# How does an introduction of premiums into the State Children's Health Insurance Program (SCHIP) affect labor supply? Evidence from Arizona*

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**Abstract**

Health insurance has played a key role in determining an individual's job choice, retirement plan, and health care utilization. This paper examines the effect of introducing premiums in the Arizona State Children's Health Insurance Program (SCHIP) in 2004 on the labor supply of adults with children. The results of a difference-in-differences approach indicated that among Arizona residents with children, men were six percentage points more likely to work and worked 4.5-5.2 more weeks per year after the policy implementation. Also, single women were 13 percentage points more likely to work and worked, on average, an additional 7.2-8.1 weeks per year. On the contrary, married women were 5.2 percentage points less likely to work and worked, on average, 8-9.6 weeks less per year after the policy change as their husbands worked more.

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# 1. Introduction

Economists have long been interested in labor supply issues and associated societal aspects. For example, labor income accounts for approximately 60% of the total economic output in the U.S. (Giandrea and Sprague, 2017) and a one percent increase in labor supply increases the total economic output by around three percent on average in U.S. industries (Akay and Dogan, 2013). At the individual level, weekly paid working hours may have negative effects on quality of life for both men and women, though the effect on women may be stronger (Knabe and Ratzel, 2010).

Labor supply also affects income which may have impacts on public welfare programs. For instance, when individuals quit working, it would result in a reduction of income. As a result, the costs of other welfare programs such as the Supplemental Nutrition Assistance Program (SNAP – formerly known as food stamps) would increase (Kenney et al., 2012; Deshpande, 2016). One such example of this was the 2008 Medicaid expansion in Oregon which led to a decrease in employment by about 3 percent, and a subsequent increase in SNAP enrollment by 2.5 percent (Baicker et al., 2014).

Medicaid is the most common public health insurance program for low-income Americans. Introduced under Title XIX of the Social Security Act of 1965, Medicaid provides affordable health care coverage to low-income, elderly, and disabled individuals. Although many low-income individuals and their children receive Medicaid coverage, it is difficult for those whose incomes are only slightly above the Medicaid threshold to afford private health insurance.

The State Children's Health Insurance Program (SCHIP) was created under Title XXI of the Balanced Budget Act of 1997 to expand health care coverage for children in low-income households. The program is jointly financed by the federal and state governments, but many states, including Arizona, run their own programs and can set their own SCHIP policies. The income requirements for SCHIP are slightly higher than those for Medicaid; households are eligible to enroll in the SCHIP by meeting some requirements shown in Table 1 and Table

2. Since its inception, SCHIP has played a key role in supporting individuals with relatively low incomes who may be above the threshold for Medicaid coverage through the provision of low-cost health insurance for their children.

Insurance premiums are a type of cost-sharing for which the insured has to pay periodically to get insurance coverage. The premium introduction could be a burden in that it might result in loss of health insurance coverage for some children. By 2008, 34 states had implemented copayments and premium cost-sharing (Ross, Horn, and Marks, 2008).

Although many states have introduced premiums into their SCHIP programs, it is worth studying the 2004 SCHIP policy change in Arizona because the amount of premium introduced was relatively large for low-income people. As shown in Figure 1, there was a sizable decrease in Arizona's state expenditure for SCHIP in 2004 and 2005.[1] This decrease is likely attributed to the introduction of SCHIP premiums in Arizona in July 2004, which resulted in larger disenrollment and smaller reenrollment compared with other years (Kenney et al., 2007). This policy introduced a monthly premium of $10 for one child and $15 for more than one child for households whose incomes are between 101% and 150% of the federal poverty line (FPL). For households earning 150%-175% of the FPL, the monthly premium was raised from $10 to $20 for the first child and $15 to $30 for two or more children. For the highes-earning category, households at 176%-200% of the FPL, the monthly premium increased from $10 to $25 for the first child and from $20 to $30 for more than one child, respectively. By contrast, for example, Michigan increased the monthly SCHIP premium from $5 to $10 for households with incomes greater than 150% but less than or equal to 200% of the FPL on March 8, 2007 regardless of the number of children. There was no monthly premium for families earning between 101% and 150% of the FPL, before and after the policy change. In addition, there was evidence that people were significantly influenced by this policy change. As a result of this policy change, the rate of disenrollment in the Arizona SCHIP increased

[1] All dollar values are converted as constant 2008 dollars inflated using the Consumer Price Index for All Urban Consumers (CPI-U) from the Bureau of Labor Statistics following Busch, Golberstein, and Meara (2014).

and the rate of reenrollment in the Arizona SCHIP decreased (Kenney et al., 2007).

Previous studies have shown that the introduction, expansion, or contraction of Medicaid changes the labor supply (Winkler, 1991; Lee and Tomohara, 2008; Strumpf, 2011; Garthwaite, Gross, and Notowidigdo, 2014; Boyle and Lahey, 2016). However, little is known about the effects of policy changes in the State Children's Health Insurance Program (SCHIP) on labor supply. Thus, the purpose of this study was to examine the effects of the 2004 Arizona SCHIP premium policy changes on individuals' labor supply. The difference-in-differences (DD) and synthetic control methods were used to analyze these effects both at the extensive margin (whether to work) and at the intensive margin (how many weeks to work in a year).

This paper contributes to the existing literature as the first to study the effect of SCHIP policy change in a particular state. Additionally, while previous studies have focused on the effects of such policy changes on women (Winkler, 1991), single women (Strumpf, 2011), married women (Lee and Tomohara, 2008), pregnant women (Dave et al., 2015), and veterans (Boyle and Lahey, 2010) and their wives (Boyle and Lahey, 2016), this analysis includes both men and women. The labor supply of one member of a household can affect the labor supply decisions of other members making it important to study the effects of policy changes on men in addition to women.

I found that men with children in Arizona were six percentage points more likely to work and worked 4.5-5.2 more weeks per year after the policy change. For women with children in Arizona as a whole, the policy change did not have an impact on their probability of working but a negative impact on their numbers of work weeks per year. I then examined the policy effects on single women and married women separately. I found single women were 13 percentage points more likely to work and on average they worked an additional 7.2-8.1 weeks per year after the policy change. By contrast, married women were 5.2 percentage points less likely to work and on average they worked 8-9.6 weeks less per year after the policy change as their husbands worked more. These results are in line with previous studies, especially from Boyle and Lahey (2010, 2016), representing that men were more likely to work after losing premium benefits of public health insurance. By contrast, wives were less likely to work after their husbands began to work. This outcome is supported by findings that single women or divorced women, who do not have husbands, increased both the intensive and extensive margin of labor supply.

The rest of the paper is organized as follows. Section 2 reviews previous literature. Section 3 introduces the major public health insurance programs for low-income people in the U.S. and SCHIP in particular as backgrounds for identification strategies. Section 4 discusses the data and the empirical strategy used. Results are presented and discussed in Section 5. The final section concludes.

## 2. Literature Review

This study is closely related to previous literature studying the impact of Medicaid on the U.S. labor supply. Winkler (1991) studied the impact of Medicaid on labor supply with a focus on females and found that Medicaid had a significant negative effect on a female head-of-household's decision to work. More specifically, a 10 percent increase in Medicaid expenditure decreased a female head-of-household's probability of working by between 0.9 and 1.3 percentage points. Although Winkler (1991) hypothesized that an increase in Medicaid expenditures would have a negative impact on hours worked; assuming leisure is a normal good, it was thought that this additional "income" (in the form of a government transfer), which may be increasing the attractiveness of being a nonworker. Results of this study that Medicaid expansion reduced a head's probability of working. However, it had an insignificant effect on the number of hours worked. The author conjectured a possible omitted variable bias, specifically a measure of initial health status, as the reason Medicaid had differential impacts on these two decisions. Medicaid benefits likely improved participants' health and therefore enabled workers to increase their hours. Similarly, Dave et al. (2015) examined the effects of Medicaid expansion in the late 1980s and early 1990s on the labor supply of pregnant women. They found that an increase in Medicaid eligibility between 1985 and 1996 significantly decreased the probability of pregnant women working.

Strumpf (2011) examined the effect of Medicaid introduction on labor supply for single women using Current Population Survey (CPS) data from 1963 to 1975. In contrast to the findings of Winkler (1991) and Dave et al. (2015), the author did not find evidence that women who qualified for Medicaid decreased their labor supply compared to ineligible women as one might expect as a result of the income effect. This finding could be due to the potential for Medicaid to increase children's health care utilization (Currie and Gruber, 1996a; 1996b). As a result, children's health would be improved and single women would be able to increase hours worked, offsetting the income effect.

Scholars have also studied the effects of Medicaid or SCHIP policy changes on labor supply in certain U.S. states. Garthwaite, Gross, and Notowidigdo (2014) studied the effect of TennCare (Tennessee's version of Medicaid) disenrollment on the labor supply of childless adults using CPS data. They found that employment rates increased by 2.5 percentage points after disenrollment. They argued that some employees might delay their retirement to maintain employer-provided coverage after the disenrollment.

Lee and Tomohara (2008) examined the effect of SCHIP implementation on labor supply of married women. They found that SCHIP affected only certain groups of married women such as non-white women. The introduction of SCHIP lowered the probability of working for non-white women, women with pre-school aged children, and those with less than high school education.

Looking at another type of public health insurance program, Boyle and Lahey (2016) studied the effects of veteran's health insurance the labor supply of married couples. They found that veterans were less likely to work after receiving VA health benefits. On the other hand, veterans' wives were more likely to work after their husbands began to receive VA health benefits. They observed two main effects of a husband's work status on a wife's work status. First, wives tended to retire with their husbands. Second, wives tended to increase their work hours after their husbands retired, likely due to financial need. The authors concluded that the second effect likely dominated the first effect as wives' probability of working increased by 1-2 percentage points once their husbands received VA health benefits.

