Information and the Persistence of the Gender Wage Gap;
Early Evidence from California's Salary History Ban

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Abstract

Reductions in wage disparities across race and gender have stagnated in the recent decades. Recent popular focus on these inequalities has led to demands for policy interventions to reduce pay gaps. The most recent legislation intended to improve wage equality prohibits employers from asking about previously earned salaries. The intent of this legislation is to redress persistent pay inequalities. Salary history bans (SHBs) have been implemented in varying degrees (public and private) in multiple cities and states. I use a synthetic control approach to measure the impact of a statewide SHB in California. After the passing of a statewide SHB, statewide female-male earnings ratios increased from 0.77 (where they have been stagnant for the last 12 years) to 0.81. Moreover, I find these results are driven by an increase of the earnings ratio in male-dominated industries.

1 Introduction

Wage inequality across genders improved substantially during the twentieth century but has since plateaued [1], despite the increase in female college enrollment (Goldin 2014; Goldin et al. 2006). Figure 1 illustrates the female to male earnings ratio over the last 50 years.

The literature lacks consensus on the underlying drivers of the gender wage gap. O'Neill and Polachek (1993), Blau and Kahn (2006a), and Mulligan and Rubinstein (2008) all present different possible explanations in the narrowing of the gender pay gap. Some explanations point to bargaining as a cause for the gender pay gap, see Babcock et al. (2003). Others claim differences in competitiveness drives the gender pay gap, see Gneezy et al. (2003) and Niederle and Vesterlund (2007). Alternatively, Manning and Saidi (2010) find little empirical evidence that competitiveness drives the gender pay gap. It is unclear what, if anything, federal, state, and municipal policy makers can do about the issue. A recent tool gaining popularity is the salary history ban (SHB).

This paper is the first to offer evidence on the causal impact of SHBs. Cities and states have recently been adopting variations of SHB laws, which prohibit employers from asking about applicants' previous compensation. These laws address wage discrimination in multiple ways with the intent to reduce salary disparity across genders. First, when current compensation is based on previous salary, past wage discrimination could be perpetuated. Second, women are more likely to work in female-dominated industries, which pay less than male dominated industries. The salary history question could be perpetuating the systemic undervaluation of women's work. SHB laws could eliminate path dependent compensation across multiple margins. Alternatively, SHB laws could have unintended consequences that cause employers to engage in more statistical discrimination. This has been seen before, notably due to the implementation of ban the box policies (Henry and Jacobs 2007; Agan and Starr 2016; Doleac and Hansen 2016; Shoag and Veuger 2016; Starr 2014).

[1] Evidence of the narrowing of the gender pay gap can be seen in Blau and Kahn (2013, 2017) and Blau and Kahn (2000, 2006a, 2006b).

Specifically, this paper focuses on the SHB passed in California in January of 2018. The legislative commentary below demonstrates that pay equality was the motivation behind California's SHB.

> *"Gender wage discrimination is destructive not only for female workers but for our entire economy. Closing the wage gap starts with barring employers from asking questions about salary history so that previous salary discrimination is not perpetuated."* - California legislature

In a competitive market, recent wages signal a worker's marginal productivity, which is of greatest interest to hiring firms (Kotlikoff and Gokhale 1992; Altonji and Pierret 2001; Oyer, Schaefer, et al. 2011; Lange 2007). Labor markets may not be perfectly competitive, but the assumption gives insight to why past wages matter to firms. A previous wage can serve as a signal about the value of previous work. And, firms do ask about prior earnings. Barach and Horton (2017) find over 80% of respondents to a nationally representative Google Survey were asked by their employer about past wages.

Some experimental work has been done on removing compensation history from an online contracting labor market (Barach and Horton 2017). They find that banning wage history results in more call backs in general and more offers to workers with lower past average wages. Their field experiment takes place in a very unique online labor market. To my knowledge, no work has been done evaluating the implementation of salary ban laws in the United States.

This research contributes to a broader literature which examines how changes in employer screening affect labor outcomes for potential employees, specifically, in the context of SHBs. This question about employer screening methods has been addressed in the context of drug testing (Wozniak 2015), credit screening (Bartik and Nelson 2016), test-based worker screening (Autor and Scarborough 2008), criminal history checks (Finlay 2009; Bushway 2004; Holzer et al. 2006, 2007; Stoll 2009), and ban the box policies (Henry and Jacobs 2007; Agan and Starr 2016; Doleac and Hansen 2016; Shoag and Veuger 2016; Starr 2014). These papers suggest limiting information can often have unintended consequences, increasing gaps, or shifting them disproportionately to other marginalized groups.

I use a synthetic control approach to estimate the causal impact of SHB laws in the state of California on gender wage ratios and other labor outcomes of interest calculated from the Basic Monthly Current Population Survey. I find that California's state wide weekly earnings ratio, which has been stagnant around 0.77 for more than 12 years, increases from 0.77 to 0.81 after adoption of a statewide SHB. These results are driven by women earning more in male dominated industries.

The paper proceeds as follows: Section 2 provides background on SHB policies. Section 3 describes the data. Section 4 presents my empirical methodology. Section 5 describes my results. Section 6 discusses and concludes.

2 Background on SHBs

Salary history bans (SHBs) prohibit employers from inquiring about a candidates former or current compensation. Currently, SHBs have been adopted by a growing number of cities and states in varying degrees. Some affect the entire population, some only state employees, and some only city employees. The rapid uptake of SHBs suggest that many entities believe SHBs will improve gender pay inequalities. Table 1 summarizes different cities and states that have adopted SHB laws. Most of the SHBs only apply to a subset of the population. The states with SHBs that affect the entire population and that have been implemented long enough to exist in my data are Delaware and California. As of July 1st 2018, Massachusetts, and Vermont have also implemented SHBs affecting the entire population. [2]

California's SHB became effective January 1 of 2018. Under California's SHB employers are prevented from seeking compensation history directly or through an agent. Like Delaware, applicants may volunteer, without prompting, their own salary history. Additionally, California restricts employers from basing salary solely on the grounds of prior salary. The SHB also requires employers to provide a salary range at the request of the applicant. After an offer

[2] The treatment of these states is too recent to show up in the data. I plan to include them in future analysis.

has been extended, Californian employers may seek the applicant's compensation history.

States that have implemented SHBs affecting state employees only include New York and New Jersey. Cities with SHBs affecting city employees only include Pittsburgh, Chicago, and Louisville. New York City, which had adopted a SHB effective for city employees, recently extended their SHB to the entire population of New York City. Oregon and Hawaii will both adopt a SHB that affects the entire population in January of 2019.

Each SHB adopting entity clearly states that they have adopted the SHB to promote pay equality. The cities and states with a SHB law also tend to be more progressive on the pay equality front. With the recent uptake of SHBs, some states have implemented laws that prevent SHBs from being passed. These states include Michigan, Wisconsin, Iowa, North Carolina, and Tennessee. Philadelphia prevented the implementation of a SHB when a district judge found the SHB to be in violation of the First Amendment's free-speech clause. States preventing the adoption of SHBs have done so with employer compliance in mind. They argue that allowing employment law to change across regions is costly for small business owners.

3 Data

I use data from the Basic Monthly Current Population Survey (CPS). The CPS is a comprehensive survey containing monthly labor force statistics. Other potential useful data sources for employment measures include the American Community Survey, the Quarterly Workforce Indicators, and the Current Employment Statistics, but each of these alternative data sources have a delayed release schedule. The CPS is published roughly 10 days after each month's end. This makes it particularly useful given that the rollout of SHBs is so recent [3]. It samples roughly 60,000 households each month using a rotating panel design and has a response rate averaging around 90 percent. I use the micro-level data, which has

[3]I obtained these data using the lowdown package for R. The data are available for download almost immediately after the end of a month.

responses by all household members as reported by the call recipient; then I aggregate to the state level. My sample includes data from 2006 to the most recent month of the CPS available. I continually update my estimates with each data release.

The CPS is administer by the Census Bureau through personal and telephone interviews. Individuals must be 15 years of age or over and not in the Armed Forces. The person who responds to the phone call is the reference person. They answer questions about all persons in the household. In the case that the reference person is not knowledgeable, the Census Bureau attempts to contact those individuals in the household directly.

I create statewide average weekly earnings ratios of female to male earnings for each state. Additionally, I calculate earnings ratios by age, and by industry of employment. I also calculate employment probabilities by sex. I use each of these calculated values as a potential employment measure of interest.

4 Methodolgy

I use the synthetic control method introduced by Abadie et al. (2010). This method uses pretreatment data to create a counterfactual group similar in outcomes to entities experiencing a discrete change in policy. This method has been used to study many different policy changes including decriminalization of prostitution (Cunningham and Shah 2017), highway police budget cuts (DeAngelo and Hansen 2014), economic liberalization (Billmeier and Nannicini 2013), and increases in minimum wage (Jardim et al. 2017). I follow the work of Botosaru and Ferman (2017) and create synthetic control groups matching outcomes only for each treated entity.

Consider an outcome of interest Y_{it} that is measured over T years, where t indexes the time and the state is indexed by i if its treated and j if its not treated, among I treated states and J untreated states. The synthetic control approach aims to estimate the treatment effect, which is the difference between the treated state, and the unobserved counterfactual.

The estimate for the unobserved counterfactual for state i in time period t is $\sum_j w_j Y_{jt}$, where w_j is the weight assigned to donor state j. The donor states chosen belong to the donor pool of potential control states. The chosen weights w_j^* minimize the distance between Y_{it} and $\sum_j w_j Y_{jt}$ for all pretreatment time periods. For treatment in period τ, the treatment effect α_i for state i in time period t is estimated as $\alpha_{it} = Y_{it} - \sum_j w_j^* Y_{jt}$ for $t \in [\tau, T]$. For each treated state, I create a synthetic control using lagged values of the dependent variable from 2006 to 2018.

To conduct hypothesis tests, I run a set of placebo tests following the method suggested by Abadie et al. (2010). I apply the same synthetic control method with the donor state removed, and the treated states added to the donor pool to create $Synth_{jt}$ for each donor state j and time period t. I compare the pre-treatment and post-treatment mean squared prediction error (MSPE) for each state. I calculate the MSPE ratio as follows:

$$MSPE\ ratio_j = \frac{\sum\limits_{t=\tau}^{T} (Y_{jt} - Synth_{jt})^2}{\sum\limits_{t=1}^{\tau-1} (Y_{jt} - Synth_{jt})^2}.$$

The MSPE measures a relative goodness of fit of the synthetic outcome generated for each state. It provides a metric of pre-treatment fit relative to post treatment fit for each state. A high MSPE ratio can be interpreted as poor post-treatment fit relative to pre-treatment fit. The ranking of the treated states relative to the placebo states provides a permutation based p-value.

I include a relatively long pretreatment window from 2006 to 2017. This allows me to match on pretreatment outcomes only. Botosaru and Ferman (2017) show that matching on covariates is not necessary if the match is made on a long set of pretreatment outcomes. I define treatment in California as the adoption of their state-wide SHB on January 1 of 2018. New York and Delaware are excluded from the potential donor pool as they each adopt a SHB at the end of 2017. The donor pool consists of 47 possible states and Washington D.C.

The synthetic control approach creates an estimate of the counterfactual for California. Absent treatment, the synthetic California should match actual California reasonably well. I test the ability of the synthetic control approach to forecast the earnings ratio in California prior to treatment. I do this by progressively rolling back a placebo treatment, matching on fewer and fewer years. Within this exercise, I examine how well the synthetic control approach does at predicting the earnings ratio within the pretreatment time period. The cross validation exercise shows that the synthetic control approach succeeds in forecasting one step ahead except for in 2018, the year actual treatment begins. This can bee seen in Figure 2. As treatment rolls back in time, the synthetic California matches the actual California in both levels and trends. This cross validation exercise also shows that the synthetic control is a reasonable counterfactual. Figure 2 shows the distribution of the MSPE ratios for the placebo states and for California. As treatment is rolled back in time, California's MSPE ratio goes from being an outlier to well within the mean of the distribution. This figure also illustrates the sensitivity of MSPE ratios. As there are fewer and fewer pretreatment years, the post treatment MSPE can get very large driving up the MSPE ratio.

The composition of the synthetic control can be seen in Figure 3. The time-series of the female to male earnings ratio before California's SHB is best reproduced by a combination of 29% Nevada, 24% Arizona, 16% D.C., 12% North Carolina, 6% Hawaii, 4% Florida, and, 1% Oregon. All other donor states are assigned a weight of zero.

The weights chosen are consistent across the placebo treatments in the cross validation exercise. Table 2 shows the composition of weights as the placebo treatment is rolled back in time. Notably, the composition of the synthetic California is stable across fewer and fewer pre treatment years. The weights chosen are consistent for each of the cross validation years and they consistently predict the actual California earnings ratio.

Using the detailed industry codes, I classify each industry in the CPS as male or female dominated. I classify male dominated industries as industries with more than 50 percent male workers and classify industries with more than 50% female workers to be female dominated.

I use the industry gender compositions reported by the Equal Employment Opportunity Commission in Cartwright et al. 2011 to classify each industry as male or female dominated. Female dominated industries are in the service producing domain and male dominated industries tend to be in the goods producing domain.

5 Results

The cross validation exercise from the previous section showed that the synthetic California generated by the synthetic control approach does well at predicting out of sample. I first consider the effect of the SHB on state-wide earnings ratios. I then investigate weekly earnings, hours worked, and hourly wages by sex. Then I turn to industry classifications reported in the CPS and analyze the effect of SHB within predominately male and predominantly female industries, as well as goods vs service industries. I split my sample by age, and investigate the impact of the SHB among older and younger populations. Finally, I investigate the impact of SHBs on the probability of employment for both males and females at the state level and within industries.

5.1 Female to Male State-Wide Earnings Ratio

Figure 4a illustrates the female to male average weekly earnings ratio in California and its synthetic counterpart from 2006 to 2018. Over the 11 year window from 2006 to 2017 California's synthetic counterpart closely matches, both in trends and levels, the observed female to male earnings ratio. In the window after California adopts the state-wide SHB, its average female to male earnings ratio diverges from from 0.77 to 0.82. Not only does the California earnings ratio diverge from its synthetic counterpart, it also diverges from the level it has been close too for the past 11 years. Figure 4b visually illustrates the statistical precision of my synthetic control estimate. The red line represents the difference between California and its synthetic counterpart. The red line hovering around zero before the SHB illustrates that synthetic California is a close match for actual California. After the SHB, California's earnings ratio diverges from its synthetic counterpart. Only a few of the placebo states deviate close to as much as California post SHB. In Figure 4c I calculate the pre MSPE to post MSPE ratio for each placebo state and California. Notably, California has the highest MSPE ratio, over 3 times higher than the next highest MSPE ratio. There is probability 1/48=0.0208 that we would observe a MSPE ratio as large as California's if we randomly assigned a SHB to a state in the data[4].

My synthetic control estimates suggest that California adopting a salary history ban increased average weekly female earnings relative to average weekly male earnings. I estimate the change in the earnings ratio from its synthetic counterpart to be .0239 which is a 10.4% decrease in the earnings gap. This finding suggests that the earnings ratio improved as a result of the SHB. I next explore potential mechanisms through which SHBs have caused the change in the earnings ratio.

5.2 Weekly Earnings, Hours Worked, and Wages by Sex

The earnings ratio could change if there is a disproportional change in the level of either male or female earnings. Changes in earnings could be a result of changes in wages or changes in hours worked. For these reasons, I investigate average weekly earnings, hours worked, and hourly wages by gender.

Figure A.1a plots average weekly earnings data for California and its synthetic counterpart by sex. For both males and females, the trends and levels of the synthetic control group closely follow California's for the years prior to the SHB. After the SHB the male earnings slightly decrease and female earnings increase relative to each of their synthetic counterparts. The point estimates corresponding with Figure A.1a are reported in Table 5 with permutation based p-values in brackets. While the increase in female earnings and decrease in male earnings are not significantly different from zero, we know they jointly significant. Figures A.1b and A.1c illustrate the precision of the synthetic control estimates. The solid red depicts California's deviation from its synthetic counterpart for each sex. The red line hovers around

[4]The p-value of 0.0208 is the lowest possible p-value given the number of states in my sample.

zero before the SHB, which illustrates that synthetic California is a close match for actual California for each sex. The red line lying well within the deviations observed in the post period for the placebo states illustrates that these slight deviations are likely due to noise.

The analogous analysis for average weekly hours worked by sex is shown in Figure A.2a. For both females and males, the synthetic control matches the levels and trends of average weekly hours worked. After the SHB, average weekly hours worked slightly decrease for males and slightly increase for females relative to their synthetic counterpart. The point estimates can be found in Table 5 with permutation based p-values in brackets. Females worked .37 hours more than their synthetic counterpart, and males worked .69 hours less than their synthetic counterpart. While the change in hours worked for males is larger than females, it is not statistically different from zero and is likely due to noise. Figures A.2b and A.2c illustrate the statistical precision of these point estimates. They show deviations from average weekly hours worked in California and its synthetic counterpart relative to the placebo states for each sex. For females, the synthetic counterpart matches actual hours worked very well. The tight match pre SHB and deviation post SHB results in a small p-value.

