The Effects of the Affordable Care Act Advance Premium Tax Credits on Household Labor Supply

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Abstract

Using Medical Expenditure Panel Survey and health insurance premium data from 2010 to 2017, I study the effects of the Affordable Care Act advance premium tax credits, or the "subsidy", on labor supply for households that are not offered employer-sponsored health insurance (ESI). Due to a sharp decrease to zero in the subsidy for households above 400% of the federal poverty line (FPL), households near this cutoff may be better off reducing their income by decreasing their labor supply at the intensive and/or extensive margins. Thus, I calculate the potential lost subsidy (PLS) for households near the subsidy cutoff – the subsidy they would receive at exactly 400% FPL but may lose if earning just above it. For the relevant households, I find that on average, the PLS equals \$100 a month for younger workers but reaches \$400 to \$600 a month for older workers and confirm that the PLS greatly varies by geographic location and family composition. Using OLS regressions with interaction terms capturing the impact of the PLS for the affected households, I examine whether the PLS negatively affects their labor supply. I find that income and hours of work do not statistically change from one year to another as the PLS increases. Moreover, the probability that one of the adults in the household stops working increases by 4% points as the PLS increases by \$100 a month, but the estimated coefficient is not statistically significant. Therefore, I find no clear evidence that households near the cutoff and not offered ESI adjust their labor supply in response to a larger PLS. However, it is important to note that the lack of data for households *very close* to 400% FPL forces me to use households between 300% and 500% in which those at both extremes are very unlikely to try adjusting to the PLS and thus, may attenuate the results towards zero.

Keywords: Health Insurance, Affordable Care Act, Labor Supply, Subsidies
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1 Introduction

One of the most important provisions of the Affordable Care Act (ACA) is the advance premium tax credits (APTC, hereafter also referred to as the "subsidy") to lower the cost of individual health insurance plans sold on state-based exchanges. By design, only households who are not offered employer-sponsored insurance (ESI) and who earn between 100% and 400% of the federal poverty line (FPL) are eligible for the subsidy (i.e., between $12,140 and $48,500 in 2019 for a single individual or between $25,100 and $100,400 for a family of four with two adults and two children). The subsidy is structured so that the out-of-pocket premium for the benchmark insurance plan of the local area is capped to a specific percentage of the household's annual income. Since the subsidy falls sharply to zero for households above 400% of the FPL, there is a discontinuity in the subsidy structure at this threshold, which I call "*potential lost subsidy*" (PLS). The PLS is defined as the subsidy a family would be eligible for if their annual income were *exactly* 400% of the FPL – with a dollar more of income the family would *lose* this subsidy. Thus, *some* households would significantly benefit from earning just below 400% of the FPL, rather than just above it.

Using panel data from the Medical Expenditure Panel Survey (MEPS) and premium data from the Robert Wood Johnson Foundation (RWJF), I construct the cost of the family premium for each household and their discontinuity had they earned exactly 400% of the FPL. For households with an income between 300% and 500% FPL and not offered ESI after 2014, I find that the PLS equals $100 a month for younger workers but reaches $400 to $600 a month for older workers on average. The data also confirm that the PLS greatly varies by geographic location and family composition. I use standard OLS regressions and a probit model with several interaction terms based on the PLS to estimate the labor supply effects of the subsidy for households near the cutoff and not offered ESI. I find no clear evidence that such households reduce their income or hours of work due to a larger PLS.

The probability that one of the adults stops working increases by 4% points as the PLS increases by $100 a month, but this coefficient is not statistically significant. Using such a large definition for being near the top cutoff may actually attenuate the results towards zero since households at both extremes are unlikely to try adjusting their income.

Several prior studies have examined the effects of various provisions of the ACA on household labor supply. Most of the prior work has focused on low-income households, mainly studying the effects of Medicaid expansion on employment or earnings (Baicker et al., 2014; Garthwaite et al., 2014; Dague et al., 2017). To date, little attention has been paid to the effects of the ACA premium tax credits. Among them, Shi (2016) estimates the effects of the ACA subsidy for households in Massachusetts and their income responses; Finkelstein et al. (2017) analyze the effects of the ACA subsidy on coverage enrollment for the low income in Massachusetts; and more recently, Kucko et al. (2018) study the ACA premium tax credits in states that did not expand Medicaid and their effects on labor outcomes of low-income people. However, these ACA subsidy studies mainly focus on low-income individuals.

In contrast, this paper focuses on moderate- or middle- income households around 400% of the FPL and try to provide a better understanding of the consequences of means-tested programs for such individuals. Rather than focusing on a single state, I exploit the geographic variation in the cost of premiums and use premium data from all fifty states and the District of Columbia.The variation in income net of out-of-pocket premiums generates a quite large PLS for *some* but not all households. The goal of this paper is to examine the labor supply effects of such discontinuity and to investigate whether there are unintended consequences from the ACA subsidy design at a time of major debate about the health care system.

The rest of this paper is organized as follows. In Section 2, I present a review of the literature related to the ACA and the premium tax credits. In Section 3, I explain the ACA subsidy design at the foundation of my analysis. In Sections 4 and 5, I describe the data and explain the method I use to study households near the subsidy cutoff, respectively. Finally, in Sections 6 and 7, I present and discuss the results, respectively, before concluding in Section 8 with future research directions.

2 Literature Review

In this paper, I focus on the effects of the income-conditional ACA premium tax credits on labor supply. There are several reasons why means-tested programs would generally reduce labor supply and among them, the fear of losing health insurance which results in creating "employment lock" or situation in which workers are primarily employed to receive health insurance coverage (Garthwaite et al., 2014; Madrian, 1994). Also, Chetty and Saez (2010) study optimal taxation and the effects of private insurance; they show that health insurance reduces labor force participation and income for mainly the self-employed. More theoretically, Moffitt (2002) presents graphical representations of the labor supply responses to welfare programs, illustrating how working hours and income negatively evolve once the Medicaid program is in place. He further argues that the effects of welfare programs on labor supply are understudied and need more attention.

In 2010, the Patient Protection and Affordable Care Act (ACA) implemented several provisions to improve the affordability of health insurance and to lower the rate of uninsured people. This generated substantial research about the effects of the ACA on various topics such as insurance take-up, employment and other labor market outcomes, to name a few. Akosa Antwi et al. (2013) estimate the effects of the ACA dependent-coverage mandate, which allows adults under 26 to stay insured under their parents' coverage. Along with finding a large decrease in the uninsured rate for young adults, they find a reduction of 3% in hours of work for these newly insured individuals. Garthwaite et al. (2014) investigate the

2005 health insurance disenrollment in Tennessee and its effects on labor force participation. They find that the loss of public health insurance generates a 6% increase in employment for low-income childless adults. The authors suggest that the ACA Medicaid expansion may lead to a large decrease in labor supply for this income group. However, other studies such as Dague et al. (2017) raise some concerns about the external validity of such results and the interpretation of the Tennessee study. In particular, they mention that the group of individuals studied by Garthwaite et al. (2014) might have been richer and more educated than the national average and may not be nationally representative. Moreover, they point out that losing health insurance may have different consequences than gaining it. Thus, the Tennessee results should not prevent further research in this area.

Overall, the literature is still quite ambiguous about the effects of health insurance on labor supply. Yelowitz (1995) finds a positive impact of health insurance expansion on labor supply. However, several studies find little or no significant change in employment and earnings due to an increase in public health insurance by studying either the impact of Medicaid expansion or the Oregon experiment (Finkelstein et al., 2012; Baicker et al., 2014; Gooptu et al., 2016; Leung and Mas, 2016; Kaestner et al., 2017; Peng et al., 2018). However, Duggan et al. (2017) find that labor force participation increases in areas where numerous people are potentially Medicaid-eligible and decreases in areas where individuals are more likely to enroll in the Exchange.

Closer to my work, Shi (2016) studies the impact of the ACA subsidy on income in Massachusetts using a regression discontinuity approach. The author finds evidence of income manipulation for self-employed individuals around 150% FPL and for workers around 300% FPL. Also, Kucko et al. (2018) study the influence of the ACA premium tax credits on low-income individuals near 100% FPL in states that did not expand Medicaid. Using tax data and the American Community Survey (ACS), they find no evidence for a change in labor market outcomes and earnings in general, but a significant bunching or excess mass occurs for the self-employed around 100% FPL. According to the authors, this may reflect a change in the reported income rather than a true change in labor supply.

Despite a large body of literature on the effects of the ACA and health insurance on coverage and labor outcomes, there is a gap in knowledge about the effects of the premium credits on labor supply for the moderate- and middle- income households. Therefore, the goal of this paper is to calculate the discontinuity in the subsidy for such population and its effects on labor outcomes such as income growth, changes in working hours and in employment status. Beyond previous research, I use the geographic variation in the cost of premiums and quantify the potential lost subsidy (PLS) of households near the top threshold.