As evidenced by the review of the existing literature, there is a gap regarding the effect of policy changes in the SCHIP on the labor supply for both men and women. This paper aims to fill that gap by studying how the labor supply was affected by the introduction of SCHIP premiums in Arizona.

## 3. Public Health Insurance Programs

Before describing the SCHIP program, Medicaid, which is the main public health insurance program for low-income people, will be briefly introduced in this section. The private health insurance market has not been able to provide affordable health insurance plans for low-income and disabled people. Therefore, Medicaid and SCHIP were developed. Medicaid is a joint federal and state program to support families with the lowest incomes. SCHIP offers essential coverage to children in families with slightly higher incomes that are not eligible for Medicaid.

### *3.1. Medicaid*

Medicaid is the state and federal program that provides health coverage for low-income or disabled people.[2] The Medicaid program was created as Title XIX in the Social Security Amendments of 1965, which are amendments to the Social Security Act of 1935. The number of Medicaid enrollees was about 71 million in 2014. People are eligible for Medicaid benefits when they meet certain income criteria as shown in Table 1.

Although eligibility varies from state to state, Title XIX of The Social Security Act specifies mandatory eligibility groups and optional eligibility groups. If states want to qualify

[2] Disabled people who have been approved for Social Security disability insurance (SSDI) benefits get Medicare, and those who have been approved for Supplemental Security Income (SSI) receive Medicaid.

for Federal funds, they must provide Medicaid coverage not only for individuals receiving public income maintenance payments (PIM) such as Temporary Assistance for Needy Families (TANF, formerly known as AFDC), but also for related groups who do not get cash payments. Column 2 in Table 1 displays the mandatory Medicaid eligibility groups.

States also have the option of offering Medicaid coverage for certain other related groups of people. These optional groups have similar characteristics as those of the mandatory groups, but states can set their own eligibility criteria. These optional groups include people in column 3 in Table 1.

Medicaid is essential for seniors and disabled people since poverty is related to both old age and disability status. Medicare covers most seniors, but the program costs are high even though many elderly people have low incomes and limited savings. It is difficult for disabled people to enroll in private health insurance if they cannot work at all or can only work part-time. Moreover, private insurance generally does not provide enough benefits to cover services for them to live an independent life society. For example, Medicaid is the main payer for long-term services and supports (LTSS) which help people with disabilities and older adults with self-care and other household tasks such as bathing, dressing, fixing meals, and managing a home.

SSI recipients may be automatically approved for Medicaid benefits in most states. However, some states including Illinois and Virginia do not obey this rule because they adopted section 209(b) of the 1972 amendments to the Social Security Act. This section allows states to have their own Medicaid eligibility criteria for the elderly and people with disabilities.

Many people receive both SSI and Social Security benefits. Medicaid is tied to the receipt of SSI benefits in most states, whereas Medicare is tied to Social Security benefits. It is possible to receive both Medicare and Medicaid. States pay the Medicare premiums for SSI beneficiaries if they also qualify for Medicaid. They would also be eligible for Extra Help with Medicare Part D without filing a separate application if they get both SSI and Medicare.

Some people have income exceeding the Medicaid eligibility threshold. This amount of surplus income is called excess income. If they spend this excess income on medical expenses, they may be eligible for Medicaid. This policy is called the Spenddown program. These Spenddown benefits are only for people who are children under 21 years old, adults over 65 years old, the blind, the disabled, or living in families with at least one parent absent, dead, disabled or unemployed. For example, suppose an individual over 65 cannot enroll in Medicaid because his or her monthly income is $30 more than the Medicaid income threshold. If he or she incurs a $30 per month medical expenditure, Medicaid will cover the rest of medical bills. In this case, the Spenddown is the $30 of medical bills.

States have the option to impose premiums and cost-sharing (out-of-pocket costs) for Medicaid enrollees. Deductibles, copayments, and coinsurance are all part of the cost-sharing. States can impose charges on people with slightly higher income more although the maximum out of pocket costs are usually restricted. Certain groups that need protection including children and pregnant women are exempt from most cost-sharing.

For instance, in 2018, most people in Arizona who are covered by the Arizona Health Care Cost Containment System (AHCCCS) do not need to pay a monthly premium. However, if they incur medical costs, they have to make payments for medical care that they use. Specifically, for people who are 19 years old or older, they need to pay copayments ranging from $2.30 to $3.40 per visit for certain medical services under AHCCCS. Certain vulnerable groups of people do not have to make copayments. These include children less than 19 years old, pregnant women, or people in hospice care.

### *3.2. SCHIP*

The Social Security Act was amended by Section 4901 of the Balanced Budget Act of 1997 (BBA) by adding SCHIP as Title XXI. Title XXI offers funds to states in order to finance the SCHIP programs. John Kasich, who at that time was the chairman of the U.S. House Budget Committee, introduced the Balanced Budget Act of 1997. The bill was passed by both the House and the Senate on June 25, 1997. President Bill Clinton signed this bill into law on August 5, 1997.

SCHIP is the partnership program between the federal and state governments based on income and family size. All 50 states participate in the SCHIP program even though it is an optional program. It provides health coverage to uninsured children under the age of 19 whose families earn a higher income than the Medicaid threshold but cannot afford private coverage. In other words, the lower-income limit for SCHIP is the Medicaid threshold. Each state has different upper-income limits as shown in Table 2. In 2016, the number of SCHIP enrollees was about 8.9 million, compared with 37 million children enrolled in Medicaid.

A state has to submit a Title XXI SCHIP policy plan to receive federal funds. Each state can create its children's health insurance program (CHIP) in the following three ways. First, a state can follow federal Medicaid rules, which is called Medicaid expansion CHIP (MSCHIP). Second, a state can design separate CHIP program (S-SCHIP). Third, a state can combine both M-SCHIP and S-SCHIP (COMBO). According to Lee and Tomohara (2008), 15 states used S-SCHIP, 19 states used M-SCHIP and 17 states used COMBO as of March 2000. In 2015, 29 States, 8 States plus 5 territories and D.C. and 11 states, used COMBO, M-SCHIP and S-SCHIP, respectively, because the Affordable Healthcare Act (ACA) expanded Medicaid to families earning up to 133% of FPL in 2014 and 11 states followed this rule. Premiums for the SCHIP programs vary by state. Table 3 lists the SCHIP premiums for two children in a three-member family in Arizona and some other states as of January 2007.

# 4. Methodology and Data

## *4.1. Data*

The data are based on the Annual Social and Economic Supplement (ASEC) of the CPS. CPS data have been collected on a monthly basis since 1940. A supplemental survey, the ASEC, is also conducted in March of each year. While the monthly CPS is designed to collect basic demographic and labor force data, the March supplement includes more in-depth information including work experience, income, noncash benefits, migration, SSI, and health status. In addition to the differences in information gathered, there are also differences in the selection criteria for the two surveys. For example, there were 74,008 respondents for the March 2006 CPS monthly survey compared to 94,097 respondents for the March 2006 ASEC supplemental survey. This difference is due to the variations in the selection criteria as well as additional respondents were drawn from CPS respondent pools in adjacent months and Hispanics were oversampled because they make up a small share of the population. Researchers can correct this through weighting.

The respondents to the supplement mainly come from respondents to the basic CPS survey in March, but some of them are respondents to the basic CPS survey in adjacent months. Also, not all respondents to the basic CPS survey in March will receive the supplement questionnaire because the supplement has different selection criteria

For this study, sampling was restricted to 2001-2007, with the exception of 2004. This sample frame was selected because SCHIP was unstable before 2001 in terms of policy changes and there was a financial crisis that did not equally affect all states in the U.S. Additionally, the observation year 2004 was dropped because Arizona introduced SCHIP premiums in July of that year. The total number of observations included in this sample frame was 1,263,731 individual respondents (99,707 households) for six years. Next, only heads/householders and spouses remain in order to leave only one person per household by gender. As a result, the number of observations was reduced to 706,639. The sample was further narrowed to include only households eligible for the SCHIP. Starting with those with children under the age of 18, the number of observations was reduced to 315,127. The final step was to apply the SCHIP income criteria in Arizona detailed in Table 4 and ones in control states group in Table 5 to the sample, resulting in a total of 8,213 observations.

## *4.2. Empirical Methods*

Difference-in-differences (DD) estimation with the synthetic control method is used to analyze the effect of the 2004 SCHIP policy change in Arizona. As the policy change happened in 2004, the years 2001 to 2003 are defined as the control period and the years 2005-2007 are done as the treatment period for work status. On the other hand, another dependent variable, weeks worked last year, is recorded as lags of the actual values. For example, if a respondent worked for 30 weeks in 2001, 30 weeks were recorded in the data in 2002. Therefore, the years between 2002 and 2004 are to be considered as a control period while 2005-2008 are to be as a treatment period. In addition, some time-varying variables such as age and the number of children under age 18 are also adjusted by subtracting one year old. Next, the treatment and control groups are to be discussed in more detail in the following subsection.

### *4.2.1. Identification Assumptions and the Treatment and Control Groups*

Boyle and Lahey (2016) pointed out that several identification assumptions need to be satisfied to use the DD method. First, individuals in the treatment group should be influenced by the policy change while individuals in the control groups should not. Second, there should no other contemporaneous shocks that affect the two groups differently other than the policy change being considered. Third, individuals in the treatment and control groups should be similar. Fourth, the treatment and control groups should have parallel trends, that is, the treatment group would have followed the same trend as the control group if there was no policy change. The treatment and control groups were constructed such that these assumptions were likely to hold.

