E797B - Problem Set 2

Jesús Lara

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Problem 1: Minimum Wage, Family income and Poverty

Part A

In this problem I am using a sample of the 1990 Census and the 2006 American Community Survey to study the effect of minimum wage on income at different levels. In particular, we are interested in how minimum wage impact income of individuals relative to the poverty line. I define the dummy variable Ij_i, which is equal to one if person i's income is less than $j\%$ the poverty line income and zero otherwise, for $j = 50, 75, 100, 125, 150$

For the estimations to be correct, the first step is to determine the appropriate covariates that will be included in the regressions. A good control should is correlated both with the outcome variable and the, in this income relative to the poverty line, and the treatment, in this case minimum wage. Such controls, if omitted, would generate a bias in the coefficient of the treatment variable.

However, a control should not be included, even if it is correlated with the outcome variable, if it is causally affected by the treatment. The inclusion of such control would also bias our estimate of the effect of the treatment.

With these elements in mind, I will include the following controls: age, sex, married, race, citizen and higher education. All these variables are correlated with the outcome variable, which is the income of individuals relative to the poverty line. However, non of these are causally affected by minimum wage. Increases in minimum wage in a state cannot, change people's age and race and in general will not change civil status, sex and citizen status. There may be a space for higher education to be causally affected by minimum wage with respect to the decisions of individuals to go to college, for example. However, I think this is would be a longer-term issue, and in the short run it is very important to control for higher education as it is a very important determinant of income.

From the list of available of controls I will not include the detailed employment status, the hours of work, the total personal income and welfare or public assistance income. I argue that, in principle, they are bad controls because are potentially causally affected by minimum wage. Employment status captures whether a person is employed, unemployed, underemployed or not in the labor force (among other combinations). Minimum wage changes can have a causal impact on this variable as it affects employers hiring and turnover decisions. This is the same reason why the hours of work should not be included as a control, as one of the concerns is that employers change the status of workers from full to part time in response to a higher minimum wage. With respect to total income, it is basically another form of our 5 outcome variables, so it should not be included. Finally, the amount of money individuals receive from welfare or public assistance depends on their current income (below or above poverty levels, for example), as well as their employment status (unemployment benefits, for example) and hence we should not include them as controls.

Hence, the two models that I will estimate are given by the following equations:

$$Ij_{it} = \beta lnMW_{it} + X_{it}\Gamma + \mu_s\Psi + \lambda_t\Phi + \epsilon_{it} \quad (1)$$

$$Ij_{it} = \beta lnMW_{it} + X_{it}\Gamma + \mu_s\Psi + \eta_d t\Omega + \epsilon_{it} \quad (2)$$

The first one is the canonical "Two-Way Fixed Effects". The estimated β is the differences-in-differences (DID hereinafter) estimate. The term μ_s controls for differences in levels across states.

However, we may be concerned about the existence of long-term trends that are not correctly captured by the TWEF. In equation (2) the term $\mu_d t\Omega$ accounts for trends at the division level (every division is a set of states and there are seven in total) and may help to solve this problem.

For the estimation I am using clustered standard errors at the state level. The reason why this is the correct approach is that treatment (minimum wage) is applied at the state level.

In the four estimations, the identification comes from within state variation in the different poverty levels, given that we are controlling for levels by including state fixed effects. The interpretation of the coefficient β is how a change in minimum wage affects the probability of being in a particular poverty threshold. But this is only true if the conditional independence assumption holds, which means that after taking into account our controls, the increase in minimum wage is as good as random. That is what is assumed in models 1 and 2. The first one is the most restrictive since ignores the effect of other variables on the income of individuals relative to the poverty line. However, neither of them allow for the effect of treatment to vary across regions. That is not the case with specifications 3 and 4, when we include division specific time effects.

The results of the estimations of equations (1) and (2), with and without controls are presented in Table 1. Overall, we observe the following results: an increase in minimum wage reduces the probability of being in the 2 lowest groups of income, and increases the probability of being in the next 3, which are sightly below and above the poverty line. However, the results are only statistically significant for all specifications only for the lowest group (<50% poverty line), and at most at the 5% level. The results are also statistically significant for specifications 3 and 4, when we control for trends at the division level. Table 1 provides some evidence in favor of the hypothesis that a higher minimum wage reduces the probability of having an income lower than the poverty line, controlling for other characteristics of individuals.

Table 1: Effect of minimum wage on income levels with respect to the poverty line

	(1)	(2)	(3)	(4)
Income $< 50\%$ Poverty Line	-0.0557*	-0.0470*	-0.0775**	-0.0772**
	(0.0243)	(0.0227)	(0.0274)	(0.0255)
Income $< 75\%$ Poverty Line	-0.0375	-0.0306	-0.0699**	-0.0744**
	(0.0197)	(0.0193)	(0.0227)	(0.0230)
Income $< 100\%$ Poverty Line	0.0107	0.0165	-0.0441	-0.0533
	(0.0289)	(0.0268)	(0.0366)	(0.0394)
Income $< 125\%$ Poverty Line	0.0335	0.0376	-0.0484	-0.0615
	(0.0340)	(0.0311)	(0.0337)	(0.0380)
Income $< 150\%$ Poverty Line	0.0534	0.0556	-0.0470	-0.0631
	(0.0438)	(0.0417)	(0.0414)	(0.0472)

State-cluster standard error in parentheses
(1) state and year fixed effects without controls.
(2) state and year fixed effects with controls.
(3) division-specific time effects no demographic and economic controls
(4) division-specific time effects with demographic and economic controls
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Discussion of the identification assumptions and results

Part B

1B i)

In this part I estimate the model given by equation (2) (division time effects and controls) but now including 10 different thresholds: 25 and 250% of the poverty line being the first an last groups. The results are shown in figure 1. The bands show the upper and lower bounds of the confidence interval at the 95% level.

These are the conditional quantile partial effects. They say how the probability of being under a particular threshold with respect to the poverty line change because of minimum wage within each cell, defined by the controls. We see that the estimates are negative and significant for the first three groups (below 25, 50 and 75% of the poverty line). The estimates are now longer significant at the 5% level after that threshold.