3 Background

Since 2014 and the implementation of the ACA, households who are not offered affordable employer-sponsored health insurance (ESI)[1] and have an annual income between 100% and 400% FPL can qualify for advance premium tax credits (APTC, or the "subsidy") to reduce their out-of-pocket premiums for medical insurance sold on the Exchange. In 2015, around 11 million people purchased their own private health insurance on a marketplace; among them, more than 8 million individuals enrolled via Healthcare.gov, the Federally-Facilitated Exchange (FFE) platform, and almost 3 million people enrolled through State-Based Marketplaces (SBM). Overall, 7 million individuals were eligible for the subsidy.[2]

By design, the ACA subsidy depends on (1) the cost of the household's benchmark plan – the second-lowest cost Silver plan in its area of residence – and (2) the household's annual

[1] In 2014, an ESI plan must cost less than 9.5% of household Modified Adjusted Gross Income (MAGI) to be affordable.

[2] ASPE (2016) – ASPE Releases Enrollment Data From Healthcare.gov And State-Based Marketplaces, Health Affairs Blog, January 8, 2016. DOI: 10.1377/hblog20160108.052598

income. On the marketplace, premiums depends on the county of residence[3], family size, and age of each family member. The amount of the subsidy varies by the family's annual income as a percentage of the FPL for the size of the household, and drops sharply to zero above 400% FPL. For subsidy-eligible households, annual expenses for health insurance are capped and vary by income. The required income contribution for the benchmark premium is shown in Figure 1.

In 2014, subsidy-eligible families near the poverty line must contribute 2-3% of their income for their annual premium while moderate income families (300-400% FPL) must pay 9.50% of their income.[4] The subsidy for each household is the difference between the cost of their benchmark plan and their required premium contribution, bringing down the benchmark premium to the required cap. The subsidy can be applied to any exchange metal plan even though its size depends on the benchmark plan. With data on the benchmark premium in each U.S. county, I construct the cost of a family benchmark plan as the sum of premiums for each family member. To compute the family premium, no more than the cost of three children under the age of 21 can be included.

Table 1 shows how to calculate the subsidy and *potential lost subsidy* (PLS) per month using examples of various family sizes and age profiles for households living in New Castle County, Delaware in 2014. A 27-year-old adult earning exactly 400% of the FPL in 2014 would not receive any subsidy, as the cost of the benchmark plan is below his annual required contribution for premiums; even a 48-year-old single individual would receive only a $6 subsidy per month, as his benchmark premium barely exceeds his required contribution. However, a couple in their late 40s with no child and the same level of income would receive a subsidy of $344 per month: their monthly benchmark plan costs $774, much higher than their required premium of $430 per month. The PLS is the difference between the

[3]More precisely, premiums depends on the rating area, for which county is a near perfect proxy.

[4]I use the year-specific IRS percentages in my calculations even though they have hardly changed.

full (unsubsidized) benchmark premium and the required premium at 400% FPL. Thus, the PLS for a couple in their late 40s is equal to \$283 a month (or \$3,394 a year – 6% of their income), but is trivial or even zero for younger singles. For a family of four (two adults and two children), the benchmark premium is \$1,234 but the subsidy at exactly 400% FPL would be \$581, so the PLS for this household would be \$488 a month (or 7% of their income). In general, the subsidy and PLS greatly vary by age and family size.

The APTC structure generates important variation in income net of out-of-pocket (OOP) premiums across households as household demographic characteristics have different impacts on premiums and lost subsidy. In fact, households expecting to earn around 400% FPL may lose a significant insurance subsidy if their income even slightly exceeds the top threshold. Thus, *some* households might reduce their labor supply to prevent their income from exceeding the eligibility threshold, as they would have a greater income net of medical insurance premium. The incentive to reduce labor supply depends on the size of the PLS, which varies both geographically and with household structure. Premiums in rural areas in the Midwest and Great Plains states tend to be higher than in metropolitan areas along the east and west coasts. In Figure 2, I show the geographic variation in the PLS by plotting the cost of the 2014 benchmark plan for various family structures not offered ESI and living in three areas: Fayette County (PA) (low price), New Castle County (DE) (mid price) and Hot Springs (WY) (high price). Outside the eligibility range for APTC, the benchmark premium is unsubsidized while inside the thresholds the benchmark premium takes into account the appropriate subsidy. Panel (a) shows that the cost of premiums for a 40-year-old adult is similar around the top cutoff whether they live in New Castle County (DE) or in Fayette County (PA), premiums being \$170 or \$180 a month, respectively. In these rating areas, such individuals are not facing any PLS or discontinuity in the cost of premium had they earn just above the eligibility threshold. However, similar individuals living in Hot Springs (WY) would have to pay \$62 more a month (or 1% of their income) for health insurance had they earned just above 400% FPL . Overall, single adults are not highly affected by the PLS regardless of their rating area even if there is some variation. However, panels (b) and (c) describe a very different situation for families with two or more children and older couples. When earning just below the top eligibility threshold, their premiums are almost the same across the three regions and equal around \$745 and \$490 a month, respectively. However, when earning just above 400% FPL, these types of households face a large discontinuity in their final out-of-pocket premiums. A family of four would not face any PLS in Fayette but would have to pay \$195 more in New Castle (2% of their income) and \$640 more in Hot Springs (8% of their income). Finally, older couples around age 50 pay \$208 more per month (4% of their income) in Fayette, \$700 more (13% of their income) in New Castle and \$1,263 more in Hot Springs (24% of their income). Thus, there is a significant variation in the PLS depending on the geographic location of individuals.

Aside from geographically, the PLS also greatly varies by household composition. In Figure 3, I illustrate this variation in the PLS by plotting income net of OOP premiums as a function of annual income for subsidy-eligible and non-eligible families in 2014, assuming they purchase the benchmark plan. For subsidy-eligible households, the income net of OOP premiums is their annual income minus the (annual) subsidized benchmark premium; however, for non-eligible households, it is equal to their annual income minus the full, unsubsidized benchmark premium. In this context, non-eligible households correspond to families that buy their health insurance on the Marketplace but with an income outside the eligibility range, or families that buy the same policy off the Exchange for some reason, or those ineligible for APTC for other reasons. The difference between the solid and the dashed line represents the U.S. average subsidy received in the eligibility income range.

At the 400% FPL cutoff, this difference is the PLS – the dollar amount of subsidy that eligible-households would lose by earning just above the threshold. For example, in 2014, a 62-year-old couple earning 400% FPL would have an annual net income of $56,150 after purchasing health insurance on the Marketplace with the subsidy, whereas their net income would be only $47,320 without the subsidy. Thus, they would have lost around $9,000 a year had they earned just above the eligibility threshold (and continued to purchase this insurance). However, for a 35-year-old adult the PLS is equal to zero as the OOP premium is the same for subsidy eligible and non-eligible around the 400% FPL cutoff. As Marketplace premiums have been rising since 2014, the PLS has been getting larger. Figure 6 shows that in 2018, the PLS for a young adult averaged around $1,000 a year and almost $20,000 a year for an older couple.

Consequently, some households that anticipate earning about 400% FPL (mainly older couples or families with children) would be better off by earning slightly less; they might choose to reduce their income and labor supply so as not to risk losing their large APTC subsidy. Therefore, the goal of this paper is to evaluate such potential behavior since the ACA marketplaces and subsidies were implemented in 2014, examining whether some unintended market distortions or income manipulation are generated by a means-tested program like the premium tax credits.

4 Data

In this paper, I use the Medical Expenditure Panel Survey and its Household Component (MEPS-HC) from 2010 to 2017 combined with premium data from the Robert Wood Johnson Foundation (RWJF).

The longitudinal data from the MEPS collected by the Agency for Healthcare Research and Quality (AHRQ) provide detailed information on medical expenditures, health insurance coverage, and demographic and socioeconomic characteristics of around 17,000 households surveyed over a two-year panel. The survey design consists of five rounds of in-person interviews in which information is reported for each family member during two consecutive years.[5] By combining or stacking the two-year panel data from 2010 to 2017, I obtain a final repeated cross-section of 33,412 households (equivalent to 94,409 individuals) with a non-negative income for which the head of household is between 21 and 64 years old.[6] Additionally, the MEPS data are a subsample of households from the National Health Interview Survey (NHIS) from the previous year, which is a nationally representative sample of the U.S. population with an oversampling of blacks and Hispanics. Since I work with survey data at the family level rather than a simple random sample, I use the family weight provided by the MEPS to generate my estimates.

In this study, I also use premium data from the Robert Wood Johnson Foundation (RWJF), particularly the HIX Compare data files from 2014 to 2017; these files gather the premiums for every insurance plan sold on the Exchanges for various family structure and age profiles. The HIX Compare dataset is the most complete dataset I find for this research as it collects monthly premiums in each county for all 50 states and D.C. since 2014. For states using the Federally Facilitated Marketplace (FFM), premium data were obtained from Healthcare.gov; for states using their own State-Based-Marketplace (SBM), premiums were collected from individual state marketplace websites. However, the RWJF data for the 2014 premiums are missing for the 17 states (including D.C) that use their own SBM. To the best of my knowledge, this information had never been aggregated for 2014. Therefore, I collect the missing monthly premiums by rating area from each state exchange website to construct a unique dataset of premiums covering all U.S. states at the county level since the implementation of the ACA. Finally, I merge the complete premium dataset

[5]For simplicity, I based my demographic analysis using information collected in the first round of interviews of each year of survey. At each round, the respondent is asked the same questions.