Figure A.3a shows average weekly hourly wages for California and its synthetic counterpart by sex. The synthetic control group does a good job of matching in levels and trends for actual California's hourly wage for both sexes. After the SHB, average weekly hourly wage slightly decreases for males and slightly increases for females relative to their synthetic counterparts. Table 6 reports the point estimates and permutation based p-values in brackets. Figures A.3b and A.3c illustrate the statistical precision of these point estimates. Similar to the figures for earnings and wages, the solid red line represents the difference from California and its synthetic counterpart. For males, the red line hovers around zero both before and after the SHB. For females, the red line increases after the SHB, but the deviation is well within the deviations observed in the post period for the placebo states.

5.3 Industry of Employment

The above results are state-wide averages, however, it is possible that the effects of the

SHB are not uniform across the state. For this reason, I investigate differential effects within male dominated and female dominated industries. As noted, I define an industry as female dominated if it has a composition of more than 50 percent females within that industry. Male dominated industries are defined analogously. I repeat the earnings ratio analysis within male and female dominated industries. Similar to above, I then investigate earnings, hours, and, wages within male and female dominated industries.

Figure A.4 illustrates the California female to male average weekly earnings ratio and their synthetic counterpart for each industry. The synthetic California earnings ratio matches actual California in both levels and trends before the SHB in both male and female dominated industries. The match is slightly better for female dominated industries. After the SHB, the actual ratio does not deviate from the synthetic ratio for female dominated industries. In male dominated industries, however, the actual California earnings ratio increases relative to its synthetic counterpart. Table 4 reports the point estimates and the permutation based p-values. Figure A.5 illustrates the statistical precision on these estimates by plotting the difference in California and each placebo state relative to its synthetic counterpart. Within female dominated industries, the difference between the actual California earnings ratio and its synthetic counterpart is close to zero both before and after the SHB. For male dominated industries, the difference between the California earnings ratio and its synthetic counterpart hovers around zero before the SHB. After the SHB, the ratio deviates from its synthetic counterpart by a large amount relative to the placebo state deviations. This results in a relatively small p-value for the changes in the earnings ratio within male dominated industries. Within female dominated industries the difference between the California earnings ratio and its synthetic counterpart hovers around zero before and after the SHB.

These results suggest the change in the state-wide earnings ratio is composed of larger changes in male dominated industries and relatively smaller changes within female dominated industries. I estimate the increase in the female to male earnings ratio to be .0579, which is a 32% decrease in the earnings gap (within male dominated industries). Next I turn to mechanisms of these findings with in male and female dominated industries.

5.3.1 Weekly Earnings, Hours Worked, and, Wages by Sex and Industry

The earnings ratio within industries could change if there is a disproportional change in the level of either male or female earnings within industries. Changes in earnings could be a results of changes in wages or changes in hours worked. For these reasons, I investigate average weekly earnings, hours worked, and hourly wages by gender within male and female dominated industries.

Figure A.6a illustrates male and female average weekly earnings in female dominated industries compared to their synthetic counterpart. For both sexes, the synthetic California matches actual California earnings in both levels and trends before the SHB. After the SHB, female earnings in female dominated industries continue to match their synthetic counterpart. Male earnings in female dominated industries deviate slightly below their synthetic counterpart. Table 5 provides the point estimates and the permutation based p-values in brackets. The p-values for both male and female earnings within female dominated industries indicate that I cannot reject the null hypothesis that the SHB caused no changes. Figures A.6b and A.6c illustrate the gap between California average weekly earnings and its synthetic counterpart vs the placebo states. For both females and males, post SHB deviations lie well within deviations of the placebo states.

Figure A.7a illustrates male and female average weekly earnings in male dominated industries compared to their synthetic counterpart. Again, for both sexes, the synthetic California matches actual California earnings in both levels and trends before the SHB. After the SHB, male earnings in male dominated industries continue to match their synthetic counterpart. Female earnings in male dominated industries increase relative to their synthetic counterpart. Figure A.7b and A.7c illustrate the gap between California weekly earnings within male dominated industries and their synthetic counterpart. Both the female and male earnings gap hover around zero before the SHB, indicating that the synthetic control is a good match.

After the SHB, the female earnings' deviation from their synthetic counterpart is among the highest of the placebo states. The point estimates and the permutation based p-values in brackets can be seen in Table 5.

Figure A.8a illustrates male and female average weekly hours worked in female dominated industries compared to their synthetic counterpart. For both sexes, the synthetic California matches actual California hours worked in both levels and trends before the SHB. After the SHB, female hours worked in female dominated industries increase 1 hour per week relative to their synthetic counterpart. Male hours worked in female dominated industries continue to match their synthetic counterpart. Table 5 provides the point estimates and the permutation based p-values in brackets. The p-value for male hours worked within female dominated industries indicate that I cannot reject the null hypothesis that the SHB caused no changes. Figures A.8b and A.8c illustrate the gap between California average weekly earnings and its synthetic counterpart vs the placebo states. For females, the post SHB deviation is among the largest of deviations for the placebo states.

Figure A.9a illustrates male and female average hours worked in male dominated industries compared to their synthetic counterpart. For both sexes, the synthetic California matches actual California worked in both levels and trends before the SHB. After the SHB, female hours worked in male dominated industries increase relative to their synthetic counterpart. Male weekly hours worked also slightly increase in male dominated industries post SHB. Table 5 provides the point estimates and the permutation based p-values in brackets. Figures A.9b and A.9c illustrate the gap between actual California's average weekly hours worked and its synthetic counterpart vs the placebo states. For females, the post SHB deviation is among the largest deviations of the placebo states. This results in a relatively small p-value. For males, the p-value suggests the point estimate is not statistically distinguishable from zero.

Figure A.10a illustrates male and female average hourly wage in female dominated industries compared to their synthetic counterpart. For both sexes, the synthetic California matches the overall trend of actual California but with less variation. After the SHB, female hourly wages in female dominated industries slightly increase relative to their synthetic counterpart. On the other hand, male hourly wages in male dominated industries slightly decrease relative to their synthetic counterpart. Table 6 provides the point estimates and the permutation based p-values in brackets. Figures A.10b and A.10c illustrate the gap between actual California's average hourly wage and its synthetic counterpart vs the placebo states. The poor match pre SHB for both males and females makes their deviation post SHB indistinguishable from zero.

Figure A.11a illustrate male and female average hourly wages in male dominated industries compared to their synthetic counterpart. For both sexes, the synthetic California matches actual California in both levels and trends before the SHB. After the SHB, female hourly wage in male dominated industries increase relative to its synthetic counterpart. Male hourly wage in male dominated industries decrease slightly relative to its synthetic counterpart. Table 6 provides the point estimates and the permutation based p-values in brackets. Figures A.11b and A.11c illustrate the gap between actual California's average weekly earnings and its synthetic counterpart vs the placebo states. For females, The deviation post SHB is among the largest of the placebo states. This combined with a relatively good pre-treatment fit results in a small p-value. The male deviation post SHB is well within the deviations of the placebo states and thus is not distinguishable from zero.

The above analysis informs which industries are contributing to the statewide increase in the earnings ratio. Within female dominated industries, the improvement in the earnings ratio is smaller than at the state level. This result is driven by a smaller decrease for females than males in the level of weekly earnings. Wages slightly increase for females and decrease for males. This combined with a larger decrease in hours worked by males than by females is consistent with the changes in weekly earnings by sex in female dominated industries referenced above. Within male dominated industries, the increase in the earnings ratio is much larger than the state level. This is driven by a larger increase in weekly earnings for females than for males. The changes in weekly earnings are driven by the joint effect of increased wages and hours for females and an increase in hours that off-set a slight decrease in wages for males.

5.4 By NAICS industries

The North American Industry Classification System (NAICS) is a slightly more common way to define industry splits. For this reason I repeat the analysis above for goods producing and service providing industries classified according to the (NAICS) codes included in the CPS. Goods producing industries are a subset of male dominated industries, while service producing industries include both female and male dominated industries. Figure A.12 illustrates the earnings ratio and its synthetic counterpart for goods producing and service providing industries. In the goods producing industries, the synthetic California matches the actual California earnings in levels and trends almost perfectly. The service providing industries also provide a decent, but not as precise match in levels and trends of the female to male earnings ratio. The point estimates and permutation based p-values are reported in Table 4. Figure A.13 illustrates the precision of these estimates. The almost exact match pre SHB and slight deviation post SHB for goods producing industries result in a large MSPE ratio and relatively small p-value. The service providing industry has a slightly noisier match. It has a considerable deviation relative to its synthetic counterpart amongst the placebo states which results in a small p-value.

The effect of the SHB becomes increasingly larger as populations decrease in size. The earnings ratio increases at the state level after the SHB. Within male dominated industries, a subset of the statewide population, the earnings ratio increases by a larger amount. Within goods producing industries, a subset of male dominated industries, the increase in the earnings ratio is larger yet. These results suggest the effects of the SHB are not uniform across subsets of the statewide population. Rather, they are largest amongst goods producing industries, all of which are composed by 50 % or more male workers.

5.5 By Age

One argument for SHBs is their potential to eliminate path dependence. The length of compensation history will vary by an individual's time spent in the labor force. For this reason, I investigate the effect of the SHB on different age groups. I split the population at age 35.

Figure A.14 plots the average weekly earnings ratio by age. For individuals younger than 35, the synthetic California matches the actual California earnings ratio in levels, but not trends. The variation in the data causes the synthetic control approach to construct a poor match. After the SHB, the actual earnings ratio increases by more than its synthetic counterpart. The permutation based p-values suggest that this observed deviation is due to statistical noise, and there is little evidence supporting an actual causal deviation.

For individuals older than 35, the synthetic group closely mirrors actual California in both trends and levels from 2006-2017. After treatment, the actual California earnings ratio increases relative to its synthetic counterpart. The point estimates and permutation based p-values are included in Table 4. Figure A.15 illustrates the precision of the estimates. For individuals older than 35 the California earnings ratio is matched well by its synthetic counterpart prior to the SHB. After the SHB the deviation is among the largest of the placebo states, resulting in a large MSPE ratio and small p-value.

5.5.1 Weekly Earnings, Hours Worked, and Wages by Sex and Age

The earnings ratio within industries could change if there is a disproportional change in the level of either male or female earnings within age groups. Changes in earnings could be a result of changes in wages or changes in hours worked. For these reasons, I investigate average weekly earnings, hours worked, and hourly wages by gender within old and young age groups.

Figure A.16a illustrates male and female average weekly earnings for individuals younger than 35 compared to their synthetic counterpart. For both sexes, the synthetic California matches actual California earnings in both levels and trends before the SHB. After the SHB, female earnings in female dominated industries continue to match their synthetic counterpart. Male earnings in female dominated industries deviate slightly below their synthetic counterpart. Table 5 provides the point estimates and the permutation based p-values in brackets. The p-values for both male and female earnings within female dominated industries indicate that the point estimates are not statistically different from zero. Figures A.16b and A.16c illustrate the gap between actual California average weekly earnings and their synthetic counterpart vs the placebo states. For both females and males, post SHB deviations lie well within deviations of the placebo states.

Figure A.17a illustrates male and female average weekly earnings for individuals older than 35 compared to their synthetic counterpart. Again, for both sexes, the synthetic California matches actual California earnings in both levels and trends before the SHB. After the SHB, male earnings among individuals older than 35 deviate slightly below their synthetic counterpart while female earnings increase slightly relative to their synthetic counterpart. Table 5 reports the point estimates and permutation based p-values in brackets. Figures A.17b and A.17c illustrate the gap between California weekly earnings among individuals above 35 and their synthetic counterpart vs the placebo states.

Figure A.18a illustrates male and female average weekly hours worked among individuals below age 35 compared to their synthetic counterpart. For both sexes, the synthetic California matches actual California hours worked in both levels and trends before the SHB. After the SHB, female hours worked continue to match their synthetic counterpart. Male hours worked continue on the same trajectory, but the synthetic counterpart increases after the SHB. Table 5 provides the point estimates and the permutation based p-values in brackets. Figures A.18b and A.18c illustrate statistical precision of the point estimates. They show the the gap between California average weekly hours worked and its synthetic counterpart vs the placebo states.

Figure A.19a illustrates male and female average weekly hours worked among individuals above age 35 compared to their synthetic counterpart. For both sexes, the synthetic California matches actual California hours worked in both levels and trends before the SHB. After the SHB, female hours worked increase slightly relative to their synthetic counterpart. Male hours decrease slightly relative to their synthetic counterpart after the SHB. Table 5 provides the point estimates and the permutation based p-values in brackets. Figures A.19b and A.19c illustrate statistical precision of the point estimates. They show the gap between actual California average weekly hours worked and its synthetic counterpart vs the placebo states. Noticeably, for both males and females, the deviation from the synthetic counterpart is well within the deviations among placebo states.

Figure A.20a illustrates male and female average hourly wage among individuals below age 35 compared to their synthetic counterpart. For both sexes, the synthetic California matches actual California average hourly wages in both levels and trends before the SHB. After the SHB, female average hourly wage among individuals below age 35 increases relative to their synthetic counterpart. Male average hourly wage among individuals below age 35 decreases slightly relative to their synthetic counterpart. Table 6 provides the point estimates and the permutation based p-values in brackets. Figures A.20b and A.20c illustrate the the statistical precision of these point estimates. They show the gap between actual California average hourly wages and their synthetic counterpart vs the placebo states. Deviations from their synthetic counterpart for both sexes post SHB are well within the deviations of the placebo states and thus is not distinguishable from zero.

Figure A.21a illustrates male and female average hourly wage among individuals above age 35 compared to their synthetic counterpart. For both sexes, the synthetic California matches actual California average hourly wage in both levels and trends before the SHB. After the SHB, female average hourly wage among individuals above age 35 increases relative to their synthetic counterpart. Male average hourly wage among individuals above age 35 decreases relative to their synthetic counterpart. Table 6 provides the point estimates and the permutation based p-values in brackets. Figures A.20b and A.20c illustrate the the statistical precision of these point estimates. They show the gap between California average hourly wages and their synthetic counterpart vs the placebo states. Deviations from their synthetic counterpart for both sexes post SHB are well within the deviations of the placebo states and thus are not distinguishable from zero.

The above analysis suggests the increase in the earnings ratio among individuals above age 35 is driven by the joint increase in female earnings and decrease in male earnings. The increase in female earnings is likely a result of females increasing average hours worked per week.

5.6 Employment Probabilities

The above effects in earnings and wages could be driven by systematic entrance to or exit from the labor market as a result of the SHB. With this in mind, I consider the effect of SHB policies on the probability that individuals are employed. I calculate employment probabilities

Figure A.22 plots the probability of employment in California against its synthetic counterpart for both females and males. The synthetic control approach matches actual California employment probabilities in both levels and trends with almost no deviation. Female employment probability does not deviate from its synthetic counterpart after the SHB. Male employment probability increases slightly relative to its synthetic counterpart after the SHB. Neither of these deviations are statistically different from zero. Table 7 contains the point estimates and permutation based p-values in brackets. Figure A.23 illustrates the statistical precision of the point estimates reported in Table 7. Both male and female employment probabilities fit their synthetic counterpart reasonably well before and after the SHB. I also calculate the change in employment probability within male and female dominated industries. Within both of these industries, the change in employment probability after the SHB is small and statistically indistinguishable from zero.

The implications of the employment probability findings are two fold. The SHB does not appear to be causing systematic entrance to or exit from the California labor market for either males or females; more specifically, within the labor markets of male dominated and female dominated industries, there does not appear to be systematic entrance or exit of either males or females. The observed change in female to male earnings ratio after implementation of the SHB is likely driven by the SHB's impact on earnings, hours worked, and wages of individuals participating in the labor market before the SHB.

5.7 Robustness

I explore the sensitivity of my results to changes in the model specification. I replicate Table 4 using multiple model specifications.

In my baseline specification, I use levels of the data reported in the CPS. Synthetic control results can be sensitive to how the data are treated. For this reason I replicate Table 4 using demeaned data. I demean the data for each state by subtracting the pretreatment mean from the entire time series. The synthetic control approach chooses donor states by matching on pretreatment levels and trends. Demeaning the data allows the synthetic control approach to choose donors by matching on variation only. Column 2 of Table 8 reports my results using demeaned data. I include my baseline results in Column 1 of Table 8, previously reported in Table 4, for ease of comparison. The magnitude and statistical precision moving from column one to column two remain relatively stable. One exception is within good producing industries, where the demeaned estimates are less than half the size of the level estimates. This is likely due to synthetic California having a donor which matches levels well, but not trends. The result is a synthetic California with a higher predicted earnings ratio than in Figure A.12.

Another possible way to scale the data is to divide the whole time series by the pretreatment mean for each state. Column 3 of Table 8 reports estimates produced using scaled data. The scaled data produces estimates similar in magnitude and statistical significance to Columns 1 and 2.

California is one of a few treated states that exist in the data. New York and Delaware also adopted SHBs around a similar time. The synthetic control approach is not able to create a synthetic counterpart that matches the actual data reasonably well for either of these states. I offer an alternative where I pool data across the three states and treat them as one state. I pool observations from California, Delaware, and New York using the micro level data. I replicate the analysis in Table 4 using pooled data from all three states. The sampling frequency of each state is population adjusted; the pooled data are roughly 60% California, 30% New York, and, 10% Delaware. The pooled estimates are reported in Column 4 of Table 8. The magnitude and statistical precision of the pooled point estimates are consistent with the baseline specification.

As a final test of model sensitivity, I replicate Table 8 in Table 9 using the replication weights provided by the CPS. The replication weights can be used for creating a representative sample. Across the two tables the point estimates are consistent in magnitude and statistical precision.

