Rev Econ Household (2023) 21:485–518
https://doi.org/10.1007/s11150-022-09637-3

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# The effect of state Earned Income Tax Credit (EITC) eligibility on food insufficiency during the COVID-19 pandemic

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Received: 15 July 2022 / Accepted: 12 December 2022 / Published online: 24 December 2022


## Abstract

This paper uses data from the Household Pulse Survey to examine whether and for how long the eligibility to receive state Earned Income Tax Credit (EITC) benefits reduced self-reported household food insufficiency among lower-income households with dependent children during the COVID-19 pandemic. The results of models estimated using difference-in-differences (DD) and difference-in-difference-in-differences (DDD) methods suggest that state EITC eligibility, on average, reduced food insufficiency by about 3 percentage points between March 2021 and early October 2021. However, the results of models estimated using an event study method show that the effect was not visible in all the post-March bimonthly periods. Overall, this paper finds some evidence to suggest that state EITC eligibility reduced food insufficiency over a short period.

**Keywords** Food insufficiency; State earned income tax credit; Household pulse survey; COVID-19 pandemic

## 1 Introduction

Food hardship, experienced by millions of lower-income households, is a major social problem in the U.S. Existing studies indicate that lower-income households with children are more likely to experience food hardship (Bukenya, 2017; Rose et al., 1998). In the early days of the COVID-19 pandemic— driven mainly by a dramatic increase in unemployment, lost access to school meals, and disruptions in the supply chain—the food insecurity rate tripled among households with children

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(George & Tomer, 2021). According to an analysis by the Center on Budget and Policy Priorities (CBPP), food hardship kept increasing until the end of 2020 and began to decrease in the early months of 2021 after federal, state, and local governments implemented generous policies to aid vulnerable households (Center on Budget and Policy Priorities, 2022). Arguably, the combined effect of all the benefits, provided through multiple programs in the first half of 2021, is visible in the descriptive analysis. Nevertheless, in terms of reducing food hardship, the unique effect of each program is not yet clear. This paper investigates whether and for how long the eligibility to receive state Earned Income Tax Credit (EITC) benefits reduced food insufficiency among eligible lower-income households with dependent children between March 2021 and early October 2021.

EITC—implemented federally and in certain states—is a means-tested cash transfer program that provides financial support primarily to lower-income working parents. At the state level, there is a wide variation in both the availability and the generosity of EITC programs, which results in a geographic heterogeneity in the total amount of EITC benefits that households are eligible to receive. The positive effects of state EITC eligibility on multiple measures of health and well-being have been documented in the literature (Baughman, 2012; Lenhart, 2019; Markowitz et al., 2017; Strully et al., 2010). Therefore, it is relevant to explore whether lower-income households with dependent children living in states with refundable EITC programs, on average, experienced lower food hardship during the pandemic compared to identical households living in states without any state-level tax credit programs. And if the eligibility to receive some additional tax refund from the state had any effect on food hardship, for how long did the effect last? To investigate both questions, this study uses the Household Pulse Survey (HPS), which provides a rich source of data collected regularly throughout the pandemic. The findings of models estimated using difference-in-differences (DD) and difference-in-difference-in-differences (DDD) methods suggest that state EITC eligibility, on average, reduced food insufficiency by about 3 percentage points between March 2021 and early October 2021. However, the findings of models estimated using an event study method show that the effect was not visible in all the post-March bimonthly periods. Considering everything, this paper finds some evidence to suggest that state EITC eligibility reduced food insufficiency over a short period.

This paper contributes to the literature on the effect of tax credit eligibility on food hardship. Given the precarious financial conditions of many lower-income households with dependent children, food hardship experienced by them may vary over the months of a calendar year. By using a high-frequency dataset, this study points our attention to the longevity of the effect of state EITC eligibility on food hardship. For policy evaluation, the findings emphasize the necessity of collecting high-frequency data on different self-reported measures of material hardship at regular intervals throughout the year.

## 2 Background

### 2.1 Measures of food hardship

In the U.S., the early estimates of food hardship were based on income in relation to the poverty threshold (Rose et al., 1998). Understandably, this income-based indirect measurement can lead to misclassification. To tackle this issue, the United States Department of Agriculture (USDA) uses two different but related self-reported measures of food hardship: (1) food insecurity and (2) food insufficiency (Economic Research Service, 2022a). According to the USDA, "Food insecurity means that households were, at times, unable to acquire adequate food for one or more household members because the households had insufficient money and other resources for food". Food insecurity is measured using a 10-item questionnaire for households without children and an 18-item questionnaire for households with children. Each question specifies the period (last 12 months or last 30 days) and points to a lack of resources as the reason for the behavior or the experience. Based on the responses to these questions, respondents are classified into one of four categories: (1) high food security, (2) marginal food security, (3) low food security, and (4) very low food security. Contrary to food insecurity, which has been widely used as an outcome variable in the literature, food insufficiency is a simpler measure that has been fielded in multiple federal surveys over the years (Economic Research Service, 2022a). According to the USDA, "Food insufficiency means that households *sometimes or often did not have enough to eat*". Food insufficiency, over a particular reference period, is measured based on the response to a simple question. For example, in the Household Pulse Survey (HPS), conducted by the United States Census Bureau (USCB) during the COVID-19 pandemic, respondents are asked: "In the last 7 days, which of these statements best describes the food eaten in your household? Select only one answer". The response options are: (1) Enough of the kinds of food (I/we) wanted to eat, (2) Enough, but not always the kinds of food (I/we) wanted to eat, (3) Sometimes not enough to eat, and (4) Often not enough to eat. Based on the USDA's definition of food insufficiency, I create a dummy variable that takes a value of 1 (food insufficient) if a respondent mentioned either *sometimes not enough to eat* or *often not enough to eat*, and a value of 0 (food sufficient) otherwise.

## 2.2 Overview of State Tax Credit Programs

By 2021, twenty-eight states and the District of Columbia (D.C.) had implemented state EITC programs (Urban Institute, 2021). There is variability in the refundability of these programs: in four states (Hawaii, Ohio, Virginia, and South Carolina), benefits are non-refundable (Urban Institute, 2021). Additionally, some states have state-level Child Tax Credit (CTC) and Child and Dependent Care Tax Credit (CDCTC) programs (Tax Credits for Workers and Families 2021). Figure 1 shows the availability of different tax credit programs at the state level in 2021. As this study aims to explore the effect of state EITC eligibility, I consider the seven states with *only refundable state EITC programs* as the treated states and the seventeen states with *no tax credit programs at the state level* as the control states. The treated states are: Connecticut, Illinois, Indiana, Massachusetts, Michigan, Montana, and Wisconsin. These states did not have state-level CTC and CDCTC programs in 2021. The control states are: Alabama, Alaska, Arizona, Florida, Mississippi, Missouri, Nevada, New Hampshire, North Dakota, Pennsylvania, South Dakota, Tennessee, Texas, Utah, Washington, West Virginia, and Wyoming. Crucially, within this subsample, while respondents from the control states were eligible to receive federal EITC, CTC, and stimulus benefits, respondents from the treated states were eligible

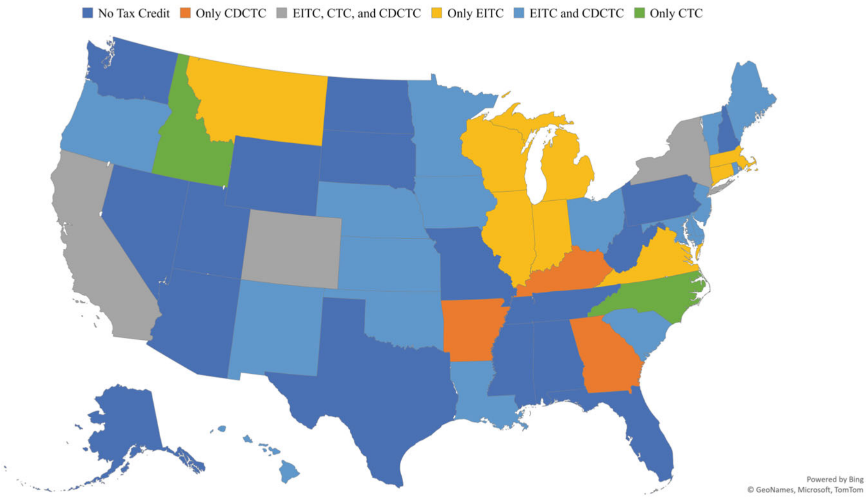


**Fig. 1** State tax credit programs in different U.S. states in 2021

to receive state EITC benefits on top of the benefits from the federal programs after filing taxes.

### 2.3 Effect of EITC on food hardship

In the existing literature, only a handful of studies investigate the relationship between EITC eligibility and food hardship. Schmidt et al. (2016) use data from the 2001–2009 Current Population Survey Food Security Supplement (CPS-FSS) to explore how food insecurity is affected by the benefits received from several major food, medical, and cash safety net programs, including federal and state EITCs. They use the average program generosity by state, year, and demographic cell as an instrument for imputed benefits. According to their findings, every additional $1000 eligibility in combined annual cash and in-kind benefits reduces annual food insecurity by 1.1 percentage points among non-immigrant low-income single-parent households. Interestingly, in one of the models, the authors find a negative but statistically insignificant coefficient of the imputed-potential-real-EITC variable when they enter the respondents' eligibility in different programs as separate explanatory variables. Bartfeld and Men (2017) use data from the 2002–2014 CPS-FSS to investigate how state-level economic and policy factors relate to household and child food insecurity. The authors use both annual and 30-day measures of food insecurity in their analyses. Based on the results of models estimated using generalized ordinal logistic regression, they find that a more generous state EITC eligibility is associated with reduced odds of both annual household food insecurity and annual child food insecurity; however, they do not find any statistically significant relationships when they use either the 30-day food insecurity or the annual food insufficiency measures as outcome variables. The lack of a consistent statistically significant association between EITC eligibility and food hardship—as found in the two studies—may be due to (1) using different measures of food hardship capturing different reference periods (food insecurity vs. food insufficiency; annual measure vs. 30-day measure), (2) targeting different populations (low-income single-parent households vs. all households with dependent children), and (3) applying distinct identification and estimation strategies (instrumental variable vs. logit models with state and year fixed effects).

