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ABSTRACT

California has the highest Earned Income Tax (EITC) supplement to the federal EITC, with an 85% supplement rate. However, we find that despite the apparent generosity of the California EITC, there is no employment effect on less-skilled single mothers, in sharp contrast to the evidence of positive extensive margin effects of other state EITC supplements, and of the federal EITC. Our analysis points to two reasons why, unlike other EITCs, California's EITC does not appear to have an extensive margin effect. First, most states simply supplement the federal EITC by a fixed percentage. In contrast, in California the maximum credit is reached at a much lower income level, the state EITC begins to phase out as soon as the maximum EITC payment is reached (i.e., there is no plateau), and the phase-out rate is as steep as the phase-in rate. The result is a much higher marginal tax rate that sets in at a much lower income level. Second, California has a very high (and rising) minimum wage. The interaction between a high minimum wage and the unique budget constraint created by the California EITC implies that workers who work more than a relatively low number of hours are unlikely to gain any extra income because of the EITC.

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Introduction

California has the highest Earned Income Tax (EITC) supplement to the federal EITC, with an 85% supplement to the federal EITC. A large body of empirical research points to positive effects of the EITC – including state supplements – on employment of lower-skilled single mothers. Moreover, the extensive margin effects are sufficiently strong that poverty is reduced substantially even without accounting for EITC payments, and of course even more so accounting for EITC payments (e.g., Hoynes and Patel, 2018; Meyer, 2010; Neumark and Wascher, 2011; Schanzenbach and Strain, 2021).

To the best of our knowledge, however, no one has extended these types of evaluations of the federal EITC and other state EITCs to California's EITC. In this paper, we carry out this evaluation. We find the surprising result that – despite the apparent generosity of the California EITC – there is no evidence of a positive employment effect for less-skilled single mothers. In a triple-difference model estimated for single, less-educated women aged 21-44, comparing California to states where the federal EITC prevailed, the estimated impact for women with children vs. no children is a negative, small, and insignificant –1.47 percentage points.

We then turn to an exploration of why, unlike other EITCs, California's EITC does not appear to have an extensive margin labor supply effect on women most likely to be affected – and women whose employment does respond positively to the federal EITC and other state EITCs. Our analysis suggests that there are two sources of this surprising result.

First, California's EITC has an unusual structure that targets high benefits on the lowest earners. Most states simply supplement the federal EITC by a fixed percentage; these percentages range from 3% in Montana, to 41.67% in South Carolina (in 2019, the last year of our analysis period), with the central tendency around 20%. Because of this fixed percentage

supplement, these state EITCs do not impact the income level at which the maximum credit is reached (\$14,950 for a family with two children, in 2021). Nor do they affect the “length” of the EITC plateau along which the EITC stays fixed (from \$14,950 to \$19,520 for a family with two children, in 2021) before phasing out. Moreover, in these other states the phase-out rate for the state component of the EITC is relatively modest, amounting to the federal phase-out rate (21.06% for a family with two children in 2021) multiplied by the state’s supplement rate (e.g., 4.2% for a state with a 20% state supplement).

In California, in contrast, the maximum credit is reached at a much lower income level – at \$8,300 for a family with two children in 2021, or just over one-half the federal maximum – and the state EITC begins to phase out as soon as the maximum EITC payment is reached. Moreover, the phase-out rate is essentially as steep as the phase-in rate (approximately 34% for a family with two children in 2021). (A small change in 2017 reduced the phase-out rate, but only at the point where most of the credit is already phased out.) The result is a much higher marginal tax rate that sets in at a much lower income level under the California EITC.

This feature of the state’s EITC was emphasized by Reuben et al. (2017), who predicted that, as a result, the state’s EITC would significantly augment the federal credit “but only for a small subset of the population of federal EITC beneficiaries in the state – that is, those with the lowest amounts of earned income...”; as a result, they predicted “its chief beneficiaries [would be] ... part-time low-wage workers or those who experience extended gaps in employment over the course of a year” (pp. 479-80, brackets added). This, by itself, could substantially reduce the observed extensive margin employment effect. Moreover, in evaluating California’s EITC, we obtain estimates pointing to negative hours effects overall for women, in contrast to the usual conclusion of modest impact (e.g., Dickert et al., 1995, based on simulations; Eissa and Hoynes,

2006, based on reduced-form estimates), which can stem from the high marginal tax rate the California EITC induces.

The second reason the California EITC may not boost employment – and one that amplifies the effects of the structure of the state’s EITC – is that California has had and continues to have among the highest minimum wages among U.S. states (\$9 in 2015 when the state EITC was adopted, and \$13 or \$14 in 2021, depending on firm size). The interaction between a high minimum wage and the unique budget constraint created by the California EITC implies that workers who work more than a relatively low number of hours are unlikely to gain any extra income because of the state’s EITC. And as the state’s minimum wage has increased sharply in recent years, the hours threshold at which even a minimum wage worker gains any extra income from the state’s EITC has declined. (The minimum wage interaction with the California EITC was also highlighted by Rueben et al., 2017, albeit with no empirical analysis of the actual effects of the policy/policies.)

Our empirical analysis consists of three steps. First, we implement a standard evaluation of the extensive margin effects of the California EITC, using a triple-difference approach that isolates the effect on less-educated single mothers. We show that there is no evidence of a positive employment effect.

Second, we extend the approach in Neumark and Wascher (2011) to examine the effects of “conventional” EITCs (designed as a percentage of the federal EITC) in 14 other states. This approach utilizes the percentage of state EITC supplement as a continuous treatment and estimates a difference-in-difference-in-differences model. We find that, in contrast to California’s EITC, conventional EITC supplements have clear positive effects on employment (and earnings).

Finally, we document and simulate how the unique structure of California’s EITC,

especially when interacted with a high minimum wage, dramatically reduces the hours threshold at which even minimum wage workers would earn more from employment under the state's EITC compared to no state EITC. Our calculations and simulations suggest that the impact of the state's EITC is likely no stronger than that of more typical state EITC's that supplement the federal EITC by very modest percentages.

Our work highlights how the structure of tax and transfer programs, and interactions with other labor market regulations – in this case, the minimum wage – can impact the behavioral responses to tax policy. In the particular case we study, our evidence suggests that a state EITC that appears less generous, by providing a smaller supplement to the federal EITC, could have much larger impacts on employment and earnings by creating stronger work incentives – and more so when the minimum wage is high.

Data and Policy Variation

We construct measures of individual-level employment, hours, and earnings for 1987-2019. We begin in 1987, which, as explained and documented below, is the year before the first state EITC we consider is implemented. We end in 2019 to avoid the confounding labor market effects of COVID.

The employment status and other individual-level characteristics are from the Annual Social and Economic Supplements of the Current Population Survey (CPS-ASEC), also known as the “March Files,” which, in addition to CPS monthly surveys, are conducted every March and provide information on individuals' labor supply and income during the prior calendar year.¹ We construct our employment indicator as whether the person worked any time during the last year. We measure annual hours worked by multiplying workers' usual hours worked per week in

¹ The last year of CPS data we use is 2020, to cover calendar year 2019.

the past year by their number of weeks worked during last year. We measure earnings as individual wage and salary income during the last year. In addition, we use March files to construct a set of control variables such as demographics, number of children (of all ages and under 6), and education levels. For each CPS record, we append state-level annual unemployment rates from the Bureau of Labor Statistics to control for business-cycle effects by state and by year.²

For the state-level information on the EITC in California and other states, we expand the data used in Neumark and Wascher (2011) to cover all the years during the 1987-2019 period based on reports published by the Center on Budget and Policy Priorities, the Tax Policy Center, and each state's Department of Revenue. What we term a "conventional" state EITC takes the form of specifying a percentage of the federal EITC. This ranges from 3% (Montana) to 41.67% (South Carolina) in 2019. In two states, this percentage varies with the level of income (Minnesota) or with the number of children (Wisconsin). Appendix Table A1 lists some other non-conventional variations of state EITCs. State supplementary EITC programs can generally be classified as refundable and non-refundable, where the former issue refunds even to families with zero tax liability or where the EITC exceeds the tax liability.

