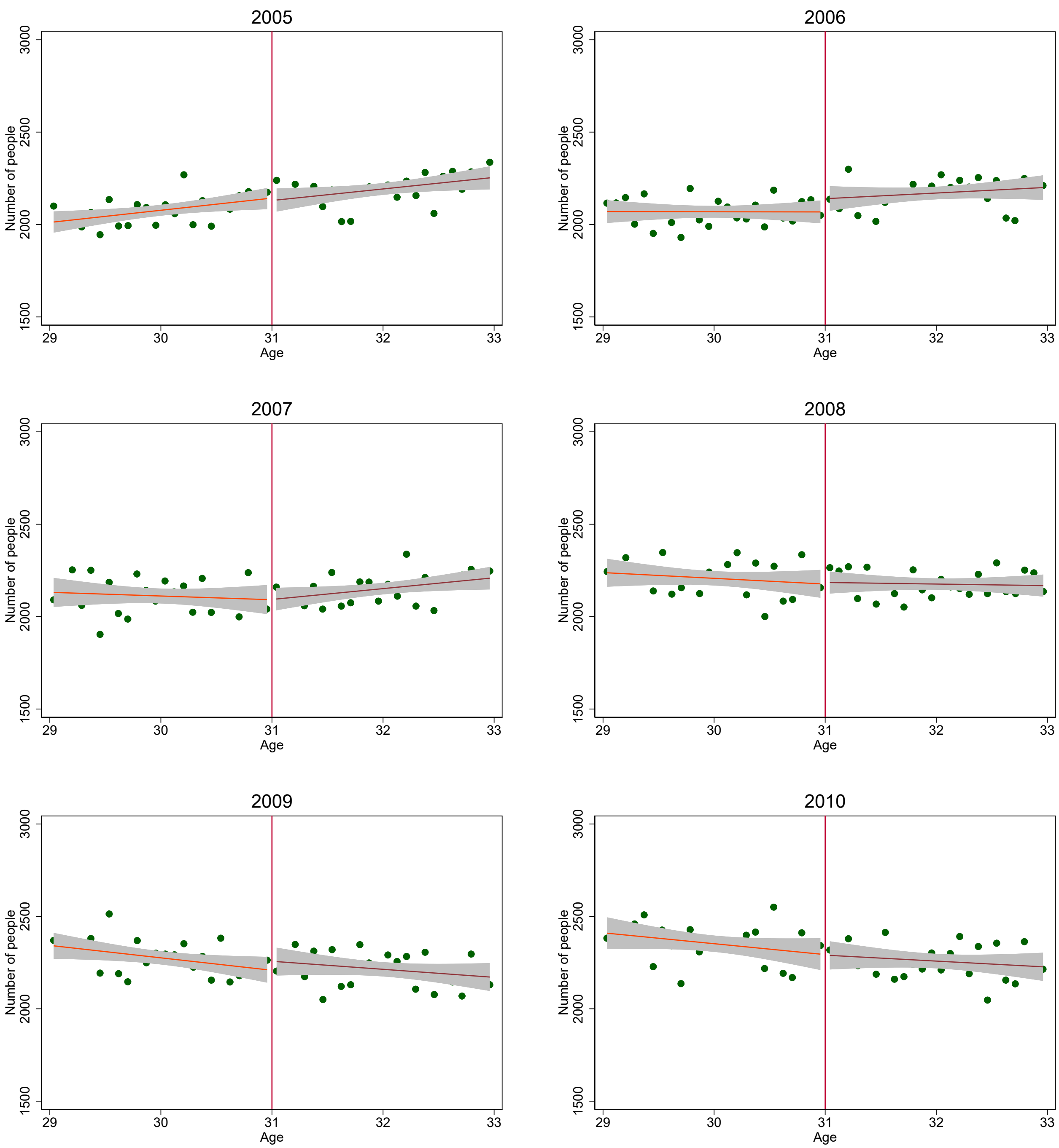
Table A3: RDD estimates for each year for people with income above the MLS threshold: Age 31 penalty

