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Tax Incentives and the Demand for Private Health Insurance

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Abstract

This paper studies the effect of an individual insurance mandate (Medicare Levy Surcharge) on the demand for private health insurance (PHI) in Australia. It uses the administrative income tax returns data to show that mandate has several distinct effects on taxpayers' behavior. First, despite the large size of the tax penalty for not having PHI cover relative to the cost of the cheapest eligible insurance policy, the compliance with mandate is relatively low: the proportion of population with PHI cover increases by 6.5 percentage points (15.6%) at the income threshold at which the tax penalty starts to apply. This effect is most pronounced for young age taxpayers, while the middle aged people seem to be least responsive to this specific tax incentive. Second, the discontinuous increase in the average tax rate at the income threshold created by the policy generates a strong incentive for tax avoidance which manifests itself through bunching in the taxable income distribution below the threshold. Finally, after imposing some plausible assumptions the effect of the policy is extrapolated to other income levels to show that overall this policy hasn't had a significant impact on the demand for private health insurance in Australia.

1 Introduction

Many countries actively intervene in the market for private health insurance (PHI) using some combination of community ratings, price subsidies and insurance mandates. While the community rating (group insurance) regulation ensures that high risk sub-groups of population are not priced out of the market, it reduces the value of insurance for low risk individuals, creating a potential for adverse selection. To overcome this problem mandates and subsidies are typically used to increase participation in the health insurance market. The main challenge faced by the policy makers consists in implementing the right mix of these policies to ensure equitable access to health care while minimizing the inefficiency associated with regulation. This is not an easy task, as evidenced for example by the debates surrounding the Affordable Care Act of 2010 in the United States, which envisions introduction of all three policies in 2014 (Gruber, forthcoming).

Knowing the magnitudes of the effects of subsidies and mandates on the demand for PHI is essential for implementing the optimal policy mix. While there exists a large literature studying the effects of price subsidies on the demand for health insurance, the number of studies looking at the insurance mandates is relatively small. This reflects the fact that mandates seem to be less popular than subsidies among policymakers. Also in the few national health systems which have them in place (e.g. Netherlands, Switzerland) there is no legal op-out option, such as paying a tax penalty, which makes them unsuitable for studying tax based insurance mandates.

This paper studies the effect of an insurance mandate on the demand for private health insurance in Australia, a country where the market for private health insurance is heavily regulated by the government. Similarly to some other countries (e.g. UK, Ireland and Spain), Australia has a universal tax financed health care system (Medicare) with private health sector playing a *duplicate* role. In particular, all Australians have access to free public hospital treatments, while treatments in private sector require out of pocket expenses. Private hospital sector is large (e.g. about 2/3 of elective surgery were performed in the private sector in the period 2006-2011 (Surgery in Australian Hospitals 2010-2011)). The advantages to patients of getting treatments in private hospitals or as private patients in public hospitals include a possibility to avoide long waiting times for elective surgery in the public sector (Johar et al. (2011)), ability to nominate a treating doctor, to have private or better quality accommodation, etc. While the costs of private treatment can be substantial, they can be greatly reduces by purchasing a private health insurance cover.

Since the introduction of public health insurance in the mid 1980s the proportion of Australian population covered by private insurance has been declining steadily, a fact commonly attributed to adverse selection caused by the community rating (Butler, 2002). In an attempt to slow down this trend, in the end of 1990s Australian government had introduced several measures aimed at increasing the take-up of private health insurance. These measures included a 30% price subsidy, a system of premium loadings designed to encourage the take-up of the PHI cover at a younger age (Life Time Health Cover) and a means-tested insurance mandate, the Medicare Levy Surcharge (MLS). Under the MLS, which is the focus of this paper, a tax penalty at the rate of 1% of *total* taxable income is imposed on taxpayers who report incomes exceeding a specified threshold and do not have an eligible PHI cover.

We use the administrative income tax returns data collected by the Australian Taxation Office to study the effect of the MLS on the demand for PHI. The MLS policy creates a discontinuous change in the average tax rate for a person who is located at a specified income threshold and does not have a PHI cover. In theory such policy should create strong incentives to purchase insurance for all taxpayers above the threshold. Moreover, taxpayers just below the MLS threshold should constitute a suitable control group which could be used for estimation of the treatment effect of the policy. This strategy however is not appropriate if the reported taxable income can be manipulated (McCrary, 2008). It is well known that reported taxable income responds to changes in the marginal tax rates (Saez, 2010; Chapman and Leigh, 2006). This suggests that the MLS might produce a similar response: facing a significant change in the average tax rate taxpayers with incomes just above the threshold and a low willingness to pay for health insurance might choose to manipulate their taxable incomes to avoid paying the tax. We verify this intuition empirically and document presence of bunching in the taxable income distribution just below the MLS threshold. Importantly, this implies that estimation of the MLS effect on PHI coverage which relies on simple comparison of the insurance rates just below and above the threshold will be misleading.

We develop a novel approach to estimating the effect of the mandate in the presence of tax avoidance which utilizes the observation that income shifting is limited to a certain interval around the MLS threshold. The first step involves estimation of the boundaries of the bunching interval in the income tax returns data using methods similar to those applied recently in the income taxation literature (Chetty et al., 2011). In the second step, the policy effect at the MLS threshold is obtained by estimating the relationship between income and the PHI coverage rate *outside* of the bunching interval and then using it to predict the values of the counterfactual probability of the PHI coverage *within* the bunching interval which would obtain if income shifting were not possible. This empirical strategy is implemented using taxable income and PHI coverage data for single individuals in the fiscal year 2007-08. After implementing various robustness checks we find that the MLS has increased private health insurance coverage at the threshold by 6.5 percentage points (15.6%). Given that the tax penalty at the threshold in 2006-07 was approximately equal to the price of the cheapest MLS eligible insurance policy, this effect is relatively small. It suggests that even if the value of PHI for the marginal individual was close to zero, many taxpayers either made dominated choices or faced large transaction cost of obtaining PHI cover. The estimates of the treatment effect for different age groups suggest that older households are least responsive to the monetary incentives created by the MLS and that the majority of tax income from the surcharge comes from younger cohorts of taxpayers. Finally, we extrapolate the MLS effect estimated at the threshold to other income levels using the assumption of constant treatment effect per dollar of the tax. This counterfactual analysis implies that overall the MLS has increases PHI coverage rate among singles from 34% to 36.6%.

This study contributes to the existing literature on the effect of monetary incentives on the demand for health insurance. An extensive literature investigating the effect of subsidies on the demand for health insurance includes, among others, Gruber and Poterba (1994), Finkelstein (2002), Emerson et al. (2001) and Rodriguez and Stoyanova (2004) for the cases of US, Canada, UK and Spain, respectively. Chandra, Gruber and McKnight (2011) study the impact of an individual mandate on the characteristics of the insurance pool in the presence of large subsidies to premiums in the US. This paper provides an evidence on the effectiveness of mandates in Australia, which has a rather different health care system. The main policy implications derived from this analysis are thus relevant for countries with public health care systems in which private insurance plays largely a supplementary role. This study also contributes to a growing literature in public economics which studies the behavioral responses to taxation using discontinuous changes in the tax rates as a source of exogenous variation, e.g. Saez (2010), Chetty et al. (2011) and Kleven and Waseem (2013). This literature is primarily concerned with using the observed responses to kink points of the income tax schedule for estimation of the elasticity of taxable income with respect to the tax rate, magnitude of which is informative about the excess burden of income taxes. Similar to the evidence presented in the Kleven and Waseem (2013), we document a pattern of sharp bunching at the MLS notch, which implies that this type of tax incentives are likely to lead to a tax avoidance behavior on a relatively large scale.

2 Medicare Levy Surcharge

At the time of its introduction in 1997 the MLS was meant to be an insurance mandate targeted towards high income uninsured, with separate income thresholds for single and married individuals. Up to the fiscal year 2008-09, the annual household income threshold was set at $50,000 for singles, and at $100,000 for families/couples. The families' threshold also applies to single parents with dependent children. For families and single parents the threshold is increased by $1,500 for each child after the first.[1] To avoid the MLS an individual must have been covered during the preceding fiscal year by the insurance policy with the front-end deductible or excess no greater than a specified limit ($500 for singles and $1,000 for families/couples). Figure 1 illustrates how the MLS policy would work with the income threshold set at $50,000 for a single individual without dependent children assuming that the marginal tax rate is equal to 30% throughout this income range: upon reaching the MLS threshold a person without PHI cover will experience a discontinuous drop in her after-tax income by $500 ($\$50,000 \cdot 0.01$), while someone who has eligible health insurance cover will not be affected by the surcharge.

PLACE FIGURE 1 HERE

The tax notch created by the MLS provides strong incentives to either purchase insurance or reduce your taxable income (i.e. engage in income shifting) either through tax evasion or tax avoidance. The relative magnitude of the two responses will depend on the price of PHI cover offered by the insurance funds. Existing evidence suggests that insurance funds take advantage of the MLS policy by designing low priced insurance policies which would still satisfy the eligibility requirements, with the cost of cheapest insurance plans approximately equal to the surcharge amount that a person without PHI at the MLS income threshold would face.[2] This implies that for some taxpayers the MLS is likely to result in a situation in which consumption can be increased by purchasing a PHI cover even if they put zero value on the insurance itself, provided that the search cost is sufficiently low. On the other

[1] In the fiscal year 2008-09 these thresholds were increased to $73,000 and $150,000 respectively and the annual indexation of the thresholds was introduced. Starting from mid 2012 the Fairer Private Health Insurance Incentives Bill introduced means testing of the 30% PHI subsidy and a tiered structure of the MLS.

[2] The insurance intermediary website *www.iselect.com.au* provides pricing information on various insurance products in Australia. Among other contracts, it advertises PHI policies designed specifically for consumers whose primary reason for buying insurance is to avoid the Medicare Levy Surcharge. In March 2012 the cheapest eligible policy for a single 40 y.o. male offered at this site has been priced at around $840 per year. With the 30% insurance premium rebate the effective cost of this policy is $588, which is far below the 2011-12 the MLS liability of $800 at the MLS income threshold for singles of $80,000. At the same time it must be noted that PHI regulations require that in order to avoid the MLS charges taxpayers must have a plan providing hospital cover with an excess no greater then $500 for singles and $1,000 for couples. This prevents insurance companies from offering plans with little or no benefit to consumers. For example, in November 2013 the cheapest eligible policy fully covers treatments as a private patient in a public hospital in a shared room with the choice of doctor for most procedures where in-hospital Medicare benefits are payable excluding dialysis, joint replacements, cataract-related procedures, obstetrics and assisted reproductive services. The most expensive policy fully covers all the above treatments in a private hospital in a private or shared room.

hand, taxpayers just above the MLS threshold can increase their consumption and leisure by lowering their earnings below the threshold or by engaging in tax avoidance (provided that the cost of avoidance is relatively low). Such responses would manifest themselves via the bunching in the income distribution near the MLS threshold.

The MLS was one of the three policies introduced in the end of 1990s to increase the proportion of population covered by the private health insurance. The other two policies were a 30% price subsidy to PHI cover for those under the age of 65, increasing to 40% for those aged 70 and over (introduced January 1999) and Life Time Health Cover (LTHC) policy providing monetary incentives for buying PHI before the 30th birthday (July 2000). The combined effect of these policies was to increase the proportion of population covered by PHI by approximately 50%: from 31% of population in early 1999 to 45.3% in mid 2001. However, because this set of policies was introduced with an explicit goal of alleviating the burden on the public health system by shifting the demand for care to the private sector, an important policy question is whether the cost of PHI incentives is exceeded by the cost savings in the public system. This issue is especially pertinent because the three incentive schemes differ vastly in terms of the burden they place on public finances: while the MLS and LTHC come at no cost to the government, the subsidy component of the policy is quite expensive, costing more than $3 billion annually (Butler, 2002). Thus the question of the relative impact of each measure on the demand for health insurance is of considerable practical importance. While ideally one would like to conduct a comprehensive analysis of all three policies taking into account that they can interact in complex ways (Ellis and Savage, 2008), this task is beyond the scope of this paper. Instead we attempt to isolate the effect of the MLS conditional on the presence of the other two policies.

3 Data and Preliminary Analysis

The dataset used in the paper was provided by the Australian Taxation Office (ATO) and is based on the population of individual income tax returns in the fiscal year 2007-08. The main dataset used in the analysis contains counts of taxpayers with private health insurance as well as total counts of individuals within narrow income bins (with the size of each bin set at $250) for single childless population and for the total population, stratified by three age groups. Because of the difficulties of inferring the total household income and the number of children in a given household (which affects the MLS threshold for families) from the individual income returns data, the paper focuses on studying the effect of the MLS on single childless individuals only. In the main part of the paper we study the behavior of single individuals overall and then present similar analysis for different age groups.

While the administrative data used in the paper is in general of high quality and is free from measurement error in income, one potential concern is that the marital status might be misreported. In particular, because the income tax in Australia is administered on the individual basis, declaration of marital status is required only in order to calculate the MLS liability. As a result, married individuals without PHI might have a stronger incentive to report their marital status correctly when their income exceeds the MLS threshold for singles to prevent the MLS tax being applied to them erroneously. This behaviour may create an upward bias in the number of uninsured singles at the income levels below the MLS threshold for singles leading to an increase in the proportion of individuals with PHI among singles above this threshold even if the true MLS policy effect on PHI is zero. Panel (a) of Figure 2 presents the relationship between income and the proportion of self-reported singles in the total population of tax returns. A notable feature of this graph is a discontinuous drop in the proportion of singles above the MLS threshold which supports our reasoning about changes in incentives to report single status correctly once individuals cross the MLS threshold for singles. In order to account for this potential sample selection bias, the estimation strategy (described in details in section 4) will combine the income distribution and PHI coverage data on all individuals with the data on singles. In particular, first an increase in the PHI coverage at the MLS threshold for singles will be estimated from the data on PHI coverage for the total population. This number will then be divided by the proportion of singles in the total population at the MLS threshold for singles. Assuming that the PHI coverage of families does not change significantly at the MLS threshold for singles this will give us an estimate of the effect of the MLS policy on single childless individuals at their MLS threshold.

Although we will not use the ATO data on PHI coverage of singles for estimation of the MLS policy effect for reasons discussed above, it is still useful to examine these data to form an expectation about the final results. Panel (b) of Figure 2 presents the relationship between the taxable income and the proportion of individuals with private health insurance coverage in 2007-08 in the single population. The PHI coverage increases with income from 0.10 at the lowest income levels to about 0.8 for incomes close to $100,000. There is a clear discontinuous increase of about 7 percentage points in the proportion of individuals with PHI at the MLS threshold for singles. However, as discussed above this increase can partly be an artifact of different incentives to report marital status correctly on the two sides of the threshold. The probability of PHI coverage never reaches unity despite the strong incentives to purchase PHI created by the MLS. There are 1,489,825 self-reported single individuals with incomes exceeding the MLS threshold for singles, of whom 1,014,430 (68%) have an eligible health insurance coverage. The remaining 475,395 individuals are liable to the MLS tax, and their MLS tax contributions amount to 321.4 million dollars in 2007-2008.

PLACE FIGURE 2 HERE

To estimate the MLS policy effect on the PHI coverage of singles the data on the taxable income distribution and PHI coverage in the total population (single and family members) in 2007-2008 will be used. The distribution of taxable income in the total population is plotted on panel (a) of Figure 3. There are 12.8 million individual tax returns in these data, with the average of 30,068 individuals per $250 income bin. The largest income income bin with 234043 individuals corresponds to yearly reported taxable income of $250 or less. The smallest income bin with 5246 individuals has the midpoint at $99,375. For privacy reasons incomes exceeding $100,000 are grouped in a single bin containing 804,652 individuals. The deciles of this income distribution are as follows: $6,625; $13,375; $20,125; $27,375; $34,375; $42,125; $51,125; $63,375; $83,125.