### 2.4 Who are the EITC recipients?

EITC recipients, the majority of whom are lower-income working parents, often lack emergency savings, and relatively small income shocks, such as a car repair, can potentially throw them into poverty (Halpern-Meekin et al., 2018). Moreover, many lower-income families face material hardships caused by high-cost and low-performance financial services, lack of insurance, and credit constraints (Barr, 2012). The evidence in the existing literature suggests that EITC recipients find momentary relief from financial stress after receiving tax refunds (Despard et al., 2015; Sykes et al., 2015).

### 2.5 Longevity of the effect of EITC on food hardship

Given the financial struggles of many EITC recipient households, the effect of receiving tax refunds on food hardship may decay over the months as the recipients run out of extra cash. Analyzing data from the Chicago EITC experiment, Andrade et al. (2019) find that for the lump-sum EITC recipient group, relative to March-June, food insecurity (in the previous 30 days) is higher in June-July. Two epidemiological studies show further evidence in favor of EITC's short-term effect hypothesis. Rehkopf et al. (2014) use data from the Third National Health and Nutrition Examination Survey (NHANES III) conducted from 1988-1994. According to their findings, EITC eligibility reduces food insecurity in the disbursement months (February–April). In another study, Batra and Hamad (2021) use data from the 1998-2016 National Health Interview Survey (NHIS), which interviewed respondents throughout the year. The authors find that EITC eligibility reduces child food insecurity in the months following EITC refund receipt. The findings of these studies, both of which use a DD method, suggest that the effect of EITC on food hardship is temporary; however, they do not show how the effect evolves over time because both papers use a binary time dummy (February-April = 1 and May–January = 0) in their models. From a theoretical and policy perspective, it is crucial to understand for how long an expected positive income shock, induced by a small cash-transfer program, reduces food hardship. Consequently, an event-study design, using data collected at more frequent intervals, can be a better approach to investigate the question, especially in the context of the pandemic.

### 2.6 Current study

In this study, I examine whether and for how long the eligibility to receive state EITC benefits impacted self-reported household food insufficiency among eligible households with dependent children between March 2021 and early October 2021. The findings potentially shed some light on the longevity of the effect of lump-sum cash-transfer programs on food hardship.

# 3 Data

## 3.1 Data source

This paper uses data from week 10 to week 39 of the HPS conducted between July 2, 2020, and October 11, 2021 by the USCB in collaboration with multiple other federal agencies (United States Census Bureau, 2022). The survey was conducted weekly in the first phase and biweekly from phase two onward[1]. The key objective of this experimental survey was to quickly and efficiently gather data on the social and economic hardships faced by American families during the COVID-19 pandemic. One major limitation of the HPS is that some key variables have missing data. In particular, missing responses to the question on pre-tax annual household income (~20%) are of particular importance in the context of this paper. I use the predictive mean matching (PMM) method to impute the missing values of the income variable based on a respondent's race, gender, Hispanic status, age, educational attainment, household size, number of dependents below 18, marital status, and employment status. The imputation is implemented in R using the mice package (van Buuren and Groothuis-Oudshoorn, 2011). All the statistical analyses are conducted with and without the imputed data. For brevity, I present findings based only on samples that include imputed data.[2]

## 3.2 Main analytical sample

I combine respondents of 30 HPS weeks (week 10 to week 39)[3] from the treated and the control states who lived in households with *less than $50,000 pre-tax annual income* and *at least one dependent below 18*. I focus on these households because of two reasons: (1) the maximum income to qualify for EITC in the tax year 2020 was $50,594 for people filing as *single, head of household, or widowed* and $56,844 for people filing as *married, filing jointly* (Internal Revenue Service 2022a) and (2) households without dependents receive either no or only a negligible amount of benefits.[4] To improve the statistical power given small sample sizes at the state-HPS-week level, I combine data from multiple HPS weeks to create bimonthly samples. Table 1 provides a description of the coding of bimonthly periods. Because the IRS does not issue federal EITC refunds before

[1] The first phase of the HPS was conducted between April 23 and July 21, 2020, and the second phase began on August 19, 2020.

[2] The key findings of this paper do not change based on the inclusion of imputed data. Nonetheless, the inclusion of imputed data increases the sample sizes of the analyses and produces lower standard errors of the estimated coefficients. The results based on unimputed data are available upon request.

[3] In total, HPS week 10 to week 39 has 2,312,555 respondents. Narrowing it down to respondents with at least one dependent below 18 and pre-tax annual household income less than $50,000 produces a sample of 233,191 respondents, out of whom 113,900 are from the treated and the control states. Among these respondents, 16,597 (14.57%) did not answer the food insufficiency question. These respondents are not considered in the analyses. Therefore, the size of the main analytical sample is 97,303.

[4] In the tax year 2020, to qualify for EITC, the maximum adjusted gross income for single filers without dependents was $15,820 and the same for joint filers without dependents was $21,710. The maximum federal EITC eligibility for households without dependents was $538.

**Table 1** Coding of bimonthly periods

| Bimonthly period | HPS weeks | Dates |
|---|---|---|
| 1 (July–August'20) | 10 | July 2–July 7 |
| | 11 | July 9–July 14 |
| | 12 | July 16–July 21 |
| | 13 | August 19–August 31 |
| 2 (September–October'20) | 14 | September 2–September 14 |
| | 15 | September 16–September 28 |
| | 16 | September 30–October 12 |
| | 17 | October 14–October 26 |
| 3 (November–December'20) | 18 | October 28–November 9 |
| | 19 | November 11–November 23 |
| | 20 | November 25–December 7 |
| | 21 | December 9–December 21 |
| 4 (January–February'21) | 22 | January 6–January 18 |
| | 23 | January 20–February 1 |
| | 24 | February 3–February 15 |
| | 25 | February 17–March 1 |
| 5 (March–April'21) | 26 | March 3–March 15 |
| | 27 | March 17–March 29 |
| | 28 | April 14–April 26 |
| 6 (May–June'21) | 29 | April 28–May 10 |
| | 30 | May 12–May 24 |
| | 31 | May 26–June 7 |
| | 32 | June 9–June 21 |
| | 33 | June 23–July 5 |
| 7 (July–August'21) | 34 | July 21–August 2 |
| | 35 | August 4–August 16 |
| | 36 | August 18–August 30 |
| 8 (September-October'21) | 37 | September 1–September 13 |
| | 38 | September 15–September 27 |
| | 39 | September 29–October 11 |

**Table 2** Summary statistics of state EITC eligibility for the respondents from the treated states

| State | Count | State EITC as a percentage of Federal EITC | Average State EITC ($) | Maximum State EITC ($) |
|---|---|---|---|---|
| Connecticut | 2909 | 30.5 | 705 | 1532 |
| Illinois | 4134 | 18 | 596 | 1199 |
| Indiana | 4483 | 10 | 256 | 521 |
| Massachusetts | 3831 | 30 | 952 | 1998 |
| Michigan | 4939 | 6 | 201 | 400 |
| Montana | 2534 | 3 | 97 | 200 |
| Wisconsin | 2921 | 4–34 | 527 | 2264 |

Note: In Wisconsin, households with more dependents receive a higher percentage of federal EITC as state EITC

mid-February (Internal Revenue Service, 2022b) and state EITC eligibility depends on federal EITC eligibility, I define the HPS weeks beginning from March 3, 2021 as the post-treatment period.[5]

Table 2 presents summary statistics of state EITC eligibility for the respondents from the treated states. [6] There is wide variability in the average state EITC eligibility across states—from as low as $97 in Montana to as high as $952 in Massachusetts. According to the data provided by the IRS, for the tax years between 2011 and 2018, in the treated states, conditional on eligibility, the average federal EITC participation rate was 79.3%, and in the control states, the same was 79.16% (Internal Revenue Service, 2021c). Also, existing evidence suggests that the federal EITC participation rate increases with the amount of refund. The participation rate among those who are eligible to receive less than $100 is 42%, whereas the participation rate among those who are eligible to receive $4000 or more is 90% (Plueger, 2009). However, the existing literature provides no estimates of the participation rates in state EITC programs for the seven treated states (Iselin et al., 2021).

Table 3 provides weighted descriptive statistics for the analytical sample. Based on most of the socio-economic characteristics, on average, respondents from the treated states appear to be slightly different from respondents from the control states. For example, for the pre-treatment period, the average number of dependents below 18 in the control state households is 1.93, and the same in the treated state households is 1.9. Also, the percentage of married respondents is 45% in the

[5] Additionally, I run models by considering February 17 (HPS week 25) as the beginning of the post-treatment period. The key findings of this paper do not change based on this alternative coding

[6] State EITC eligibility is imputed based on a respondent's pre-tax annual household income, number of dependents below 18, marital status, and state of residence using the TaxSim model (version 32) developed by the National Bureau of Economic Research (Feenberg, 2019). For TaxSim imputation purposes, we need numeric values of the income variable. However, the HPS presents the value of the income variable in categories. I use a value of $20,000 for the respondents with income below $25,000, a value of 30,000 for the respondents with income above $25,000 and less than $35,000, and a value of $42,500 for the respondents with income above $35,000 and less than $50,000. The imputed values should be interpreted with caution, given the measurement error in the income variable used in this paper.