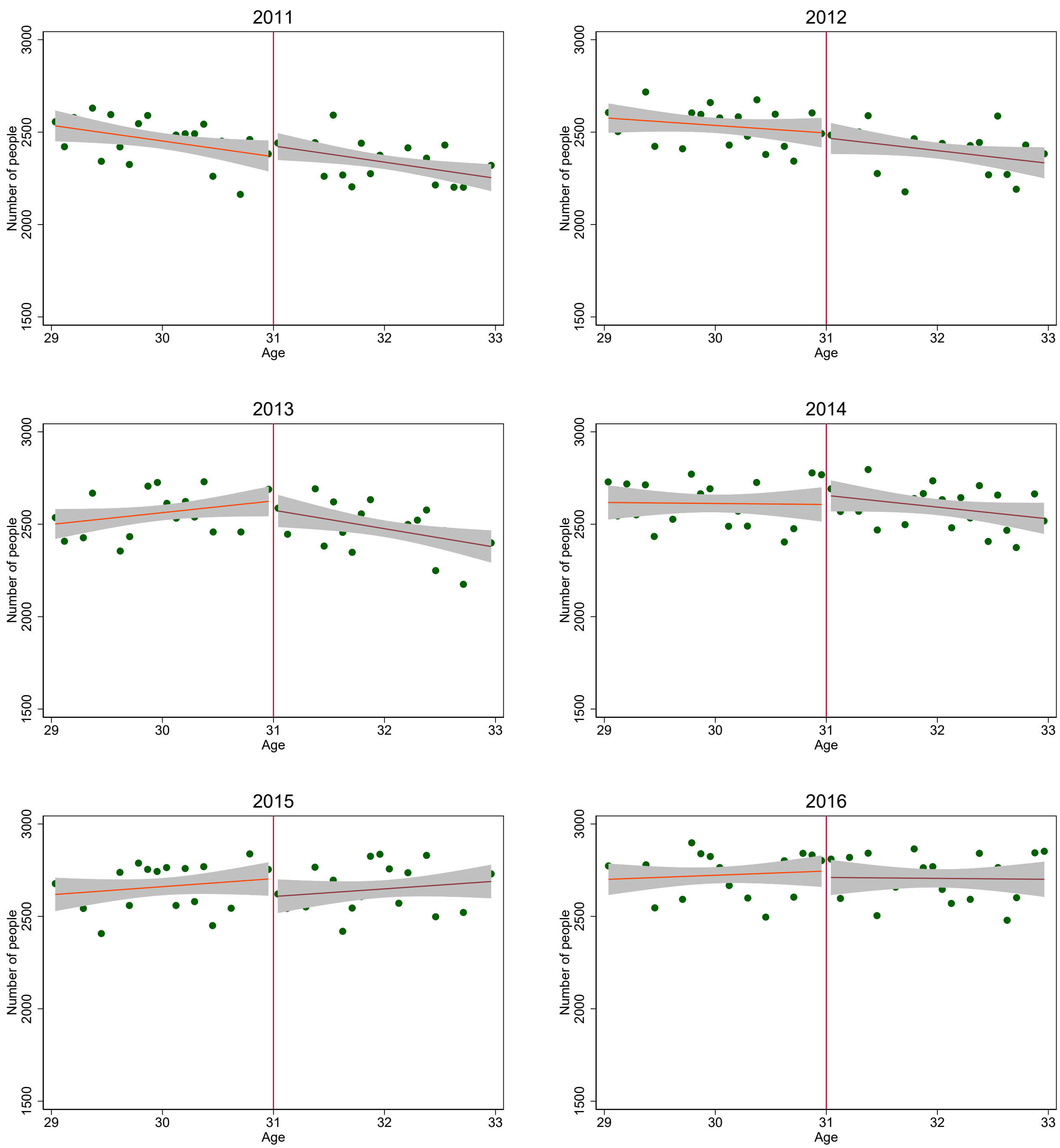
Year	Estimate	Std. Error	Mean	Est./Mean	BW	Obs.	Poly. order	Controls
2000	0.0179	0.0167	0.6114	0.0293	3.64	15105	1	No
2001	0.0496	0.0121	0.7514	0.0660	3.96	15957	1	No
2002	0.0280	0.0142	0.7672	0.0365	3.96	15914	3	Yes
2003	0.0160	0.0133	0.8197	0.0195	3.88	16035	3	Yes
2004	0.0184	0.0184	0.8191	0.0224	3.56	15656	1	No
2005	0.0273	0.0131	0.8168	0.0334	3.56	16453	1	No
2006	-0.0195	0.0110	0.8343	-0.0234	3.96	18609	3	Yes
2007	0.0210	0.0124	0.8622	0.0243	3.56	19102	1	No
2008	0.0160	0.0097	0.8617	0.0185	3.96	22406	1	No
2009	0.0111	0.0095	0.8571	0.0129	3.96	22748	1	No
2010	0.0144	0.0114	0.8803	0.0163	3.48	22221	1	No
2011	0.0215	0.0076	0.8403	0.0256	3.56	24317	1	No
2012	0.0096	0.0108	0.8437	0.0114	3.56	25851	1	No
2013	0.0135	0.0093	0.7383	0.0183	3.88	37986	1	No
2014	0.0097	0.0106	0.7838	0.0124	3.40	33350	3	Yes
2015	0.0241	0.0096	0.8161	0.0295	3.48	34723	3	Yes
2016	0.0326	0.0087	0.7565	0.0430	3.88	39142	1	No
2017	0.0251	0.0098	0.7254	0.0346	3.40	34000	1	No
2018	0.0061	0.0093	0.7659	0.0080	3.64	35858	1	No

