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Separating the Effects of Tax Penalties and Subsidies on Private Health Insurance Demand

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Separating the Effects of Tax Penalties and Subsidies on Private Health Insurance Demand*

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Abstract

We provide the first separate estimates of the independent demand effects of Australia's two main private health insurance (PHI) instruments: the Medicare Levy Surcharge (MLS), a tax penalty for uninsured higher-income individuals, and the PHI rebate, an income- and age-differentiated premium subsidy. Prior work estimated only bundled effects because the 2012 reform moved MLS and rebate thresholds jointly. We exploit the fact that rebate rates vary not just by income but, for given income, by age and over fiscal years, enabling separate GMM identification of MLS and rebate effects using administrative tax data from the Person Level Integrated Data Asset (2010–2020). Our jointly estimated effects allow us, for the first time, to assess the relative importance of penalty and subsidy incentives on PHI demand and fiscal balance. We present counterfactual experiments assessing budget-neutral simultaneous changes to both instruments that raise population PHI coverage. Our estimates are directly applicable to recent proposals to equalise PHI rebate rates across age groups: equalising at the under-65 rate would reduce PHI take-up among older Australians modestly, with fiscal savings accruing primarily through reduced payments to infra-marginal existing policyholders.

Keywords: private health insurance; tax-based penalty; rebates; Australia.
JEL classification: H51, I13, I18

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1 Introduction

Many high-income countries operate health systems that combine universal public coverage with an actively supported private health insurance (PHI) market, using financial incentives to shape private sector participation. Premium subsidies—or rebates—are the most widely used instrument to encourage PHI take-up, while income-linked tax penalties for the uninsured are comparatively rare (Kettlewell & Zhang 2024*b*). If penalties are shown to generate coverage through a distinct behavioural channel from subsidies, governments elsewhere may consider them as a complement to existing rebate programmes. Australia offers a uniquely valuable setting for this question: all residents receive free hospital treatment through Medicare, yet approximately 44 percent hold PHI for hospital services, obtaining greater physician choice, shorter waiting times for elective procedures, and access to private hospital facilities (Doiron & Kettlewell 2018, Colombo & Tapay 2004). To encourage PHI take-up, the Australian government operates two main financial instruments: a premium subsidy (the PHI rebate) and a tax penalty for uninsured high-income individuals (the Medicare Levy Surcharge, or MLS). The fiscal cost is considerable: the PHI rebate alone accounts for approximately AUD 7.6 billion in annual government expenditure (Butler 2025), representing one of the largest single items in the federal health budget. Whether these instruments independently achieve their coverage objectives—and whether combining a penalty with a rebate offers advantages over relying on rebates alone—remains unresolved, because no prior study has separately identified the demand effect of each instrument. The urgency of this question has recently increased: in April 2026 the Minister for Health announced a proposal to eliminate the age-differentiated rebate structure, standardising rates across age groups while retaining income-based variation (Butler 2026). Evaluating the coverage and fiscal consequences of this reform requires precisely the separate estimate of the rebate demand effect that existing studies have been unable to provide.

The MLS is an income-contingent tax penalty levied on high-income individuals who do not hold complying PHI: those above the income threshold face an additional levy of 1 to 1.5 percent of taxable income. The rebate is a direct subsidy on PHI premiums, reducing the out-of-pocket cost of coverage. Together, these instruments create a financial environment in which the effective price of PHI falls sharply for high-income earners relative to those below the MLS threshold. A landmark structural reform in 2012 simultaneously restructured both instruments: the MLS was converted from a flat-rate single-threshold scheme to a three-tier schedule, and the rebate was means-tested for the first time, phasing out entirely for the highest earners. This reform generated substantial quasi-experimental variation in both the penalty for non-insurance and the subsidy for insurance across the income distribution—variation we exploit to identify causal demand responses.

Despite the fiscal scale of these policies, identifying their independent demand effects is complicated by the high co-linearity of the policies, which share the same income thresholds. Rather than separately identifying each instrument's demand effect, prior studies have recovered only a bundled response. Early aggregate analyses such as Palangkaraya & Yong (2005) focused on the rapid sequence of policy introductions between 1997 and 2000—the MLS, the rebate, and Lifetime Health Cover were introduced within three years—but did not separate their individual contributions. Threshold-based analyses exploiting income discontinuities, including Stavrunova & Yerokhin (2014), Buchmueller et al. (2021), and Kettlewell & Zhang (2024*b*), estimate demand responses at the income cutoffs that trigger the MLS; but since the 2012 reform aligned the rebate means-testing thresholds with the same income cutoffs, each threshold simultaneously triggers a higher MLS rate and a lower rebate. These designs therefore also capture only the net bundled effect of both instruments changing together and cannot attribute the demand response separately to the penalty or the subsidy. Bilgrami et al. (2021) explicitly study the 2012 reform but face the same issue: their treated groups experienced simultaneous changes in both the MLS rate and the rebate entitlement, preventing separate identification. A second limitation shared by all panel studies is reliance on survey data that face sample-size constraints particularly acute near the income thresholds that generate identification, and that are subject to income measurement error which attenuates threshold-based estimates.

This paper addresses both problems. The key to separating the MLS and rebate effects is that the PHI rebate carries additional sources of variation that are orthogonal to income: age-differentiated and inflation-indexed rates. Since its introduction, the rebate has paid higher rates to older Australians—35 percent for those aged 65–69 and 40 percent for those aged 70 and above, compared to 30 percent for younger policyholders. These age-based rebate differentials, together with year-to-year variation in rebate rates arising from their indexation to private health insurance premiums and CPI growth, generate variation in the effective rebate rate that is independent of income and hence independent of MLS exposure. By combining income threshold variation—which identifies the bundled MLS-plus-rebate response at each income cutoff—with age-based and indexed rebate variation—which identifies the pure rebate demand effect—we recover separate demand elasticities for each instrument for the first time. We implement this strategy using a one percent random sample drawn from the Person Level Integrated Data Asset (PLIDA), a longitudinal administrative dataset linking Australian Taxation Office records, Medicare claims, and PHI status for the Australian resident population. The key advantage over existing survey-based analyses is measurement quality: taxable income — the central identifying variable — is recorded administratively from tax returns, eliminating the self-report measurement error that might be present in threshold-based estimates using survey data such as HILDA (Household, Income and Labour Dynamics in Australia). PHI status is likewise recorded administratively, removing recall bias. Apart from the quality of measurement, even our one percent random sample is one order of magnitude larger than typical sample sizes used in survey-based studies, which makes it possible to estimate the separate effects of PHI and rebates with high statistical precision. We estimate a dynamic panel model using the Generalised Method of Moments (GMM) to account for the strong state dependence documented in PHI, as individuals who hold PHI in one period are substantially more likely to hold it in the next, independent of contemporaneous price incentives. Our identifying variation comes from the 2012 reform, which restructured the income-threshold schedules for both instruments simultaneously, combined with continuous income variation across the MLS threshold schedule, as well as age-based variation and indexation in rebate rates that is orthogonal to income and MLS exposure.

Our main findings are as follows. The MLS exerts a moderate positive effect on PHI take-up: a one percentage-point increase in the MLS liability rate raises the probability of holding PHI by 2.44 percentage points for singles and 0.70 percentage points for families in the short run. The rebate effect is also positive and statistically significant: a one percentage point increase in the rebate rate raises PHI take-up by 0.093 percentage points for singles and 0.057 percentage points for families. Because a one percentage-point change in the MLS rate represents a much larger dollar amount than a one percentage-point change in the rebate rate, these coefficients are not directly comparable in magnitude. Evaluated at the MLS income threshold for singles, a rebate increase with the same dollar value as a one percentage-point increase in the MLS rate would raise PHI take-up by 3.28 percentage points, compared with 2.44 percentage points for the MLS increase itself. We estimate a state dependence parameter of approximately 0.449, implying that long-run demand responses are approximately 1.8 times the short-run effects. Using our estimates for a fiscal analysis, we calculate the government cost or surplus of various substitutions between the MLS and rebate rates that leave the demand for PHI constant, as well as cost-neutral substitutions that lead to increased demand. The possibility of fiscal savings is driven by the infra-marginal nature of the rebate: while changes in the MLS affect only the narrow group of uninsured MLS-liable individuals, rebates are paid to all existing policyholders, the majority of whom would have held cover regardless.

Our paper makes four contributions. First, we provide the first separate estimates of the independent demand effects of the MLS and the PHI rebate, exploiting age-based and inflation-indexed rebate rates as a source of variation orthogonal to income and MLS exposure. Second, we use PLIDA administrative data that records taxable income directly from lodged tax returns, eliminating the potential self-report measurement error in threshold-based estimates of existing HILDA-based analyses. Third, our compensating variation and fiscal analysis provide the first systematic evidence on the relative fiscal implications of adjusting the two instruments jointly, showing that the infra-marginal nature of the rebate means broad subsidy decreases can be offset by targeted penalty increases to keep PHI demand unaffected while producing a net fiscal gain. Fourth, our estimates are directly applicable to the April 2026 proposal to equalise rebate rates across age groups (Butler 2026), enabling quantitative predictions of the coverage and fiscal consequences of this reform.