[6]Individuals 65 and older are very likely to be eligible for Medicare.

onto the 2014-2017 MEPS datasets by county FIPS code to estimate more accurately the cost of the benchmark plan for households in their specific place of residence.[7] For the pre-ACA period, I merge the 2014 premiums data onto the pre-ACA MEPS panels and use these premiums as a placebo: the PLS is nonexistent and should not have any effect prior to 2014.

Using my master dataset of 7 panels since 2010 along with the ACA age-rating function[8] described in Table 8 of the Appendix, I calculate the cost of the benchmark plan and the PLS that every household would potentially face if they were purchasing their own private health insurance on the Marketplace. As shown in the background section, premiums greatly vary across and within states, which is why detailed premium data for all U.S. states and counties are crucial to provide complete insights on whether the PLS affects household's labor supply. In this way, this paper tries to capture an important feature of the ACA subsidy design and fills a gap in the literature regarding the impact of the premium tax credits on income growth, change in hours of work and employment status.

In my analysis, I use the health insurance family unit definition proposed by SHADAC (2012) to compute family income as a percentage of the FPL and create one of my main variables. I define households not offered ESI using the variable from the MEPS HC asking whether individuals have been offered health insurance through their current main job. Overall, 7,572 households are not offered ESI from 2010 to 2017. And I only keep the reference person record for each household along with socioeconomic information on their children, spouse and other adults in the household, so that my unit of analysis is a household-year pair.[9] Table 2 shows the descriptive statistics of households with an annual

[7]MEPS data at the state and county level are restricted information for reasons of confidentiality. Thus, I performed the merge and subsequent analysis at the AHRQ Data Center in Rockville, MD, where the final dataset is now stored and accessible upon request.

[8]The age rating function links the premium of a 21-year-old to the premium for an individual of any age.

[9]I also use the health insurance information of the spouse to make sure that if the spouse is offered ESI

income near the top cutoff in pre- and post-ACA panels. In the 2011-2012 and 2014-2015 panels, I have 5,227 and 4,677 households respectively, for which the reference person is between 21 and 64 years old. Among them, around 20% of the sample is near the top cutoff (300-500% FPL) during these panels. The mean statistics are very close to each other across panels, but some differences appear. The income growth is between 1.7% and 3.4% across panels. The usual hours of work are between 34 to 37 hours per week and stay relatively constant across panels for the two income groups. The percentage of employed heads of household also stays constant to around 87% over the panels for both income groups.[10] Households near 400% FPL are mainly single adults or couples with no child (around 39% and 15% of households, respectively) and with a head of household between 42 to 45 years old on average. Over the panels, most households (86% to 94%) have a private health insurance (through either their employer or the Marketplace in post-ACA). As expected by the level of income, the percentage of households with public health insurance is low and around 1 to 4%. Also, the rate of uninsured families between 401% and 500% FPL dropped from 6% to 3% from pre- to post-ACA panels. However, almost 10% for households are still uninsured with an income just below 400% FPL in post-ACA period. Lastly, total medical expenditures are on average around $4,000 a year in both panels.

Figure 4 shows the cumulative distribution of the PLS over time since the ACA premium tax credits implementation. Around 40% to 60% of the households near 400% FPL and not offered ESI have a zero PLS from 2014 to 2016. However, there is a clear shift to the right in the distribution of the PLS as a consequence of much higher premiums in 2017. In fact, the marketplace average benchmark premiums increased by 16%, from $299 to $349,

then the reference person as well. However, no adjustments were needed.

[10] A head of household is considered employed if the individual has a full-time job or a job to return during the round of interview.

from 2016 to 2017.

Finally, Figure 5 illustrates the evolution of the monthly PLS since 2014 by age group for the relevant households. They represent 685 households in my dataset. For households with a reference person between 45 and 54 years old, the PLS is around \$200 a month which is twice the PLS faced by younger households (aged 21-34 or aged 35-44) and it rises over time. For older households with a head aged 55 to 64, the PLS is around \$400 a month with a peak to almost \$600 a month in 2015 and 2017 – years in which premiums rose significantly.

5 Method

The goal of this paper is to study the effects of the ACA subsidy discontinuity or tax notch on labor supply. Kleven and Waseem (2013) show that large notches generate strong incentives for excess mass below cutoffs and missing mass above cutoffs; however, agents face adjustment cost or other type of frictions that tend to make them unresponsive to tax incentive. The authors offer an important framework to better study notch using a bunching analysis. However, such approach requires very large datasets such as administrative data like used in Kucko et al. (2018). In this paper, I use the short-panel structure provided by the MEPS data and do not have enough power to perform a bunching analysis. Instead, I use a standard OLS regression approach with interaction terms capturing the plausible exogenous variation in the PLS (from household size, age, and geographic location) that may impact their labor supply. Indeed, once controlling for households being around the cutoff, households do not adjust the composition of their family or place of residence due to the ACA premium tax credit. With a two-year panel design stacked from 2010 to 2017, several regressions can be used to study the effect of the PLS on labor supply depending on the control group chosen.

First, I use the post-ACA sample (two-year panels starting in 2013 and ending in 2017) to estimate the impact of an increase in household's PLS on the change in labor supply for households near the cutoff and not offered ESI using the following regression:

$$\begin{aligned}\Delta Y_{it} = {} & \beta_0 \mathbf{X}_{it} + \beta_1 NearCutoff_i + \beta_2 NotOfferedESI_i + \beta_3 PLS_{it} \\ & + \beta_4 NearCutoff_i \times NotOfferedESI_i + \beta_5 NearCutoff_i \times PLS_{it} \\ & + \beta_6 NotOfferedESI_i \times PLS_{it} \\ & + \beta_7 NearCutoff_i \times NotOfferedESI_i \times PLS_{it} + \epsilon_{it},\end{aligned} \tag{1}$$

where $\Delta \mathrm{Y}_{it}$ is measuring the change on the intensive margin. In specification (1), I take $\Delta \mathrm{Y}_{it}$ as the income growth of household i, defined as the difference in log annual income over two consecutive years of survey. The PLS is computed as the difference between the family's benchmark premium and the statutory contribution based on the percentage of income required at 400% FPL (9.50% of the annual income in 2014, 9.56% in 2015, 9.66% in 2016 and 9.69% in 2017), with a minimum of zero. In specification (2), $\Delta \mathrm{Y}_{it}$ represents the change in the (usual) weekly hours of work within household i over the two years. The vector of covariates $\mathbf{X}_{it}$ includes other household-level factors that potentially affect the intensive margin of labor supply such as age, sex, race, education, family size, marital status, self-reported health status, self-employment status, job industry and health care expenditures from the previous year. I also include in $\mathbf{X}_{it}$ year and state or region dummies to control for different years and trends in regional labor markets as the difference in labor supply and income growth may come from specific characteristics of the state households live in, e.g., rural/urban state or state with low/high unemployment rate. Finally, $NearCutoff_i$ and $NotOfferedESI_i$ are indicators for whether or not households have an annual income between 300% and 500% FPL and are being offered ESI at their current main job. The coefficient of interest is β_7 from the three-way interaction; this coefficient captures the partial effect of the PLS on the intensive margin for the affected households, holding everything else constant. The coefficient on PLS alone, β_3, should have no explanatory power for income growth or change in hours when the double interaction term is included.

In the above specification, the control group consists of households offered ESI and the model compares labor outcomes between households offered and not offered ESI, who may be intrinsically different. Therefore, a second model can instead compare changes in labor supply for *only* households not offered ESI in pre- versus post-ACA such that:

$$\begin{aligned}\Delta Y_{it} = \beta_0 \mathbf{X}_{it} &+ \beta_1 NearCutoff_i + \beta_2 Y2post_{it} + \beta_3 PLS_{it} \\ &+ \beta_4 NearCutoff_i \times PLS_{it} + \beta_5 Y2post_{it} \times PLS_{it} \\ &+ \beta_6 NearCutoff_i \times Y2post_{it} \\ &+ \beta_7 NearCutoff_i \times Y2post_{it} \times PLS_{it} + \epsilon_{it},\end{aligned} \tag{2}$$

where $Y2post$ is an indicator for whether or not the second year of interview is in 2014 or later. When using the "not offered" sample, the coefficient of interest is β_7 from the three-way interaction; this coefficient captures the partial effect of the PLS on the intensive margin for the affected households, holding everything else constant.