6 Conculsion

Salary history bans (SHBs) are being implemented in cities and states as a popular policy to help close the gender wage gap. The intent of these policies is to remove path dependence in compensation. Removing information from the hiring process has been shown to unintentionally incentivize statistical discrimination in other settings. For example, ban the box policies have been shown to increase statistical discrimination by employers (Henry and Jacobs 2007; Agan and Starr 2016; Doleac and Hansen 2016; Shoag and Veuger 2016; Starr 2014).

In this paper, I provide the first evidence of the causal impact of statewide salary history bans. I find that implementation of a SHB increases female earnings relative to male earnings. I estimate SHBs cause the state level earnings ratio to increases by .0298, a 10% decrease in the gender earnings gap. The effect of the SHB is particularly robust across multiple model specifications, including pooling three treated states into one state. Based on the trend that existed in the earnings ratio before the SHB, a 0.0298 increase would have taken 5 or more years.

These results are driven by females earning more relative to males within male dominated industries. The earnings ratio increases by .0579 in industries with more than 50% males, a 30% decrease in the gender earnings gap within male dominated industries. Within male dominated industries, systemic gender discrimination is more likely to be present. SHBs create one more safeguard against pay discrimination, and thus have the largest impact where the most pay discrimination is taking place.

I find no evidence that males or females are systematically entering or exiting the labor market as a result of the SHB. The observed increase in the earnings ratio is likely driven by changes in earnings among individuals who participated in the labor market before implementation of the SHB.

Given the recent implementation of SHBs, this paper is limited to identifying the immediate impacts of SHBs. This paper also only examines one potential margin (female to male earnings) for pay disparity. Eliminating path dependent compensation could redress pay disparities across other margins as well. Future research will shed light on the long run impact of SHBs, as well as the impact of SHBs on other populations that have historically experienced disparities in pay. SHB policies were designed with the goal of reducing gender-based pay disparities. This research on the early effects of California's SHB shows that this policy has the intended result of reducing pay inequities experienced by female employees. The immediate effects of the SHB do not appear to cause an increase in unintended statistical discrimination toward the population for which the policy was designed to help, as in similar labor policies such as ban the box. The effects of California's SHB on the female to male earnings ratio suggests that SHBs may be an effective policy for reducing the gender pay gap.

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Tables

Table 1: Salary History Ban Laws by Date and Region

Adoption Date	Region	Population
12/4/16	NYC	City employees
1/9/17	New York	State employees
1/25/17	New Orleans	City employees
3/01/17	Pittsburgh	City employees
10/31/17	NYC	All
12/14/17	Delaware	All
1/1/18	California	All
4/10/18	Chicago	City employees
2/1/18	New Jersey	State employees
5/17/18	Louisville	City employees
7/1/18	Massachusetts	All
7/1/18	San Francisco *(strong)*	All
7/1/18	Vermont	All
7/26/18	Kansas City	City employees
1/1/19	Oregon	All
1/1/19	Hawaii	all

Table 3: California Synthetic Control
Female to Male Average Weekly Earnings

Year	Actual	Synthetic	Difference
2006	0.767	0.764	0.0031
2007	0.764	0.767	-0.0023
2008	0.766	0.767	-0.0007
2009	0.763	0.764	-0.0014
2010	0.780	0.777	0.0036
2011	0.784	0.786	-0.0012
2012	0.776	0.777	-0.0016
2013	0.788	0.785	0.0031
2014	0.789	0.789	-0.0003
2015	0.785	0.783	0.0021
2016	0.781	0.780	0.0008
2017	0.770	0.771	-0.0007
2018	0.801	0.77	0.0303

Table 2: Cross Validation Weights

	Weight by Placebo Treatment Year							
Donor State	2018	2017	2016	2015	2014	2013	2012	2011
Alabama	-	-	-	-	-	-	-	-
Alaska	-	-	-	-	-	-	-	-
Arizona	24%	23%	23%	26%	28%	26%	25%	28%
Arkansas	-	-	-	-	-	-	-	-
Colorado	-	-	-	-	-	-	-	-
Connecticut	-	-	-	-	-	-	-	-
District of Columbia	16%	16%	16%	15%	17%	16%	16%	14%
Florida	4%	5%	4%	-	-	10%	12%	-
Georgia	-	-	-	-	-	-	-	-
Hawaii	6%	6%	6%	6%	1%	1%	2%	25%
Idaho	-	-	-	-	-	-	-	-
Illinois	-	-	-	-	-	-	-	-
Indiana	-	-	-	-	-	-	-	-
Iowa	-	-	-	-	-	-	-	-
Kansas	-	-	-	-	-	-	-	-
Kentucky	-	-	-	-	-	-	-	-
Louisiana	-	-	-	-	-	-	-	-
Maine	-	-	-	-	-	-	-	-
Maryland	-	-	-	-	-	-	-	-
Massachusetts	-	-	-	-	-	-	-	-
Michigan	-	-	-	-	-	-	-	-
Minnesota	-	-	-	-	-	-	-	-
Mississippi	7%	6%	7%	7%	9%	-	-	-
Missouri	-	-	-	-	-	-	-	-
Montana	-	-	-	-	-	-	-	-
Nebraska	-	-	-	-	-	-	-	-
Nevada	29%	28%	30%	32%	32%	18%	18%	-
New Hampshire	-	-	-	-	-	-	-	-
New Jersey	-	-	-	-	-	-	-	-
New Mexico	-	-	-	-	-	-	-	-
North Carolina	12%	13%	13%	12%	12%	22%	23%	24%
North Dakota	-	-	-	-	-	-	-	-
Ohio	-	-	-	-	-	-	-	-
Oklahoma	-	-	-	-	-	-	-	-
Oregon	1%	1%	-	-	-	1%	-	7%
Pennsylvania	-	-	-	-	-	-	-	-
Rhode Island	-	-	-	-	-	-	-	-
South Carolina	-	-	-	-	-	-	-	-
South Dakota	-	-	-	-	-	-	-	-
Tennessee	-	-	-	-	-	-	-	-
Texas	-	-	-	-	-	-	-	-
Utah	-	-	-	-	-	-	-	-
Vermont	-	-	1%	1%	-	-	-	-
Virginia	-	-	-	-	-	-	-	-
Washington	-	-	-	-	-	-	-	-
West Virginia	-	-	-	-	-	-	-	-
Wisconsin	-	-	-	-	-	-	-	-
Wyoming	-	-	-	-	-	-	-	-

Table notes here

Table 4: Change in Average Weekly Male to Female Earnings Ratio

	State-Wide			
SHB	0.0303**			
P-Value	[0.020]			
	Younger Than 35	Older Than 35		
SHB	0.0115	0.0256**		
P-Value	[0.694]	[0.020]		
	Female Dominated Industries	Male Dominated Industries	Service Proving Industries	Good Producing Industries
SHB	0.0084	0.0419	0.0280**	0.0539**
P-Value	[0.429]	[0.102]	[0.020]	[0.020]

Table notes here

Table 5: Change in Average Weekly Earnings and Hours Worked

	Weekly Earnings		Weekly Hours Worked	
State-Wide				
	Female	Male	Female	Male
SHB	3.1296	3.1627	0.3279**	-0.299
P-Value	[0.857]	[0.837]	[0.041]	[0.388]
Male Dominated industries				
	Female	Male	Female	Male
SHB	54.2317	26.2456	0.3314*	0.2654
P-Value	[0.122]	[0.122]	[0.082]	[0.653]
Female Dominated Industries				
	Female	Male	Female	Male
SHB	-7.9003	-24.4772	0.2556	-0.8066
P-Value	[0.429]	[0.327]	[0.143]	[0.102]
Younger Than 35				
	Female	Male	Female	Male
SHB	25.9226	14.0185	0.6374**	-1.2215**
P-Value	[0.224]	[0.551]	[0.041]	[0.020]
Older Than 35				
	Female	Male	Female	Male
SHB	-5.6522	-7.811	0.1354	-0.5514
P-Value	[0.714]	[0.714]	[0.224]	[0.286]

Table notes here

Table 6: Change in Hourly Wage by Sex and Industry

	Female	Male
State-Wide		
	Female	Male
SHB	0.213	0.0889
P-Value	[0.224]	[0.857]
Male Dominated industries		
	Female	Male
SHB	0.9587**	0.3321
P-Value	[0.020]	[0.388]
Female Dominated Industries		
	Female	Male
SHB	0.0314	-0.5352
P-Value	[0.918]	[0.367]
Younger Than 35		
	Female	Male
SHB	0.4215	-0.1834
P-Value	[0.204]	[0.327]
Older Than 35		
	Female	Male
SHB	-0.0399	-0.3345
P-Value	[0.939]	[0.286]

Table notes here

Table 7: Change in Employment Probability by Sex and Industry

	Level Data		Demeaned Data	
State-Wide				
	Female	Male	Female	Male
SHB	0.0069	0.0004	-0.0462	0.0004
P-Value	[0.163]	[0.816]	[0.571]	[1.000]
Male Dominated industries				
	Female	Male	Female	Male
SHB	-0.0046	0.0086**	0.0023	0.0088**
P-Value	[0.102]	[0.041]	[0.918]	[0.020]
Female Dominated Industries				
	Female	Male	Female	Male
SHB	0.0048	-0.0076	-0.0527	-0.0253
P-Value	[0.796]	[0.245]	[0.653]	[0.510]

Table notes here

Table 8: Robustness

	(1) Baseline	(2) Demeaned Data	(3) Scaled Data	(4) Pooled Data
State-Wide				
SHB	0.0303**	0.0232**	0.0301**	0.0218**
P-Value	[0.020]	[0.020]	[0.020]	[0.020]
Younger Than 35				
SHB	0.0115	-0.0109	-0.0140	0.0138
P-Value	[0.694]	[0.367]	[0.327]	[0.449]
Older Than 35				
SHB	0.0256**	0.0129**	0.0170**	0.021**
P-Value	[0.020]	[0.020]	[0.020]	[0.041]
Female Dominated Industries				
SHB	0.0084	0.0078	0.0102	0.0084
P-Value	[0.429]	[0.245]	[0.224]	[0.490]
Male Dominated Industries				
SHB	0.0419	0.0283	0.0329*	0.042
P-Value	[0.102]	[0.102]	[0.061]	[0.102]
Goods Producing Industries				
SHB	0.0539**	0.0288**	0.0298**	0.0103
P-Value	[0.020]	[0.020]	[0.020]	[0.245]
Service Providing Industries				
SHB	0.0280**	0.0211**	0.0215**	0.018**
P-Value	[0.020]	[0.041]	[0.041]	[0.020]

Table notes:
Column (1) reports my baseline estimates
Column (2) reports estimates using data that has been demeaned by its pretreatment mean for each state
Column (3) reports estimates using data that has been scaled by its pretreatment mean for each state
Column (4) reports estimates using pooled data from California, New York, and, Delaware.

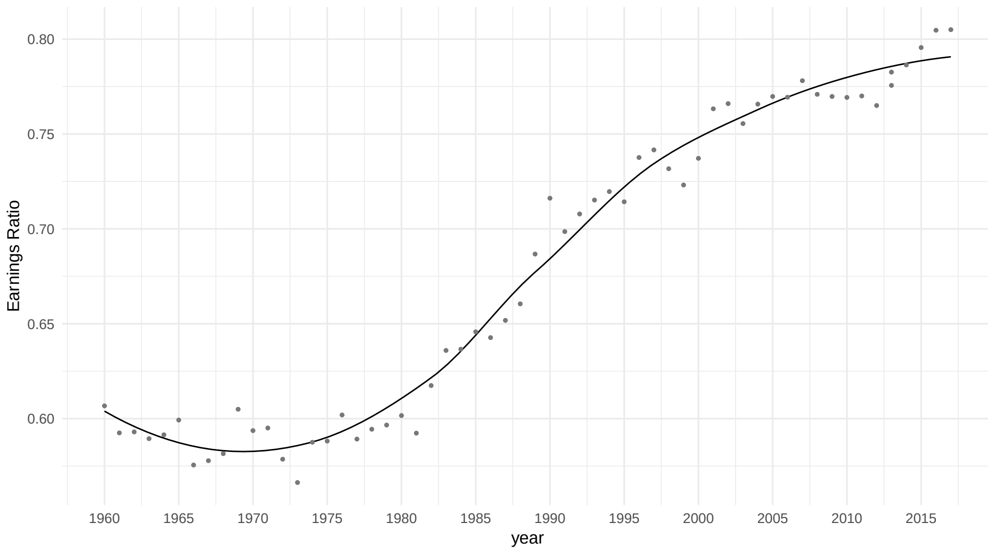
Table 9: Robustness Using CPS Replicate Weights

	(1) Baseline	(2) Demeaned Data	(3) Scaled Data	(4) Pooled Data
State-Wide				
SHB	0.0218*	0.0169**	0.0228**	0.0136
P-Value	[0.061]	[0.020]	[0.020]	[0.102]
Younger Than 35				
SHB	-0.0039	-0.0195	-0.0270	0.014
P-Value	[0.898]	[0.265]	[0.184]	[0.388]
Older Than 35				
SHB	0.0223**	0.0160**	0.0209**	0.0209**
P-Value	[0.020]	[0.020]	[0.020]	[0.041]
Female Dominated Industries				
SHB	0.0030	0.0050	0.0066	-0.0003
P-Value	[0.837]	[0.571]	[0.531]	[1.000]
Male Dominated Industries				
SHB	0.0370	0.0238	0.0274	0.0426*
P-Value	[0.122]	[0.102]	[0.102]	[0.082]
Goods Producing Industries				
SHB	0.0757**	0.0457**	0.0342**	0.0391**
P-Value	[0.020]	[0.020]	[0.020]	[0.020]
Service Providing Industries				
SHB	0.0220**	0.0205**	0.0269**	0.0126*
P-Value	[0.020]	[0.041]	[0.041]	[0.082]

Table notes:
Column (2) reports my baseline estimates
Column (2) reports estimates using data that has been demeaned by its pretreatment mean for each state
Column (3) reports estimates using data that has been scaled by its pretreatment mean for each state
Column (4) reports estimates using pooled data from California, New York, and, Delaware.

Figures

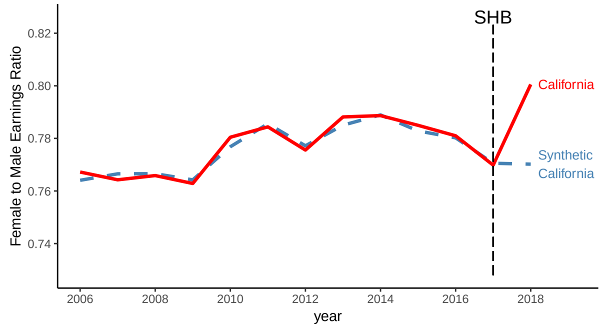
Figure 1: Female to Male Median Earnings Ratio of Full-Time Workers



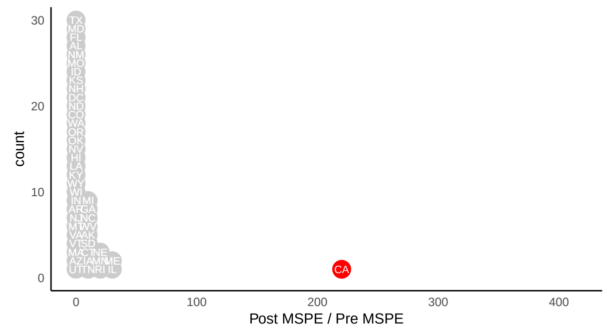
Notes:

Figure 2: California Cross Validation

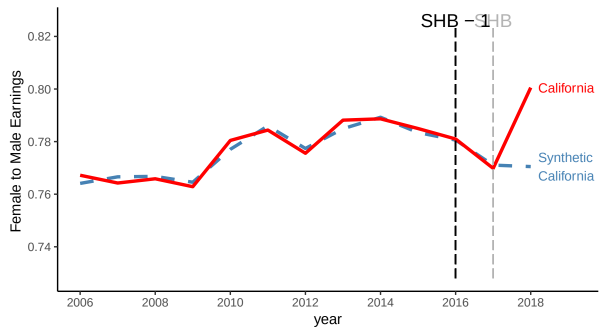
(a) Treatment in 2018



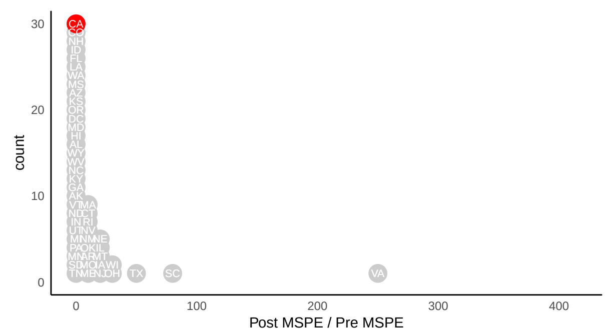
(b) MSPE Ratio Distribution for Treatment in 2018