The paper proceeds as follows. Section 2 describes the institutional setting and reviews the relevant literature. Section 3 presents the data and empirical framework. Section 4 reports our econometric estimates. Section 5 conducts fiscal and policy analysis. Section 6 concludes.

2 Background and literature review

2.1 Institutional setting

Australia's healthcare system combines universal public insurance with a large duplicate private market. Medicare, introduced in 1984, provides all residents with free hospital treatment, subsidised medicines, and subsidised doctor services. Despite universal coverage, approximately 44 percent of Australians hold PHI for hospital services, motivated by greater physician choice, shorter waiting times for elective procedures, and access to private hospital facilities (Doiron & Kettlewell 2018, Colombo & Tapay 2004). PHI is best characterised as duplicate insurance: it covers services also freely available under Medicare rather than filling gaps in public coverage (Colombo & Tapay 2004). Insurers operate under community rating—premiums cannot vary by health risk or prior utilisation—and PHI is not tied to employment, making Australia an unusually clean setting for demand estimation (Doiron & Kettlewell 2018). Waiting periods for pre-existing conditions may exceed one year, and for obstetric services may extend further, creating anticipatory demand among women planning to start families (Doiron & Kettlewell 2020).

To encourage PHI participation, the government operates three main financial instruments. The MLS, introduced in July 1997, levies an additional tax of 1–1.5 percent on high-income individuals without complying PHI cover; the single-person threshold began at \$50,000, was raised to \$70,000 in 2005, and indexed annually thereafter (reaching \$80,000 by 2011–12). The PHI rebate, introduced in January 1999, provides a direct premium subsidy. The rebate has always carried age-differentiated rates: 30 percent for those aged under 65, 35 percent for those aged 65–69, and 40 percent for those aged 70 and above (Table 1, Panel A). In April 2026, the government proposed eliminating this age differentiation, standardising the rebate within each income tier across all age groups (Butler 2026) — a reform whose demand and fiscal consequences our estimates are uniquely positioned to quantify. The Lifetime Health Cover (LHC) loading, introduced in July 2000, imposes a 2 percent premium surcharge for each year without PHI after age 31, up to a maximum of 70 percent (Kettlewell & Zhang 2024*a*).

A landmark reform effective 1 July 2012 simultaneously restructured both the MLS and the rebate: the MLS became a three-tier schedule—Tier 1 (incomes \$84K–\$97K in 2012–13, rate 1.0%), Tier 2

($97K–$130K, 1.25%), Tier 3 (above $130K, 1.5%, with thresholds subsequently indexed annually)—while the rebate was means-tested and reduced in line with MLS tiers, phasing out entirely at Tier 3 (Table 1, Panels A and B). The result is that income-based variation post-2012 simultaneously shifts both instruments for the same individuals. However, the age-based rebate differentials—which are orthogonal to income—remain independently informative about the rebate's causal demand effect, and can be used as a source of identifying variation. Moreover, rebate rates were adjusted yearly to PHI premiums and CPI growth from 2014-15 on while MLS rates have remained constant, providing additional longitudinal variation that can be exploited to separately estimate MLS and rebate effects.

2.2 Related literature

Research on PHI demand in Australia establishes that take-up rises sharply with income, is higher among couples, and exhibits both adverse and favourable selection through distinct preference channels (Cameron et al. 1988, Hopkins & Kidd 1996, Buchmueller et al. 2013, Doiron et al. 2008). Public hospital waiting times are a quantitatively important demand driver: longer expected waits increase PHI take-up independent of financial incentives (Johar et al. 2011). The holding of PHI also exhibits strong positive state dependence: individuals insured in one period are substantially more likely to hold cover in the next, arising from switching costs, inertia, and accumulating pre-existing conditions that raise the cost of re-entry (Handel 2013, Bolhaar et al. 2012). Doiron & Kettlewell (2020) estimate a state dependence parameter implying current coverage raises the probability of future coverage by approximately 25 percentage points. Failure to account for this persistence biases contemporaneous price effect (Buchmueller et al. 2021), motivating our dynamic GMM specification.

The causal effects of the MLS and rebate on PHI take-up have been studied using income threshold discontinuities and panel difference-in-differences. Using Australian Taxation Office (ATO) administrative data, Stavrunova & Yerokhin (2014) document significant bunching in taxable income at the MLS threshold and reduced non-insurance rates at the cutoff. Kettlewell & Zhang (2024*b*) apply a regression discontinuity design to a large administrative panel, estimating demand responses to the MLS threshold across both extensive and intensive margins. Buchmueller et al. (2021) provide widely-cited panel estimates using the HILDA survey, reporting a short-run MLS effect of approximately 14 percent for singles, but acknowledge that this includes the simultaneously changing rebate. Bilgrami et al. (2021) frame the 2012 reform as a natural experiment in which treated groups face changes in both MLS and rebate rates. Thus, all these studies are affected by the fundamental problem that, since the 2012 reform aligned rebate means-testing thresholds with the same income cutoffs as the MLS, income-based variation simultaneously captures a higher MLS rate and a lower rebate entitlement. Estimates from threshold or reform-based designs therefore recover the bundled net demand response to both instruments changing together; they cannot separate the independent contribution of the penalty from the subsidy. The early aggregate analysis of Palangkaraya & Yong (2005), which studied all three incentive policies introduced between 1997 and 2000, faces the same fundamental bundling problem.

Whether PHI subsidies generate offsetting public hospital savings is a key policy question. Cheng (2014) finds that the rebate is not self-financing: the reduction in public hospital utilization it generates falls short of its direct fiscal cost. Doiron & Kettlewell (2018) estimate a large substitution from public to private hospital admissions (approximately +16 percentage points private, −13 percentage points public), with a moderate net positive effect on total admissions of around 4 percentage points. Yang et al. (2024) find that a one percentage point increase in PHI coverage reduces public hospital waiting times for elective surgery by approximately 0.34 days on average, operating through substitution from public to private care; the effect is statistically significant but modest in practical magnitude, suggesting that changes in PHI coverage have broader welfare spillovers beyond the insured population. Our fiscal analysis in Section 5 extends this work to compare the cost-effectiveness of the MLS and rebate jointly.

This paper's contribution

Four contributions distinguish this paper. First, no prior study separately identifies the independent demand effects of the MLS and the PHI rebate. Existing analyses fall into three groups—those relying on time-series variation (Palangkaraya & Yong 2005), threshold-based panel analyses (Stavrunova & Yerokhin 2014, Buchmueller et al. 2021, Kettlewell & Zhang 2024*b*), and difference-in-differences (Bilgrami et al. 2021)—all of which recover a bundled MLS and rebate effect. We resolve this by exploiting the age-differentiated and inflation-indexed rebate rates as a source of rebate variation that is orthogonal to income and hence to MLS exposure. Combining this with income threshold variation allows us to recover, for the first time, separate demand elasticities for each instrument.

Second, the existing Australian panel literature on PHI demand largely relies on HILDA (Bilgrami et al. 2021, Buchmueller et al. 2021), which is subject to income measurement error that can produce misclassification in MLS liability and PHI status. Misclassification bias can produce complicated patterns of under- and over-estimation (Chen et al. 2021). PLIDA records taxable income directly from lodged tax returns and PHI status from the tax file, eliminating self-report error in both the key identifying variable and the outcome. This administrative measurement quality is particularly important for threshold-based identification, where spurious income misreporting around cutoffs can generate misleading demand responses.

Third, we provide the first fiscal comparison of the two instruments. Prior work has studied the fiscal cost of the rebate (Cheng 2014) or the demand effect of the MLS (Buchmueller et al. 2021, Kettlewell & Zhang 2024*b*) in isolation. By jointly estimating both effects and computing a compensating variation between the instruments, we quantify the fiscal implications of adjusting the two instruments jointly—an approach of direct relevance to ongoing debates about whether Australia should reduce or restructure the rebate.

Fourth, our estimates are directly applicable to the April 2026 proposal to equalise rebate rates across age groups (Butler 2026), enabling quantitative predictions of the coverage and fiscal consequences of this reform—an evaluation that requires precisely the separate rebate demand estimate that prior studies have been unable to provide.