The bracket cutoffs of the income tax schedule (kink points) in this period were $6,000, $30,000 and $75,000. While the nominal tax free threshold was set at $6,000, the low income tax offset policy in place during this time resulted in the effective tax free income thresholds being set at $11,000. The taxable income distribution shows clear evidence of bunching at the kink points of the income tax schedule in this period. Consistent with the evidence from other countries, the pattern of bunching at all of the kink points is diffuse, with the excess mass on both sides of the kink points. Another notable feature of this income distribution is the existence of bunching at the MLS threshold for singles at $50,000. The pattern of bunching at the MLS threshold is qualitatively different from that observed at the kink points of the income tax schedule. Similar to the patterns of bunching at the tax notches documented by Kleven and Waseem (2013), the bunching at the MLS threshold is sharp, with the excessively high density below the threshold and excessively low density above the threshold. These distinct patterns of bunching can be explained by the different incentives created by the increases in the marginal tax rate as opposed to the MLS policy. In particular, for the MLS tax avoidance to be profitable the reported taxable income must be strictly below the threshold.

Panel (b) of Figure 3 shows the relationship between the taxable income and the proportion of individuals with private health insurance coverage in 2007-08 in the total population.

The PHI coverage rate increases with income, from about 0.2 at the lower end of the income distribution to approximately 0.75 at the income level of $100,000. The effect of the MLS manifests itself as a discontinuous increase in the coverage rate at the MLS threshold for singles. As expected, the size of this increase is smaller than that in panel (b) of Figure 2 because only a fraction of individuals in this graph is affected by the MLS threshold for singles.

PLACE FIGURE 3 HERE

Despite the highly visible discontinuous jump at the MLS threshold for singles in the relationship between income and PHI coverage rate, the behavior of the coverage rate is non-monotone in the vicinity of the thresholds. In particular, the proportion of taxpayers with insurance cover is excessively low just below the threshold and excessively high immediately above the threshold. This pattern is simply an artifact of income shifting caused by the MLS with those above the threshold who do not wish to purchase a PHI cover ending up with the reported taxable incomes just below the threshold, which simultaneously depresses the coverage rate below the threshold and increases it above the threshold. Importantly, this implies that the causal effect of the insurance mandate cannot be estimated simply by comparing the coverage rates below and above the threshold. In the next section we develop an estimation approach which allows one to correct for the consequences of bunching.

4 Empirical Analysis

This section studies empirically the effect of the MLS policy. It presents our strategy for estimation of the MLS effect at the MLS threshold and applies this strategy to the data described earlier. In the subsequent material we utilize the following notation: Y is true taxable income level (different from the reported taxable income Y_r near the MLS threshold where individuals engage in income shifting), T is the MLS income threshold, t is the MLS tax rate, I is an indicator of private health insurance status (i.e., $I = 1$ in individual has PHI and $I = 0$ otherwise), E is the amount of income shielded from taxation, $P(I = 1)$ is the probability of PHI coverage.

4.1 Estimation Strategy

The main effect of interest in this study is the difference between the probability of PHI coverage with and without the MLS tax, i.e. $P(I = 1|Y, t = 0.01) - P(I = 1|Y, t = 0)$ for all income levels Y above the MLS threshold. However, the counterfactual probability $P(I = 1|Y : Y > T, t = 0)$ is not observable. If data on the true taxable incomes rather than the reported incomes were available, one could attempt to estimate the MLS effect at the threshold by comparing the insurance rates of individuals with incomes just above and just below the threshold. This strategy would give a consistent estimate of the effect of the policy at the threshold if the densities of all other determinants of the insurance status were continuous around the threshold, which is a standard assumption of the regression discontinuity identification methodology. However, as discussed above, in our data only the reported taxable income is observed, which is likely to be different from the true income for individuals without PHI with true incomes exceeding the MLS threshold. Moreover, this strategy will underestimate the full effect of the policy because near the threshold individuals can avoid the MLS tax by misreporting their income rather than purchasing the PHI.

Our approach to estimation is based on the following arguments which are formally developed in the Appendix. Suppose that it is costly to shield income from taxation and that the marginal cost of tax avoidance is increasing in E.[3] Then there will be income level $\overline{Y} > T$ after which it will be more costly to shield excess income from taxation than either to pay the MLS tax or to purchase a PHI coverage. Individuals with true incomes in the interval $(T, \overline{Y})$ who do not have PHI will report incomes slightly less than T. Hence there will be a shortage of mass in the distribution of the reported income between T and $\overline{Y}$ and an excess mass in a small interval to the left of T. Let $\underline{Y}$ denote the lower boundary of this interval.[4] Since only the uninsured individuals engage in misreporting, the PHI rate will be excessively low in the reported taxable income interval $(\underline{Y}, T)$ and excessively high in the reported taxable income interval $[T, \overline{Y})$. Outside of the bunching interval $(\underline{Y}, \overline{Y})$ true incomes are reported and the relationship between income and PHI rate is the same as in the situation where tax avoidance is not possible for any income level. The MLS tax will have its full intended effect on individuals with incomes above $\overline{Y}$ because they no longer

[3]The following arguments will still apply in the case when the marginal cost of tax avoidance is constant and is greater than the MLS tax rate t.

[4]In theory we would expect that all individuals who engage in income shifting will report the $49,999 income, but in reality it is not always possible to attain this number precisely when filing a tax return, hence there will be an interval of excess mass to the left of T rather than a single peak at $49,999.

have an option of avoiding the MLS tax by engaging in income shifting.[5] If there were no income gradient in PHI coverage this full effect could be estimated as the difference between the PHI coverage rate at $\overline{Y}$ and at $\underline{Y}$. However, in our data there is a strong positive income gradient in PHI coverage so this approach will produce an upward biased estimate of the MLS effect. Therefore we will instead attempt to estimate by how much the PHI rate would have increased at the MLS income threshold if tax avoidance was not possible, i.e. $E = 0$. It is easy to show that in this case the MLS policy would produce a discontinuous increase in the PHI coverage at the MLS threshold if consumers are rational and utility maximizing. We denote this increase as $\Delta P|(Y = T)$:

$$\Delta P|(Y = T) \equiv P(I = 1|Y = T, t = 0.01, E = 0) - P(I = 1|Y = T, t = 0, E = 0).$$

To estimate $\Delta P|(Y = T)$ we will extrapolate the relationship between income and PHI for income levels $Y : Y < \underline{Y}$ and $Y : Y > \overline{Y}$ to T and take the difference between the latter and the former predictions. The accuracy of this estimator will depend on the shape of the relationship between income and PHI rate outside of the bunching interval (e.g., a linear relationship being more accurately extrapolated than a non-linear one) and on the distance between T and $\overline{Y}$ and $\underline{Y}$ (i.e., a larger distance leads to poorer quality of extrapolation). It turns out that characteristics of our data are such that $\Delta P|(Y = T)$ can be estimated rather accurately. Hence, estimation of $\Delta P|(Y = T)$ will involve the following four steps:

1. Estimate the boundaries of the bunching interval $\overline{Y}$ and $\underline{Y}$ using the distribution of the reported taxable income.

2. Estimate $P(I = 1|Y = T, t = 0, E = 0)$ by extrapolating the conditional probability of PHI coverage $P(I = 1|Y : Y < \underline{Y})$ to income level $Y = T$.

3. Estimate $P(I = 1|Y = T, t = 0.01, E = 0)$ by extrapolating the probability of PHI $P(I = 1|Y : Y > \overline{Y})$, to income level $Y = T$.

4. Estimate $\Delta P|(Y = T)$ by subtracting the result obtained in step 2 from that obtained in step 3.

In principle, this strategy should be applied to the income tax returns and PHI coverage of the group of individuals who are directly affected by the policy, i.e. single individuals with

[5] All these predictions are derived formally in the Appendix using a theoretical model of tax avoidance/ health insurance choice.

no children. However, as discussed above, the self-reported single status in our data may be an unreliable indicator of belonging to this group and the propensity to report single status correctly can change as one crosses the MLS threshold. For this reason we use the data on the total population (single and married individuals) to estimate the policy effect on all individuals, $\Delta P^{All}|(Y = T)$ by performing the four steps discussed earlier. After imposing the assumption that the effect on married individuals (who are not affected by the policy at the MLS income threshold for singles) is equal to zero, the total effect can be expressed as $\Delta P^{All}|(Y = T) = P(S|Y = T) \cdot \Delta P^{S}|(Y = T)$, where $P(S|Y = T)$ is the probability of being in the treatment group (i.e single without children) and $\Delta P^{S}|(Y = T)$ is the policy effect on the treated group. After estimating probability of being single at the MLS income threshold $P(S|Y = T)$ using data plotted on panel (a) of Figure (2), the effect on the treated group can be computed as $\Delta P^{S}|(Y = T) = \frac{\Delta P^{All}|(Y=T)}{P(S|Y=T)}$.

4.2 Estimation of the bunching interval

As outlined in the previous section, the first step of the empirical analysis is to find the lower and upper bounds $\underline{Y}$ and $\overline{Y}$ of income interval where bunching behavior distorts the densities of the reported taxable income and the PHI rate. To do this we employ the methodology used in the studies of bunching behavior (e.g. Chetty et al. (2011); Kleven and Waseem (2013)). In particular, we use data on all individuals (single and married) to fit the following flexible polynomial model to the empirical density of the reported taxable income:

$$\begin{aligned} C_i &= \beta_0 + \sum_{j=1}^{3} \beta_j Y_{ri}^j + \sum_{k=1}^{5} \gamma_k \cdot \iota(T - 250 \cdot k < Y_{ri} < T - 250 \cdot (k-1)) \\ &+ \sum_{k=1}^{15} \alpha_k \cdot \iota(T + 250 \cdot (k-1) < Y_{ri} < T + 250 \cdot k) + \varepsilon_i \end{aligned} \tag{1}$$

where C_i is counts of individuals in income bin i, Y_{ri} is the mid-point of the reported taxable income bin i, $\beta_0 + \sum_{j=1}^{3} \beta_j Y_{ri}^j$ is the (counterfactual) distribution of the reported taxable income in the absence of tax avoidance, γ_k measures the excess mass of individuals in the income bins immediately to the left of the MLS threshold, and α_k measures a shortage of mass in the income bins immediately to the right of the MLS threshold. As long as individuals with true incomes above T and without PHI engage in income shifting, we expect that some γ_k closest to T will be positive and statistically significant, and some α_k closest to T will be negative and statistically significant. Because the excess mass in the distribution of the reported income to the left of T should be equal to the shortage of mass on the interval $[T, \overline{Y}]$

we impose an adding up constraint by requiring that the coefficients γ_k and α_k in equation (1) sum to zero: $\sum_{k=1}^{5} \gamma_k + \sum_{k=1}^{15} \alpha_k = 0$.

We define $\underline{Y}$ as the midpoint of the income bin closest to T on the left whose corresponding coefficient γ is not statistically significant. That is, $\underline{Y} \equiv T - 125 - (k^* - 1) \cdot 250$ where $k^* \equiv min\{k : \gamma_k = 0\}$. Similarly, $\overline{Y}$ is defined as the midpoint of the income bin closest to T on the right whose corresponding α coefficient is not statistically significantly different from zero. That is, $\overline{Y} \equiv T + 125 + (k^* - 1) \cdot 250$ where $k^* \equiv min\{k : \alpha_k = 0\}$. Table 5 presents the results from fitting equation (1). In going from Model 1 to Model 2 we have removed dummies corresponding to income bins whose coefficients γ_k and α_k are not statistically significantly different from zero in Model 1. Model 2 is the final specification which includes only those γ_k and α_k that are statistically significant at 10% level.

The results of Model 2 suggest that there exists an excess mass in the distribution of the reported taxable income in the three income bins to the left of \$50,000, and a shortage of mass in the 10 income bins to the right of \$50,000. Hence, individuals without PHI would underreport up to \$3,250 (\$250 · 13) in order to avoid paying the MLS surcharge. The midpoint of the income bin corresponding to γ_4 (i.e. the first γ_k to the left of \$50,000 that is not statistically significant) is our estimate of $\underline{Y}$, which gives $\underline{Y} = \$49,125$. Similarly, the midpoint of the income bin corresponding to α_{11} (i.e. the first α_k to the right of \$50,000 that is not statistically significant) is our estimate of $\overline{Y}$, implying that $\overline{Y} = \$52,625$. To illustrate these results Figure 4 plots the actual and counterfactual income distributions obtained from Model 2.

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4.3 Estimation of the policy effect

The next step is to estimate the PHI coverage rates to the right and to the left of the MLS threshold which would exist if bunching were not possible. As discussed in section 4.1, we do this by first estimating the models for the PHI coverage rate as a function of the reported taxable income using data from the intervals $Y \leq \underline{Y}$ and $Y \geq \overline{Y}$ and then extrapolating the estimated relationships to $Y = T$. The first model is then used to predict the PHI coverage rate an the threshold in the absence of the MLS tax $P(I = 1|Y = T, t = 0, E = 0)$, while the second model is used to predict the coverage rate at the threshold in the presence of the MLS tax $P(I=1|Y=T,t=0.01,E=0)$. We set the value of the MLS threshold at T=$50,125, that is the first income bin to the right of the actual MLS threshold of $50,000.