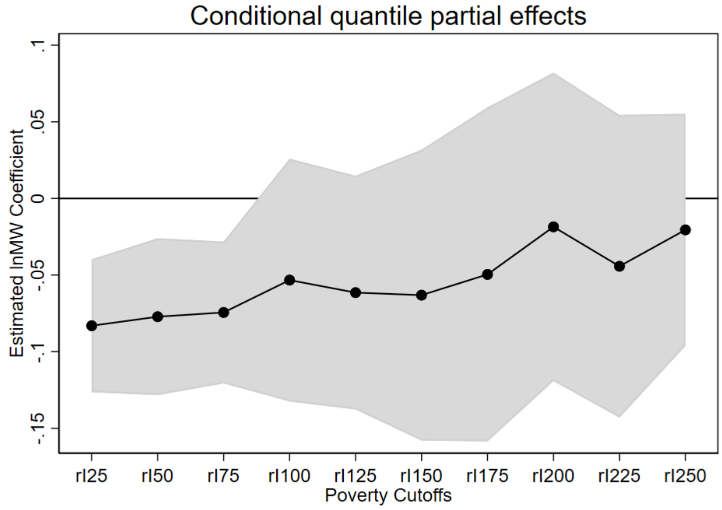

Figure 1: Conditional quantile partial effects

1B ii)

To estimate the unconditional quantile effects, I divide the conditional estimates by the value of the probability density function of poverty at the stipulated cutoffs. Then I confirm using the rifreg command in Stata. My results are shown in Table 2. There is a difference of ± 2 between my calculations and those obtained with rifreg. The reason is that rifreg only accepts quantities defined at two decimal points, so I had to round the real quantiles at the given cuttofs. Nevertheless, the results are pretty similar.

Table 2: Conditional and unconditional qunatile partial effects

	PDF	Conditional	Own Calculations	Rifreg
25	0.0014	-0.0831	59.7947	57.4648
50	0.0020	-0.0772	39.3087	38.4581
75	0.0026	-0.0744	28.4820	26.3662
100	0.0028	-0.0533	18.9102	20.3325
125	0.0031	-0.0615	20.0766	19.9586
150	0.0033	-0.0631	18.8753	18.6730
175	0.0034	-0.0496	14.5931	14.6089
200	0.0035	-0.0185	5.2896	5.2797
225	0.0035	-0.0443	12.5047	12.2233
250	0.0036	-0.0205	5.6894	6.3022

They are also plotted in figure 2. They show the elasticities at the various the poverty cutoffs: how minimum wage changes the income of individuals who are in different groups relative to the poverty line. Hence, according to these results, a higher minimum wage has a significant positive effect at the 95% level until cutoff 150. After that, the impact is no longer significant.

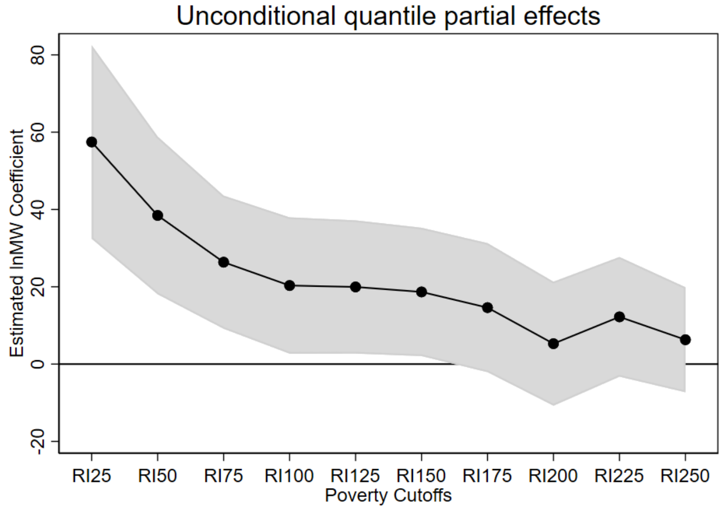

Figure 2: Unconditional quantile partial effects

Problem 2

Part A

2A i)

In this part and in the following I will perform several variations of a DID estimation of the effect of the increase in minimum wage in California on four outcome variables: wages (for teens and the overall workforce) and employment (for teens and the overall workforce. We know that, for our estimate to be correct, the crucial assumption is parallel trends or Conditional Independence. Hence, the first step is to do a visual inspection of the trends followed by the treatment unit and the control group. We an see that in figure 3, where I plot the outcome variables in CA and the average of these variables for the 35 donor states. The donor states are those that did not raise the minimum wage during the relevant period. There seem to be parallel trends for overall wage. That is also the case for teen wages until period (-2). In contrast, parallel trends do not seem a good assumption for employment, especially when considering only teens.

I perform a DID estimation for all outcome variables. The results are shown in column 1 of Table 3. According to this estimates, the treatment (increase in MW) increased average wages by 8.6% for teens and 2.5 % for the overall workforce. However, this last estimate is significant only at the 10% level. Additionally, from the results we cannot conclude that the rise in minimum wage had a negative impact on employment. The estimate is, in fact, positve for and significant at the 10% level for the overall worforce

Table 3: Effect of minimum wage increase in California on employment and wage for teens and overall workforce

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wage: Teen	0.0859***	-0.0679***	-0.0526***	0.0243*	0.1274***	0.0143	0.0372
	(0.0115)	(0.0126)	(0.0000)	(0.0111)	(0.0186)	(0.0371)	(0.0319)
Wage: Overall	0.0249*	-0.0320***	-0.0159***	0.0071**	0.0817***	0.0110	-0.0091
	(0.0092)	(0.0074)	(0.0000)	(0.0026)	(0.0112)	(0.0336)	(0.0425)
Employment: Teen	0.0228*	0.0381*	-0.1410***	-0.0080	0.0682	0.0421	0.0369
	(0.0108)	(0.0163)	(0.0000)	(0.0050)	(0.0381)	(0.0198)	(0.0200)
Employment: Overall	-0.0010	0.0086**	0.0009***	-0.0041***	0.0103	0.0029	-0.0036
	(0.0032)	(0.0028)	(0.0000)	(0.0008)	(0.0065)	(0.0046)	(0.0041)

Clustered standard errors at the state-level in parenthesis. Reported coefficients of dummy=1 if state is California after 1983q2 (1) Two way fixed effects model (DID). (2) DID using 3 lags and 3 leads on treatment (3) DID using 3 lags and 3 leads on treatment and division-specific time effects (4) DID using 3 lags of outcome variable with no fixed effects (5) Propensity Score Reweighting using a logit model (6) DID using weights obtained from Synthetic Controls Estimation using average pre-treatment outcomes and covariates (7) DID using weights obtained from Synthetic Controls Estimation using covariates as predictors