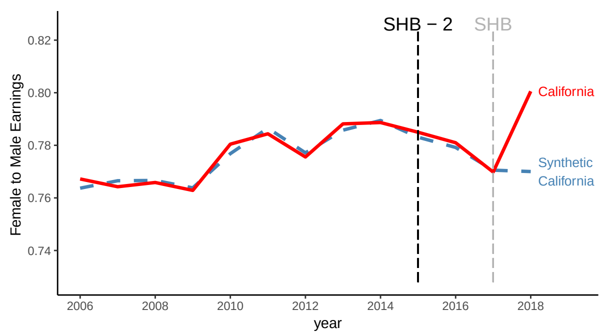
(c) Treatment in 2017



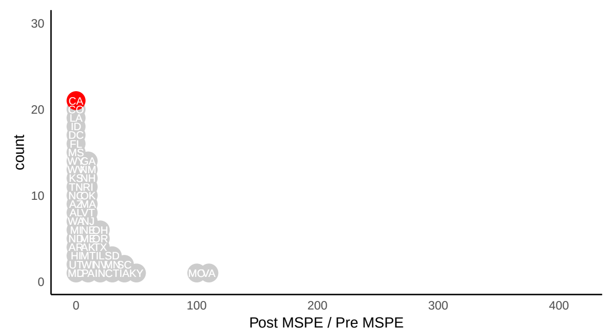
(d) MSPE Ratio Distribution for Treatment in 2018



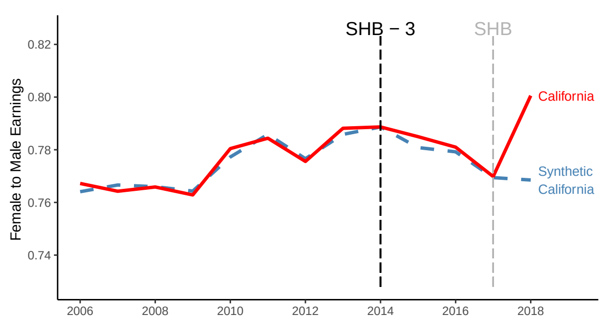
(e) Treatment in 2016



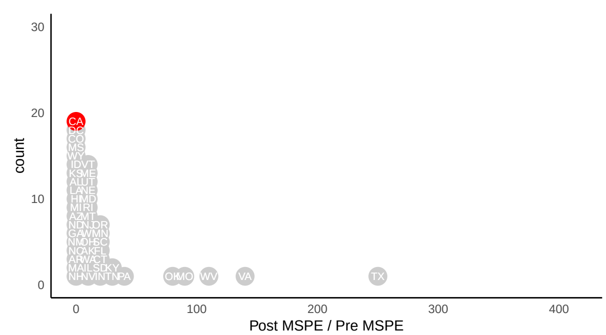
(f) MSPE Ratio Distribution for Treatment in 2016



(g) Treatment in 2015



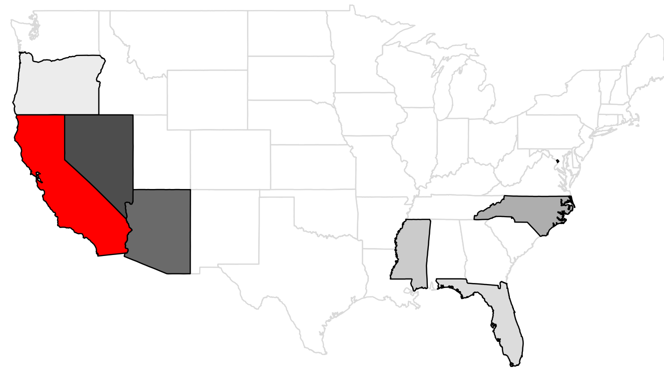
(h) MSPE Ratio Distribution for Treatment in 2015



Notes: This figure illustrates the ability the synthetic control approach to forecast out of sample. For each subfigure, matching only occurs to the left of the treatment line.

Figure 3: Composition of Synthetic California

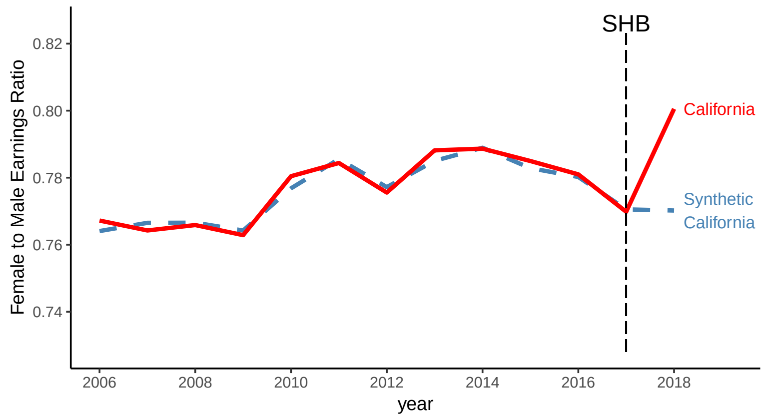
Donor State	Weight
Nevada	29%
Arizona	24%
District of Columbia	16%
North Carolina	12%
Mississippi	7%
Hawaii	6%
Florida	4%
Oregon	1%



Notes: This figure shows the composition of donor states used to make a synthetic California. States are shaded in proportion to their weighted Contribution towards synthetic California.

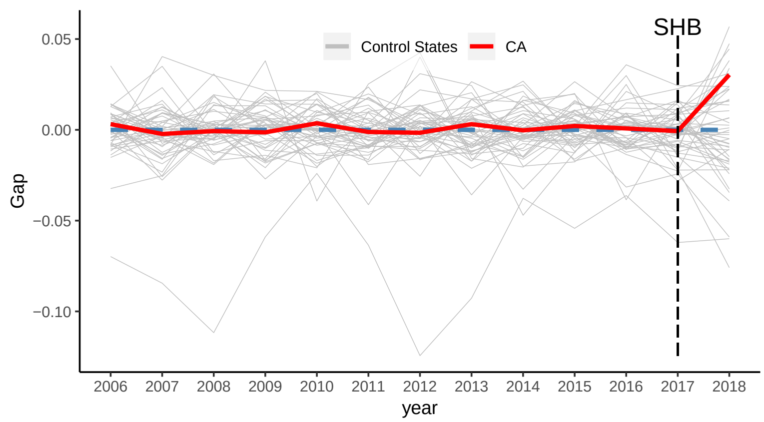
Figure 4: California Male to Female Earnings Ratio

(a) Synthetic Control



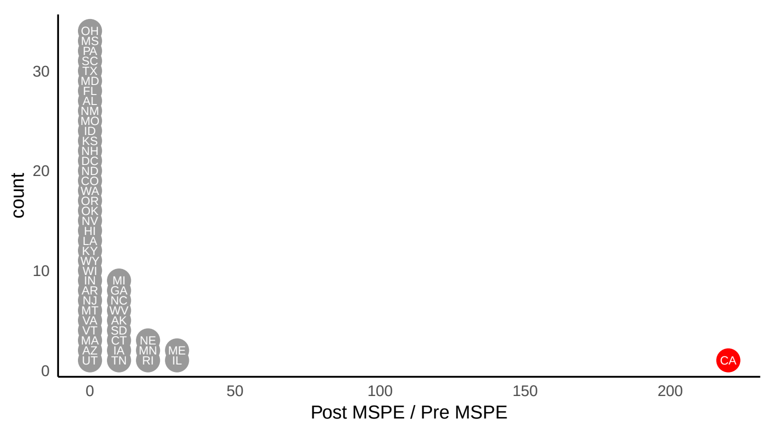
Notes: This figure shows the annual time series of California's earning (red) and the time series of the synthetic California (blue)

(b) Actual California - Synthetic California vs. Placebo States



Notes: This figure shows the difference between the synthetic control and the actual earnings ratio for each placebo state.

(c) MSPE Ratio Distribution

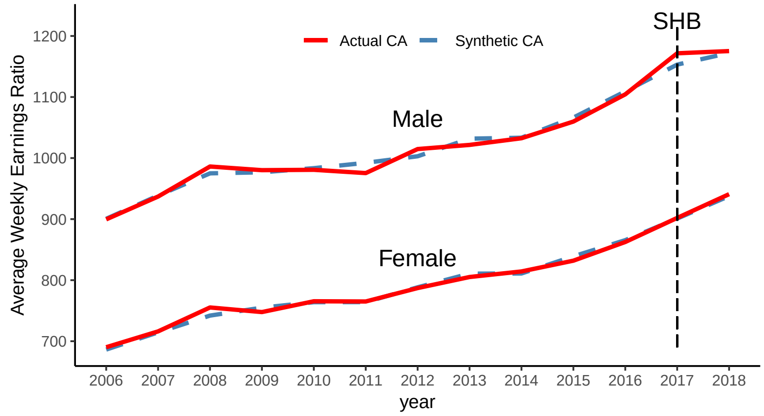


Notes: This figure shows the distribution of MSPE ratios for each of the control states and California. The ratio compares pre treatment versus post treatment fit for each state.

Appendix

Figure A.1: Average Weekly Earnings by Gender

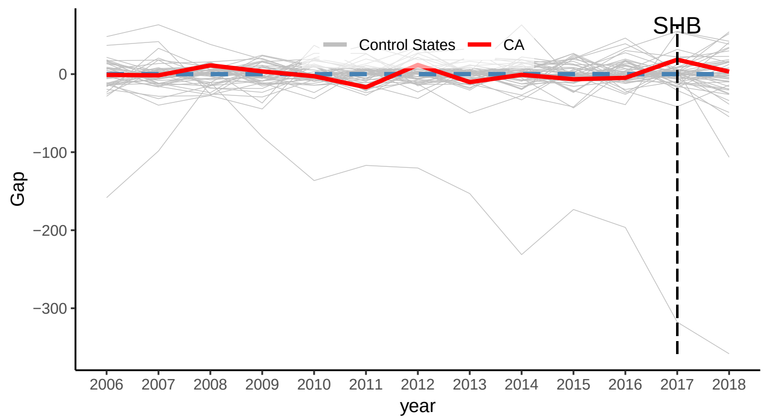
(a) Average Weekly Earnings by Gender



Notes:

(b) Male Earnings

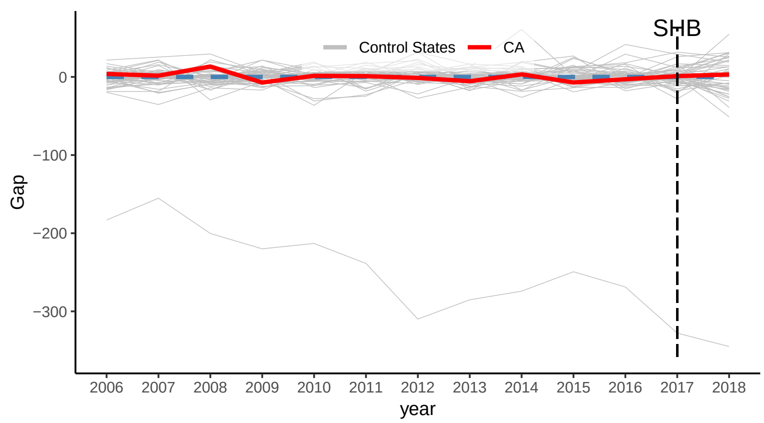
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Earnings

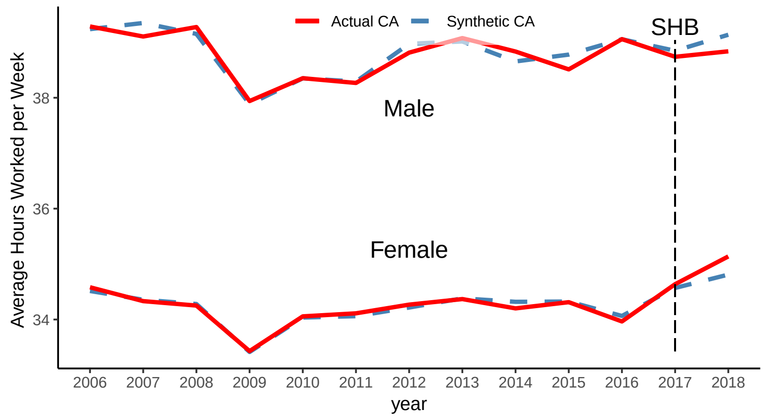
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.2: Average Weekly Hours Worked by Gender

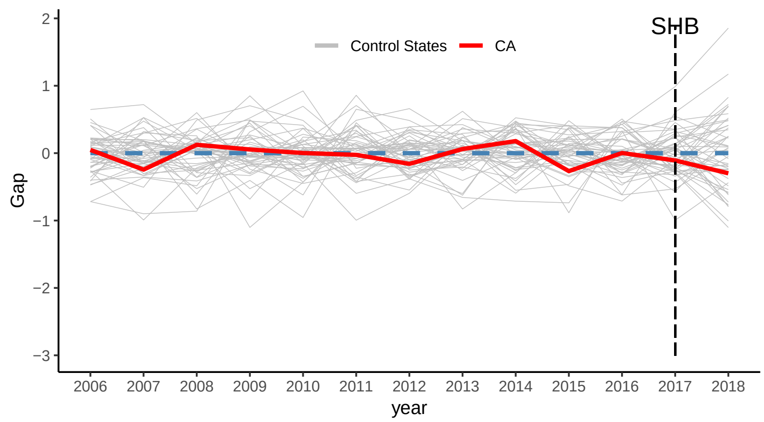
(a) Average Weekly Hours Worked by Gender



Notes:

(b) Male Hours:

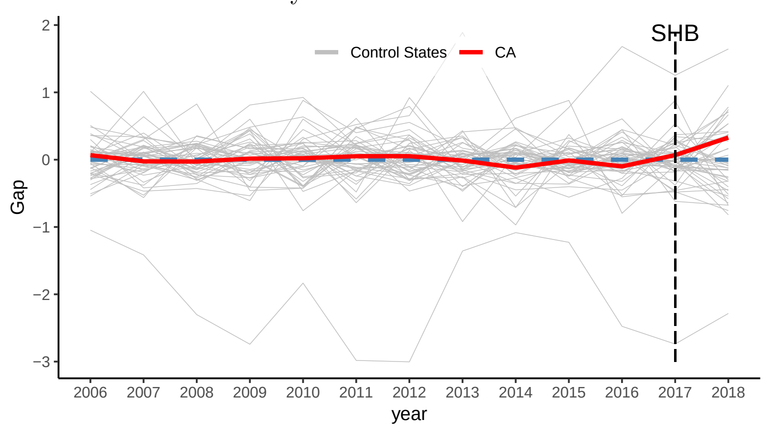
Actual - Synthetic California vs Placebo States



Notes:

(c) Female Hours:

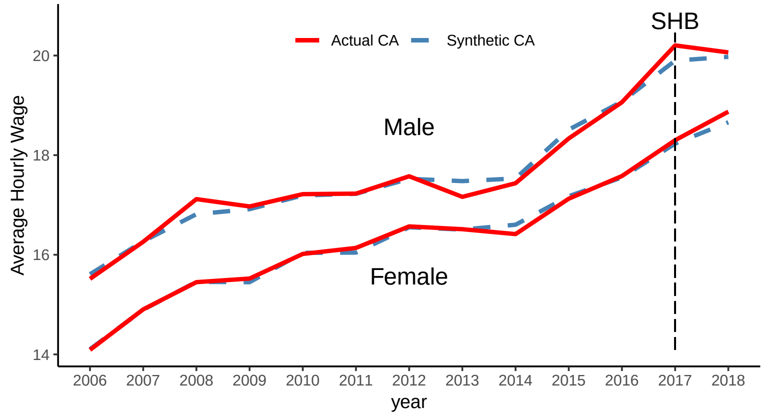
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.3: Average Weekly Hourly Wage by Gender

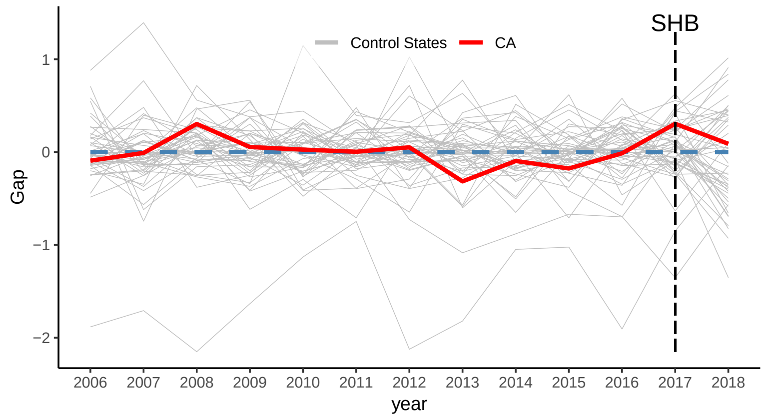
(a) Average Weekly Hourly Wage by Gender



Notes:

(b) Male Hourly Wage:

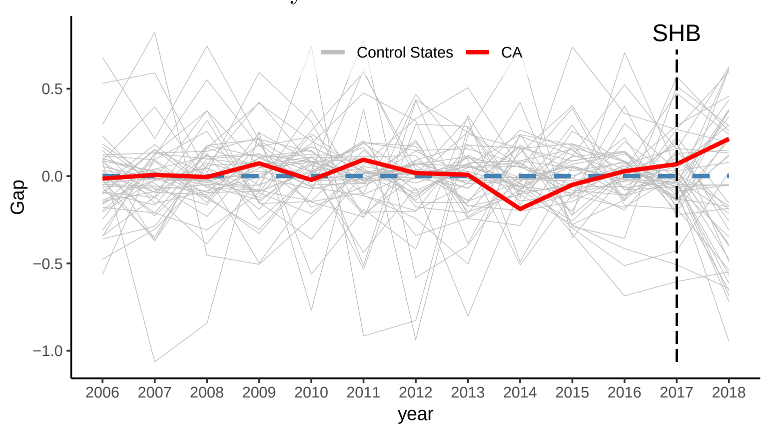
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Hourly Wage:

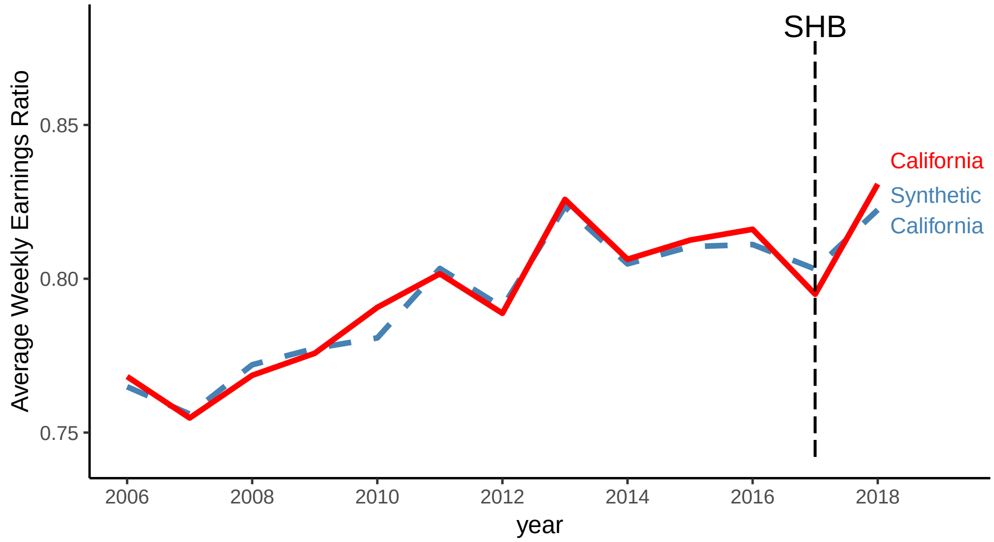
Actual California - Synthetic California vs Placebo States



Notes:

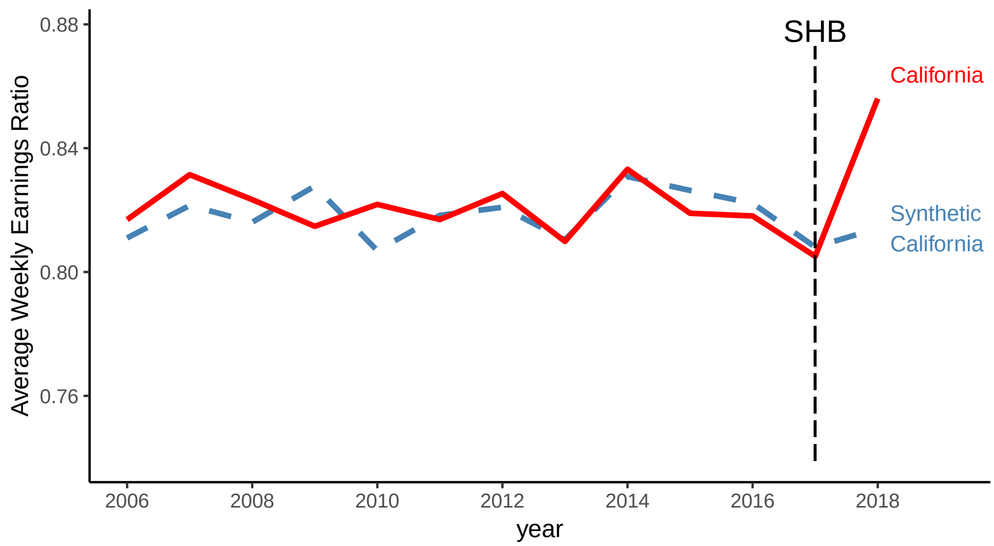
Figure A.4: Average Weekly Earnings Ratio by Industry Type

(a) Female Dominated Industries



Notes: This figure shows the average weekly earnings ratio in industries that are more than 50% female.

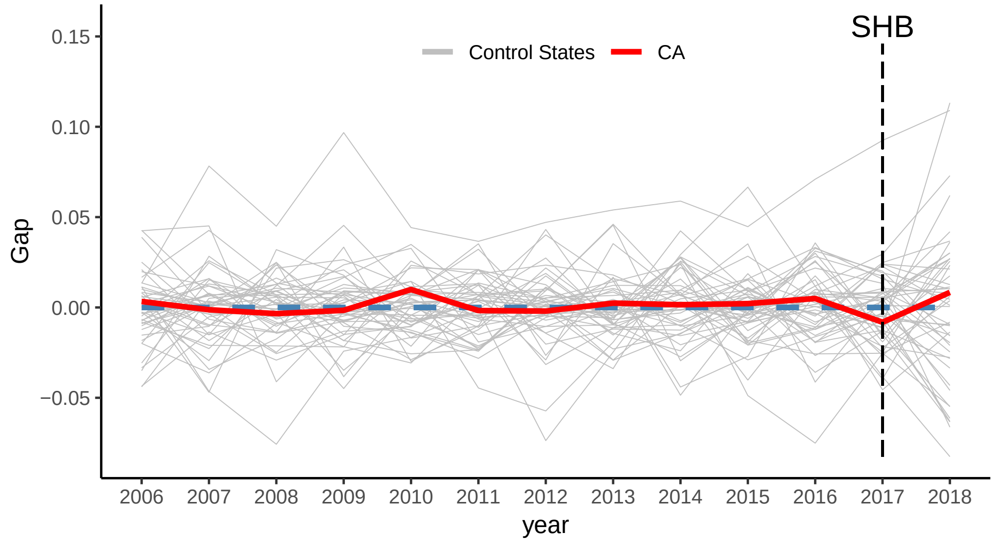
(b) Male Dominated Industries



Notes: This figure shows the average weekly earnings ratio in industries that are more than 50% male.

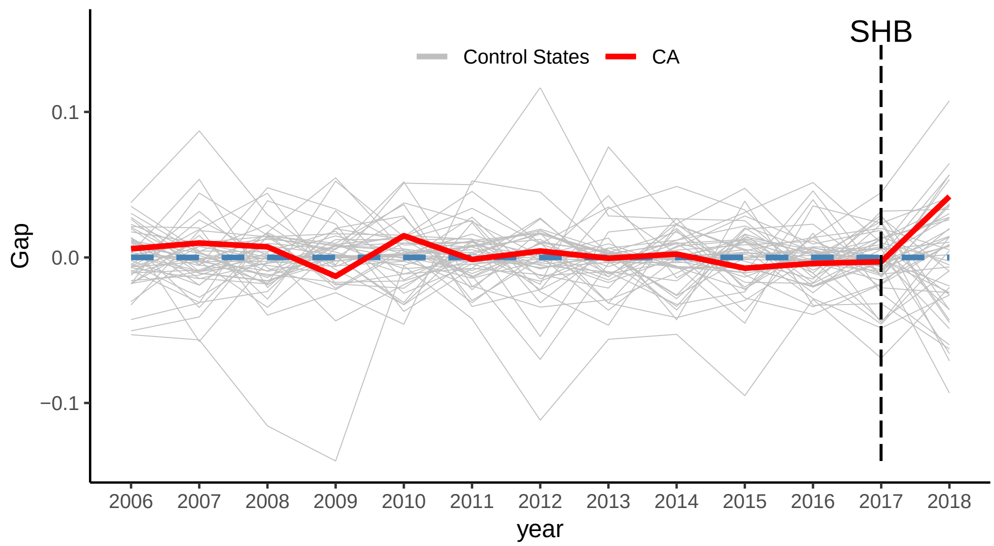
Figure A.5: Actual California - Synthetic California vs Placebo States by Industry Type

(a) Female Dominated Industries



Notes:

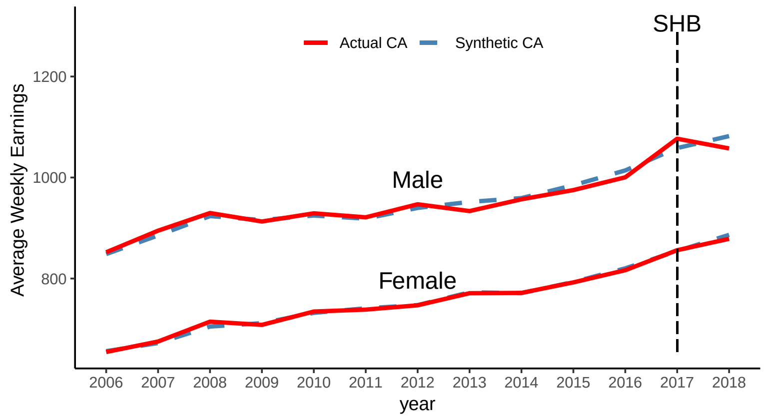
(b) Male Dominated Industries



Notes:

Figure A.6: Average Weekly Earnings by Gender Within Female Dominated Industries

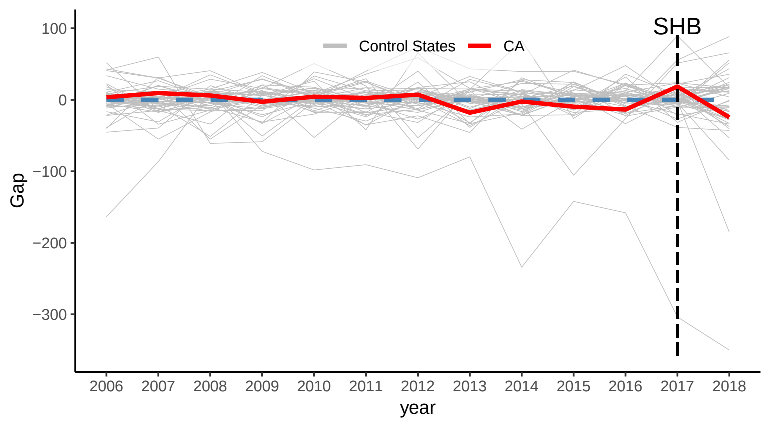
(a) Average Weekly Earnings by Gender



Notes:

(b) Male Earnings

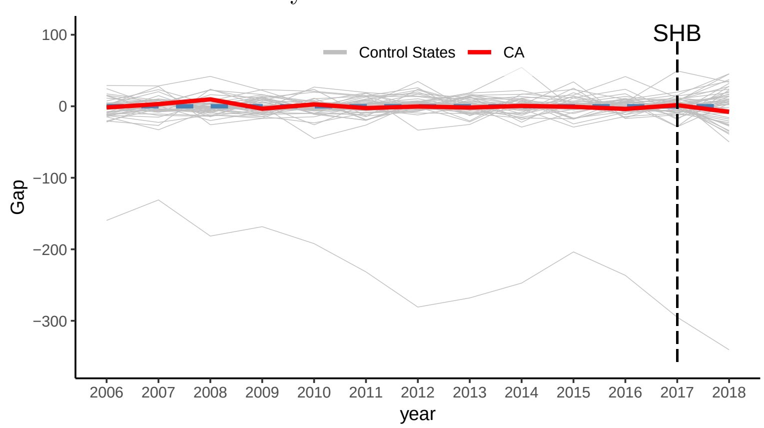
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Earnings

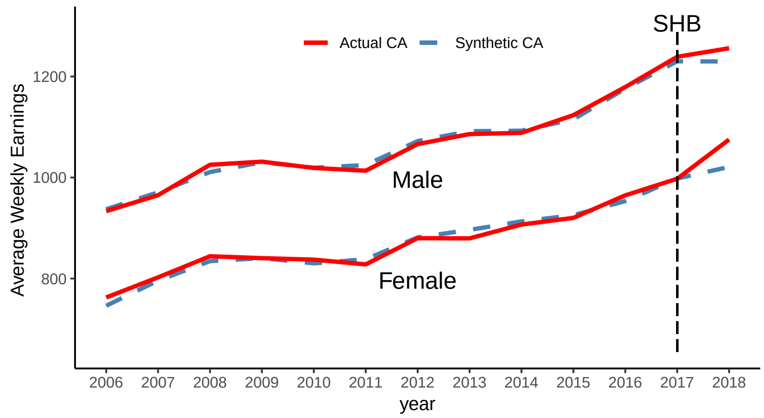
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.7: Average Weekly Earnings by Gender Within Male Dominated Industries

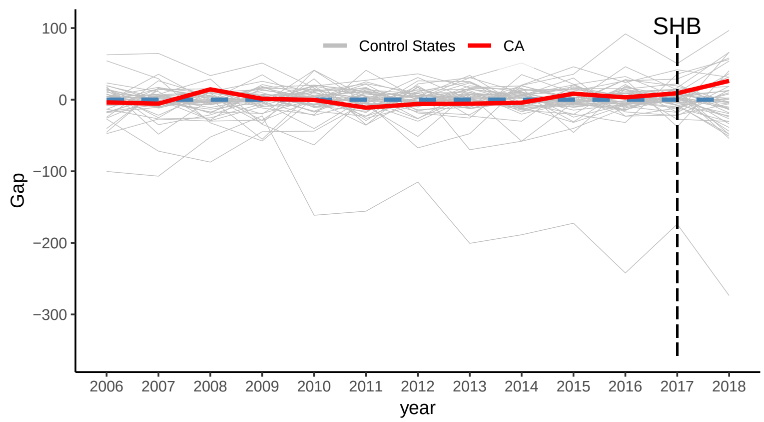
(a) Average Weekly Earnings by Gender



Notes:

(b) Male Earnings

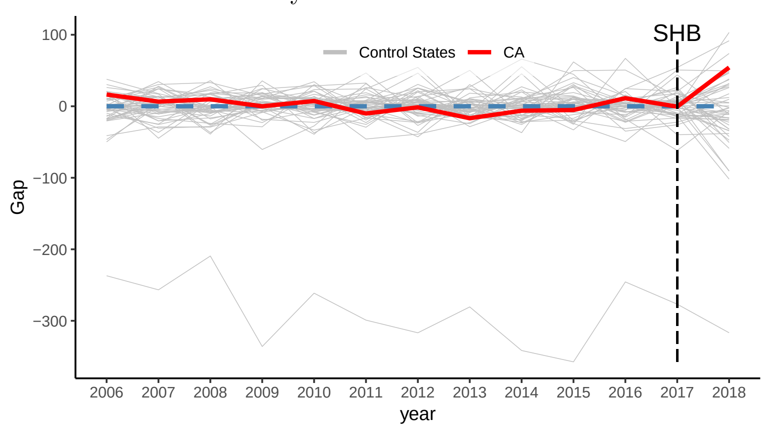
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Earnings

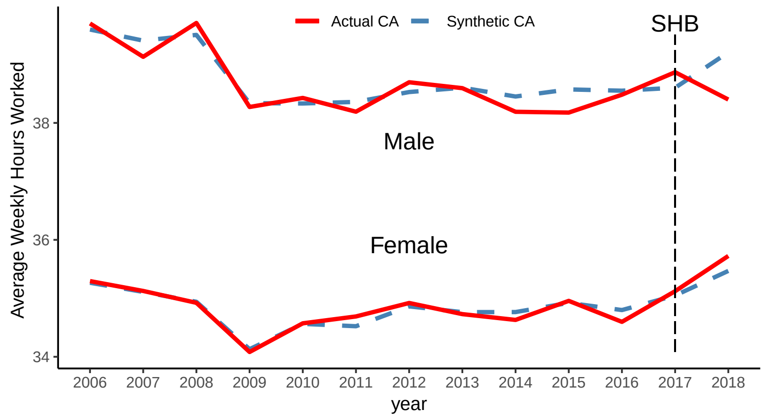
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.8: Average Weekly Hours Worked by Gender Within Female Dominated Industries

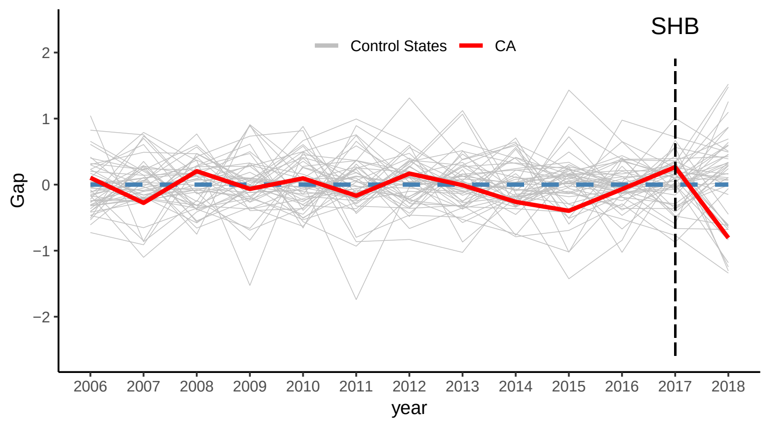
(a) Average Weekly Hours Worked by Gender



Notes:

(b) Male Hours Worked

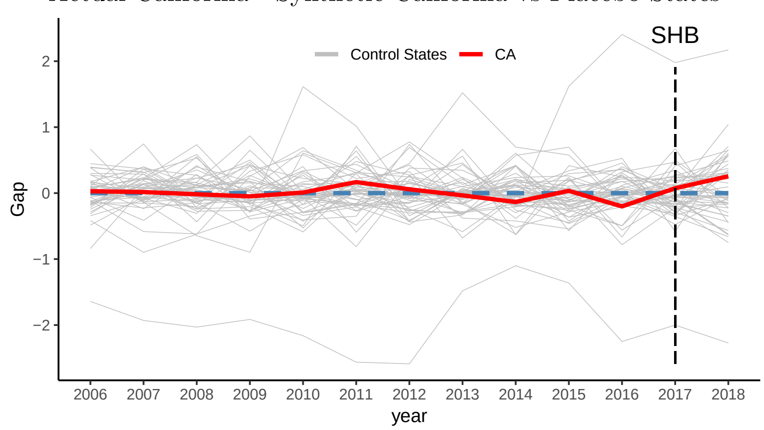
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Hours Worked