Since our estimate of $P(I=1|Y=T,t=0,E=0)$ is essentially a 4-step ahead forecast of the relationship between income and PHI for $Y \leq \underline{Y}$, while $P(I=1|Y=T,t=0.01,E=0)$ is a 10-step ahead forecast of the relationship between income and PHI for $Y \geq \overline{Y}$ we need to select a procedure for estimation of the relationship between income and PHI that has good forecasting properties. In particular, we choose the sample size, (i.e. the number of bins) from which the relationship it to be estimated, as well as the functional form of this relationship to minimize the mean squared difference between the out-of-sample and in-sample forecasts obtained from a very flexible model with the regressions R-squared close to 0.99.[6] We find that the linear model estimated using 23 income bins gives the best forecast for the relationship between income and PHI for $Y \leq \underline{Y}$, while the linear model estimated using 18 income bins gives the best out-of-sample forecast for $Y \geq \overline{Y}$. Therefore, to estimate $\Delta P^{All}|(Y=T)$ we first use the data on all individuals (single and married) to fit the model:

$$PHI_i = (\beta_1^0 + \beta_2^0 Y_{ri})\iota(Y_{ri} <= \underline{Y}) + (\beta_1^1 + \beta_2^1 Y_{ri})\iota(Y_{ri} >= \overline{Y}) + \varepsilon_i \tag{2}$$

where PHI_i is the proportion of individuals with PHI in income bin i, and Y_{ri} is the mid-point of the reported taxable income bin i. The midpoint of the smallest income bin in the estimation sample is equal to $43,625, the midpoint of the largest income bin is equal to $56,875, while $\underline{Y} = \$49,125$ and $\overline{Y} = \$52,625$. The estimate of $\Delta P^{All}|(Y=T)$ is then given by

$$\Delta P^{All}|(Y=T) = (\beta_1^1 + \beta_2^1 \cdot 50,125) - (\beta_1^0 + \beta_2^0 \cdot 50,125) \tag{3}$$

To estimate equation (2) we use a two-step feasible GLS method. In the first step we obtain estimates of β_1^0, β_2^0, β_1^1 and β_2^1 as $\mathbf{b}_w = (\mathbf{X}'\Omega^{-1}\mathbf{X})^{-1}\mathbf{X}'\Omega^{-1}\mathbf{I}$, where $\mathbf{X}$ is the matrix of covariates from equation (2), $\mathbf{I}$ is the vector of PHI rates corresponding to the income bins in the estimation sample, and Ω is a diagonal matrix with the diagonal element ω_{ii} equal to the inverse of the total number of individuals in the income bin i, i.e. $\omega_{ii} = \frac{1}{C_i}$. It is easy to show that this estimate is equivalent to that of the linear probability model (LPM) obtained from the individual-level data on PHI status and income, where all individuals in income bin i are assigned income level equal to the midpoint of their $250 bin. However, the variance-covariance matrix of this weighted least squares estimator, $(\mathbf{X}'\Omega^{-1}\mathbf{X})^{-1}$, will underestimate the true variance of the coefficients in the LPM model because the dependent

[6] In the Appendix we discuss in details how the specification was selected.

variable used to obtain $\mathbf{b}_w$ is equal to the within-bin proportion of individuals with PHI, rather than to the actual realizations of the binary PHI status. However, the available data allows computation of the efficient GLS variance of the coefficients in the LPM model estimated from individual-level data even though actual realizations of the individual PHI status are not known. Assuming that all individuals in the income bin i are assigned income levels equal to the midpoint of the income bin, the efficient GLS variance of the LPM coefficients estimated from the individual-level data is given by $V_{GLS} = (\mathbf{X}'\widetilde{\Omega}^{-1}\mathbf{X})^{-1}$, where $\widetilde{\Omega}$ is a diagonal matrix with the diagonal elements $\widetilde{\omega}_{ii} = \frac{P_i(1-P_i)}{C_i}$ and P_i is the probability of PHI coverage of individual with income equal to the midpoint of the income bin i (see e.g. Gujarati and Porter, p. 545). Hence in the second step we estimate P_i as $\widehat{P}_i = \mathbf{X}\mathbf{b}_w$ and then compute estimates of β_1^0, β_2^0, β_1^1 and β_2^1 as $\widehat{\boldsymbol{\beta}}_{GLS} = (\mathbf{X}'\widetilde{\Omega}^{-1}\mathbf{X})^{-1}\mathbf{X}'\widetilde{\Omega}^{-1}\mathbf{I}$ after replacing P_i with $\widehat{P}_i$ in $\widetilde{\Omega}$. The variance-covariance matrix $\widehat{V}_{GLS}$ is computed similarly.

The results of the GLS estimation of equation 2 and the GLS standard errors are presented in Table 2. The number of individuals within each bin in the estimation sample varies between 26,010 and 37,324, resulting in the total of 1,322,409 individual observations. Figure 5 shows the in- and out-of-sample fit of this model to the data. The dashed vertical lines around 50,000 indicate the bunching interval (i.e. ($49,125,$52,625)) within which the PHI coverage is forecasted out of sample using estimates in Table 2. Weighted least squares estimates $\mathbf{b}_w$ and GLS estimates $\widehat{\boldsymbol{\beta}}_{GLS}$ are practically identical, while the standard errors obtained from $(\mathbf{X}'\Omega^{-1}\mathbf{X})^{-1}$ are about 200 times smaller than the standard errors obtained from V_{GLS}.

PLACE TABLE 2 HERE

PLACE FIGURE 5 HERE

We then substitute estimates from Table 2 into equation (3) to obtain:

$$\Delta P^{All}|(Y = T) = (.0125840 + .0092023 \cdot 50.125) - (0.0914307 + .0070741 \cdot 50.125) = 0.0278 \tag{4}$$

Hence, our estimate of the MLS effect at the threshold for singles in the absence of tax avoidance $\Delta P^{All}|(Y = T)$ is equal to 0.0278 and it's standard error is equal to 0.0029[7], which makes the estimate statistically significantly different from zero at any significance level. This implies that in the population the probability of having a PHI cover increases by 2.8 percentage points at the MLS threshold for singles. This is the size of the vertical

[7]This standard error was computed using the lincom Stata command.

distance between the dashed and solid lines at the income of \$50,125 on Figure 5.

As a robustness check we also estimated the placebo MLS effect using the income tax returns data from 2009-10, in which one would not expect to see a discontinuity at the 2007-08 MLS threshold of \$50,000 because the threshold for singles has been increased to \$73,000 in 2008-09.[8] We find that the estimated effect of the MLS is equal to -.005 with the standard error of .003. The p-value associated with the null hypothesis that this effect is equal to zero is 0.073. These results suggest that using our estimation approach we are unlikely to obtain a positive policy effect of a magnitude and statistical significance that we obtain using the 2008 data from the data in which this effect is not present. The details of this analysis are given in the Appendix.

To obtain the MLS effect on the treated population we need to divide the total effect by the proportion of single individuals with no dependent children in the total population at the MLS threshold for singles. The self-reported single status available in the ATO data and plotted on panel (a) of Figure 2 can be used to estimate the proportion of singles at this threshold. The irregularities in these data where the proportion of singles is artificially low in the reported taxable income bins just to the right of the threshold, and is artificially high just to the left of the threshold are limited to the bunching interval $\underline{Y}, \overline{Y}$. Therefore to predict the proportion of singles at the MLS threshold we utilize the forecasting technique described earlier. We estimate a linear model specified in equation (2) with the proportion of singles in the income bin i as the dependent variable using data outside of the bunching interval and then forecast this proportion to the MLS threshold for singles using the relationship estimated for income levels $Y > \overline{Y}$. We choose the forecast to the right of the threshold as an estimate of single status at the threshold because, as discussed above, individuals have a stronger incentive to report their true marital status to the right of the MLS threshold for singles. The estimation results are presented in Table 7 of the Appendix. The estimated proportion of singles at the threshold is equal to $0.426 \sim 0.43$.[9] [10] This gives us the following

[8]We did not attempt to estimate the MLS effect in 2010 at the new threshold because the income tax threshold was very close to the MLS threshold and it made it very difficult to obtain reliable out of sample predictions of the coverage at the threshold. Visual inspection suggests that the effect is even smaller than at the 2007-08 threshold.

[9]This number is consistent with the proportion of single individuals with income \$50,000 estimated from the year 2007 wave of HILDA data (Household Income and Labour Dynamics in Austraia Survey). HILDA is a primary Austalian longitudinal household-level data set, which contains detailed socio-economic information on 7,682 households and 19,914 individuals over 12 years starting from 2001.

[10]The estimated proportion of singles immediately to the left of the threshold is equal to 0.46 and the difference between the proportion to the left and the proportion to the right of the threshold is highly statistically significant.

MLS effect on the treated group:

$$\Delta P^S|(Y=T) = \frac{\Delta P^{All}|(Y=T)}{P(S|Y=T)} = \frac{0.0278}{0.43} = 0.065.$$

In other words, our results suggest that the MLS increases the rate of PHI coverage at the threshold among singles by 6.5 percentage points.

To estimate the percentage increase in the PHI coverage of singles at the threshold we need first to estimate the PHI coverage of singles either to the left or to the right of the threshold. To this end we use the PHI coverage data of self reported singles plotted on panel (b) of Figure 2. These data exhibit the same irregularities around the MLS threshold for singles as the total population PHI coverage data due to the bunching behavior. To predict the proportion of singles with PHI at the MLS threshold we use the same forecasting technique as before, and find that the predicted PHI coverage of this group at the presence of the MLS tax in the case when bunching is not possible is 0.486 at the MLS threshold for singles (i.e. at income level of $50,125).[11] The estimation results are presented in Table 7 of the Appendix. Hence, in the absence of the MLS policy the PHI rate of singles at income level of $50,125 would be 0.486-0.065=0.421, and in percentage terms the MLS effect on the PHI rate at the threshold is 100*0.065/0.417=15.6% for the treated group.

4.4 Extrapolation of the MLS effect at the threshold to other income levels

The estimated effect at the threshold is relatively large and is comparable in magnitude to the effect of the Life Time Health Cover reported in the literature. However, this estimate is not fully informative about how much the total coverage in the treatment group is affected by the policy. In order to estimate the total effect of the policy we will assume that the MLS effect *per dollar of the tax* is constant. In this case the treatment effect of the MLS at any income level Y is proportional to the dollar amount of the payable MLS tax. In other words the change in the PHI rate at income Y due to the MLS tax t, $\Delta PHI|Y,t$, is equal $\Delta PHI|Y,t = \alpha \cdot t \cdot Y$, where α is the per dollar effect of the policy. The estimated effect at the MLS threshold suggests that $\alpha = 0.065/501.25$ (recall that with the MLS tax rate

[11] Using these data the predicted PHI coverage of singles immediately to the left of the MLS threshold for singles in the case of no bunching is 0.409. Hence, the estimated MLS policy effect obtained from the ATO PHI coverage data of singles is equal to 7.7 percentage points, which is higher than our preferred estimate of 6.5 percentage points, as expected.

of 0.01 the MLS tax of a person with income \$50,125 who has no PHI is \$501.25). Hence, to obtain the counterfactual PHI rates for singles (i.e. PHI rate at the absence of the MLS policy) we use the observed PHI rates to compute $PHI_i^{CF} = PHI_i - [0.01 \cdot Y_i] \cdot \frac{0.065}{501.25}$ for each income bin above the threshold. The estimate of the total policy effect thus obtained can be interpreted as an upper bound on the actual effect, since in reality one would expect that taxpayers with higher incomes might be less responsive to the tax of a given size compared to those in the middle of the income distribution.

Figure 6 shows actual and counterfactual PHI coverage for single individuals with the reported taxable income above \$50,000 obtained after imposing these assumptions, and Table 3 summarizes the numerical results. In particular, we compute by how much the total coverage in this group was increased by the policy, taking into account the number of individuals in each income bin. The total *number* of people with PHI increases by approximately 146,459 individuals as a results of the MLS policy, which is equivalent to a 7.2% increase in the number of insured singles. The aggregate PHI *rate* of this group increases from 34.2% to 36.6%. These results suggest that overall the MLS policy had at best a modest effect on the PHI coverage rate (among singles) in the sample period. This conclusion is consistent with circumstantial evidence of the weak effect of the MLS, in particular no effect on the aggregate PHI coverage rate at the time of introduction of the MLS 1997, as well as absence of significant changes in the PHI coverage rate after the MLS thresholds for singles and married taxpayers were substantially increased in 2009.

We also compute the additional cost to the budged of the 30% private health insurance premium rebate induced by the MLS. Since we do no know which policies are chosen by individuals driven into the PHI coverage by the MLS, we consider three scenarios. In the first scenario these individuals are assumed to purchase the cheapest eligible policy. The costs of such policies are usually close to the MLS tax liability, hence we assume that the PHI price P in the first scenario is equal to \$500. In the second scenario we assume that individuals purchase a policy with out of pocket costs (after the 30% subsidy rebate) exactly equal to their MLS tax liability, i.e. $P = 0.1 \cdot Y/0.7$. Finally, in the third scenario we assume that all individuals purchase the policy with the most comprehensive coverage. The cost of such a policy for a 40 years old male in 2013 is \$ 2718 according to the iSelect.com.au, which gives an approximate cost of \$2283 for a similar policy in 2008 after CPI deflation. The costs of the subsidy to the budget under each of these scenarios are presented in Table 3. In all three scenarios budget revenue from the MLS far exceeds the extra costs associated with the premium rebate.

PLACE FIGURE 6 HERE

PLACE TABLE 3 HERE

4.5 The effect of the MLS for different age groups

We also estimate the effect of the MLS tax on PHI coverage for the three age groups of single individuals: "young" (between 15 years old and 32 years old), "middle-aged" (between 33 and 50 years old) and "old" (older than 50 years old). The details of the estimation are contained in the Appendix. The results suggest that there exist some important heterogeneities in the way taxpayers from the different age groups respond to the tax incentives. In particular, the taxpayers in the old age group exhibit the strongest reaction to the tax incentives: their coverage rate increases by 9.2 percentage points from a relatively large baseline of 58% (67%-9.2%), implying a 15.9% increase. The coverage rate of the young taxpayers increases by 7.4 percentage points from the baseline of 32.6% (40%-7.4%), a 22.5% increase. The middle aged group appears to be the least sensitive to the incentives created by the MLS policy, with an increase of 5 percentage points or 11%. Taxpayers of the old age group also exhibit the highest increase in the overall PHI rate coverage, which goes up by 4 percentage points as a result of the policy. Intuitively, the policy seems to affect the most the segment of the population which has the highest expected benefit from owing PHI, namely the older people. In absolute terms young taxpayers contribute the largest fraction of budget revenue from the MLS. This group also has the largest percentage of taxpayers (among those liable to pay the tax) who chose not to comply with the MLS mandate: 44% compared to 30% in the middle age group and 21% in the old age group. Their average MLS tax liability however is slightly lower compared to the two other age groups due to the fact that younger taxpayers tend to have relatively lower incomes. The large number of non-compliers among the young might reflect their lower valuation of the benefits of the private health insurance or lack of knowledge about the PHI tax incentives.

5 Conclusion

This paper has studied the effect of an individual insurance mandate, the Medicare Levy Surcharge (MLS), on the demand for PHI in the context of the Australian national health care system. The use of the administrative income tax returns data for the population of Australian taxpayers in 2007-08 allows to obtain estimates of the effect of the policy at the MLS income threshold for single individuals. We find that the policy has resulted in the increase in the PHI coverage rate by 6.5 percentage points or 15.6% at the threshold, while overall this policy has increased the total number of insured singles by 7.2% and increased the PHI rate of singles by 2.4 percentage points. These results indicate that the MLS has had at best very modest effect on the demand for private health insurance in Australia in the study period. The effect of policy seems to be the strongest among older taxpayers. There is also a significant number of individuals who choose not to comply with the mandate and pay the MLS tax instead. This pattern is especially pronounced among younger people, with 44% of taxpayers younger than 30 with incomes above the MLS threshold choosing not to comply with the mandate. The interpretation of these results must at least in part draw upon the supplementary role that the PHI coverage plays in the Australian mixed public/private health care system. In particular, with the tax financed Medicare system guaranteeing free treatment in the public sector, attractiveness of the private insurance is greatly reduced. It is not surprising then that a large proportion of younger individuals will have low willingness to pay for the PHI cover. At the same time the supplementary role played by the PHI cannot be the only explanations for the low effectiveness of the mandate. In particular, it is clear that many of the uninsured high income taxpayers would be able to purchase PHI cover at the cost lower than their MLS tax liability. It must be the case then that these individuals either face significant transaction costs of purchasing insurance or make dominated choices. Since these frictions appear to have a significant effect on the effectiveness of the policy, understanding their nature remains an important topic for future research.

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6 Tables and Figures

Table 1: Estimation of $\underline{Y}$ and $\overline{Y}$

	Model 1		Model 2	
Variable	Coefficient	P-value	Coefficient	P-value
Y	1636.73	0	1745.413	0
$Y^2/100^2$	-516401.715	0	-537159.815	0
$Y^3/100^3$	350569.776	0	363457.612	0
γ_1	11599.627	0	11494.594	0
γ_2	3025.017	0	2919.442	0
γ_3	1304.348	0	1198.252	0.001
γ_4	479.637	0.184		
γ_5	463.93	0.199		
α_1	-3675.88	0	-3780.354	0
α_2	-2377.506	0	-2481.402	0
α_3	-1663.303	0	-1766.605	0
α_4	-1401.311	0	-1504.006	0
α_5	-1294.542	0	-1396.615	0
α_6	-1004.043	0.006	-1105.482	0.003
α_7	-830.839	0.022	-931.633	0.011
α_8	-914.968	0.012	-1015.107	0.006
α_9	-749.455	0.039	-848.93	0.021
α_{10}	-683.348	0.059	-782.152	0.033
α_{11}	-414.677	0.25		
α_{12}	-572.459	0.113		
α_{13}	–645.746	0.075		
α_{14}	-265.553	0.461		
α_{15}	-378.928	0.293		
const	35795.864	0	33948.618	0
N	131		131	
R^2	0.998		0.998	
$\underline{Y}$			$49,125	
$\overline{Y}$			$52,625	

Note: The dependent variable is counts of individuals in the reported taxable income bin with width of $250. The reported taxable income Y is measured in thousands of dollars. Estimation sample includes income bins between $39,125 and $71,625. The counts of individuals within income bins varies between 16,771 and 44,279 in the estimation sample.