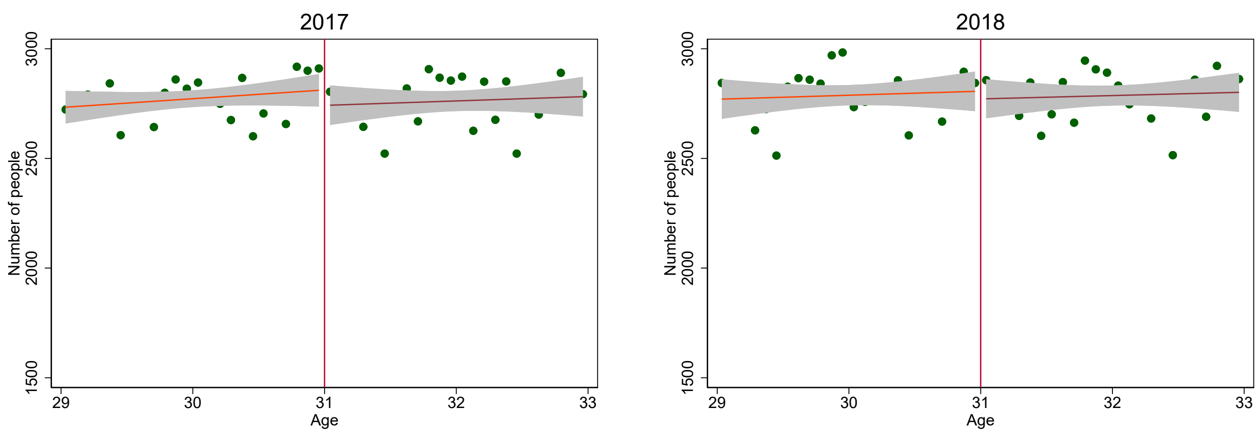
Note: Alife 2018 release including tax files 1999-2018. The sample is restricted to people whose wage adjusted income is above $88,000 AUD-2014. Each row corresponds to a separate RDD estimate. Australians file taxes in financial years that run from July 1 to next June 30; 2000 data covers July 1 1999 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 30 June 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 one-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 + one 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.

Figure A9: Counts of people by month-of-birth




2005
2006
2007
2008
2009
2010
Number of people
1500
2000
2500
3000
Age
29
30
31
32
33

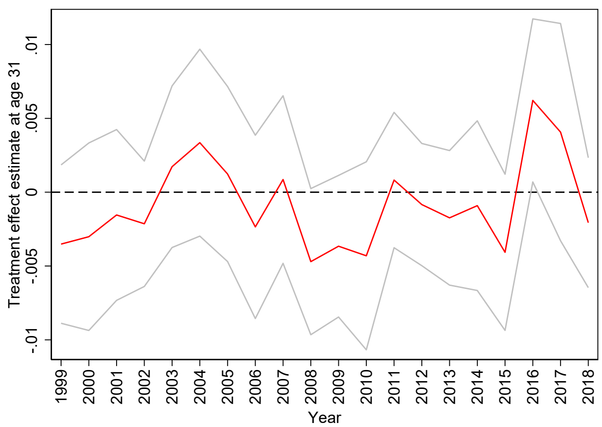

2011
2012
2013
2014
2015
2016
Number of people
1500
2000
2500
3000
Age
29
30
31
32
33



Note: Alife 2018 release. 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, the first deadline for LHC. Each scatter-point corresponds to the average number of taxfilers at each age in one-month bins. Linear best fit lines and 95% confidence intervals are also presented separately for each side of the age 31 threshold.

