Evaluating State-Level EITC Impact on Poverty and Labor with Synthetic Control

Brandon Williams and Scott Kjorlien

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1   Introduction

The Earned Income Tax Credit (EITC) is a tax credit that is designed to benefit workers earning relatively low wages. The program was created at the federal level in the 1970s with a dual purpose: encourage families in poverty to enter the workforce and reduce the tax burdens for low-wage working families with children. Since then, the EITC has been expanded and increased several times, becoming a significant anti-poverty measure. Some estimates suggest that the EITC has lifted more children out of poverty than any other government program (Zahradnik and Llobrera, 2004). In 2020, the IRS reported that 25 million workers received over $60 million in EITC credits, with the average amount being $2,411 per family. The American Rescue Plan of 2021 further leveraged the EITC as a main means of fighting poverty in the wake of the COVID-19 pandemic by expanding the credit for childless workers and increasing income limits, indicating just how important it has become in the policymaker's anti-poverty arsenal.

While much economic literature has focused on this tool at the federal level, very few papers have examined state EITCs, even though 29 states currently offer their own EITC to supplement the federal credit. We exploit two major changes to state EITCs in the last ten years: namely, the elimination of North Carolina's EITC in 2014 and the creation of California's EITC in 2015. Using a synthetic control design, we explore the state-level EITC impact on poverty rate and labor force participation. We find a modest increase in the labor force participation in the presence of a state EITC, but no effect on the overall poverty rate regardless of the creation or elimination of a state EITC.

2   Background

The EITC is designed to "phase in" beginning with the first dollars a worker earns. In 2021, a married couple with two children, for example, had a phase-in rate of 40 percent, meaning that the EITC increases by 40 cents for each dollar earned. At a certain income threshold, the EITC plateaus at a maximum amount, where it stays constant even as the worker's income increases. Finally, it reaches a "phase out" period, where the EITC amount reduces as a percentage of the worker's income until it eventually reaches zero. In 2021, this phase-out ended for childless earners at $15,820, $42,158 for those with on child, $47,915 for those with two children, and so on. This creates an acute trapezoid shape to the credit

that increases and decreases proportionally with income. Figure 1 shows the structure of the credit based on income, with the American Rescue Plan included.

Figure 1: Design of EITC
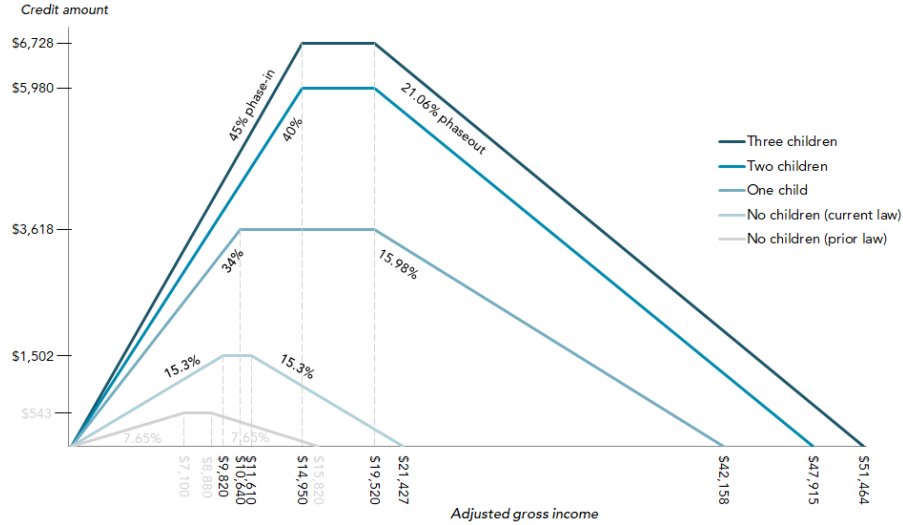
Source: Tax Policy Center

Proponents of the EITC generally argue that it avoids the adverse incentives of other traditional welfare programs by encouraging workforce participation while simultaneously targeting low-income earners. Economic theory would suggest that the EITC would be especially pronounced at the point of entry for the labor supply, encouraging those on the sidelines to enter the workforce because it rewards earnings and gives no payout if the tax filer is not in the labor force (Eissa and Hoynes, 2006). EITCs also avoid the mired debates about the minimum wage by increasing earnings for workers without shifting the cost to employers. In short, EITCs enjoy support from a diverse coalition of policymakers for the purpose of raising the earned income of low-wage individuals and families, without discouraging work.

Because of the dual-pronged motivation of the EITC, economists have been interested in studying the effects on poverty and labor supply. While the causal effects of the federal program can be difficult to discern, Neumark and Wascher (2001) found that the EITC effectively raised a number of households above the poverty line and positively increased the labor supply rate, particularly at the point of labor entry, finding it to be a more effective intervention than the minimum wage. Given the trapezoidal shape of the policy, economic theory would also suggest that it creates natural "kink points" in the earned income of workers. Saez (2010) finds some evidence that workers bunch at the phase-out kink point, but very little evidence that workers choose to reduce hours during the phase-in period. Meanwhile, since the EITC does not provide any benefit to individuals who are not working, it should have a direct impact on labor force participation decisions at the extensive margin (the decision to enter the workforce), but others have argued that the effect at the margins is negligible (Kleven, 2019). There is also some evidence that the incentives are obfuscated by the complicated nature of tax law (Chetty and Saez, 2013).

