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Impact of children's health insurance benefit on labor supply of adults: evidence from newly arrived immigrants

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Abstract

This paper exploits the State Children's Health Insurance Program of the United States to investigate impact of a publicly funded health insurance benefit for children on work behavior of adult men and women. Drawing data from the Annual Social and Economic Supplement of the Current Population Survey and employing a triple-difference identification strategy, we find that public health insurance benefit for children decreases labor supply of women but increases that of men. Estimates suggest that, on average, labor force participation rate of women decreased by 7.4 percentage points while that of men increased by 5.5 percentage points as their families became eligible for State Children's Health Insurance Program. Our findings are supported by several robustness checks and a falsification exercise.

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1. Introduction

A major concern in implementing means-tested public benefit programs is their impact on work behavior of potential beneficiaries. Impending distortions in labor supply, if large enough, can alter overall attractiveness of benefit programs under consideration. This concern has motivated a large number of studies on labor supply effects of public benefits such as unemployment insurance (Cullen & Gruber, 2000), cash transfers to poor families (Fraker & Moffitt, 1988; Galiani & McEwan, 2013), health insurance coverage for low income families (Yelowitz, 1995; Dave, Decker, Kaestner, & Simon, 2015), and a variety of other government assistance programs (Erosa, Fuster, & Kambourov, 2012). However, the issue of how providing publicly funded health insurance coverage for *children* may affect the labor supply of adults has received little attention.

On average, US families spend approximately 25.6% of their income on child care (OECD, 2016). In select states like Massachusetts, single parents pay up to 61% of their income for infant care. Since child care costs are important determinants of labor supply (Heckman, 1974; Blau & Robins, 1988; González, 2013), publicly funded health insurance coverage for children is likely to play a significant role in adults' choice of whether to work and how much to work. However, such benefit can affect labor supply in multiple ways making it difficult to predict the impact *a priori*. On one hand, children's health insurance benefit can increase families' disposable income by reducing or eliminating insurance premiums that would otherwise be paid for private coverage. The benefit can also reduce out-of-pocket expenses related to children's medical care. This can cause a reduction in labor supply, both at extensive and at intensive margin, due to income effect.[1] On the other hand, such coverage can encourage adult labor force participation by reducing the financial risk arising from potential illnesses associated with day care centers (Bell et al., 1989). The increase in labor supply, at the intensive margin, may also result from fewer no-shows at work due to better health of children achieved through higher levels of medical access (Kuhlthau & Perrin, 2001).

In this study, we exploit a natural experiment provided by the State Child Health Insurance Program (SCHIP) to evaluate the impact of a publicly funded children's health insurance benefit on work behavior of adult men and women. The natural experiment results from a unique variation in eligibility rules for newly arrived immigrants across US states. Drawing data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) and implementing a difference-in-difference-in-differences (DDD) strategy that eliminates the effects of a range of confounding variables, we find that children's health insurance benefit has negative effect on labor force participation of women but positive effect on labor force participation of men. Estimates suggest that, on average, SCHIP decreased women's labor force participation by approximately 7.4 percentage points and increased labor force participation rate of men by 5.5 percentage points. These results obtained from a novel source of identification have implications for public policy.

[1] A higher level of unearned income can increase the reservation wage by increasing the value of leisure (Imbens, Rubin, & Sacerdote, 2001), thus influencing labor force participation.

2. Background and Identification Strategy

SCHIP, also known simply as Children's Health Insurance Program (CHIP), is a US benefit program that provides health insurance coverage to uninsured children in low income families that do not qualify for Medicaid. The program is a partnership between the federal government and state governments. SCHIP is a widely popular program that covered approximately nine million children in fiscal year 2016.[2]

Researchers have previously examined SCHIP to explore the program's labor market effects. For example, Tomohara and Lee (2007) conduct a difference-in-diferences analysis to estimate the impact of SCHIP on labor supply of married women. Using data from the ASEC, the authors find no impact on a nationally representative sample of married women. Lee and Tomohara (2008) estimate the effect of SCHIP on labor supply of several sub-groups of women and conclude that SCHIP caused an overall decline in labor supply of non-white wives, and married women with pre-school children. More recently, Schuttringer (2013) looks at the impact of SCHIP on the labor supply of single mothers and finds no discernible impact. While useful preliminary assessments, one methodological limitation common to the aforementioned studies is that they define their treatment and control groups based on whether individuals qualify for SCHIP per the income thresholds set by respective states. Since income is endogenously determined by individual's choice of labor supply, the treatment in such framework is less likely to be exogenous. This makes estimates in existing studies prone to bias and inconsistency (Meyer, 1995).

In this study, we circumvent the treatment endogeneity problem by defining treatment and control groups based on SCHIP eligibility rules for immigrants that vary across states and years. Our identification strategy closely resembles the one used by Borjas (2003) to examine the effect of 1996 welfare reform on health insurance coverage and labor supply of immigrants. However, we depart from Borjas (2003) in two important ways. First, while Borjas (2003) estimates the labor supply effects of overall welfare cutbacks including Temporary Assistance of Needy Families (TANF), Medicaid, food assistance, and Supplemental Security Income (SSI), we zero in on the effects of publicly funded health insurance for children on labor supply of adults. Second, our study benefits from much longer post-policy time frame enabling us to explore the persistent effects of the policy change.

To appreciate how variation in SCHIP eligibility rules for immigrants provides a unique opportunity for causal identification, it is necessary to understand the circumstances created by the 1996 welfare reform. An important step of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996 was to ban all non-naturalized immigrants who have been in the US for less than five years, henceforth newly arrived immigrants, from receiving any federal means-tested benefits including the Medicaid. The substantive negative effect of this ban on health insurance coverage among immigrant population is documented by Kaushal and Kaestner (2005), Buchmueller, Lo Sasso, and Wong (2008), and Lurie (2008).

Immediately following the enactment of PRWORA, the Congress passed SCHIP in 1997

[2]For comparison, the Medicaid enrolled approximately 37 million children during the fiscal year 2016. See latest annual enrollment report at `https://www.medicaid.gov/chip/downloads/fy-2016-childrens-enrollment-report.pdf` (Accessed Aug 6, 2017).

to cover uninsured children across the country. States were quick to adopt SCHIP and all states had implemented some form of the program by 2000. However, the program greatly varied across states in terms of both covered population groups and benefit levels. Taking advantage of the ample autonomy the states were given in designing the program, 15 states including the District of Columbia (DC), henceforth generous states, used state funds to include children of newly arrived immigrants in their SCHIP. The remaining 36 states, referred to as less generous states hereafter, did not provide coverage to newly arrived immigrants. We present the details on exact dates of SCHIP implementation and immigrant coverage across states in Table I.

The inter-state variation in SCHIP coverage for immigrants essentially created a natural experiment whereby new immigrants in generous states were treated with children's health insurance benefit (the treatment group) and those in less generous states were not (the control group). We contend that such categorization of treatment and control group is superior to defining the groups on the basis of income eligibility because immigrants cannot endogenously choose a 'newly arrived immigrant' status.[3]

3. Data and Model

3.1. Data

We draw data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) for the years 1994 to 2009.[4] The ASEC, also known as the March CPS, is US government's primary source of information on labor market characteristics, income statistics, and benefit utilization. In addition to detailed demographic information, the ASEC provides comprehensive data on employment status, occupation, industry, number of weeks worked in a year, and usual hours worked per week. The ASEC is particularly suitable for this analysis because it includes information on immigration status (naturalized versus non-naturalized) and year of entry into the country.

We restrict the main analysis to a nationally representative sample of 25-64 year old immigrants residing in families with at least one child. As labor market experiences vary significantly across gender, we conduct separate analyses of male and female samples.

There are two outcome variables of interest in this analysis. One is a binary indicator denoting labor force participation status and the other is a continuous variable measuring number of hours worked in a year.[5]

[3] To the extent that some new immigrants might be able to make themselves eligible for SCHIP by finding ways to naturalize or by moving across states, this assumption can be violated. We address the first concern by excluding all naturalized newly arrived immigrants from the analysis. To see if immigrants are crossing state borders in response to SCHIP generosity, we examine the pattern of immigrant arrival to generous states before and after SCHIP implementation. No distinct change in trend is observable. Moreover, there is little evidence that inter-state movement of immigrants is motivated by availability of welfare benefits (Frey, Liaw, Xie, & Carlson, 1996; Levine & Zimmerman, 1999).

[4] Data preceding 1994 cannot be used because no question on immigrant status was asked. In 2009, the Child Health Insurance Program Reauthorization Act (CHIPRA) allowed all states to cover immigrant children, irrespective of when they entered the country, with federal funds. Thus the identifying variation persists only until 2009.

[5] All individuals reporting to be not working and not looking for work are classified as out of labor force.

Table I: SCHIP implementation and immigrant coverage by state

State	Date of SCHIP implementation	Coverage for new immigrants
Alaska (AK)	March 1999	Yes
Alabama (AL)	February 1998	No
Arkansas (AR)	October 1998	No
Arizona (AZ)	October 1997	No
California (CA)	July 1998	Yes
Colorado (CO)	April 1998	No
Connecticut (CT)	October 1997	No
District of Columbia (DC)	September 1997	Yes
Delaware (DE)	October 1998	Yes
Florida (FL)	April 1998	No
Georgia (GA)	September 1998	No
Hawaii (HI)	January 2000	Yes
Iowa (IA)	July 1998	No
Idaho (ID)	October 1997	No
Illinois (IL)	January 1998	Yes
Indiana (IN)	October 1997	No
Kansas (KS)	July 1998	No
Kentucky (KY)	July 1998	No
Louisiana (LA)	November 1998	No
Massachusetts (MA)	October 1997	Yes
Maryland (MD)	July 1998	No
Maine (ME)	July 1998	No
Michigan (MI)	May 1998	No
Minnesota (MN)	September 1998	Yes
Missouri (MO)	October 1997	No
Mississippi (MS)	July 1998	No
Montana (MT)	January 1998	No
North Carolina (NC)	October 1998	No
North Dakota (ND)	October 1998	No
Nebraska (NE)	May 1998	Yes
New Hampshire (NH)	May 1998	No
New Jersey (NJ)	February 1998	Yes
New Mexico (NM)	May 1998	Yes
Nevada (NV)	october 1998	No
New York (NY)	April 1998	Yes
Ohio (OH)	January 1998	No
Oklahoma (OK)	December 1997	No
Oregon (OR)	July 1998	No
Pennsylvania (PA)	June 1998	Yes
Rhode Island (RI)	October 1997	No
South Carolina (SC)	October 1997	No
South Dakota (SD)	July 1998	No
Tenessee (TN)	October 1997	No
Texas (TX)	July 1998	No
Utah (UT)	August 1998	No
Virginia (VA)	October 1998	Yes
Vermont (VT)	October 1998	No
Washington (WA)	January 2000	Yes
Wisconsin (WI)	April 1999	No
West Virginia (WV)	July 1998	No
Wyoming (WY)	April 1999	No

Source: (Rosenbach et al., 2001). The information on coverage for new immigrants pertains to years prior to 2009. In 2009, the Child Health Insurance Program Reauthorization Act (CHIPRA) allowed all states to cover immigrant children, irrespective of when they entered the country, with federal funds.

Given the rich data set, we are able to control for a number of demographic variables relevant for labor supply decisions. Specifically, we control for age, education, marital status, household size, race, ethnicity, and city resident status. Additionally, the repeated cross-sectional nature of data allows us to control for state fixed effects, year fixed effects, and state-specific linear trends to account for macro-economic differences across states and years.[6]

3.2. Model

First, we estimate a simple difference-in-differences (DD) model to compare the labor supply decisions of newly arrived immigrants in generous states versus less generous states. Specifically, we estimate the model:

$$Y_{ist} = \alpha + \beta_1.Gen_s.Post_{st} + \beta_2.Gen_s + \beta_3.Post_{st} + X'_{ist}.\gamma + \eta_s + \lambda_t + \theta.t\eta_s + \epsilon_{ist} \quad (1)$$

where Y_{ist} is an outcome variable (either indicator for labor force participation or log of total number of hours worked in a year) associated with a newly arrived immigrant i, in state s and year t, Gen_s indicates whether the state is a generous state, $Post_{st}$ indicates whether the year is after the SCHIP implementation in the state s, X'_{ist} is a vector of individual characteristics potentially correlated with the outcome variables, and ϵ_{ist} is random error term. The βs and γ are the parameters of the model. η_s, λ_t, and the term $\theta.t\eta_s$ respectively capture the state fixed effects, year fixed effects, and state-specific linear trends. When the usual assumptions of a regression model are met, the parameter β_1 gives the effect of SCHIP on labor supply of newly arrived immigrants.

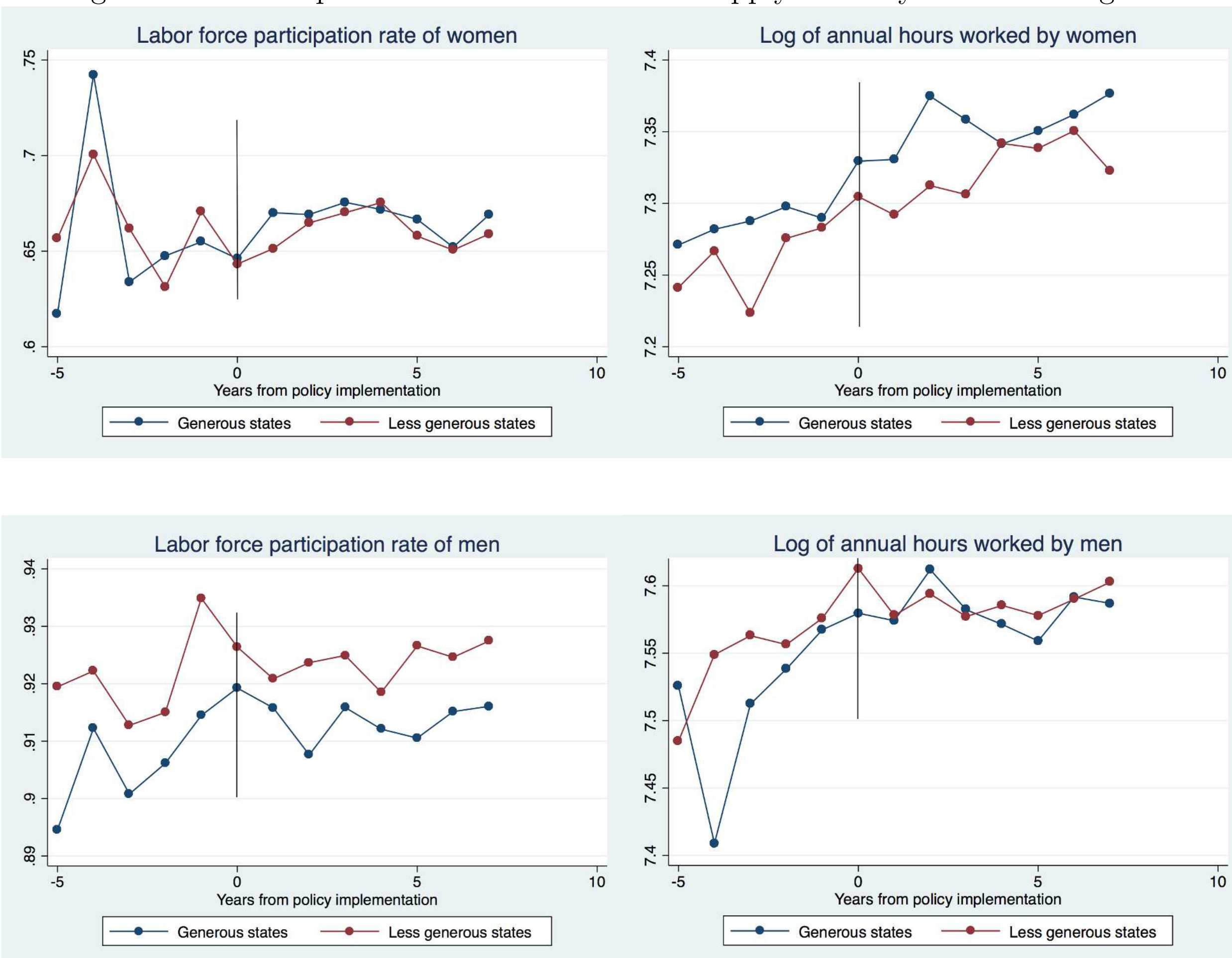
A threat to causal identification in the DD model is that there may be unobserved non-SCHIP factors that differentially affect work behavior of individuals in generous and less generous states. In the literature this is frequently referred to as the violation of parallel trends assumption required for DD. We examine the unadjusted trends in our outcome variables and present them in Figure 1.

While it is convincing to see that pre-policy trends in generous and less generous states are fairly similar, the data are pretty noisy. To address any lingering concern regarding parallel trends, we obtain a difference between the labor supply of 'old' immigrants - i.e. those who have been in the country for five or more years and are not affected by the policy change - in generous versus the less generous states, and subtract the difference from DD estimate. In other words, we estimate a difference-in-difference-in-differences (DDD) model:

We construct the 'number of hours worked in a year' variable by multiplying the number of hours worked per week by the numbers of weeks worked in year.

[6] We do not control for state unemployment rate in main regressions as this could be bad control because labor supply decisions directly affect unemployment rates. In regressions not reported here but available upon request, we control for seasonally adjusted state unemployment rate. The results are not appreciably different.

Figure 1: Pre and post-SCHIP trends in labor supply of newly arrived immigrants



$$
\begin{aligned}
Y_{ist} = \delta &+ \psi_1.New_i.Gen_s.Post_{st} + \psi_2.New_i.Gen_s + \psi_3.New_i.Post_{st} \\
&+ \psi_4.Gen_s.Post_{st} + \psi_5.New_i + \psi_6.Gen_s + \psi_7.Post_{st} + X'_{ist}.\mu \\
&+ \eta_s + \lambda_t + \tau.t\eta_s + \nu_{ist} \quad (2)
\end{aligned}
$$

where New_i indicates whether an immigrant i is a new immigrant; δ, ψs, μ, and τ are parameters of the model; ν is error term; and all other symbols have the same meaning as in Equation 1. In the model represented by Equation 2, ψ_1 gives the impact of SCHIP on labor supply behavior of newly arrived immigrants. The triple-difference identification scheme allows for differences between generous and less generous states, differences between individuals over time, and differences between immigrants who are new and those who are not.

4. Results

In the upper panel of Table II, we present results generated in the baseline DD model. The first two columns show that SCHIP decreased labor force participation rate of newly arrived immigrant women by 8.7 percentage points but increased that of men by 5.1 percentage points. The third and the fourth columns show that the impact on the annual hours worked by men and women was indistinguishable from zero.

The lower panel of Table II presents results generated in the preferred DDD model. Consistent with the results from DD model, these estimates indicate SCHIP's negative impact on the labor force participation rate of women and positive impact on the labor force participation rate of men. Specifically, SCHIP reduced the labor force participation of newly arrived immigrant women by 7.4 percentage points and increased that of men by 5.5 percentage points. The magnitude of the policy impact suggested by our estimates is comparable to that implied by estimates in Garthwaite, Gross, and Notowidigdo (2014) and Dave et al. (2015).[7]

The DDD estimates suggest that SCHIP did not influence men's annual hours but reduced women's annual hours by 15.6%. This decrease in women's hours is considerably larger than the 9% reduction estimated by Borjas (2003) but it is in the same ballpark as the 4 hour per week reduction calculated by Tomohara and Lee (2007). We note that the DDD estimate of the impact of SCHIP on women's annual hours is almost double the size of our DD estimate. The nontrivial difference between the two estimates suggests that DD estimates are likely muddled by the unobserved non-SCHIP factors that differentially affect work behavior of individuals in generous and less generous states.

5. Robustness Checks

Next, we conduct a number of robustness checks to ensure the credibility of estimates presented in the previous section. The models estimated thus far compare work behavior of individuals in households with at least one child. One concern with this sample is that fertility decisions are likely to be influenced by SCHIP eligibility, thereby contaminating the estimates based on households with children. To address this concern, we obtain DDD estimates from an extended sample that includes newly arrived immigrants from all households, irrespective of whether the households have any children. The results generated in these models are presented in the upper panel of Table III. These results are qualitatively similar to those presented in Table II. As expected, the coefficients in these regressions suggest slightly smaller effects.

Often a large discrepancy between estimates from weighted and unweighted models can be a warning sign of specification error. To compare with the main results which are obtained from weighted least squares models, we estimate unweighted DDD regressions and present

[7] Specifically, Garthwaite et al. (2014) estimate the effect of public health insurance on labor supply by exploiting a large public health insurance disenrollment that occurred in Tennessee. Their estimated effects range from 2.5 to 4.6 percentage points. Additionally, Dave et al. (2015) estimate the impact of Medicaid expansions in the late 80s and 90s on labor supply of unmarried women with less than a high school education and find it to be in the range of 13 to 16 percent.

Table II: Impact of Children's Health Insurance Benefit on Labor Supply (CPS 1994-2009)

	Labor force participation		**Annual hours**	
	Women	Men	Women	Men
Sample mean	0.635	0.941	1714.783	2112.898
Difference-in-differences:				
$\beta_{Gen*Post}$	-0.087**	0.051**	0.071	-0.012
	(0.040)	(0.021)	(0.084)	(0.060)
R^2	0.0594	0.0569	0.0314	0.0469
Observations	10,745	7,934	5,194	7,123
Difference-in-difference-in-differences:				
$\psi_{New*Gen*Post}$	-0.074***	0.055**	-0.156**	-0.013
	(0.025)	(0.041)	(0.058)	(0.706)
R^2	0.0792	0.0426	0.0325	0.0338
Observations	66,455	58,397	41,203	54,470

Notes: Coefficients represent regression estimate of the impact of SCHIP on outcomes of newly arrived immigrants. Labor force participation is a binary indicator for whether an individual participated in the labor force. Annual hours is the natural logarithm of total number of hours worked during a year. Models for labor force participation are estimated as linear probability models and models for annual hours are estimated by Ordinary Least Squares. All models control for demographic variables (age, education, marital status, household size, race, ethnicity, and city resident status), state fixed effects, year fixed effects, and state-specific linear trends. Sample weights are applied. Robust standard errors clustered at the state level reported in parentheses. ***, **, and * indicate significance at 1%,5%, and 10% level.

results in the lower panel of Table III. Estimates from unweighted models are fairly close to those from weighted models presented in Table II. This similarity signals absence of serious specification error.

An additional concern regarding DD and DDD estimators is that these estimators may simply be picking up effects of other unobserved contemporaneous changes rather than effect of policy changes. A set of falsification tests, also known as placebo tests, can be conducted to see if falsely assigning policy changes yields results similar to those obtained in original regressions. If placebo treatments do not yield same effects as observed in main results, it is an indication that the effects suggested by DDD estimator are indeed due to the treatment. In Table IV, we present absolute values of t-statistics associated with the coefficients of interest when placebo treatments are assigned one period, two period, and three period ahead of actual treatment. The t-statistics become progressively smaller as the placebo treatments occur farther from the actual implementation indicating that the effects given by DDD estimator are indeed the effects of SCHIP.[8]

[8]The placebo treatments one period and two periods before the actual policy implementation show sig-

Table III: Robustness Checks: Estimates from Alternative Samples (CPS 1994-2009)

	Labor force participation		**Annual hours**	
	Women	Men	Women	Men
Extended sample:				
$\psi_{New*Gen*Post}$	-0.043**	0.049***	-0.114***	-0.046
	(0.019)	(0.014)	(0.036)	(0.030)
R^2	0.0822	0.0440	0.0324	0.0298
Observations	109,783	104,767	71,106	95,046
Unweighted sample:				
$\psi_{New*Gen*Post}$	-0.074***	0.040*	-0.215***	-0.023
	(0.023)	(0.022)	(0.057)	(0.036)
R^2	0.0781	0.0361	0.0314	0.0320
Observations	66,455	58,697	41,203	54,470

Notes: Coefficients represent regression estimate of the impact of SCHIP on outcomes of newly arrived immigrants. Labor force participation is a binary indicator for whether an individual participated in the labor force. Annual hours is the natural logarithm of total number of hours worked during a year. Models for labor force participation are estimated as linear probability models and models for annual hours are estimated by Ordinary Least Squares. All models control for demographic variables (age, education, marital status, household size, race, ethnicity, and city resident status), state fixed effects, year fixed effects, and state-specific linear trends. Sample weights are applied except when explicitly mentioned otherwise. Robust standard errors clustered at the state level reported in parentheses. ***, **, and * indicate significance at 1%,5%, and 10% level.

Finally, the DDD strategy can be invalid if generous states simultaneously implement non-SCHIP policies that affect newly arrived immigrants but not 'old' immigrants. While we cannot completely rule out this possibility, a comprehensive review of benefits available to immigrants across US states suggests that it is unlikely to have happened (Fortuny & Chaudry, 2012). Additionally, it is reassuring to see that researchers have utilized similar identification strategy to study other labor market effects of SCHIP (Olds, 2016).

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nificant effect on women's labor force participation. This can happen if individuals change labor supply in anticipation of SCHIP. Additionally, the placebo treatment one period before the actual policy implementation shows significant effect on annual hours worked by men. This is somewhat puzzling but this is likely to have happened merely by chance as all other placebos and the actual treatment show no effect on annual hours worked by men.

Table IV: Robustness Check: Falsification Exercise with Placebo Treatments (CPS 1994-2009)

	Labor force participation		**Annual hours**	
Timing	Women	Men	Women	Men
Post policy	2.71**	2.10**	2.70**	0.38
One period before policy	2.38**	0.48	0.27	2.72**
Two periods before policy	1.99**	0.79	1.24	0.03
Three periods before policy	0.88	0.36	1.43	0.62

Notes: Estimates are the absolute values of t-statistics from DDD regression including demographic controls, state fixed effects, year fixed effects, and state-specific linear trends. ***, **, and * indicate significance at 1%,5%, and 10% level.

6. Discussion

Negative impact of children's health insurance benefit on labor supply of women and positive impact on that of men, at least at the extensive margin, is consistent with traditional roles of men and women in families with children. In particular, the negative effect of the children's health insurance benefit on women's labor supply is in line with the findings of Tomohara and Lee (2007) and Lee and Tomohara (2008). Increased disposable income resulting from public funding of children's health insurance likely induced some women to withdraw from labor force and/or to cut hours. It is also likely that SCHIP encouraged some women to withdraw from labor market for fertility reasons thereby pushing men into labor force to compensate for losses in household income (Hotz & Miller, 1988) .

Our finding that provision of SCHIP increased labor supply of immigrant men is somewhat in contrast with Borjas (2003) who concludes that PRWORA-induced welfare cutbacks increased labor force participation among immigrant men. However, we emphasize that our estimates represent the effects of SCHIP alone while that of Borjas (2003) represent effects of simultaneous cutbacks in several welfare programs including TANF, Medicaid, food assistance and SSI. Moreover, we analyze labor supply responses over a longer period of time and thus benefit from the virtues of larger sample size and the ability to control for state-specific trends. Nevertheless, we note that care should be taken in generalizing our results to other population groups as labor supply response to particular life situations tend to differ across cultures and countries (Niu, 2016).

7. Conclusion

This study extends literature on the impact of children's health insurance benefit on labor supply of adults by using a novel and plausibly more credible source of identification. The estimates, supported by several robustness checks, suggest a negative impact of children's health insurance benefit on labor supply of women but a positive impact on that of men. The results not only underscore the labor supply distortions associated with welfare benefits but also highlight the heterogeneity, in the impact of such benefits, across gender. Future research that explores the dynamics of intra-household substitution of labor supply in response to children's health insurance benefit would further our understanding of labor market effects of such public programs.

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