As required by the first identification assumption discussed above, it was first necessary to distinguish people who were eligible for the SCHIP in order to define the treatment group. Table 4 shows the Medicaid and SCHIP income thresholds in Arizona). Income thresholds are based on Federal Poverty Guidelines (FPL) which are issued by the Department of Health and Human Services (HHS) annually. Medicaid and SCHIP income thresholds vary by age. First, for children under the age of 1, Medicaid covers children from families whose incomes are up to 140 percent of the FPL while SCHIP covers children from families whose incomes are between 141 and 200 percent of the FPL. For children between the ages of 1 and 5, Medicaid covers those with families whose incomes are up to 133 percent of the FPL, whereas SCHIP covers children with families whose incomes are between 134 and 200 percent of the FPL. For children between 6 and 18, Medicaid covers those from families whose incomes are up to the 100% FPL while SCHIP covers children from families whose incomes are between 101 and 200 percent of the FPL. Based on this information, the treatment group was defined as adults in Arizona with children under age 1 and whose family incomes are between 141-200% of the FPL, with children between the ages of 1 and 5 and whose family incomes are between 134-200% FPL, or with children between 6 and 18 and whose family incomes are between 101-200% of the FPL.

The following steps present how the control group was constructed. The control group should consist of SCHIP recipients in those states where SCHIP policies did not change between 2001 and 2007 in order to satisfy the first identification assumption discussed above. Many states have introduced or increased SCHIP premiums due to budget shortfalls. As a result, premiums had changed in all but 19 states during this period. Those 19 states were: Arkansas, Colorado, Delaware, Iowa, Louisiana, Mississippi, Montana, Nebraska, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, South Carolina, South Dakota, Virginia, and Wyoming.

Among these 19 states, Colorado, Delaware, Louisiana, Montana, New York, North Carolina, Oregon, South Dakota, Virginia, and Wyoming changed state income thresholds for SCHIP during the period of interest. For example, in January 2003, Oregon increased its SCHIP income threshold from 170% of the FPL to 185% of the FPL. After eliminating these states, the following nine states remained: Arkansas, Iowa, Mississippi, Nebraska, New

Mexico, North Dakota, Ohio, Oklahoma, and South Carolina. Of these remaining states, it was found that Mississippi changed SCHIP copayments in 2005, raising the copayment for prescriptions from \$1 to \$3 per generic drug prescription. Therefore, Mississippi was removed, leaving eight states as candidates for the control group.

With these final eight candidate states, a control group was built following their own income criteria, detailed in Table 5. The fourth identification assumption discussed above is that the treatment group and the control group should have parallel trends if there was no policy change. One way to make this assumption more likely to hold is to construct a synthetic control group, which is a weighted combination group from the original control group. By doing this, the constructed synthetic control group has similar trends as the treatment group during the control period (Abadie and Gardeazabal, 2013; Abadie, Diamond and Hainmueller, 2011). Obtaining synthetic control units as a control group, DD estimation can be applied instead of the original control group. Following Fitzpatrick (2008), Courtemanche and Zapata (2014), and Dillender, Heinrich, and Houseman (2016), the weights from the synthetic control method were multiplied by the CPS weights. This enabled the application of the synthetic control strategy to individual-level data and optimized the CPS sample design.

#### *4.2.2. Synthetic Control Method with Eight Candidate States*

Let $J$ denote the number of available candidate states, that is, $J = 8$. In essence, the synthetic control method is to find $W = (w_1, ..., w_J)'$, a $J \times 1$ vector of non-negative weights with $w_1 + w_2 + ... + w_J = 1$ so that the outcomes for the treatment state (Arizona) are very similar to the weighted average outcomes for the control states when $W$ is used as the vector of weights during the control period. More specifically, let $X_1$ denote the $(K \times 1)$ vector of $K$ independent variables for Arizona and $X_0$ do the $(K \times J)$ matrix containing the values for the same variables for the $J$ candidate states. Then, the optimal weighting vector $W^*$ is chosen by minimizing the following distance function,

(1) $\|X_1 - X_0W\| \, V = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}$

,where $V$ is a $(K \times K)$ diagonal matrix reflecting the relative importance of the variables in $X_0$ and $X_1$. $V$ is selected by minimizing the mean squared prediction error (MSPE) of the outcome variable over the control period. Specifically, let $Z_1$ be the $(T_p \times 1)$ vector of the outcome variable (work status or weeks worked last year) for Arizona during the control period and $Z_0$ be the $(T_p \times J)$ analogous matrix for the control states, where $T_p$ is the number of years in the control period. Then $V$is selected by minimizing the following function,

$$(2)\ V^* = \underset{V \in \Upsilon}{\arg\min}\, (Z_1 - Z_0 W^*(V))'(Z_1 - Z_0 W^*(V))$$

,where $\Upsilon$ is the set of all positive definite and diagonal matrices. Figure 2 through Figure 5 show the time series plots of the outcome variable, work status for all women with children, all men with them, married women with children, or single women with the ones, in Arizona and the synthetic control group constructed using the method described above. Figures 6 through 9 depict the similar plots for the other outcome variable, weeks worked last year, for the four groups. The dotted vertical line represents a boundary one indicating the control period, one year before the policy implementation. The outcome variables for the treatment group and the synthetic control group largely follow a similar trend during the control period, justifying the use of DD methods based on these two groups.

The third identification assumption above requires that individuals in the treatment group are similar to the ones in the control group during the control period. Tables 6 through 9 report descriptive statistics for both the dependent and explanatory variables for individuals in the treatment group and the synthetic control group by gender and the dependent variable. With a few exceptions, the differences are small, lending support to the third identification assumption.

### *4.2.3. Econometric Models*

For the outcome variable, work status, the following probit difference-in-difference model is estimated:

(3) $Work^*_{ist} = \alpha_0 + \alpha_1(Treat_s \times Post_t) + \alpha_2 Year_t + \alpha_3 State_s + X'_{ist}\beta + \varepsilon_{ist}$.

The dependent variable is $Work_{ist}$, which denotes observed work status. $Work^*_{ist}$ is a latent variable for an individual $i$ in state $s$ and in year $t$, where $Work_{ist} = 1$ if $Work^*_{ist} \geq 0$, $Work_{ist} = 0$ otherwise. $Post_t$ is a dummy variable indicating the treatment period from 2005 to 2007 and zero for the control period from 2001 to 2003. $Treat_s$ is a dummy variable which is one if a respondent belongs to the treatment group defined above and 0 otherwise. $Treat_s \times Post_t$ is an interaction term between treatment period and group indicators, and the coefficient of it, $\alpha_1$, can be interpreted as the policy effect. To control for other heterogeneity across different individuals, a vector of characteristics $X_{ist}$ is added. $X_{ist}$ includes age, age squared, race, health status, education, marital status for all men or all women, the number of children under the age of 5 or 18, and citizen. $\varepsilon_{it}$ is an error term. Based on this information, we can process the following procedures for the probit estimation.

$P(Work_{ist} = 1|\mathbb{X}) = G(\alpha_0 + \alpha_1(Treat_s \times Post_t) + \alpha_2 Year_t + \alpha_3 State_s + X'_{ist}\beta)$

, where $\mathbb{X}$ is a vector of independent variables and $G(\cdot)$ is a function, which takes on values such that $0 < G(z) < 1$, for all real numbers $z$. In this probit model, $G(\cdot)$ is the standard normal cumulative distribution function, which can be denoted as $G(z) = \Phi(z) = \int_{-\infty}^{z} \phi(v)dv$ , where $\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2}$.[3] We can obtain the following response probability for $y$ in order to examine the effects of the SCHIP premiums on the response probability, $P(Work_{ist} = 1|\mathbb{X})$. $P(Work_{ist} = 1|\mathbb{X}) = P(Work^*_{ist} > 0|\mathbb{X}) = P[\varepsilon_{ist} > -(\alpha_0 + \alpha_1(Treat_s \times Post_t) + \alpha_2 Year_t + \alpha_3 State_s + X'_{ist}\beta)|\mathbb{X}] = 1 - G\left[-(\alpha_0 + \alpha_1(Treat_s \times Post_t) + \alpha_2 Year_t + \alpha_3 State_s + X'_{ist}\beta)\right] = G\left[(\alpha_0 + \alpha_1(Treat_s \times Post_t) + \alpha_2 Year_t + \alpha_3 State_s + X'_{ist}\beta\right]$

Next, the log-likelihood function is considered with the following density of $Work_{ist}$ given $\mathbb{X}$. $\log\left[f(Work_{ist}|\mathbb{X};\mathbb{B})\right] = Work_{ist}\log[G(\alpha_0 + \alpha_1(Treat_s \times Post_t) + \alpha_2 Year_t + \alpha_3 State_s + X'_{ist}\beta)] + (1 - Work_{ist})\log\left[G(\alpha_0 + \alpha_1(Treat_s \times Post_t) + \alpha_2 Year_t + \alpha_3 State_s + X'_{ist}\beta)\right]$ , where $\mathbb{B}$ is a set of parameters. The log-likelihood, $\mathcal{L}(\mathbb{B}) = \sum_{i=1}^{n} \log\left[f(Work_{ist}|\mathbb{X};\mathbb{B})\right]_i$

[3] The biggest difference between the probit model and the logit model is that $G(\cdot)$ in the logit model is the logistic function such as the cumulative distribution function,$G(z) = \frac{e^z}{1+e^z}$, for a standard logistic random variable. In this paper, an only probit model is used.

with a sample size $i$, can be calculated by adding the log-likelihood function. The maximum likelihood estimation (MLE) of $\mathbb{B}$, especially $\alpha_1$, maximizes this log-likelihood.