3 Methods

3.1 Data and key variables

PLIDA administrative data

We use July 1 2010–June 30 2020 data from the Person Level Integrated Data Asset (PLIDA). PLIDA is a longitudinal dataset combining information on health, education, government payments, income and taxation, employment, and population demographics (including the Census). The data files we use in this paper are from the July 1 2010–June 30 2020 personal income tax return data (PIT). PIT data covers all tax filers in Australia (e.g., 13,444,382 individuals in 2011). Australians file taxes in financial years that run from 1 July to 30 June the following year, so the 2011–12 tax year covers the period immediately before the 2012 policy change, and the 2012–13 tax year covers the first year after. Our estimation sample therefore spans two pre-reform years and eight post-reform years. We end the sample in June 2020 (financial year 2019–20) to avoid the confounding effects of the COVID-19 pandemic, which caused substantial disruptions to health service use and insurance behaviour from 2020–21 onwards.

PHI indicator

Our outcome variable is a PHI indicator from the PIT file, recording whether the individual held PHI coverage for the full financial year. Because the Australian government uses tax incentives to encourage PHI enrolment, the PIT file tracks coverage status each year. Taxes are levied at the individual level in Australia and household members cannot be directly linked in the tax return data; we use the spouse's taxable income field to classify individuals as singles or families and to construct family income.

Figure 1 shows the proportion of Australian tax filers covered by PHI over our study period (solid line). Over the whole period, the share lies roughly in the middle between 50% and 60%, with little trending behaviour discernible. A modest increase can be seen after the reform year 2012. The figure also shows PHI coverage disaggregated by singles and families. Families have higher average coverage rates, with close to 70% over most of the period, while about 40% of singles were covered in the 2010 decade that we study. While both types of tax filers coverage shares are similarly flat, more families purchased PHI after 2012 (driving the modest aggregated increase) whereas singles coverage dipped somewhat after 2012 but returned to pre-2012 levels subsequently.

MLS liability and PHI rebate levels

We use income information (i.e., total taxable incomes) collected in the PIT to derive four indicators of liability for the MLS according to the thresholds detailed in Table 1: MLS0 for no MLS, MLS1 for tier 1 at 1%, MLS2 for tier 2 at 1.25%, and MLS3 for tier 3 at 1.5%. Previous to 2012, all three tiers coincide. As an illustration of the evolution of MLS liability, Figure 2 shows the share liable for MLS over time, for singles. While at the beginning of the period about 15% of singles are MLS-liable, this proportion dips to about 12% just after the reform. Wage growth and inflation bring the proportion up over time so that towards the end of the study period the share of singles liable is just under the value it was pre-reforms. Figure 2 also shows that the evolution of the share liable for MLS is nearly uniform across the three MLS tiers.

Finally, we also use the information on income in PIT to construct our second policy variable of interest, $rebate_{it}$, which indicates the theoretical rebate in percent that an individual or family is entitled to for their purchase of PHI coverage according to the thresholds documented in Table 1.

Sample

Descriptive figures are drawn from a 10 percent random sample of tax filers with positive income from PLIDA, which provides sufficient precision for characterising population-level trends in PHI coverage and MLS liability. GMM estimation is conducted on a 1 percent random sample, which yields approximately 130,000 individuals and remains substantially larger than the HILDA survey in the income ranges that generate identification; the smaller sample is used for computational tractability given the demands of the Arellano-Bond estimator on large panel datasets.

3.2 Econometric model and estimation

To estimate the separate effects of the Medicare Levy Surcharge (MLS) and the PHI rebate on insurance demand, we specify a dynamic linear probability model for holding PHI coverage. Our approach is closely related to the dynamic framework used by Buchmueller et al. (2021), who emphasise that PHI status exhibits substantial persistence over time due to switching costs, inertia, and the long-term nature of insurance decisions. Individuals who hold PHI in one year are considerably more likely to continue holding PHI in subsequent years, even after controlling for contemporaneous financial incentives and observable characteristics. Ignoring this state dependence would risk overstating the contemporaneous effect of policy variables.

Let PHI_{it} denote an indicator equal to one if individual i holds PHI in year t. We estimate the following stylised dynamic specification:

$$PHI_{it} = \beta_1 MLS_{it} + \beta_2 rebate_{it} + X_{it}'\gamma + \rho PHI_{it-1} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{1}$$

where MLS_{it} measures exposure to the Medicare Levy Surcharge and $rebate_{it}$ denotes the applicable PHI rebate rate. The vector X_{it} contains various time-varying demographic and socioeconomic controls (income, income squared, age, age squared, number of dependent children, occupation fixed effects based on first-digit occupational codes), which are discussed further below. The term α_i captures time-invariant unobserved individual heterogeneity, while δ_t denotes year fixed effects absorbing aggregate shocks and common policy changes affecting all individuals. The error term ε_{it} captures idiosyncratic shocks to PHI demand.

Persistence in PHI demand is captured by permanent unobserved heterogeneity (α_i) as well as state dependence through the lag in PHI. The value of its coefficient ρ quantifies this state dependence: a positive value of ρ implies that PHI status is persistent over time, consistent with the presence of switching costs, behavioural inertia, or long-term contractual relationships between consumers and insurers. In this framework, the coefficients β_1 and β_2 represent short-run policy effects, while the corresponding long-run effects are given by

$$\frac{\beta_1}{1-\rho} \qquad \text{and} \qquad \frac{\beta_2}{1-\rho}; \tag{2}$$

see also Buchmueller et al. (2021) for other intermediate effects derivable from this model.

A key econometric challenge is that transformations of model (1) that remove α_i lead to mechanical correlation between the lagged dependent variable PHI_{it-1} and the idiosyncratic error, rendering standard fixed-effects estimation inconsistent in short panels. To address this issue, we estimate equation (1) using the Arellano-Bond Generalised Method of Moments (GMM) estimator (Arellano & Bond 1991). The estimator first differences the model to eliminate the individual fixed effects:

$$\Delta PHI_{it} = \beta_1 \Delta MLS_{it} + \beta_2 \Delta rebate_{it} + \Delta X_{it}'\gamma + \rho \Delta PHI_{it-1} + \Delta\delta_t + \Delta\varepsilon_{it}, \tag{3}$$

where $\Delta W_{it} \equiv W_{it} - W_{it-1}$ for any variable W_{it}, and then instruments the differenced lagged dependent variable using deeper lags of PHI_{it} in levels, under the standard moment conditions that the error term exhibits no serial correlation beyond first order.

Identifying variation in the model comes, first, from the 2012 reform, which simultaneously altered the MLS schedule and introduced means-testing of the rebate. The MLS effect is identified through changes in surcharge exposure generated by the tiered income thresholds. The rebate effect is separately identified through age-based and inflation-indexing variation in rebate entitlements that is orthogonal to MLS exposure by construction. Because rebate rates differ systematically across age groups independently of taxable income, and indexing changed rebates rates during a period in which MLS rates remained constant, the model is able to separately recover the marginal effect of the subsidy from that of the tax penalty.

We estimate the model separately for singles and families, reflecting the distinct MLS thresholds and PHI decision environments applying to these groups. Standard errors are clustered at the individual level to account for serial correlation in unobserved determinants of PHI holding over time.

The control variables included in X_{it} are intended to capture observable sources of time-varying heterogeneity in PHI demand and control for an extensive set of characteristics that are commonly used in studies of health insurance demand (e.g. Cheng 2014 and Doiron et al. 2014; also see King & Mossialos 2005 for a review). More generally, many determinants of PHI demand commonly discussed in the literature are either time-invariant or common across individuals within a given year, and are therefore absorbed by the fixed effects structure of the model. For example, persistent preferences for private healthcare, risk aversion, long-run attitudes toward insurance, chronic health conditions, education, ethnicity, or stable aspects of socioeconomic background are captured by the individual fixed effects α_i. Similarly, aggregate macroeconomic conditions, nationwide changes in PHI market conditions, premium inflation, insurer competition, public hospital waiting times, and federal policy changes affecting all individuals in a given year are absorbed by the year fixed effects δ_t. The fixed-effects structure therefore substantially reduces the scope for omitted-variable bias arising from unobserved confounding factors that are constant over time or common across the population.

Two particularly important variables in X_{it} are taxable income and age, both of which enter flexibly through a second-order polynomial. Income is central to PHI demand both because PHI is a normal good and because MLS liability is directly tied to taxable income thresholds. Figure 3 illustrates the strong positive relationship between income and PHI coverage over time, with substantially higher PHI participation rates among individuals in the upper income deciles. Including both income and income squared allows the model to capture potentially nonlinear income gradients in PHI demand independently of the discrete policy effects generated by the MLS thresholds.

Age deserves particular attention because it plays two conceptually distinct roles in the identification strategy. First, age may independently affect PHI demand through lifecycle mechanisms. Older individuals typically face higher expected healthcare utilisation, greater perceived value from private coverage, and stronger preferences for reduced waiting times and provider choice. Figure 4 shows clear differences in PHI participation across age groups over time, with substantially higher coverage rates among older Australians. Our specification with linear and quadratic terms for age accounts for these potentially nonlinear lifecycle patterns.[1] Second, age determines eligibility for higher PHI rebate rates. Individuals aged 65–69 receive a larger rebate than younger adults, while those aged 70 and above receive a larger rebate still. Crucially, identification of the rebate effect does not rely on smooth age-related differences in PHI demand, which are controlled for directly through the flexible age polynomial. Instead, identification comes from the discrete jumps in rebate generosity occurring at the policy thresholds. Conditional on the underlying age profile captured by the age controls, these discontinuous changes in subsidy rates provide quasi-experimental variation that, together with the separate longitudinal variation in rebate vs MLS rates stemming from the inflation indexation of the former, identifies the marginal effect of the rebate independently of the MLS. These features of the institutional setting are central to our ability to separately estimate the effects of the tax penalty and the subsidy.