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

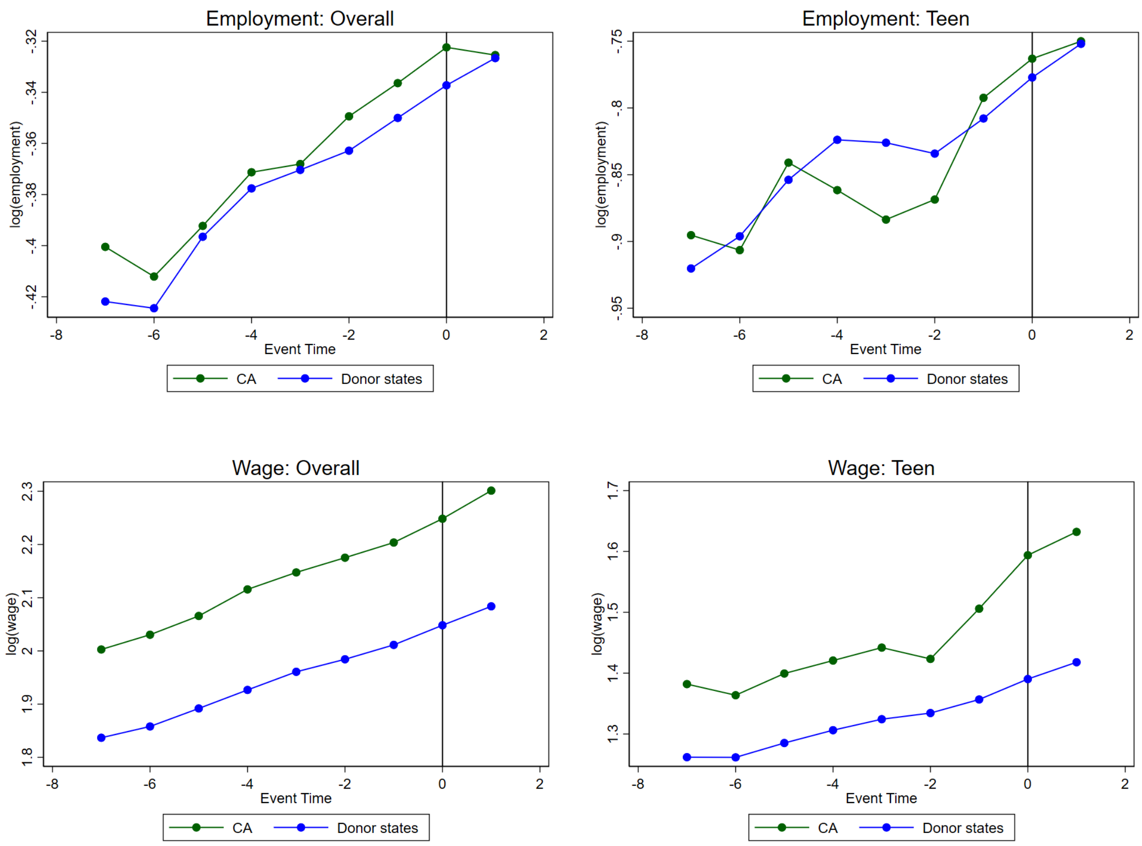

Figure 3: Outcome variables for California and donor states using quarterly bins. Vertical line at the treatment period

2A ii)

In this part I perform three additional estimations. The results are shown in columns (2) to (4) of Table 3. First, I included 3 lags (3 quarters) and 3 leads for my treatment variable. For column (3) I also added division-specific time effects. For column (4) I didn't add lags to the treatment variable, but included 3 lags of the outcome variables as predictors. The introduction of lags and leads of the treatment as covariates change the sign of the treatment on wage. In contrast, the basic results are maintained when we include only lags for the dependent variables.

Table 4: Synthetic Controls Estimates

	Wage (Teen)	Wage(Overall)	Employment(Teen)	Employment(Overall)
Specification 1 $\hat{\alpha}$	0.0197	0.0119	0.0434	0.0033
Specification 2 $\hat{\alpha}$	0.0526	-0.0067	0.0377	-0.0036

2A iii)

In this part I estimate a propensity-score re weighted model. The basic idea is that we want to give more weight to the states that are "more likely" to be treated (increase minimum wage) based on how similar they are to California in some key variables. Those variables are age, race, and Hispanic shares.

I estimate a logit model where treatment in the pre-period is the dependent variable and the averages of the shares mentioned above are the predictors. I use the fitted values to obtain the weights for each state. These are shown in table 5. The states with the greatest weights are NM, AL and TX.

I use these weights to estimate a weighted DID regression. The results are shown in column 5 of Table 2. There we observe that the basic results obtained from a basic DID remain. However, the estimates for Wage as dependent variable are greater (12% increase). According to this specification. the increase in minimum wage did not have a significant effect on employment.

2A iv)

In this part I estimate a confidence interval at the 90% level using Conley-Taber's method. This method corrects the standard errors, that will not be consistent because we have a single treated unit. The results are shown in table 6. We see that all values for the lower bound are negative, and all of them are positive for the upper bound. Hence, according to this methods, we don't have evidence to assert that the increase in minimum wage had a significant effect on average wages and employment.

Table 5: Weights to Each State: Logit

	Weights Logit
AL	0.2193
AK	0.0022
AZ	0.0008
AR	0.0173
CO	0.0014
DE	0.0026
FL	0.0047
GA	0.0098
ID	0.0001
IL	0.0043
IN	0.0004
KS	0.0008
KY	0.0001
LA	0.0331
MD	0.0052
MI	0.0011
MS	0.0004
MO	0.0304
MT	0.0005
NE	0.0017
NV	0.0003
NJ	0.0012
NM	0.5623
NY	0.0035
NC	0.0055
OH	0.0004
OK	0.0035
SC	0.0159
SD	0.0005
TN	0.0008
TX	0.1783
UT	0.0038
VA	0.0016
WV	0.0000
WY	0.0002

Table 6: Confidence Interval with Conley Taber's method

	LowerBound(90%)	UpperBound(90%)
Wage(Teen)	-0.076	0.222
Emp(Teen)	-0.135	0.122
Wage(Overall)	-0.107	0.123
Emp(Overall)	-0.034	0.038

Part B

In this part I expand my findings obtained by regression analysis with the use of the synthetic control method.

I will consider two specifications. For the first one, I include all pre-treatment quarterly outcomes as predictors. For the second one, I use the average of pre-treatment outcomes and demographic shares as predictors. This methods will generate a "synthetic California" for our 4 outcome variables. SC California is a weighted average of the donors. The weights are chosen to minimize the Sum of Squares Residuals over the pre-treatment period.