**Table 3** Descriptive statistics for the analytical sample ($N = 97,303$)

| | Pre | | | Post | | |
|---|---|---|---|---|---|---|
| | Control ($N = 44149$) | Treated ($N = 15968$) | Difference | Control ($N = 27403$) | Treated ($N = 9783$) | Difference |
| *Age* | | | | | | |
| Mean | 42.73 | 42.92 | −0.19 | 42.86 | 42.51 | 0.35. |
| *Number of dependents below 18* | | | | | | |
| Mean | 1.93 | 1.90 | 0.03*** | 1.90 | 1.84 | 0.06*** |
| *Household size* | | | | | | |
| Mean | 4.77 | 4.62 | 0.15*** | 4.73 | 4.62 | 0.11*** |
| *Annual household income* | | | | | | |
| <$25,000 | 0.39 | 0.38 | 0.01* | 0.40 | 0.39 | 0.01* |
| $25,000–$34,999 | 0.29 | 0.29 | 0 | 0.29 | 0.29 | 0 |
| $35,000–$49,999 | 0.32 | 0.32 | 0 | 0.31 | 0.30 | 0.01* |
| *Marital status* | | | | | | |
| Married (1/0) | 0.45 | 0.43 | 0.02*** | 0.46 | 0.42 | 0.04*** |
| *Educational attainment* | | | | | | |
| College degree or Higher (1/0) | 0.09 | 0.08 | 0.01*** | 0.10 | 0.09 | 0.01*** |
| *Gender* | | | | | | |
| Male (1/0) | 0.39 | 0.36 | 0.03*** | 0.39 | 0.38 | 0.01* |
| *Employment status* | | | | | | |
| Employed (1/0) | 0.49 | 0.48 | 0.01** | 0.51 | 0.51 | 0 |
| *Race* | | | | | | |
| White (1/0) | 0.67 | 0.67 | 0 | 0.70 | 0.69 | 0.01* |
| Black (1/0) | 0.21 | 0.21 | 0 | 0.19 | 0.19 | 0 |
| Asian (1/0) | 0.04 | 0.03 | 0.01*** | 0.03 | 0.02 | 0.01*** |
| Other (1/0) | 0.09 | 0.08 | 0.01** | 0.08 | 0.08 | 0 |
| *Hispanic status* | | | | | | |
| Hispanic (1/0) | 0.34 | 0.20 | 0.14*** | 0.33 | 0.19 | 0.14*** |
| *Home ownership status* | | | | | | |
| Homeowner (1/0) | 0.41 | 0.41 | 0 | 0.43 | 0.43 | 0 |
| *Food insufficiency* | | | | | | |
| Insufficient (1/0) | 0.25 | 0.25 | 0 | 0.21 | 0.18 | 0.03*** |

Numbers are rounded to two decimal places. For annual household income and race, proportions may not add up to 1 due to rounding. Significance codes: '***' $p < 0.001$, '**' $p < 0.01$, '*' $p < 0.05$, '.' $p < 0.1$

control states and 43% in the treated states. Although these differences are quite small, the difference in the percentage of Hispanic respondents between the two groups (14 percentage points) is substantial. Finally, the *post-pre change in food insufficiency* for the treated group is 3 percentage points lower than the same for the control group.

Figure 2 shows the bimonthly variation in the percentage of respondents reporting food insufficiency. From the figure, it seems that the descriptive findings are sensitive

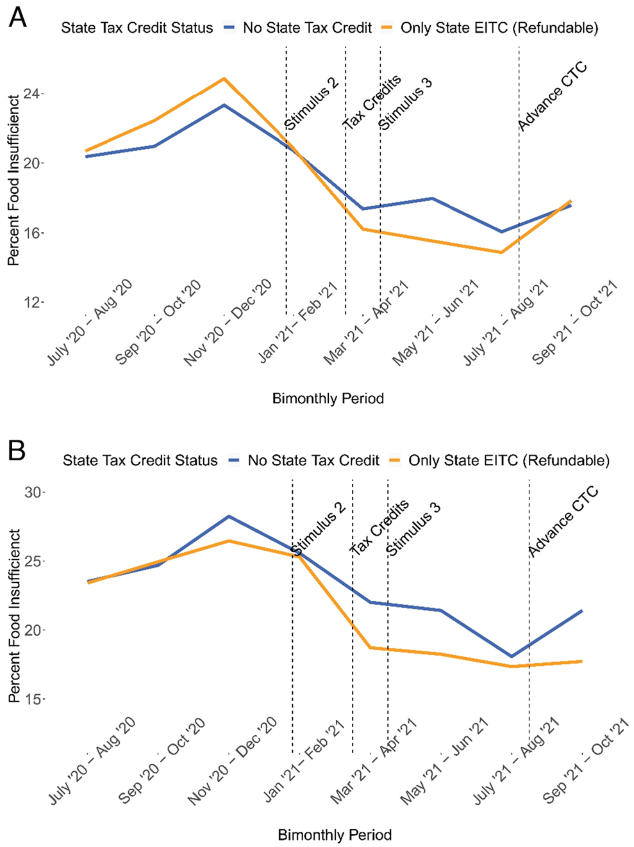


**Fig. 2** Bimonthly variation in the percentage of respondents reporting food insufficiency. Notes: Sample ($N = 97{,}303$) consists of respondents from the Household Pulse Survey week 10 to week 39 with at least one dependent below 18 and pre-tax annual household income below $50,000. These respondents are from the states with either only refundable state EITC programs (treated states) or no state-level tax credit programs (control states). In both panels, the $Y$ axis shows the percentage of respondents reporting food insufficiency. Panel **A** and Panel **B** show unweighted and weighted findings, respectively

to the usage of survey weights. For example, for the last bimonthly period (September–October'21), the results of the unweighted analysis (panel A) suggest no noticeable difference in the average food insufficiency between the two groups; however, based on the results of the weighted analysis (panel B), the control group, on average, experienced markedly higher food insufficiency. In terms of the change in food insufficiency before and after tax credit eligibility, although there was a larger drop among the treated respondents in the first post-treatment bimonthly period (March–April'21), the trend of a steeper decrease had begun sometime before March. In the context of this paper, the important question is: to what extent can we attribute the observed difference in the pre-and post-treatment change in average food insufficiency between the respondents from the two types of states to state EITC eligibility? In the next section, I describe the empirical strategy used in this paper to explore the question.

## 4 Estimation

### 4.1 Difference-in-Differences (DD)

Similar to existing studies, I estimate the following model using a DD approach to explore whether state EITC eligibility had any effect on the food insufficiency experienced by the treated group in the post-treatment period:

$$Food\ Insufficiency_{ist} = \gamma_s + \gamma_t + \alpha\, SEITC_s * Post_t + \epsilon_{ist} \tag{1}$$

where, *Food Insufficiency*$_{ist}$ refers to food insufficiency in the previous 7 days reported by respondent $i$ from state $s$ in bimonthly period $t$, $\gamma_s$ represents state fixed effects, $\gamma_t$ represents bimonthly fixed effects, $SEITC_s$ is a dummy which takes a value of 1 if the respondent lives in a treated state and a value of 0 if the respondent lives in a control state, $Post_t$ is a dummy which takes a value of 1 for the bimonthly periods between March 3, 2021 and October 11, 2021 and 0 otherwise,[7] and $\in_{ist}$ is the error term. This empirical strategy attempts to identify any short-term effect that exists in the post-treatment period within a year but cannot identify any long-term effect that persists across years. I assume that every state-EITC-eligible household becomes eligible in March 2021. This assumption implies that the treatment *(i.e., state EITC eligibility)* is assigned in all the treated states to every eligible recipient at the same time, and thus there is no variation in treatment timing. For the model shown in Eq. (1), under the *parallel trends* assumption, $\alpha$ is a consistent estimator of the effect of state EITC eligibility on food insufficiency reported by the respondents from the treated states in the post-treatment period. The parallel trends assumption can be stated as follows: in the absence of being eligible to receive state EITC benefits, the change in average food insufficiency over time among the respondents from the treated states would be identical to the change in average food insufficiency over time among the respondents from the control states.

It should be noted that the amount of state EITC benefits a household is eligible to receive is a continuous variable. Consequently, a binary categorization of the variable violates the *no two versions of the same treatment* assumption (Schwartz et al., 2012). To tackle this issue to some extent, I estimate Eq. (1) by using two continuous measures: (1) state EITC as a percentage of federal EITC and (2) maximum state EITC eligibility. Operationalizing the treatment as a continuous variable requires making two strong assumptions[8] (Callaway et al., 2021), which can be simply

[7] Additionally, as an attempt to estimate models identical to the ones estimated by Batra & Hamad, 2021 and Rehkopf et al., 2014, I create a $Post_t$ dummy that takes a value of 1 for the HPS weeks between week 25 (begins from February 17, 2021) and week 29 (ends on May 10, 2021) and 0 otherwise. This different coding of the $Post_t$ dummy in Eq. (1) does not change the key conclusion of the study. Also, as a falsification test, I estimate the models, as in Eqs. (1) and (2), on the subsample of HPS respondents without any dependents below 18 and pre-tax annual household income between $25,000 and $50,000 from the treated and the control states. I select this subsample because they were not eligible to receive any EITC benefits. As there was no difference in the overall tax credit eligibility between the two groups based on their state of residence, for this subsample, we expect no effect of state EITC eligibility on food insufficiency. Results of these falsification tests are provided in appendix Table 9 and Fig. 8. As expected, we observe no effect of state EITC eligibility on the food insufficiency experienced by the ineligible respondents living in the treated states in the post-treatment period.

[8] I present these assumptions in detail in the appendix.

summarized as follows: the change in average food insufficiency over time for respondents eligible to receive a lower level of state EITC can serve as the counterfactual of the change in average food insufficiency over time that would have been experienced by the respondents eligible to receive a higher level of state EITC had their eligibility been lower.