Finally, the full model (2010-2017) uses a four-way interaction term following the same pattern as the specifications above. In this last model, the primary variable of interest takes into account the fact that the PLS is only relevant since 2014 and only for households near the top threshold who are not offered ESI. Therefore, the main variable of interest becomes $NearCutoff \times NotOfferedESI \times Y2post \times PLS$ and its estimated coefficient represents the partial effect of the PLS on labor supply outcomes (such as income growth or hours of work) for households near the top threshold and not offered ESI. A significant and negative coefficient estimate would suggest that a \$100 increase in the PLS generates a particular decrease in labor supply for households that reasonably risk losing the PLS. Similar to the prior specification, the coefficient estimate on $NearCutoff \times NotOfferedESI \times PLS$ tests whether the PLS had any effect on labor supply prior to 2014 and is expected to be not significant – the PLS in pre-ACA years does not exist, and placebo values based on 2014 premiums are used for the analysis. The counterfactual is what would have happened to labor supply if households had *zero* PLS while having the same income level, family age and size profiles. Thus, in this specification the control group consists of households with similar income (similar % FPL).

The main identification threat in linear regressions is endogeneity bias in the form of omitted variable bias. Thus, I try to control for most of the variables that could be correlated with my main variables of interest via all the above covariates and interaction terms. Moreover, the (short) panel structure of my data is crucial for my identification strategy, as it allows me to analyze changes in labor supply *within* households over two consecutive years and to effectively control for each household's unobserved factors that generated their outcomes in the previous year. Lastly, I do not believe that my identification suffers from a serious endogeneity problem as households may not have adjusted their location due to the PLS.

To measure the effect of the ACA subsidy on the extensive margin, I use a probit model and estimate changes in employment status for any adult in the household over the two consecutive years of interview. I use the same regressions and models as above (1-2). Here, my goal is to evaluate whether there is switching behavior in labor force participation among adults in the household as the PLS becomes larger. The outcome variable is now binary and equals one if any adult in household i (head of household, spouse or other adult dependent) stops working in the second year of the survey, and equals zero if all individuals stay employed (currently employed or with a job to return in the current round of interview). A positive and significant coefficient estimate would then suggest that an adult member is more likely to stop working if the household is near 400% FPL, not offered ESI and has a larger PLS after ACA implementation.

6 Results

Table 3 presents the main coefficient estimates from the income growth regressions using the post-ACA sample in column 1, the sample of not offered ESI in column (2) and the full sample in column (3). The regression tables with the coefficients for socio-economic variables can be found in Tables 8 to 11 of the Appendix. Using either the post-ACA sample or the full model, I find a significant and negative effect of not being offered ESI on income growth. Over 2010 to 2017, households who are not offered health insurance through their employer experience an income growth 5.4% lower than those offered ESI, holding everything else constant. Such households in the post-ACA sample face an even larger differential as their income growth is 7.1% lower, which could suggest that the earnings gap between the ESI and non-ESI households is getting wider since the ACA. In all three specifications the coefficient for the variable of interest is negative or close to zero. In the Post-ACA sample households with an income near 400% of the FPL and not offered ESI decrease their income growth by 0.3% as the PLS increases by $100 a month; in the sample of "not offered ESI", the coefficient estimate is very close to zero and in the full model, income growth of such households increases by less than 1% as the PLS gets larger. These coefficients estimates are not statistically significant but have small standard errors. To test the validity of the main parameter estimate, it is important to check its potential impact in the pre-ACA period for households near the cutoff and not offered ESI. Prior to 2014, the PLS should not have any effect as the Marketplace and the subsidies do not exist – the "PLS" used is a placebo value, calculated using 2014 premiums. As a consequence, income growth should not vary due to a change in PLS. Indeed, the coefficient estimate for the PLS for the affected households in the pre-ACA period are very close to zero (and economically insignificant), and their respective p-values confirm that these estimates are not statistically significant. Thus, my models confirm that the PLS is not coincidentally correlated with excluded predictors of income growth.

Table 4 shows the estimates of the change in weekly hours of work over two consecutive years – the intensive margin of the labor supply. I find that the main coefficients of interest are negative in the "not offered" sample (-0.11) but not significant in the post-ACA sample or in the full sample. However, it is important to note that it may be difficult for households to adjust their hours of work in general. One of the limits of this paper is that the MEPS data do not provide the total amount of hours worked during a year, but rather the usual hours of work per week.

Finally, Table 5 reports the impact of the PLS on the extensive margin of family labor supply: the probability that any adult aged 21 to 64 stops working in the second year of interview conditional on being employed in the first year. For households in both the post-ACA and the not offered ESI samples, an increase in the PLS by $100 increases the probability that an adult stops working by 4% points, respectively. For households in the full sample, the probability increases by almost 3% points. However, in all three specifications these main coefficients of interest are not significant. Thus, the PLS has no clear significant impact on the intensive or extensive margins of the family labor supply.

7 Discussion

To further evaluate the sensitivity of my results, I restrict the sample to households living in states that have their own Marketplace or Exchange, rather than using Healthcare.gov, the federally facilitated exchange (FFE). Previous studies like Frean et al. (2017) have shown that in such states, individuals are more aware of the premium tax credits because those states tend to provide more accessible information and support during the open enrollment period. Table 6 presents the results on income growth, hours of work and change in employment status for households living in the twelve states with State-Based Marketplaces (SBM) and D.C. since 2014 (5,331 households). As in the all state sample in Table 3, I find a negative and small impact of the PLS on income growth for the relevant households equals to -0.6%, and the probability that one of the adult stops working is also close to 0 (0.2% points) as the monthly PLS gets larger. However, these results are not statistically significant. Similar to those results, I do not find a statistically significant impact on hours of work. Thus, when analysis is restricted to states using the SBM there is no evidence for an adjustment of labor supply due to the PLS either at the intensive or extensive margin.

Another specification of great interest is to study the probability that households have an annual income below 400% FPL due to a change in the PLS, conditional on being near the cutoff. Thus, I run a first specification using a restrictive sample for households near the cutoff, not offered ESI and interviewed in post-ACA, and a second specification comparing such households in pre- and post-ACA. As expected, the coefficient on the annual income in first year is negative and significant in both specifications– as households have a larger annual income they are less likely to be below 400% FPL in the second year of interview. In specification (1), the variable of interest is the PLS alone. I would expect its coefficient to be positive; however, I find its marginal effect to be negative and not statistically significant. In specification (2), the variable of interest is $PostACA \times PLS$. I would expect its marginal effect to be positive; however, it is also negative and not statistically significant. Finally, the coefficient on PLS itself corresponds to the impact of the PLS in pre-ACA, and as expected, is very close to zero but not statistically significant.

However, it is hard to categorically rule out that there is no effect of the PLS. Overall, the large definition for being *near* is needed not to lose power in the study but it also implies that households at both extremes are also considered as treated while they would likely not consider adjusting their income. Therefore, there is a lot of near-zero intensive margin households along with households who would have larger effects on the intensive margin – those *closer* to 400% FPL. As a consequence, my coefficient estimates may be attenuated toward zero.

8 Conclusion

In this paper, I study the labor supply effects of a specific provision of the ACA, the premium tax credit. Because the subsidy falls sharply to zero above 400% FPL, households near this cutoff experience a potential lost subsidy (PLS). This discontinuity in the subsidy greatly varies by geographic location and family structure. For most of the moderate- and middle- income households, the PLS represents a small dollar amount or even zero. However, for older couples, families of four, or families living in states with high-cost premiums, it can represent around 8% to 15% of their income.

Using the MEPS and premium data from 2010 to 2017, I find that the PLS equals \$100 a month for younger workers but reaches \$400 to \$600 a month for workers above 55 years old, on average. I do not find clear evidence, however, that households not offered ESI and between 300% and 500% FPL reduce their labor supply either at the intensive or extensive margins. It is still hard to categorically rule out that there is no effect. Overall, the broad definition for being *near* the top threshold implies that households at both ends are also evaluated as treated while they would likely not consider adjusting their income. Therefore, there is a lot of near-zero intensive margin households along with households who would have larger effects on the intensive margin – those *closer* to 400% FPL. As a consequence, my coefficient estimates are attenuated toward zero. To examine more precisely the labor supply effects of the PLS a larger dataset on such individuals would be needed. With more data it would also be interesting to see whether self-employed workers compared to regular wage earners adjust their income since they have more flexibility when reporting their earnings.

To conclude, this research contributes to today's debate about health care reform and the impacts of the ACA. As for individual insurance market regulations and the premium tax credits, the impacts on labor supply are still unclear. Thus, further study would be needed in this area which echoes some of the future research directions made by Gruber and Sommers (2019). Moreover, for the 2020 marketplace insurance plans, Gavin Newsom, Governor of California, proposed to extend the subsidy to households up to 600% FPL so that families near 400% FPL can access affordable health insurance and avoid facing a large PLS. This state initiative confirms the concerns about this discontinuity and reinforces the need for research on that topic. Also, the current uncertainty about the future of the ACA fuels the rising of premiums and thus, of the PLS. When the federal government ended the cost sharing reduction (CSR) payments to insurers in October 2017, the premiums experienced a surcharged from 7% to 38% the following year, as explained in KFF (2017). A larger PLS may accentuate changes in labor supply over time for moderate- and middle-income households. Thus, future research may want to use larger and more recent data to replicate this work. Finally, the discontinuity in the ACA subsidy design offers great opportunities for researchers to study potential changes not only on labor supply but also on coverage enrollment, health care utilization and health outcomes.