4 Results

This section presents the main estimation results for the effects of the Medicare Levy Surcharge (MLS) and the PHI rebate on private health insurance take-up. Results have been multiplied by 100 to be read directly as percentage points. We begin by presenting the sequential estimates for families and singles separately, illustrating how the estimated policy effects evolve as additional controls, fixed effects, and dynamics are introduced. We then present our preferred specification based on the dynamic GMM estimator.

Families

Table 2 reports the estimates for families. Columns (1)–(3) present progressively richer linear probability models, while column (4) reports the preferred Arellano-Bond GMM estimates incorporating state dependence. We discuss column (5) in detail further below. In the simple pooled specification shown in column (1), becoming liable for MLS Tier 1 is associated with a 29.1 percentage point increase in the probability of holding PHI, while the estimated rebate effect implies that a one percentage point increase in the rebate rate increases PHI participation by 0.46 percentage points. These estimates

[1] The linear age term is collinear with the individual and year fixed effects and is therefore dropped from specifications with year and individual fixed effects. We retain the linear age in estimations of specifications without fixed effects.

decline considerably once observable controls and fixed effects are introduced.

The preferred GMM estimates in column (4) indicate considerably smaller but still statistically significant effects. For families, MLS Tier 1 liability increases the probability of holding PHI by approximately 1.01 percentage points. The corresponding estimates for Tier 2 and Tier 3 are 0.73 and 0.21 percentage points respectively, though the Tier 3 effect is no longer statistically significant at conventional levels. The rebate effect is positive and statistically significant: a one percentage point increase in the rebate rate increases PHI participation by approximately 0.034 percentage points.

The lagged dependent variable enters strongly and positively across specifications. In the preferred model, the estimated coefficient on lagged PHI status is approximately 0.442, implying substantial persistence in insurance holding over time. This result is consistent with the presence of switching costs, inertia, or persistent preferences for private healthcare coverage.

The contrast between the pooled and dynamic fixed-effects estimates is economically informative. Specifications that fail to account for unobserved heterogeneity and state dependence attribute much of the persistent cross-sectional variation in PHI holding to contemporaneous policy incentives, thereby substantially overstating the short-run responsiveness of PHI demand to both the MLS and rebate.

Singles

Table 3 presents the corresponding estimates for singles. The overall pattern closely mirrors the results for families, though the estimated policy effects are consistently larger in magnitude. In the pooled specification, MLS liability is associated with very large increases in PHI participation. For example, liability for MLS Tier 1 is associated with a 41.9 percentage point increase in PHI coverage, while Tier 3 liability is associated with an increase exceeding 61 percentage points. As with the family estimates, however, these effects decline sharply once fixed effects and state dependence are incorporated.

The preferred GMM specification indicates that MLS Tier 1 liability increases PHI participation among singles by approximately 2.45 percentage points. The corresponding effects for Tiers 2 and 3 are 2.86 and 3.04 percentage points respectively. The estimated rebate effect is positive and statistically significant: a one percentage point increase in the rebate rate increases PHI participation by approximately 0.078 percentage points. The estimated persistence parameter is again large, with the coefficient on lagged PHI status equal to approximately 0.449.

Several patterns emerge from comparing singles and families. First, MLS responsiveness is consistently stronger among singles than among families. This likely reflects differences in insurance decision-making environments and institutional incentives. Family PHI decisions may be less sensitive to marginal financial incentives due to the joint nature of coverage decisions, the presence of dependent children, or stronger baseline preferences for insurance coverage. Second, the rebate effect is statistically significant for both groups. The raw rebate coefficient is numerically smaller than the MLS coefficient, but as we discuss in the elasticities section below, this comparison is not directly meaningful because the two instruments operate on very different dollar scales.

Elasticities for MLS and rebates

The preceding specifications modelled MLS exposure using three indicator variables corresponding to the three MLS tiers. This flexible specification allows the effect of MLS liability to vary non-parametrically across the policy schedule and provides a transparent description of how PHI participation differs across individuals exposed to different surcharge rates. However, for the fiscal simulations conducted in the next section, it is useful to summarise the MLS effect using a single continuous policy variable directly measuring the surcharge rate quantitatively.

We therefore re-estimate the preferred dynamic specification replacing the three tier indicators with a single variable, MLS_{it}, defined as the applicable MLS rate expressed as a percentage of taxable income. The variable takes the values 0, 1, 1.25, or 1.5 depending on the individual's income tier and filing status. The rebate variable continues to measure the applicable PHI rebate rate in percentage points. This formulation allows the coefficients to be interpreted directly as semi-elasticities of PHI participation with respect to the two policy instruments.

Columns (5) in Tables 2 and 3 report the resulting GMM estimates for families and singles, respectively. The estimates are quite stable across the specifications. For singles, a one percentage point increase in the MLS rate increases PHI participation by approximately 2.44 percentage points. For families, the corresponding estimates is 0.70 percentage points. Similarly, the rebate effects remain very similar across the specifications from columns (4) and (5). For singles, a one percentage point increase in the rebate increases PHI participation by approximately 0.093 percentage points in the specification of column (5). For families, the corresponding estimates is 0.057 percentage points.

Several conclusions emerge from these estimates. First, the persistence parameters imply that the long-run effects of permanent policy changes are substantially larger than the contemporaneous short-run effects. Across specifications, the estimated coefficient on lagged PHI status is approximately 0.45, implying a long-run multiplier of $1/(1-\hat{\rho}) \approx 1.8$. Consequently, the long-run impact of a permanent change in MLS rates or rebate generosity is approximately 80 percent larger than the corresponding short-run effect. This reinforces the importance of modeling PHI participation dynamically rather than treating insurance choices as static one-period decisions.

Second, while the estimated MLS coefficient is numerically larger than the rebate coefficient, the two are not directly comparable in percentage-point terms. A one percentage-point increase in the MLS rate represents an additional annual tax liability equal to one percent of taxable income. By contrast, a one percentage-point increase in the rebate rate reduces the annual premium cost by one percent. To make the magnitude comparable across MLS and rebate, we express them in dollar value. Let c_{it} denote the annual PHI premium of individual i in year t, and y_{it} is i's taxable income in t. Then, the rebate effect with the same dollar value corresponding to the one-percentage-point MLS effect β_1 is $\beta_2 \times y_{it}/(100c_{it}) \times 100\% = \beta_2 \times y_{it}/c_{it}\%$. As an example, consider an individual with $y_{it} = \$90,000$, which is the marginal income for MLS liability from 2014-15 on, and let $c_{it} = \$2,553$, which is the value of the average premium paid by MLS liable individuals in 2018 in the data. Then, to have the same dollar value as a one-percentage-point increase in the MLS rate, the corresponding rebate rate would have to increase by 35.25 percentage points ($= y_{it}/c_{it} \times 100\%$) and would have an effect of increasing PHI by 3.28 percentage points ($= 0.093 \times 90,000/2,553\%$). Thus, converting to a common dollar scale, the effective per-dollar demand responses of the two instruments are considerably closer in magnitude than the raw coefficients suggest. If anything, the behavioural responsiveness is slightly larger for rebates than for MLS.

Finally, our estimates can be compared with those of Buchmueller et al. (2021), who estimate the effect of MLS liability using HILDA survey data. While the specifications are not identical, the estimated magnitudes are broadly comparable once the policy variables are expressed on a common scale. Whereas Buchmueller et al. (2021) estimate a single indicator for MLS liability, our preferred specification uses either separate indicators for the three MLS tiers or a quantitative measure of the MLS rate. Evaluated at the average MLS rate of approximately 1.2 percent, our elasticity estimates imply effects of around 0.84 percentage points for families and 2.9 percentage points for singles, compared with estimates of approximately 1.5 and 1.1 percentage points, respectively, reported by Buchmueller et al. (2021). The principal difference between the studies therefore lies less in the magnitude of the estimated effects than in their precision. The substantially larger PLIDA sample, together with the use of administrative rather than self-reported income data, yields considerably smaller standard errors and allows us to estimate statistically significant tier-specific and rate-specific MLS effects. More importantly, the increased precision makes it possible to separately identify the effects of the MLS and the PHI rebate. Whereas Buchmueller et al. (2021), and the wider literature, estimate a joint response to the two highly correlated policy instruments, our approach exploits independent variation in rebate rates to recover separate demand effects for the MLS and rebate for the first time.