Next, to investigate the longevity of the effect of state EITC eligibility on food insufficiency, I estimate the following model using an event study approach:

$$\begin{gathered} Food\,Insufficiency_{ist} = \gamma_s + \gamma_t + \\ \sum_{\tau=-3}^{-1} \delta_\tau\, SEITC_s * Bimonthly_\tau + \\ \sum_{\tau=1}^{4} \delta_\tau\, SEITC_s * Bimonthly_\tau + \epsilon_{ist} \end{gathered} \tag{2}$$

where $\tau = 0$ corresponds to bimonthly period 4 (January-February'21) which is the reference period. Importantly, unlike the conventional DD method, the DD event study method allows for the treatment effect to vary over the bimonthly periods. Although the parallel trends assumption is fundamentally untestable (Cunningham, 2021), the absence of any leading effect serves as evidence in support of it. All the models in this paper are estimated in R using the *fixest* package (Berge, 2018). Standard errors are clustered at the state level.

### 4.2 Difference-in-Difference-in-Differences (DDD)

As an attempt to guard against the possibility that state-level policy changes and other temporal events explain the results of models based on Eqs. (1) and (2), I estimate the following models using a DDD approach:

$$\begin{gathered} Food\,Insufficiency_{ist} = \gamma_s + \gamma_t + \beta_1\, dep_i + \beta_2\, dep_i * SEITC_s \\ + \beta_3\, dep_i * Post_t + \beta_4\, SEITC_s * Post_t + \sigma\, SEITC_s \\ * Post_t * dep_i + \epsilon_{ist} \end{gathered} \tag{3}$$

$$\begin{aligned} &Food\,Insufficiency_{ist} = \gamma_s + \gamma_t + \beta_1\, dep_i + \beta_2\, dep_i * SEITC_s \\ &\quad + \sum_{\tau=-3}^{-1} \alpha_\tau\, dep_i * Bimonthly_\tau + \sum_{\tau=1}^{4} \alpha_\tau\, dep_i * Bimonthly_\tau + \\ &\quad \sum_{\tau=-3}^{-1} \pi_\tau SEITC_s * Bimonthly_\tau + \sum_{\tau=1}^{4} \pi_\tau\, SEITC_s * Bimonthly_\tau + \\ &\quad \sum_{r=-3}^{-1} \delta_\tau dep_i * SEITC_s * Bimonthly_\tau + \sum_{\tau=1}^{4} \delta_\tau\, dep_i * SEITC_s * Bimonthly_\tau + \epsilon_{ist} \end{aligned} \tag{4}$$

Here, $dep_i$ is a dummy variable that takes a value of 1 if respondent $i$ lives in a household with at least one dependent below 18 and 0 otherwise. For these models, the analytical sample consists of two groups of respondents from the treated and the control states: (1) with no dependents below 18 and pre-tax annual household income between \$25,000 and \$50,000 (EITC ineligible), and (2) with at least one dependent below 18 and less than \$50,000 pre-tax annual household income (EITC eligible). These models include the EITC-ineligible group to account for temporal events that affected everyone identically within a state. For $\sigma$ in Eq. (3) to be a consistent estimator of the effect of state EITC eligibility on food insufficiency, a different *parallel trends* assumption needs to hold (Cunningham, 2021). The assumption can be expressed as follows: in the absence of state EITC eligibility, the gap in average food insufficiency between respondents with and without dependents in the treated states over time would evolve similarly to the gap in average food insufficiency between respondents with and without dependents in the control states. Finally, similar to the DD event study, the DDD event study allows for the treatment effect to vary over time and indicates its stability in the post-treatment bimonthly periods.

### 4.3 Heterogeneity in the effect based on the number of dependents

As EITC eligibility increases with the increase in the number of dependent children (holding other factors constant), there may be a heterogeneous effect between households with one dependent and households with two or more dependents. To explore the possibility, for the main analytical sample (which includes households with at least one dependent below 18 and annual income less than \$50,000), I estimate the following models using a DDD approach:

$$\begin{aligned} Food\,Insufficiency_{ist} &= \gamma_s + \gamma_t + \beta_1\, two.dep_i + \beta_2\, two.dep_i \\ &* SEITC_s + \beta_3\, two.dep_i * Post_t + \beta_4\, SEITC_s * Post_t + \\ &\eta\, SEITC_s * Post_t * two.dep_i + \epsilon_{ist} \end{aligned} \tag{5}$$

$$\begin{aligned} &Food\,Insufficiency_{ist} = \gamma_s + \gamma_t + \beta_1\, two.dep_i + \\ &\beta_2 two.dep_i * SEITC_s + \sum_{\tau=-3}^{-1} \alpha_\tau\, two.dep_i * Bimonthly_\tau + \\ &\sum_{\tau=1}^{4} \alpha_\tau\, two.dep_i * Bimonthly_\tau + \sum_{\tau=-3}^{-1} \pi_\tau\, SEITC_s * Bimonthly_\tau + \\ &\sum_{\tau=1}^{4} \pi_\tau\, SEITC_s * Bimonthly_\tau + \sum_{\tau=-3}^{-1} \delta_\tau two.dep_i * SEITC_s * Bimonthly_\tau \\ &+ \sum_{\tau=1}^{4} \delta_\tau\, two.dep_i * SEITC_s * Bimonthly_\tau + \epsilon_{ist} \end{aligned} \tag{6}$$

Here, $two.dep_i$ is a dummy variable that takes a value of 1 if respondent $i$ lives in a household with *two or more dependents below 18* and 0 if they live in a household with *only one dependent below 18*. A non-zero value of $\eta$ in Eq. (5) would indicate a heterogenous effect of state EITC eligibility on food insufficiency based on the number of dependents.

## 5 Estimation results

Following suggestions by Solon et al. (2015), I estimate all the models with and without person-level weights provided in the HPS. I present the weighted findings

**Table 4** Effect of state EITC eligibility on food insufficiency among the eligible in the post-treatment period (DD, weighted)

| | Binary Treatment | | | | Continuous Treatment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Maximum State EITC ($100) | | | | State EITC as % of Federal EITC | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $SEITC_s*Post_t$ | −2.4* (1) | −2.6* (0.95) | −2.8** (0.88) | −0.68 (4.1) | −0.2** (0.06) | −0.21*** (0.05) | −0.23*** (0.05) | −0.21** (0.07) | −0.12* (0.05) | −0.14** (0.05) | −0.15** (0.04) | −0.10 (0.08) |
| State fixed effects | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No |
| Division fixed effects | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| Period fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual/household controls | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| State-level temporal controls | No | No | Yes | Yes | No | No | Yes | Yes | No | No | Yes | Yes |
| Division-period interaction | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| $R^2$ | 0.01 | 0.07 | 0.07 | 0.07 | 0.01 | 0.07 | 0.07 | 0.07 | 0.01 | 0.07 | 0.07 | 0.07 |

Sample ($N = 97{,}303$) consists of respondents from the Household Pulse Survey week 10 to week 39 with at least one dependent below 18 and pre-tax annual household income below $50,000 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states). Individual/household controls are household size, age, annual household income, number of dependents below 18, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are in parentheses and are clustered at the state level. Significance codes: '***' $p < 0.001$, '**' $p < 0.01$, '*' $p < 0.05$, '.' $p < 0.1$

here and the unweighted findings in the appendix. Table 4 shows the results of the model based on Eq. (1). Columns 1–4 present the findings of the specifications in which state EITC eligibility is operationalized as a binary variable. For the specification without any control variables (column 1), the estimated effect suggests that, on average, state EITC eligibility reduced food insufficiency among the eligible households by 2.4 percentage points (95% CI [−4.42, −0.29], $p < 0.05$). Next, I add individual-level/household-level control variables[9] to the model, and the estimated effect (column 2) becomes slightly larger in magnitude ($\alpha = -2.6$, 95% CI [−4.6, −0.67], $p < 0.05$). Also, I estimate the model by incorporating both individual-level/household-level controls and state-level temporal controls.[10]The estimated effect in this specification (column 3) increases further in magnitude ($\alpha = -2.8$, 95% CI [−4.62, −0.96], $p < 0.01$). Lastly, I estimate the model using division[11] fixed effects, bimonthly fixed effects, and interactions among them. Although negative, in this specification (column 4), the estimated effect is not significantly different from 0 at the 5% significance level. Table 7 in the appendix shows the findings of the same specifications estimated without the survey weights. In the unweighted specifications, generally, both estimated coefficients and associated standard errors tend to be smaller; nevertheless, the findings are quite similar.

Columns 5-8 show the estimated effects for specifications in which the value of $SEITC_s$ for the respondents from state $s$ is set to the maximum value of state EITC eligibility in that state (in \$100). The estimated effect in specification 5 suggests that with every \$100 increase in state EITC eligibility, on average, food insufficiency decreases by 0.2 percentage points (95% CI [−0.32, −0.08], $p < 0.01$). In the other specifications (columns 6−8), the estimated effects are also negative and significantly different from 0 at the 5% significance level. These estimates are possibly downward biased because the state EITC eligibility of most eligible respondents is less than the maximum state EITC eligibility. Finally, we observe similar findings when the value of $SEITC_s$ is operationalized as a percentage of the federal EITC (columns 9-12).

Figure 3 displays the DD event study findings[12] (Eq. 2). Looking at the figure, we observe no leading effect as none of the estimated coefficients in the periods before event period 0 (January-February'21) is significantly different from 0 at the 5% significance level, which provides some support in favor of the parallel trends assumption. Apparently, the effect becomes visible in event period 2 (May–June'21) but not in event period 1 (March–April'21). One possibility is that because lower-

9 Individual-level/household-level controls are household size, age, annual household income, number of dependents below 18, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days.

10 State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly period.

11 I use the 9 divisions defined by the USCB. These divisions are: (1) New England, (2) Middle Atlantic, (3) East North Central, (4) West North Central, (5) South Atlantic, (6) East South Central, (7) West South Central, (8) Mountain, and (9) Pacific (United States Census Bureau, 2013).

12 I estimate all the event study models (as in Eqs. 2, 4, and 6) with and without control variables. The estimated coefficients remain mostly unchanged depending on the addition of the control variables. For brevity, throughout this paper, I present the findings of the models that include both individual/household controls and state-level temporal controls.