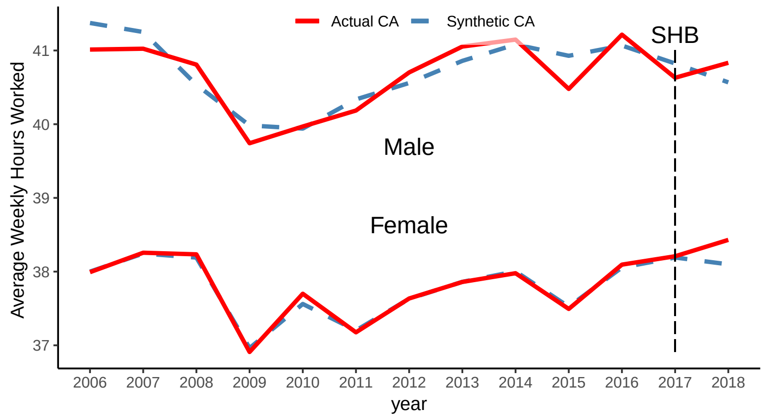
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.9: Average Weekly Hours Worked by Gender Within Male Dominated Industries

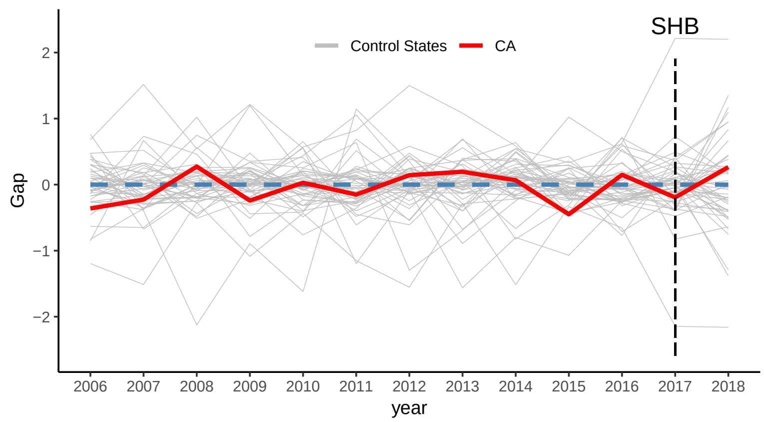
(a) Average Weekly Hours Worked by Gender



Notes:

(b) Male Hours Worked

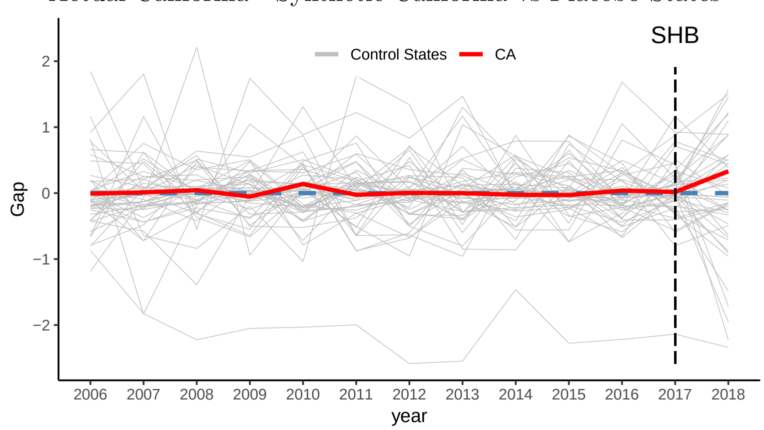
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Hours Worked

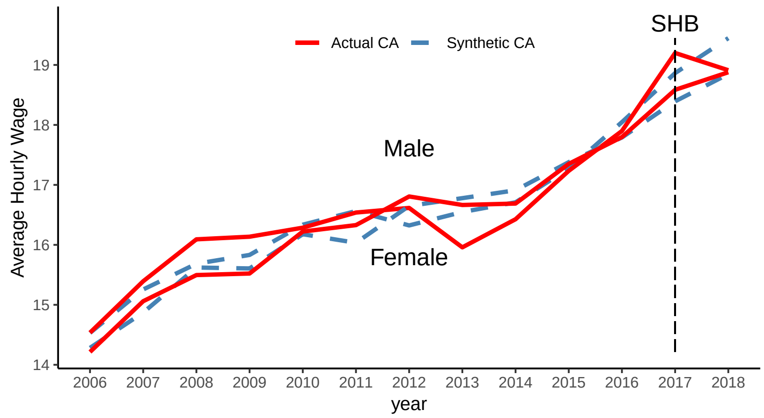
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.10: Average Hourly Wage by Gender Within Female Dominated Industries

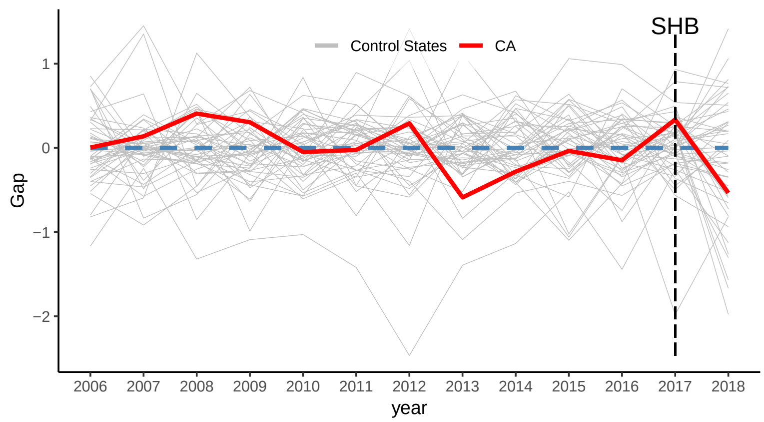
(a) Average Hourly Wage by Gender



Notes:

(b) Male Hourly Wage

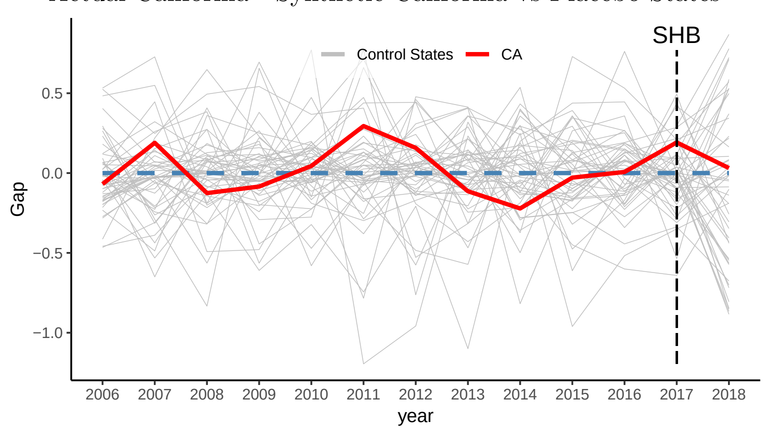
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Hourly Wage

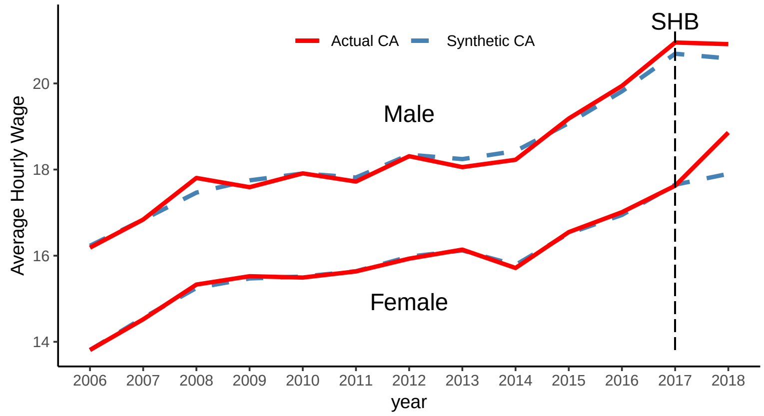
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.11: Average Hourly Wage by Gender Within Male Dominated Industries

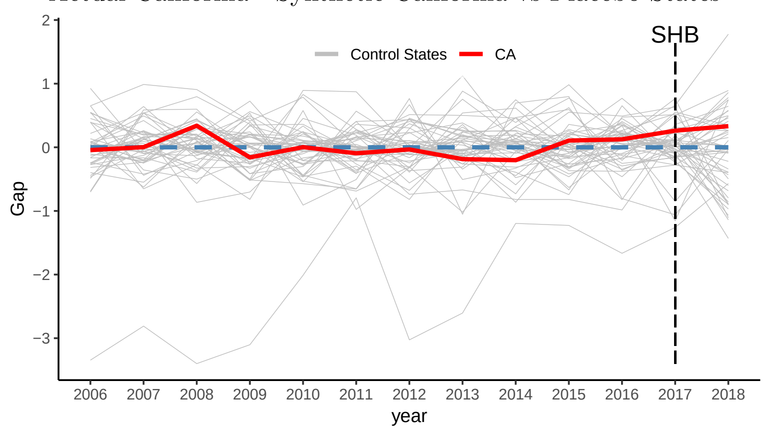
(a) Average Hourly Wage by Gender



Notes:

(b) Male Hourly Wage

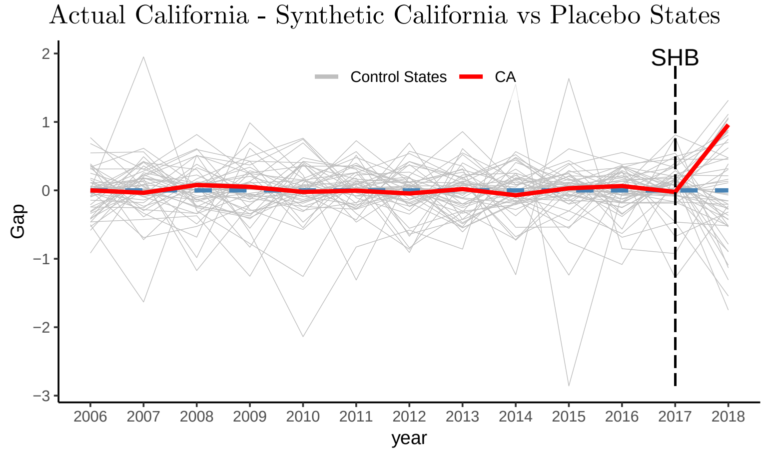
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Hourly Wage

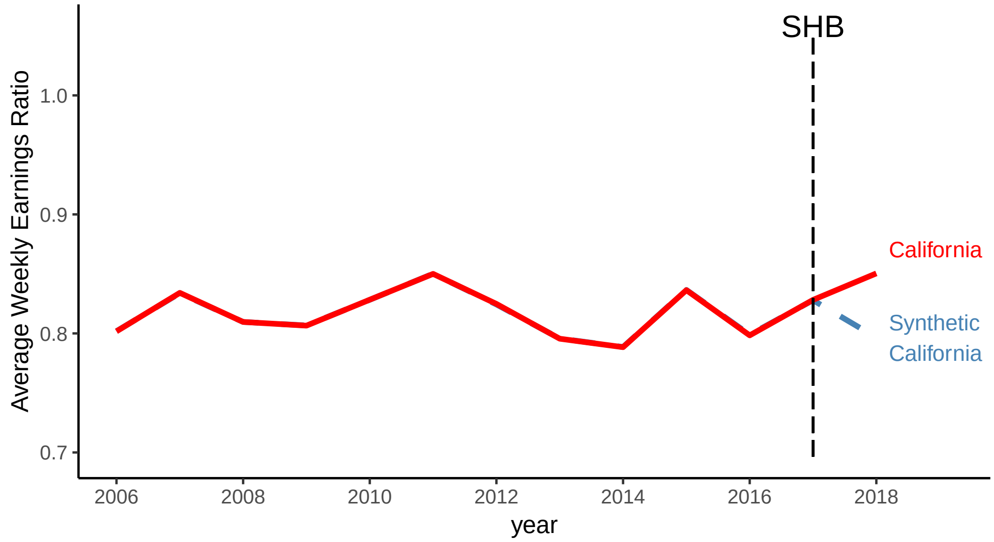
Actual California - Synthetic California vs Placebo States



Notes:

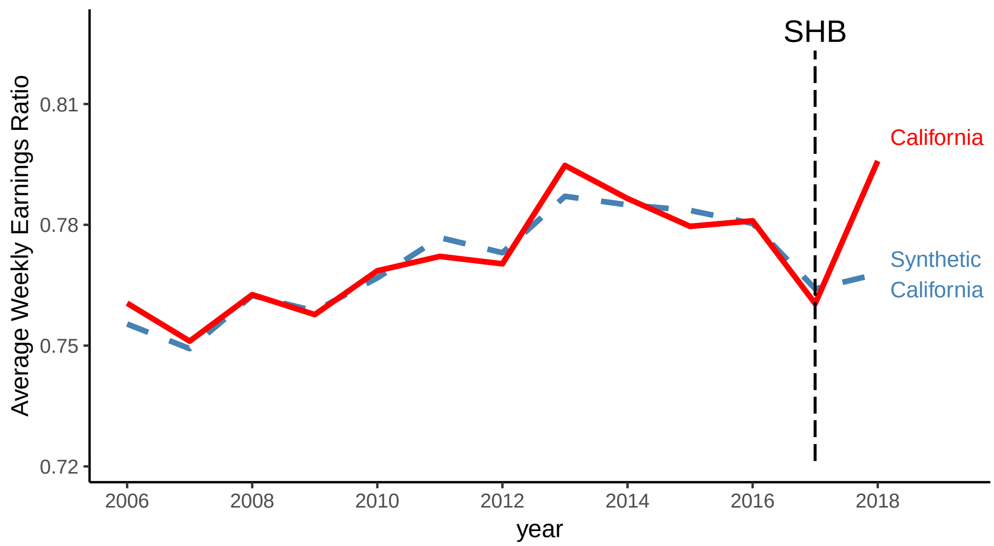
Figure A.12: Average Weekly Earnings Ratio by Industry Type

(a) Goods Producing Industries



Notes: This figure shows the average weekly earnings ratio in industries that are classified by NAICS as goods producing.

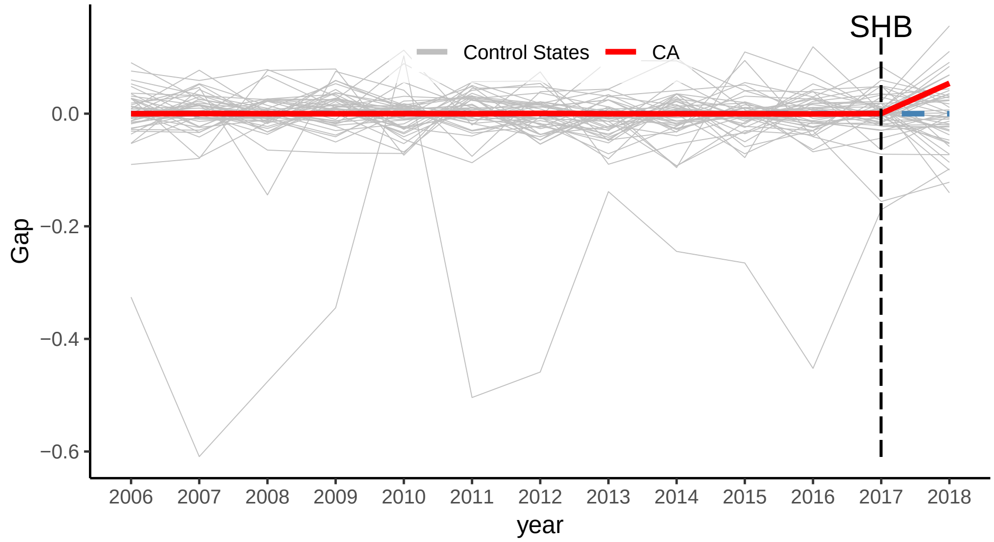
(b) Service Providing Industries



Notes: This figure shows the average weekly earnings ratio in industries that are classified by NAICS as service providing.