2B i)

In tables 7 and 8 I show the weights assigned to each state for every variable and the two different specifications. For wage, we can see that, in general, the same states are picked by the all methods and variables, with a few exceptions. The weights in turn vary from a minimum of 0.006 to a maximum of .253. For employment (Table 8) the same is true although there seems to be more variation in the number of states picked. In particular, for overall employment and specification 1, positive weights are assigned to 14 out of 35 donor states.

Discussion

Optional: Map with the state and weights

2B ii)

In figures 5 to 8 I present the time evolution of California and Synthetic California for all outcome variables using quarterly bins. Employment is in figures 4 (S1) and 5(S2). The figures with the red line plot the difference between real and synthetic CA. From these figures we can see that the match for overall-employment is very good, whereas there are some important gaps for teen employment. Furthermore, S1 seems to do better at matching, although that is not surprise since we explicitly included all pre-treatment outcomes as predictors. In all four figures, there seems to be a change in the trend of the difference between real and Synthetic California after the increase in minimum wage.

The results for wage are presented in figures 6 and 7. In contrast to employment, we can see that the match obtained by the SC methods is very good for both specifications (although still better for specification 1). The estimated causal effect of minimum wage on the outcome variables is better summarized in Table 9. There I report the estimate $\hat{\alpha} = Y_{j,T} - \sum_{i \neq j} Y_{i,t}$, which in this model is the average difference between real and synthetic CA for the post-treatment period.

Table 7: Weights to Each State: Wage

	State Number	S1:Overall Wage	S2:Overall Wage	S1:Teen Wage	S2:Teen Wage
AL	1	0	0	0	0
AK	2	.237	.218	.165	.25
AZ	4	.105	.052	.027	.086
AR	5	0	0	0	0
CO	8	0	0	0	0
DE	10	0	0	.061	0
FL	12	0	0	0	0
GA	13	0	0	0	0
ID	16	0	0	0	0
IL	17	.092	0	0	0
IN	18	.027	0	0	0
KS	20	0	0	0	0
KY	21	0	0	0	0
LA	22	0	0	.027	0
MD	24	.158	0	0	0
MI	26	0	.274	0	.213
MS	28	0	0	0	0
MO	29	0	0	0	0
MT	30	0	0	0	0
NE	31	0	0	0	0
NV	32	0	0	.207	.006
NJ	34	0	0	.338	.154
NM	35	0	0	0	0
NY	36	.253	.456	.068	.29
NC	37	0	0	0	0
OH	39	0	0	0	0
OK	40	0	0	0	0
SC	45	0	0	0	0
SD	46	0	0	0	0
TN	47	0	0	.027	0
TX	48	.128	0	.012	0
UT	49	0	0	.068	0
VA	51	0	0	0	0
WV	54	0	0	0	0
WY	56	0	0	0	0

Table 8: Weights to Each State: Employment

	State Number	S1:Overall Emp	S2:Overall Emp	S1:Teen Emp	S2:Teen Emp
AL	1	0	0	.07	0
AK	2	0	0	0	0
AZ	4	0	0	0	0
AR	5	.049	0	0	0
CO	8	0	0	0	0
DE	10	.01	.026	0	0
FL	12	.161	0	.457	.012
GA	13	.267	0	0	0
ID	16	0	.227	0	.358
IL	17	0	0	0	0
IN	18	0	0	0	0
KS	20	.001	0	0	0
KY	21	0	0	.027	0
LA	22	0	0	0	0
MD	24	0	0	0	0
MI	26	0	0	.079	.152
MS	28	0	0	0	0
MO	29	0	0	0	0
MT	30	.096	0	0	0
NE	31	0	0	0	0
NV	32	0	.096	0	0
NJ	34	0	0	0	0
NM	35	0	.121	.009	.185
NY	36	.106	.247	.185	.292
NC	37	0	.197	0	0
OH	39	.049	0	0	0
OK	40	.091	0	.127	0
SC	45	.037	0	0	0
SD	46	.064	.085	0	0
TN	47	0	0	0	0
TX	48	0	0	.006	0
UT	49	0	0	0	0
VA	51	.01	0	0	0
WV	54	.005	0	0	0
WY	56	.055	0	.04	0