For the other outcome variable, "weeks worked last year," the tobit model is used because the number of weeks worked in a year ranges from 0 to 52 and is censored from sides. The specific form of two-limit tobit is as follows,

$$(4)\ y^*_{ist-1} = \gamma_0 + \gamma_1(Treat_s \times Post_{t-1}) + \gamma_2 Year_{t-1} + \gamma_3 State_s + X'_{ist-1}\delta + \nu_{ist-1}$$

$$,\text{where } y_{ist-1} = \begin{cases} y^*_{ist-1}, & if\ \ 0 < y^*_{ist-1} < 52 \\ 0, & if\ \ y^*_{ist-1} \leq 0 \\ 52, & if\ \ 52 \leq y^*_{ist-1} \end{cases} \qquad \text{and} \quad \nu_{ist-1}|\mathbb{X} \sim Normal(0, \sigma^2).$$

Since the dependent variable, weeks worked last year, consists of the lagged (past period) values, $y^*_{ist-1}$ is used for a latent variable assuming a normal and homoscedastic distribution with a linear conditional mean. We observe $y_{ist-1}$, which is bounded between 0 and 52. It is worth noting that the analysis of the total number of weeks worked last year is a type of count variable, which can be estimated by count regression models. Poisson or negative binomial regression can be used depending on whether or not over-dispersion exists. In this study, the negative binomial regression is to be exploited because the distribution of medical utilization shows over-dispersion for the count model. The following equation (5) shows the Poisson regression model.

$$(5)\ y_{ist-1} \sim Poisson(\lambda_{ist-1})$$

$$,\text{where } \lambda_{ist-1} = \exp(\mu_0 + \mu_1(Treat_s \times Post_{t-1}) + \mu_2 Year_{t-1} + \mu_3 State_s + X'_{ist-1}\theta + \text{offset}_{ist-1})$$ [4]

Based on Poisson regression, we can consider the negative binomial regression in expression (6) if it has over-dispersion problem, and there is omitted variable $\omega_{ist-1}$, such that $e^{\omega_{ist-1}}(1/\alpha, \alpha)$ with mean 1 (=$1/\alpha \times \alpha$) and variance $\alpha$ (=$1/\alpha \times \alpha^2$), where $\alpha$ is the over-dispersion parameter.

[4]The offset is set to be zero because this paper is based on CPS panel data, and individual-level data are to be used. For regional data, the population is normally used for the offset.

(6) $y_{ist-1} \sim Poisson(\lambda^*_{ist-1})$

,where $\lambda^*_{ist-1} = \exp(\mu_0 + \mu_1(Treat_s \times Post_{t-1}) + \mu_2 Year_{t-1} + \mu_3 State_s + X'_{ist}\theta + \text{offset}_{ist-1} + \omega_{ist-1})$

The larger $\alpha$ is, the greater variance the dependent variable has. If $\alpha$=0, Poisson regression is the same as negative binomial regression.

# 5. Results and Discussion

It is important to examine the impact of the 2004 SCHIP premium change in Arizona at both the extensive and the intensive margin, to understand women and men's labor supply behavior. In labor economics, extensive margin refers to whether to work, and intensive margin means how much to work. Also, about 90% of the men with children were married in both Arizona and control states in the sample period, whereas only 60-70% of women with children were married in those states during the same time period. As a result, men were analyzed as a whole, but married and single women separately.

## *5.1. Work Status*

Estimation results for the probit regressions are reported in Table 10 which highlights the effects of SCHIP premiums on all men, all women, married women, and single women. All values reported in the tables are marginal effects at means.

The policy had a positive effect on men. Specifically, the introduction of SCHIP premium in Arizona increased men's probability of working by 6 percent points. This result can be interpreted by men's need to cover the additional expenses and moving to an employer-provided health insurance plan. First, men who did not work would need to find a job to cover the additional expenses as the expenses for SCHIP increased due to the policy change. The change in policy probably prompted some men to find a job for health insurance coverage, so that the family no longer needs SCHIP. According to Kenney et al. (2007), the new premiums in Arizona increased the rate of disenrollment and decreased the rate of re-enrollment. The rate of disenrollment increased by 38 percent and children in Arizona were less likely to re-enroll after the policy change. It is possible that individuals who disenrolled from SCHIP found another health insurance provider.

In contrast, Column (2) in Table 10 shows that the SCHIP premium introduction did not affect women's labor supply when all women were analyzed as a single group. More interesting results are found when married and single women were analyzed separately in Column (3) and Column (4) in Table 10. Column (3) in Table 10 shows that SCHIP premium introduction negatively affected married women's probability of working by 5 percentage points. Married women have husbands. As men are found to increase their chance of working, some women may quit the job to better take care of the children. Then the next natural question is why the policy change triggered men to increase the probability of working and their wives to decrease the probability of working. This can be explained by the wage difference between men and women. If a husband earns more money, then it is desirable for the husband to work in order to maximize the benefit of the family under the constraint of having to take care of the children at the same time. Likewise, if the wife makes more money per hour than her husband, then it is more efficient for the wife to work and for the husband to care for a child.

To examine the plausibility of this explanation, I looked at the actual average income earned by men and women in Arizona. Married women earned, on average, \$6,900 annually between 2001 and 2007, whereas the average earnings for married men were \$18,200 during the same period. Excluding zero incomes, married men earned \$19,300 and those married women made \$9,800 over that period. Therefore, it is clear that the husband working while the wife contributes to their household such as taking care of the children maximizes the benefits of the family.

On the other hand, Column (4) in Table 10 also shows that the policy change triggered single women to increase their probability of working. Like men, some single women who did not work chose to find a job so that they could afford the additional expenses or replace SCHIP with an employer-provided health plan.

There are some other results in Column (1) and Column (2) in Table 10 that are worth discussing. First, the probability of working increases as women get older, holding all other independent variables constant. However, age and educational variables did not significantly affect men's probability of working. For women, the higher the level of education, the higher the probability of participation in the labor market. Second, both men and women are more likely to work when they have better health conditions. Third, women of non-white races including white Hispanic are more likely to work than white women. Fourth, women living in urban areas are more likely to work than those who in rural areas. Fifth, men are more likely to work if they have children under the age of 18.

In Column (3) and (4) in Table 10, the results for married and single women separately regarding the control variables are similar to those for women as a whole in Column (1) and Column (2) except races, the age of children and the place of residence. Being of black and other races is no longer found to affect the probability of their working. Whether living in a city is found to have an influence on married women only. Finally, single women are found to be less likely to work if they have children under the age of 5.

## *5.2. Weeks Worked Last Year*

Tobit regression and negative binomial results for the other outcome variable, that is, the number of weeks worked last year, are reported in Tables 11 and 12. Again, the values in the tables are marginal effects. The main results are that men worked 4.5 more weeks, married women worked 8 weeks less, and single women worked 7 more weeks per year in the tobit model due to the introduction of SCHIP premiums in Arizona. These patterns are similar to those of work status in Table 10. The results from the count model are similar to the ones from the tobit model, but those from negative binomial estimation are larger than those from the tobit model.

The signs of regression coefficients for other explanatory variables are similar to those from the probit model except for several variables. First, education for men is not significant in probit model in Table 10 and in the count model in Table 11, and therefore it does not affect men's probability of working, whereas education has a negative effect on the number of weeks worked per year by men from tobit estimation, as shown in Table 11. Second, single men with children worked more weeks compared to married men with children even though marital status does not affect their probability of working, as shown in Table 10. Third, white-Hispanic men worked about 3.2-4.5 more weeks per year than Non-Hispanic whites. Fourth, Table 12 shows that black married women worked 1.5-3 more weeks than married women in other races, whereas there is no such effect for black single women with the tobit model and the negative effect for them with the negative binomial model. Fifth, women having children less than 5 years old, both married and single, tended to reduce their labor supply. One possible reason is that they should spend more time taking care of children under the age of five. The values of the coefficients for weeks worked last year may be considered large because it can be thought that single women in Arizona who had already worked in 2001-2003 worked seven weeks more in 2005-2007. In this case, the coefficient (8-9.6 weeks) would be large. However, the results should be interpreted differently because it includes people who did not work at all in 2001-2003. For example, if an adult who did not work (0 weeks) in 2003 worked for 30 weeks in 2005 after the policy change, the average looks larger. That is, single women who did not work before the policy will increase the mean largely. There are two reasons why I did not divide the sample into two groups: people who had already worked and those who had not worked. First, I mainly study the effect of SCHIP premiums on not only the people who worked in the control period but also the ones who did not work. In other words, I examine the effect of the policy change on whole adults with children in Arizona. Second, the number of the samples is small, and therefore it is difficult to divide the sample more because I have already divided the small sample into 4 groups (men, women, single women, and married women).

# 6. Conclusion

The introduction of policies such as SCHIP premiums has caused spill-over effects across the country such as a change in labor supply, medical utilization, and health outcomes. Policy changes for public insurance not only affect health outcomes and health care utilization but also the labor market. These policies may stimulate or discourage incentives to work depending on various demographic characteristics such as age, gender, and race. A substantial decrease in Arizona's expenditure for SCHIP in 2004 and 2005 resulted from the introduction of SCHIP premiums in July 2004. In turn, there were many dis-enrollees and less re-enrollees in the SCHIP. These individuals likely found another way to obtain health insurance, and there was a remarkable change in the labor supply of Arizona.

In order to examine this phenomenon, the DD with the synthetic control method was employed. There were various effects related to the introduction of the SCHIP premiums in Arizona in 2004 on parents' labor supply. Men and single women were more likely to work and worked more weeks per year to find ways to make up for the loss of their public insurance while married women reduced their labor supply both at the extensive and intensive margin so that they could take care of their children when their husband worked more.

Making the SCHIP more expensive through the introduction of premiums may cause some families to drop insurance for their children, which would certainly impact children's access to health care and health outcomes. Therefore, the effects of this policy change on children's health care utilization and health outcomes is also of interest and will be explored in future studies.