Given that California's EITC is refundable, when we contrast California's EITC to other state EITCs, we restrict to those with refundable EITCs. In addition, to avoid other sources of variation in the effects of other states' EITCs, we also restrict the comparison states to conventional EITCs. (California's EITC is not conventional, but also does not have closer

² The unemployment rates, sourced from the Current Population Survey (CPS), are published by the Bureau of Labor Statistics within their report of Unemployment Rate for States and Local Areas. The data we utilize are compiled over 1989-2019 by the Federal Reserve Bank of St. Louis (<https://fredhelp.stlouisfed.org/>).

parallels with any other state EITCs.) Finally, for our estimation for other states we require the state EITC was enacted no later than 2019. These restrictions lead to 14 EITC comparison states: Colorado, Connecticut, Illinois, Iowa, Kansas, Louisiana, Massachusetts, Michigan, Nebraska, New Mexico, New Jersey, New York, Oregon, and Vermont. Appendix Table A1 provides the details on each of these dimensions of state EITCs (conventionality, refundability, and timing), and highlights the states we use.

We characterize the generosity of these state EITCs by this percentage in each state and year. Table 1 lists the state EITC supplement percentages for the states we study from 1989-2019.

Figure 1 depicts the eligible credit amounts in 2015 across different income levels for the federal EITC (Panel A), California EITC supplement (Panel B), and combined credits (Panel C). We plot the credit amount for families with two children for easier comparison, although both programs' schemes vary based on the number of children. One can also think of the solid line in Panel C as the total eligible EITC credit in 2014, right before California enacted its EITC program, and think of the dashed line as the increase in the tax credit in 2015 (aside from the small adjustment of the federal EITC from 2014 to 2015 due to inflation). Figure 1 shows that although the California EITC offers a substantial increase in the credit at low income levels (\$0.34 for \$1 earned), its generosity fades out quickly, as the maximum credit is attained at the relatively low income threshold of \$6,950, and the phase-out rate (-0.34) is as high as the phase-in rate, implying a high marginal tax rate at low earnings levels.³

³ A modification to the California EITC in 2017 introduced a more gradual phase-out range on the higher end of the income spectrum. Despite the expansion of the income limit to \$22,350, workers earning within this extended range receive a very modest credit of \$0-\$250. Therefore, we do not focus on this change in our analysis, although its impact would be reflected in our event-study estimates.

Estimated Effects of the California EITC

Approach

We use a reduced-form approach to estimating the effects of the California EITC. This follows most of the existing literature on federal and state EITCs. In addition, applying reduced-form methods avoids problems such as workers' imperfect knowledge about the EITC (Neumark and Wascher, 2011), as well as inflexibility in adjusting hours (Liebman, 1998; Romich and Weisner, 2000).

We estimate the effects of the California EITC relative to the states where, in the sample period, the federal EITC was binding (i.e., the states that did not have or enact an EITC over this period).⁴ We start with a triple-difference model. We estimate the model for single, less-educated (high school degree or below) women aged 21-44 over a 10-year window around the start of the state EITC program (5 years before and 5 years after including the initial year, or 2010-2019). Our triple-difference estimate compares California to states without supplemental EITCs, and women with and without children.⁵ The underlying assumption is that single women with different numbers of children react similarly to changes in the economy besides the EITC; Meyer (2010) notes that this assumption appears to generally hold, with minor exceptions.

The model for California takes the form:

$$(1) Y_{ist} = \alpha + \beta_1 \cdot CA_s \cdot Post_t \cdot Kid_{ist} + \beta_2 \cdot CA_s \cdot Post_t + \beta_3 \cdot CA_s \cdot Kid_{ist} \\ + \beta_4 \cdot Post_t \cdot Kid_{ist} + \beta_5 \cdot CA_s + \beta_6 \cdot Post_t + \beta_7 \cdot Kid_{ist} + X_{ist}\eta + \epsilon_{ist}$$

⁴ The non-EITC states are Alabama, Alaska, Arizona, Arkansas, Florida, Georgia, Idaho, Kentucky, Mississippi, Missouri, Nevada, New Hampshire, North Carolina, North Dakota, Pennsylvania, South Dakota, Tennessee, Texas, Utah, West Virginia, and Wyoming.

⁵ As described in Meyer (2010), studies of the employment effects of the EITC generally compare single mothers to single childless women (or, less commonly, do comparisons among single mothers with different numbers of children).

In equation (1), Y_{ist} is the employment status (or other labor market outcome) for individual i in state s , observed in year t . CA_s is a dummy variable for living in California versus in states without any state EITC programs. Given that the California EITC was implemented in 2015, $Post_t$ is a dummy variable equal to 1 for observations in or after 2015. Kid_{ist} is a dummy variable indicating whether one or more of the woman's children are present in the home. X_{ist} is a set of control variables, including: the state unemployment rate; age and its square term; a dummy variable for education (=1 if graduated from high school); dummy variables for each marital status (married (partner present), married (partner not present), divorced, separated, widowed, never married); a dummy for each unique number of children (of all ages); a dummy for each unique number of children under 6; and dummy variables for Black and for Hispanic.

The model specification in equation (1) has a number of features that make it compelling for identifying the extensive margin effects of the EITC, which is why similar specifications have been used in the literature. First, like the federal and other state EITC programs, California's EITC is much more generous to families with children. In 2020, the maximum credit for families with 2 children is \$2,691, while it is only \$243 for families without children. It thus makes sense to treat the EITC for those without children as largely irrelevant, in which case the comparison between changes in outcomes for less-educated single women with and without children captures the likely effects of the EITC while holding constant labor market shocks likely to affect these women similarly whether or not they have children. Second, by restricting attention to less-educated women, and single women, we focus on those more likely to respond on the extensive margin incentives of the EITC because they are more likely to be on the phase-in segment of the budget constraint.

In equation (1), β_1 is our key parameter of interest, as it measures the effect of

California's EITC on employment (or other outcomes) by comparing California and states without EITC supplements, pre-2015 and post-2015, for less-educated single women with children relative to those without children. It is worth noting that one should take caution when trying to interpret β_2 as the effect for women without children because the specification in equation (1) does not control for state-by-year fixed effects.⁶ Therefore, β_2 may pick up any other shocks to the California labor market that coincide with the state EITC change.

Given that the data are at the individual level, but the policy variation is at the state level, we need to cluster the standard errors for inference regarding the parameter estimates from equation (1). The common approach to clustering is based on an assumption that there is a sufficiently large number of total clusters and of treated clusters. Both conditions are likely violated in our case, and clearly the second. First, our sample includes only 22 states; and second, the number of treatment clusters is limited, as the policy change affects only one state (California). As highlighted by Cameron et al. (2008), Conley and Taber (2011), and MacKinnon and Webb (2019, 2020), these scenarios can lead to underestimated standard errors and thus an increased likelihood of Type I errors. To address these concerns, we employ the wild bootstrap randomization inference (WBRI) procedure proposed by MacKinnon and Webb (2019). This method integrates the advantages of the wild cluster bootstrap (Cameron et al., 2018) and randomization inference (Conley and Taber, 2011; MacKinnon and Webb, 2020).

Effects of the California EITC

Table 2 presents the estimates of equation (1), the triple-differences estimates of the effect of California's EITC relative to the states where the federal EITC prevailed throughout the sample period. Towards the bottom of the table, we recalculate the p-values for estimates of β_1

⁶ If we included these, β_2 would not be identified.

using the WBRI-t method proposed in MacKinnon and Webb (2019), which addresses the over-rejection problem caused by an insufficient number of clusters.

The estimates of β_1 indicate substantial differences relative to other estimates of the effects of the EITC on low-skilled women with children. First and foremost, we find no detectable extensive margin effect in increasing employment. Indeed, the estimate is negative (-1.467), albeit small. The estimate is statistically insignificant based on conventional clustering of standard errors at the state level; the WBRI-t p-value in column (1) (0.744) confirms that the estimated effect of the California EITC on employment is not significant. This result contrasts with the positive employment effect most studies find.⁷

Second, there are negative intensive margin effects on hours, both conditional on working (-72.137) and unconditional (-75.233); these estimates are significant at the 1% level using conventional clustering, but are not significant at the 10% level using WBRI. The substantial negative point estimates contrast with much research on the hours (intensive-margin) effects of the EITC, which finds small or zero effects (see the review in Nichols and Rothstein, 2016, as well as individual studies such as Eissa and Liebman, 1996, and Eissa and Hoynes, 2006). Finally, there is a negative effect on earnings (both conditional and unconditional on working); these estimates are significant at the 5% level using conventional clustering, but not significant using WBRI. Other research also finds that the EITC reduces wages (Neumark and Wascher, 2011), and if conditional hours decline (per column (2)), this might further reduce annual earnings for those who are employed. The point estimate for unconditional earnings is similar.