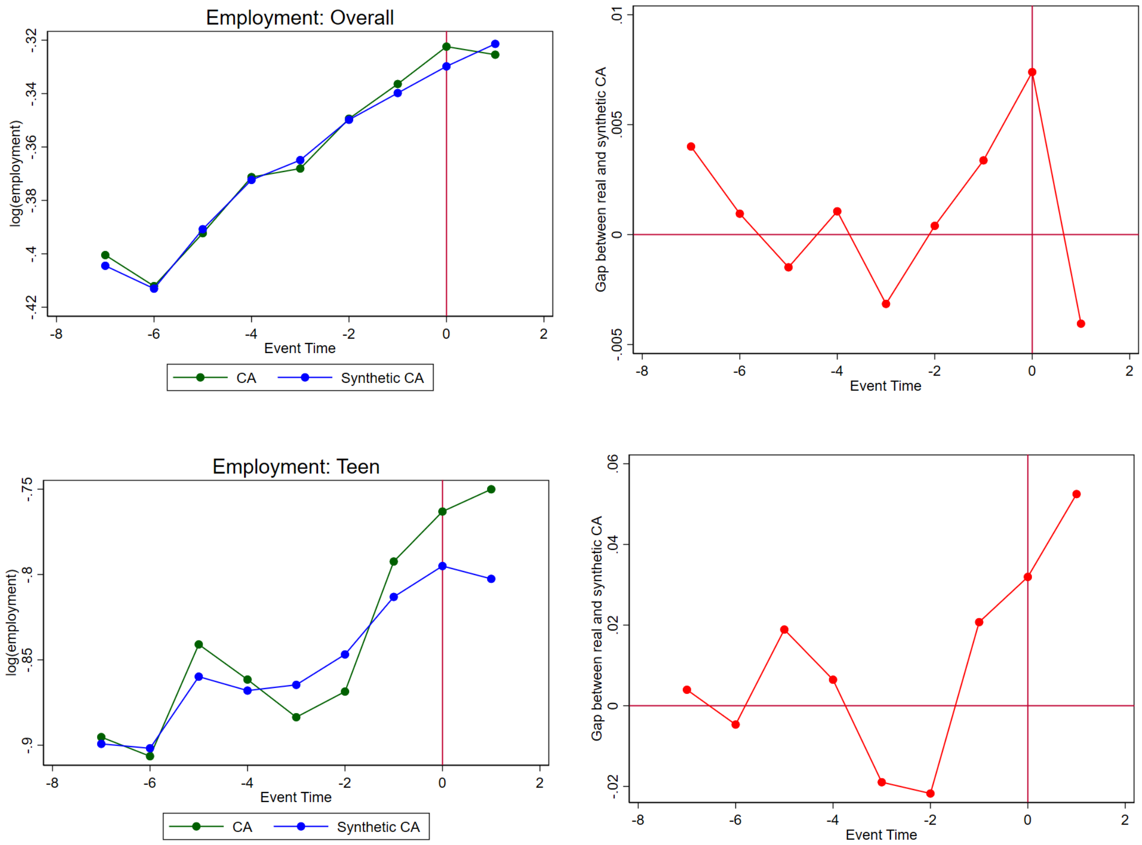

Figure 4: Employment Specification 1

There we can see that the estimated effect of minimum wage is positive for all variables and specifications except overall wage and employment using specification 2. I focus my comparison on column 1 of table 3, that shows the results for the simple DID estimation. There, all the estimates were positive but only wage teen significant at the 1% level of significance. The estimate for employment for the overall workforce was negative but not significantly different from zero. Hence, with respect to the sign, the results using SC and DID are pretty similar.

Table 9: Synthetic Controls Estimates

	Wage (Teen)	Wage(Overall)	Employment(Teen)	Employment(Overall)
Specification 1 $\hat{\alpha}$	0.0197	0.0119	0.0434	0.0033
Specification 2 $\hat{\alpha}$	0.0526	-0.0067	0.0377	-0.0036

2B iii)

However, we are concerned that results of the Synthetic Control method were obtained by chance. Hence, to know the real significance of my results, I perform a randomization inference exercise. I will make the same exercise as before but considering the remaining 35 donor states as placebo

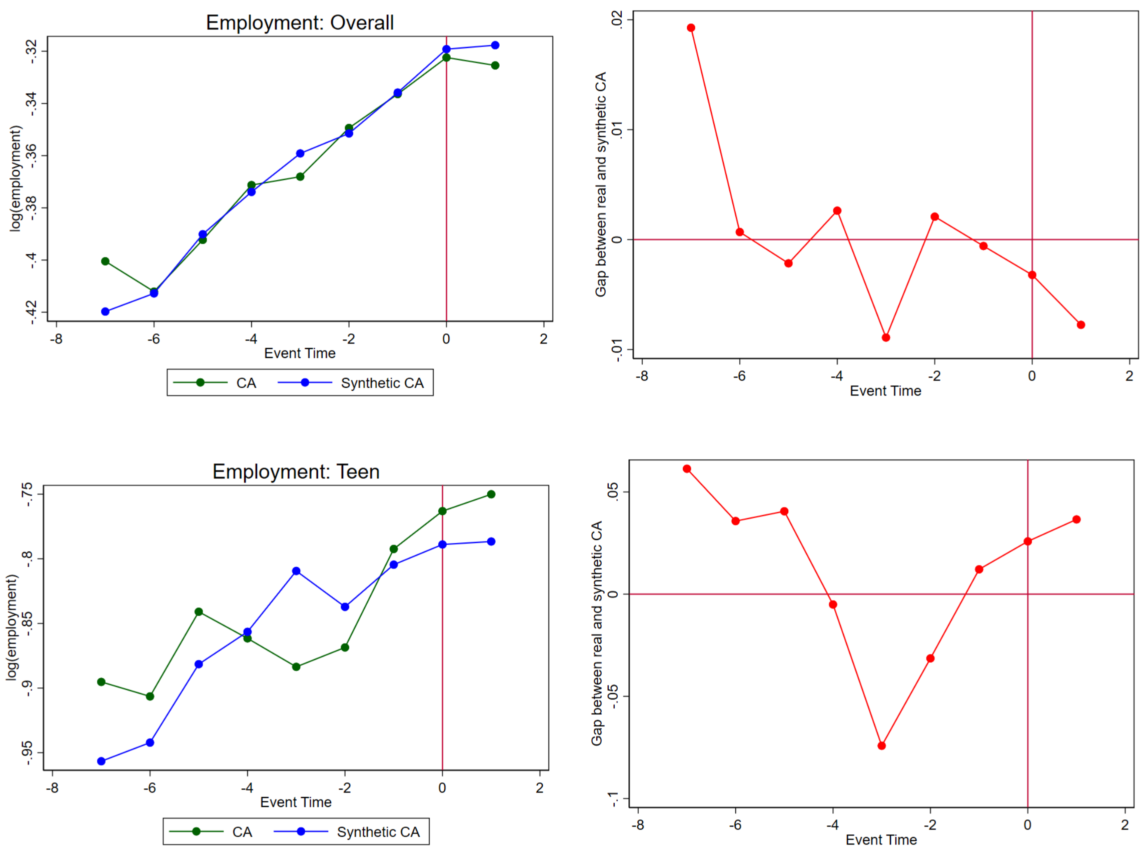

Figure 5: Employment Specification 2

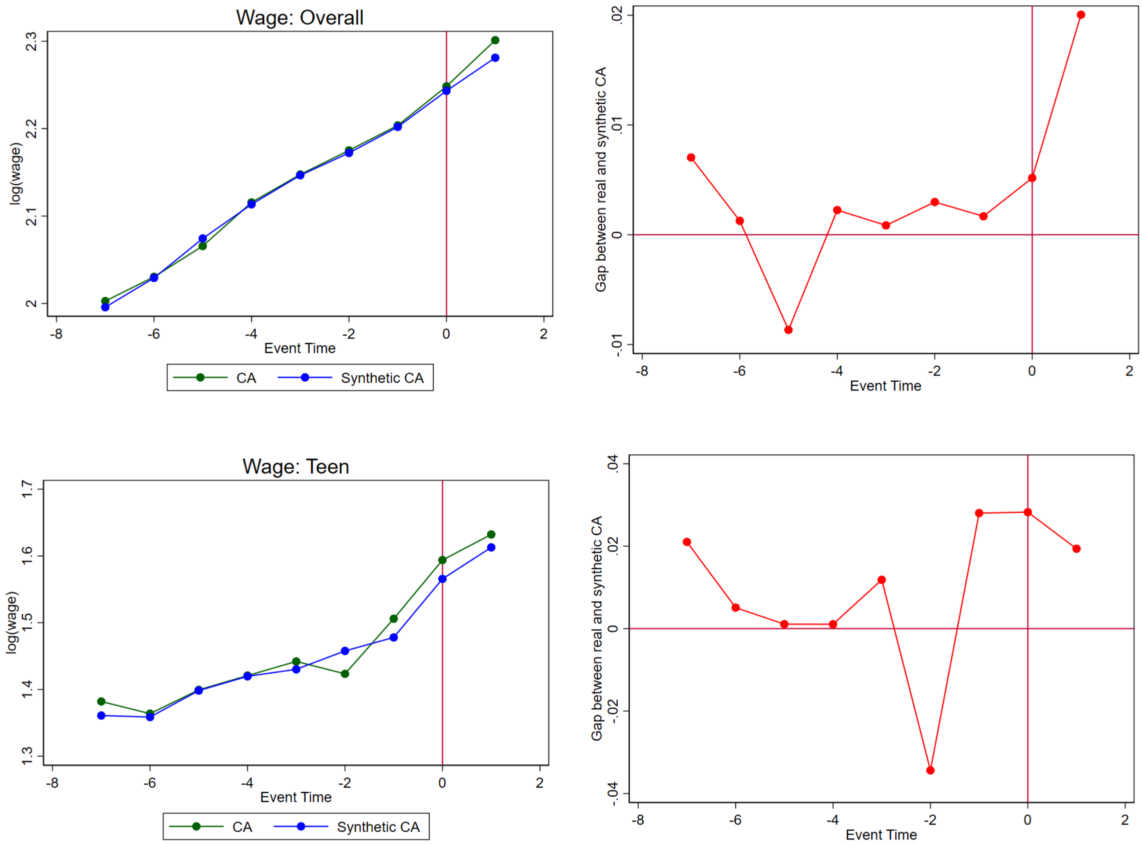

Figure 6: Wage Specification 1

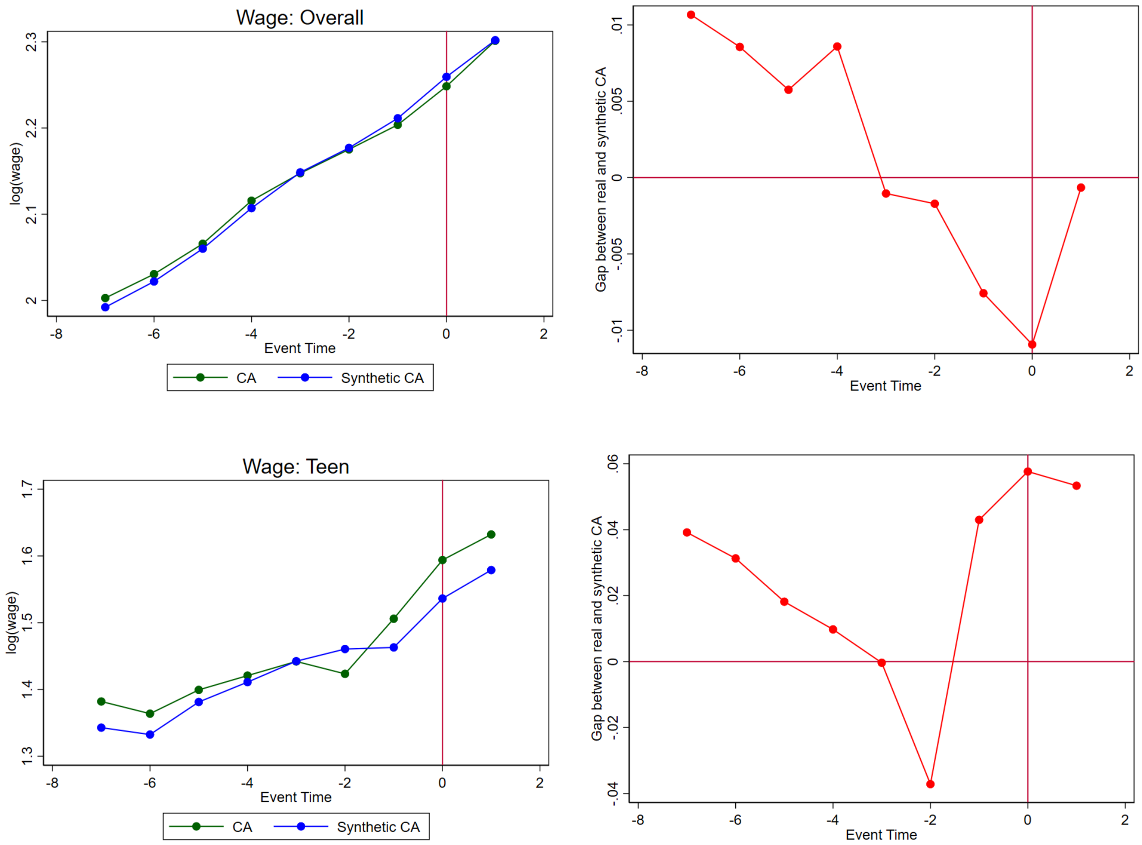

Figure 7: Wage Specification 2

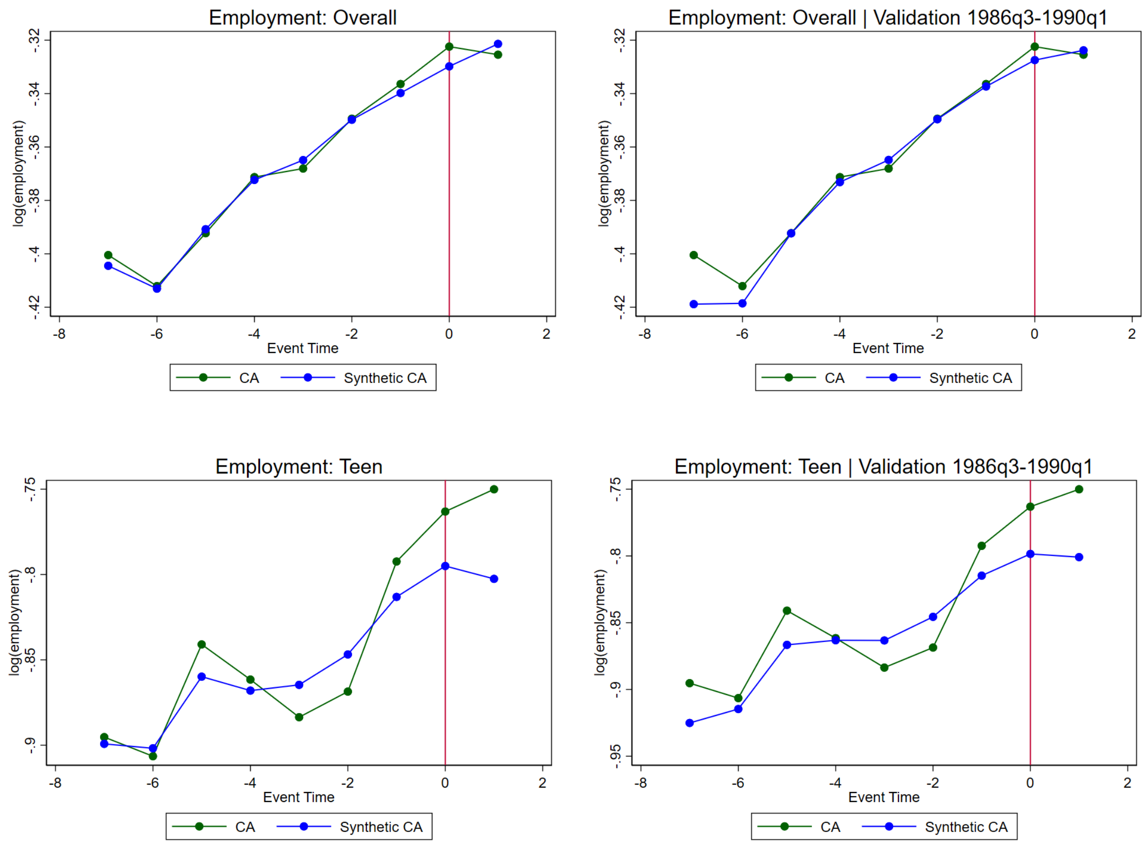

Figure 10: Employment Specification 1

treated. If it happens that the gap between real and synthetic CA is not greater relative to most of the other donors, then we do not have enough statistical evidence to reject the null hypothesis that the increase in minimum wage had no impact on our four outcome variables.

More formally, I apply the synthetic control method to all states (I do not incude California in the donor pool) and get a synthetic "j" that I will call $\hat{Y}_j$. I estimate the Root Mean Sum of Square Errors for the pre and post treatment periods and for all states. That is, I estimate:

$$\hat{r_j} = \frac{RMSPE_{post}}{RMSPE_{pre}}$$

For all states j (including CA, r_1). With these estimates I get an estimated distribution of r called $\hat{F}_e$. Hence, I test the null hypothesis H_0 :

In this part I use 1983q1-1986q2 as the training and 1989q2 as the validation period and repeat the same analysis of part i. This means that the weights used to construct a synthetic California will be chosen to minimize the Sum of Square Residuals only during the validation period. In contrast, in part 1 they were minimized over the whole period. This approach is also known as a "placebo in time" and is used as an additional robustness test for the SC estimations. I perform a visual inspection of