While the EITC is available to single filers without children, the benefits afforded to those workers are relatively modest compared to the credit given to workers with dependents. Therefore, much of the literature has focused on the effects on low-income families, especially single mothers. Evans and Garthwaite (2014) found that indicators of health and self-reported well-being of single mothers both increased with the expansion of the federal credit in 1993. Other papers have explored the EITC's effect on birth rates (Baughman and Dickert-Conlin, 2003).

In the wake of the federal EITC and its various expansions, more than 25 states have adopted their own state-level EITCs to supplement low-income earners at the local level. State-level EITCs generally function as a proportion of the federal credit, with a few exceptions, as seen in Table 1. Amounts of state EITC vary significantly, from 5% of the federal EITC amount (Louisiana) to 83% (South Carolina). We focus on the state-level EITCs that are refundable, meaning that even if a filer has no tax liability, they still receive a credit, effectively making their net tax amount negative. While some states offer non-refundable EITCs (meaning they can use the credit only to reduce their tax burden), we concentrate on the EITCs which function as a proper government cash transfer. All told, 23 states and the District of Columbia currently offer a state-level refundable EITC, and an additional 6 currently offer a non-refundable EITC.

Table 1: States with EITC

State	% of Federal EITC	Refundable
California[1]	Max 46.9%	Yes
Colorado	10%	Yes
Connecticut	23%	Yes
Delaware	4.5%	Yes
Hawaii	20%	No
Illinois	18%	Yes
Indiana	9%	Yes
Iowa	15%	Yes
Kansas	17%	Yes
Louisiana	5%	Yes
Maine	12%	Yes
Maryland	45%	Yes
Massachusetts	30%	Yes
Michigan	6%	Yes
Minnesota[2]	25% to 45%	Yes
Montana	3%	Yes
Nebraska	10%	Yes
New Jersey	40%	Yes

New Mexico	20%	Yes
New York	30%	Yes
Ohio	30%	No
Oklahoma	5%	Yes
Oregon	9%	Yes
Rhode Island	15%	Yes
South Carolina	83.33%	No
Utah	15%	No
Vermont	36%	Yes
Virginia	20%	No
Wisconsin[2]	4% to 34%	Yes
District of Columbia	55%	Yes

[1]Uses different income thresholds than federal EITC

[2]Percent changes by the number of children or income

While there is substantial research on the federal Earned Income Tax Credit, literature on the state-level EITCs is much sparser. Baughman (2012) found some evidence that state EITCs improved child health in those states. Others have looked at the relationship between state EITCs and suicide (Lenhart, 2019) and how to increase uptake of state-level EITC credits (Linos et al., 2020). Given this relative dearth of study, we endeavor to apply the changes in EITC in California and North Carolina to explore the effects of a state-level EITC.

In 2014, North Carolina eliminated its state-level EITC, the only state to do so in over 30 years. The eliminated benefit was modest, at 5% of the federal EITC, but at the time of elimination, it was claimed by 22 percent of North Carolina residents. Conversely, in 2015, California created and implemented its first state EITC (CalEITC). This policy uses thresholds independent of the federal EITC, with CalEITC credits available up to $3,160 for a family with three children (nearly half of the available federal EITC credit at that level). The Public Policy Institute of California estimates that in the first year of creation, the CalEITC was claimed by 14% of households in the state, with more than 90% of claimants having dependent children. They also estimate that without both state and federal EITCs, 840,000 more Californians would be in poverty, including an estimated 376,000 children.

3   Data

We use annual state-level panel data for the period 2007 through 2019. This window gives us sufficient pre-treatment data to fit a synthetic control, although we were limited in our post-treatment period by the availability of our variables of interest, namely, poverty rates and labor force participation. We use data for both of these variables from the Census Bureau's American Community Survey (ACS),[1] which was not released in 2020 due to the COVID-19 pandemic.

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[1]https://www.census.gov/programs-surveys/acs/data.html

As we will discuss further in the Methodology section, a synthetic control model creates a weighted average of control states based on predictors of our dependent variables, minimizing the distance between the treatment state and the weighted average of control states in the pre-treatment period. Therefore, the set of control states differs whether we are modeling the effects of North Carolina removing their EITC in 2014, and California passing their EITC law in 2015. Focusing on states with a refundable EITC, the control group for the California models include the 21 states that do not have an EITC, after removing North Carolina. The control group for the North Carolina models include the 21 states that do offer a refundable EITC, after removing California.

For our predictors, we retrieved demographic data from the National Cancer Institute's Surveillance, Epidemiology, and End Results Program (SEER),[2] and economic indicators from the Bureau of Economic Analysis (BEA).[3] SEER's data is categorized by race (black, white, other), sex (male, female), and age, grouped by 5 years (5-9, 10-14, etc.). We created 18 demographic variables as percentage of total population, using race, sex, and three age categories: under 20 (U20), working age, which includes age 20 through 64 (WA), and over 65 (65o). The economic indicators we chose to use are real per capita personal income, and real per capita GDP. Finally, we created a population density variable using our aggregated demographic data, and state areas. A full summary of our data can be found on table 2 in the Appendix.

4   Methodology

In this study, we employ a comparative case study using synthetic control (SC), motivated by Abadie et al. (2010). In SC, we choose a weight vector W to minimize the distance function, $|X_1 - X_0 W|$ in the pre-treatment period, where X_1 is a $(k \times 1)$ vector of predictor variables and outcome variables from our treatment state, X_0 is a $(k \times J)$ matrix where J is the number of units in the control group, and W is a $(J \times 1)$ vector of weights to apply to each control unit. The function to minimize is

$$\sum_{m=1}^{k} v_m (X_{1m} - X_{0m} W)^2$$

where v_m weights the importance of variable m. Since the weights V and W are chosen to minimize this function in the pre-treatment period, notable variations in trend between the treatment state and the synthetic state in the post-treatment periods are interpreted as the causal effect of the EITC on the dependent variable of interest.