Figure A10: RDD estimates for other variables

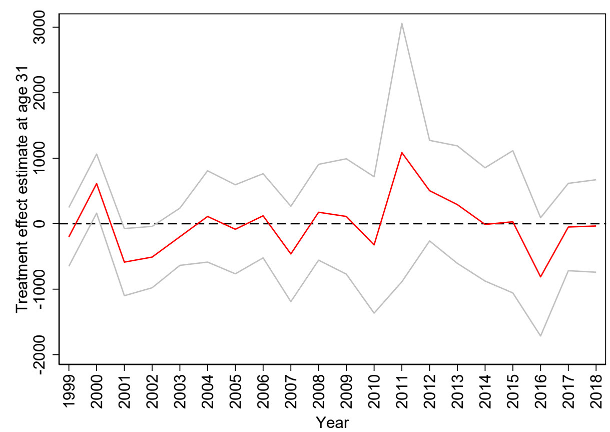
(a) Self employment



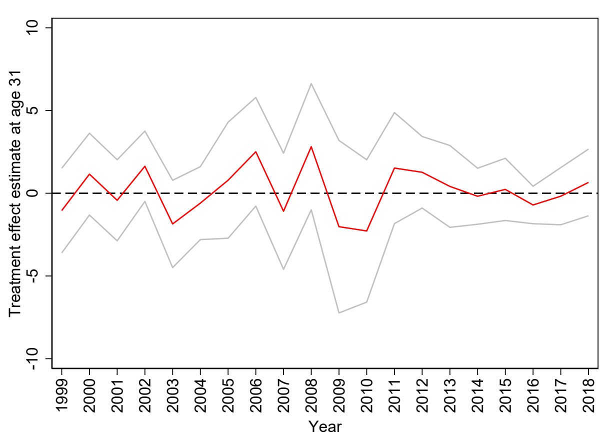
(b) Total income

(c) Total deductions

(d) Government transfers

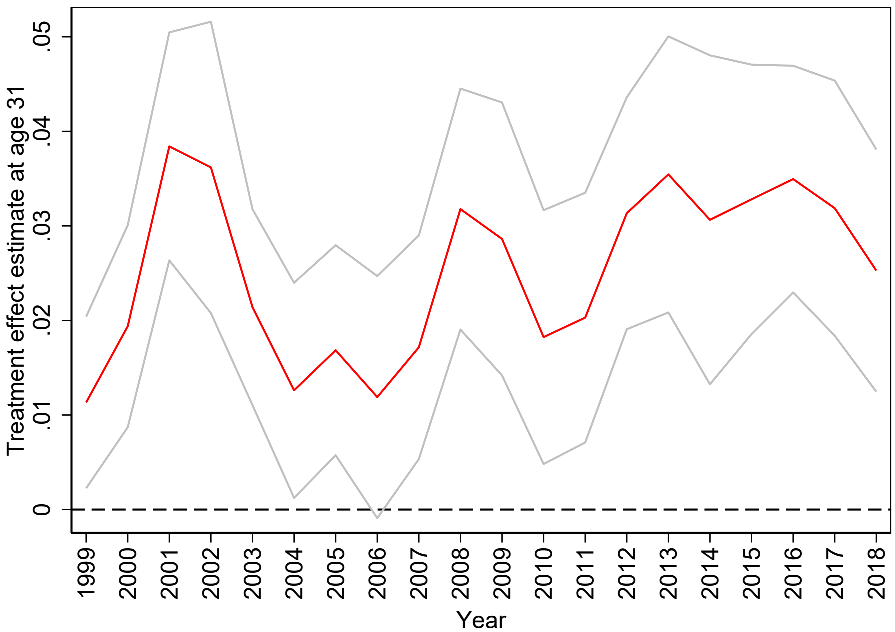


(e) Medical expenses tax offset available



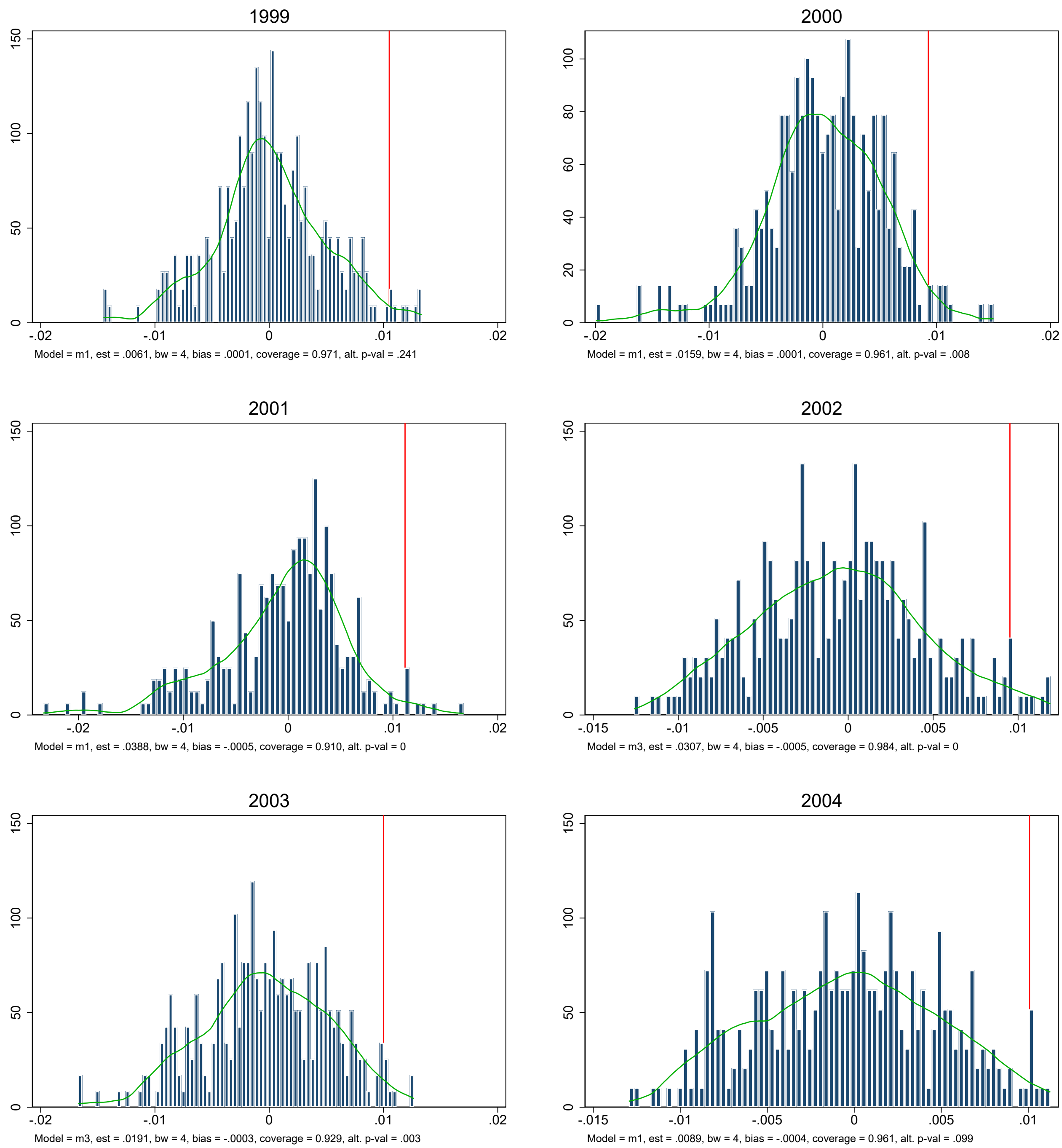
Note: Alife 2018 release version that include tax return files from 1999 to 2018. Each year corresponds to a separate RDD estimate. Dependent variables are: (a) flag for evidence of some degree of self-employment; (b) total income (loss); (c) total amount of tax deductions; (d) income from government allowances and payments; (e) amount claimed for medical expenses tax offset. Grey lines are 95% asymptotic confidence intervals with standard errors clustered at the month of birth level. Further details on the RDD specifications are in Table 1