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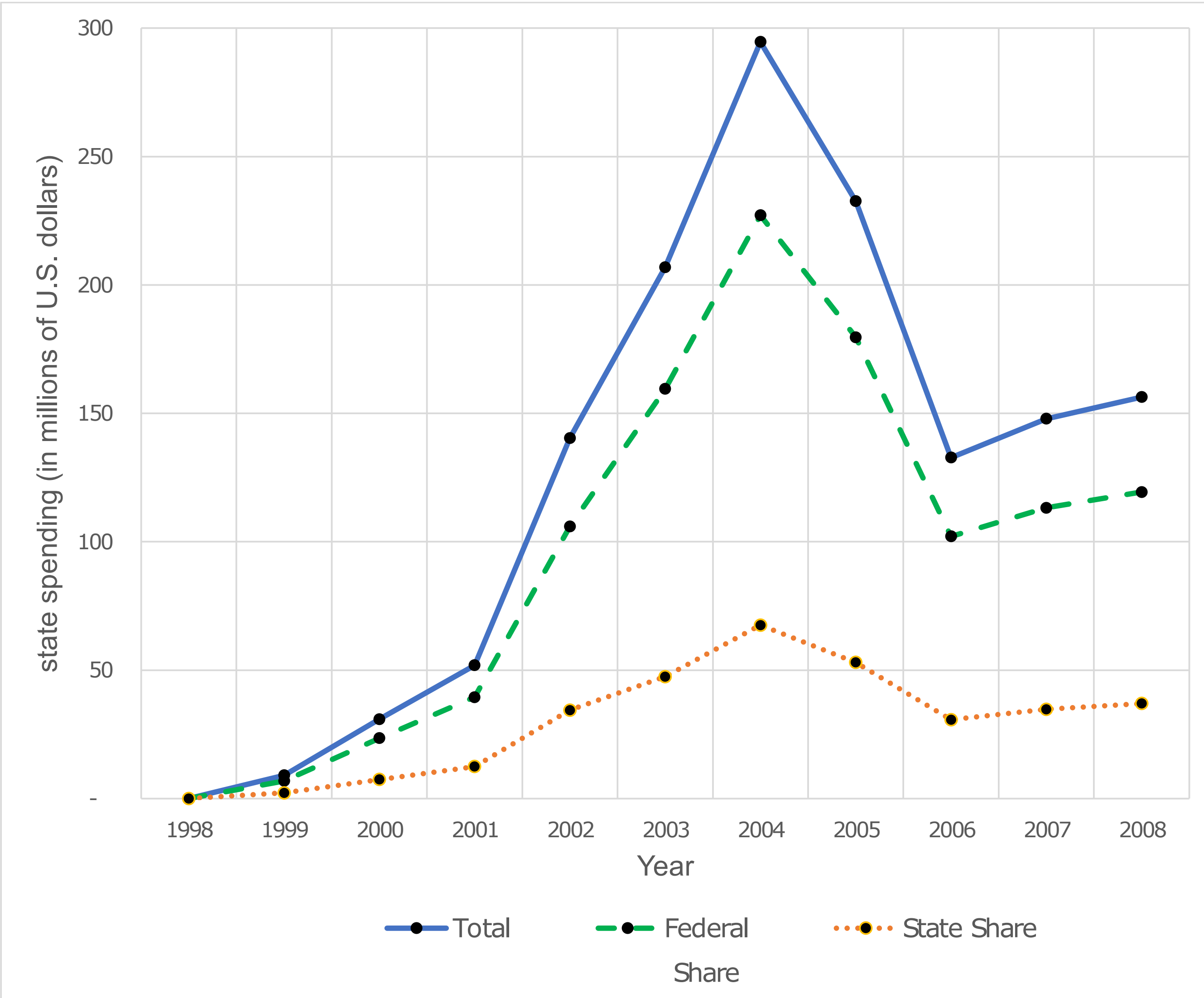


Fig. 1. Trend of SCHIP Expenditure in Arizona
Source: Financial Management Report between 1998 and 2008 from Medicaid.gov.

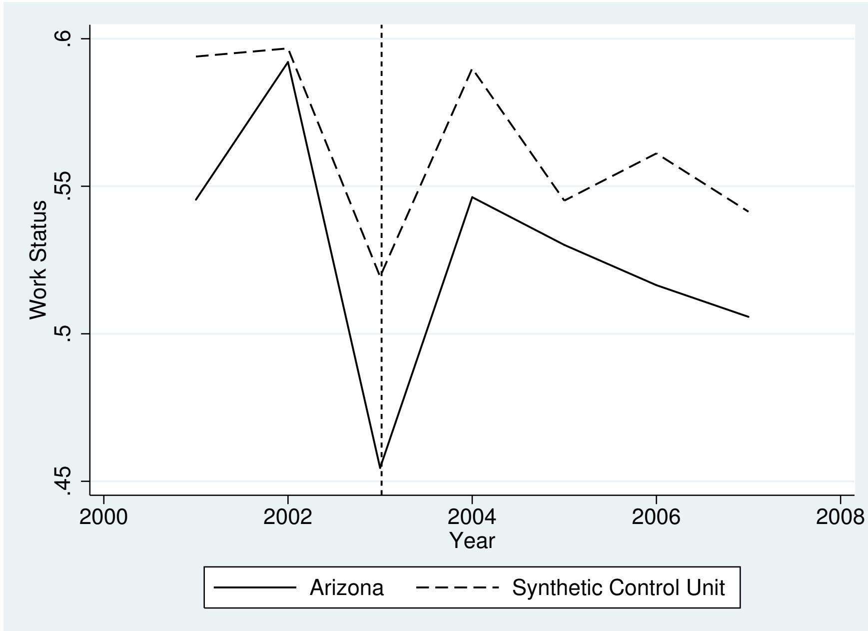


Fig. 2. Trend of work status for all women in Arizona and synthetic control group.

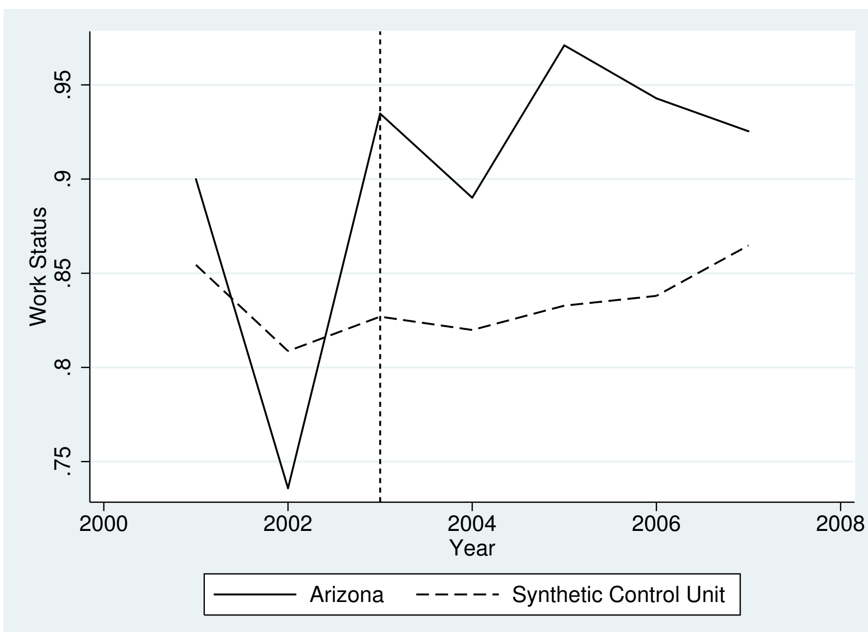


Fig. 3. Trend of work status for all men in Arizona and synthetic control group.

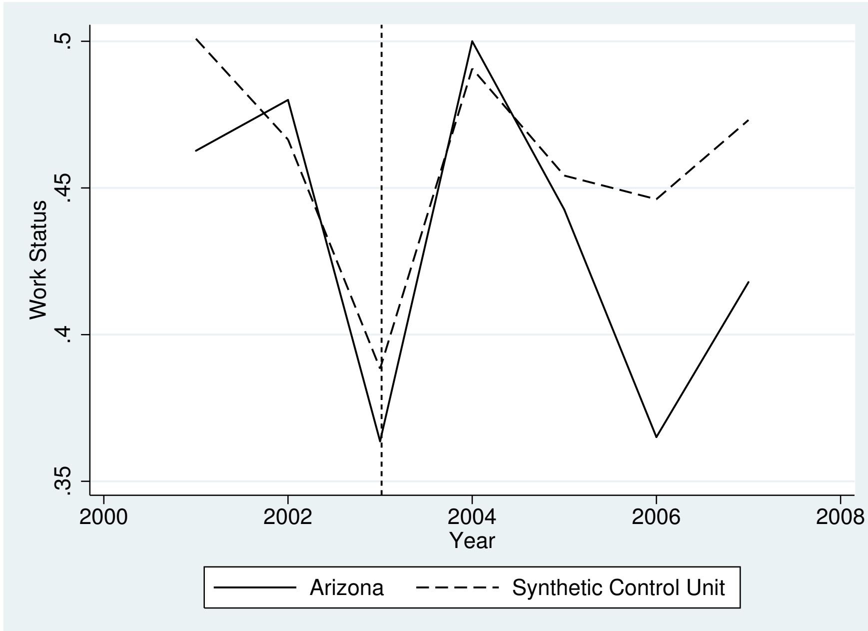


Fig. 4. Trend of work status for married women in Arizona and synthetic control group.