⁷ One recent exception is Kleven's (2019) analysis of a number of federal EITC expansions, which claims that none of these expansions increased employment of single mothers. However, Schanzenbach and Strain (2021) re-evaluate this evidence and claim that Kleven's results are driven by omitting business cycle controls and not focusing on less-educated women. There is a 2021 revision of Kleven's paper on the NBER website that claims their estimates are outliers in a range of estimates.

But this estimate, too, is consistent with the evidence we find suggesting an unconditional hours decline (column (3)). The fact that the point estimates for hours and earnings are similar whether or not we condition on employment reinforces the evidence that EITC does not substantially change employment on the extensive margin.⁸

Figure 2 presents event-study estimates for the model corresponding to equation (1), where we allow for separate treatment effects for each post-treatment year and each pre-treatment year, normalizing the effect in 2014 to zero. Confidence intervals are omitted from the graphs; we just saw that conventional clustered standard errors are too small given the low numbers of clusters, and confidence intervals adjusting for this issue are very large. However, the conclusions based on the point estimates remain similar: the treatment effects on employment for each year are slightly negative and very close to zero. There is no evidence of pre-treatment changes that could bias the estimated effects. The graphs for hours and earnings point estimates are also consistent with our findings in Table 2, and there is no evidence of pre-trends.

Contrast to Other State EITCs

The estimates for California appear quite different from other research on the EITC. Most comparably, perhaps, Neumark and Wascher (2011) estimate the effect of state EITC supplements on employment using a similar triple-differences approach, while incorporating variation in the percentage of each state's EITC supplement relative to the federal EITC. Because of the controls included, the paper identifies the effects of the EITC solely from variation in state EITCs. The estimates from that paper imply that, for less-educated single mothers a 10-percentage point increase in a conventional state EITC supplement raises the likelihood of

⁸ Appendix Table A2 reports results for the difference-in-differences model including only single mothers, which entails dropping the *Kid* variables in equation (1). The estimates are qualitatively similar, although the point estimates are closer to zero.

employment 3.1 percentage points (an estimate that is constrained to be equal across all states).⁹

Neither that paper (nor other studies) presents state-specific estimates like those reported above for California. As we have demonstrated, however, we can likely get much more informative estimates of the effects of the EITC from combining states that enacted the policy. Thus, to provide more reliable evidence for other states, Table 3 replicates the Neumark and Wascher (2011) results, but for an expanded sample extended to include the period of California's EITC. This sample includes 14 states that enacted EITCs during the 1987-2019 period, and the same 21 control states used for estimating the effects of California's EITC in Table 2. This approach also uses information on the continuous variation in state EITC policy.

The regression equation is:

$$(2) Y_{ist} = \alpha + \beta_1 \cdot EITC(\%)_{st} \cdot Kid_{ist} + \beta_2 \cdot EITC(\%)_{st} + X_{ist}\lambda + G_s\mu + M_t\nu + \epsilon_{ist}$$

Compared to our previous model, equation (2) replaces the state-level treatment indicator ($CA_s \cdot Post_t$) with a continuous variable $EITC(\%)_{st}$, which captures the generosity of the state EITC supplement as a percentage of the federal EITC (which we rescale from 0 to 1). X_{ist} includes the same set of control variables as in equation (1) as well as a set of dummy variables for numbers of children, so we do not need to include a separate Kid_{ist} term. G_s and M_t are vectors of state and year fixed effects. β_1 estimates the effect of a continuous treatment using the EITC percentages.

In Table 3, the 0.267 point estimate in column (1) implies that a 10% state EITC supplement leads to an increase in overall employment among single mothers by 2.67 percentage

⁹ This result is reported in Table 2a of Neumark and Wascher (2011). That paper focused on minimum wage-EITC interactions, finding heterogeneous effects – with a higher minimum wage amplifying the positive employment effects of the EITC on single, less-educated mothers, but also amplifying adverse effects on workers who compete with them (less-skilled minority men and women without children). Given no impact in California of the EITC when considered in isolation, we do not study minimum-wage EITC interactions in California in the present paper. It is also not clear how one could do this in a reduced-form context, since there is only one EITC change in California. At best, one could compare the effects of minimum wage increases before and after the EITC took effect.

points. The estimated effect is significant at the 1% level based on the clustered standard error, and at the 5% level based on the wild bootstrap (WB) method.¹⁰ Column (2) indicates a negative effect of EITC supplements on hours (although only marginally significant based on WB p-values). The last column shows that a 10% EITC supplement boosts earnings (unconditional on working) by 2.89%, and this estimate is statistically significant at the 5% or 10% level regardless of our choice of p-values. The estimates in Table 3 draw a quite dramatic contrast to the estimates for the California EITC (Table 2 and Figure 2). Most notably, the conventional state EITC supplements produce substantial employment increases, whereas California's produces no increase (the point estimate is not even positive), despite the other states having percentage supplements lower than California's 85% rate (and generally much lower).

Why Does the California EITC Fail to Increase Employment?

We next turn to the question of why the California EITC does not have the positive extensive margin employment effects we might expect based on both other research and the evidence for some states presented in this paper, coupled with the high phase-in rate the California EITC creates. We first show that the low maximum credit and large phase-out rate of the California EITC reduce substantially the potential credit a person gets from the California EITC. We then show that the high (and rising) minimum wage in California exacerbates this problem.

We start by comparing the California and federal EITC amounts based on the distribution of earnings for single, less-educated women aged 21-44 in California, drawn from CPS data in

¹⁰ We use a pure wild bootstrap approach (Cameron et al., 2008) in this analysis because the model involves continuous treatment across many states rather than treatment of a single state, and hence is not subject to the issue of having too few treatment clusters.

2014.¹¹ In Table 4, column (1) in Panel A reports the quartiles and other moments of this earnings distribution. Panels B and C report the implied federal and California EITC amounts. As shown in Panel B, the federal EITC offers sizable income supplements even at the 3rd quartile of the income distribution (\$2,412). However, a comparison with Panel C shows that the California EITC is far less generous, with the payment reduced to zero by the median of the distribution, even though a woman at this level of income (here, earnings) qualifies for a federal EITC credit of \$5,150. Even those at the 1st quartile are only eligible for a California EITC amount of \$1,540 despite the California EITC phase-in range supplementing the federal EITC credit (\$3,744 at the 1st quartile) by 85%. This discrepancy highlights the fact that the structure of the California EITC means that the perceived generosity of the program, given the 85% phase-in rate, is actually quite low (although to be sure this structure does deliver substantial benefits to the lowest earners).

We next show, in the same table, that the rising minimum wage in California makes this problem far worse, because it leads to workers losing much or all of their potential California EITC payments, based on 2014 work hours. We calculate hypothetical earnings (i.e., based on actual hours and hypothetical wages) and corresponding EITC credits for each value of the state minimum wage in the years in which it changed. (Our data for the estimated EITC effects in earlier tables and figures use the data through 2019, but we show two subsequent minimum wage increases as well in Table 4). These calculations are reported in columns (2)-(7) of the table.

The hypothetical earnings in column (2) result in EITC credits that mirror those from actual incomes in column (1), with a substantial majority of the women we study receiving

¹¹ This is the year before the California EITC was enacted. We choose 2014 because income in or after 2015 could be affected by the California EITC program (see Table 2). We use 2015 EITC parameters.

nothing from the California EITC, owing to it phasing out below median earnings. The remaining columns show how the rising minimum wage exacerbates this issue. By the time the minimum wage reaches \$13 in 2021, the EITC payment at the 1st quartile declines to only \$129; and at higher minimum wages it falls to zero. In other words, the average California EITC payment falls to near zero at higher minimum wages.