Figure A11: RDD estimates for each year with artificial jump in coverage at each age: Age 31 penalty

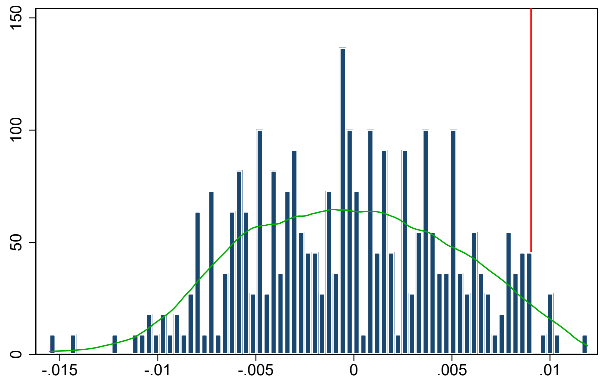


Note: Alife 2018 release version that include tax return files from 1999 to 2018. Australians file taxes in financial years that run from July 1 to next June 30, so Alife 1999 data covers from July 1 1998 to June 30 1999; 2000 data covers July 1 1999 to June 30 2000, the first deadline for LHC. Each year corresponds to a separate RDD estimate. RDD estimates use the KS selection algorithm considering models with bandwidths between 1-4 years in one-month increments, linear and quadratic control function, and with/without controls, after artificially adding 0.03 to the dependent variable (private health insurance indicator) for every year after age 32. Grey lines are 95% asymptotic confidence intervals with standard errors clustered at the month of birth level.

Figure A12: Distribution of placebo estimates

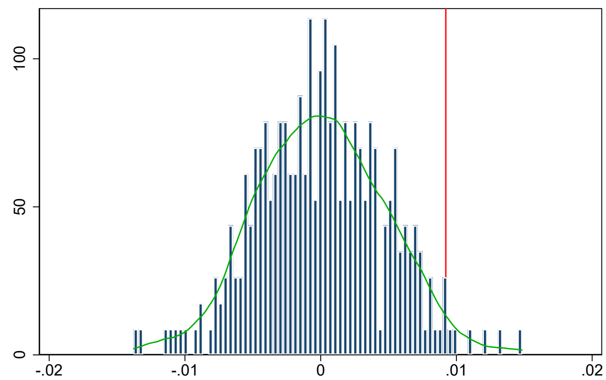


2005



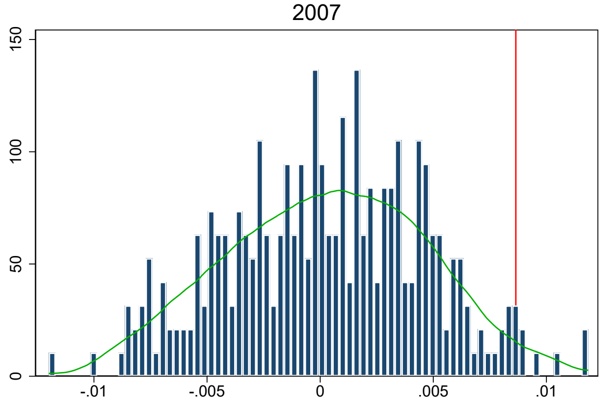
Model = m1, est = .0127, bw = 4, bias = -.0003, coverage = 0.974, alt. p-val = .026

2006



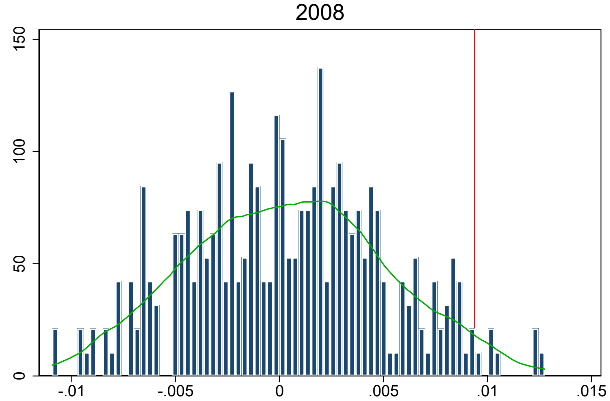
Model = m3, est = .0075, bw = 4, bias = 0, coverage = 0.952, alt. p-val = .133