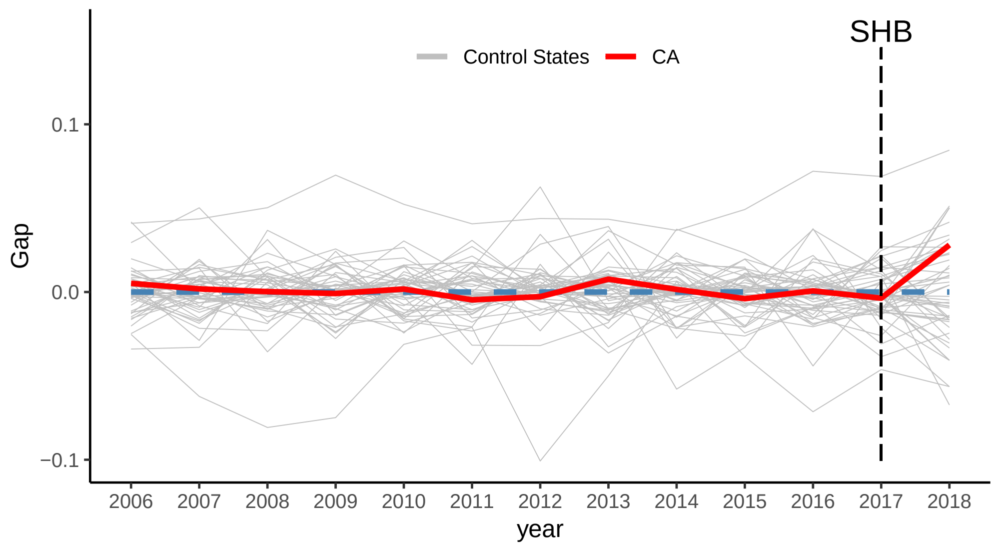
Figure A.13: Actual California - Synthetic California vs Placebo States by Industry Type

(a) Goods Producing Industries



Notes:

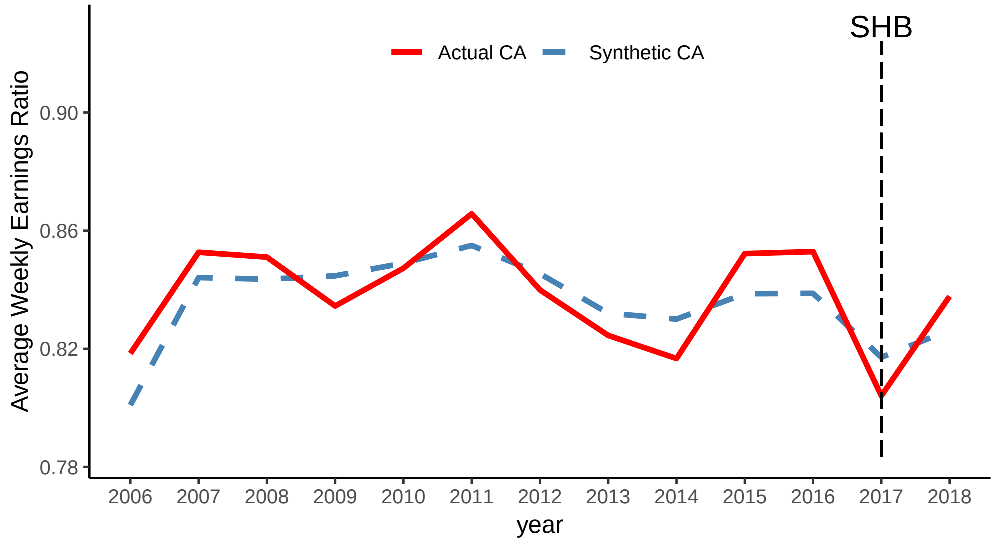
(b) Service Providing Industries



Notes:

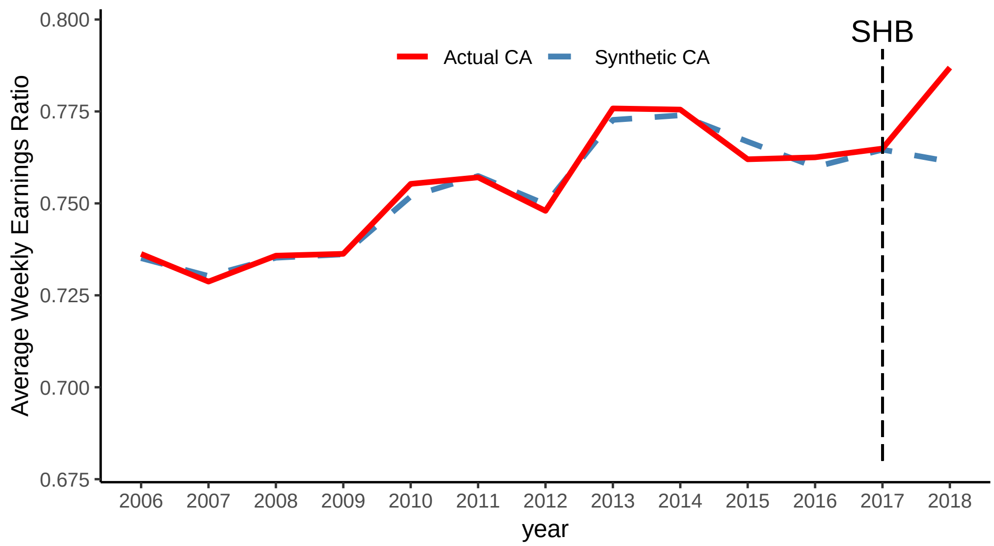
Figure A.14: Average Weekly Earnings Ratio by Age

(a) Younger Than 35



Notes: This figure shows the average weekly earnings ratio in California among individuals younger than 35 relative to its synthetic counterpart

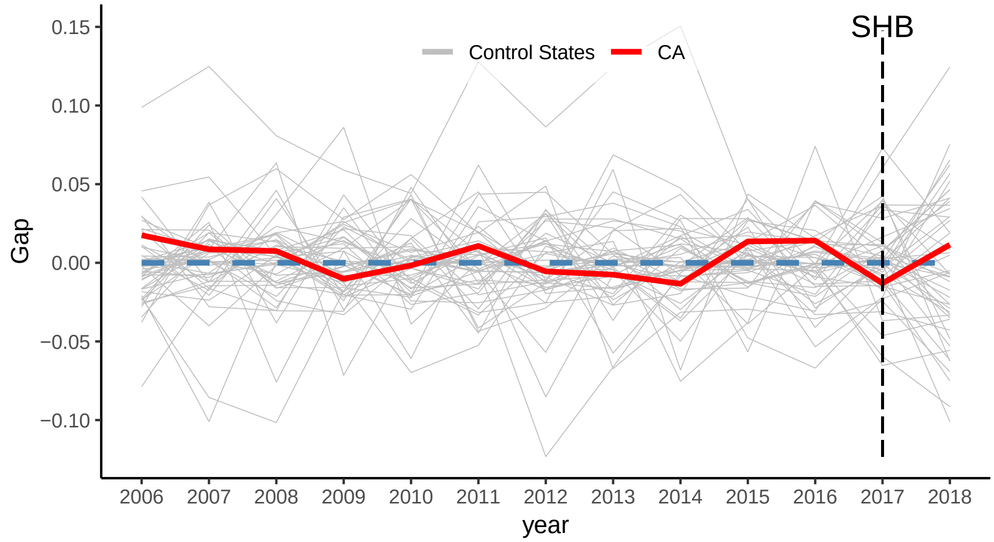
(b) Older Than 35



Notes: This figure shows the average weekly earnings ratio in California among individuals older than 35 relative to its synthetic counterpart.

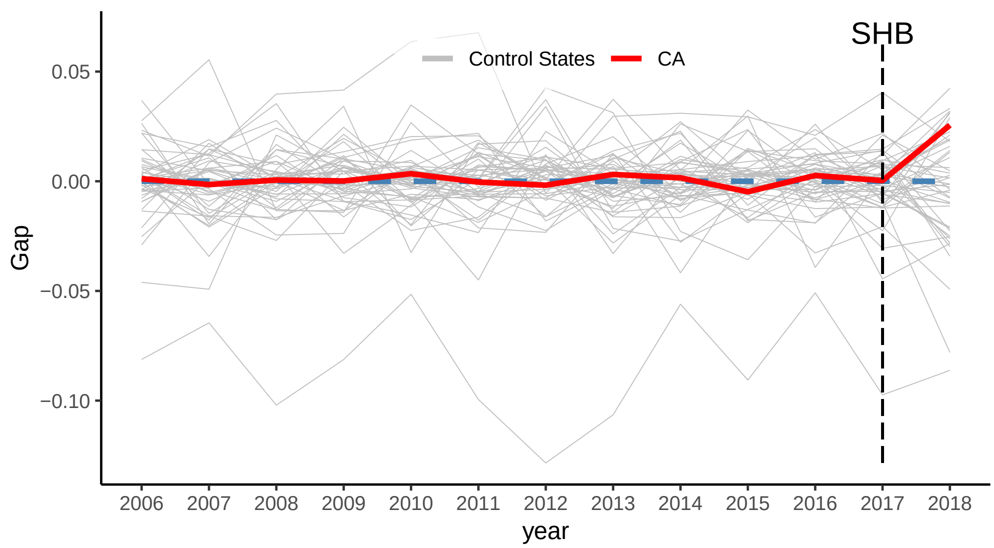
Figure A.15: Actual California - Synthetic California vs Placebo States by Age

(a) Younger Than 35.



Notes:

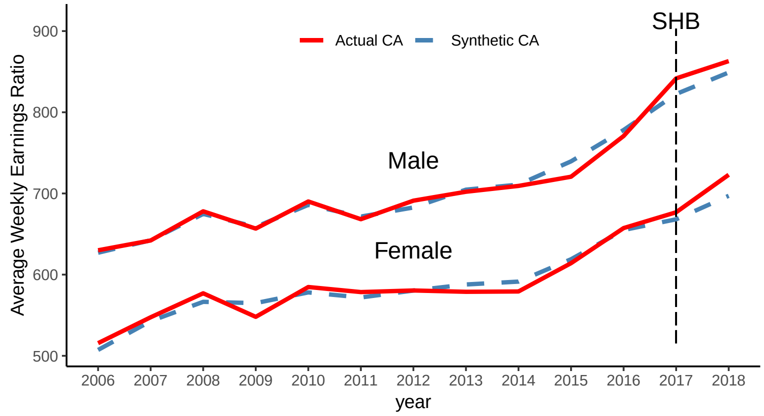
(b) Older Than 35



Notes:

Figure A.16: Average Weekly Earnings by Gender Among Individuals Below Age 35

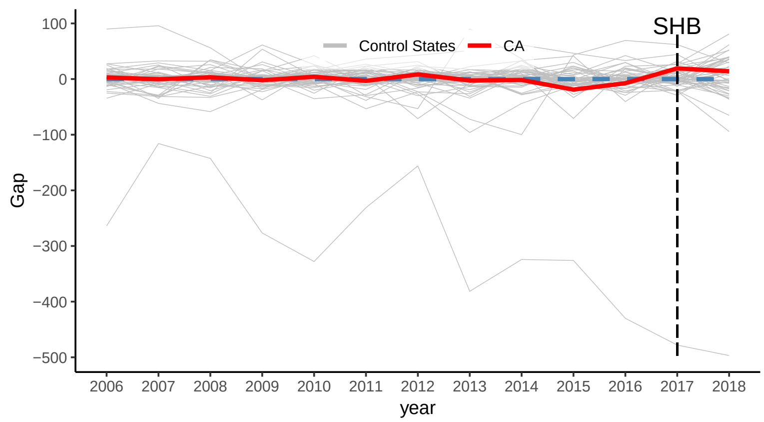
(a) Average Weekly Earnings by Gender



Notes:

(b) Male Weekly Earnings

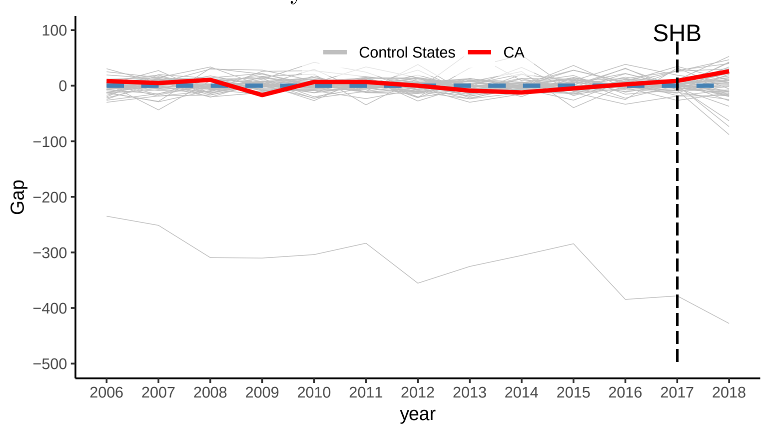
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Weekly Earnings

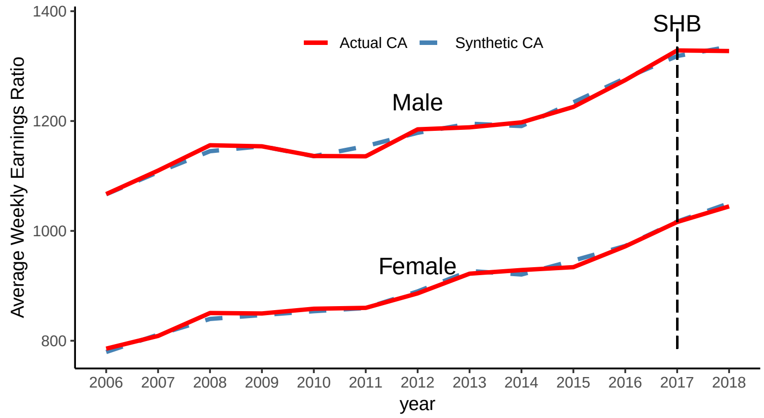
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.17: Average Weekly Earnings by Gender Among Individuals Above Age 35

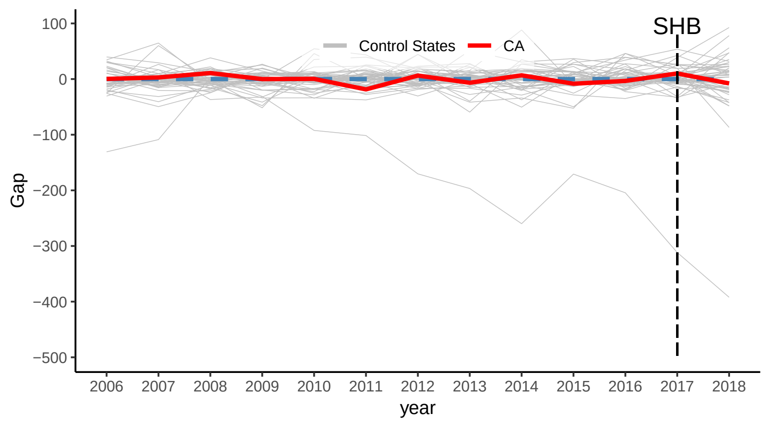
(a) Average Weekly Earnings by Gender



Notes:

(b) Male Weekly Earnings

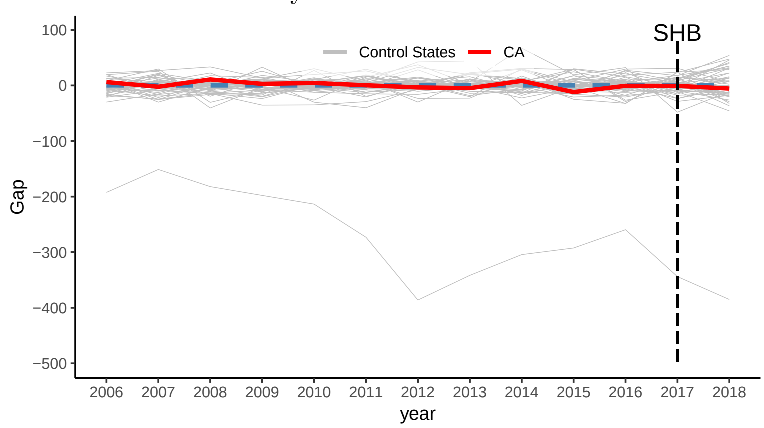
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Weekly Earnings

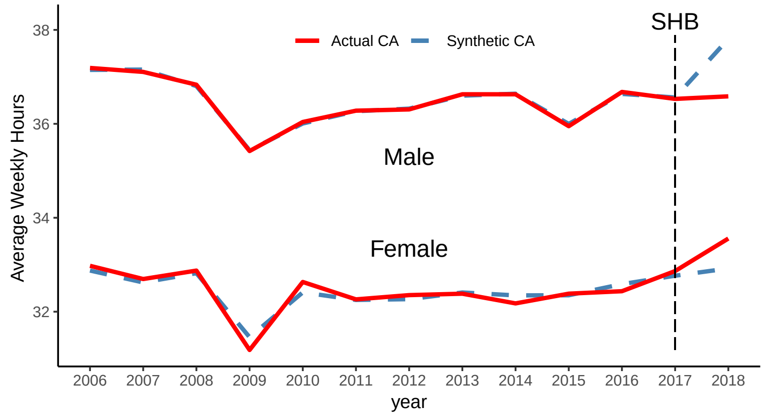
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.18: Average Weekly Hours Worked by Gender Among Individuals Below 35

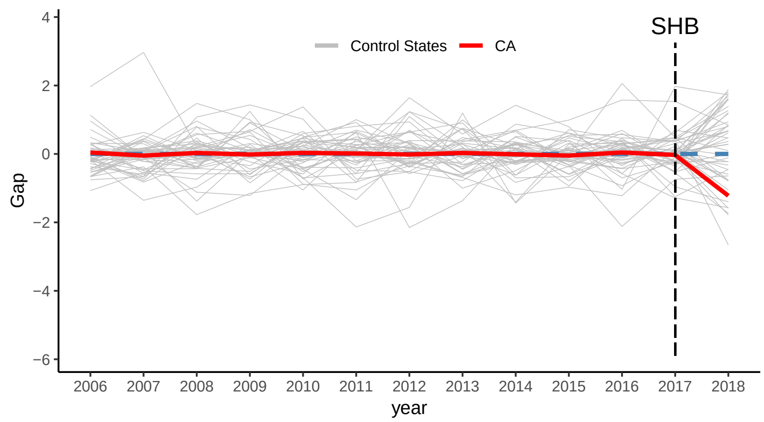
(a) Average Weekly Hours Worked by Gender