In contrast, because the federal EITC has a higher maximum credit, a plateau over which the credit does not decline, and a lower phase-out rate, the value of the federal EITC is much more resilient to minimum wage increases. In fact, in the lower part of the earnings distribution the federal EITC amount *increases* with a higher minimum wage, because the effect of the higher minimum wage in increasing earnings along the phase-in range outweighs the impact of higher earnings in lowering the EITC payment along the phase-out range.¹² At the median and 3rd quartiles, the federal EITC payment decreases as the state minimum wage increases, but it remains sizable, and well above zero (\$3,229) even at the 3rd quartile with a \$14 minimum wage. As a consequence, as reported in the last row of Panel D, the average California EITC as a percentage of the average federal EITC, which starts at a quite low 14.3%, declines even more as the minimum wage increases – all the way to 7.3% in 2022 (with at \$14 minimum wage), or 8.4% in the last year used in our estimation (2019, with an \$11 minimum wage).¹³

¹² The federal EITC credit at the 1st quartile of the hypothetical earnings distribution given a \$14 minimum wage is \$5548 (the maximum credit).

¹³ Other research has considered the interaction between the EITC and the minimum wage. Nichols and Rothstein (2016) suggest that because the EITC pushes down the market wage, a higher minimum wage can make the EITC more effective and prevent employers from capturing the credit (pp. 141, 170). Neumark and Wascher (2011) suggest this argument is incorrect, in the sense that if the higher minimum wage prevents the market wage from falling, employers will not hire the additional workers looking for work because of a higher EITC. (Nichols and Rothstein recognize this, but appeal to some studies that fail to find minimum wage reduce employment (p. 171), although most studies do (Neumark and Shirley, 2022).) However, Neumark and Wascher find positive interactions for some groups, and negative interactions for others. In particular, there is a positive interaction for single low-skilled mothers, likely because of a high reservation wage that the minimum wage helps overcome. But there is a negative

In addition to the limited phase-in range and lack of a plateau, the California EITC also has a much steeper phase-out rate than the federal EITC (and hence other states with EITCs that are a percentage supplement to the federal EITC). This amounts, of course, to a high marginal tax rate on workers' earnings above the kink point where the phase-out begins. We summarize this by computing the marginal credit the program offers per \$1 earned, which is closely related to workers' incentives to work more.

Panel A of Table 5 illustrates the marginal EITC credit for the California EITC and for four different percentages of federal EITC – the latter structure corresponding to other state EITCs. (This table is also based on 2015 EITC parameters.) The California EITC offers a large marginal credit (\$0.34 per \$1 earned) for workers with an annual income of 0-\$6,950, which is more than twice as large as a conventional state EITC that supplements the federal EITC by 40%. However, because the phase-out begins as soon as income reaches \$6,950, the positive marginal credit turns rapidly into a tax rate of 34% and continues until income reaches \$13,900. Consequently, this high marginal tax rate provides incentives for workers to reduce their work time to stay at the peak, which may explain our finding in Table 2 suggesting negative hours effects.¹⁴ By way of comparison, over the range where the California EITC imposes a high marginal tax rate, conventional state EITCs either have a marginal subsidy (on the phase-in range) or zero credit (on the plateau), and would only impose a marginal tax rate at higher income levels (not shown).

interaction for female teenagers, likely because of increased competition from the lower-skilled mothers who enter the labor market (and no positive incentive effect from the EITC for female teenagers).

¹⁴ Note that the rapid phase-out in California creates only a negative intensive margin effect. It does not create a negative extensive margin effect. Rather, the point about extensive margin effects is that the California EITC fails to create a positive employment incentive because the high state minimum wage combined with the rapid phase-out implies that pay (earnings plus EITC) are only increased at very low hours.

Panel B of Table 5 translates income ranges to hour ranges based on various hypothetical hourly wages – the same minimum wages used in Table 4. On the extensive margin, the EITC is expected to promote employment if the EITC increases the marginal return to work. However, as suggested by Panel B, even at the lowest (\$9) minimum wage, this positive effect only arises for workers working 772 hours or less (15.4 hours per week). As the minimum wage increases, this number shrinks to an even lower level – for example, 632 hours at the \$11 minimum wage that prevailed in the last year of the data used in estimating the effects of the EITC, or 9.5 hours per week.

It seems likely that there are in fact few jobs that offer such low hours, meaning that most workers with positive hours of work after the California EITC was implemented would face a higher marginal tax rate.¹⁵ This can explain the hours reductions suggested by the estimates in Table 2 (as a result of both the substitution effect of the marginal tax rate, and the income effect of the EITC). Moreover, the earnings threshold at which the California EITC provides no supplement (above \$13,900 in 2015) – and hence does not increase the return to work at all – also occurs at relatively low hours, especially at higher minimum wages.¹⁶ And because of the

¹⁵ Low-hours jobs may be unlikely for two reasons. One, that has received attention in the labor supply literature, is fixed costs of labor supply (from transportation, clothing, child care, etc.) that deter labor market entry at low hours (Cogan, 1980 and 1981). A second factor, considered by Card (1990), is increasing productivity with hours at low levels of hours, creating a non-convexity that can prevent firms from offering low hours jobs. Moffitt (1982) models labor supply choices with minimum hours constraints (which could arise from firms' responses to fixed costs of labor supply for workers. Appendix Figure A1 demonstrates the severe paucity of workers employed for fewer than 20 hours per week.

¹⁶ If employers violate minimum wage laws by paying lower wages than the statutory minimum, then this earnings threshold would occur at higher hours. However, this is unlikely to be an important phenomenon in California. First, there is no tip credit in California in this period, so there is less reason to expect lower effective minimum wages because “wage theft” may be easier for tipped workers (e.g., Minkler et al., 2014). Second, Clemens and Strain (2022) show that noncompliance is lower where enforcement of minimum wage violations is stronger, and rank California one of the states having the strongest enforcement. The data also indicate the problem is minimal. Based on hourly workers in the CPS Outgoing Rotation Group files (for whom we can measure hourly wages most accurately), the share paid below the minimum wage ranges from 5.2% to 11.3% between 2015 and 2019, and the numbers are lower

high marginal tax rate, at much lower hours the California EITC payments would be quite low (consistent with the evidence reported in Table 4). Together, these can explain the absence of employment effects of the California EITC.

Conclusions

California's Earned Income Tax (EITC), with an 85% supplement to the federal EITC, appears at first blush to be far more generous than other state EITCs. However, when we estimate the effects of the California EITC for less-educated single mothers, we find no evidence of an extensive margin employment effect (as well as evidence of hours declining, if anything) – results that are inconsistent with prior literature on the federal and state EITCs, as well as updated estimates on other state EITCs that simply add a percentage to the federal EITC.

There appear to be two factors that explain these findings. First, California's EITC has an unusual structure that targets high benefits on the lowest earners, and these benefits phase out quickly. The consequence is that the program either imposes a high marginal tax rate or offers no benefit to workers even at low hours.

Second, California's high and increasing minimum wage accentuates these features of the state's EITC. The interaction between a high minimum wage and the unique budget constraint created by the California EITC implies that workers working more than a relatively low number of hours are unlikely to gain any extra income because of the EITC. And as the state's minimum wage has increased sharply in recent years, the hours threshold at which even a minimum wage worker gains any extra income from the state's EITC has declined.

The context we study provides a powerful example of how the structure of tax and

if we allow for rounding (e.g., the share paid more than \$1 below the minimum ranges from 1.67% to 6.65%).

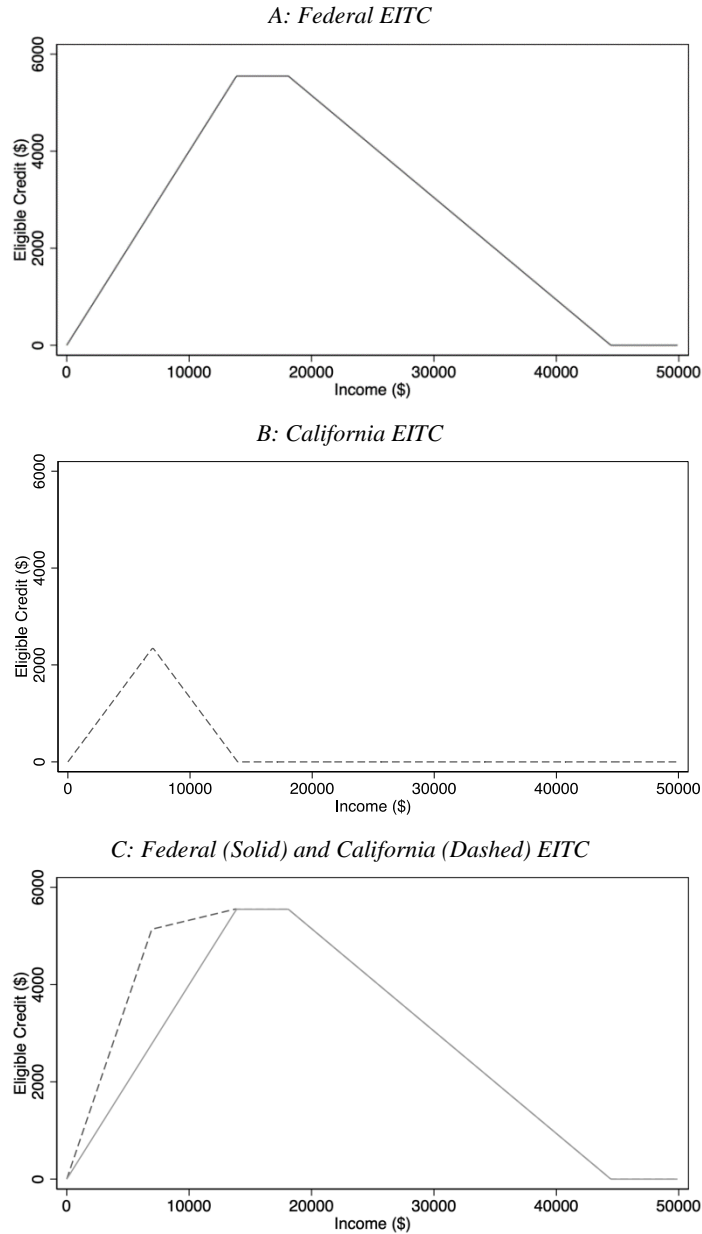
transfer programs, and interactions with other labor market regulations – in this case, the minimum wage – can impact the behavioral responses to policy and hence the effects of that policy. In the particular case we study, our evidence suggests that a state EITC that appears less generous – by providing a smaller supplement to the federal EITC – could have much larger impacts on employment and earnings by creating stronger work incentives, although that would trade off with lower EITC benefits to the lowest earners. As an example at the federal level, Hoynes et al. (2017) propose a simple expansion of the credit rate, which would preserve the plateau and lower phase-out rate of the current federal EITC. Our findings suggest this would be far more likely to further boost employment of single low-skilled mothers than an EITC change like the one implemented in California.

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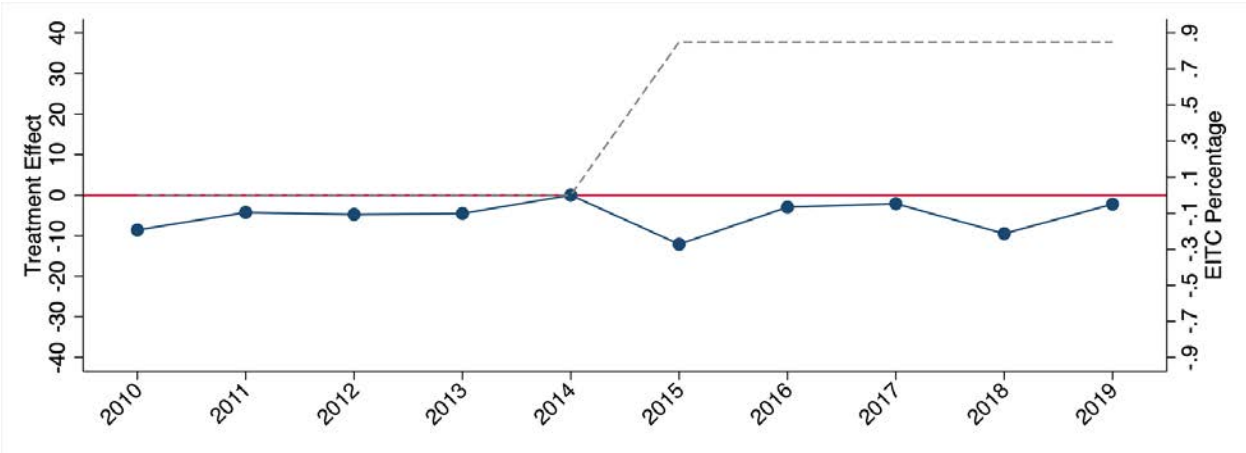
Figure 1: Federal EITC and California EITC (2015)



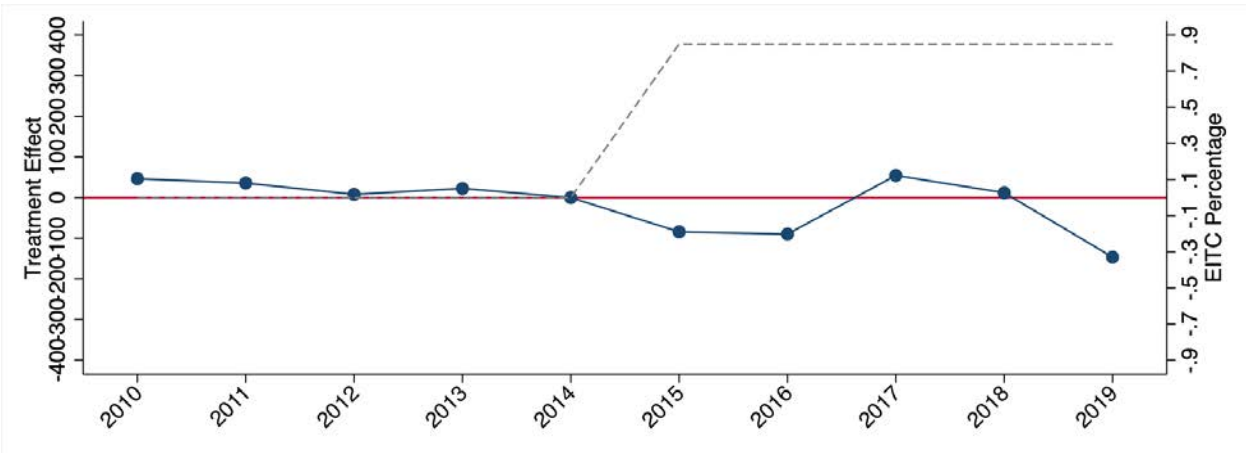
Notes: This figure plots the EITC credits under the 2015 federal EITC (Panel A) and California (Panel B) EITCs by income, for two-child families, as well as the combined credits (Panel C). The solid lines reflect the federal EITC and the dashed lines the California EITC. The 2015 EITC parameters define three income segments for the federal EITC and two for the California EITC. For the federal EITC, the phase-in range is from \$0 to \$13,870, followed by a plateau from \$13,870 to \$18,110, and a phase-out from \$18,110 to \$44,454. In contrast, the California EITC features a phase-in range from \$0 to \$6,950 and a phase-out range from \$6,950 to \$13,900. In 2017, California expanded the income coverage of its EITC by making workers with an income between \$13,850 and \$22,350 eligible for a small amount of credit (\$125 on average, for two-child families)

Figure 2: Triple-Difference Event Study Estimates of Effects of California EITC on Less-Educated Single Mothers

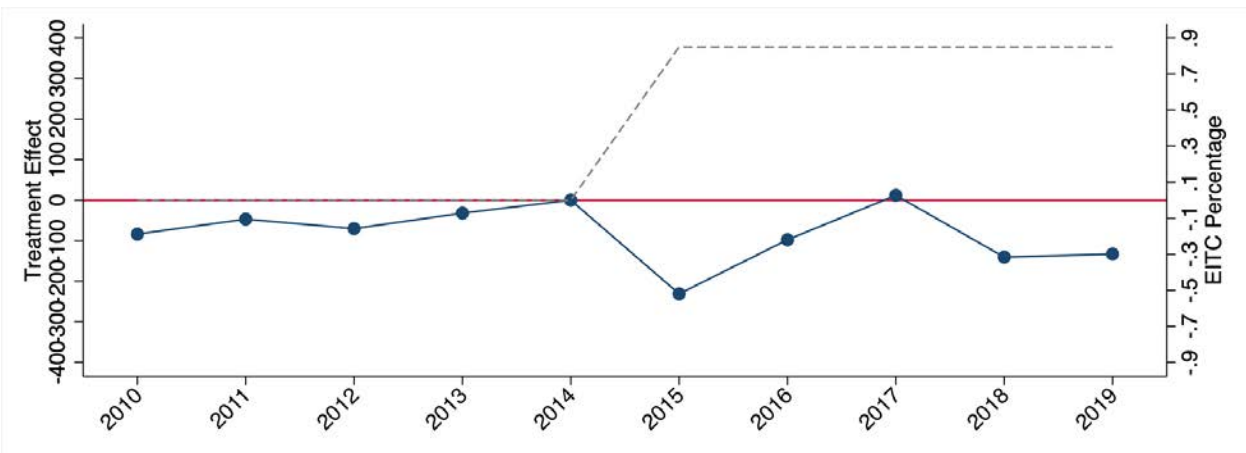
A: Employment



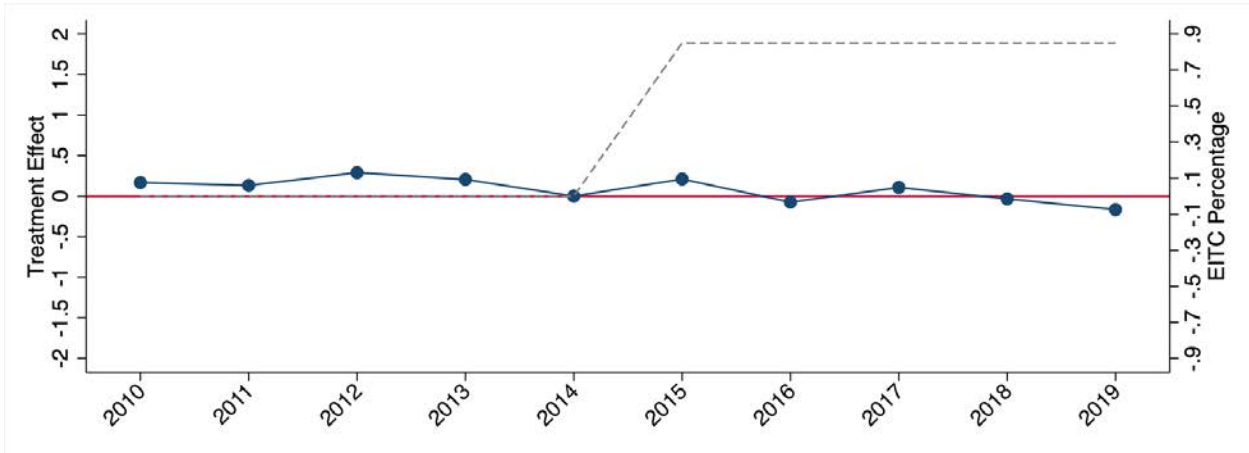
B: Hours (conditional on working)



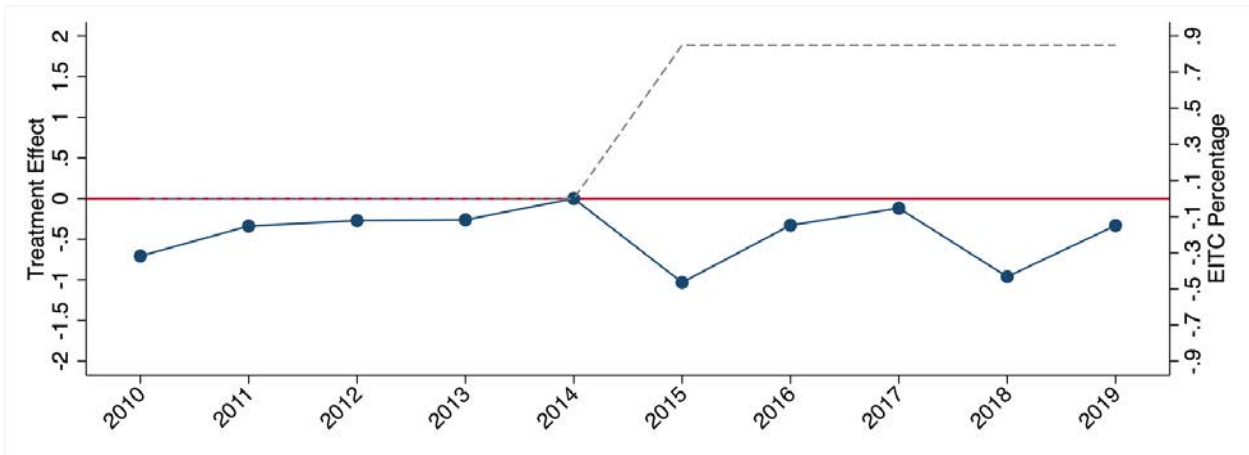
C: Hours (unconditional)



D: Earnings (conditional on working)



E: Earnings (unconditional)



Notes: Estimates are based on modified version of equation (1), with separate treatment effects for each post-treatment year. See Table 2 for details on controls, sample, etc. The gray dashed lines indicate the percentage EITC supplement in California for each year.

Table 1: EITC Parameters by State and Year (% Supplement to Federal EITC)

	CA	CO	CT	IL	IA	KS	LA	MA	MI	NE	NJ	NM	NY	OR	VT
1987	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1988	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23
1989	0	0	0	0	5	0	0	0	0	0	0	0	0	0	28
1990	0	0	0	0	5	0	0	0	0	0	0	0	0	0	28
1991	0	0	0	0	7	0	0	0	0	0	0	0	0	0	28
1992	0	0	0	0	7	0	0	0	0	0	0	0	0	0	28
1993	0	0	0	0	7	0	0	0	0	0	0	0	0	0	28
1994	0	0	0	0	7	0	0	0	0	0	0	0	8	0	25
1995	0	0	0	0	7	0	0	0	0	0	0	0	10	0	25
1996	0	0	0	0	7	0	0	0	0	0	0	0	20	0	25
1997	0	0	0	0	7	0	0	10	0	0	0	0	20	5	25
1998	0	0	0	0	7	10	0	10	0	0	0	0	20	5	25
1999	0	9	0	0	7	10	0	10	0	0	0	0	20	5	25
2000	0	10	0	5	7	10	0	10	0	0	10	0	23	5	32
2001	0	10	0	5	7	10	0	15	0	0	15	0	25	5	32
2002	0	0	0	5	7	15	0	15	0	0	18	0	28	5	32
2003	0	0	0	5	7	15	0	15	0	0	20	0	30	5	32
2004	0	0	0	5	7	15	0	15	0	0	20	0	30	5	32
2005	0	0	0	5	7	15	0	15	0	0	20	0	30	5	32
2006	0	0	0	5	7	15	0	15	10	8	20	0	30	5	32
2007	0	0	0	5	7	17	0	15	10	8	20	8	30	5	32
2008	0	0	0	5	7	17	3.5	15	10	10	22.5	10	30	6	32
2009	0	0	0	5	7	17	3.5	15	20	10	25	10	30	6	32
2010	0	0	0	5	7	18	3.5	15	20	10	20	10	30	6	32
2011	0	0	30	5	7	18	3.5	15	20	10	20	10	30	6	32
2012	0	0	30	7.5	7	18	3.5	15	6	10	20	10	30	6	32
2013	0	0	30	10	14	17	3.5	15	6	10	20	10	30	6	32
2014	0	0	27.5	10	15	15	3.5	15	6	10	20	10	30	8	32
2015	85	10	30	10	15	17	3.5	15	6	10	30	10	30	8	32
2016	85	10	27.5	10	15	17	3.5	23	6	10	35	10	30	8	32
2017	85	10	23	10	15	17	3.5	23	6	10	35	10	30	8	32
2018	85	10	23	18	15	17	3.5	23	6	10	35	10	30	8	36
2019	85	10	23	18	15	17	5	30	6	10	37	17	30	8	36

Notes: Numbers in this table are percentages of each state's EITC credits relative to the federal EITC credits. Data are collected based on a series of reports published by the Center on Budget and Policy Priorities, the Tax Policy Center, and each state's Department of Revenue. For California's EITC, we treat the percentage as 85% of the federal EITC because the phase-in rate (34%) is 85% of the federal EITC's phase-in rate (40%).

Table 2: Estimated Effects of the California EITC: Triple-Difference Regressions for Less-Educated Single Women

	(1)	(2)	(3)	(4)	(5)
	Employment (%)	Hours (cond.)	Hours (unc.)	Earnings (cond.)	Earnings (unc.)
<i>CA·Post·Kid</i>	-1.467 (1.004)	-72.137 (20.097)	-75.233 (24.697)	-0.161 (0.039)	-0.260 (0.107)
<i>CA·Kid</i>	-0.825 (1.100)	52.730 (23.100)	23.076 (25.669)	0.156 (0.036)	0.028 (0.110)
<i>Post·Kid</i>	0.89 (0.978)	64.389 (20.344)	57.919 (24.685)	0.085 (0.040)	0.147 (0.105)
<i>CA·Post</i>	1.584 (0.990)	15.884 (21.542)	33.093 (24.560)	0.099 (0.030)	0.224 (0.103)
<i>CA</i>	-1.468 (1.017)	-82.155 (28.187)	-74.639 (28.908)	-0.047 (0.040)	-0.172 (0.114)
<i>Post</i>	-1.879 (1.449)	9.172 (20.542)	-20.68 (30.665)	0.038 (0.043)	-0.157 (0.149)
<i>Kid</i>	6.638 (1.085)	-50.819 (16.568)	86.423 (23.553)	-0.078 (0.039)	0.624 (0.115)
Dep. variable mean	69.741	1619.755	1129.628	9.274	6.773
WBRI-t p-value	0.744	0.311	0.523	0.316	0.636
R ²	0.043	0.095	0.075	0.098	0.053
Observations	45044	31508	45044	31508	45044

Notes: This table reports estimated coefficients from equation (1) for California. The sample consists of less-educated single women, aged 21-44, from California (N=9,804) and donor states (N=35,240) (defined as never has any state EITC supplement) based on CPS March 2010-2019; California's EITC started in 2015. Employment is defined as a dummy variable for being employed during the calendar year prior to the survey year. Hours are usual hours worked per week multiplied by weeks worked during the prior year. Earnings are the log of the sum of salary income and business income (if self-employed, set to zero if negative). For both hours and earnings, we define both conditional (earnings >0) and unconditional versions. We apply the inverse hyperbolic function ($y = \text{asinh}(x)$) to both versions of earnings. Control variables include: the state unemployment rate; age and its square term; a dummy variable for education (=1 if graduated from high school); dummy variables for each marital status (married (partner present), married (partner not present), divorced, separated, widowed, never married); a dummy for each unique number of children (of all ages); a dummy for each unique number of children under 6; and dummy variables for Black and for Hispanic. Robust standard errors are clustered at the state level. Wild bootstrap randomization inference p-values (for each estimated coefficient for *CA·Post·Kid*) come from a wild bootstrap approach to calculate clustered standard errors with small number of treated and total clusters (MacKinnon and Webb, 2019); for these, ††† p<0.01, †† p<0.05, † p<0.1 (although no p-values are below these thresholds in this table).

Table 3: EITC as Continuous Treatment for All States with Conventional State EITC

	(1)	(2)	(5)
	Employment rate	Hours (cond.)	Log earnings (uncond.)
<i>EITC (%)·Kid</i>	0.267†† (0.052)	-4.479 (1.481)	2.888† (0.699)
<i>EITC (%)</i>	0.057 (0.063)	1.065 (1.044)	0.130 (0.693)
Dep. variable mean	0.728	36.740	6.831
R ²	0.165	0.076	0.124
Observations	108090	81373	108090

Notes: The CPS Sample includes 14 states with a conventional EITC program and 21 states that never had a state EITC program during the period 1987-2019. California is excluded. Appendix Table A1 summarizes our inclusion criteria. EITC is the state EITC eligible credit as a percentage (from 0 to 1) of the federal EITC. We add 1 to the earnings variable before taking log to make it comparable to the estimates in Neumark and Wascher (2011). Control variables include: the state unemployment rate; age marital status; race; ethnicity; dummies for each number of children (under 18 and under 6); and dummies for each education level (less than HS, HS graduates, some college, and college graduates); these controls follow Neumark and Wascher (2011). Robust standard errors are clustered at the state level; for these, *** p<0.01, ** p<0.05, * p<0.1. Wild bootstrap p-values come from a wild bootstrap approach to calculate clustered standard errors (Cameron et al., 2008), for these, ††† p<0.01, †† p<0.05, † p<0.1.

Table 4: Earnings and EITC Credits (\$) by Earnings Quartiles and Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Earnings, EITC Credits	Hypothetical Earnings & Credits: Minimum Hourly Wage Times Actual Hours Worked					
	2014	\$9/hr. (2014)	\$10/hr. (2016)	\$11/hr. (2019)	\$12/hr. (2020)	\$13/hr. (2021)	\$14/hr. (2022)
<i>Panel A: Earnings</i>							
1st quartile	9360	9360	10400	11440	12480	13520	14560
Median	20000	16380	18200	20020	21840	23660	25480
3rd quartile	33000	18720	20800	22880	24960	27040	29120
Max	1099999	46332	51480	56628	61776	66924	72072
Mean	25722	14155	15728	17301	18874	20446	22019
<i>Panel B: Eligible Federal EITC Credits Corresponding to Annual Earnings in Panel A</i>							
1st quartile	3744	3744	4160	4576	4992	5408	5548
Median	5150	5548	5529	5146	4762	4379	3996
3rd quartile	2412	5420	4982	4543	4105	3667	3229
Max	0	0	0	0	0	0	0
Mean	3945	5548	5548	5548	5387	5056	4725
<i>Panel C: Eligible California EITC Credits Corresponding to Annual Earnings in Panel A</i>							
1st quartile	1540	1540	1187	834	482	129	0
Median	0	0	0	0	0	0	0
3rd quartile	0	0	0	0	0	0	0
Max	0	0	0	0	0	0	0
Mean	0	0	0	0	0	0	0
<i>Panel D: Average Eligible Federal & California EITC Credits</i>							
Fed avg	2862	4360	4244	4090	3904	3701	3474
CA avg	411	442	388	342	306	274	254
CA/fed	14.3%	10.1%	9.2%	8.4%	7.8%	7.4%	7.3%

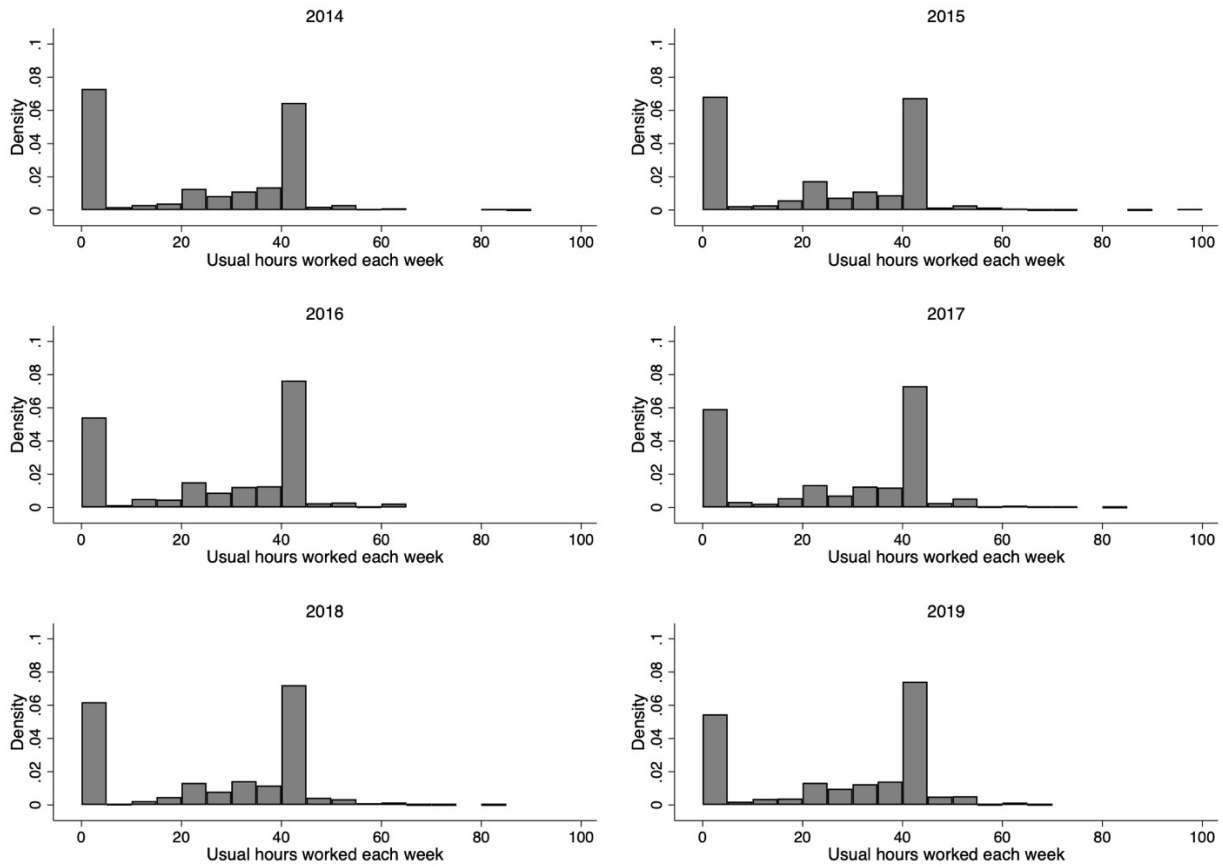
Notes: Panel A displays quartiles and means of annual earnings, both actual and hypothetical, based on California minimum wages by year. Actual annual earnings, defined as the sum of wage and salary income and business income (for self-employed only), are based on the sample of less-educated single women aged 21-44 in the CPS March file in 2014. Hypothetical earnings are calculated as the worker's reported hours worked during the last year times the value of the minimum wage in California, which ranges from \$9 (starting in 2014) to \$14 (starting in 2022). Panel B calculates the federal EITC credits corresponding to the annual earnings in Panel A. It shows the credits for the 1st quartile, median, 3rd quartile, maximum, and mean earnings. Panel C calculates the California EITC credits corresponding to the annual earnings in Panel A. It presents credits for the 1st quartile, median, 3rd quartile, maximum, and mean earnings. Panel D presents the calculated weighted average of both federal and California EITC eligible credits in the sample, and details the proportion of California EITC credits as a percentage of the federal credits. EITC values are based on 2015 EITC parameters.