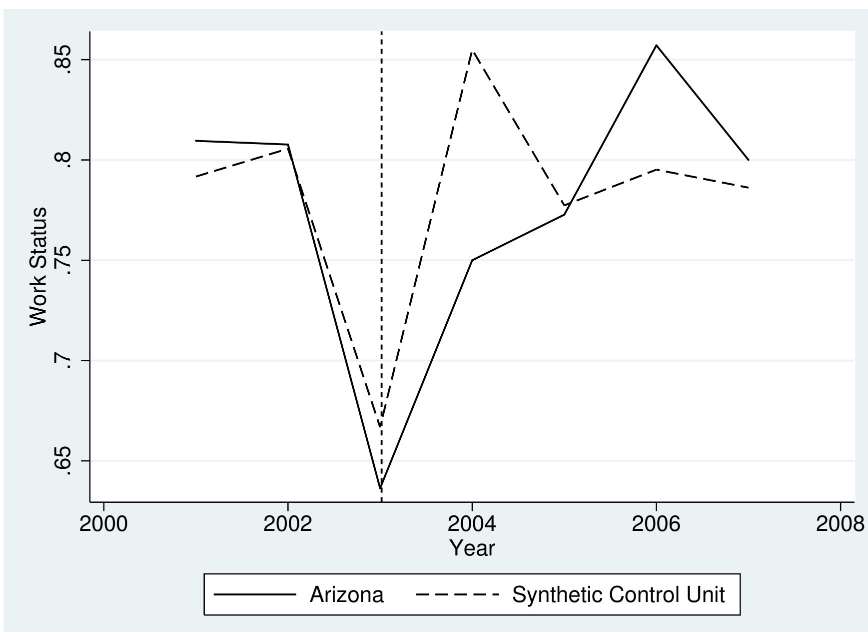


Fig. 5. Trend of work status for single women in Arizona and synthetic control group.

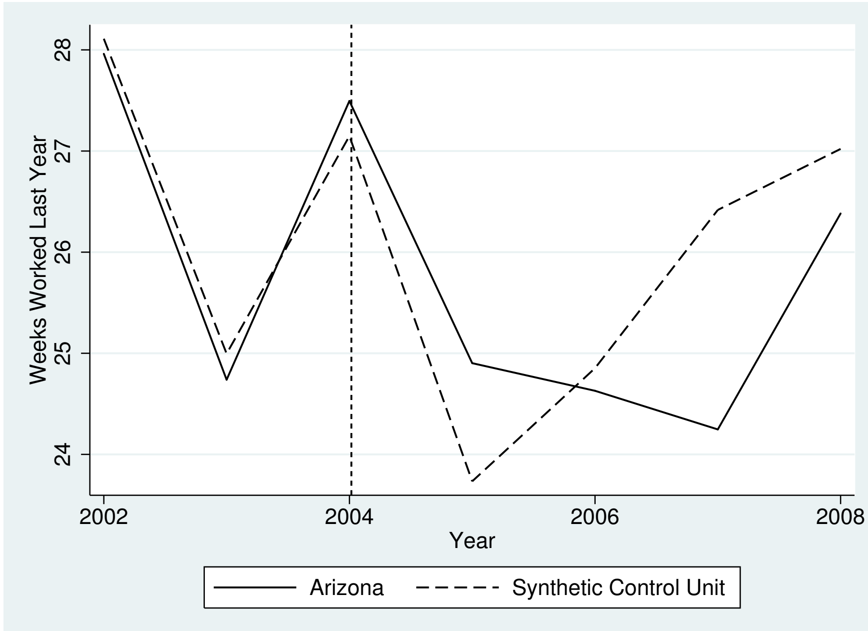


Fig. 6. Trend of weeks worked last year for all women in Arizona and synthetic control group.

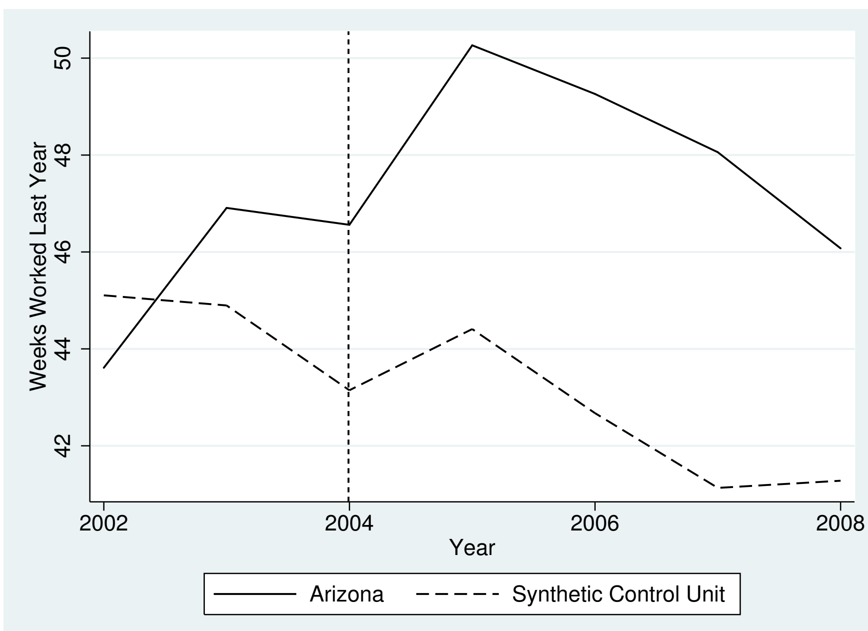


Fig. 7. Trend of weeks worked last year for all men in Arizona and synthetic control group.

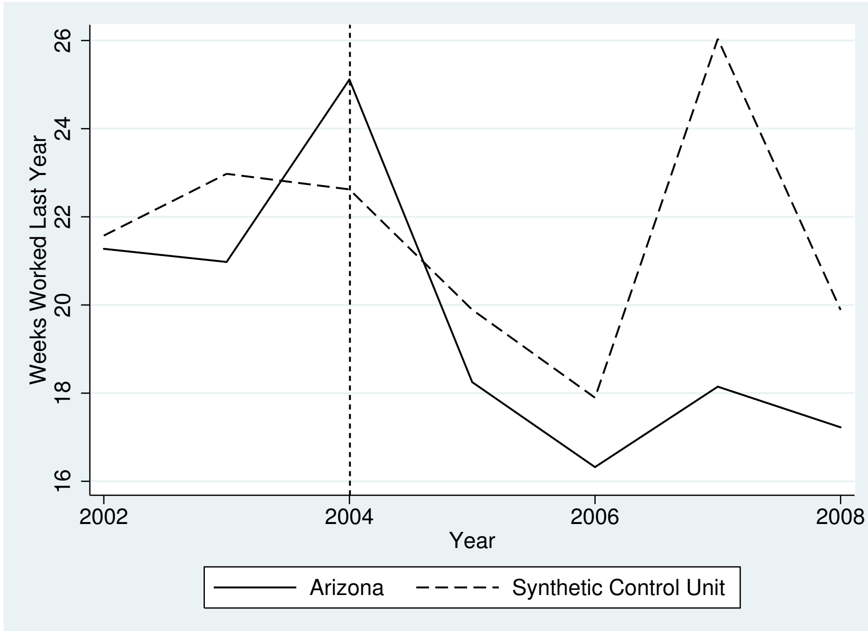


Fig. 8. Trend of weeks worked last year for married women in Arizona and synthetic control group.

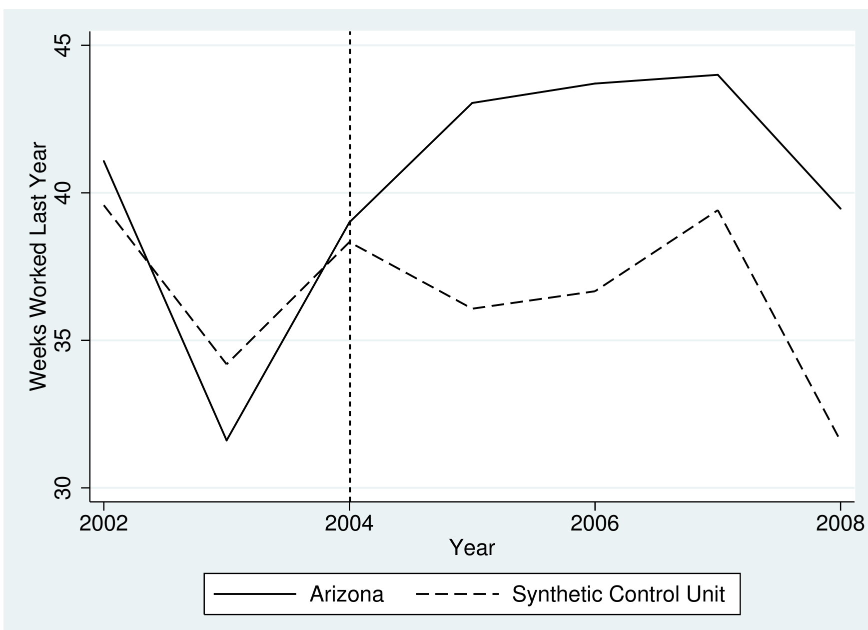


Fig. 9. Trend of weeks worked last year for single women in Arizona and synthetic control group.

Table 1: SCHIP Income Eligibility Upper Limits as a Percent of the Federal Poverty Level on January 1, 2017

| **Eligibility Category** | Mandatory Coverage | Optional Coverage |
|---|---|---|
| **Infants under 1** | ≤133% FPL | ≤185% FPL |
| **Children 1-5** | ≤133% FPL | * |
| **Children 6-19** | ≤100% FPL | * |
| **Pregnant women** | ≤133% FPL | ≤185% FPL |
| **Parents** | Below state's 1996 Aid to Families with Dependent Children (AFDC) limit | * |
| **Parents in welfare-to-work families** | ≤185% FPL | * |
| **Elderly and disabled Supplemental Security Income (SSI) beneficiaries** | SSI limits | Above SSI limits, but below 100% FPL |
| **Certain Working disabled** | | Variable, SSI level to 250% FPL |
| **Elderly - Medicare assistance only (payment for Medicare cost-sharing requirements)** | Variable, up to 175% FPL | Variable up to 175% FPL |
| **Nursing home residents** | | Above SSI limits, but below 300% SSI |
| **Medically needy** | | "Spend down" medical expenses to state set income level |

Note: This table shows the federal policy. * means that there is no federal optional threshold for the category and states decide on the threshold.
Sources: Teitelbaum and Wilensky (2016) and Schneider et al., (2002).

Table 2: SCHIP Income Eligibility Upper Limits as a Percent of the Federal Poverty Level on January 1, 2017

| State | Upper Limit | State | Upper Limit | State | Upper Limit |
|---|---|---|---|---|---|
| **Alabama** | 317% | **Kentucky** | 218% | **North Dakota** | 175% |
| **Alaska** | 208% | **Louisiana** | 255% | **Ohio** | 211% |
| **Arizona** | 205% | **Maine** | 213% | **Oklahoma** | 210% |
| **Arkansas** | 216% | **Maryland** | 322% | **Oregon** | 305% |
| **California** | 266% | **Massachusetts** | 305% | **Pennsylvania** | 319% |
| **Colorado** | 265% | **Michigan** | 217% | **Rhode Island** | 266% |
| **Connecticut** | 323% | **Minnesota** | 288% | **South Carolina** | 213% |
| **Delaware** | 217% | **Mississippi** | 214% | **South Dakota** | 209% |
| **D.C.** | 324% | **Missouri** | 305% | **Tennessee** | 255% |
| **Florida** | 215% | **Montana** | 266% | **Texas** | 206% |
| **Georgia** | 252% | **Nebraska** | 218% | **Utah** | 205% |
| **Hawaii** | 313% | **Nevada** | 205% | **Vermont** | 317% |
| **Idaho** | 190% | **New Hampshire** | 323% | **Virginia** | 205% |
| **Illinois** | 318% | **New Jersey** | 355% | **Washington** | 317% |
| **Indiana** | 262% | **New Mexico** | 305% | **West Virginia** | 305% |
| **Iowa** | 307% | **New York** | 405% | **Wisconsin** | 306% |
| **Kansas** | 244% | **North Carolina** | 216% | **Wyoming** | 205% |

Source: Medicaid and CHIP Eligibility, Enrollment, Renewal, and Cost-Sharing Policies as of January 2017: Findings from a 50-State Survey, Kaiser Family Foundation, January 2017. Based on a national survey conducted by the Kaiser Commission on Medicaid and the Uninsured with the Georgetown University Center for Children and Families, 2017.

Table 3: Premium Payments for Two Children in A Family of Three at Selected Income Levels in Arizona and candidates of control states in January 2007 (Unit: dollars, $)

| **State** | Frequency of payment | Income Level at which State begins Requiring Premiums (FPL) | Amount at 101% of the Federal Poverty Line | Amount at 151% of the Federal Poverty Line | Amount at 200% of the Federal Poverty Line |
|---|---|---|---|---|---|
| **Arizona** | Monthly | 101 | 15 | 30 | 35 |
| **Arkansas** | None | None | - | - | - |
| **Colorado** | Annually | 151 | 0 | 35 | 35 |
| **Delaware** | Monthly | 101 | 10 | 15 | 25 |
| **Iowa** | Monthly | 151 | 0 | 20 | 20 |
| **Louisiana** | None | None | - | - | - |
| **Mississippi** | None | None | - | - | - |
| **Montana** | None | None | - | - | - |
| **Nebraska** | None | None | - | - | - |
| **New Mexico** | None | None | - | - | - |
| **New York** | Monthly | 160 | 0 | 0 | 18* |
| **North Carolina** | Annually | 151 | 0 | 100 | 100 |
| **North Dakota** | None | None | - | - | - |
| **Ohio** | None | None | - | - | - |
| **Oklahoma** | None | None | - | - | - |
| **Oregon** | None | None | - | - | - |
| **South Carolina** | None | None | - | - | - |
| **South Dakota** | None | None | - | - | - |
| **Virginia** | None | None | - | - | - |
| **Wyoming** | None | None | - | - | - |

Note: * Eligibility for maximum poverty level in New York is higher than 200%, therefore, $18 shows the amount at 201% of the Federal Poverty Line.
Source: Ross, D. C., A. Horn, and C. Marks (2008) " Health Coverage for Children and Families in Medicaid and SCHIP: State Efforts Face New Hurdles: A 50-State Update on Eligibility Rules, Enrollment and Renewal Procedures, and Cost-Sharing Practices in Medicaid and SCHIP in 2008," The Henry J. Kaiser Family Foundation.

Table 4: Medicaid and SCHIP Income Thresholds by Children's Age in Arizona

| **Childrens' age** | Medicaid Income Threshold (as percentages of FPL) | SCHIP Income Threshold (as percentages of FPL) |
|---|---|---|
| **<1** | 1-140% | 141-200% |
| **1-5** | 1-133% | 134-200% |
| **6-18** | 1-100% | 101-200% |

Source: Ross, D. C., A. Horn, and C. Marks (2008)

Table 5: SCHIP Income Thresholds by Children's Age in Eight States for the Control Group

| | SCHIP Income Threshold (as percentages of FPL) | | | |
|---|---|---|---|---|
| **Children's age** | Arkansas | Iowa | Nebraska | New Mexico |
| **<1** | 0-200% | 134-200% | 0-185% | 0-235% |
| **1-5** | 0-200% | 134-200% | 0-185% | 0-235% |
| **6-18** | 0-200% | 134-200% | 0-185% | 0-235% |
| | North Dakota | Ohio | Oklahoma | South Carolina |
| **<1** | 134-140% | 0-200% | 101-185% | 0-185% |
| **1-5** | 134-140% | 0-200% | 101-185% | 0-150% |
| **6-18** | 101-140% | 0-200% | 101-185% | 0-150% |

Source: Ross, D. C., A. Horn, and C. Marks (2008)

Table 6: Descriptive Statistics for work status of all women

| Variable | Treated | Synthetic |
|---|---|---|
| **Work Status** | 0.53 | 0.57 |
| **Age** | 34.43 | 34.47 |
| **<High School** | 0.39 | 0.19 |
| **High School** | 0.26 | 0.45 |
| **More than College** | 0.35 | 0.36 |
| **Excellent** | 0.34 | 0.27 |
| **Very good** | 0.29 | 0.31 |
| **Good** | 0.27 | 0.27 |
| **Fair or Poor** | 0.09 | 0.14 |
| **Married** | 0.7 | 0.65 |
| **Separated, Divorced, or Widowed** | 0.18 | 0.23 |
| **Never married/single** | 0.13 | 0.12 |
| **White (Non-Hispanic)** | 0.35 | 0.6 |
| **White (Hispanic)** | 0.55 | 0.15 |
| **Black** | 0.05 | 0.16 |
| **Others** | 0.05 | 0.08 |
| **# of children age $\leq$5** | 0.74 | 0.73 |
| **# of children age$\leq$18** | 2.29 | 2.19 |
| **Dummy whether living in a city** | 0.83 | 0.53 |

Table 7: Descriptive Statistics for work status of all men

| Variable | Treated | Synthetic |
|---|---|---|
| **Work Status** | 0.86 | 0.83 |
| **Age** | 36.31 | 37.68 |
| **<High School** | 0.43 | 0.22 |
| **High School** | 0.28 | 0.42 |
| **More than College** | 0.29 | 0.35 |
| **Excellent** | 0.38 | 0.28 |
| **Very good** | 0.27 | 0.36 |
| **Good** | 0.27 | 0.27 |
| **Fair or Poor** | 0.09 | 0.1 |
| **Married** | 0.88 | 0.9 |
| **Separated, Divorced, or Widowed** | 0.04 | 0.05 |
| **Never married/single** | 0.08 | 0.04 |
| **White (Non-Hispanic)** | 0.31 | 0.77 |
| **White (Hispanic)** | 0.65 | 0.18 |
| **Black** | 0.03 | 0.03 |
| **Others** | 0.01 | 0.02 |
| **# of children age $\leq$5** | 0.84 | 0.86 |
| **# of children age$\leq$18** | 2.34 | 2.51 |
| **Dummy whether living in a city** | 0.86 | 0.33 |

Table 8: Descriptive Statistics for weeks worked last year of all women

| Variable | Treated | Synthetic |
|---|---|---|
| **Weeks worked last year** | 26.73 | 26.75 |
| **(Age-1)** | 33.75 | 33.73 |
| **<High School** | 0.39 | 0.22 |
| **High School** | 0.28 | 0.44 |
| **More than College** | 0.33 | 0.35 |
| **Excellent** | 0.34 | 0.24 |
| **Very good** | 0.3 | 0.31 |
| **Good** | 0.27 | 0.27 |
| **Fair or Poor** | 0.1 | 0.18 |
| **Married** | 0.71 | 0.59 |
| **Separated, Divorced, or Widowed** | 0.17 | 0.24 |
| **Never married/single** | 0.12 | 0.18 |
| **White (Non-Hispanic)** | 0.34 | 0.63 |
| **White (Hispanic)** | 0.57 | 0.08 |
| **Black** | 0.03 | 0.22 |
| **Others** | 0.06 | 0.08 |
| **# of children age $\leq$6** | 0.85 | 0.8 |
| **# of children age$\leq$19** | 2.25 | 2.23 |
| **Dummy whether living in a city** | 0.84 | 0.62 |