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Table 1: Monthly Calculation of a Family's Subsidy in New Castle County, DE (2014)

	(A)	(B)	(C) = (9.5% x B)	(A) - (C)
HH Composition	**Full Premium**	**Monthly Income at 400% FPL**	**Required Premium at 400% FPL**	**PLS**
(27)	\$237	\$3,830	\$364	\$0
(48)	\$370	\$3,830	\$364	\$6
(48, 50)	\$774	\$5,170	\$491	\$283
(35) + 2C	\$564	\$6,510	\$618	\$0
(38,40) + 2C	\$858	\$7,850	\$746	\$112
(48,50) + 2C	\$1,061	\$7,850	\$746	\$315
(52,55) + 2C	\$1,234	\$7,850	\$746	\$488

Notes: The full premium is the cost of the unsubsidized benchmark plan per month for a non-smoker in New Castle County (DE) as listed by the 2014 Kaiser Family Foundation (KFF) Calculator.

Table 2: Mean characteristics of households near the 400% FPL subsidy threshold in a pre-ACA (2011-2012) and post-ACA panel (2014-2015)

	2011-2012		2014-2015	
Income as % FPL	***300 - 400***	***401 - 500***	***300 - 400***	***401 - 500***
Sample (# of HH)	**717**	**462**	**579**	**407**
% of my sample	14%	9%	12%	9%
Estimated Pop. (million)	7.7	5.3	5.7	4.9
At household level:				
Annual Income	$ 58,139	$ 76,068	$ 61,998	$ 78,840
Income growth	3.4%	1.9%	1.7%	3.7%
Employment characteristics				
Hours of work	35	35	34	37
Employed	85%	87%	86%	89%
Self-employed	7%	10%	6%	6%
Demographics				
Family Structure				
single: with no child	40%	33%	39%	33%
with 1 child	7%	4%	4%	4%
with 2 children	2%	2%	2%	1%
with 3 children or +	0%	0%	0%	0%
couple: with no child	17%	20%	15%	22%
with 1 child	7%	11%	11%	14%
with 2 children	12%	16%	14%	13%
with 3 children or +	7%	4%	6%	3%
3 adults or +	8%	11%	9%	9%
Age of Household head	42.5	45	42.8	44
White	82%	82%	81%	82%
Black	12%	11%	12%	10%
Other (Asian, Hispanic etc.)	6%	7%	7%	8%
Health status (Self reported)				
Excellent	30%	31%	27%	23%
Very good	35%	36%	38%	41%
Good	26%	23%	24%	24%
Fair	8%	9%	8%	11%
Poor	2%	2%	2%	1%
Insurance Coverage				
Any private insurance	87%	93%	86%	94%
Public insurance only	3%	1%	4%	3%
Uninsured	10%	6%	9%	3%
Not offered ESI	11%	10%	16%	11%
Tot. ann. healthcare expenses	$ 4,085	$ 3,721	$ 4,113	$ 3,670

Table 3: Main OLS regression results on household income growth

	(1) Post	(2) Not ESI	(3) Full
Near 400% FPL	.0882***	.09497***	.09486***
300% FPL < Annual Income < 500% FPL	(.011)	(.026)	(.008)
Not Offered ESI	-.07125***		-.05418***
	(.024)		(.018)
Monthly PLS ($100)	-3.73e-04	-4.70e-04	.00634***
	(.0024)	(.0065)	(.0024)
Near 400% FPL × Not Offered ESI	.006494		-.01024
	(.035)		(.027)
Not Offered ESI × PLS	.00641*		.00382
	(.0039)		(.0034)
Near 400% FPL × PLS	.00631**	.00325	.00702
	(.003)	(.0092)	(.0044)
Near 400% FPL × Not Offered ESI × PLS	-.003		-.00817
	(.0082)		(.0086)
Post-ACA × PLS		.00106	-.00591**
		(.0067)	(.0027)
Near 400% FPL × Post-ACA × PLS		6.69e-04	-.00249
		(.011)	(.0046)
Near 400% FPL × Not Offered ESI × Post-ACA × PLS			.00927
			(.0098)
N	18,905	7,572	33,412
R^2	.06844	.08252	.06261
Industry dummies	X	X	X
State FE	X		X
Region FE		X	
Year FE	X	X	X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is the income growth. All variables are at the household level and use the MEPS family weights. Models control for socio-economic variables not reported in this table such as head of household's age, age squared, sex, marital status, self-reported health status, self-employment status, medical expenses of the first year of survey, industry dummy and income level dummy (below 150% FPL, between 150 and 300% FPL, between 450 - 600% FPL and above 600% FPL, the omitted group) both linear and interacted with the not offered ESI variable.

Table 4: Main OLS regression results on change in hours of work

	(1) Post	(2) Not ESI	(3) Full
Near 400% FPL	-.1113	-.7994	-.3635
300% FPL < Annual Income < 500% FPL	(.34)	(.77)	(.25)
Not Offered ESI	.5364		.2785
	(.69)		(.51)
Monthly PLS ($100)	-.1288*	-.2611	-.1889**
	(.066)	(.21)	(.074)
Near 400% FPL × Not Offered ESI	-1.646		-.6084
	(1.1)		(.84)
Not Offered ESI × PLS	.1876*		.2007**
	(.11)		(.099)
Near 400% FPL × PLS	.05364	.1841	.3169***
	(.081)	(.34)	(.099)
Near 400% FPL × Not Offered ESI × PLS	.2128		-.2382
	(.22)		(.33)
Post-ACA × PLS		.1982	.03655
		(.19)	(.077)
Near 400% FPL × Post-ACA × PLS		-.1131	-.2573**
		(.35)	(.11)
Near 400% FPL × Not Offered ESI × Post-ACA × PLS			.3238
			(.31)
N	18,905	7,572	33,412
R^2	.1414	.03083	.1388
Industry dummies	X	X	X
State FE	X		X
Region FE		X	
Year FE	X	X	X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the change in hours of work from one year to another. All variables are at the household level and use the MEPS family weights. Models control for socio-economic variables reported in the Appendix such as age of head of household, age squared, sex, marital status, self-reported health status, self-employment status, medical expenses in the first year of survey, industry dummies, year dummies and state or region fixed effects as well as both linear and interacted income level dummies (below 150% FPL, between 150 and 300% FPL, and above 500% FPL the omitted group) with the not offered ESI variable.

Table 5: Probability that any household member stops working

	(1) Post	(2) Not ESI	(3) Full
Near 400% FPL	.02165*	.03233	.01097
300% FPL < Annual Income < 500% FPL	(.011)	(.026)	(.0079)
Not Offered ESI	-.001949		.01645
	(.018)		(.015)
Monthly PLS ($100)	.00696***	.01764***	.00868***
	(.0014)	(.0051)	(.0013)
Near 400% FPL × Not Offered ESI	.0294		.01461
	(.032)		(.02)
Not Offered ESI × PLS	2.84e-04		6.41e-04
	(.0021)		(.0019)
Near 400% FPL × PLS	-.00266	-.00279	-2.71e-04
	(.0021)	(.0073)	(.0023)
Near 400% FPL × Not Offered ESI × PLS	.00518		4.37e-04
	(.0047)		(.0051)
Post-ACA × PLS		-.00728	-.00172
		(.0047)	(.0015)
Near 400% FPL × Post-ACA × PLS		.00819	-4.77e-04
		(.0089)	(.0025)
Near 400% FPL × Not Offered ESI × Post-ACA × PLS			.0039
			(.0055)
N	18,905	7,572	33,412
Year FE	X	X	X

Marginal effects; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the probability that one of the adult of the household leaves the labor force. The results are the marginal effects of the probit regression. All variables are at the household level and use the MEPS family weights. Models control for socio-economic variables reported in the Appendix such as age of head of household, age squared, sex, marital status, self-report health status, self-employment status, medical expenses in the first year of survey, year dummies and both linear and interacted income level dummies (below 150% FPL, between 150 and 300% FPL, and above 500% FPL the omitted group) with the not offered ESI variable.