2007



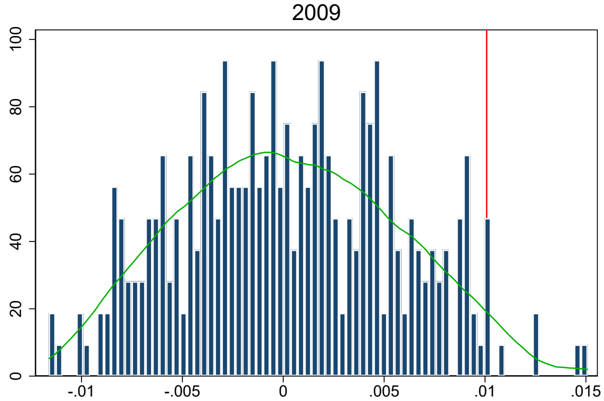
Model = m1, est = .0134, bw = 4, bias = .0003, coverage = 0.971, alt. p-val = .008

2008



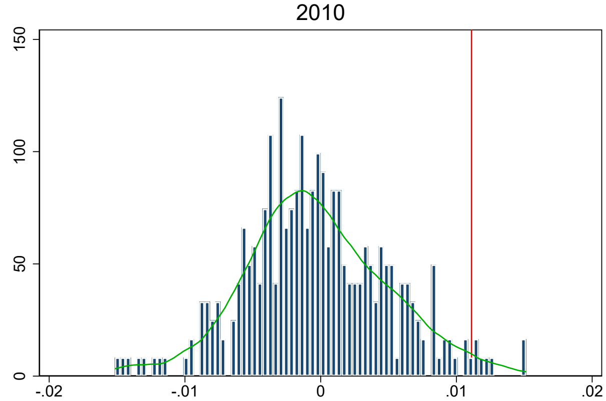
Model = m1, est = .0265, bw = 4, bias = .0004, coverage = 0.936, alt. p-val = 0

2009

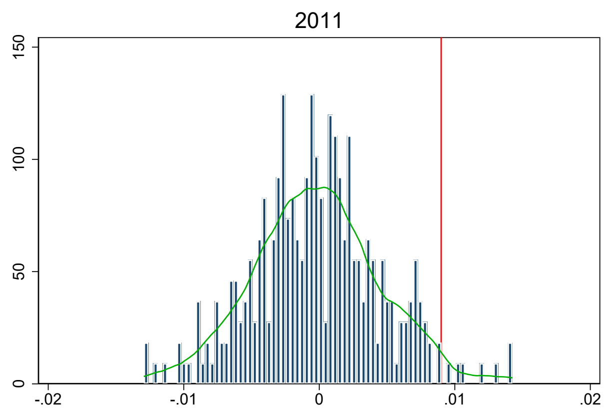


Model = m1, est = .0254, bw = 4, bias = .0003, coverage = 0.910, alt. p-val = .001

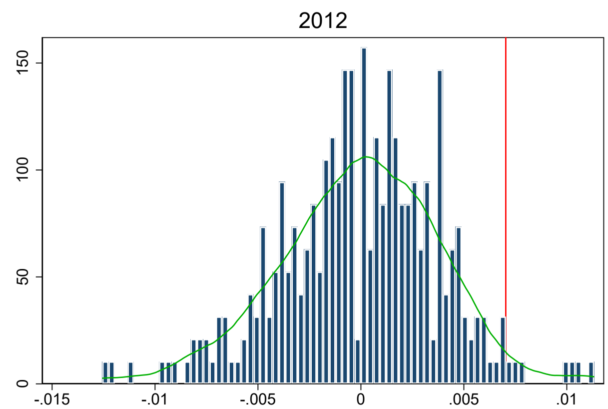
2010



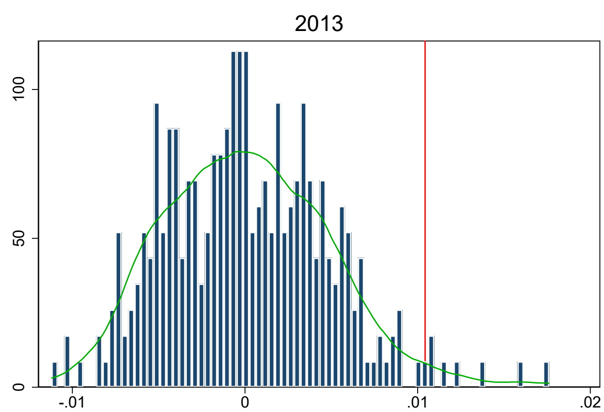
Model = m1, est = .0193, bw = 3, bias = -.0003, coverage = 0.932, alt. p-val = .002