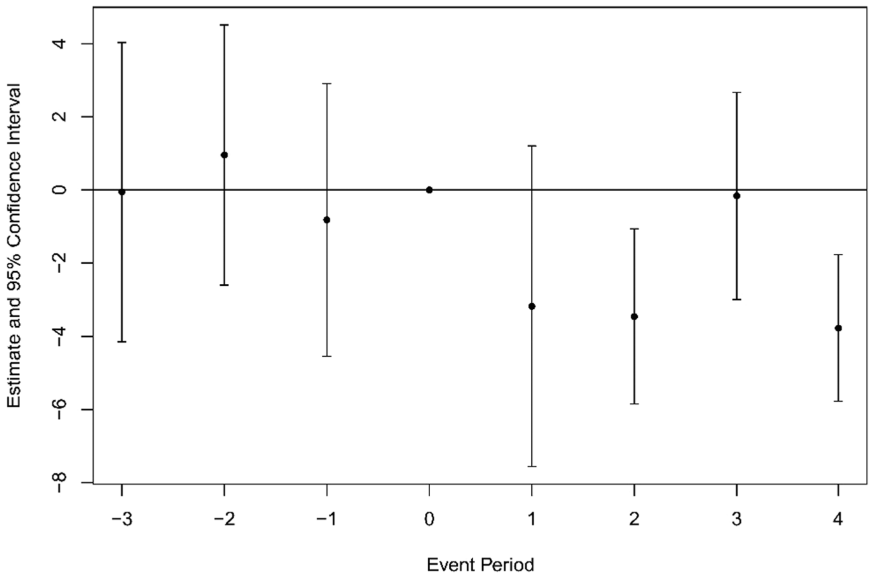


**Fig. 3** Effect of state EITC eligibility on food insufficiency among the eligible over the bimonthly post-treatment periods (DD event study, weighted). Notes: Period 0 refers to January-February, 2021. Sample ($N = 97{,}303$) consists of respondents from the Household Pulse Survey week 10 to week 39 with at least one dependent below 18 in the household and with pre-tax annual household income below $50,000 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states). Individual/household controls are household size, age, annual household income, number of dependents below 18, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are clustered at the state level. The error bars show 95% confidence intervals

income households with dependent children in both the treated and the control states were eligible to receive federal tax credit benefits after filing their taxes and stimulus benefits in March, there was identical change in average food insufficiency in March–April'21 relative to January-February'21 for the two groups. Given that these households, on average, have similar monthly spending patterns, households in the control states, after a while, might have run out of federal benefits. In contrast, some households in the treated states might have additional cash received from state EITC left to spend on food, which resulted in the effect observed in May–June'21. Surprisingly, the effect seems to reappear in period 4 (September–October'21) after disappearing in period 3 (July–August'21) in the weighted analysis; however, we do not observe this reappearance in the unweighted analysis (appendix Fig. 6).

Table 5 presents the findings of the models estimated using a DDD approach (Eq. 3). In general, the estimated effects appear to be larger in magnitude in these models compared to the DD estimates. It is worth noting that unlike DD specification 4 (Table 4), the effect is statistically significantly negative in DDD specification 4. The estimated effects in the unweighted DDD specifications (appendix Table 8) tend to be smaller, but all of them are negative and significantly different from 0 at the 5% significance level. From the weighted DDD event study findings presented in Fig. 4, it appears that the effect was significantly different from 0 only

**Table 5** Effect of state EITC eligibility on food insufficiency among the eligible in the post-treatment period (DDD, weighted)

| | Binary treatment | | | | Continuous treatment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Maximum State EITC ($100) | | | | State EITC as % of Federal EITC | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $SEITC_s$*$Post_t$*$DEp_i$ | –2.8* (1.1) | –3** (1) | –3** (1) | –2.7*(1) | –0.23*** (0.06) | –0.23** (0.06) | –0.23** (0.06) | –0.21** (0.06) | –0.16** (0.05) | –0.17** (0.05) | –0.17** (0.05) | –0.15*** (0.04) |
| $SEITC_s$*$Post_t$ | 0.45 (0.52) | 0.34 (0.54) | 0.25 (0.50) | 1.2 (0.85) | 0.02 (0.04) | 0.02 (0.04) | 0.007 (0.04) | –0.04 (0.03) | 0.04 (0.03) | 0.03 (0.03) | 0.03 (0.03) | 0.02 (0.04) |
| State fixed effects | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No |
| Region fixed effects | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| Period fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual/household controls | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| State-level temporal controls | No | No | Yes | Yes | No | No | Yes | Yes | No | No | Yes | Yes |
| Region-period interaction | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| $R^2$ | 0.03 | 0.09 | 0.09 | 0.09 | 0.03 | 0.09 | 0.09 | 0.09 | 0.03 | 0.09 | 0.09 | 0.09 |

Sample ($N = 244{,}975$) consists of respondents from the Household Pulse Survey week 10 to week 39 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states) and from two types of households: (1) at least one dependent below 18 and pre-tax annual household income below $50,000 and (2) no dependents below 18 and pre-tax annual household income above $25,000 and below $50,000. Individual/household controls are household size, age, annual household income, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are clustered at the state level. Standard errors are in parentheses and are clustered at the state level

Significance codes: '***' $p < 0.001$, '**' $p < 0.01$, '*'$p < 0.05$, '.'$p < 0.1$

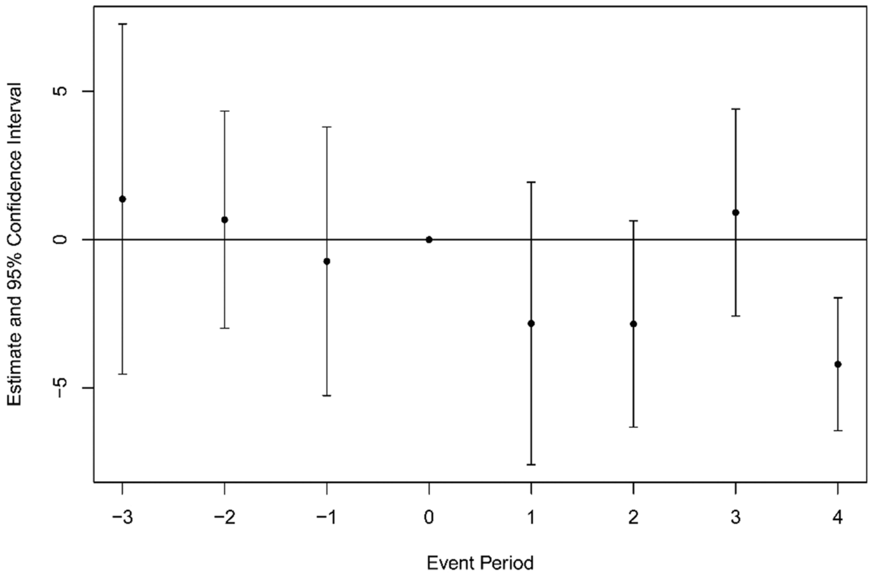


**Fig. 4** Effect of state EITC eligibility on food insufficiency among the eligible over the bimonthly post-treatment periods (DDD event study, weighted). Notes: Period 0 refers to January-February, 2021. Sample ($N = 244{,}975$) consists of respondents from the Household Pulse Survey week 10 to week 39 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states*)* and from two types of households: (1) at least one dependent below 18 and pre-tax annual household income below \$50,000 and (2) no dependents below 18 and pre-tax annual household income above \$25,000 and below \$50,000. Individual/household controls are household size, age, annual household income, marital status, race, Hispanic status, female indicator, educational attainment, home-ownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are clustered at the state level. The error bars show 95% confidence intervals

in period 4 (September-October'21); however, the unweighted DDD event study estimates (appendix Fig. 7) indicate that the effect was not significant in any of the post-treatment bimonthly periods.

Table 6 shows the results of the models estimated to explore the heterogeneity in the effect based on the number of dependents (one dependent vs. two or more dependents). Except specification 4, in all the specifications, the estimated coefficients of $SEITC_s{*}Post_t$ are negative and significantly different from 0 at the 5% significance level, indicating that state EITC eligibility reduced food insufficiency among the households with one dependent. The estimated coefficients of $SEITC_s{*}Post_t{*}two.dep_i$ are positive, and in some specifications, they are significantly different from 0 at the 10% significance level. However, in the unweighted models (appendix Table 10), the estimated coefficients are not significantly different from 0 in any of the specifications. Overall, these findings suggest that the effect was either the same or possibly lower among the households with two or more dependents compared to households with one dependent. Also, the event study results, as presented in Fig. 5 (weighted) and in appendix Fig. 9 (unweighted), suggest no significant difference in the effect between these two groups in any of the post-treatment

**Table 6** Heterogeneity in the effect of state EITC eligibility on food insufficiency based on one dependent vs. two or more dependents among the eligible in the post-treatment period (weighted)

| | Binary treatment | | | | Continuous treatment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Maximum State EITC ($100) | | | | State EITC as % of Federal EITC | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $SEITC_s$*$Post_t$*$two.dep_i$ | 1.9 (1.4) | 2.5. (1.3) | 2.5. (1.3) | 2.5. (1.3) | 0.14 (0.10) | 0.16 (0.09) | 0.16 (0.09) | 0.17* (0.08) | 0.11 (0.07) | 0.12. (0.07) | 0.12. (0.07) | 0.13. (0.07) |
| $SEITC_s$*$Post_t$ | −3.3* (1.3) | −4** (1.2) | −4.2** (1.2) | −2.2 (3.2) | −0.28*** (0.07) | −0.3*** (0.07) | −0.31*** (0.07) | −0.32*** (0.08) | −0.18* (0.06) | −0.2** (0.06) | −0.22** (0.06) | −0.18* (0.08) |
| State fixed effects | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No |
| Division fixed effects | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| Period fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual/household controls | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| State-level temporal controls | No | No | Yes | Yes | No | No | Yes | Yes | No | No | Yes | Yes |
| Division-period interaction | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| $R^2$ | 0.01 | 0.07 | 0.07 | 0.07 | 0.01 | 0.07 | 0.07 | 0.07 | 0.01 | 0.07 | 0.07 | 0.07 |