Table 2: Relationship between income and PHI coverage, equation (2)

Coefficient	Estimate	St.err	P-value
β_1^0	.0914307	.0150	0.000
β_2^0	.0070741	.0003	0.000
β_1^1	.0125840	.0298	0.673
β_2^1	.0092023	.0005	0.000

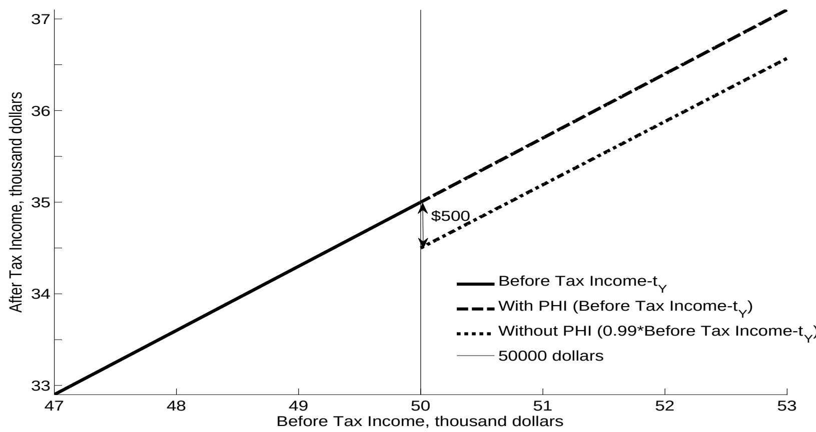
Note: The dependent variable is the proportion of individuals with PHI in the reported taxable income bin with width of $250. The explanatory variable (reported taxable income Y) is measured in thousands of dollars. Estimation sample includes income bins between $43,625 and $49,125, and between $52,625 and $56,875. R^2 is close to unity.

Table 3: Extrapolating the MLS effect to income levels above the MLS threshold

1	Total counts, singles	5,948,290
2	Total counts with PHI, actual	2,175,680
3	Total counts with PHI, counterfactual	2,029,221
4	Δ (2-3)	146,459
5	Δ, percent (100%*4:3)	7.2%
6	Overall PHI rate, actual (2:1)	36.57%
7	Overall PHI rate, counterfactual (3:1)	34.1%
8	Budget revenue, mln.	321.4
9	Budget cost of 30% premium rebate, mln, $P = \$500$	22
10	Budget cost of 30% premium rebate, mln, $P = 0.1 \cdot Y/0.7$	48
11	Budget cost of 30% premium rebate, mln, $P = \$2283$	100

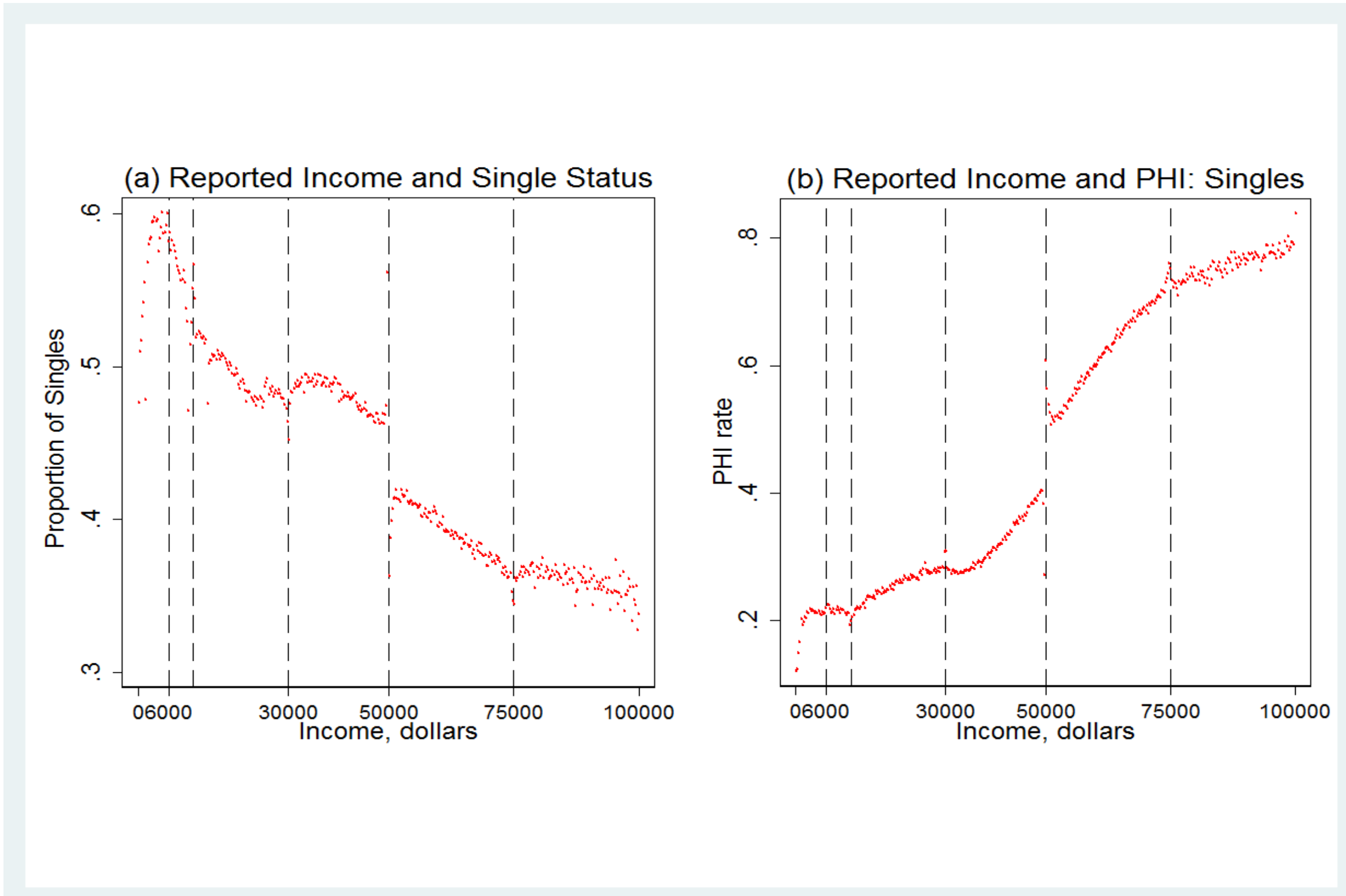
Note: Budget revenue is computed as 1% of the total reported taxable income of single population without PHI with reported incomes exceeding $50,000

Figure 1: How the MLS works: single individuals, no children, 2008



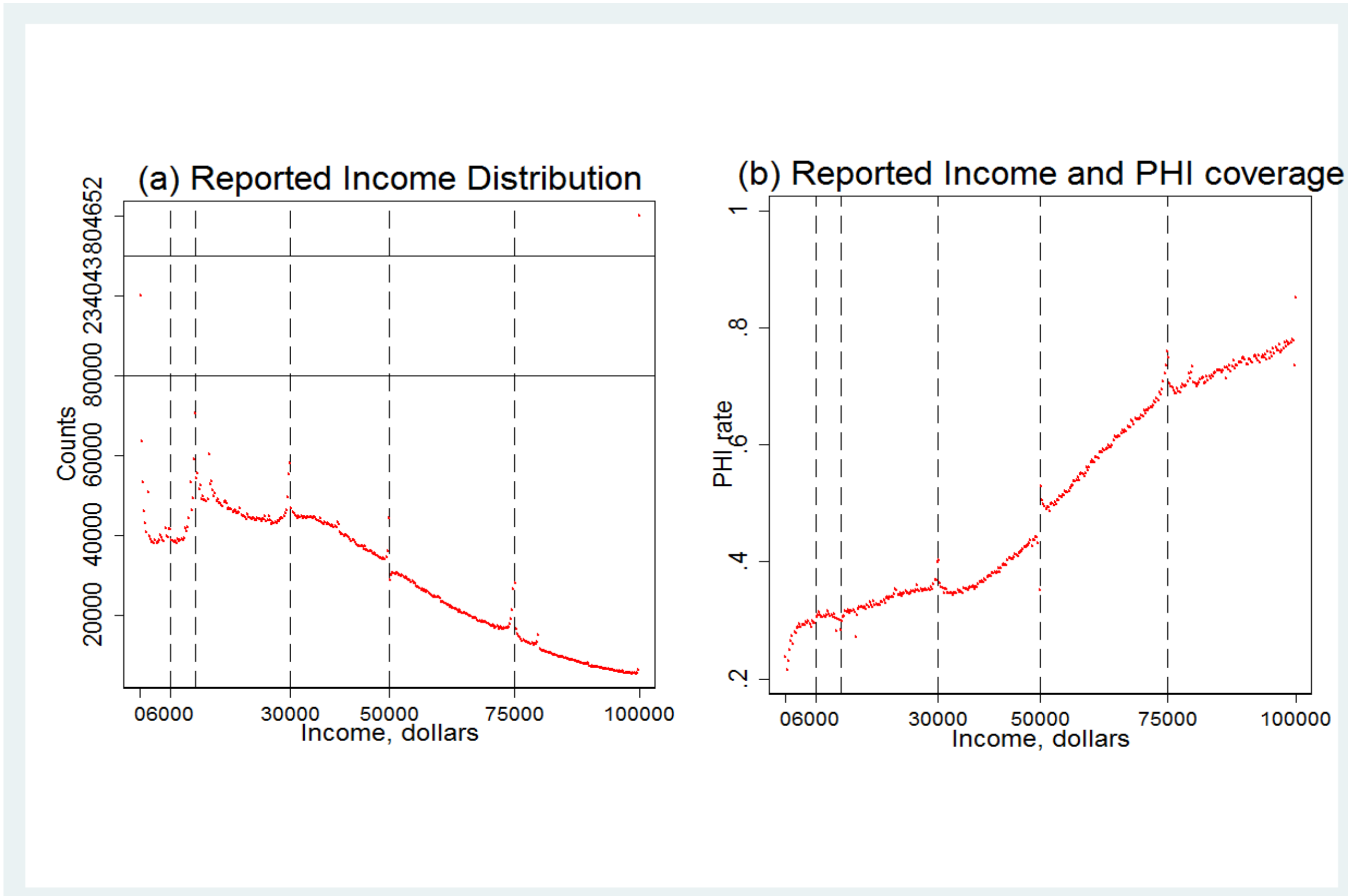
Note: In the Figure t_Y denotes income tax liability, i.e. $t_Y = Y \cdot t$, where Y is before tax income and t is the income tax (set to 0.30 in the Figure).

Figure 2: Single status and PHI coverage of singles: 2008 returns



Note: Vertical dashed lines indicate income tax thresholds at $6,000, $30,000 and $75,000, the MLS threshold for singles at $50,000 and the effective tax free income threshold at $11,000 (not labeled).

Figure 3: Reported taxable income distribution and PHI coverage: total population, 2008 returns



Note: Vertical dashed lines indicate income tax thresholds at \$6,000, \$30,000 and \$75,000, the MLS threshold for singles at \$50,000 and the effective tax free income threshold at \$11,000 (not labeled).

Figure 4: Reported taxable income distributions: total population, 2008 returns

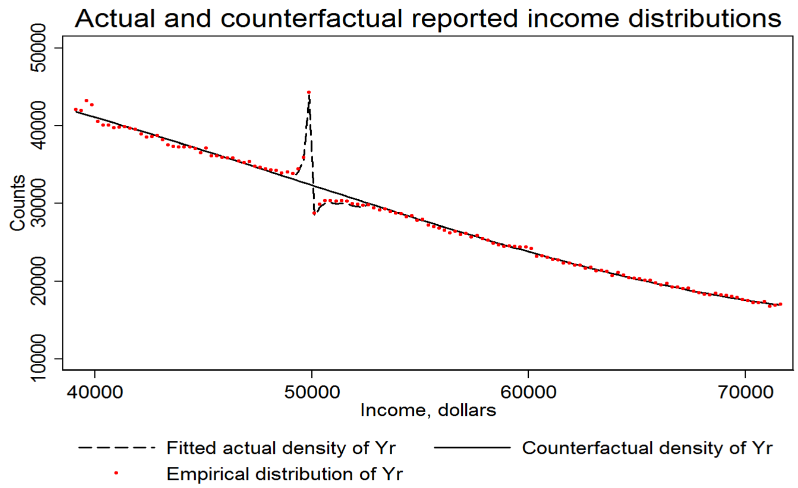
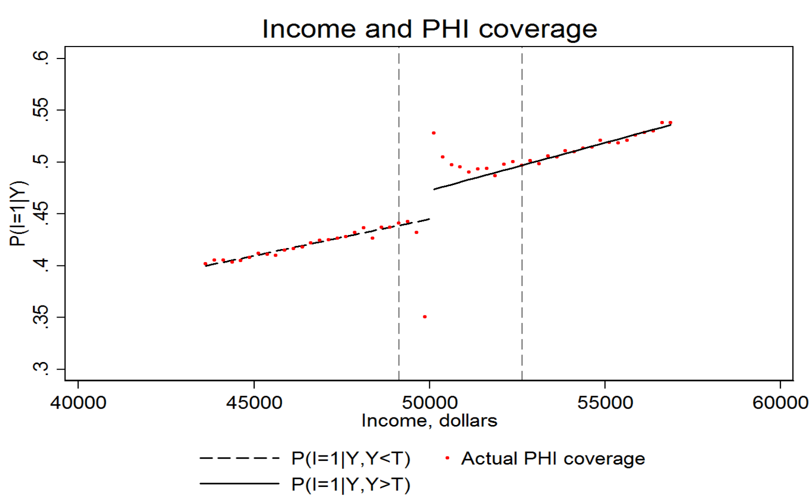
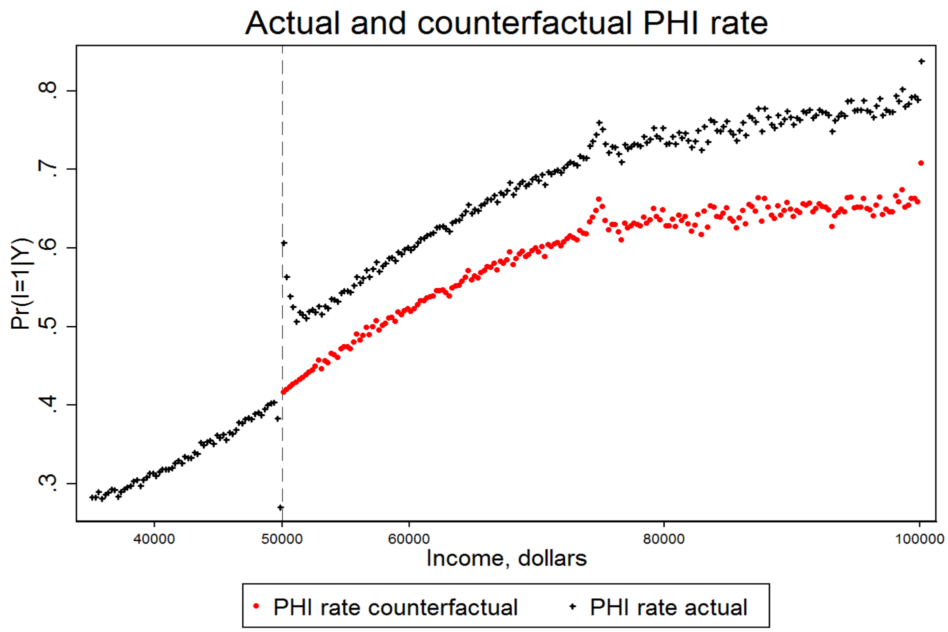


Figure 5: Reported taxable income and PHI coverage if bunching was not possible: total population, 2008 returns



Note: The dashed and solid sloped lines are fitted values from equation (2). The dashed vertical lines around 50,000 indicate the bunching interval (i.e. (\$49,125,\$52,625)) within which the PHI coverage is forecasted out of sample using estimates in Table 2.