Table 6: State-Based Marketplace Regressions: main variables

	(1) Income Growth	(2) Change in Hours of Work	(3) Probability to stop working
Near 400% FPL	.09521***	.2466	.03633*
300% FPL < Annual Income < 500% FPL	(.018)	(.64)	(.02)
Not Offered ESI	-.08285**	-.4722	.04153
	(.034)	(1.8)	(.041)
Monthly PLS ($100)	-7.01e-05	-.0667	.00969***
	(.0043)	(.1)	(.0028)
Near 400% FPL × Not Offered ESI	.03071	-1.908	-.01476
	(.049)	(2.1)	(.034)
Not Offered ESI × PLS	.0045	.1712	2.18e-04
	(.0065)	(.25)	(.004)
Near 400% FPL × PLS	.00881	.1214	-.00661*
	(.0059)	(.19)	(.0038)
Near 400% FPL × Not Offered ESI × PLS	-.0062	.1617	.00204
	(.011)	(.41)	(.0088)
N	5,331	5,331	5,331
R^2	.08442	.149	
Industry dummies	X	X	
Year FE		X	X

Marginal effects; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The State-based Marketplaces are the 11 following states CA, CO, CT, ID, MD, MA, MN, NY, RI, VT, WA, and DC. These regressions are using the post-ACA sample restricted to households living in those states. All variables are at the household level and use the MEPS family weights. Models control for socio-economic variables not reported in the Appendix such as age of head of household, age squared, sex, self-employment status, medical expenses in the first year of survey, industry dummies, and both linear and interacted income level dummies (below 150% FPL, between 150 and 300% FPL, and above 500% FPL the omitted group) with the not offered ESI variable.

Table 7: Probability to fall below 400% FPL in the second year (Y2)

	(1) Near & NotESI & Post	(2) Near & Not ESI
Family Income as % FPL in Y1	-.003721***	-.003657***
	(.00041)	(.0003)
Monthly PLS ($100)	-.01123	3.28e-04
	(.012)	(.014)
Post-ACA × PLS		-.01083
		(.017)
Post-ACA		.04284
		(.066)
Age	-.03971**	-.0248*
	(.017)	(.013)
Age squared	.0005035**	.0003146**
	(.0002)	(.00016)
Female	.01963	.05681
	(.052)	(.04)
Log of medical expenses	-.01665**	-.01413**
in year 1	(.0078)	(.006)
Self-employed in year 1	-.07561	-.07787
	(.068)	(.052)
Married	.04136***	.02854**
	(.015)	(.013)
Family size	.01793	.01925
	(.021)	(.018)
Very good health	-.04062	-.02987
	(.063)	(.047)
Good health	.03566	.0152
	(.071)	(.054)
Fair health	-.0814	.01255
	(.092)	(.071)
Poor health	.2836***	.0706
	(.1)	(.16)
N	685	1,157

Marginal effects; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Cap on Required Premium for Subsidy-Eligible Individuals in 2014

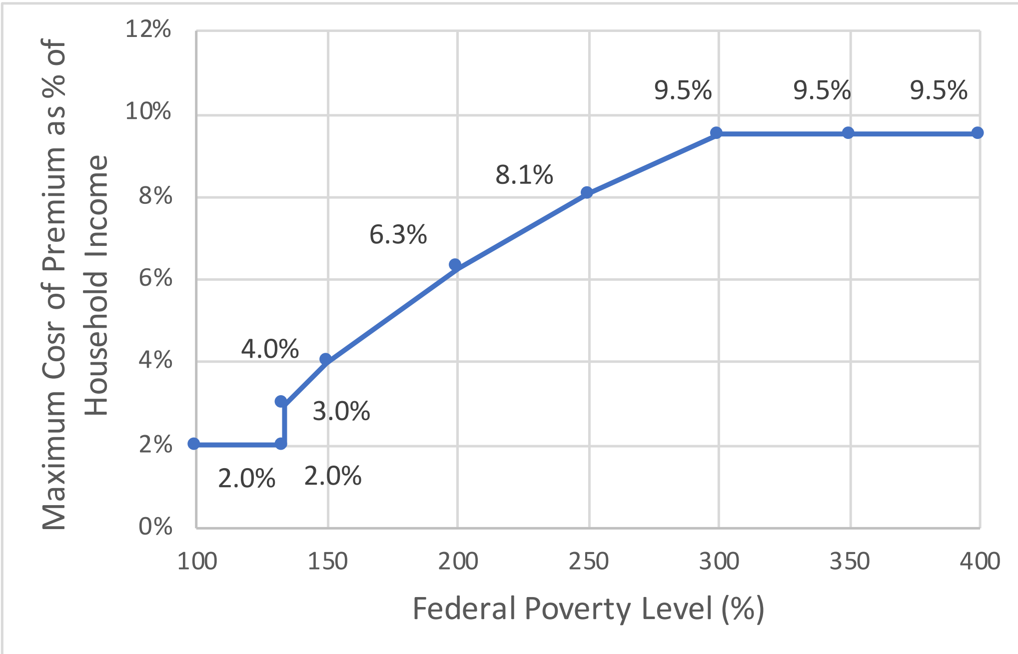
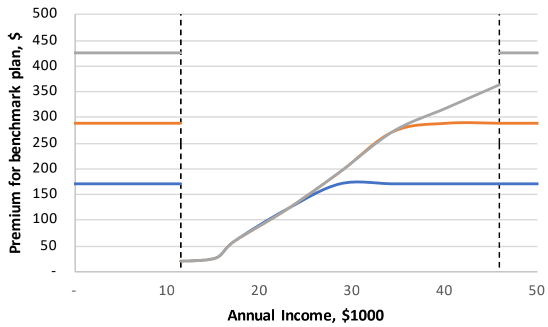
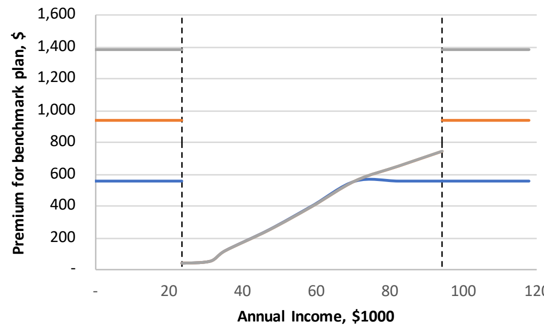


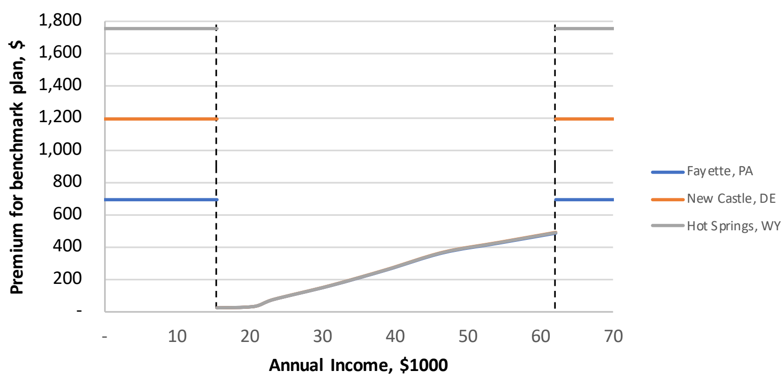
Figure 2: Variation of Monthly Premiums by Geographic Location, Family Structure and Annual Income (2014)



(a) Premiums for a 40-year-old Single



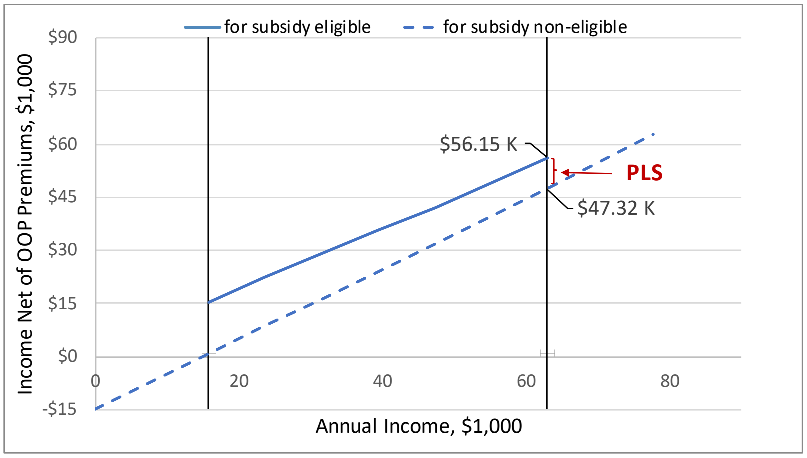
(b) Premiums for a Family of Four



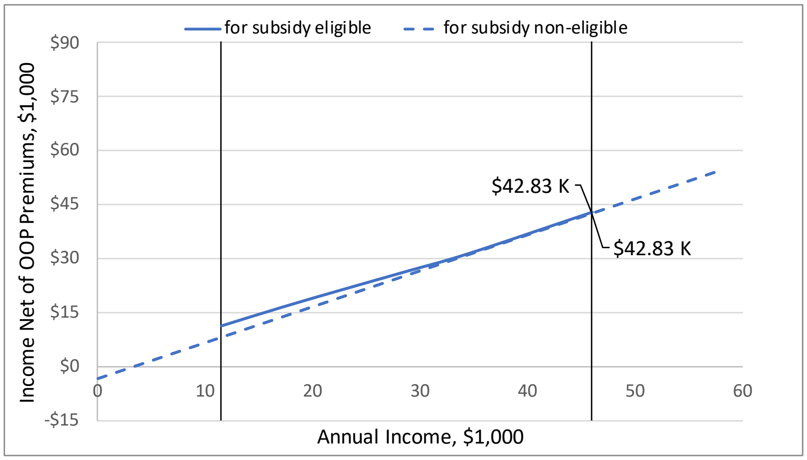
(c) Premiums for an Older Couple

Notes: Premiums are from the 2014 Kaiser Family Foundation (KFF) Calculator for non-smoker individuals living in Fayette County, Pennsylvania, in New Castle County, Delaware or in Hot Springs County, Wyoming. Here, older couple is a 58- and 60- year old couple; a family of four is a 45-year-old couple with 2 children under 21. The vertical dashed lines represent the 100% and 400% FPL subsidy cutoffs for the corresponding household. In the subsidy-eligible range, the premium cost is the subsidized premium while outside this range it is the full (unsubsidized) premium paid by households in their local rating area.

Figure 3: Income Net of Out-Of-Pocket Premiums (2014, U.S. average)



(a) For a 62-year-old couple



(b) For a 35-year-old individual

Notes: The vertical lines represent the 100% and 400% of the FPL for a couple (panel a) or a single individual (panel b) using the 2013 FPL guidelines. The income net of out-of-pocket premiums refers to the annual income minus the subsidized premium (for subsidy-eligible) or minus the full premium (for non-eligible). Premium data are obtained from the Kaiser Family Foundation calculator for 2014 for non-tobacco users.

Figure 4: Distribution of the PLS (2014-2017)

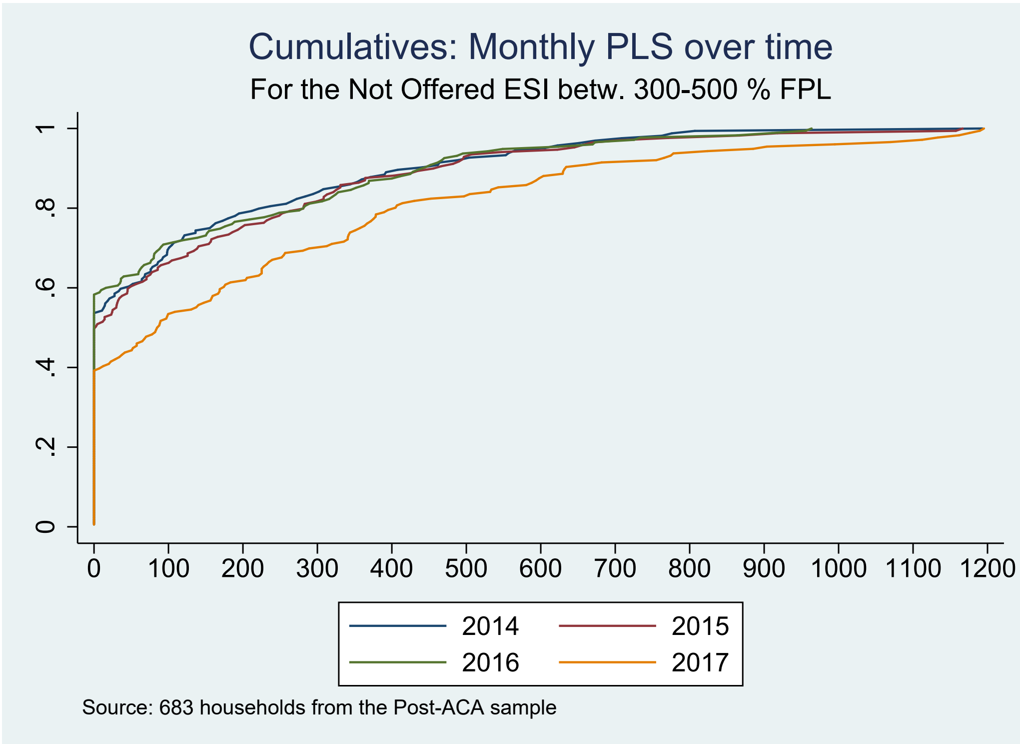
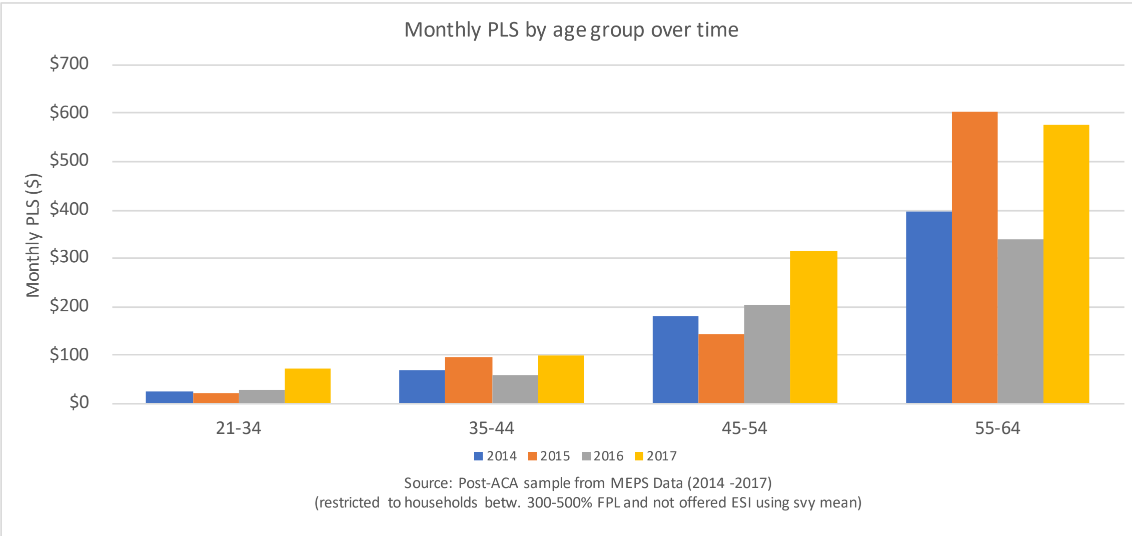


Figure 5: PLS per month by age group over time (2014-2017)



Appendix

Table 8: Federal Standard Age Curve

AGE	Premium Ratio	AGE	Premium Ratio
0-14	0.765	40	1.278
15	0.833	41	1.302
16	0.859	42	1.325
17	0.885	43	1.357
18	0.913	44	1.397
19	0.941	45	1.444
20	0.970	46	1.500
21	1.000	47	1.563
22	1.000	48	1.635
23	1.000	49	1.706
24	1.000	50	1.786
25	1.004	51	1.865
26	1.024	52	1.952
27	1.048	53	2.040
28	1.087	54	2.135
29	1.119	55	2.230
30	1.135	56	2.333
31	1.159	57	2.437
32	1.183	58	2.548
33	1.198	59	2.603
34	1.214	60	2.714
35	1.222	61	2.810
36	1.230	62	2.873
37	1.238	63	2.952
38	1.246	64	3.000
39	1.262		

Source: CMS Insurance Standard Bulletin Series, 2016

Table 9: Income Growth Regression: socio-economic variables

	(1) Post	(2) Not ESI	(3) Full
Age	-.0009251	-.009133**	-.001368
	(.0024)	(.0045)	(.0019)
Age squared	-.0000108	.0000912*	-5.05e-06
	(.000029)	(.000055)	(.000023)
Female	-.01667**	-.03207**	-.02085***
	(.0072)	(.014)	(.0056)
High school	-.004368	.002396	-.01873
	(.015)	(.031)	(.014)
Some college	.02785*	.04284*	.0144
	(.015)	(.026)	(.014)
College	.07238***	.05109**	.04934***
	(.012)	(.024)	(.011)
Black	-.02441***	-.05425***	-.0285***
	(.0079)	(.015)	(.0067)
Other race	.03753	.06415	.03383*
	(.024)	(.042)	(.02)
Log of medical expenses	.003776***	.004056**	.003094***
in year 1	(.0011)	(.0019)	(.00081)
Self-employed in year 1	.003635	.06639***	.005882
	(.017)	(.019)	(.012)
Married	-.01128***	-.02241***	-.01098***
	(.0028)	(.0038)	(.0021)
Family size	-.01375***	-.02109***	-.01494***
	(.0029)	(.0041)	(.0021)
Very good health	-.009487	-.008744	-.01363*
	(.0089)	(.016)	(.0073)
Good health	-.03709***	-.0549***	-.03872***
	(.0095)	(.015)	(.0076)
Fair health	-.06436***	-.06568***	-.07023***
	(.015)	(.024)	(.011)
Poor health	-.05032**	-.09239*	-.08266***
	(.024)	(.053)	(.017)
constant	.01339	.2044**	.01773
	(.06)	(.095)	(.052)
N	18,905	7,572	33,412
R^2	.06844	.08252	.06261

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Change in hours Regression: socio-economic variables