Notes: Sample (N = 97,303) consists of respondents from the Household Pulse Survey week 10 to week 39 with at least one dependent below 18 in the household and with pre-tax annual household income below $50,000 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states). Individual/household controls are household size, age, annual household income, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are in parentheses and are clustered at the state level

Significance codes: '***' $p < 0.001$, '**' $p < 0.01$, '*' $p < 0.05$, '.' $p < 0.1$

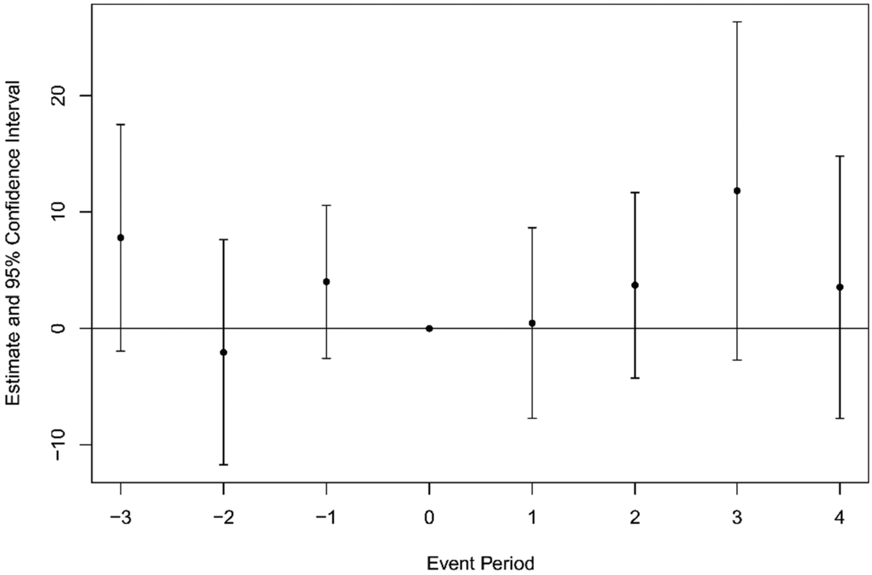


**Fig. 5** Heterogeneity in the effect of state EITC eligibility on food insufficiency based on one dependent vs. two or more dependents among the eligible over the bimonthly post-treatment periods. Notes: Period 0 refers to January-February, 2021. Sample ($N = 97{,}303$) consists of respondents from the Household Pulse Survey week 10 to week 39 with at least one dependent below 18 and pre-tax annual household income below $50,000 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states). Individual/household controls are household size, age, annual household income, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are clustered at the state level. The error bars show 95% confidence intervals

bimonthly periods. Although several existing studies, for example, Averett and Wang (2018) and Meyer (2002), suggest that EITC eligibility has a greater effect on a multitude of outcomes (such as employment, home environment quality for children, children's health, etc.) among households with two or more children compared to households with only one child, these studies do not consider any food hardship measure as the outcome variable. Moreover, these studies investigate the effect across years in the context of federal EITC expansions. The finding of this paper–suggesting no variation in the effect of state EITC eligibility on food insufficiency between households with one dependent and households with two or more dependents – is not necessarily contradictory to the existing literature, given the differences in research questions and study designs.

## 6 Discussion and conclusion

Consistent with the findings of Rehkopf et al. (2014) and Batra and Hamad (2021), the results of the models estimated using DD and DDD methods indicate that state EITC eligibility, on average, reduced food insufficiency by about 3 percentage points among the eligible households with dependent children between March 2021 and early October 2021. Given that the average state-EITC-eligible households from the treated states were eligible to receive an amount approximately between $100 and $950 and households in the lowest quintile, on average, spent about $94 per week on food in 2021 (Economic Research Service, 2022b), the critical question is: for how long did this relatively small amount of cash reduce food insufficiency? To investigate the possibility of temporal heterogeneity in the effect, I estimated models using an event study method. Although findings vary based on the model specifications and the usage of survey weights, they generally suggest that the effect was not significantly different from 0 in all post-March bimonthly periods. Findings of some of the event study models indicate that state EITC eligibility reduced food insufficiency over a bimonthly period. All things considered, these findings provide some evidence that state EITC eligibility reduced food insufficiency among eligible households with dependent children over a short period in 2021.

In terms of understanding the possible short-term effect of state EITC eligibility on food insufficiency, it is essential to consider how people spend their tax credit benefits. In the existing literature, several studies find that EITC recipients mostly pay down their debt and increase consumption in the short run (Despard et al., 2015; Sykes et al., 2015). Contrary to these findings, Goodman-Bacon and McGranahan (2008) and Romich and Weisner (2000) find that EITC-eligible households become more likely to purchase big-ticket items (for example, vehicles and other durable goods) in response to tax credit payments. Furthermore, Romich and Weisner (2000) argue that people perceive lump-sum tax money differently from periodic income, which aligns with the behavioral life-cycle hypothesis (Shefrin & Thaler, 1988). If the average EITC recipient allocates tax credit benefits mostly to pay down debt and/or buy expensive items, the implication is that they cannot use these benefits to meet the necessities of life over an extended period. Moreover, as reported by the IRS, about a quarter of federal-EITC-eligible households do not claim benefits. The same may be true in the case of claiming state EITC benefits. Overall, given the relatively small amount of benefits, the spending patterns of the recipients, and the fact that many eligible households leave benefits on the table, the small effect of state EITC eligibility on food insufficiency – in terms of both magnitude and time span – does not seem surprising.

Similar to many existing studies on the effect of EITC, this paper has several limitations. First, based on the HPS data, we cannot accurately identify who the state EITC recipients were and exactly when they received the benefits. In reality, the reception of EITC benefits, and not just the eligibility, can affect food hardship. Due to this limitation, the causal estimand targeted in this study is an intent-to-treat effect (ITT) which is possibly lower than the average treatment effect on the treated (ATT). In the empirical literature, this issue will continue to exist unless the publicly available surveys include questions that directly ask about the reception of tax credit benefits (i.e., whether a respondent's household received and when they received). Second, because the HPS is a repeated cross-section (not a panel), this paper could not control for household fixed effects, which would have strengthened the identification strategy. Third, sample sizes become smaller at the state-bimonthly-period level, which makes the event study estimates less precise. Also, the event study estimates are sensitive to the usage of person-level weights provided in the HPS. Fourth, this paper ignored the HPS respondents who did not answer the food insufficiency question. If the responders differ from the non-responders, the estimates may be biased. Fifth, this paper investigated the effect of state EITC eligibility in the context of a global pandemic; therefore, the generalizability of the findings beyond this particular period may be limited. Also, as many events were happening simultaneously in 2021, the estimated models may not have controlled for all the time-varying confounding variables. Sixth, food insufficiency, the outcome measure used in this study, is a more severe condition than food insecurity, the outcome measure used in most studies. This limitation makes it difficult to compare this study's findings against the existing studies' findings. Nevertheless, the results of this study have several empirical, theoretical, and policy implications. Below I elaborate on how the results can inform both practitioners and policymakers.

In terms of evaluating the effect of tax credit programs on food hardship and other self-reported measures of material hardship, we should not ignore the crucial fact that these measures are states and not traits; therefore, the temporal component in the measurement process is of paramount importance. For example, because most EITC recipients receive the benefits as a lump-sum payment sometime between late February and April, a paper that uses data gathered in March may find a significant reduction in a self-reported measure of material hardship. However, given the financial struggles experienced by many lower-income households with dependent children, another study that analyzes data on the same outcome—but collected in November—may not find any statistically significant effect of the policy despite using the same survey questionnaire and an identical empirical strategy. Consequently, if self-reported measures of material hardship are used for policy evaluation purposes, data should be gathered in regular intervals over the months of a calendar year. The HPS provides an excellent source of high-frequency data on several indicators of material hardship. The continuation of the HPS and/or the introduction of similar surveys will be beneficial for policy evaluation. At the same time, the availability of high-frequency data will not be sufficient unless researchers estimate appropriate empirical models. Although it is difficult to decide which model sufficiently approximates reality, the findings of this paper suggest that the application of a less appropriate empirical strategy, despite the usage of high-frequency data, may mask the temporal heterogeneity in the effect of a lump-sum cash transfer program.

Theoretically, given the existence of cyclical food hardship, a relevant question for household economics is: under what time interval do households smooth consumption (as assumed in many standard models of consumption)? For example, does the average lower-income household with children smooth consumption of essential goods and services from year to year but struggle to achieve the same from month to month within a calendar year? Lastly, from a policy perspective, the crucial question is: which policy actions can help these households solve their cyclical material hardships? With regard to EITC programs, one possible policy action is to reintroduce the option of claiming advanced periodic payments. In this context, investigating the effect of the periodic Advance Child Tax Credit payments, as provided in

2021, on different indicators of material hardship can be helpful. The success of such an investigation will depend on the availability of high-frequency and high-quality data and the estimation of appropriate empirical models with explicit discussions on causal identification assumptions.

**Data availability** This paper uses publicly available Household Pulse Survey data. It can be found here: https://www.census.gov/programs-surveys/household-pulse-survey/datasets.html.

**Acknowledgements** The author thanks Michael Collins, Yiwei Zhang, Jeffrey Smith, Judith Bartfeld, and Sarah Halpern-Meekin for their helpful comments and suggestions. The author would also like to thank the two anonymous reviewers for their thoughtful questions and suggestions, which helped improve this manuscript.

**Author contributions** The author confirms sole responsibility for the following: study conception and design, data analysis, interpretation of results, and manuscript preparation.

**Compliance with ethical standards**

**Conflict of interest** The authors declare no competing interests.

## 7 Appendix

### Assumptions for interpreting the coefficient of $SEITC_s*Post_t$ (continuous treatment) in Eq. 1 in causal terms

1. Strong parallel trends: For all the values of the state EITC eligibility, the average change in food insufficiency over time across all respondents had they been eligible to receive a particular level of benefit is the same as the average change in food insufficiency over time for all respondents who were eligible to receive the same level of benefit.
2. Treatment effect homogeneity:

i. *No treatment effect dynamics:* The effect of state EITC eligibility on food insufficiency is identical over time.
ii. *Homogenous casual response across groups:* The effect of state EITC eligibility on food insufficiency is identical for every respondent in the dataset regardless of their state of residence (and other group characteristics such as race, ethnicity, income, etc., if control variables are added to the model).
iii. *Homogenous causal response across dosage:* Food insufficiency changes to the same extent with every additional unit change in state EITC eligibility.

Figures 6–9; Tables 7–10

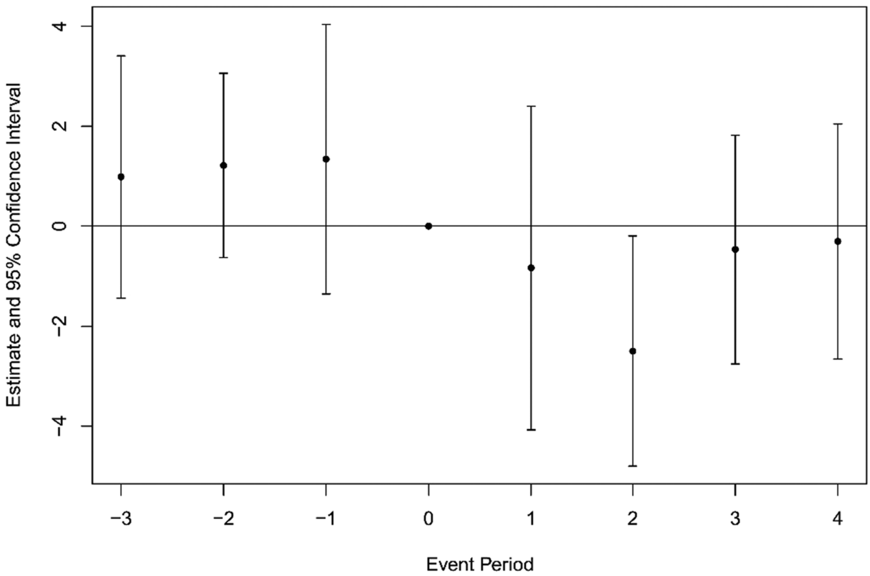


**Fig. 6** Effect of state EITC eligibility on food insufficiency among the eligible over the bimonthly periods (DD event study, unweighted). Notes: Period 0 refers to January–February, 2021. Sample ($N = 97{,}303$) consists of respondents from the Household Pulse Survey week 10 to week 39 with at least one dependent below 18 in the household and with pre-tax annual household income below $50,000 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states). Individual/household controls are household size, age, annual household income, number of dependents below 18, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are clustered at the state level. The error bars show 95% confidence intervals

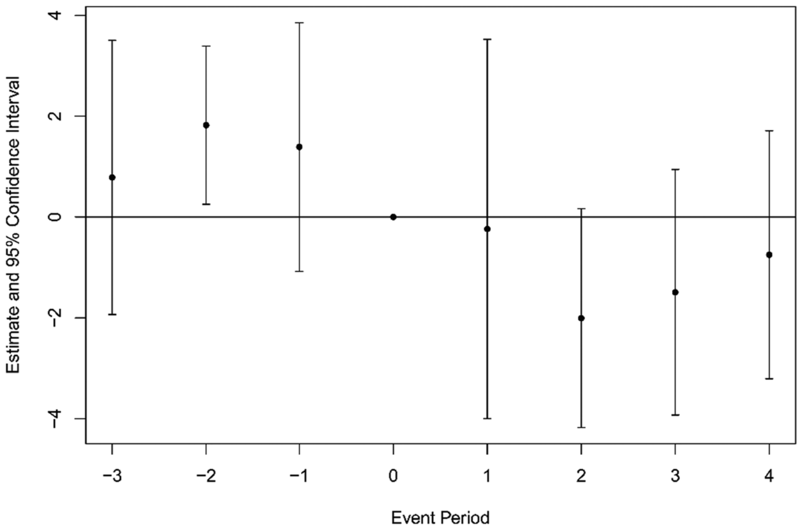


**Fig. 7** Effect of state EITC eligibility on food insufficiency among the eligible over the bimonthly periods (DDD event study, unweighted). Notes: Period 0 refers to January-February, 2021. Sample ($N = 244{,}975$) consists of respondents from the Household Pulse Survey week 10 to week 39 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states) and from two types of households: (1) at least one dependent below 18 and pre-tax annual household income below \$50,000 and (2) no dependents below 18 and pre-tax annual household income above \$25,000 and below \$50,000. Individual/household controls are household size, age, annual household income, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are clustered at the state level. The error bars show 95% confidence intervals

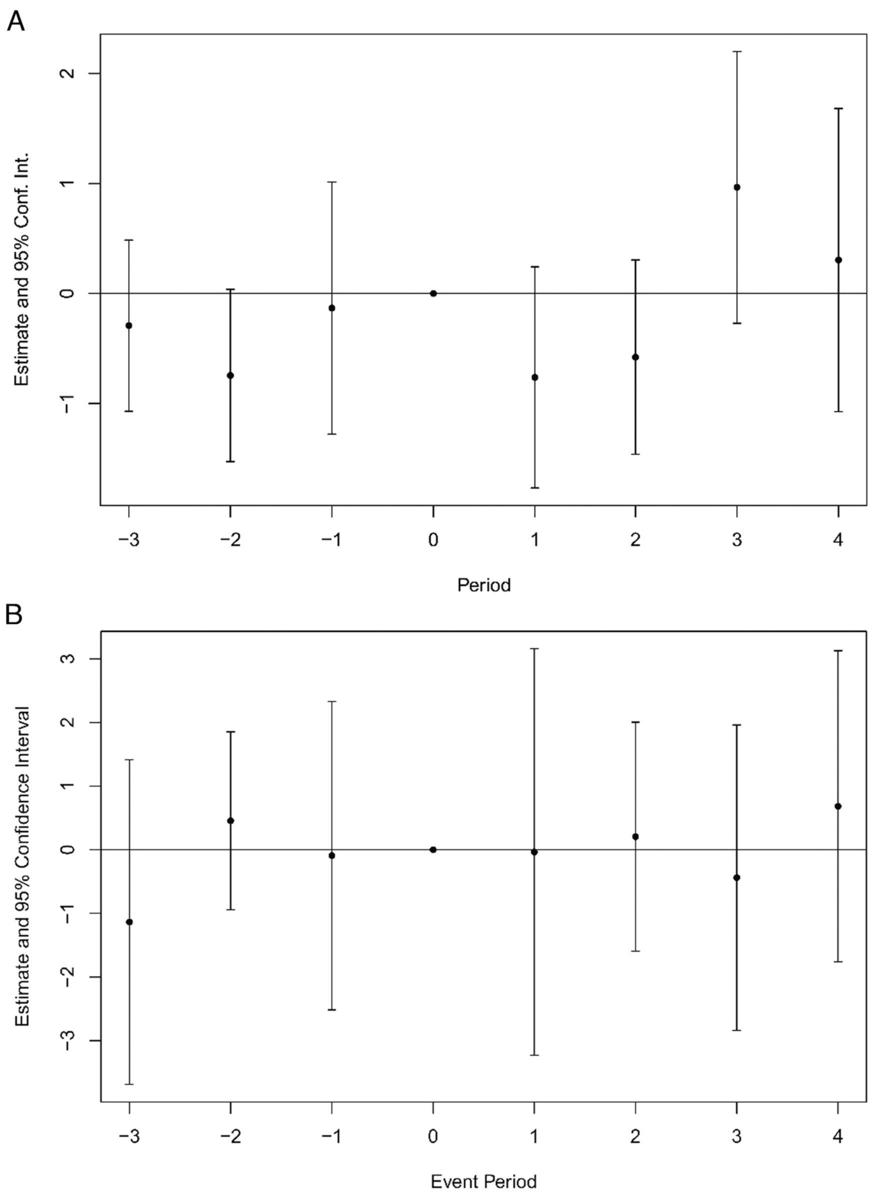


**Fig. 8** Effect of state EITC eligibility on food insufficiency among the ineligible over the bimonthly periods (DD, falsification study). Panel **A** and Panel **B** show unweighted and weighted findings, respectively. Notes: Sample ($N = 147{,}672$) consists of respondents from the Household Pulse Survey week 10 to week 39 with no dependents below 18 in the household and with pre-tax annual household income above \$25,000 and below \$50,000 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states). Individual/household controls are household size, age, annual household income, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are in parentheses and are clustered at the state level. Significance codes: '***' $p < 0.001$, '**' $p < 0.01$, '*' $p < 0.05$, '.' $p < 0.1$