Table 9: Descriptive Statistics for weeks worked last year of all men

| Variable | Treated | Synthetic |
|---|---|---|
| **Weeks worked last year** | 45.69 | 44.38 |
| **(Age-1)** | 35.71 | 36.33 |
| **<High School** | 0.42 | 0.24 |
| **High School** | 0.25 | 0.44 |
| **More than College** | 0.33 | 0.32 |
| **Excellent** | 0.37 | 0.31 |
| **Very good** | 0.31 | 0.33 |
| **Good** | 0.22 | 0.26 |
| **Fair or Poor** | 0.1 | 0.1 |
| **Married** | 0.87 | 0.88 |
| **Separated, Divorced, or Widowed** | 0.04 | 0.08 |
| **Never married/single** | 0.09 | 0.04 |
| **White (Non-Hispanic)** | 0.32 | 0.64 |
| **White (Hispanic)** | 0.64 | 0.22 |
| **Black** | 0.03 | 0.04 |
| **Others** | 0.01 | 0.11 |
| **# of children age $\leq$6** | 1 | 0.86 |
| **# of children age$\leq$19** | 2.3 | 2.27 |
| **Dummy whether living in a city** | 0.87 | 0.49 |

Table 10: The Effect of SCHIP Premiums on Work Status for All Women, All Men, Married Women, and Single Women

| VARIABLES | (1) All Men | (2) All Women | (3) Married Women | (4) Single Women |
|---|---|---|---|---|
| **Treat$_s$ × Post$_t$** | 0.060*** | 0.010 | -0.050* | 0.129*** |
| | (0.014) | (0.021) | (0.026) | (0.034) |
| **Age** | 0.007 | 0.033*** | 0.016*** | 0.051*** |
| | (0.005) | (0.003) | (0.003) | (0.011) |
| **Age squared** | -0.000** | -0.000*** | -0.000*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| **High School** | -0.007 | 0.177*** | 0.166*** | 0.166* |
| | (0.022) | (0.046) | (0.054) | (0.100) |
| **College or above** | 0.021 | 0.192*** | 0.144*** | 0.146 |
| | (0.018) | (0.061) | (0.047) | (0.089) |
| **Health Status (Good)** | 0.151*** | 0.325*** | 0.218*** | 0.242*** |
| | (0.015) | (0.010) | (0.076) | (0.030) |
| **Health Status (Very Good)** | 0.152*** | 0.360*** | 0.230*** | 0.311*** |
| | (0.031) | (0.017) | (0.074) | (0.017) |
| **Health Status (Excellent)** | 0.182*** | 0.274*** | 0.138** | 0.370*** |
| | (0.016) | (0.047) | (0.064) | (0.008) |
| **Separated, Divorced, or Widowed** | -0.044*** | 0.319*** | | |
| | (0.014) | (0.114) | | |
| **Never married/Single** | -0.007 | 0.280*** | | |
| | (0.044) | (0.054) | | |
| **White (Hispanic)** | 0.015 | 0.145*** | 0.128*** | 0.205*** |
| | (0.017) | (0.021) | (0.042) | (0.065) |
| **Black** | -0.027 | 0.068*** | 0.018 | 0.023 |
| | (0.079) | (0.012) | (0.024) | (0.048) |
| **Others** | 0.019 | 0.132** | 0.111 | 0.086 |
| | (0.071) | (0.053) | (0.130) | (0.059) |
| **# of children age≤5** | -0.011 | -0.031 | -0.029 | -0.115* |
| | (0.009) | (0.028) | (0.054) | (0.064) |
| **# of children age≤18** | 0.017** | -0.017 | -0.002 | 0.047 |
| | (0.009) | (0.013) | (0.016) | (0.048) |
| **Dummy whether living in a city** | -0.006 | 0.060*** | 0.071*** | -0.067 |
| | (0.009) | (0.016) | (0.024) | (0.072) |
| **Observations** | 1,275 | 2,344 | 1,469 | 726 |
| **Year FE** | YES | YES | YES | YES |
| **State FE** | YES | YES | YES | YES |

Note: Cluster-robust standard errors in parentheses. The dependent variable is work status. Each column shows marginal effects of probit model. All predictors are at their mean value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11: The Effect of SCHIP Premiums on Work Weeks for Men and Women

| **VARIABLES** | (1) tobit All Men | (2) NBReg All Men | (3) tobit All Women | (4) NBReg All Women |
|---|---|---|---|---|
| **Treat$_s$ × Post$_t$** | 4.452*** | 5.235*** | -3.555*** | -5.723*** |
| | (0.994) | (1.871) | (0.845) | (1.202) |
| **Age-1** | 0.394 | 0.918 | 1.274*** | 1.572*** |
| | (0.311) | (1.033) | (0.376) | (0.530) |
| **(Age-1) squared** | -0.006* | -0.015 | -0.019*** | -0.022*** |
| | (0.004) | (0.014) | (0.005) | (0.007) |
| **High School** | -0.801 | 0.346 | 7.820*** | 9.751*** |
| | (0.733) | (0.889) | (0.670) | (1.226) |
| **College or above** | -0.609** | 0.508 | 7.333*** | 8.743*** |
| | (0.268) | (0.744) | (0.722) | (0.574) |
| **Health Status (Good)** | 7.425*** | 17.123*** | 9.624*** | 10.484*** |
| | (1.634) | (5.434) | (2.059) | (2.265) |
| **Health Status (Very Good)** | 10.181*** | 19.491*** | 11.432*** | 11.789*** |
| | (0.879) | (4.951) | (2.282) | (2.601) |
| **Health Status (Excellent)** | 10.963*** | 20.630*** | 9.635*** | 10.341*** |
| | (0.891) | (4.759) | (2.333) | (2.243) |
| **Separated, Divorced, or Widowed** | -1.995*** | -4.332*** | 14.213*** | 12.758*** |
| | (0.560) | (0.738) | (2.816) | (3.048) |
| **Never married/Single** | 8.002*** | 4.578*** | 12.390*** | 12.528*** |
| | (2.038) | (0.665) | (4.368) | (4.422) |
| **White (Hispanic)** | 3.264*** | 4.502*** | 3.508*** | 4.160*** |
| | (0.944) | (0.931) | (0.976) | (1.049) |
| **Black** | -1.481 | -1.632 | -0.563 | 0.163 |
| | (1.742) | (3.587) | (1.734) | (1.754) |
| **Others** | -1.894 | -3.492 | 2.016 | 1.234 |
| | (1.603) | (2.776) | (1.611) | (0.754) |
| **# of children age ≤6** | -0.823 | -0.991** | -3.131*** | -3.194*** |
| | (0.694) | (0.486) | (0.515) | (0.450) |
| **# of children age≤19** | 1.110*** | 1.110*** | 0.627 | 0.430 |
| | (0.187) | (0.133) | (1.135) | (1.248) |
| **Dummy whether living in a city** | 1.524 | 2.142 | 2.597*** | 3.382*** |
| | (0.986) | (1.554) | (0.826) | (1.256) |
| **Observations** | 1,633 | 1,633 | 3,079 | 3,079 |
| **Year FE** | YES | YES | YES | YES |
| **State FE** | YES | YES | YES | YES |

Note: Cluster-robust standard errors in parentheses. The dependent variable is weeks worked last year. Each column shows marginal effects of tobit or negative binomial (NBReg) model. All predictors are at their mean value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: The Effect of SCHIP Premiums on Work Weeks for Married Women and Single Women

| VARIABLES | (1) tobit Married Women | (2) NBReg Married Women | (3) tobit Single Women | (4) NBReg Single Women |
|---|---|---|---|---|
| **Treat$_s$ $\times$ Post$_t$** | -7.981*** | -9.638*** | 7.171*** | 8.108*** |
| | (0.689) | (0.683) | (0.434) | (0.905) |
| **Age-1** | 0.478** | 0.792*** | 1.947*** | 3.546** |
| | (0.214) | (0.156) | (0.658) | (1.542) |
| **(Age-1) squared** | -0.009*** | -0.013*** | -0.029*** | -0.051** |
| | (0.003) | (0.001) | (0.009) | (0.021) |
| **High School** | 9.374*** | 10.727*** | 2.688** | 3.674*** |
| | (0.758) | (1.095) | (1.174) | (0.138) |
| **College or above** | 7.379*** | 8.377*** | 0.471 | 4.595*** |
| | (0.460) | (0.207) | (0.628) | (0.576) |
| **Health Status (Good)** | 7.395*** | 7.748*** | 6.702 | 12.529 |
| | (0.412) | (0.333) | (4.678) | (7.723) |
| **Health Status (Very Good)** | 7.782*** | 8.474*** | 13.269*** | 16.696*** |
| | (1.124) | (0.439) | (1.607) | (5.576) |
| **Health Status (Excellent)** | 6.483*** | 7.567*** | 8.387** | 13.641** |
| | (1.141) | (0.469) | (3.338) | (6.919) |
| **White (Hispanic)** | 5.059** | 6.079*** | 2.961** | 2.480** |
| | (2.227) | (2.225) | (1.165) | (1.263) |
| **Black** | 1.490*** | 3.028*** | -2.932 | -3.786* |
| | (0.417) | (0.077) | (2.341) | (2.240) |
| **Others** | 0.217 | 0.131 | 2.937 | -0.293 |
| | (0.958) | (0.584) | (3.280) | (2.301) |
| **# of children age $\leq$6** | -2.881*** | -2.998*** | -3.526*** | -2.890** |
| | (0.409) | (0.426) | (0.657) | (1.455) |
| **# of children age$\leq$19** | 0.612 | 0.528 | 2.475 | 2.015*** |
| | (0.967) | (1.327) | (1.977) | (0.557) |
| **Dummy whether living in a city** | 6.010*** | 5.769*** | -2.122 | -2.285 |
| | (1.362) | (1.385) | (2.893) | (3.463) |
| **Observations** | 1,386 | 1,386 | 609 | 609 |
| **Year FE** | YES | YES | YES | YES |
| **State FE** | YES | YES | YES | YES |

Note: Cluster-robust standard errors in parentheses. The dependent variable is weeks worked last year. Each column shows marginal effects of tobit or negative binomial (NBReg) model. All predictors are at their mean value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$