	(1) Post	(2) Not ESI	(3) Full
Age	.2734***	-.0954	.2561***
	(.094)	(.14)	(.067)
Age squared	-.004271***	.0006911	-.003904***
	(.0011)	(.0018)	(.0008)
Female	-.6069***	-.5476	-.5674***
	(.23)	(.4)	(.17)
High school	.4383	.4163	.3596
	(.43)	(.76)	(.41)
Some college	.1005	.03247	.07572
	(.51)	(1.3)	(.49)
College	.2617	-.4076	.04438
	(.44)	(.96)	(.35)
Black	-.04512	-1.06**	-.05745
	(.27)	(.48)	(.21)
Other race	-.865	-2.971	-.12
	(1.3)	(3.1)	(.88)
Log of medical expenses	-.2436***	-.1591**	-.2394***
in year 1	(.04)	(.07)	(.034)
Self-employed in year 1	1.851***	-.1777	1.417***
	(.33)	(.56)	(.25)
Married	.2561***	.04376	.2915***
	(.083)	(.13)	(.06)
Family size	-.1005	-.2435*	-.03664
	(.098)	(.14)	(.071)
Very good health	-.1854	-.5075	-.2514
	(.27)	(.49)	(.2)
Good health	-.3723	-.7958	-.423**
	(.3)	(.5)	(.21)
Fair health	-1.965***	-3.075***	-2.407***
	(.38)	(.83)	(.32)
Poor health	-5.331***	-2.705*	-4.712***
	(.59)	(1.5)	(.41)
constant	9.15***	4.299	9.313***
	(2.1)	(3.3)	(1.6)
N	18,905	7,572	33,412
R^2	.1414	.03083	.1388

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Probability that any household member stops working: socio-economic variables

	(1) Post	(2) Not ESI	(3) Full
Age	-.007608***	-.01454***	-.007458***
	(.0018)	(.0036)	(.0013)
Age squared	.0000778***	.000155***	.0000744***
	(.000021)	(.000045)	(.000016)
Female	-.0182***	-.01548	-.025***
	(.0046)	(.01)	(.0036)
High school	-.001002	-.02523	-.0003483
	(.)	(.021)	(.0094)
Some college	.01761*	.008426	.01868*
	(.01)	(.025)	(.011)
College	-.007211	-.001558	-.005223
	(.008)	(.019)	(.0073)
Black	-.002651	.008835	-.0002665
	(.0065)	(.013)	(.0046)
Other race	.04378*	.1007*	.04998***
	(.025)	(.055)	(.017)
Log of medical expenses	.001046	.003782**	.0006859
in year 1	(.00079)	(.0018)	(.00065)
Self-employed in year 1	.007525	-.02898	.01148*
	(.0098)	(.018)	(.0067)
Married	-.01752***	-.01749***	-.01768***
	(.0019)	(.0041)	(.0014)
Family size	.002344	.003747	.001284
	(.0018)	(.0036)	(.0014)
Very good health	.006724	-.004279	.004821
	(.0065)	(.013)	(.0045)
Good health	.01002	.008373	.01233**
	(.0071)	(.014)	(.0055)
Fair health	.009122	.09188***	.01834**
	(.0095)	(.025)	(.0081)
Poor health	.01163	.09357**	.00404
	(.015)	(.046)	(.011)
N	18,905	7,572	33,412
Year FE	X	X	X

Marginal effects; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: State-Based Marketplace Regressions: socio-economic variables

	(1) Income Growth	(2) Change in Hours of Work	(3) Probability to stop working
Age	-.006476	.1217	.000514
	(.0047)	(.15)	(.0035)
Age squared	.0000549	-.00274	-.0000179
	(.000056)	(.0017)	(.000041)
Female	-.01724	-.6766	-.02064**
	(.014)	(.49)	(.0089)
High school	-.02193	1.722*	.01096
	(.029)	(1)	(.018)
Some college	-.0117	-.5961	.01515
	(.021)	(.79)	(.019)
College	.08423***	.4885	-.01609*
	(.023)	(.66)	(.0095)
Black	-.02112	-.01661	.001108
	(.019)	(.45)	(.014)
Other race	-.004613	.336	.006577
	(.036)	(.93)	(.02)
Log of medical expenses	.005226***	-.3089***	.001047
in year 1	(.0019)	(.084)	(.0015)
Self-employed in year 1	-.003189	2.707***	-.004445
	(.025)	(.5)	(.014)
Married	-.01757***	-.03345	-.007183**
	(.0058)	(.14)	(.0036)
Family size	-.01786***	-.1759	.00984***
	(.0046)	(.2)	(.003)
Very good health	-.01182	.3724	-.0142
	(.018)	(.5)	(.0099)
Good health	-.04385***	-.228	-.004019
	(.016)	(.44)	(.01)
Fair health	-.04546	-1.208**	.00644
	(.03)	(.55)	(.014)
Poor health	.06	-3.464***	-.004301
	(.063)	(.95)	(.027)
N	5331	5331	5331
R^2	.08442	.149	
Industry dummies	X	X	
Year FE		X	X

Marginal effects; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

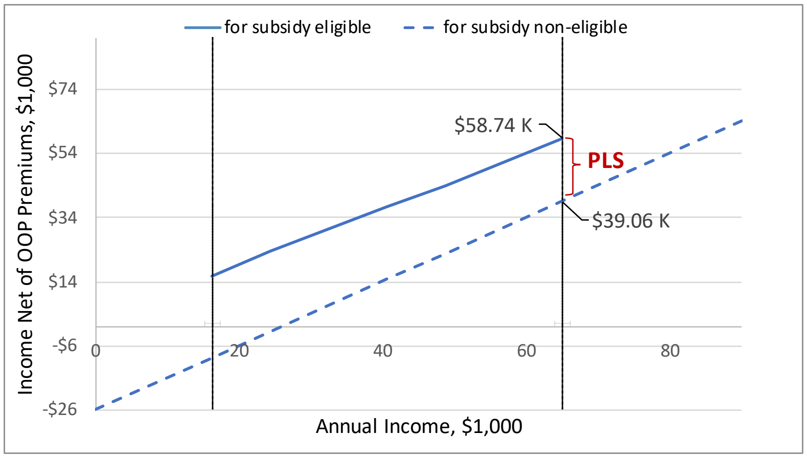
Table 13: Probability to be below 400% in Y2: socio-economic variables

	(1) Near & NotESI & Post	(2) Near & Not ESI
Age	-.03971**	-.0248*
	(.017)	(.013)
Age squared	.0005035**	.0003146**
	(.0002)	(.00016)
Female	.01963	.05681
	(.052)	(.04)
High school	-.05514	-.009902
	(.067)	(.075)
Some college	-.1469	-.1234
	(.11)	(.1)
College	-.08416	-.05583
	(.068)	(.063)
Black	.09888	.05512
	(.073)	(.054)
Other race	.05844	.04565
	(.11)	(.085)
Log of medical expenses	-.01665**	-.01413**
in year 1	(.0078)	(.006)
Self-employed in year 1	-.07561	-.07787
	(.068)	(.052)
Married	.04136***	.02854**
	(.015)	(.013)
Family size	.01793	.01925
	(.021)	(.018)
Very good health	-.04062	-.02987
	(.063)	(.047)
Good health	.03566	.0152
	(.071)	(.054)
Fair health	-.0814	.01255
	(.092)	(.071)
Poor health	.2836***	.0706
	(.1)	(.16)
N	685	1,157

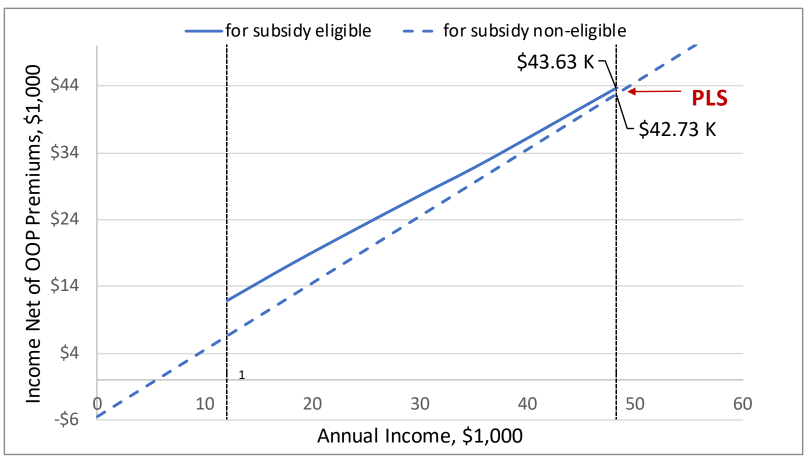
Marginal effects; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 6: Income Net of Out-Of-Pocket Premiums (2018, U.S. average)



(a) For a 62-year-old couple



(b) For a 35-year-old individual

Notes: The vertical lines represent the 100% and 400% of the FPL for a couple (panel a) or a single individual (panel b) using the 2017 FPL guidelines. The income net of out-of-pocket premiums refers to the annual income minus the subsidized premium (for subsidy-eligible) or minus the full premium (for non-eligible). Premium data are obtained from the Kaiser Family Foundation calculator for 2018 for non-tobacco users.