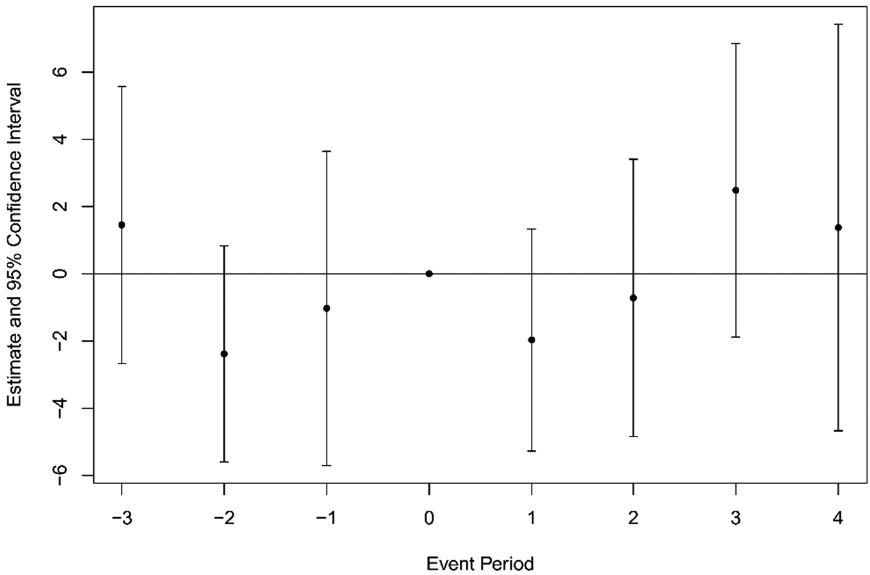


**Fig. 9** Heterogeneity in the effect of state EITC eligibility on food insufficiency based on one dependent vs two or more dependents among the eligible over the post-treatment bimonthly periods (Unweighted). Notes: Period 0 refers to January-February, 2021. Sample ($N = 97{,}303$) consists of respondents from the Household Pulse Survey week 10 to week 39 with at least one dependent below 18 in the household and with pre-tax annual household income below \$50,000 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states). Individual/household controls are household size, age, annual household income, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are clustered at the state level. The error bars show 95% confidence intervals

**Table 7** Effect of state EITC eligibility on food insufficiency among the eligible in the post-treatment period (DD, unweighted)

| | Binary Treatment | | | | Continuous Treatment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Maximum State EITC ($100) | | | | State EITC as % of Federal EITC | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $SEITC_s{*}Post_t$ | −2.4*** (0.63) | −2.2*** (0.56) | −2.2*** (0.54) | −0.5 (1.2) | −0.15*** (0.03) | −0.15*** (0.03) | −0.15*** (0.03) | −0.16*** (0.03) | −0.09** (0.03) | −0.09** (0.03) | −0.09** (0.02) | −0.06. (0.03) |
| State fixed effects | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No |
| Division fixed effects | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| Period fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual/ household controls | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| State-level temporal controls | No | No | Yes | Yes | No | No | Yes | Yes | No | No | Yes | Yes |
| Division-period interaction | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| $R^2$ | 0.01 | 0.07 | 0.07 | 0.08 | 0.01 | 0.07 | 0.07 | 0.08 | 0.01 | 0.07 | 0.07 | 0.08 |

Sample ($N = 97{,}303$) consists of respondents from the Household Pulse Survey week 10 to week 39 with at least one dependent below 18 in the household and with pre-tax annual household income below $50,000 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states). Individual/household controls are household size, age, annual household income, number of dependents below 18, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are in parentheses and are clustered at the state level

Significance codes: ‘***’ $p < 0.001$, ‘**’ $p < 0.01$, ‘*’$p < 0.05$, ‘.’$p < 0.1$

**Table 8** Effect of state EITC eligibility on food insufficiency among the eligible in the post-treatment period (DDD, unweighted)

| | Binary treatment | | | | Continuous treatment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Maximum State EITC ($100) | | | | State EITC as % of Federal EITC | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $SEITC_s$*$Post_t$*$DEp_i$ | −2.4** (0.71) | −2.4** (0.66) | -2.3** (0.66) | −2.1** (0.69) | −0.16*** (0.03) | −0.16*** (0.03) | −0.16*** (0.03) | −0.12*** (0.03) | −0.10** (0.03) | −0.10** (0.03) | −0.10** (0.03) | −0.08** (0.03) |
| $SEITC_s$*$Post_t$ | 0.07 (0.34) | 0.13 (0.32) | 0.13 (0.28) | 0.04 (0.41) | 0.01 (0.02) | 0.009 (0.01) | 0.009 (0.01) | -0.04* (0.02) | 0.007 (0.01) | 0.007 (0.01) | 0.010 (0.01) | -0.02 (0.02) |
| State fixed effects | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No |
| Region fixed effects | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| Period fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual/household controls | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| State-level temporal controls | No | No | Yes | Yes | No | No | Yes | Yes | No | No | Yes | Yes |
| Region-period interaction | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| $R^2$ | 0.03 | 0.09 | 0.09 | 0.09 | 0.03 | 0.09 | 0.09 | 0.09 | 0.03 | 0.09 | 0.09 | 0.09 |

Sample ($N = 244{,}975$) consists of respondents from the Household Pulse Survey week 10 to week 39 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states) and from two types of households: (1) at least one dependent below 18 and pre-tax annual household income below $50,000 and (2) no dependents below 18 and pre-tax annual household income above $25,000 and below $50,000. Individual/household controls are household size, age, annual household income, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are in parentheses and are clustered at the state level

Significance codes: '***' $p < 0.001$, '**' $p < 0.01$, '*'$p < 0.05$, '.'$p < 0.1$

**Table 9** Effect of state EITC eligibility on food insufficiency among the ineligible in the post-treatment period (DD, falsification test)

(Unweighted)

| | Binary treatment | | | | Continuous treatment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Maximum State EITC ($100) | | | | State EITC as % of Federal EITC | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $SEITC_s*Post_t$ | 0.1 (0.35) | 0.15 (0.32) | 0.18 (0.29) | −0.11 (0.13) | 0.01 (0.02) | 0.009 (0.01) | 0.01 (0.02) | −0.02 (0.02) | 0.007 (0.01) | 0.007 (0.01) | 0.01 (0.01) | -0.03 (0.02) |
| State fixed effects | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No |
| Division fixed effects | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| Period fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual/household controls | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| State-level temporal controls | No | No | Yes | Yes | No | No | Yes | Yes | No | No | Yes | Yes |
| Division-period interaction | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| $R^2$ | 0.003 | 0.06 | 0.06 | 0.06 | 0.003 | 0.06 | 0.06 | 0.06 | 0.003 | 0.06 | 0.06 | 0.06 |

(Weighted)

| | Binary Treatment | | | | Continuous treatment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Maximum State EITC ($100) | | | | State EITC as % of Federal EITC | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $SEITC_s*Post_t$ | 0.49 (0.52) | 0.35 (0.53) | 0.34 (0.48) | 1.4 (1.3) | 0.02 (0.04) | 0.02 (0.04) | 0.02 (0.04) | -0.003 (0.04) | 0.04 (0.03) | 0.03 (0.03) | 0.04 (0.03) | 0.05 (0.05) |
| State fixed effects | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No |
| Division fixed effects | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| Period fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual/household controls | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| State-level temporal Controls | No | No | Yes | Yes | No | No | Yes | Yes | No | No | Yes | Yes |

**Table 9** continued

(Weighted)

| | Binary Treatment | | | | Continuous treatment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Maximum State EITC ($100) | | | | State EITC as % of Federal EITC | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Division-period interaction | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| $R^2$ | 0.004 | 0.07 | 0.07 | 0.07 | 0.004 | 0.07 | 0.07 | 0.07 | 0.004 | 0.07 | 0.07 | 0.07 |

Sample ($N = 147{,}672$) consists of respondents from the Household Pulse Survey week 10 to week 39 with no dependents below 18 in the household and with pre-tax annual household income above $25,000 and below $50,000 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states). Individual/household controls are household size, age, annual household income, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are in parentheses and are clustered at the state level

Significance codes:'***' $p < 0.001$, '**' $p < 0.01$, '*' $p < 0.05$, '.' $p < 0.1$

**Table 10** Heterogeneity in the effect of state EITC eligibility on food insufficiency based on one dependent vs. two or more dependents among the eligible in the post-treatment period

(Unweighted)

| | Binary treatment | | | | Continuous treatment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Maximum state EITC ($100) | | | | State EITC as % of Federal EITC | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $SEITC_s$*$Post_t$*$two.dep_i$ | −0.17 (0.97) | 0.4 (0.77) | 0.42 (0.77) | 0.34 (0.80) | -0.02 (0.08) | 0.01 (0.06) | 0.01 (0.06) | 0.06 (0.08) | 0.02 (0.04) | 0.03 (0.03) | 0.03 (0.03) | 0.04 (0.03) |
| $SEITC_s$*$Post_t$ | −2.2** (0.72) | −2.4*** (0.61) | −2.4*** (0.59) | −1.2 (1.2) | −0.14** (0.04) | −0.15*** (0.03) | −0.16*** (0.03) | −0.19** (0.06) | −0.10** (0.03) | −0.11*** (0.03) | −0.11*** (0.03) | −0.08* (0.03) |
| State fixed effects | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No |
| Division fixed effects | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| Period fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual/household controls | No | Yes | Yes | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| State-level temporal controls | No | No | Yes | Yes | No | No | Yes | Yes | No | No | Yes | Yes |
| Division-period interaction | No | No | No | Yes | No | No | No | Yes | No | No | No | Yes |
| $R^2$ | 0.01 | 0.07 | 0.07 | 0.08 | 0.01 | 0.07 | 0.07 | 0.08 | 0.01 | 0.07 | 0.07 | 0.08 |

Sample ($N = 97{,}303$) consists of respondents from the Household Pulse Survey week 10 to week 39 with at least one dependent below 18 in the household and with pre-tax annual household income below $50,000 living in states that have either only refundable state EITC programs (treated states) or no tax credit program (control states). Individual/household controls are household size, age, annual household income, marital status, race, Hispanic status, female indicator, educational attainment, homeownership status, and employment status in the last 7 days. State-level temporal controls are covid case count per capita, number of deaths per capita, and unemployment rate in the bimonthly periods. Standard errors are in parentheses and are clustered at the state level

Significance codes: '***' $p < 0.001$, '**' $p < 0.01$, '*' $p < 0.05$, '.' $p < 0.1$

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