Table 5: Distribution of Different Earnings and Corresponding EITC Credits

		0-\$6,950	\$6,950-\$13,650	\$13,650-\$13,900	\$13,900-\$17,830
<i>Panel A: Marginal state EITC credit per \$1 earned</i>					
<i>CalEITC vs. conventional state EITC</i>	CalEITC	0.34	-0.34	-0.34	0
	10% of federal	0.04	0.04	0	0
	20% of federal	0.08	0.08	0	0
	30% of federal	0.12	0.12	0	0
	40% of federal	0.16	0.16	0	0
<i>Panel B: Corresponding annual hour range given hypothetical hourly wage</i>					
<i>Hourly wage</i>	\$9	0-772	772-1517	1517-1544	1544-1981
	\$10	0-695	695-1365	1365-1390	1390-1783
	\$11	0-632	632-1241	1241-1264	1264-1621
	\$12	0-579	579-1138	1138-1158	1158-1486
	\$13	0-535	535-1050	1050-1069	1069-1372
	\$14	0-496	496-975	975-993	993-1274

Notes: This table presents marginal state EITC credits and corresponding hour ranges given different minimum wages. Each column reflects one income range within which the phase-in or phase-out pattern of both EITC programs are constant. In Panels A and B, we compare the California EITC with a conventional state EITC supplement (a simple proportion of the federal EITC) with the conventional percentage varying from 10% to 40% of the federal EITC. Panel A computes the marginal state EITC credit per \$1 earned. Panel B presents hour ranges corresponding to the income ranges (as shown on the top of the table) under different minimum wages (\$9 to \$14). EITC values are based on 2015 EITC parameters.

Appendix Figure A1: Distribution of Hours Worked by Single, Less-Educated Women in California: 2014-2019



Notes: The sample consists of less-educated single women in California aged 21-44 (N=9,804). The hours variable is derived from the CPS March file question of “*In the (one week/weeks) that (name/you) worked, how many hours did (you/he/she)(work that week?/usually work per week?)*”. For respondents who did not report working last year, hours worked are recoded as zero.

Appendix Table A1: All U.S. States with EITC Supplements

State	First Year	Refundable	Conventional	CPS Availability	Included in Analysis
California	2015	Yes		Yes	Yes
Colorado	2015	Yes	Yes	Yes	Yes
Connecticut	2011	Yes	Yes	Yes	Yes
Delaware	2005		Yes	Yes	
District of Columbia	2000	Yes		Yes	
Hawaii	2018		Yes	Yes	
Illinois	2000	Yes	Yes	Yes	Yes
Indiana	1999	Yes		Yes	
Iowa	1989	Yes	Yes	Yes	Yes
Kansas	1998	Yes	Yes	Yes	Yes
Louisiana	2007	Yes	Yes	Yes	Yes
Maine	2000	Yes		Yes	
Maryland	1987	Yes		Yes	
Massachusetts	1997	Yes	Yes	Yes	Yes
Michigan	2006	Yes	Yes	Yes	Yes
Minnesota	1991	Yes		Yes	
Montana	2020	Yes	Yes		
Nebraska	2006	Yes	Yes	Yes	Yes
New Jersey	2000	Yes	Yes	Yes	Yes
New Mexico	2007	Yes	Yes	Yes	Yes
New York	1994	Yes	Yes	Yes	Yes
Ohio	2013			Yes	
Oklahoma	2002		Yes	Yes	
Oregon	1997	Yes	Yes	Yes	Yes
Rhode Island	1975		Yes	Yes	
South Carolina	2018		Yes	Yes	
Vermont	1988	Yes	Yes	Yes	Yes
Virginia	2004		Yes	Yes	
Washington	2021	Yes			
Wisconsin	1989	Yes			

Notes:

1. Washington D.C.'s EITC is not considered as conventional as it is specified as 40% of the federal EITC for families with children, and 100% for families without children.
2. Maine's EITC is not considered as conventional as it is specified as 12% of the federal EITC for families with children, and 25% for families without children.
3. Maryland's EITC is not considered as conventional as it is specified as 28% of the federal EITC if a refundable option is chosen, and 50% if not.
4. Minnesota's EITC is not considered as conventional as it is based on income instead of the federal EITC.
5. Wisconsin's EITC is not considered as conventional as its percentage of the federal varies by the number of children.
6. Indiana's EITC started 1999 with an unconventional scheme but later switched to conventional in 2003.
7. Rhode Island's EITC started in 1975 but remained non-refundable until 2005.
8. Our sample is limited to states that enacted EITC programs before 2019. This selection is due to the availability of employment data from the Current Population Survey (CPS) starting in 1987 and the start of COVID-19 pandemic in 2020. As a result, Montana is not included.

Appendix Table A2: Estimated Effects of the California EITC: Double-Difference Regressions for Less-Educated Single Mothers

	(1)	(2)	(3)	(4)	(5)
	Employment (%)	Hours (cond.)	Hours (unc.)	Earnings (cond.)	Earnings (unc.)
<i>CA·Post</i>	0.232 (1.061)	-61.010 (24.985)	-44.649 (27.129)	-0.044 (0.034)	-0.013 (0.115)
<i>CA</i>	-2.314 (1.315)	-2.570 (26.750)	-34.224 (30.694)	0.113 (0.043)	-0.146 (0.140)
<i>Post</i>	-1.255 (1.691)	63.430 (19.341)	27.030 (35.493)	0.151 (0.030)	-0.015 (0.162)
Dep. variable mean	70.671	1653.234	1168.359	9.988	7.059
WBRI-t p-value (<i>CA·Post</i>)	0.967	0.525	0.707	0.756	0.980
R ²	0.046	0.061	0.074	0.088	0.061
Observations	21981	15615	21981	15615	21981

Notes: This table reports estimated coefficients from a difference-in-differences model. The notes to Table 2 apply, with the following exceptions. The variables involving the indicator for children (*Kid*) in equation (1) are dropped from the model, and non-mothers are dropped from the sample. The sample consists of less-educated single women with one or more children, aged 21-44, from California (N=3,969) and donor states (N=18,012) (defined as never had any state EITC supplement between 2010 and 2019) based on CPS March 2010-2019. Wild bootstrap randomization inference p-values (for each estimated coefficient for *CA·Post*) come from a wild bootstrap approach to calculate clustered standard errors with small number of treated and total clusters (MacKinnon and Webb, 2019); for these, ††† p<0.01, †† p<0.05, † p<0.1 (although no p-values are below these thresholds in this table).