5 Fiscal and Policy Analysis

This section evaluates some fiscal and policy implications of the two principal PHI policy instruments: the Medicare Levy Surcharge (MLS) and the PHI premium rebate. Using the demand estimates from

Section 4, we first quantify the extent to which the two instruments can substitute for each other in maintaining PHI coverage, and we conduct a back-of-the-envelope fiscal exercise comparing their relative cost-effectiveness. The analysis builds directly on the estimated short-run policy effects obtained from the dynamic panel specification. We conclude by discussing fiscal implications of equalising the rebate rates across age groups.

5.1 Compensating variation between the MLS and rebate

The separate identification of the MLS and rebate effects allows us to consider two types of natural policy questions. The first consists of how to achieve a given amount of government spending or saving through changes in the two policy instruments, under the constraint that aggregate PHI demand remain constant. The second consists of how to achieve budget-neutral increases or reductions in the demand for PHI through changes in the instruments. The answer to such questions rests on the compensating variation (CV) between the two instruments.

Let the probability of holding PHI be given by

$$P(PHI_{it} = 1) = \beta_1 MLS_{it} + \beta_2 rebate_{it} + X'_{it}\gamma + \rho PHI_{it-1} + \alpha_i + \delta_t, \tag{4}$$

where the probability is conditional on $\{MLS_{it}, rebate_{it}, X_{it}, PHI_{it-1}, \alpha_i, \delta_t\}$, but we suppress this in the notation to avoid clutter. A policy change that leaves PHI take-up unchanged must satisfy

$$\Delta P(PHI = 1) = \beta_1 \Delta MLS + \beta_2 \Delta rebate = 0. \tag{5}$$

Solving for the rebate adjustment required to compensate for a change in the MLS yields

$$CV = \frac{\Delta rebate}{\Delta MLS} = -\frac{\beta_1}{\beta_2}. \tag{6}$$

Using the preferred GMM estimates for singles reported in column (5) of Table 3, we obtain $CV = -2.439/0.093 = -26.22$. This estimate implies that a one percentage point reduction in the MLS rate would require approximately a 26.2 percentage point increase in the rebate rate to maintain PHI coverage among singles. Note that the CV is smaller than the dollar-value-equalised rebate rate change calculated in the previous section, which was 35.25 percentage points. That is, the change in the rebate rate required to keep demand constant (26.2 p.p.) is smaller than the rebate rate change required to compensate an MLS-paying individual (35.25).

The compensating variation (6) describes the rebate increase required for individuals directly affected by the MLS. However, MLS policy changes apply only to the share of the population above the MLS threshold, whereas rebate changes can be applied broadly across PHI holders. It is therefore useful to derive a population-adjusted compensating variation.

Let m denote the share of the population liable for the MLS. Then the rebate adjustment required to offset a change in the MLS at the population level is

$$\Delta rebate = -\frac{\beta_1}{\beta_2} m \Delta MLS \quad \Rightarrow \quad CV^{pop} = -\frac{\beta_1}{\beta_2} m \tag{7}$$

In the data, approximately 19.5 percent of singles are liable for the MLS ($m_s = 0.195$). Consider a decrease in the MLS rate of 1 percentage point. Using the estimated CV (6) applied to singles implies that PHI participation among the MLS-liable population could be maintained by increasing the rebate by 26.22. However, when expressed as a uniform rebate increase applied population-wide, the required increase falls to approximately $CV^{pop} = -0.195 \times 2.439/0.093 = 5.11$ percentage points. This distinction is important for policy design. Although the MLS is highly targeted, the rebate is not. As a consequence, replacing the MLS with higher rebates necessarily subsidises a much broader population than the group whose behaviour is directly affected by the MLS.

5.2 Fiscal Implications of Alternative PHI Policies

We now examine the fiscal consequences of alternative combinations of MLS and rebate policies. The objective is not to construct a full structural model of the PHI market, but rather to provide a transparent accounting framework that combines the estimated demand elasticities from Section 4 with observed administrative data on PHI coverage, premiums, and taxable income. Throughout this subsection we focus on short-run effects and on single individuals, for whom all quantities required for calibration are directly observable. Analogous calculations for families would require information on family-level PHI premiums that are not readily available. Singles account for approximately 57.6 percent of Australian tax filers (Australian Taxation Office 2024), making them a useful benchmark group for illustrating the fiscal mechanisms.

Our analysis adopts a partial-equilibrium perspective. We assume that policy changes affect PHI participation through the estimated demand elasticities, but do not alter the underlying population composition. In particular, the proportion of singles in the population, the proportion of individuals above the MLS thresholds, average taxable incomes, and average PHI premiums are treated as fixed. These assumptions are likely to be reasonable for the moderate policy changes considered below, although they may become less accurate for very large reforms that potentially could substantially alter behaviours such as truthful reporting of taxable income or civil status.

Let σ denote the MLS rate and ϱ the rebate rate. Net expected per-capita government expenditure associated with PHI policy is defined as

$$C(\sigma, \varrho) = E(\sigma, \varrho) - R(\sigma, \varrho), \tag{8}$$

where $R(\sigma, \varrho)$ denotes government per-capita revenue collected through the MLS and $E(\sigma, \varrho)$ denotes government per-capita expenditure on PHI rebates. Government revenue from the MLS is given by

$$R(\sigma, \varrho) = m_s \left[1 - p_s^{MLS}(\sigma, \varrho)\right] y_s^{MLS} \sigma, \tag{9}$$

where m_s is the proportion of singles liable for the MLS, $p_s^{MLS}(\sigma, \varrho)$ is the PHI participation rate among MLS-liable singles, and y_s^{MLS} is average taxable income among MLS-liable singles. Government expenditure on PHI rebates is given by

$$E(\sigma, \varrho) = \varrho \left[(1 - m_s) p_s^{NO}(\varrho) c_s^{NO} + m_s p_s^{MLS}(\sigma, \varrho) c_s^{MLS}\right], \tag{10}$$

where $p_s^{NO}(\varrho)$ denotes PHI participation among singles not liable for the MLS, while c_s^{NO} and c_s^{MLS} denote average annual PHI premiums paid by non-MLS-liable and MLS-liable singles, respectively. The model is calibrated using observed values from the ATO administrative data for 2018:

$$\begin{aligned} m_s &= 0.195, \quad p_s^{NO} = 0.364, \quad p_s^{MLS} = 0.804, \quad y_s^{MLS} = 118,988, \\ c_s^{NO} &= \$2{,}151, \quad c_s^{MLS} = \$2{,}553, \quad \bar{\sigma} = 0.012, \quad \bar{\varrho} = 0.258. \end{aligned}$$

These values imply that approximately 19.5 percent of singles are liable for the MLS, that PHI coverage among MLS-liable singles exceeds 80 percent, and that average PHI premiums are about 20 percent higher for MLS-liable than for non-liable individuals.

Reforms are defined by changes in the MLS and rebate rates $(\Delta\sigma, \Delta\varrho)$, and we evaluate their per-capita fiscal impact by $\Delta C = C(\bar{\sigma} + \Delta\sigma, \bar{\varrho} + \Delta\varrho) - C(\bar{\sigma}, \bar{\varrho})$ where $C(\cdot, \cdot)$ is defined in (8). Changes in p_s^{MLS} and p_s^{NO} are given by the total derivative of (1) with respect to MLS_{it} and $rebate_{it}$; that is, $\Delta p_s^{MLS}(\Delta\sigma, \Delta\varrho) = \beta_1 \Delta\sigma + \beta_2 \Delta\varrho$, and we replace the coefficients β_1 and β_2 with estimates from Table 3, Column (5). To obtain aggregate figures, we scale the per-capita values to the approximately $15,100,000 \times 0.576 \approx 8,700,000$ single tax filers in Australia.

We first consider a PHI-neutral, fiscally expansionary reform consisting of a reduction in the MLS rate of one percentage point combined with a five percentage point increase in the rebate rate; see Table 4, reform (1). As shown in Section 5.1, this policy combination approximately preserves aggregate

PHI participation among singles as the ratio of changes is approximately equal to $CV^{pop} = 5.11$. The reform is fiscally expansive because reducing penalties and increasing subsidies both affect the government budget negatively. Applying the calibrated model, the increase in rebate expenditure amounts to approximately \$53.64 per single tax filer, while the reduction in MLS revenue amounts to approximately \$26.42, resulting in a net government expenditure of \$80.06 per single tax filer. This translates into an increase in annual government expenditure of roughly AUD \$696 million, which represents approximately 9.16 percent of current annual PHI rebate expenditure of AUD \$7.6 billion. The reverse contractionary reform — increasing the MLS rate by one percentage point while reducing rebates by five percentage points, Table 4 reform (2) — produces an approximately symmetric fiscal gain of AUD \$695 million among singles.

The contrast between reforms (3) and (4) helps explain the large fiscal effects of the PHI-neutral reforms in rows (1) and (2). Reform (3), which reduces the rebate by five percentage points without changing the MLS, lowers PHI coverage by approximately 0.46 percentage points but generates fiscal savings of around AUD \$466m. Reform (4), which increases the MLS rate by one percentage point while holding the rebate fixed, increases PHI coverage by approximately 0.48 percentage points and simultaneously generates fiscal savings of around AUD \$229m. The asymmetry arises because rebate changes are largely infra-marginal. While a one percentage point MLS reduction affects only the approximately 3.8 percent of singles who are both MLS-liable and uninsured, a one percentage point rebate increase is paid to all PHI holders — roughly 45 percent of singles — the majority of whom would have held cover regardless of the reform. Consequently, reductions in the MLS and increases in the rebate are both fiscally costly, whereas increases in the MLS and reductions in the rebate are both fiscally beneficial.

Rows (5) and (6) report approximately budget-neutral reforms. Reform (5) combines a one percentage point increase in the MLS rate with a 2.455 percentage point increase in the rebate rate, while reform (6) doubles both changes. By construction, the additional rebate expenditure is almost exactly offset by increased MLS revenue, leaving the overall fiscal position essentially unchanged. Nevertheless, both reforms increase PHI participation. Reform (5) raises PHI coverage among singles by approximately 0.70 percentage points, while reform (6) raises it by 1.41. These results illustrate that it is possible to increase PHI take-up without increasing net government expenditure, provided that subsidy increases are accompanied by sufficiently large increases in the MLS. More generally, they suggest that reallocating policy effort away from broad-based subsidies and towards targeted penalties can improve the cost-effectiveness of policies designed to encourage PHI participation.

5.3 Policy application: equalising rebates across age groups

Our estimates also bear directly on the April 2026 government proposal to standardise PHI rebate rates across age groups, eliminating the higher rates currently paid to individuals aged 65–69 and 70 and above (Butler 2026). Under the current Rebate Adjustment Factor, the effective Tier 0 rates are approximately 25.1 percent for those aged under 65, 29.2 percent for those aged 65–69, and 33.4 percent for those aged 70 and above. Equalising at the under-65 rate would reduce rebates by approximately 4 percentage points for those aged 65–69 and 8 percentage points for those aged 70 and above.

Applying our estimated rebate semi-elasticity of $\hat{\beta}_2 = 0.093$ percentage points per one percentage point change in the rebate rate for singles, the reform would reduce PHI take-up among singles aged 65–69 by approximately 0.39 percentage points in the short run and 0.71 percentage points in the long run. For singles aged 70 and above, the corresponding reductions are approximately 0.78 and 1.42 percentage points. Effects for families are smaller given the lower family rebate semi-elasticity of 0.057. These predicted reductions are modest, suggesting that equalising rebates across age groups would not cause a substantial exit from PHI among older Australians. For instance, we estimate that in the long run between 14,821 and 42,498 individuals would drop their PHI coverage using ancillary official statistics.[2]

Critically, the fiscal saving from this reform operates through the infra-marginal channel: the government reduces rebate payments to all existing older PHI holders, not only those at the margin of dropping coverage. The saving per insured individual aged 65–69 is approximately 4 percent of their annual premium; for those aged 70 and above it is approximately 8 percent. Since older policyholders tend to hold higher-value policies, aggregate fiscal savings may be proportionally larger than for younger age groups. Again using additional published statistics, we project savings of about $730 million to $940 million a year by 2028-29.[3] We note that our $\hat{\beta}_2$ is estimated from the full age distribution; if older Australians are less price-sensitive than younger ones (Liu & Zhang 2022), the true coverage reduction for this group may be even smaller than our projections.

6 Conclusions

This paper studies the separate effects of Australia's two main financial incentives for private health insurance: the Medicare Levy Surcharge (MLS) and the PHI premium rebate. Although both in-

[2] This band uses 95% confidence intervals for the two rebate semi-elasticities, projected insured population for 2028-2029 in the relevant age brackets from Department of Health, Disability and Ageing (2026), and an estimated partnering rate for older individuals from Australian Institute of Health and Welfare (2024).

[3] These numbers use population and rebate cuts from Department of Health, Disability and Ageing (2026), hospital and extras cover population by age from Australian Prudential Regulation Authority (2026), and hospital premiums from Australian Government Department of Health and Aged Care (2023).

struments are central to Australia's mixed public–private health financing system, their independent effects have been difficult to identify because MLS liability and rebate entitlement are closely linked to taxable income. We address this problem by combining income-threshold variation in MLS exposure with age-based and inflation-indexed variation in rebate rates, using longitudinal administrative data from PLIDA. The results show that both instruments have moderate, statistically significant effects on PHI take-up. In the preferred dynamic specification, a one percentage point increase in the MLS rate raises PHI participation by 2.44 percentage points for singles and 0.70 percentage points for families in the short run. The corresponding rebate effects are 0.093 percentage points for singles and 0.057 percentage points for families. While these coefficients differ substantially in percentage-point terms, they are not directly comparable because a one percentage point change in the MLS rate and a one percentage point change in the rebate rate correspond to very different dollar amounts. When evaluated at equivalent dollar values, the implied demand responses of the two instruments are of broadly comparable magnitude. Strong state dependence in PHI holding implies that long-run effects are approximately 1.8 times the short-run estimates.

Several limitations should be kept in mind. First, while age-based rebate variation provides a source of identification orthogonal to MLS income thresholds, the age gradient in PHI take-up also reflects health-related demand and LHC loading accumulation. We address this by including age and age-squared controls and by restricting the rebate-identifying variation to changes in the age-differentiated rates rather than cross-sectional age differences. Second, year-to-year income fluctuations—which generate variation in MLS liability within individuals over time—may partly reflect transitory income shocks rather than permanent income changes, potentially attenuating our within-person MLS estimates. Third, our PHI indicator captures full-year hospital cover only; partial-year coverage and transitions within the year are not observed. Finally, the fiscal simulations are partial-equilibrium exercises that hold population composition, taxable incomes, and premiums fixed; they are therefore most informative for moderate reforms rather than large-scale policy redesign.

The empirical approach developed in this paper opens the door to policy analysis that is not possible when the MLS and rebate effects are estimated only as a bundled response. By separately estimating the demand effects of the tax penalty and the subsidy, we can evaluate PHI-neutral, budget-neutral, deficit-increasing, and deficit-reducing combinations of the two instruments. The fiscal analysis shows that replacing MLS reductions with broad rebate increases is costly because rebate payments are largely infra-marginal: they are paid to all PHI holders, many of whom would remain insured without the additional subsidy. Conversely, increasing the MLS while reducing or holding fixed the rebate can increase PHI participation while improving or preserving the fiscal position. The broader policy implication is that the MLS is a more fiscally targeted instrument for encouraging PHI take-up, whereas the rebate delivers more diffuse support at a higher fiscal cost per additional insured person. More generally, the paper demonstrates how large-scale administrative tax data can be used to disentangle the effects of closely related policy instruments and thereby improve the evidence base for the design and evaluation of health insurance policy.

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Figures

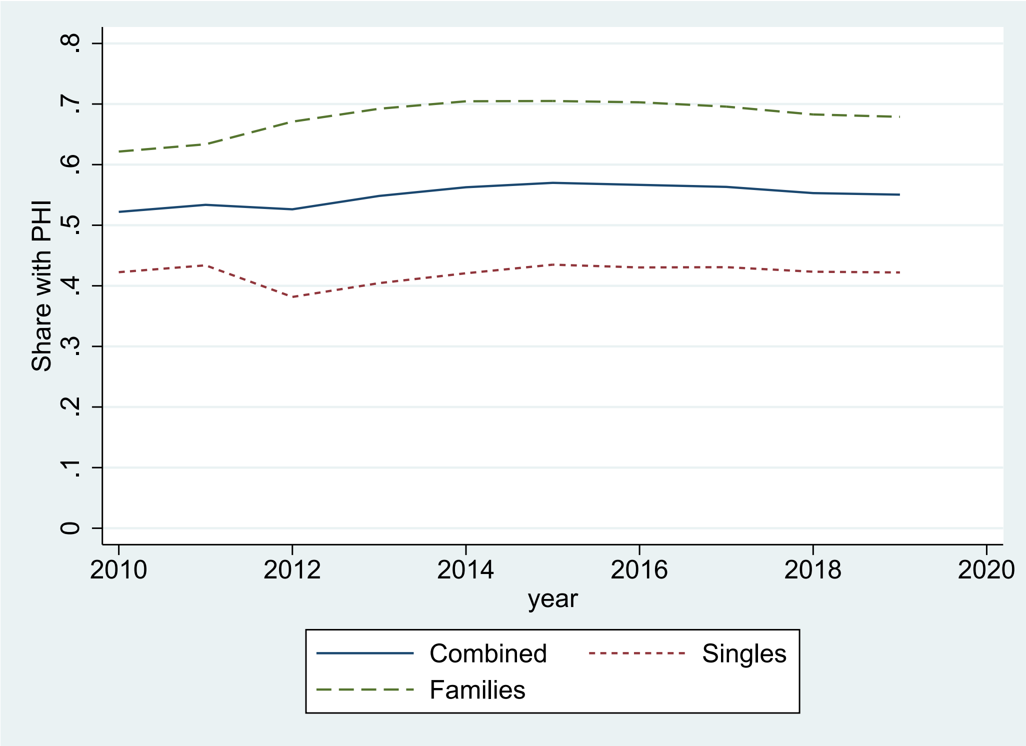

Figure 1: Share with Private Health Insurance (2010/2011 — 2019/2020)

Notes: Lines show the share of tax filers holding private hospital insurance cover in each financial year, separately for all filers, singles, and families. A family is defined as an individual with a non-missing spouse taxable income in the PIT file. *Source*: PLIDA ATO (FY10/11–19/20) 10% random sample; own calculations.

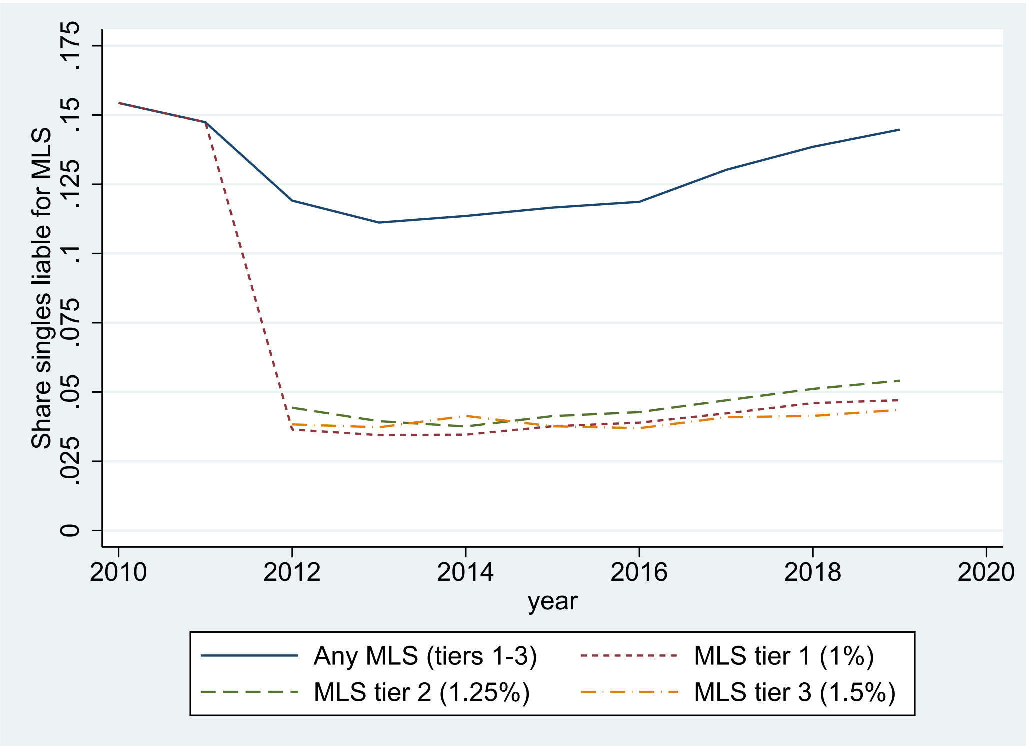

Figure 2: Share liable for Medicare Levy Surcharge (2010/2011 — 2019/2020)

Notes: Each line shows the share of singles whose taxable income falls in each MLS tier (Tier 1: 1% surcharge; Tier 2: 1.25%; Tier 3: 1.5%) in a given financial year. The 2012–13 reform introduced the three-tier schedule; pre-reform, a single threshold applied. *Source*: PLIDA ATO (FY10/11–19/20) 10% random sample; own calculations.

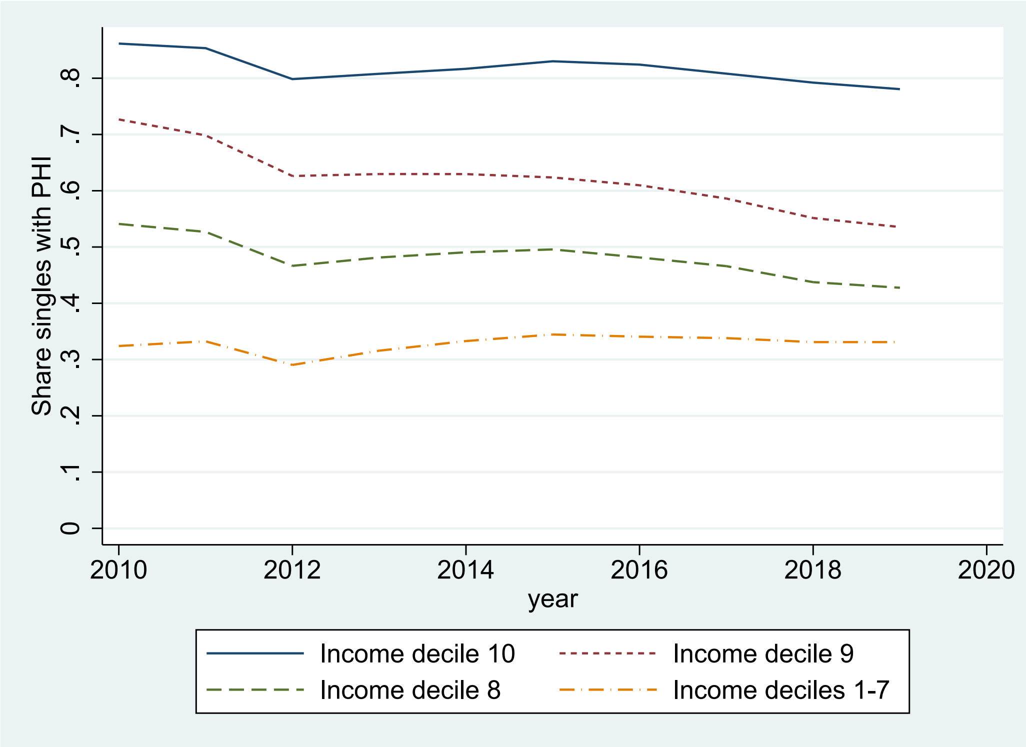

Figure 3: Share with Private Health Insurance: By income (2010/2011 — 2019/2020)

Notes: Each line shows the share of tax filers holding PHI in each financial year for a given taxable income decile. Income deciles are computed separately for each year. Vertical dashed lines indicate the MLS income threshold (Tier 1) for singles in the corresponding year. ***Source***: PLIDA ATO (FY10/11–19/20) 10% random sample; own calculations.

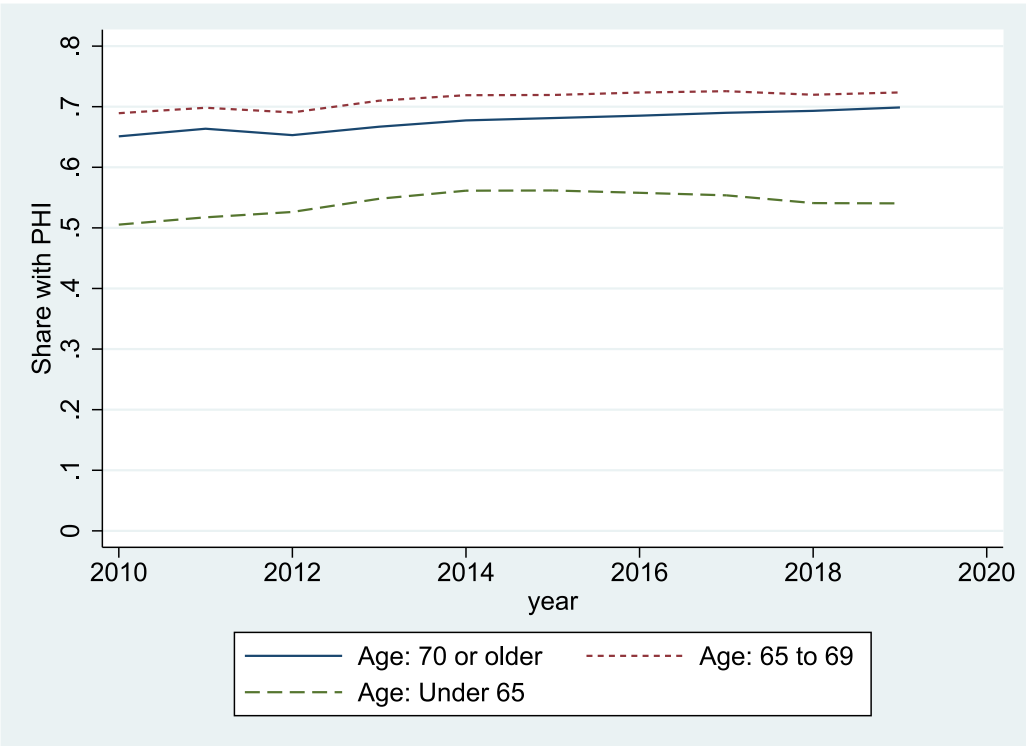

Figure 4: Share with Private Health Insurance: By age (2010/2011 — 2019/2020)

Notes: Each line shows the share of tax filers holding PHI in each financial year for a given age group. Age groups correspond to the PHI rebate rate thresholds: under 65 (base rebate rate), 65–69 (higher rebate rate), and 70 and above (highest rebate rate). ***Source***: PLIDA ATO (FY10/11–19/20) 10% random sample; own calculations.

Tables

Table 1: Medicare Levy Surcharge and PHI Rebate policy parameters

			PHI Rebate (%)		
Income group	Threshold ($'000)	MLS (%)	Age <65	Age 65–69	Age 70+
Panel A: Policy structure					
Pre-reform: 2010–11 (threshold $77K) and 2011–12 (threshold $80K)					
Below threshold		0.00	30	35	40
Above threshold		1.00	30	35	40
Post-reform: 2012–13 (shown); thresholds indexed in 2013–14, frozen 2014–15 onwards[a]					
Tier 0	<84	0.00	30	35	40
Tier 1	84–97	1.00	20	25	30
Tier 2	97–130	1.25	10	15	20
Tier 3	≥130	1.50	0	0	0
Panel B: Base tier (Tier 0) rebate rates and income threshold by financial year[b]					
FY	Threshold ($'000)	MLS (%)	Age <65	Age 65–69	Age 70+
2010–11	<77	0.00	30.000	35.000	40.000
2011–12	<80	0.00	30.000	35.000	40.000
2012–13	<84	0.00	30.000	35.000	40.000
2013–14	<88	0.00	30.000	35.000	40.000
2014–15	<90	0.00	29.040	33.880	38.720
2015–16	<90	0.00	27.820	32.457	37.094
2016–17	<90	0.00	26.791	31.256	35.722
2017–18	<90	0.00	25.934	30.256	34.579
2018–19	<90	0.00	25.415	29.651	33.887
2019–20	<90	0.00	25.059	29.236	33.413

[a] Post-reform MLS thresholds: Tier 0/1/2/3 boundaries were $84/97/130K in 2012–13, $88/102/136K in 2013–14, and frozen at $90/105/140K from 2014–15 to 2022–23. Family thresholds are approximately twice the singles thresholds shown.
[b] Rates shown are as of 1 July each year. From April 2014, a Rebate Adjustment Factor was applied each April, slightly reducing rates mid-year. Tier 1 and Tier 2 rebates equal the Base tier rate minus approximately 10 and 20 percentage points respectively at introduction, subsequently indexed at the same annual rate. Tier 3 rebate is always 0%. Sample period: 2010–11 to 2019–20.

Table 2: Results for families: Estimates of linear probability models for PHI (×100)

	(1)	(2)	(3)	(4)	(5)
MLS: Tier 1 (=1 if liable)	29.144***	22.832***	3.270***	1.013***	
	(0.211)	(0.640)	(0.204)	(0.160)	
MLS: Tier 2 (=1 if liable)	34.269***	23.548***	2.177***	0.730***	
	(0.221)	(0.629)	(0.249)	(0.188)	
MLS: Tier 3 (=1 if liable)	40.847***	24.000***	0.697*	0.208	
	(0.283)	(0.845)	(0.353)	(0.238)	
MLS (×100)					0.697***
					(0.135)
Rebate (×100)	0.460***	0.630***	0.074*	0.034*	0.057***
	(0.017)	(0.131)	(0.030)	(0.014)	(0.014)
PHI_{t-1}				44.239***	44.286***
				(0.609)	(0.608)
Control variables[1]		✓	✓	✓	✓
Fixed effects[2]			✓	✓	✓
Estimator	OLS	OLS	OLS	GMM	GMM
Observations	722,291	466,859	466,859	321,285	321,285

Notes: The dependent variable is an indicator for PHI coverage, multiplied by 100 so coefficients are in percentage points. MLS tier indicators equal one if the individual's taxable income falls in the respective tier (see Table 1 for thresholds). In column (5), MLS is the applicable surcharge rate (0, 1, 1.25, or 1.5 percent of taxable income), measured as a continuous variable. Rebate is the applicable annual rebate rate in percentage points. Columns (1)–(3) report OLS estimates with progressively richer controls and fixed effects; columns (4)–(5) report Arellano-Bond GMM estimates with individual and year fixed effects. Standard errors are clustered at the individual level. * $p < 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.
N= 112,231 unique individuals. $\overline{PHI} = 0.6805$. Share liable for any MLS tier: $\overline{MLS1} + \overline{MLS2} + \overline{MLS3} = 0.1271$.
[1]Income, income sq., age, age sq., no. of dependent children, first-digit-occupation-code fixed effects.
[2]Individual and year fixed effects.
Source: PLIDA ATO (FY10/11–19/20) 1% random sample; own calculations.

Table 3: Results for singles: Estimates of linear probability models for PHI (×100)

	(1)	(2)	(3)	(4)	(5)
MLS: Tier 1 (=1 if liable)	41.916***	27.438***	7.362***	2.451***	
	(0.317)	(0.570)	(0.397)	(0.384)	
MLS: Tier 2 (=1 if liable)	49.817***	32.337***	8.789***	2.863***	
	(0.585)	(0.897)	(0.660)	(0.514)	
MLS: Tier 3 (=1 if liable)	61.264***	32.546***	7.308***	3.038***	
	(0.812)	(1.443)	(0.993)	(0.777)	
MLS (×100)					2.439***
					(0.359)
Rebate (×100)	0.406***	0.364***	0.074*	0.078**	0.093***
	(0.027)	(0.048)	(0.033)	(0.027)	(0.023)
PHI_{t-1}				44.899***	44.899***
				(0.878)	(0.878)
Control variables[1]		✓	✓	✓	✓
Fixed effects[2]			✓	✓	✓
Estimator	OLS	OLS	OLS	GMM	GMM
Observations	671,165	351,944	351,944	176,616	176,616

Notes: The dependent variable is an indicator for PHI coverage, multiplied by 100 so coefficients are in percentage points. MLS tier indicators equal one if the individual's taxable income falls in the respective tier (see Table 1 for thresholds). In column (5), MLS is the applicable surcharge rate (0, 1, 1.25, or 1.5 percent of taxable income), measured as a continuous variable. Rebate is the applicable annual rebate rate in percentage points. Columns (1)–(3) report OLS estimates with progressively richer controls and fixed effects; columns (4)–(5) report Arellano-Bond GMM estimates with individual and year fixed effects. Standard errors are clustered at the individual level. * $p < 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.
N= 138,406 unique individuals. $\overline{PHI} = 0.4199$. Share liable for any MLS tier: $\overline{MLS1} + \overline{MLS2} + \overline{MLS3} = 0.1948$.
[1]Income, income sq., age, age sq., no. of dependent children, first-digit-occupation-code fixed effects.
[2]Individual and year fixed effects.
Source: PLIDA ATO (FY10/11–19/20) 1% random sample; own calculations.

Table 4: Fiscal estimates of alternative PHI policies for single tax filers

Reform			Per-capita changes			Aggregate changes	
No.	$\Delta\sigma$	$\Delta\varrho$	ΔE	ΔR	ΔC	ΔC	ΔPHI
(1)	-1.00	5.00	53.64	-26.42	80.06	696.32m	-0.01
(2)	1.00	-5.00	-53.62	26.33	-79.95	-695.33m	0.01
(3)	0.00	-5.00	-53.59	0.01	-53.61	-466.24m	-0.46
(4)	1.00	0.00	0.03	26.30	-26.27	-228.50m	0.48
(5)	1.00	2.455	26.28	26.29	-0.01	-0.07m	0.70
(6)	2.00	4.90	52.46	52.46	-0.00	-0.03m	1.41

Notes: Reforms are defined by changes in the MLS rate ($\Delta\sigma$) and the rebate rate ($\Delta\varrho$) expressed in percent ($\times 100\%$). Changes in government expenditures (ΔE), revenues (ΔR) and net cost ($\Delta C = \Delta E - \Delta R$), are expressed in 2018 Australian dollars. 'm' stands for million. Changes in aggregate PHI coverage of singles (ΔPHI) are expressed in percent ($\times 100\%$). PHI demand elasticity parameters used for calculations based on estimates from Table 3, column (5).
Source: PLIDA ATO (FY10/11–19/20); own calculations.

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