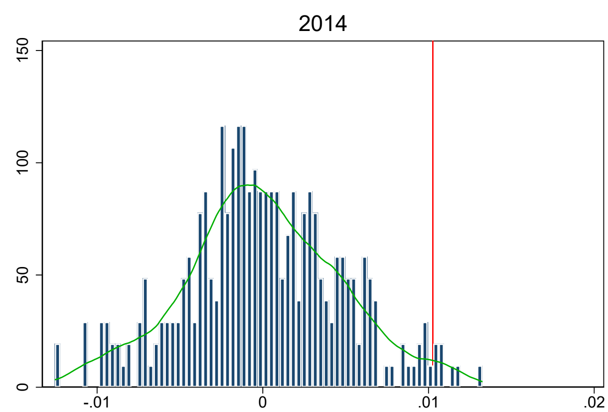
Model = m1, est = .0194, bw = 4, bias = -.0002, coverage = 0.974, alt. p-val = .001



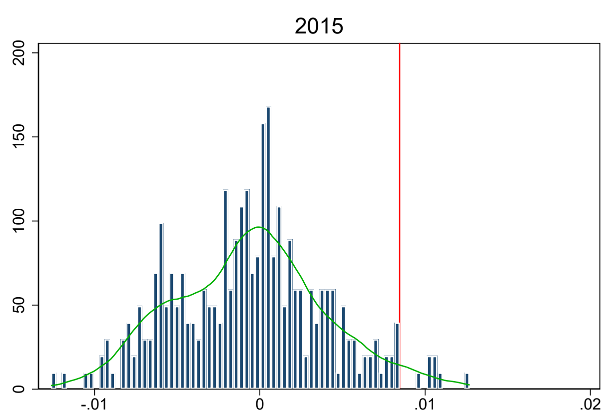
Model = m1, est = .028, bw = 4, bias = -.0001, coverage = 0.984, alt. p-val = 0



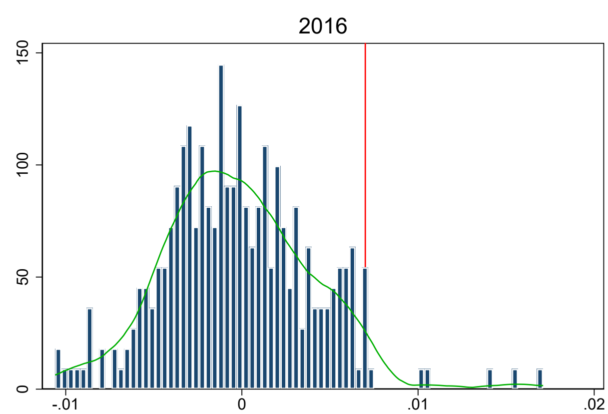
Model = m1, est = .0342, bw = 4, bias = .0001, coverage = 0.958, alt. p-val = 0



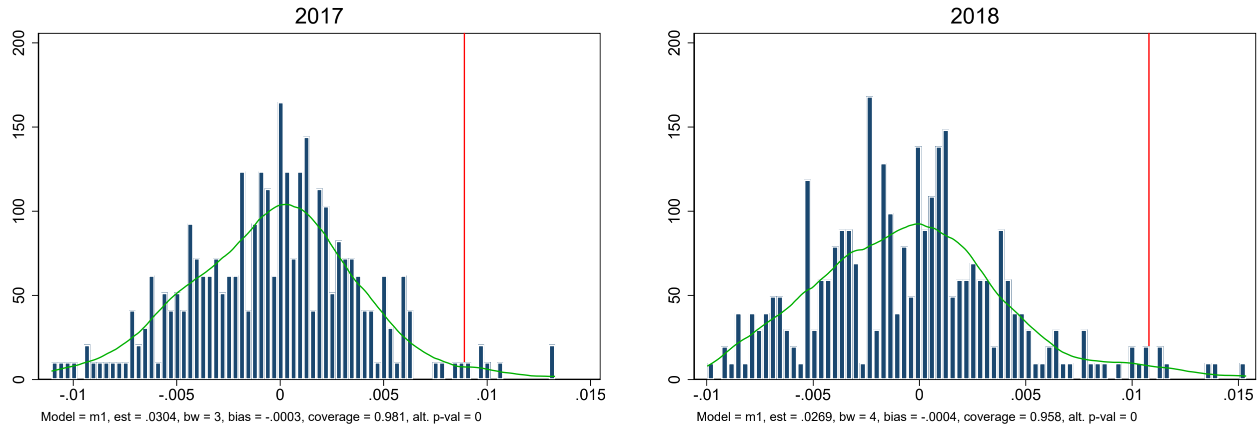
Model = m3, est = .0306, bw = 3, bias = 0, coverage = 0.977, alt. p-val = 0