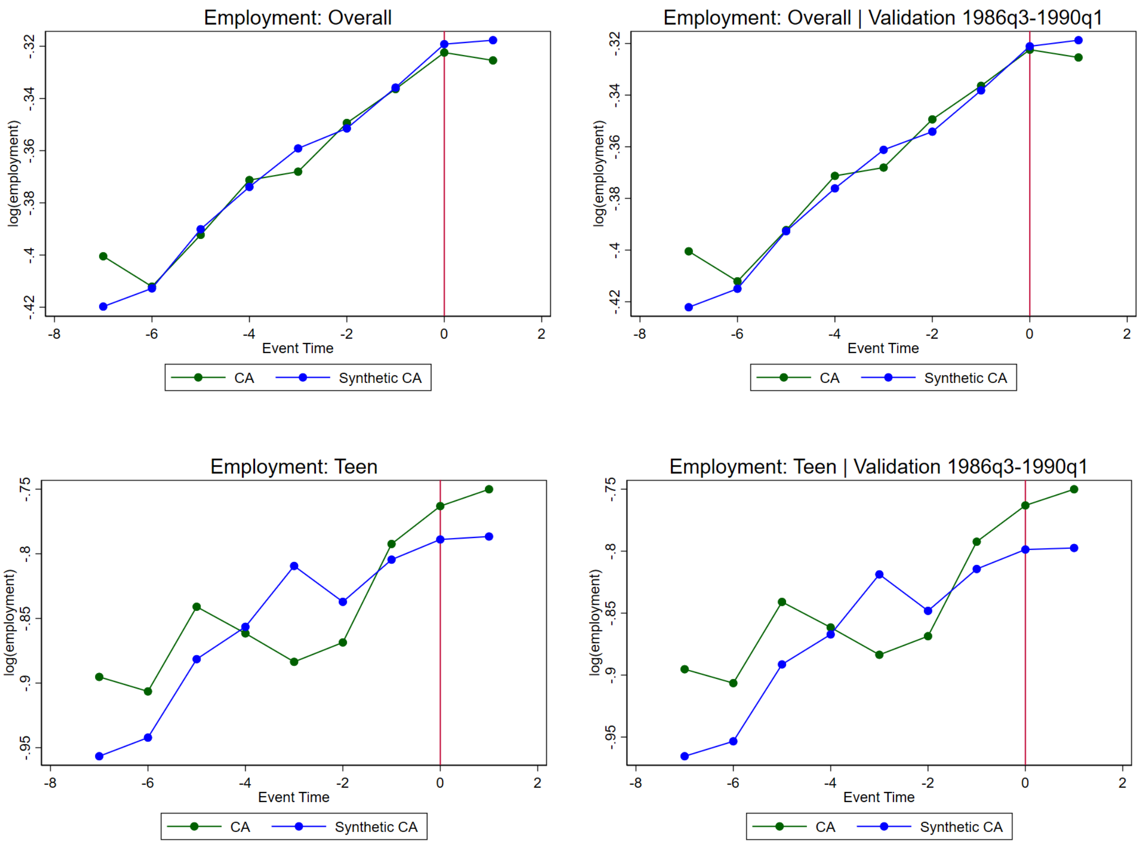

Figure 11: Employment Specification 2

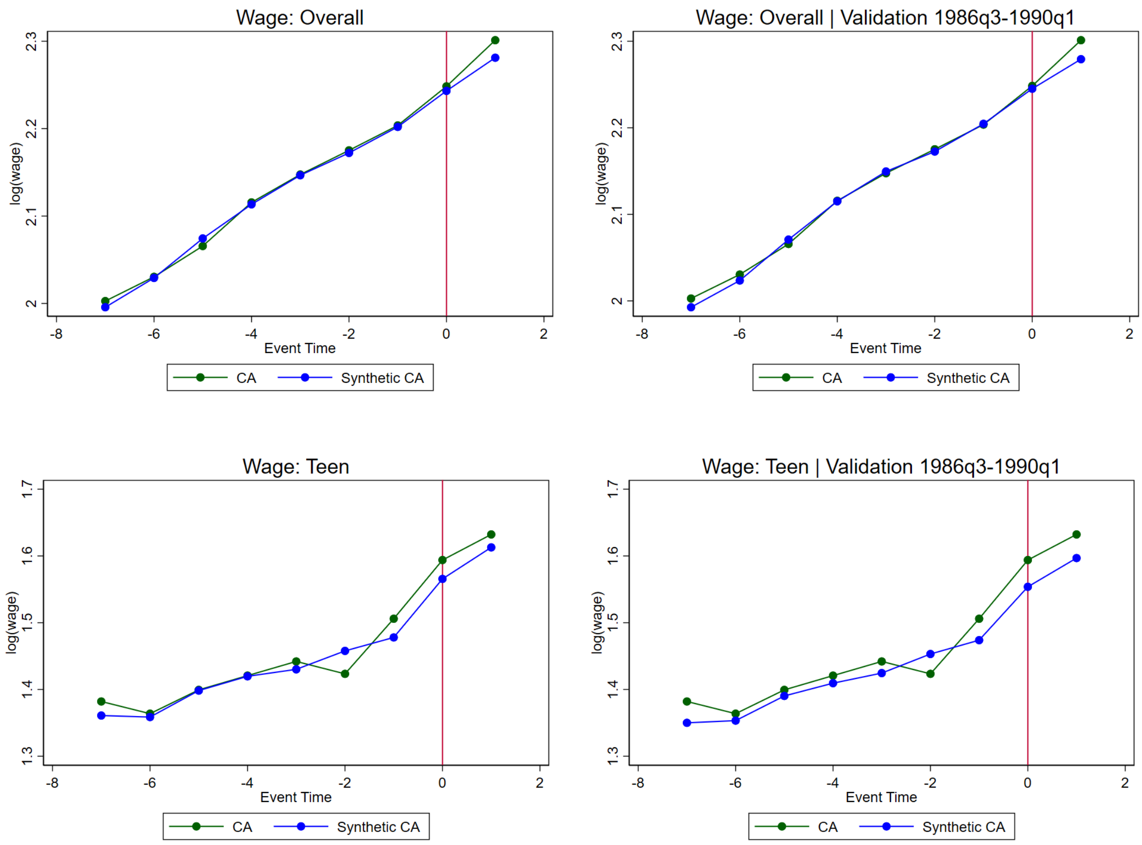

Figure 12: Wage Specification 1

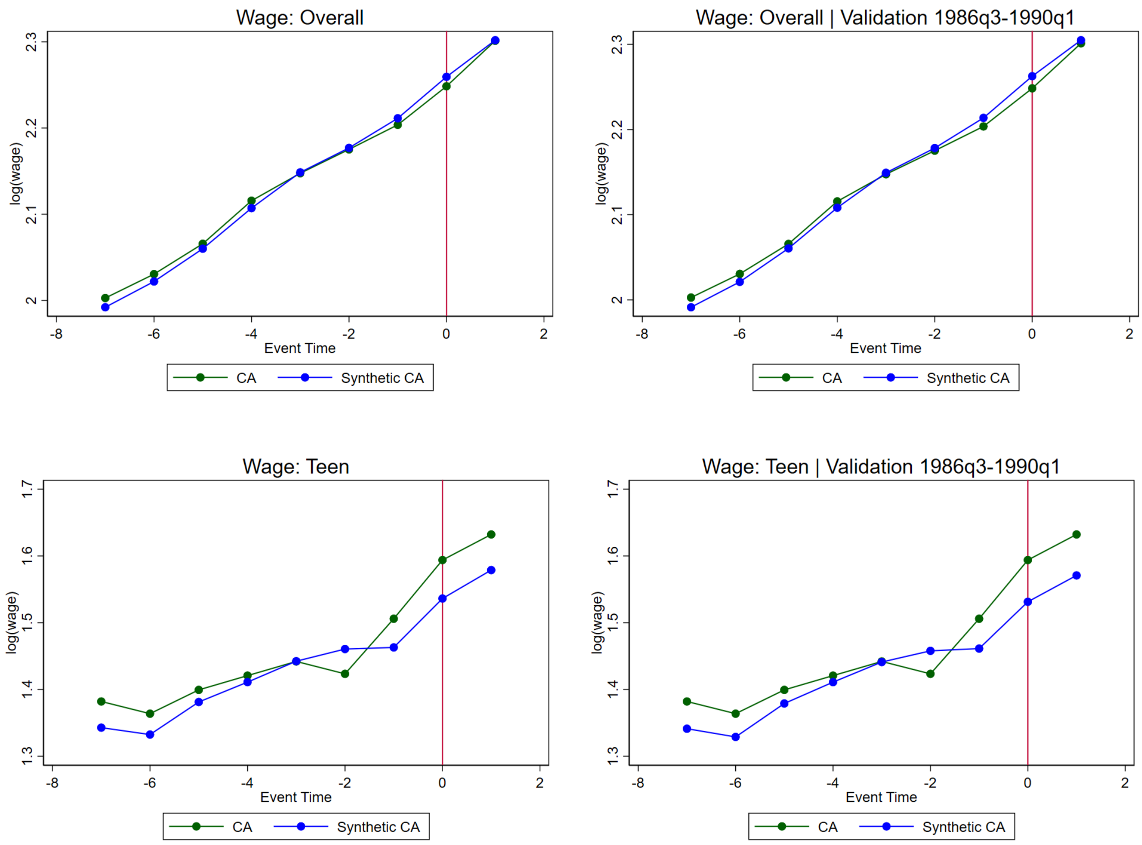

Figure 13: Wage Specification 2

the results, which are found in figures 10 to eleven. On the left we have real and Synthetic California using all the pre-treatment period to minimize the SSR, and in the right using a validation period. We can see that for all variables and specifications, both are practically identical, with a very few small deviations. Hence, focusing on a shorter period doe snot alter the results we obtained in part 2bi.

2B v)

In this part I estimate what I call a "pseudo Synthetic DID", because that estimation method is still not available in Stata. To approximate as much as possible to that method, I perform a weighted DID (Two-way-fixed effects model), using the state-weights obtained using Synthetic Controls that are shown in tables 7 and 8. This method is supposed to reduced the DID bias. The results of the estimation are shown in columns 6 and 7 of Table 3. Column 6 uses the weights obtained from specification 1 and column 7 from S2. The most salient feature of these methods is that no of the estimates are statistically significant. This is surprising given that most estimations find a positive impact of the treatment on average log wage both for teen and overall. Also, the estimates are in general smaller than those obtained with a DID and Propensity Score reweighting.