Figure 6: Extrapolating the MLS effect to income levels above the MLS threshold



7 Appendix

7.1 Theoretical Framework

This section develops a model of the demand for private health insurance in the presence of an individual income based insurance mandate which is designed to capture the main features of the MLS policy as well as institutional details of the Australian health care system. In the model a consumer makes a choice between a publicly provided private good of a basic quality (i.e. health care services in the public sector) and a higher quality alternative supplied by the private sector, with private health insurance providing coverage for the private health expenditures. There exists an insurance mandate which applies after a given income threshold and takes a form of a tax penalty. An individual with the reported taxable income above the threshold can either (i) pay the penalty, (ii) purchase PHI cover or (iii) reduce the reported taxable income. While we assume that this income shifting is costly to the individual, we do not take a stand on the legality or social efficiency of this behavior.[12] We

[12]Income shifting might occur through illegal tax evasion or legal tax avoidance. It might also take a form of potentially welfare enhancing activities such as charity donations

show that this conceptual framework is capable of reproducing the main patterns observed in the data as described in the previous section. We also show that it can be used to develop an intuitive approach to the estimation of the treatment effect of the MLS policy in the presence of income shifting.

7.1.1 Model Setup

Consider an individual who faces a given probability π of becoming ill and experiencing a disutility of health restoring treatment, whose preferences are defined over a composite consumption good. The treatment can be obtained either from public or private health care sector. As is typically assumed in these type of models (e.g. Martin and Smith, 1999) the disutility of treatment is lower in the private sector, reflecting the fact that private treatment as a rule involves shorter waiting times, ability to choose the treating doctor and other quality enhancements. However, treatment in the private sector commands a higher price. An individual can purchase private health insurance to cover the cost of treatment in the private sector. To simplify exposition we assume that (i) insurance provides full coverage, implying that insured individual will always choose private treatment; and (ii) the price of private treatment is sufficiently high to induce someone without insurance to always choose public sector treatment. Under these assumptions the choice of insurance status completely determines the choice of the health care sector, resulting in the expected utility function defined over the composite consumption good and insurance status given by

$$u(c, I) = m(c) - \pi(I \cdot \tau_{pr} + (1 - I) \cdot \tau_{pb}) - I \cdot \xi$$

Here $m(c)$ denotes individual's consumption utility, I is private health insurance indicator, τ_{pb} and τ_{pr} are the disutilities of treatment in a public and private sectors, respectively, and ξ denotes an additive psychic search cost associated with purchasing a private insurance. In what follows the price of treatment in the public sector and the disutility of treatment in the private sector τ_{pr} will be both normalized to zero.

The MLS policy stipulates that if the individual's income is greater than a given threshold T, they must pay a Medicare Levy Surcharge of t percent of the total reported taxable income. Let Y denote the true taxable income earned by the individual. The reported taxable income Y_r can be lower than Y if an individual decides to engage in income shifting. We assume that the cost of underreporting is linear in the amount of the underreported income $E = Y - Y_r$ and is given by $C(E) = aE$. Because MLS is the only reason to engage

Table 4: Utility function

	$Y < T$	$Y \geq T$
$I = 0$	$m(Y) - \pi \cdot \tau_{pb}$	$m(Y - t \cdot (Y - E) \cdot \iota(Y - E \geq T) - aE) - \pi \cdot \tau_{pb}$
$I = 1$	$m(Y - P) - \xi$	$m(Y - P) - \xi$

in income shifting, an individual might have $E > 0$ only if the true income exceeds the MLS threshold ($Y \geq T$). Throughout the analysis we assume that the marginal cost of avoidance is higher than the surcharge rate, $a > t$.[13] This guarantees that there exists a threshold level of income above which no avoidance takes place. Under these assumption the individual's utility maximization problem amounts to choosing c, I and the amount of underreported income E to maximize the expected utility function $u(c, I)$ subject to the following budget constraint

$$c \leq Y - I \cdot P - (1 - I) \cdot t \cdot (Y - E) \cdot \iota(Y - E \geq T) - aE,$$

where $\iota(.)$ is an indicator function equal to 1 if the expression in parenthesis is true, and is equal to zero otherwise and P denotes the insurance premium. Note, that apart from the insurance premium P, the costs of health care do not enter the budget constrain because it is assumed that (i) treatment is free in the public sector; (ii) insurance covers fully the cost of treatment in the private sector; (iii) it is never optimal for a person without PHI to choose private treatment. Using this budget constraint one can substitute for consumption in the utility function, which reduces maximization problem to the choice of insurance status and amount of income shifting. Table (4) shows utilities of insured and uninsured individuals with incomes below and above the MLS threshold after imposing the normalization $\tau_{pr} = 0$.

If the individual's true income is below the threshold, the utility maximization problem reduces to the choice of the insurance status, which is affected by the disutility of treatment in the public sector, insurance premium and the search cost of insurance. On the other hand, a person with income above the MLS threshold decides whether to buy insurance as well as how much income to underreport if no insurance is purchased.

The insurance choice problem can be further simplified by solving for the optimal amount of income shifting chosen by a person with income above the threshold conditional on not

[13]Without this assumption it will always be optimal for individuals with true incomes exceeding T and without PHI to report incomes less than T, resulting in PHI coverage rate of unity above the MLS threshold. This pattern is not consistent with the observed data. It is easy to show that a linear cost function with the restriction $a > t$ results in similar model predictions as a quadratic cost function $C(E) = E^2$. Although the quadratic cost function is perhaps more realistic, we chose the linear specification because it is much easier to analyze.

having insurance. First note that the structure of MLS implies that a person engaged in underreporting will need to report income below the MLS threshold to avoid paying the tax. Because underreporting is costly, the optimal reported taxable income, conditional on engaging in income shifting, must be strictly below but as close as possible to the MLS threshold T. In practice such exact manipulation of income will be difficult to implement, and one would expect that underreported incomes will fall into some small interval below the threshold. To formalize this intuition, let $\epsilon > 0$ denote the length of the interval and assume that by choosing the target level of reported income equal to $T-\epsilon$ a person engaging in income shifting can guarantee that the actual realization of the reported income is a draw of random variable distributed uniformly on $[T-\epsilon, T)$. Under this assumption the optimal amount of underreporting is given by $Y - T + \epsilon$. Next note that because the marginal cost of underreporting, a, is higher than the MLS rate t, not everyone who is not insured will engage in income shifting. In particular, there exists a threshold level of income $\overline{Y}$ such that for income levels satisfying $T < Y \leq \overline{Y}$ it would be optimal to underreport income by exactly $Y - T + \epsilon$, while for income levels $Y > \overline{Y}$ it is optimal to report income truthfully and pay the tax. An individual with the income level $\overline{Y}$ must be indifferent between reporting the income level just below the MLS threshold and reporting truthfully. The value of $\overline{Y}$ is determined by the following equality:

$$\overline{Y} - a \cdot (\overline{Y} - T + \epsilon) = \overline{Y} - t\overline{Y}$$

Solving this equation for $\overline{Y}$ we get

$$\overline{Y} = \frac{a(T-\epsilon)}{a-t}. \tag{5}$$

The above arguments taken together imply that the structure of the individual's insurance choice problem will depend on the individual's true taxable income Y as follows.

Case 1: $Y < T$. True taxable income is reported. Utility without insurance is $u(I = 0) = m(Y) - \pi \cdot \tau_{pb}$. Utility with insurance is $u(I = 1) = m(Y - P) - \xi$.

Case 2: $T \leq Y \leq \overline{Y}$. True taxable income is reported if insured, and $Y - T + \epsilon$ is reported otherwise. The actual realization of the reported taxable income for those without insurance follows uniform distribution on $[T-\epsilon, T)$. Utility without insurance is $u(I = 0) = m(Y - a(Y - T + \epsilon)) - \pi \cdot \tau_{pb}$. Utility with insurance is $u(I = 1) = m(Y - P) - \xi$.

Case 3: $Y > \overline{Y}$. True taxable income is reported. Utility without insurance is $u(I = 0) = m(Y - t \cdot Y) - \pi \cdot \tau_{pb}$. Utility with insurance is $u(I = 1) = m(Y - P) - \xi$.

7.1.2 Model Predictions

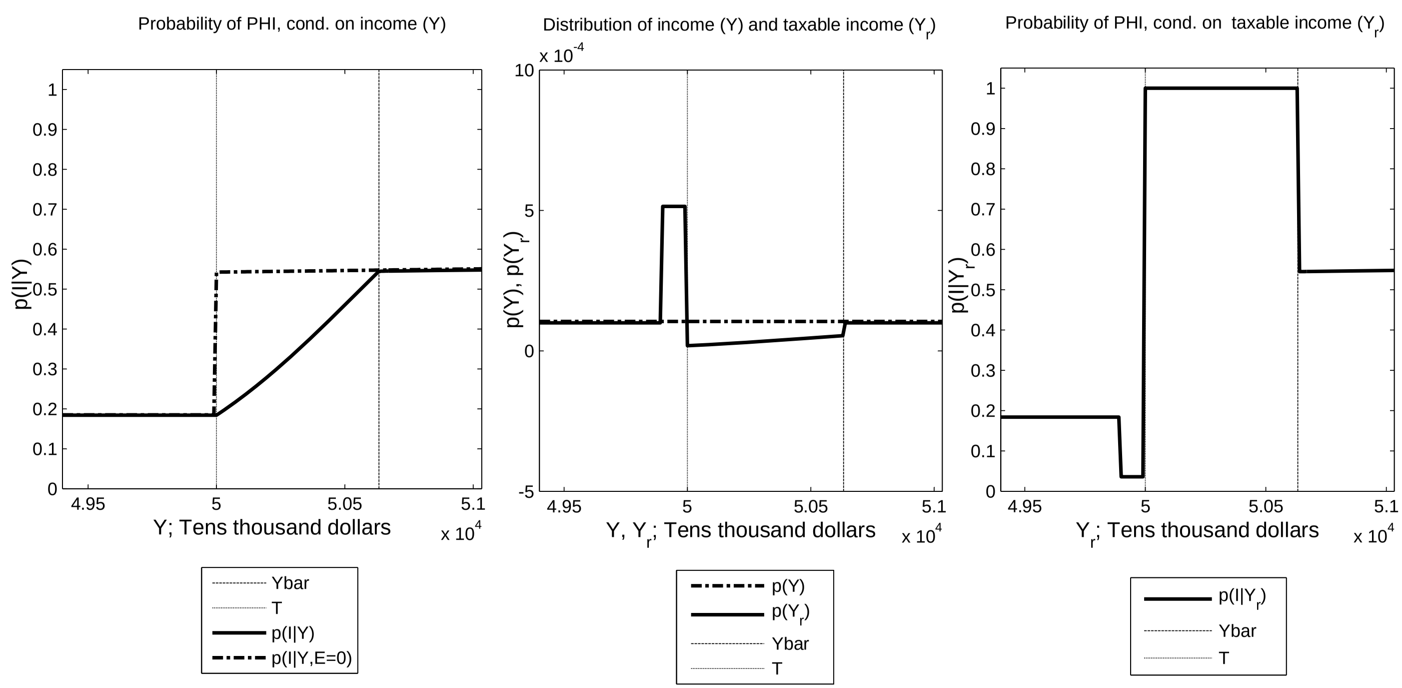
The model outlined above can be used to derive predictions about taxpayers' responses to the incentives embedded in the MLS policy. In this section we impose assumptions on the functional forms and parameter distributions to illustrate graphically model's predictions, while the analytical results are derived in the Appendix. We start by describing the relationship between the distribution of the true income, the probability of having insurance conditional on the true income (both of which are not fully observed in the data), on the one hand, and the distribution of the reported taxable income and the probability of having insurance conditional on the reported income (both are fully observed in the data). We then discuss how the data on the reported taxable income and insurance rates can be used to estimate (i) the amount of income shifting caused by MLS; and (ii) the treatment effect of MLS on the PHI coverage rate.

Let $\eta \equiv \pi \cdot \tau_{pb} - \xi$ denote the expected net psychic benefit of private health insurance. Since π, τ_{pb} and ξ are all non-negative, η can take any value on the real line. Suppose that η and Y are identically and independently distributed in the population.[14] Let $G(\eta)$ denote the cumulative distribution function (cdf) of η. The cdf of η can be used to compute the probability that an individual is insured, conditional on the reported income Y_r, as well as conditional on the true income Y. Let $p_y(Y)$ denote the probability density function of Y and $p_r(Y_r)$ denote the probability density of Y_r.

The predictions of the model obtained under these assumptions are illustrated in Figure 7. The graphs in this figure are constructed for the income range from \$49,000 to \$51,000 under the following parameterization: Y is distributed uniformly on this interval, the consumption utility is assumed to be linear, $m(Y) = Y$, η has a standard normal distribution independent of Y, $a = 0.8$ and $\epsilon = \$100$. The solid line in the leftmost panel of the figure shows the relationship between actual income Y and probability of having insurance coverage obtained from the model with income shifting. Note that because only the reported (and not actual) income is observed, this relationship cannot be compared to what is observed in the data. The dashed line in the same panel depicts the same relationship for the case when income shifting is not possible (for example because the marginal cost a is too high). The probability of coverage jumps discontinuously at the MLS threshold, with the size of the jump representing the treatment effect of the MLS at the threshold. On the other hand, when the income shifting is possible insurance coverage increases gradually after the threshold, and the policy effect reaches it's full magnitude only at $\overline{Y}$, when income shifting is no longer profitable

[14] This assumption can be relaxed without affecting main results.

Figure 7: Model Predictions



for the taxpayers. Note also that in both cases (with and without income shifting) the relationship between income and the PHI coverage rate is the same when income is below T or above $\overline{Y}$.

The middle panel of Figure 7 plots the probability densities of Y and Y_r. The density of the reported income illustrates the phenomenon of bunching observed in the data: this density is excessively high (compared to that of Y) in the interval below the threshold T, and is excessively low in the interval to the right of T (these two intervals are defined as Region 2 and Region 3, respectively, in the analytical derivations presented in section 8.2). Finally, the rightmost panel of the Figure plots the relationship between the reported income Y_r and PHI coverage rate. As discussed above, there is a dip in the coverage rate below the threshold in Region 2, while the coverage rate rises to 100 percent to the right of the threshold in Region 3. This pattern is an artifact of the income shifting by the taxpayers who choose not to buy the insurance. The behavior of the density of the reported income and the insurance conditional on the reported income predicted by the model mirrors closely the patterns observed in the data (Figure3).[15] Also note that in the rightmost panel of Figure 7, the relationships between insurance coverage and reported income Y_r and actual income Y are the same when $Y_r < T_\epsilon$ or $Y_r > \overline{Y}$, because these are the intervals where the behavior of individuals is not distorted by income shifting. This observation forms the basis for our estimation strategy, described in section 4.1.