A major challenge with synthetic control is that there is limited guidance on best practice in tuning the model by adding or removing predictors Ferman et al. (2020). In practice, there are a variety of techniques employed by the researcher. We chose to begin by including as predictors pre-treatment means of all of 21 of our covariates (18 demographic variables, two economic variables, and density), and lags for every pre-treatment year of our dependent variable. We proceeded to scale back the model by removing demographic predictors, lags, and economic variables that had little to no effect on the minimization function.

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[2]https://seer.cancer.gov/popdata/download.html
[3]https://www.bea.gov/

The process outlined above was repeated for each of our four models, using combinations of poverty and labor force participation as our dependent variables, and California and North Carolina as our treatment states. Recall that the control for each treatment was chosen to reflect the status of the EITC policy in the pre-treatment period. Tables 3 though 6 in the Appendix show the balance tables from each of these analyses.

5   Results

In Figure 2, we compare the trend of our synthetic California and North Carolina to their real counterparts in both labor force participation rate and poverty rate. The models were tuned to closely match pre-treatment trend, so deviation following treatment can be interpreted as a causal effect of the policy. Following the implementation of CalEITC in 2015, we see an increase in labor force participation (about 1%) and a decrease poverty rate (about 1%), relative to our synthetic California. Following North Carolina's elimination of the EITC, we see a decrease in labor force participation of about 0.8%. However, the poverty rate in North Carolina is also below the synthetic level, bucking economic theory that would presume poverty rates to increase following removal of the EITC. Figure 3 shows how the weights of our synthetic controls are generated. One interesting thing of note is that weights for both control units and variables are generated differently for each outcome variable of interest; that is, synthetic California is comprised of a different convex combination for poverty and labor force participation, and likewise for North Carolina. For instance, for California's labor model, lags of the dependent variable were not as important to the fitting of the pre-treatment trend as it was for the poverty model.

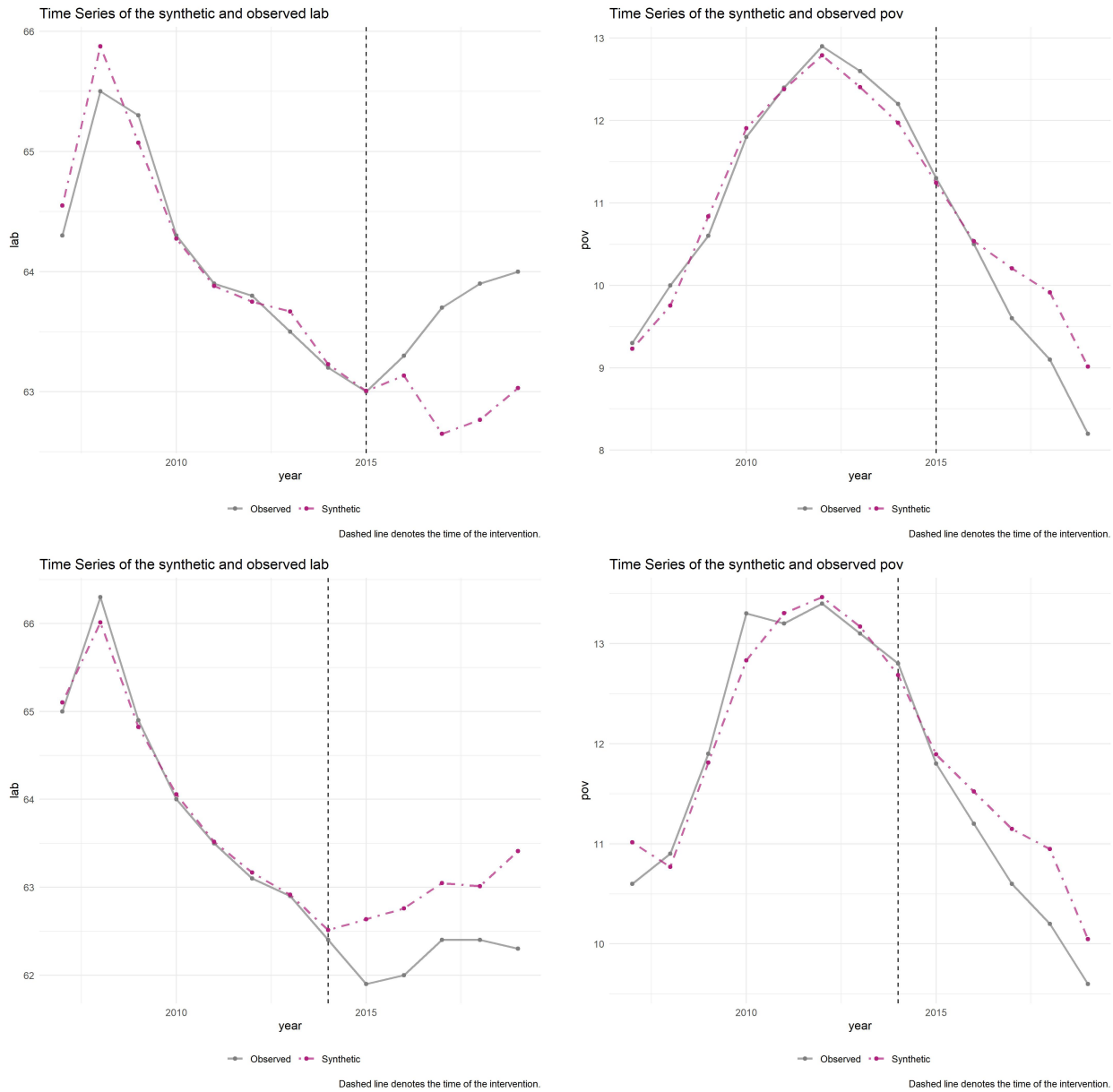Figure 2: Poverty and Labor Force Participation in California and North Carolina with Synthetic Control

Time Series of the synthetic and observed lab

Time Series of the synthetic and observed pov

Dashed line denotes the time of the intervention.

Time Series of the synthetic and observed lab

Time Series of the synthetic and observed pov

Dashed line denotes the time of the intervention.

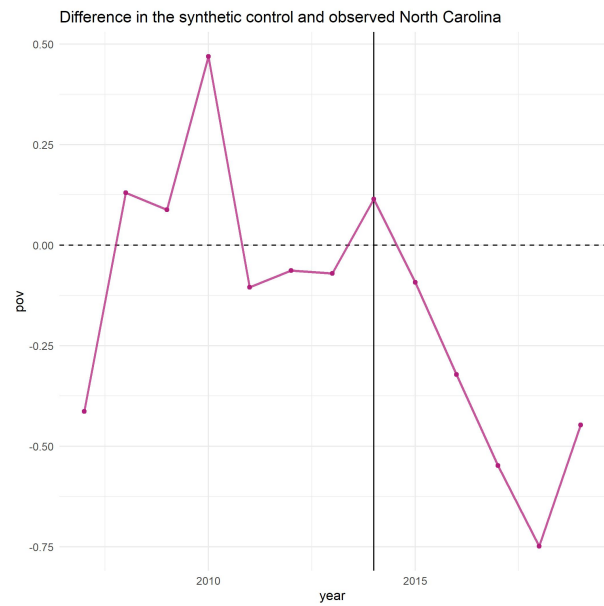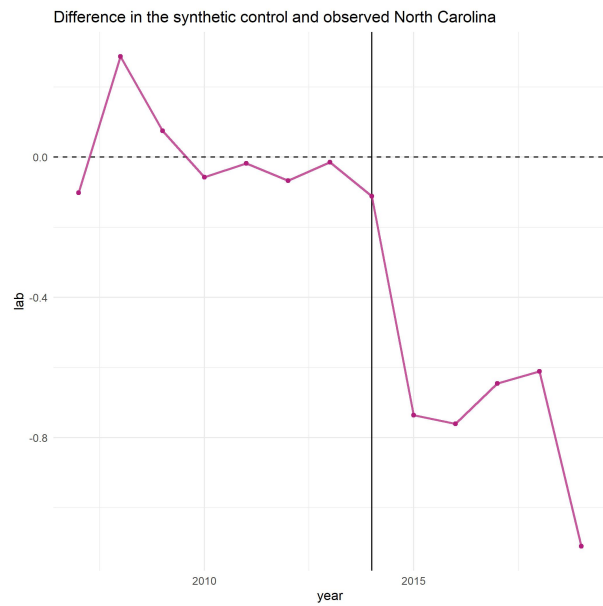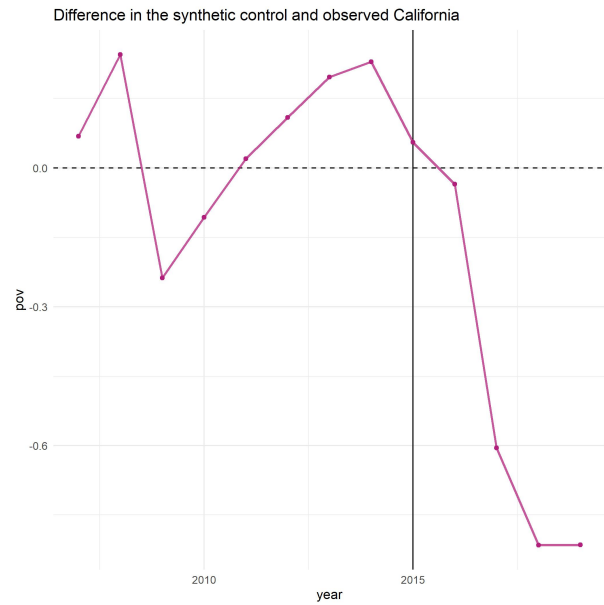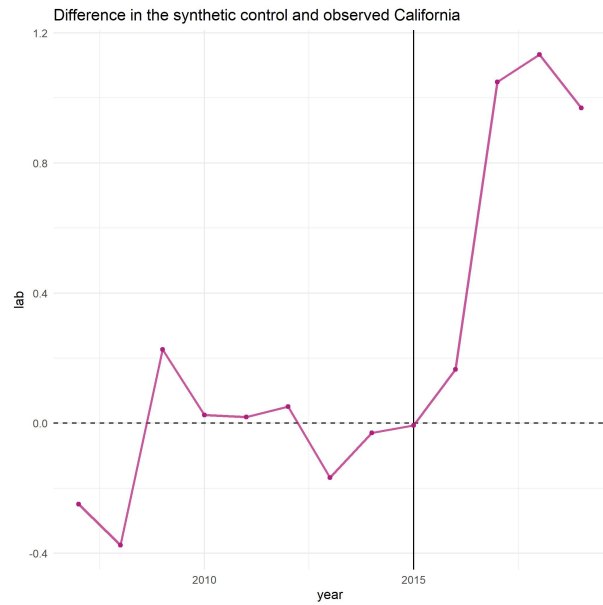Figure 3: Weights Assigned for Synthetic California and North Carolina
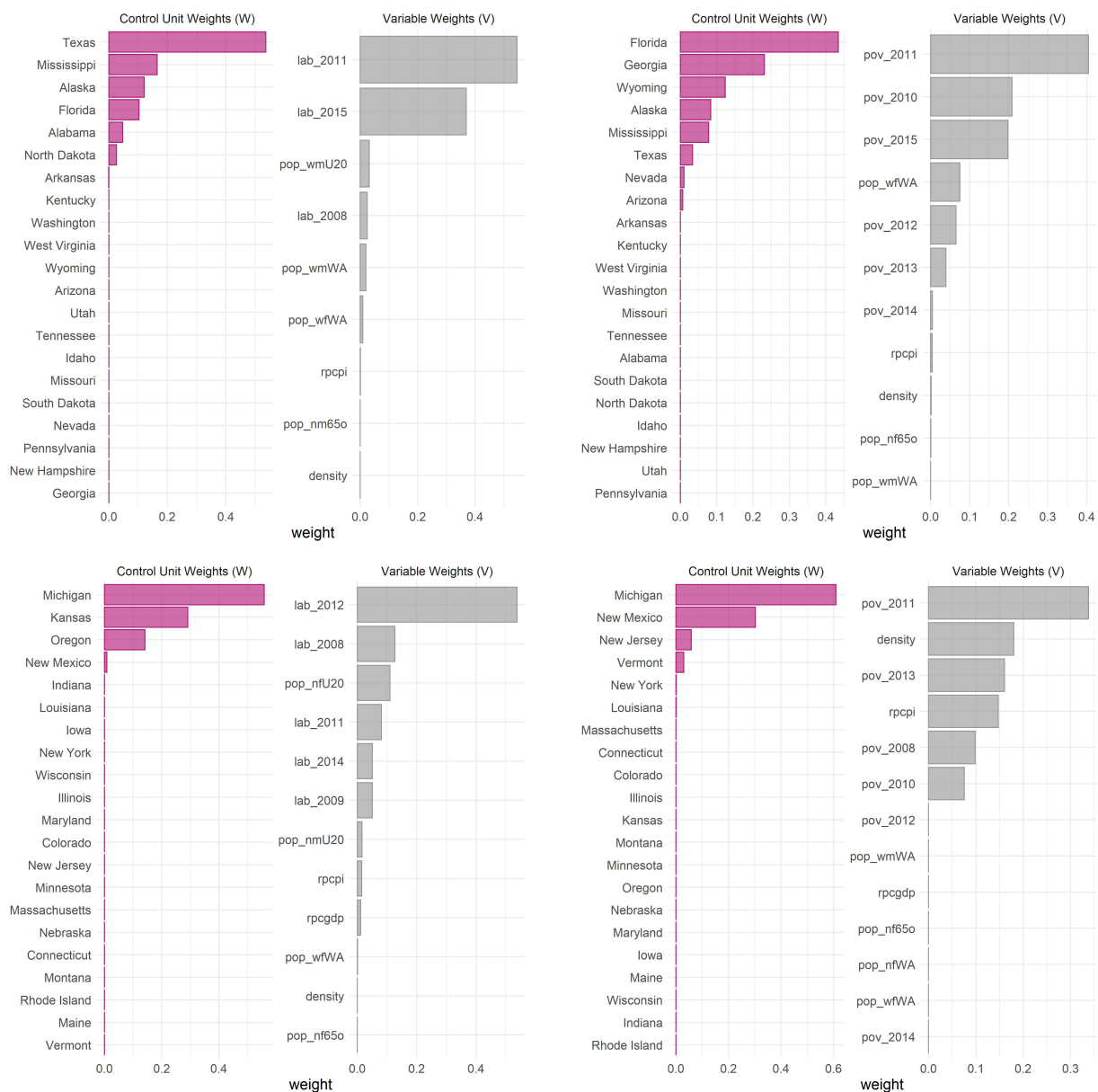
Figure 4 allow us to look closely at the difference between the synthetic state and the real state. Following the implementation of CalEITC, we observe a noticeable increase in labor force participation. It peaks at near 1.1% increase over our synthetic California before returning to a 1% difference. Conversely, after the elimination of the EITC in North Carolina, there is an observable decrease in labor force participation, deviating below 1% of synthetic North Carolina. The difference between our observed states and their synthetic counterparts lends some support to the theory that the EITC encourages work at the extensive margin.

Looking at the effect of our policy on poverty rates, we notice a decrease in poverty rates compared to the control for both California (a 0.8% decrease), and North Carolina (a 0.75% decrease). This is puzzling, because while theory would suggest that the adoption of a state-level EITC would reduce poverty, as we see in California, North Carolina's results suggest a decrease in poverty after elimination of the EITC. This leads us to a discussion of inference with synthetic control.

Figure 4: Difference Between Synthetic State and Real State

Difference in the synthetic control and observed California

Difference in the synthetic control and observed California

Difference in the synthetic control and observed North Carolina

Difference in the synthetic control and observed North Carolina

test

In order to test the significance of these results, we generate a series of placebos by repeating our synthetic control model on each state in the control group, and compare the results of the placebos to the results we have seen in figures 2 and 4. This allows us to determine if we are indeed detecting a causal effect of a policy, or if our results could be generated by chance.

Figure 5: Poverty Gap in California and Poverty Placebo Gaps

Difference of each 'state' in the donor pool

Pruned all placebo cases with a pre-period RMSPE exceeding five times the treated unit's pre-period RMSPE.
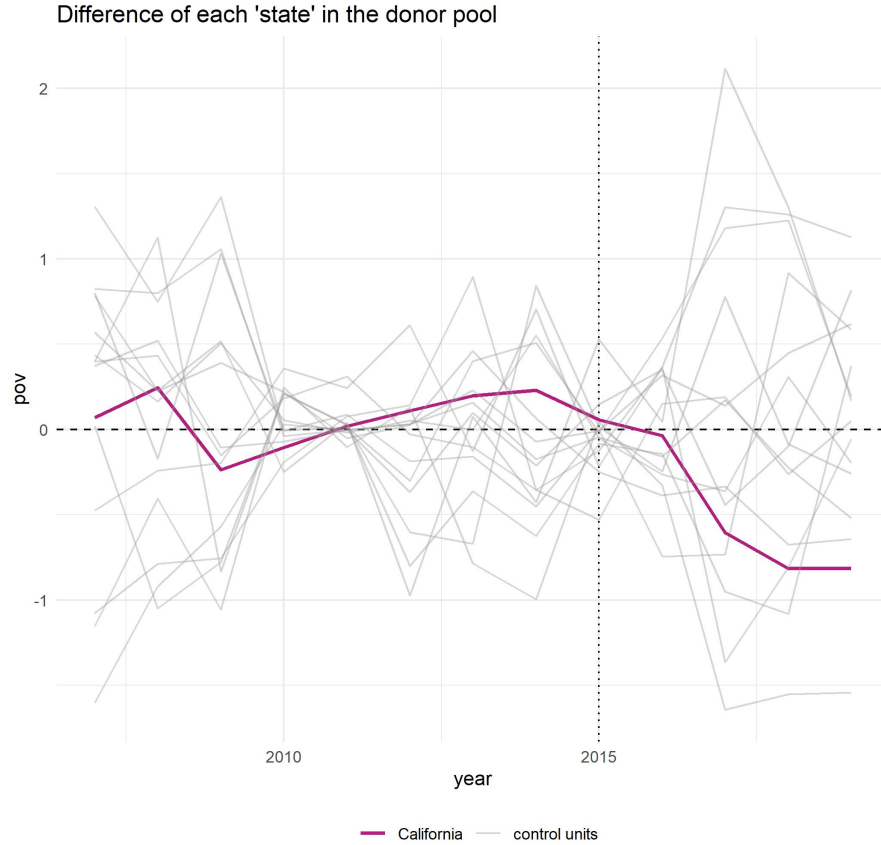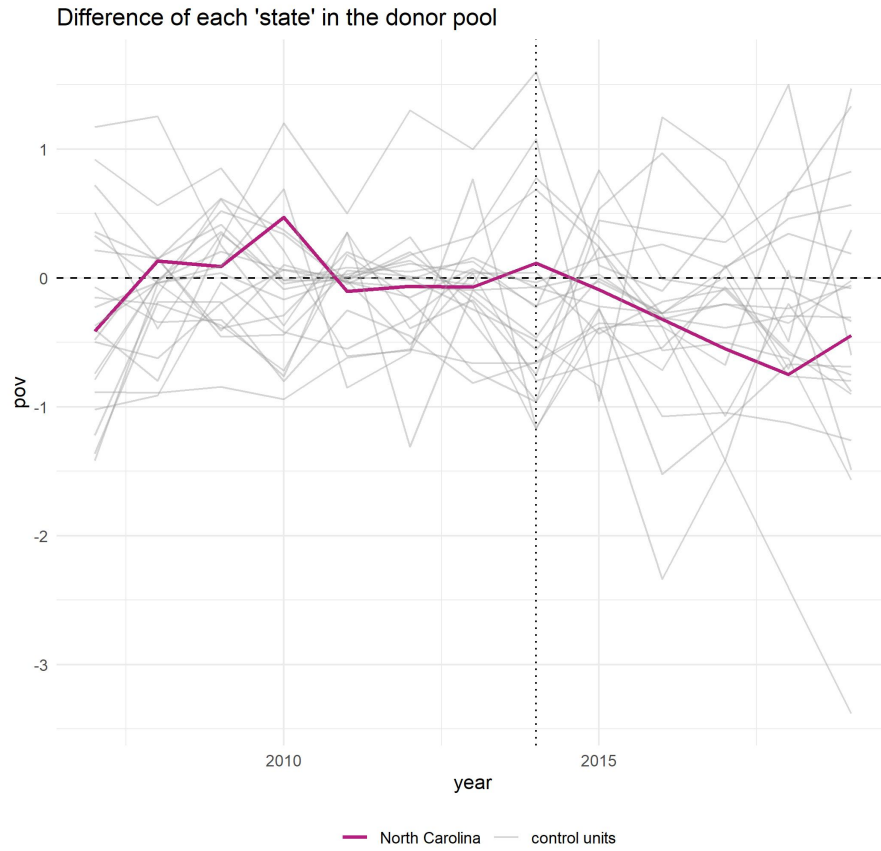
Beginning with our poverty rate models, Figure 5 shows some evidence in a decrease in the poverty rate. To determine a causal effect from a plot like this, we would hope to see the state's difference trend close to zero in the pre-treatment period, and then move along the outer margin of the other placebos. While there is some decrease in poverty following the treatment, it would be difficult to claim that the post-treatment trend is significantly lower than the placebos. There is some evidence about CalEITC's impact on the poverty rate in California, but it is hard to state conclusively that the EITC caused a reduction in poverty rates.

For North Carolina, seen in Figure 6, the results are even more underwhelming. Although we fit our synthetic model well enough in the pre-treatment period, the post-treatment

trend compared to placebos indicates that the effect of a decrease in poverty rates following elimination of the EITC in North Carolina could be produced by random chance. Therefore, we cannot confidently tease out a causal effect of removing the EITC policy on poverty rates in North Carolina.
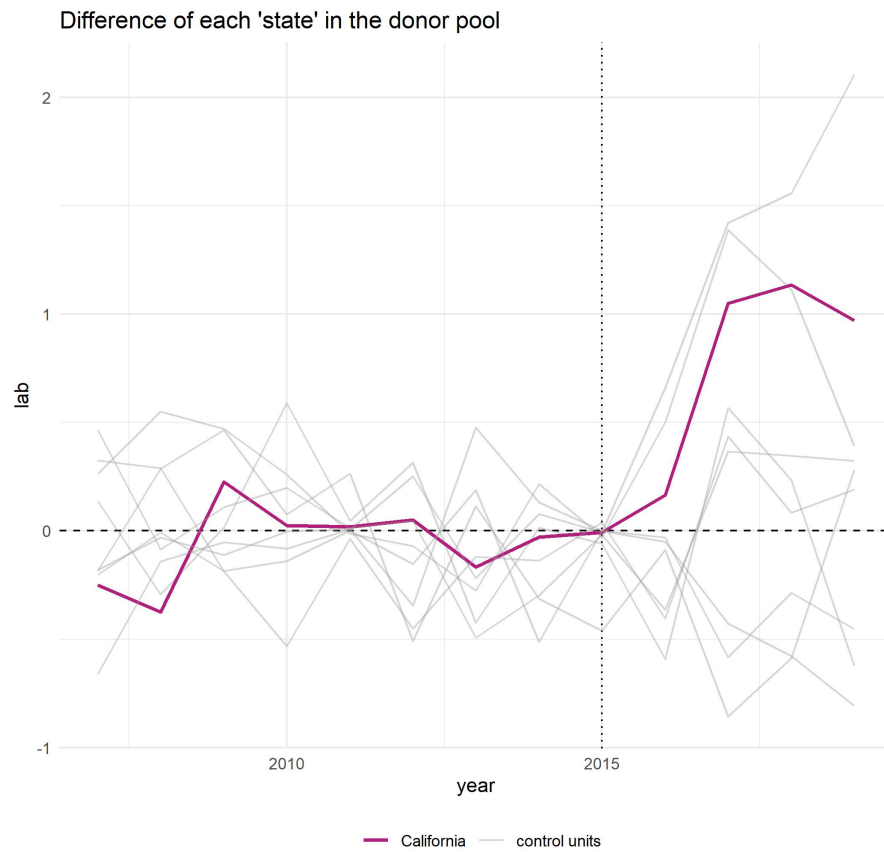
Figure 6: Poverty Gap in North Carolina and Poverty Placebo Gaps

Pruned all placebo cases with a pre-period RMSPE exceeding five times the treated unit's pre-period RMSPE.

Returning to labor force participation, where we previously saw some evidence of a positive relationship with the EITC, we apply the same iterative process to the states in the control groups to generate our placebos. These results are shown in Figures 7 and 8. Similar to the case of our poverty models, our pre-treatment fit of the synthetic control is quite good, as evidenced by the state differenced trend hovering around zero. For both states, the superimposed purple line indicates a deviation from the control units after treatment. North Carolina in particular is unusual in the donor pool, indicating that labor force participation was decreasing while the majority of the control units saw increases in the gap. Economic theory would suggest this relationship, but the results are still surprising given how modest the EITC was in North Carolina before it was eliminated. Notice that for these models, we pruned the population of placebos by removing states whose fit was more than two times the root mean-squared error of California and North Carolina, a cutoff that is considered highly

restrictive, and provides strong evidence that we would not see this outcome by chance.

Figure 7: Poverty Gap in North Carolina and Poverty Placebo Gaps

Difference of each 'state' in the donor pool

Pruned all placebo cases with a pre-period RMSPE exceeding two times the treated unit's pre-period RMSPE.

Figure 8: Labor Force Participation Gap in North Carolina and Labor Force Participation Placebo Gaps
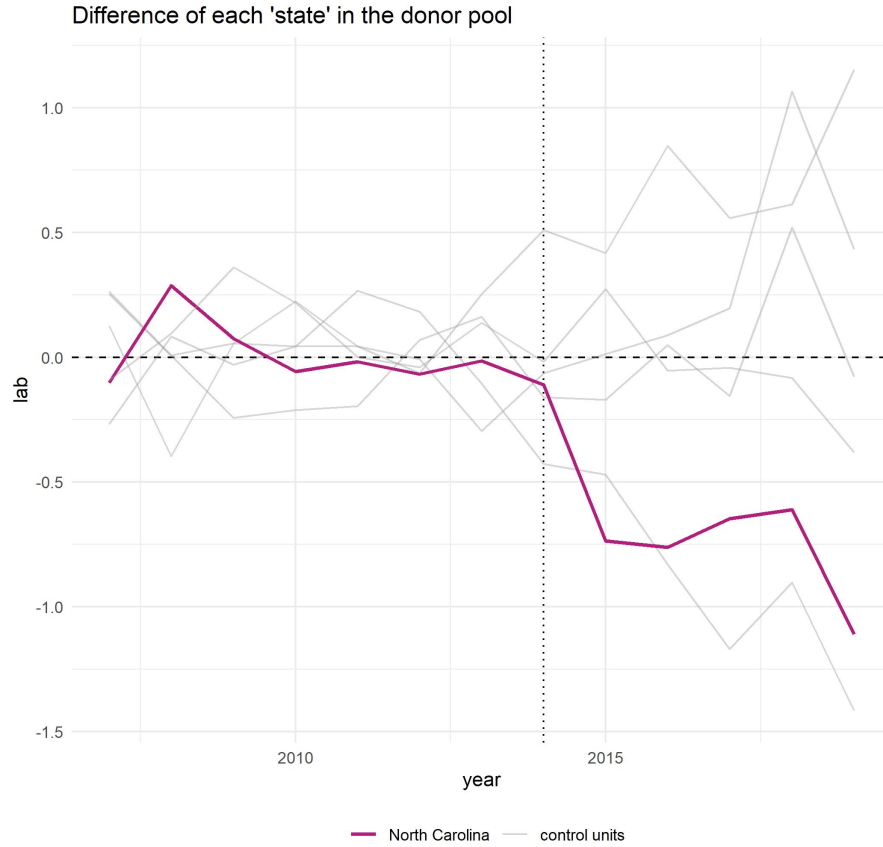
Difference of each 'state' in the donor pool

Pruned all placebo cases with a pre-period RMSPE exceeding two times the treated unit's pre-period RMSPE.

6   Conclusion

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Appendix

Table 2

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
pov	650	9.82	2.82	4.00	7.60	11.88	19.20
lab	650	64.52	3.82	52.40	62.20	67.50	73.60
density	650	187.30	240.07	1.15	40.61	217.89	1,134.73
rpcgdp	650	51,166.98	9,947.27	33,068.46	43,899.64	56,308.00	80,434.26
rpcpi	650	44,915.69	8,234.20	29,554	38,791.8	49,853.2	74,930
pop_wm65o	650	0.06	0.01	0.02	0.05	0.06	0.10
pop_wmU20	650	0.10	0.02	0.02	0.09	0.11	0.17
pop_wmWA	650	0.24	0.04	0.09	0.23	0.27	0.30
pop_wf65o	650	0.07	0.02	0.02	0.06	0.08	0.11
pop_wfU20	650	0.10	0.02	0.02	0.09	0.11	0.16
pop_wfWA	650	0.24	0.04	0.07	0.22	0.26	0.30
pop_bm65o	650	0.004	0.004	0.000	0.001	0.01	0.02
pop_bmU20	650	0.02	0.01	0.002	0.01	0.03	0.07
pop_bmWA	650	0.03	0.03	0.002	0.01	0.04	0.10
pop_bf65o	650	0.01	0.01	0.000	0.001	0.01	0.03
pop_bfU20	650	0.02	0.01	0.002	0.01	0.03	0.06
pop_bfWA	650	0.03	0.03	0.001	0.01	0.05	0.12
pop_nm65o	650	0.003	0.01	0.000	0.001	0.003	0.06
pop_nmU20	650	0.01	0.01	0.001	0.004	0.01	0.10
pop_nmWA	650	0.02	0.03	0.003	0.01	0.02	0.21
pop_nf65o	650	0.004	0.01	0.000	0.001	0.003	0.08
pop_nfU20	650	0.01	0.01	0.001	0.004	0.01	0.10
pop_nfWA	650	0.02	0.03	0.003	0.01	0.03	0.22

Table 3: Balance Table - Labor in California

	California	Synthetic California	Control
rpcpi	$46,653.220$	$41,324.850$	$40,364.860$
density	236.980	100.380	90.720
pop_wmU20	0.110	0.110	0.110
pop_nm65o	0.010	0	0
pop_wmWA	0.230	0.230	0.250
pop_wfWA	0.220	0.230	0.250
lab_2008	65.500	65.870	65.940
lab_2011	63.900	63.880	63.680
lab_2015	63	63.010	62.630

Table 4: Balance Table - Poverty in California

	California	Synthetic California	Control
rpcpi	46, 653.220	41, 476.430	40, 364.860
density	236.980	189.900	90.720
pop_wfWA	0.220	0.220	0.250
pop_wmWA	0.230	0.230	0.250
pop_nf65o	0.010	0	0
pov_2010	11.800	11.910	11.330
pov_2011	12.400	12.380	11.770
pov_2012	12.900	12.790	11.800
pov_2013	12.600	12.400	11.450
pov_2014	12.200	11.970	11.240
pov_2015	11.300	11.240	10.690

Table 5: Balance Table - Labor in North Carolina

	North Carolina	Synthetic North Carolina	Control
rpcpi	37, 567.880	38, 909.520	43, 824.230
rpcgdp	46, 492.670	44, 566.410	51, 638.630
density	182.190	111.160	267.100
pop_nfU20	0.010	0.010	0.010
pop_nmU20	0.010	0.010	0.010
pop_nf65o	0	0	0
pop_wfWA	0.220	0.250	0.250
lab_2008	66.300	66.010	67.850
lab_2012	63.100	63.170	65.830
lab_2009	64.900	64.820	67.140
lab_2014	62.400	62.510	65.220
lab_2011	63.500	63.520	66.120

Table 6: Balance Table - Poverty in North Carolina

	North Carolina	Synthetic North Carolina	Control
rpcpi	$37,567.880$	$37,545.500$	$43,824.230$
rpcgdp	$46,492.670$	$43,466.440$	$51,638.630$
density	182.190	176.530	267.100
pop_wfWA	0.220	0.250	0.250
pop_nfWA	0.010	0.020	0.020
pop_wmWA	0.220	0.240	0.250
pop_nf65o	0	0	0
pov_2008	10.900	10.770	8.350
pov_2010	13.300	12.830	9.740
pov_2011	13.200	13.300	10.080
pov_2012	13.400	13.460	10.140
pov_2013	13.100	13.170	10.140
pov_2014	12.800	12.690	9.850