Model = m3, est = .0321, bw = 3, bias = -.0006, coverage = 0.984, alt. p-val = 0

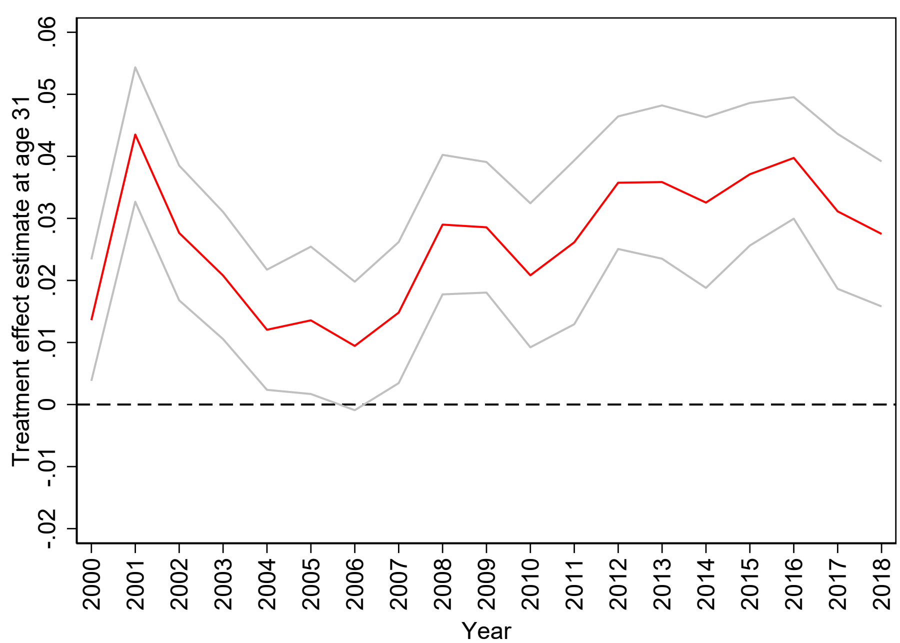


Model = m1, est = .0354, bw = 4, bias = -.0002, coverage = 0.984, alt. p-val = 0



Note: 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, the first deadline for LHC. Each panel shows the distribution of placebo estimates from the model selected using the KS model selection algorithm (see Table 1 for details). The red vertical line corresponds to the 97.5th percentile of the distribution. Model = m1 means the best model is linear RDD without controls; m3 means with controls. Bias is the average value of the placebo estimates. Coverage is the rate at which the placebo estimate fails to reject zero. Alt. p-val is the p-value based on the randomization inference approach described in KS.

Figure A13: RDD estimates for each year excluding incomes below the TFT: Age 31 penalty



Note: Alife 2018 release version that include tax return files from 2000 to 2018. Australians file taxes in financial years that run from July 1 to next June 30, so Alife 2000 covers July 1 1999 to June 30 2000, the first deadline for LHC. Each year corresponds to a separate RDD estimate. Grey lines are 95% asymptotic confidence intervals with standard errors clustered at the month of birth level. Further details on the estimates are in Table A4.

Table A4: RDD estimates for each year excluding income below the TFT: Age 31 penalty

Year	Estimate	Std. Error	Mean	Est./Mean	BW	Obs.	Poly. order	Controls
2000	0.0136	0.0049	0.3258	0.0417	3.64	149595	1	No
2001	0.0435	0.0055	0.4205	0.1035	3.96	161379	1	No
2002	0.0277	0.0055	0.3923	0.0705	3.96	160621	3	Yes
2003	0.0208	0.0052	0.3964	0.0525	3.88	159036	3	Yes
2004	0.0121	0.0049	0.4171	0.0289	3.56	147613	1	No
2005	0.0136	0.0060	0.4075	0.0333	3.56	147664	1	No
2006	0.0094	0.0052	0.4323	0.0218	3.96	161106	3	Yes
2007	0.0148	0.0057	0.4648	0.0319	3.56	148337	1	No
2008	0.0290	0.0057	0.4651	0.0624	3.96	168954	1	No
2009	0.0286	0.0053	0.4970	0.0575	3.96	171420	1	No
2010	0.0208	0.0058	0.4920	0.0423	3.48	156075	1	No
2011	0.0261	0.0066	0.4977	0.0525	3.56	167386	1	No
2012	0.0358	0.0054	0.5110	0.0700	3.56	174414	1	No
2013	0.0359	0.0062	0.5254	0.0683	3.88	192308	1	No
2014	0.0326	0.0069	0.6039	0.0539	3.40	176435	3	Yes
2015	0.0371	0.0058	0.5990	0.0620	3.48	184216	3	Yes
2016	0.0397	0.0049	0.5763	0.0690	3.88	204384	1	No
2017	0.0311	0.0063	0.5549	0.0561	3.40	185720	1	No
2018	0.0275	0.0059	0.5221	0.0527	3.64	201929	1	No

Note: Alife 2018 release including tax files 1999-2018. The sample excludes people with wage adjusted income below $18,200 AUD-2013. Wage inflation data are from the Australian Bureau of Statistics. 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 30 June 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 one-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 + one 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.

Table A5: 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%	60.44%	60.29%
Actual mean age	46.77	46.77	46.77
Counterfactual mean age	46.80	46.83	46.87
Mean premium reduction	$1.90	$4.47	$7.47

Note: Alife 2018 dataset. 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 PHI coverage by subtracting $k_i *$'treatment effect' ppts where k_i is a triangular weight with $k_{31} = 1$ and $k_{max\ age\ bring\ forward} = 0$. For each month-of-birth bin we calculate total premiums paid using average premium per person (supplied by insurers to the ATO) multiplied by the number of people. We assume that insurers retain 'revenue passed on' of premiums from those joining because of LHC as profits and then pass those profits on evenly through lower premiums, which gives the 'mean premium reduction'.