7.2 Choosing an Econometric Model for Forecasting PHI Coverage at the MLS Threshold

To select the model for the relationship between income and PHI for $Y \leq \underline{Y}$ for forecasting $P(I = 1|Y = T, t = 0, E = 0)$ using the data on the PHI coverage rate in the total population we compare various combinations of the estimation sample size and functional forms in their ability to forecast out-of-sample 8 PHI rates corresponding to 8 income bins closest to T=$50,125 on the left that are not contaminated by the bunching behavior.[16] Similarly, we choose the specification for the relationship between income and PHI rate for $Y \geq \underline{Y}$ for forecasting $P(I = 1|Y = T, t = 0.01, E = 0)$ by comparing the out-of-sample forecasting

[15] An obvious exception is that the observed insurance coverage rate in the Region 3, while excessively high, is not 100% as predicted by the model. This is the result of the simplifying assumption that everyone has the same marginal cost of income shifting. Introducing heterogeneity in this parameter will result in some taxpayers without insurance reporting incomes above the MLS threshold, as observed in the data.

[16] In particular, we are forecasting for the 8 income bins with the mid-points between $47,375 and $49,125, with the increment of $250. Note that $49,125 is our estimate of $\underline{Y}$.

performance for 8 income bins closest to \$50,125 to the right that are not contaminated by the bunching behaviour (i.e. the 8 income bins to the right of and including \$52,625, which is our estimate of $\overline{Y}$).[17] We are comparing these various specifications in their ability to the in-sample forecasts from the following flexible model for the relationship between income and PHI rate:

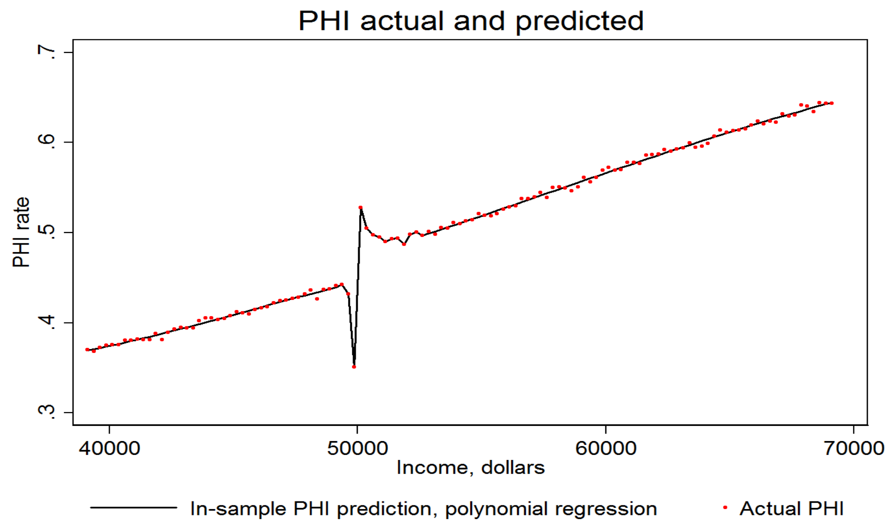
$$\begin{aligned} PHI_i &= \beta_0^0 + \sum_{j=1}^{3} \beta_j^0 Y_i^j + \sum_{k=1}^{3} \gamma_k \cdot \iota(T - 250 \cdot k < Y_i < T - 250 \cdot (k-1)) \\ &+ \beta_0^1 \cdot MLS_i + \sum_{k=1}^{10} \alpha_k \cdot \iota(T + 250 \cdot (k-1) < Y_i < T + 250 \cdot k) \\ &+ \sum_{j=1}^{3} \beta_j^1 (Y_i - 50,000)^j \cdot MLS_i + \varepsilon_i \end{aligned} \qquad (6)$$

where PHI_i is the PHI coverage rate in income bin i, $MLS_i = 1$ if $Y_i > \$50,000$, and $MLS_i = 0$ otherwise, and income ranges are restricted to $39,125 \leq Y \leq 69,125$. This is a flexible model with very good in-sample predictions of PHI coverage.

We believe that this type of model would be appropriate for estimation of the effects of the MLS using the same data in a counterfactual situation where tax avoidance was not possible. Having bin averages rather than individual-level data limits the ability to conduct a non- or semi-parametric estimation of the policy effect as in Hahn, Todd and van der Klaauw (2001) and Porter (2003) (i.e. a local linear regression). An attempt at nonparametric estimation (which would simply amount to comparing the PHI coverage in the income bins immediately to the left and to the right of the MLS threshold) would overestimate the policy effect at the threshold because any estimated difference will be partially driven by the clear upward income trend in the PHI coverage. Therefore, we would have to resort to a parametric model like (6). In this counterfactual case the parameters γ_1-γ_3 and α_1-α_{10} would be equal to zero and our estimate of the MLS policy effect would be β_0^1. By matching the out-of-sample forecasts with the in-sample forecasts obtained from specification (6) we are essentially trying to come up with the estimates of the policy effect closest to those that would obtain in this counterfactual situation using model (6). The fit of specification (6) is shown in Figure 8. It turns out that for income levels $Y \leq \underline{Y}$ the linear model estimated using 23 income bins gives the best out-of-sample forecasts, while for $Y \geq \overline{Y}$ the linear model

[17] In particular, we compare forecasts for the 8 income bins with the mid-points between \$52,625 and \$54,375, with the increment of \$250.

Figure 8: Fit of specification (6)



estimated using 18 income bins gives the best out-of-sample forecasts. Below we describe in detail how these specifications were chosen.

Tables 5 and 6 detail how the out of sample forecasting performance of various models was evaluated. Table 5 details this procedure for forecast of the PHI coverage from below the MLS threshold, while Table 6 does it for forecasting for above the MLS threshold. In these tables $\widehat{PHI}$ denotes the in-sample prediction of PHI rate from the model in equation (6), $\widehat{\widehat{PHI}}_j$ denotes out-of-sample forecasts of PHI rate, where $j = lin$ for a model that is linear in income Y, $j = quad$ for a model quadratic in Y and $j = cub$ for a model cubic in Y. $RMSE_j$ is the root mean squared error computed using $\widehat{PHI}$ and $\widehat{\widehat{PHI}}_j$: $RMSE_j = \sqrt{\frac{1}{8}\sum_{i=1}^{8}(\widehat{PHI}_i - \widehat{\widehat{PHI}}_{ji})^2}$, where the summation is taken over the 8 income bins for which the forecasts are obtained. $R\widetilde{MSE}_j$ is the root mean squared error computed using actual PHI rate and $\widehat{\widehat{PHI}}_j$: $R\widetilde{MSE}_j = \sqrt{\frac{1}{8}\sum_{i=1}^{8}(PHI_i - \widehat{\widehat{PHI}}_{ji})^2}$.

For example, the first 8 rows of Table 5 show the performance of the linear, quadratic and cubic in income models estimated on the sample of 46 income bins in their ability to forecast PHI coverage in 8 income bins just to the left of and including $\underline{Y}$. In particular, we are forecasting for the income bins with the following mid-points: \$47,375, \$47,625, \$47,875, \$48,125, \$48,375, \$48,625, \$48,875, and \$49,125. These income bins are listed in Table 5 in the column labeled "income". The 46 income bins estimation sample for obtaining the

4-steps ahead out-of sample forecast of PHI coverage in the income bin with the midpoint of \$47,375 starts with the bin with the midpoint of \$35,125 and ends with the bin with the midpoint of \$46,375. The actual PHI coverage of the income bin with the midpoint of \$47,375 is 0.427 (column PHI), the in-sample prediction of this coverage rate obtained from model (6) is 0.427 (column $\widehat{PHI}$), while the 4-step ahead forecasts obtained from the linear, quadratic and cubic in income forecasting models are 0.422, 0.429 and 0.423, respectively (columns $\widehat{\widehat{PHI}}_{lin}$, $\widehat{\widehat{PHI}}_{quad}$, $\widehat{\widehat{PHI}}_{cub}$). To obtain the 4-steps ahead out-of-sample forecast of PHI coverage in the income bin with the midpoint of \$47,625 we have to shift the 46 bin estimation window to the right by one bin: the new estimation sample starts at \$35,375 and ends at \$46,625. The estimation windows are successively shifted by one bin to the right to obtain the out-of-sample forecasts for the remaining income bins in the column labeled "income". The reported $RMSE_j$ and $\widetilde{RMSE}_j$ in row 9 are taken over the 8 forecasts reported in rows 1-8. Among the models estimated on 46 income bins the quadratic model has the lowest RMSE of 0.0018. Similarly, the first estimation window of the estimation sample consisting of 45 income bins which are used to obtain the PHI prediction for the income bin with midpoint of \$47,375 starts at 35,375 and ends at 46,375. The second estimation window of the estimation sample consisting of 45 income bins which are used to obtain the PHI prediction for the income bin with midpoint of \$47,625 starts at 35,625 and ends at 46,625, and so on. Again, the quadratic model produces the smallest RMSE among the three competing models for the estimation sample of 45 income bins.

Figure 9 plots the $RMSE$ computed over the predictions for 8 income bins to the left of and including $\underline{Y}$ against the number of income bins in the estimation sample of the prediction model, for the linear, quadratic and cubic polynomial specifications. It is easy to see that the linear model estimated on the sample of 23 income bins results in the lowest $RMSE$. For this reason we are using the estimation sample consisting of 23 income bins and a linear model to predict the PHI rate at the absence of the MLS tax for income of \$50,125.

The assessment of the goodness of the out-of-sample forecasting performance of different specifications and sample sizes for PHI rate in the presence of the MLS tax (to the right of the MLS threshold) is detailed in Table 6 and Figure 10. It turns out that the linear model estimated on 37 income bins produces the lowest out-of-sample RMSE, and we adopt this specification in section 4.3 to obtain the prediction of PHI rate in the presence of the MLS tax and at the absence of bunching for income level of \$50,125.

The sizes of the forecast errors allow us to estimate lower and upper bounds on the MLS effect. In the interval below the threshold the largest negative and positive forecast errors

Table 5: Out of Sample Forecast for $Y < T$

Window	start	stop	Income	PHI	$\widehat{PHI}$	$\widehat{PHI}_{lin}$	$\widehat{PHI}_{quad}$	$\widehat{PHI}_{cub}$
n bins=46								
1	35125	46375	47375	0.427	0.427	0.422	0.429	0.423
2	35375	46625	47625	0.428	0.429	0.424	0.430	0.426
3	35625	46875	47875	0.432	0.430	0.427	0.432	0.429
4	35875	47125	48125	0.437	0.432	0.429	0.434	0.431
5	36125	47375	48375	0.427	0.434	0.431	0.436	0.433
6	36375	47625	48625	0.437	0.436	0.433	0.437	0.435
7	36625	47875	48875	0.437	0.438	0.436	0.439	0.439
8	36875	48125	49125	0.441	0.440	0.438	0.442	0.443
RMSE						0.0034	0.0018	0.0023
$\widetilde{RMSE}$						0.0046	0.0037	0.0037
n bins=45								
1	35375	46375	47375	0.427	0.427	.422	.428	.423
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
8	37125	48125	49125	0.441	0.440	.438	.441	.444
RMSE						0.003	0.0014	0.0024
$\widetilde{RMSE}$						0.0043	0.0035	0.0038
⋮								

Figure 9: Quality of out of sample forecasts of PHI coverage just below the MLS threshold

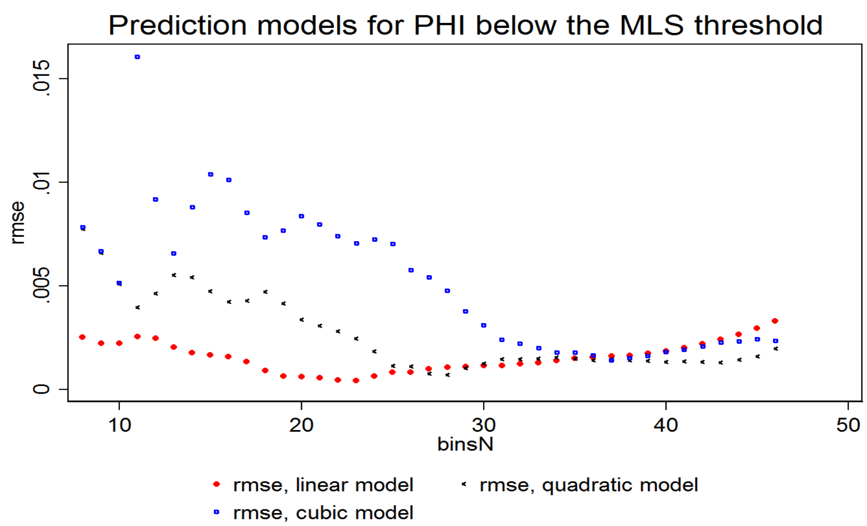
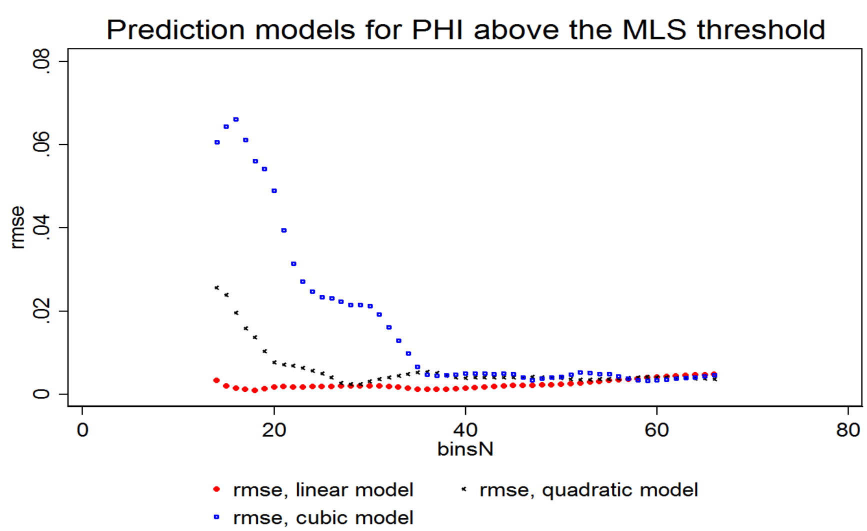


Table 6: Out of Sample Forecast for $Y > T$

Window	start	stop	Income	PHI	$\widehat{PHI}$	$\widehat{PHI}_{lin}$	$\widehat{PHI}_{quad}$	$\widehat{PHI}_{cub}$
n bins=66								
1	73125	56875	54375	0.513	0.513	0.518	0.512	0.508
2	72875	56625	54125	0.510	0.511	0.516	0.510	0.508
3	72625	56375	53875	0.511	0.509	0.514	0.507	0.505
4	72375	56125	53625	0.505	0.507	0.511	0.504	0.503
5	72125	55875	53375	0.506	0.505	0.509	0.500	0.501
6	71875	55625	53125	0.498	0.503	0.506	0.497	0.497
7	71625	55375	52875	0.501	0.501	0.503	0.494	0.493
8	71375	55125	52625	0.497	0.499	0.500	0.491	0.490
RMSE						0.0037	0.0049	0.0059
$\widetilde{RMSE}$						0.0047	0.0043	0.0052
n bins=65								
1	72875	56875	54375	0.513	0.513	.518	512	.508
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
8	71125	55125	52625	0.497	0.499	.500	.491	.490
RMSE						0.0036	0.0051	0.0057
$\widetilde{RMSE}$						0.0047	0.0044	0.0050
⋮								

Figure 10: Quality of out of sample forecasts of PHI coverage just above the MLS threshold

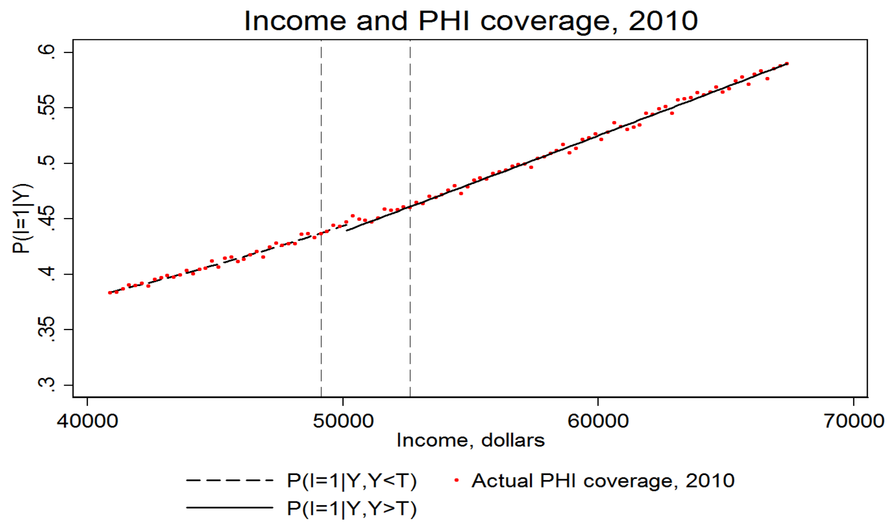


among the 8 forecasts (i.e. $\widehat{PHI}_i - \widehat{\widehat{PHI}}_i$, where $\widehat{PHI}_i$ is the in-sample forecast from the equation 6, while $\widehat{\widehat{PHI}}_i$ is the four steps ahead out-of-sample forecasts from the linear model estimated on 23 income bins) were -0.0007 and 0.0008. Similarly, in the interval above the threshold the largest negative and positive forecast errors among the 8 ten steps ahead forecasts were -0.0009 and 0.0014. Because our prior belief based on observing the data is that the MLS effect is relatively small, we want to obtain an upper bound of this effect at the MLS threshold. We know that we either over or underestimate the PHI coverage at the threshold. To obtain the upper bound on the effect we have to adjust the estimated total population effect at the MLS threshold for singles of 2.78 percentage points so that it reflects the most optimistic estimate. This can be done by adding the maximum by which the coverage is likely to be overestimated from below the threshold (0.0007) and the maximum by which the coverage is likely to be underestimated from above the threshold (0.0014) to 0.0278 to obtain the upper bound of 0.0299. Similarly, we can obtain the lower bound on the MLS effect as 0.0278-0.0008-0.0009=0.0261.

7.3 Placebo analysis using 2010 data

As a robustness check we also estimated the placebo effect using the income tax returns data for the total population from 2009-10, in which one would not expect to see a discontinuity at the 2007-08 MLS threshold of \$50,000 because the threshold has been increased to \$73,000 in 2008-09. We use the same approach to selection of specification of the model to be used to forecast PHI rate at the income of \$50,125 from the left of the MLS threshold (4-steps ahead forecast) and from the right of the threshold (10 steps ahead forecast) for 2010 data. Interestingly, for the 2010 PHI data the quadratic model which uses 34 income bins for $Y < 50,000$ and 60 income bins for $Y > 50,000$ was found to produce the best out of sample forecasts for the sixteen income bins described above. Hence, the estimation sample consisting of the income bins between \$40,875 and \$49,125 was used to obtain the 4-step ahead forecast from below the threshold, while the estimation sample consisting of income bins between \$52,625 and \$67,375 is used to obtain a 10-step ahead forecast from above. Using this specification we find that the estimated effect of the MLS is equal to -.005 with the standard error of .003, implying that this effect is not statistically significantly different from zero at 5% or lower significance levels. The p-value associated with the null hypothesis that this effect is equal to zero is 0.073. The fit of the prediction models used to estimate the MLS effect from 2010 data is shown on Figure 11. These results suggest that using our estimation approach we are unlikely to obtain a positive policy effect of a magnitude and

Figure 11: Estimation of the MLS effect at $50,125 using 2010 data



statistical significance that we obtain using the 2008 data from the data in which this effect is not present.

7.4 Estimation of the proportion of singles and the proportion of singles with PHI at the MLS threshold

We first estimate the following model using the same estimation sample as for the equation (2):

$$PS_i = (\beta_1^0 + \beta_2^0 Y_{ri})\iota(Y_{ri} <= \underline{Y}) + (\beta_1^1 + \beta_2^1 Y_{ri})\iota(Y_{ri} >= \overline{Y}) + \varepsilon_i \tag{7}$$

where PS_i is the proportion of single individuals in income bin i, Y_{ri} is the mid-point of the reported taxable income bins, and income bins where bunching behavior occurs are excluded from the estimation sample. The estimation results are presented in Table 7. The proportion of reported singles to the left of the threshold in the case when bunching is not possible is forecasted to be 0.46, while the proportion to the right is 0.43. We test whether the counterfactual (in the absence of bunching) probability of being single is the same immediately to the left and to the right of the threshold by testing the restriction $\beta_1^0 + \beta_2^0 \cdot 50.152 - \beta_1^1 - \beta_2^1 \cdot 50.125 = 0$. The estimated difference is equal to 0.036 with the standard error of 0.003 and is statistically significant at any level. So, the data supports

Table 7: Relationships between probability of being single, PHI coverage rate of singles, and income

Coefficient	Estimate	St.err	P-value
	Dependent variable: Proportion of singles		
β_1^0	.5620822	.0154167	0.000
β_2^0	-.0020114	.0003326	0.000
β_1^1	.5850878	.029325	0.000
β_2^1	-.0031834	.000536	0.000
	Dependent variable: Proportion of singles with PHI		
β_1^0	-.0751433	.0232281	0.000
β_2^0	.0096474	.0005015	0.000
β_1^1	-.1273144	.0461804	0.009
β_2^1	.0122267	.000844	0.000

Note: The dependent variables are: (i) the proportion of single individuals in the reported taxable income bin with width of \$250; (ii) the proportion of single individuals with PHI in the reported taxable income bin with width of \$250;. The explanatory variable reported taxable income Y_r is measured in thousands of dollars. Estimation sample includes income bins between \$43,625 and \$49,125, and between \$52,625 and \$56,875. Both R^2's are near unity.

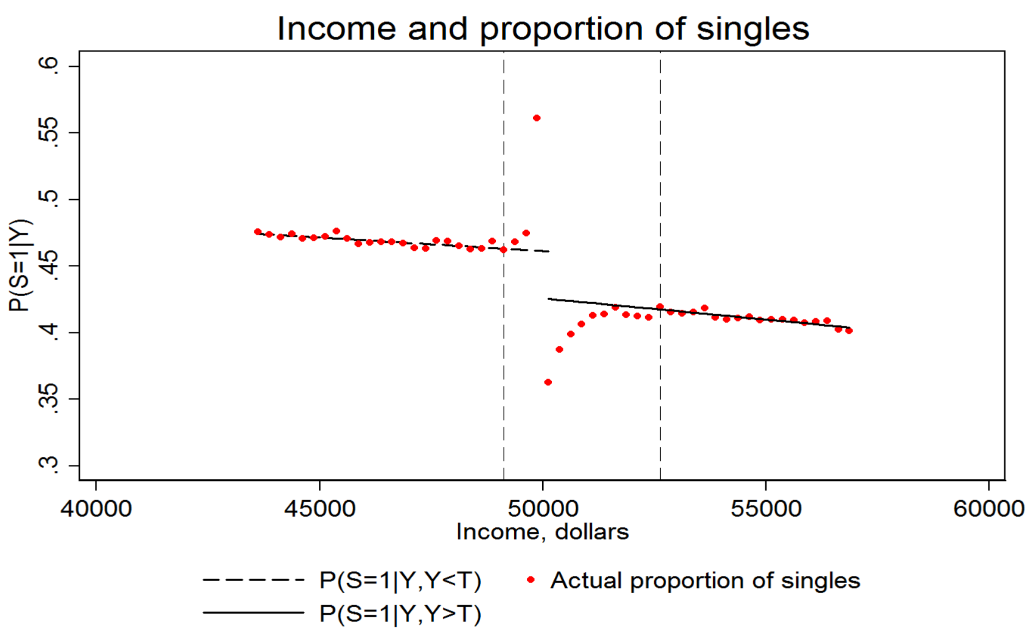
the hypothesis that there is less misreporting of marital status to the right of the MLS threshold for singles. Figure 12 shows the counterfactual probability of being single within the bunching interval which would obtain if tax avoidance was not possible.

We use the PHI coverage data of the self-reported single individuals to estimate their PHI coverage to the right of the MLS threshold, as we believe that self-reported single status is likely to be free of misreporting to the right of the MLS threshold for the reasons discussed above. Using specification (7), but with the PHI rate of self-reported single individuals as a dependent variable we find that the predicted PHI coverage of this group (in the case of no bunching) at the income level of \$50,125 is 0.486. The in- and out-of sample fit of model 2 to the PHI rate of self-reported singles is shown in Figure 13.

7.5 Heterogeneity of the policy effect by age

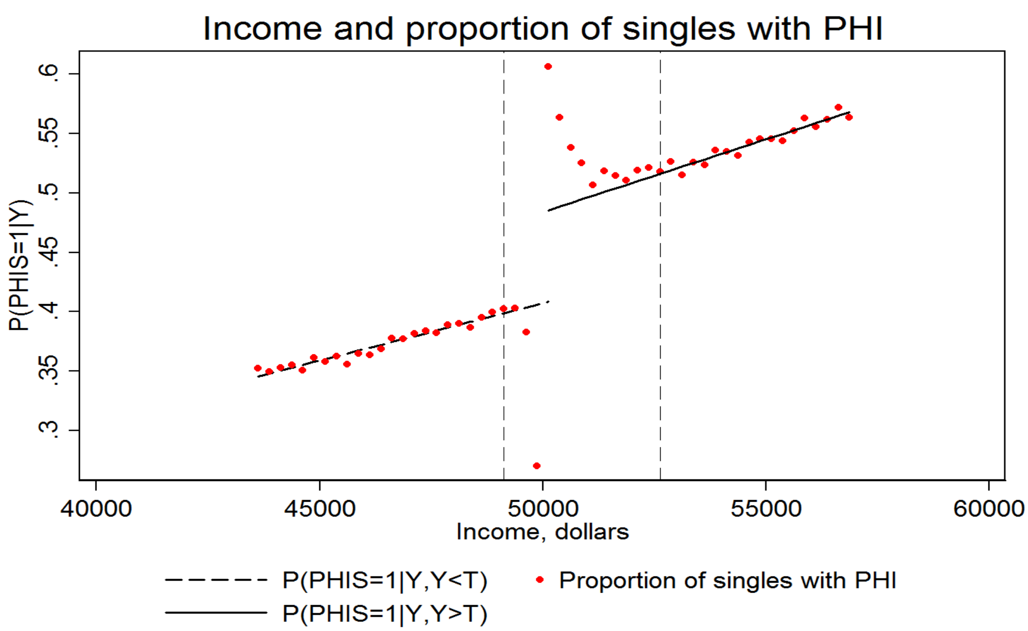
We estimate the effect of the MLS tax on PHI coverage for the three age groups of single individuals: "young" (between 15 years old and 32 years old), "middle-aged" (between 33 and 50 years old) and "old" (older than 50 years old). To estimate the MLS effect for each age group we use the methodology developed in section 4. In particular, for each of

Figure 12: Estimation of probability of being single $P(S|Y)$



Note: Vertical dashed lines mark the bunching interval within which the probability of being single is forecasted using the relationships estimated from data outside of the bunching interval.

Figure 13: Estimation of probability of PHI coverage using data on self-reported singles



Note: Vertical dashed lines mark the bunching interval within which the PHI coverage probability is forecasted using the relationships estimated from data outside of the bunching interval.

the three groups we first estimate the MLS effect at the threshold for all individuals (both married and single) which would obtain in the absence of bunching using the m-steps ahead forecasts. The number of steps in the forecasts, the specification of the prediction model and the estimation sample for the prediction model were chosen for each group separately. We then adjust the estimated policy effect by the group specific probability of being single to obtain the policy effect at the threshold for the treated group (singles with no children) of a given age. Finally we estimate the effect of the policy for income levels above the MLS threshold after imposing the same assumptions on the utility function and the distribution of η as in the previous section. To save space we do not report the detailed numerical results for these three age groups,[18] but summarize the main results graphically and in the tabular form.

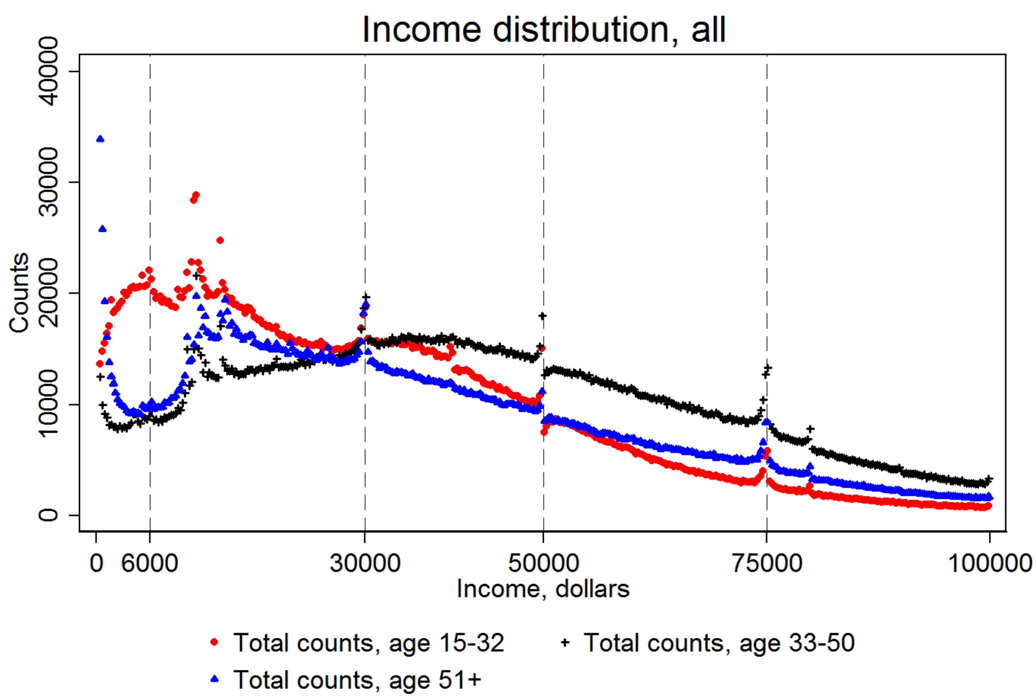
Before discussing the results we first discuss some of the sample statistics for the three age groups. Figure 14 shows income distribution of all individuals (single and married) in these groups. As expected, the probability of higher income levels are highest for the individuals of 32-50 years of age, while older and younger individuals are more likely to have relatively low incomes. Figure 15 shows income distributions for single individuals (according to the self-reported marital status) of the three age groups. As one would expect, young individuals make up a larger proportion of singles than other age groups. Both figures have a clear evidence of bunching at the kink points of income tax schedule, as well as at the MLS income threshold for singles ($50,000). Figure 15 also suggests that there is a discontinuous decrease in the number of self-reported singles at the MLS threshold.

Figure 16 shows PHI coverage rate for the three age groups of single individuals, while Figure 17 shows the PHI coverage rate for all taxpayers (single and married) in these age groups. As expected, PHI coverage increases with age. Also, there exists a discontinuous increase in the PHI coverage at the MLS threshold for all income groups. However, for reasons discussed in the previous section and due to the possible discontinuity in the income distribution of singles around the MLS threshold we will not attempt to estimate the MLS effect using data on PHI rates of singles. Instead, we will estimate the policy effect using PHI coverage rate data of all individuals (single and married).

After performing the estimation procedure described in the previous section we obtain the estimates of the MLS policy effects for singles for the three age groups. These estimates are presented in Table 9. We also show the in- and out-of-sample fit of the forecasting models used to estimate these policy effects in Figures (18)-(20). In Table 8 we summarize the

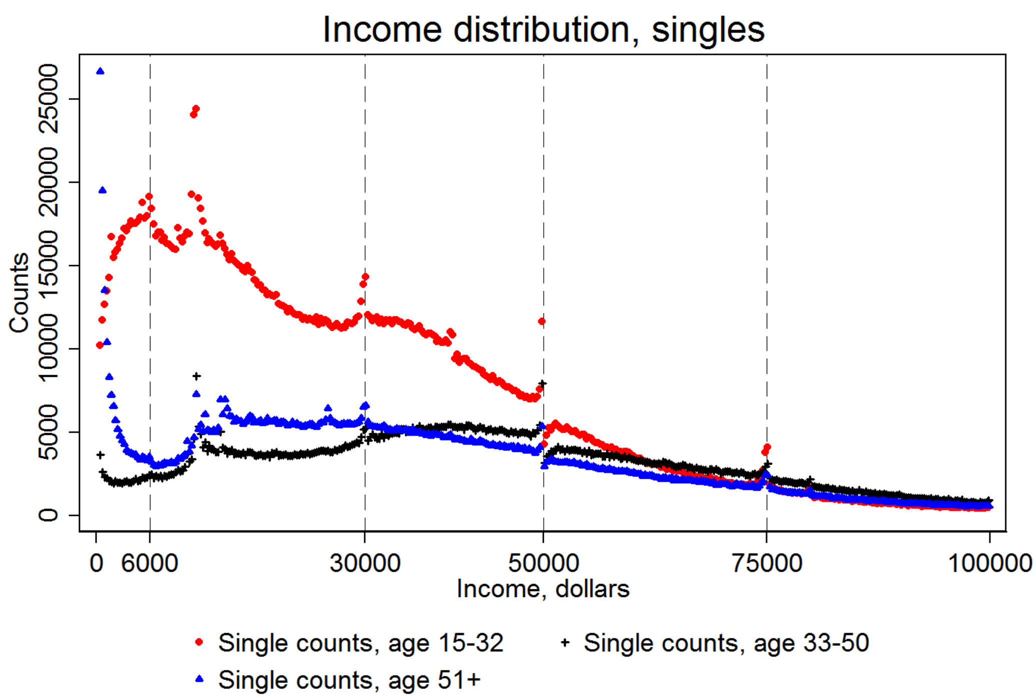
[18] The detailed results are available from the authors upon request.

Figure 14: Income distribution by age group



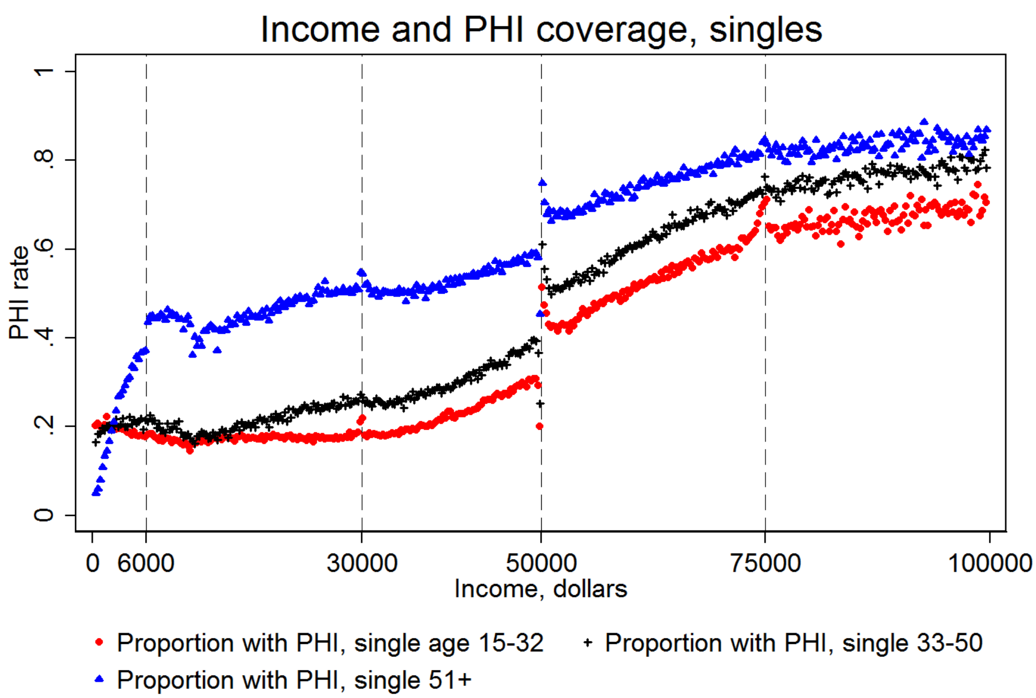
Note: Counts of individuals in the first income bin ($0-$250) and in the last income bin (>$100,000) are not shown on the graph.

Figure 15: Income distribution by age group, single individuals



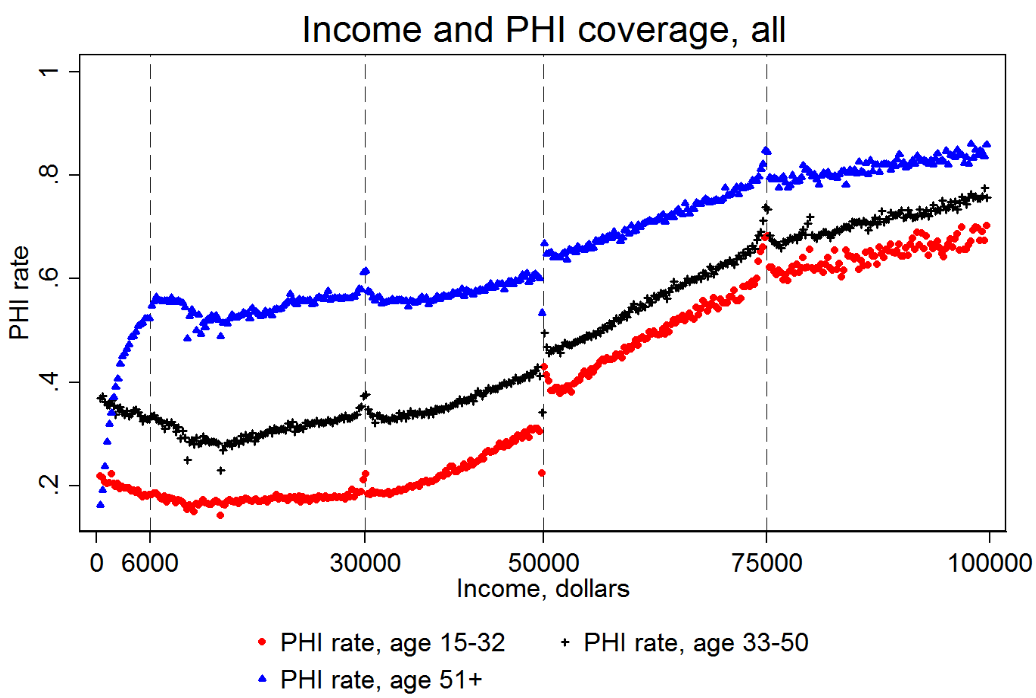
Note: Counts of individuals in the first income bin ($0-$250) and in the last income bin (>$100,000) are not shown on the graph.

Figure 16: PHI coverage rate by age group, singles



Note: PHI rates in the first income bin ($0-$250) and in the last income bin (>$100,000) are not shown on the graph.

Figure 17: PHI coverage rate by age group, all individuals



Note: PHI rates in the first income bin ($0-$250) and in the last income bin (>$100,000) are not shown on the graph.

Table 8: Characteristics of the forecasting models for the three age groups.

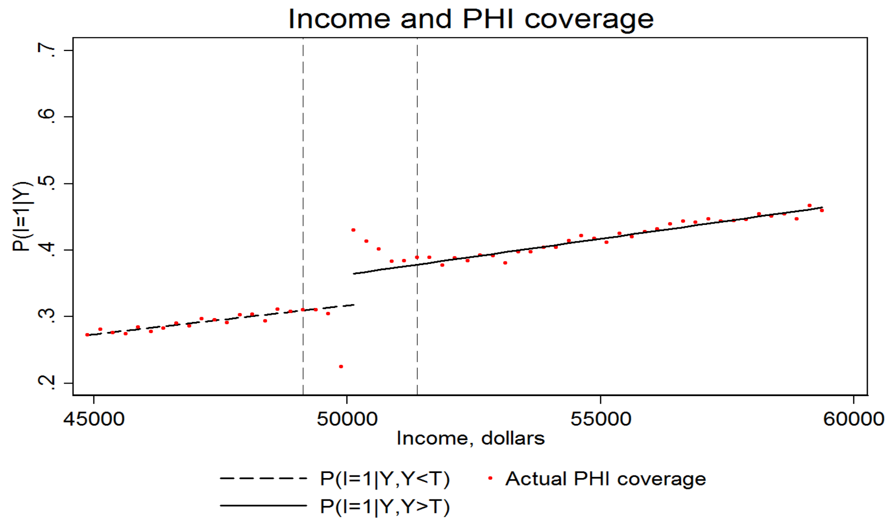
Characteristic	Young age	Middle age	Old age
$\underline{Y}$	49,125	48,875	49,375
$\overline{Y}$	51,375	52,875	50,625
Steps ahead from below	4	5	3
Steps ahead from above	5	11	2
Forecasting model from below $50,000	linear	linear	linear
Forecasting model from above $50,000	linear	linear	quadratic
Estimation sample from below $50,000	18 bins; 44,875-49,125	39 bins; 39,375-48,875	22 bins; 44,125-49,375
Estimation sample from above $50,000	33 bins; 59,375 -51,375	41 bins; 62,875 - 52,875	23 bins; 56,125-50,625

Table 9: The MLS effects by age groups

		Young age	Middle age	Old age
1	$\Delta P^{All}\|(Y = T)$	0.047	0.015	0.035
2	$P(S\|(Y = T))$	0.63	0.31	0.38
3	$\Delta P^{S}\|(Y = T)$ (1:2)	0.074	0.050	0.092
4	$P(PHIS = 1\|Y = T, t = 0.01)$	0.40	0.49	0.67
5	$\%\Delta P^{S}\|(Y = T)$ (3:(4-3))	22.5%	11%	15.9%
6	Total counts of singles	3,042,050	1,451,460	1,505,725
7	Total counts of singles with PHI, actual	752,135	625,555	807,365
8	Total counts of singles with PHI, counterfactual	704,755	581,715.1	747,129.3
9	Δ (7-8)	47,380	43,839.88	60,235.75
10	Δ, percent (9:8)	6.7%	7.5%	8.06%
11	Overall PHI rate, actual (7:6)	24.7%	43%	53.6%
12	Overall PHI rate, counterfactual (8:6)	23.2%	40%	49.6%
13	MLS budget revenue, millions.	133	123	63
14	Number of MLS non-compliers	204,240	177,705	91,155
15	Average MLS amount paid, $	651	692	691
16	Percent of MLS non-compliers	44%	30%	21%

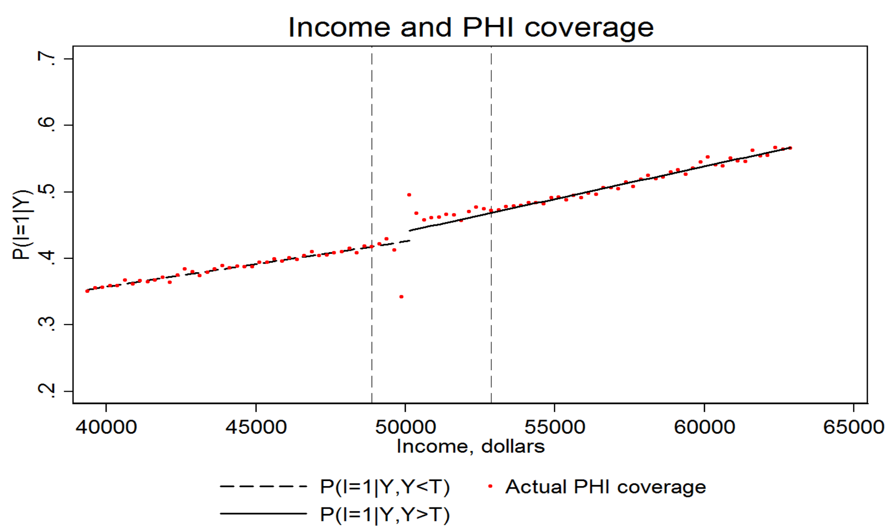
characteristics of the forecasting models used to estimate $\Delta P^{All}|(Y = T)$ for the three age groups. In particular, specifications described in Table 8 produce the lowest mean squared prediction error for the out of sample forecasts of PHI rate of 8 income bins to the left of and including $\underline{Y}$ and to the right of and including $\overline{Y}$. The parameters $\underline{Y}$ and $\overline{Y}$ which as before denote the boundaries of the bunching interval around the MLS threshold were estimated separately for each age group.

Figure 18: Estimation of $\Delta P^{All}|(Y = T)$ for young age individuals



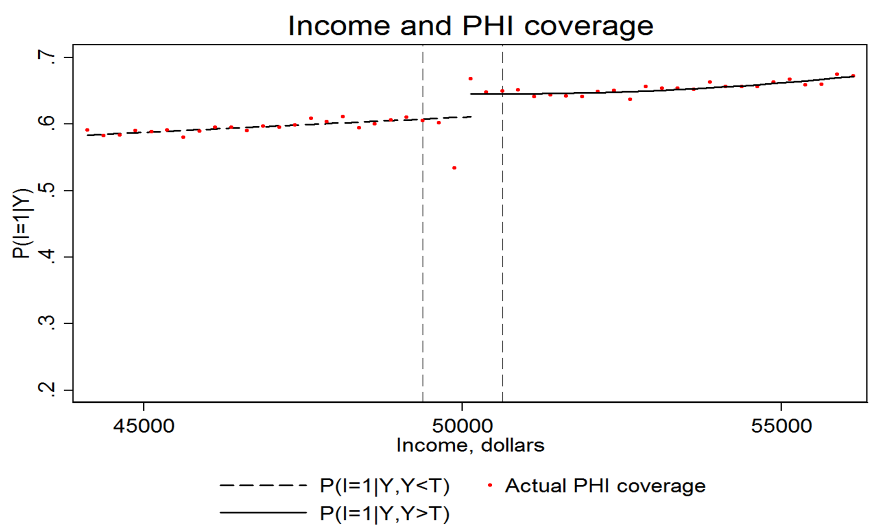
Note: Vertical dashed lines mark the bunching interval within which the PHI coverage probability is forecasted using the relationships estimated from data outside of the bunching interval.

Figure 19: Estimation of $\Delta P^{All}|(Y = T)$ for middle age individuals



Note: Vertical dashed lines mark the bunching interval within which the PHI coverage probability is forecasted using the relationships estimated from data outside of the bunching interval.

Figure 20: Estimation of $\Delta P^{All}|(Y = T)$ for old age individuals



Note: Vertical dashed lines mark the bunching interval within which the PHI coverage probability is forecasted using the relationships estimated from data outside of the bunching interval.