Notes:

(b) Male Hours Worked

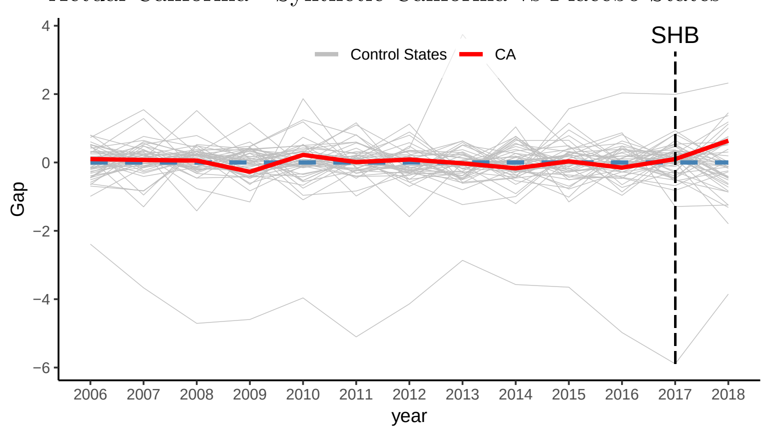
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Hours Worked

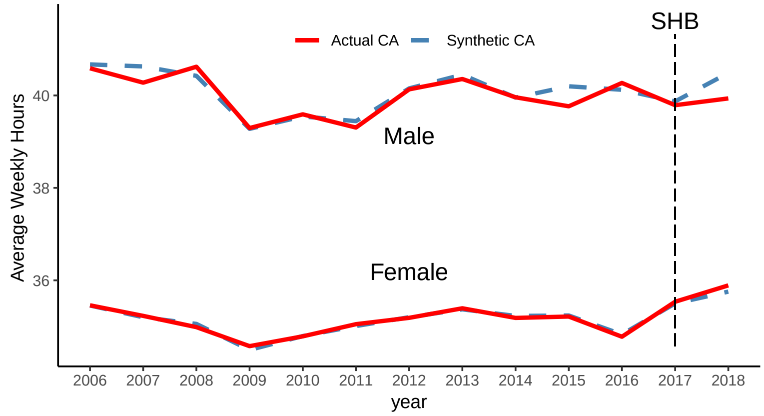
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.19: Average Weekly Hours Worked by Gender Among Individuals Above 35

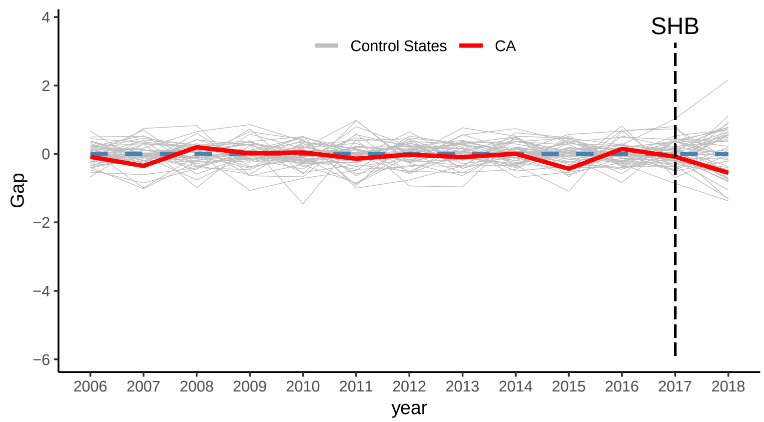
(a) Average Weekly Hours Worked by Gender



Notes:

(b) Male Hours Worked

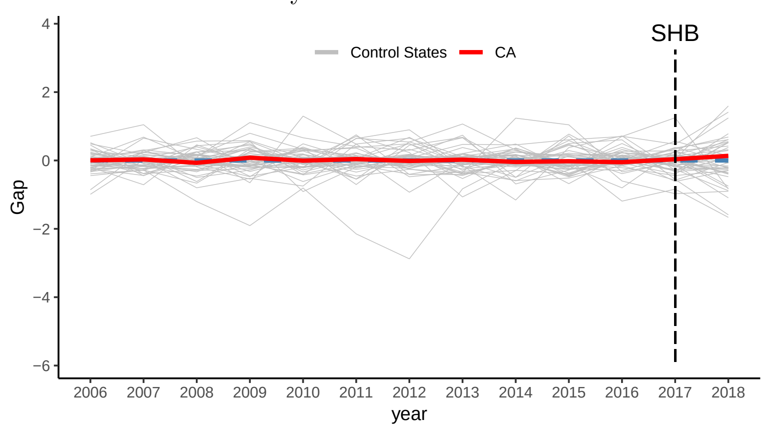
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Hours Worked

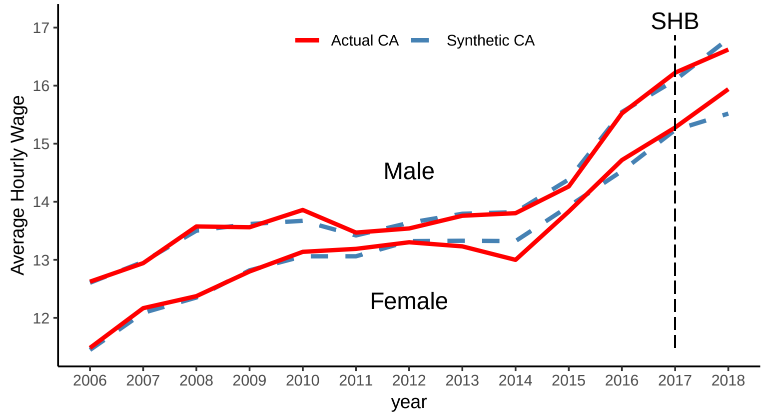
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.20: Average Hourly Wage by Gender Among Individuals Below 35

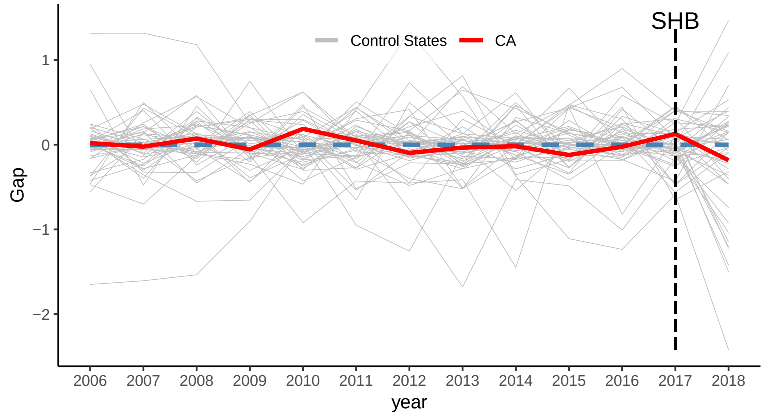
(a) Average Hourly Wage by Gender



Notes:

(b) Male Hourly Wage

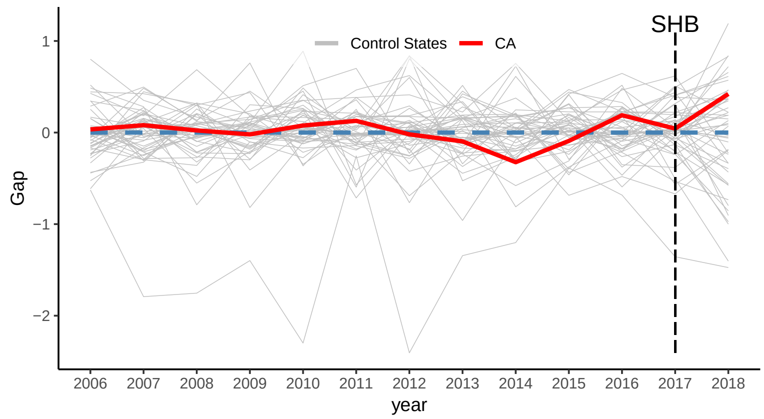
Actual California - Synthetic California vs Placebo States



Notes:

(c) Female Hourly Wage

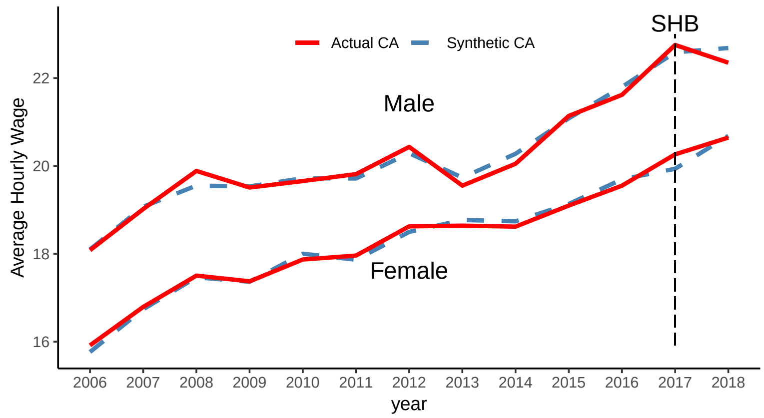
Actual California - Synthetic California vs Placebo States



Notes:

Figure A.21: Average Hourly Wage by Gender Among Individuals Above Age 35

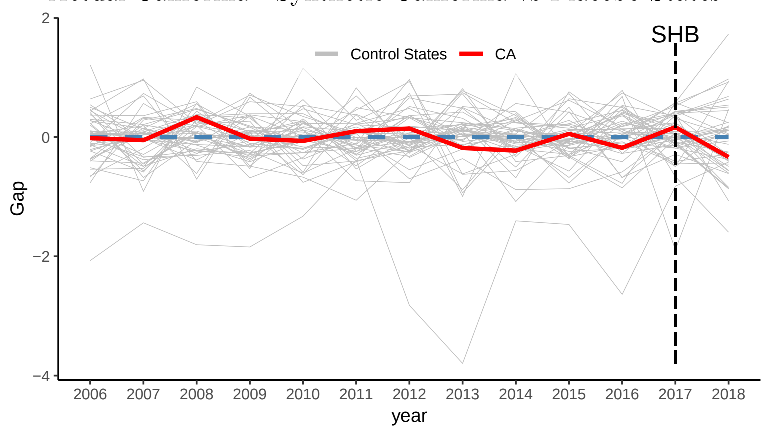
(a) Average Hourly Wage by Gender



Notes:

(b) Male Hourly Wage

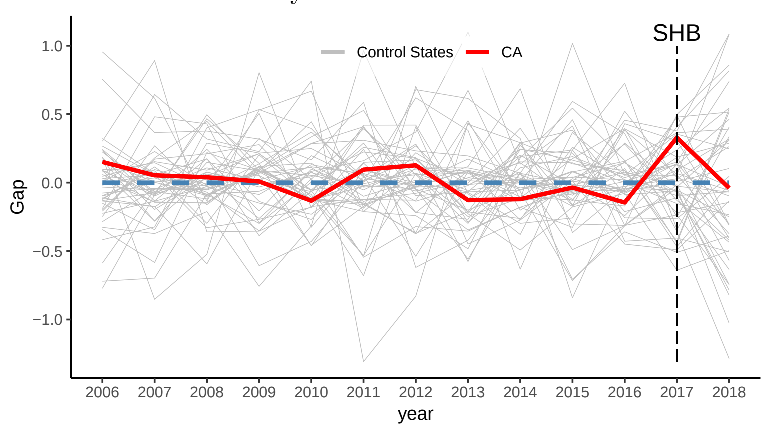
Actual California - Synthetic California vs Placebo States



Notes:

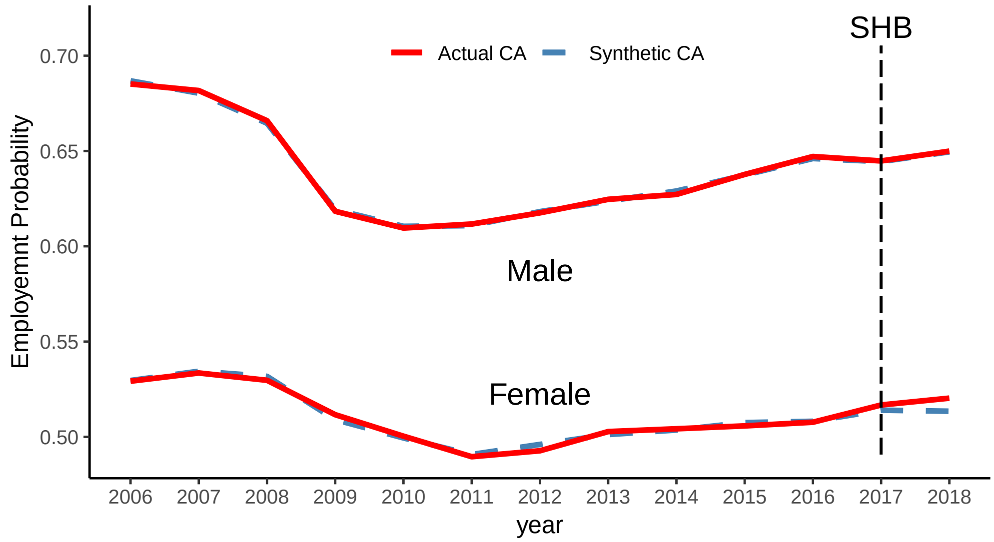
(c) Female Hourly Wage

Actual California - Synthetic California vs Placebo States



Notes:

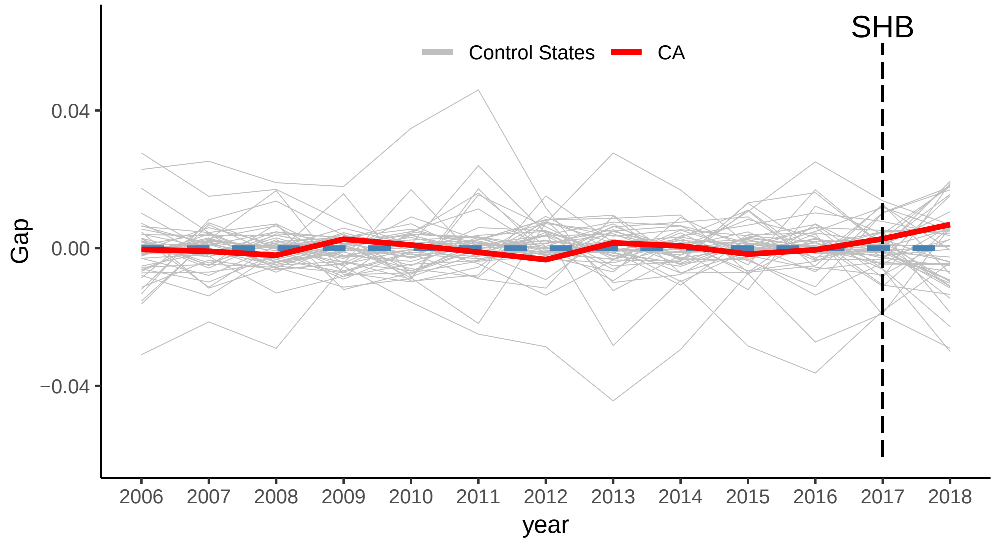
Figure A.22: Employment Probabilities by Sex



Notes: This figure shows average probability of employment by gender.

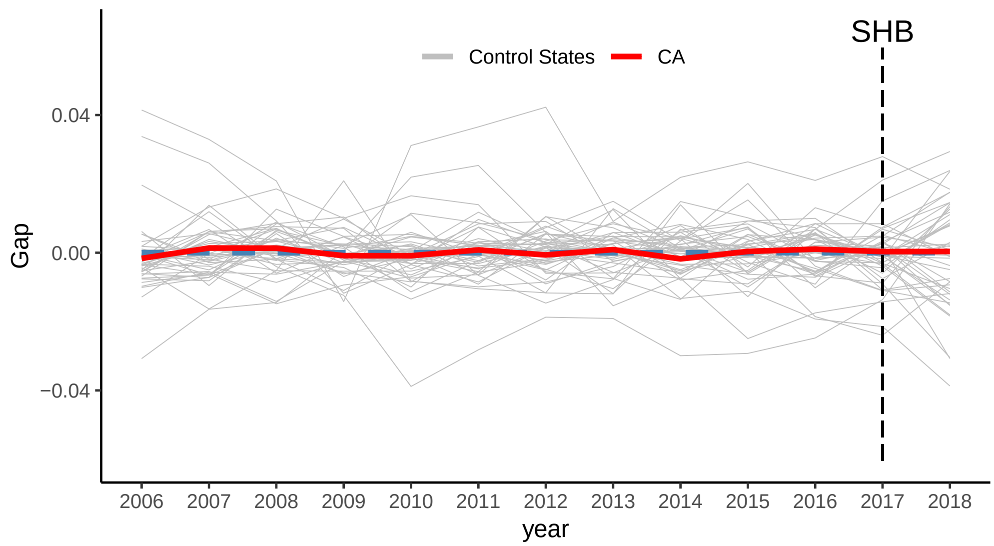
Figure A.23: Actual California - Synthetic California vs Placebo States by Sex

(a) Female Employment Probability



Notes:

(b) Male Employment Probability



Notes: